REAL TIME PIXELATED CAMOUFLAGE TEXTURE GENERATION

A thesis submitted to the
UPES

For the award of
Doctor of Philosophy
in
Computer Science & Engineering

BY
SACHI CHOUDHARY

April 2023

SUPERVISOR
DR. RASHMI SHARMA

Department of Computer Science & Engineering
School of Computer Science
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SUPERVISOR
DR. RASHMI SHARMA
Former Assistant Professor (Selection Grade)
School of Computer Science
UPES, Dehradun, India
Currently, Associate Professor
Shri Vaishnav Institute of Computer Applications,
Indore, Madhya Pradesh, India

Department of Computer Science & Engineering
School of Computer Science
UPES, Dehradun-248007; Uttarakhand
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DECLARATION

I declare that the thesis entitled **"Real Time Pixelated Camouflage Texture Generation"** has been prepared by me under the guidance of Dr. Rashmi Sharma (Supervisor), Former Assistant Professor (Selection Grade), School of Computer Science, UPES, Dehradun, Associate Professor, Shri Vaishnav Institute of Computer Applications, Indore, Madhya Pradesh, India. No part of this thesis has previously formed the basis for the award of any degree or fellowship.

Sachi Choudhary
School of Computer Science
UPES, Dehradun
Uttarakhand, India
Date: 03rd April 2023

CERTIFICATE

I certify that Ms. Sachi Choudhary has prepared her thesis entitled "Real Time Pixelated Camouflage Texture Generation", for the award of PhD degree of the UPES, Dehradun, India, under my guidance. She has carried out the work at the School of Computer Science, UPES, Dehradun, India.

Supervisor
Dr. Rashmi Sharma
Former Assistant Professor (Selection Grade)
School of Computer Science
UPES, Dehradun, India
Currently, Associate Professor
Shri Vaishnav Institute of Computer Applications,
Shri Vaishnav Vidhyapeeth Vishwavidyalaya,
Indore, Madhya Pradesh, India

Date-20/08/2023

ABSTRACT

For defence organizations, secrecy is critical. Camouflage is one method of accomplishing this goal. There are numerous examples from ancient wars where camouflage was used. During World War I, the French military relied on camouflage to hide military equipment from the eyes of the enemy. During World War II, camouflage became a science rather than a military art form. That historical period saw an increase in the demand for defence against photography and human visual observation to locate a wide variety of military objects. This sparked a scientific revolution in the fields of camouflage and deception.

Camouflage is the way to match the surroundings by adapting to natural uniformity in color, shape, texture and other perceived environmental factors. Many species and the armed forces use camouflage to hide from predators. Species with camouflage ability analyze their surroundings to change their skin color and/or pattern accordingly. Camouflage is also used by militaries to hide the presence and position from enemy. Reducing and hiding identities in background environments is a major area of concern for Army vehicles, equipment, and soldiers. Traditional camouflage patterns used by the armed forces depend on the designer's experience and include irregular spot shapes and stripes. It may also have poor and unmatched color combinations with the area in which it is to be used. The reason camouflage technology is used to hide in the surrounding environment is directly related to the psychological aspect of human vision and the brain. The ability of the human eye to detect any object around depends on the size and shape of its boundaries and the reflection of light from that object.

The evolution of military standard camouflage patterns and color combination have a big history with improvements in its accuracy and performance. Research conducted from different perspectives by researchers has explored this area in detail. To work with changeable environment, the camouflage pattern must blend with its surrounding. Therefore, this is an area of interest among researchers to develop an adaptive camouflage system, which can generate the color and pattern

depending on the surroundings. Many researchers over the year have contributed their findings in this area to produce effective camouflage patterns.

It is critical to understand the real environment in which the military forces are deployed. The army personal and equipment needs to be camouflaged for self-defence and greater concealment. The industry demands an intelligent system that can categorize the battlefield before generating texture for camouflaging their assets and objects, allowing them to adopt the conspicuous features of the scene. A novel pixelated camouflage texture generation method for real time environment is proposed to achieve the objectives. The technique consists of four main modules, one is Terrain Classification Model (TerrainCNN), color clustering, shape selection and texture generation, and finally model evaluation. A Convolutional Neural Network (CNN) - based battlefield classification model has been developed to learn background information and to classify the terrain into three categories-Desert land, Forest area and Snowfield. Color clustering using K-means has been used to obtain the primary perceiving colors in the background image. Various shapes of different dimensions are stretched onto a blank canvas and then filled in the respective proportions of standardized primary colors. The study also intended to develop the texture for specific terrain by matching its salient features and boosting the effectiveness of the camouflage.

Experiments have been carried out to detect camouflage object(s) in the scene to evaluate the performance of the resultant camouflage texture generated for a real time environment. Photo simulation and saliency maps for hidden object detection have been used to evaluate the effectiveness of generated textures.. A saliency map was utilized to assess the efficiency of camouflage textures produced during experimentations. The performance of the camouflage texture generated for a specific scene demonstrates effectiveness of object concealing and blending in the surrounding environment. The generated patterns can be utilized to conceal army personnel, vehicles, and weaponry from direct enemy vision.

ACKNOWLEDGMENT

I would like to express my deep appreciation to my PhD supervisor, Dr. Rashmi Sharma, for her unwavering support and guidance throughout my PhD journey. Her exceptional expertise, patience, and encouragement has been invaluable in shaping my research and helping me grow as a scholar.

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I would like to express my heartfelt gratitude to my parents, in-laws and brother for their unwavering love, support, and encouragement throughout my academic journey. Their guidance, sacrifices, and belief in me have been instrumental in shaping me as a person and a scholar.

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Last, I would like to dedicate a small line to my 4-year-old kid Adhyansh. Your contagious energy, innocent laughter, and endless hugs reminded me of what is truly important in life and motivated me to complete my thesis.

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
CNN	Convolutional Neural Network
CV	Computer Vision
DCNet	Diffusion Convolutional Network
DDCN	Dense De-convolution Network
DIP	Digital Image Processing
DL	Deep Learning
FCM	Fuzzy C-Means
GAN	Generative Adversarial Network
GC	Global Contrast
GCNN	Graph Convolutional Neural Network
GM	Geometric Mean
HC	Histogram Contrast
HM	Harmonic Mean
HSV	Hue, Saturation, and Value
LED	Light Emitting Diode
ML	Machine Learning
NATO	North Atlantic Treaty Organization
PSO	Particle Swarm Optimization
RC	Region Contrast
RGB	Red, Green, Blue
SINet	Search & Identification Net
SOAT	State of Art Techniques
YOLO	You Look Only Once

CHAPTER - 1

INTRODUCTION AND ORGANIZATION OF THESIS

1. INTRODUCTION AND ORGANIZATION OF THESIS

1.1. Overview

Many bio-species and military forces employ camouflage to hide from predators and go unnoticed. Camouflage has been used to hide soldiers and equipment on the battlefield for decades. As technology grows and impacts every industry, this research intends to implement a digital system to generate an effective camouflage texture for a real environment. This chapter aims to introduce the field of study, the biological camouflaging techniques that motivated it, and its importance in the defence industry. The report's overall structure is laid out in this chapter as well.

1.2. Camouflage

Camouflage is word in French that means "disguise," (Rao, 1999), which refers to efforts used to deceive the enemy by misrepresenting the genuine character of a living organism, or any non-living object. It refers to the employment of colors and textures similar to those found in the surrounding environment to conceal something or to disguise oneself as someone else. It is the process of concealing something from view or giving it the appearance of something else by using colors and textures that blend in with the surroundings (Eysenck, 1940; Y. Li & Correll, 2018; Merilaita et al., 2017). Both nature and humans have used camouflage for generations. When battling for survival, camouflage is used to get near the prey to overwhelm it or trick the enemy using camouflaging tactics (Baumbach, 2012). Figure 1-1 shows some sample images of camouflaged animals and body painted person concealed in surrounding environment.

1.2.1. Visual Camouflage

Visual camouflage, a technique used to blend an object with its surroundings, making it difficult to see or detect (*Camouflage, Concealment, and Decoys*, 2010; Rao, 1999; Tankus & Yeshurun, 2001). Camouflaging effect can be achieved using various ways, including color matching, texture matching, and shape modification. In nature, animals often use visual camouflage to protect themselves from predators or to hunt prey more effectively (Caro et al., 2017; Cuthill & Troscianko, 2009; Merilaita et al., n.d.; Stevens & Merilaita, 2009). In military and tactical situations, visual camouflage can be used to conceal soldiers and equipment from enemy forces (Hua et al., 2018; Talas et al., 2017). Visual camouflage can be used in design and art for aesthetic or creative purposes.

1.3. Camouflage in nature

Camouflage is the ability of an animal to blend in with its atmospheres to avoid being perceived by predators or prey. This can be achieved through a variety of means, including physical adaptations, such as coloring or patterning that matches the background, or behavioral adaptations, such as remaining motionless or making very little noise. The ability of some biological creatures to change their skin color and texture to blend into their surroundings has inspired military camouflage (Houston et al., 2007; Y. Li & Correll, 2018; Niu et al., 2018; Stevens & Merilaita, 2009). Therefore, a study has been done to analyze natural camouflage ways employed by bio-species taxonomy to get concealment.

Self-preservation is a significant issue in biological evolution. Survival requires the ability to adapt to a changing environment. Every animal in a food chain is preyed upon. Both predators and prey should devise techniques to survive, and they use a variety of methods, including camouflage, to remain unnoticed (R. Hanlon, 2007; R. T. Hanlon et al., 2009; Stevens et al., 2006). Camouflage is an important survival strategy for many species, as it can help them avoid being detected and captured by predators. For prey species, this can mean the difference between life and death. Similarly, predators may use camouflage to sneak up on their prey or to avoid being detected by other predators.

In addition to helping animals avoid detection, camouflage can also be used for other purposes, such as attracting mates or communicating with other members of the same species. For example, some species use bright colors or patterns as a form of sexual dimorphism, with males and females having distinct markings that help them identify each other.

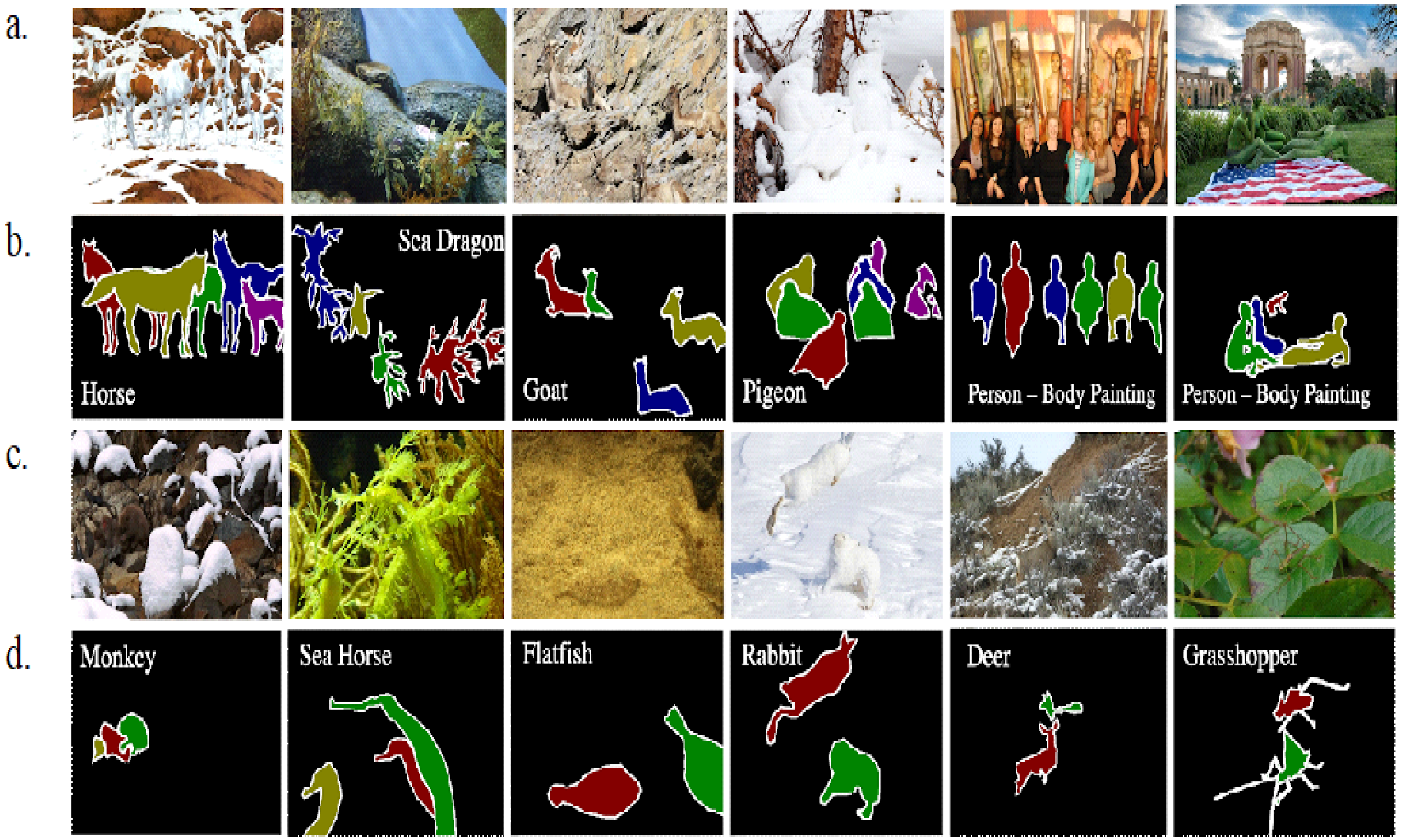


Figure 1-1: a) & c) Images containing camouflaged animals or body painted human, b) & d) Segmented camouflaged objects) (Le et al., 2022)

Camouflage is a common adaptation found in many different species living in a various habitats and regions around the globe. Some examples of animals that use camouflage include:

- *Chameleons:* These lizards are well-known for their ability to alter the coloration of their outer skin to blend in with their environment. They do this by controlling the pigments in their skin cells, which allows them to match the colors and patterns of their environment.
- *Leaf insects:* These insects are found in tropical regions and are known for their ability to closely resemble leaves. They have thin, elongated bodies and legs that easily blend in with the leaves of trees and plants.
- *Snow leopards:* These big cats are found in the snowy, mountainous regions of Central and South Asia. They have thick fur coats that are white or pale grey, which helps them blend in with the snow and rocky terrain of their habitat.
- *Cuttlefish:* These marine creatures are found in the shallow waters of the Mediterranean and the eastern Atlantic Ocean. They can change their skin colors and pattern to blend in with their surroundings.
- *Arctic foxes:* These small, arctic-dwelling mammals have a thick, white coat of fur that helps them blend in with the snow and ice of their habitat. In the summer months, their coat turns a brownish-grey color to match the tundra.

There is a long history of camouflage research in biology due to the wide variety of hiding and disguising mechanisms in the animal territory (Merilaita et al., n.d.; Stevens & Merilaita, 2009). Therefore, camouflage in its many varieties is now a classic case of evolutionary change. The most popular method many organisms employ to express their emotions and hide from predators is camouflage. Animals with the ability to disguise themselves study their environment and alter their pattern or color of skin to blend in (Duarte et al., 2017, 2018). Figure 1-2 shows the images of some bio species having capabilities of camouflaging themselves. The images are taken from CAMO++ dataset (Le et al., 2019).

1.3.1.1. Characteristics of visual camouflage in nature

Visual camouflage is the utilization of color, pattern, or other physical features to blend in with the surroundings to avoid being noticed. Some characteristics of visual camouflage include (Duarte et al., 2017; Jia et al., 2016; Y. Li et al., 2022; Ramsley, 1979; Rao, 1999):

- *Color matching:* Many animals use coloration that matches the colors of their surroundings to blend in. For example, a grasshopper living in a grass field may have a green body that helps it blend in with the grass.
- *Pattern matching:* Some animals have patterns on their bodies that help them blend in with their surroundings. For example, a leopard living in a forest may have spots that resemble the dappled sunlight on the forest floor.
- *Shape matching:* Some animals have physical adaptations that help them blend in with their surroundings by resembling specific shapes or structures. For example, the octopus has the ability to change the shape of its body to resemble rocks or coral to blend in with its surroundings.

Mimicry: Some animals have physical adaptations that allow them to mimic the appearance of other species to blend in. For example, the viceroy butterfly has markings that resemble those of the poisonous monarch butterfly, which helps it avoid being eaten by predators.

1.4. Camouflage in defence

Soldiers and equipment must be concealed in the surrounding environment on the battlefield. Camouflage in the military serves primarily to conceal the presence, location, and purpose of a military force from the enemy. Figure 1-3 shows some images of camouflaged defence person and objects. Camouflage textures have been used for decades as a deception tool to conceal an individual, vehicles, weapons, aircraft, guided missile deployment positions, landing sites, and many others (TAYLOR, 1959). The use of camouflage in battle went back many centuries and was inspired by bio-species. However, defence forces have been deploying various camouflage techniques since the First and Second World Wars (Rao, 1999).

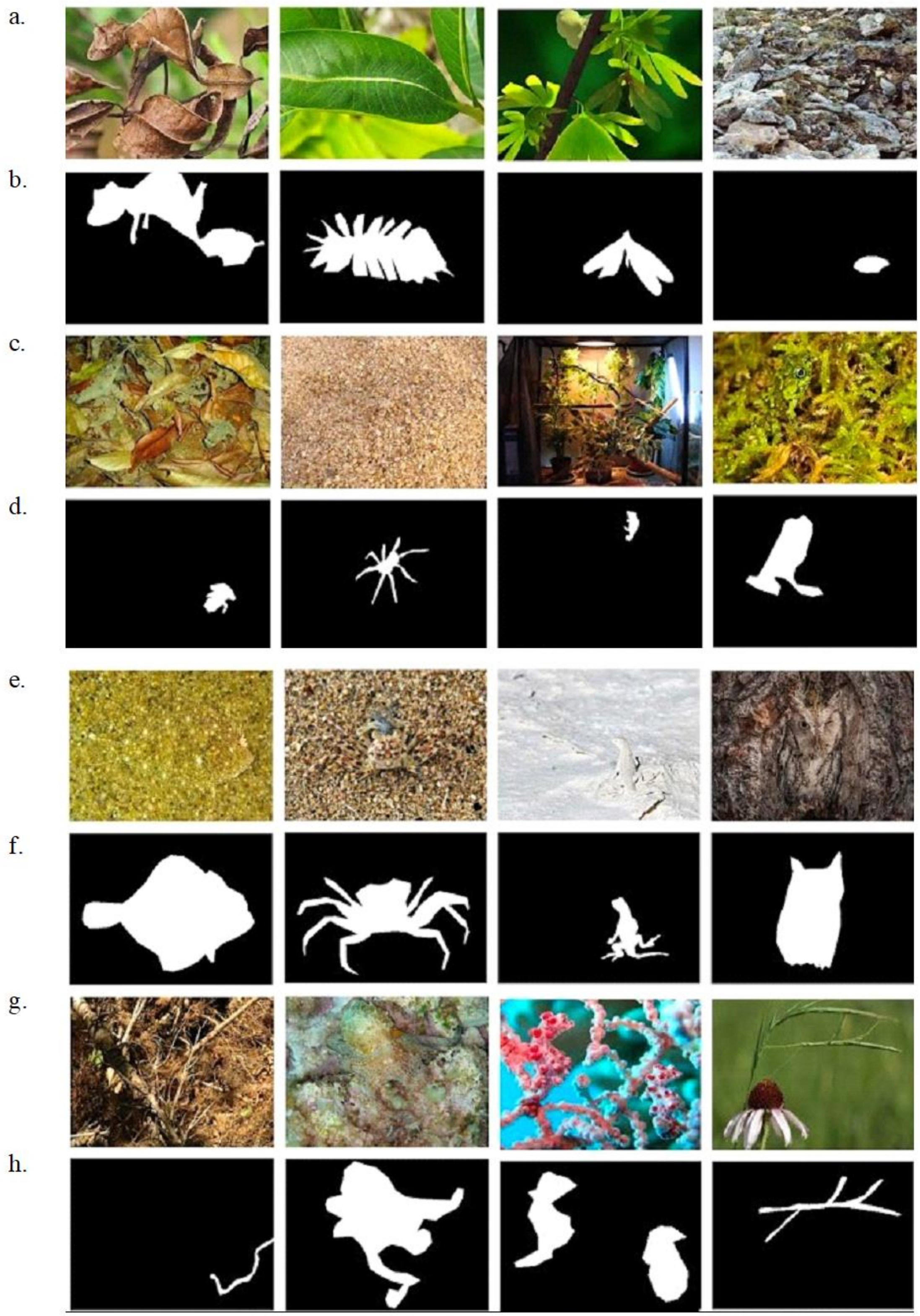


Figure 1-2: a), c), e), and g) Images containing camouflaged bio species, b), d), f) and h) respective ground truth images. (Le et al., 2019)

Camouflage patterns and colors are designed to mimic and match the specific terrain or environment in which they will be used, such as forests, deserts, or urban areas. Traditional and manual methods of camouflage creation were initially used by the military. Using traditional and manual techniques of camouflage production has several problems, such as patterns of varying shape and size, poor color combination, and a lack of strong borders among others ("Camouflage in Modern Warfare," 1940; Dugas et al., n.d.; Thornley, 1940; Wilkinson, 1919). The military has begun adopting digital camouflage designs to overcome the limitations of manual and traditional camouflage. The first country to use digital camouflage (CADPAT) was Canada, according to camopedia. Since then, pixelated camouflage patterns have been used by armed forces in several countries.

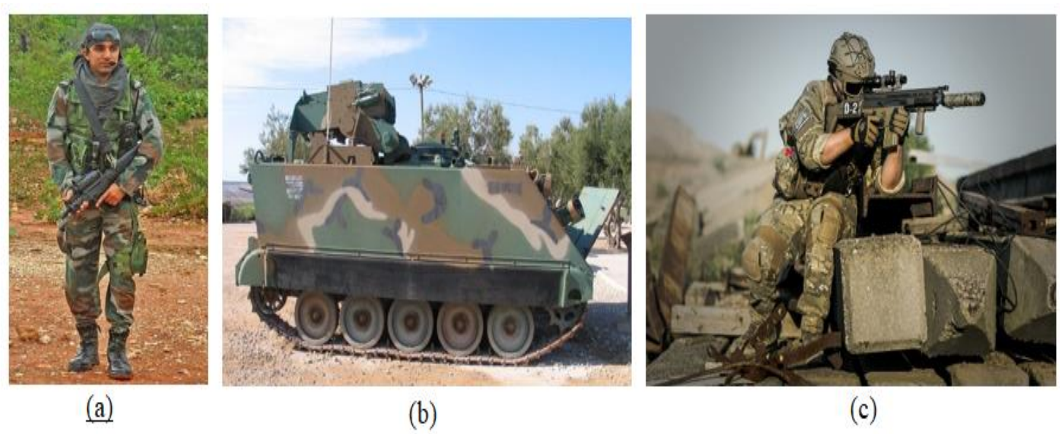


Figure 1-3: Images containing (a)(c) defence personal and (b) equipment (File:M901-TOW-Wikimedia Commons, n.d.; Soldier Near Concrete · Free Stock Photo, n.d.; Kaswa, 2011)

1.4.1. Traditional camouflage

There are several traditional methods for generating textures for camouflage (*Camouflage, Concealment, and Decoys*, 2010; Dugas et al., n.d.; Mortlock, 2018; Talas et al., 2017):

- *Screen printing:* This involves using a screen and ink to transfer a pattern onto a surface. The screen is placed over the surface and ink is forced through the open areas of the screen onto the surface, creating a pattern.

- *Stenciling*: This involves using a stencil and paint to create a pattern on a surface. The stencil is placed over the surface and paint is applied through the open areas of the stencil onto the surface.
- *Hand painting:* This involves using brushes or other tools to apply paint by hand to create a pattern on a surface.
- *Airbrushing:* This involves using an airbrush and paint to create a pattern on a surface. The airbrush uses compressed air to atomize the paint and apply it to the surface.
- *Digital printing:* This involves using a digital printing process to transfer a pattern onto a surface. The pattern is created digitally and then printed onto the surface using specialized equipment.

Some traditional camouflage textures are presented in Figure 1-4.

a) Woodland b) OCP-Woodland c) Multi-terrain pattern d) Canadian disruptive pattern e) Tiger-strip pattern

Figure 1-4: Examples of military camouflage patterns (List of Military Clothing Camouflage Patterns - Wikipedia, n.d.)

Traditional and manual camouflage tactics in defense involve using various methods to conceal soldiers, equipment, and structures from enemy forces. Some common tactics include:

- *Using natural materials:* Soldiers can use branches, leaves, and other natural materials to camouflage themselves and their equipment.
- *Wearing camouflage uniforms:* Soldiers can wear uniforms that use color and texture to blend in with the surrounding environment.
- *Using camouflage netting:* Camouflage netting can be used to cover vehicles, structures, and other equipment to help conceal them.
- *Painting objects:* Objects can be painted with camouflage patterns or colors to help them blend in with their surroundings.

- *Using decoys:* Decoys, such as dummy tanks or aircraft, can be used to mislead enemy forces and divert their attention away from real targets.
- *Using camouflage tents:* Camouflage tents can be used to conceal soldiers and their equipment from enemy observation.
- *Using camouflage screens:* Camouflage screens can be used to block the view of enemy forces, helping to conceal soldiers and their equipment.

1.4.2. Digital camouflage

Digital camouflage is a type of camouflage pattern that uses pixelated shapes and colors to break up the outline of an object. It is often used on military uniforms, vehicles, and equipment. Digital camouflage textures can be created using computer software, such as graphic design programs or specialized camouflage design software (Xue et al., 2016; H. Yang & Yin, 2015; W. D. Xu et al., 2014; Yu & Hu, 2012). The textures can be created and adjusted using various parameters, such as color, shape, and size. There are various computational methods to generate camouflage texture involving the following characteristics:

- *Color matching:* This involves using paint or other materials to match the colors of the surrounding environment. This can help an object blend in with its surroundings and be less noticeable.
- *Texture matching:* This involves using materials with a similar texture to the surrounding environment to help an object blend in. For example, a soldier wearing a camouflage suit with a rough texture might blend in better in a forest than a soldier wearing a smooth suit.
- *Shape modification:* This involves altering the shape of an object to make it blend in with its surroundings. For example, a soldier might use branches or other natural materials to help conceal their outline.
- *Disruptive coloration:* This involves using bold patterns or colors that break up the outline of an object, making it harder to see. This can be effective in certain environments, such as forests or grasslands.
- *Crypsis:* This involves using a combination of color, texture, and shape to conceal an object in its surroundings.

- *Mimicry:* This involves using an object's appearance to mimic something else in the environment, such as a rock or a leaf.
- *Counter-shading:* This involves using a gradient of colors, with the top of an object being darker and the bottom being lighter. This can help an object blend in with the shadows and highlights of its surroundings.
- *Concealment:* This involves using natural or man-made materials to physically cover an object, such as using a camouflage net to cover a vehicle.

1.5. Digital camouflage texture and its need

Traditionally, camouflage patterns used in the defence industry have been designed to mimic the colors and patterns found in natural environments, such as forests, deserts, and grasslands . These patterns typically consist of a combination of colors, such as greens, browns, and grays, arranged in a way that helps break up the wearer's outline or equipment and makes it harder to spot .

One of the main drawbacks of traditional camouflage patterns is that they are often designed for specific environments and may not be as effective in other types of terrain (Baumbach, 2012; "Camouflage in Modern Warfare," 1940). For example, a camouflage pattern designed for use in a forest may not be as effective in a desert or urban environment. Another drawback of traditional camouflage patterns is that they can be disrupted by changes in lighting or background, such as shadows or reflections. This can make it easier for the enemy to spot the wearer or equipment, mainly if the camouflage pattern is not a good match for the environment.

Digital camouflage is a type of camouflage pattern that uses a pixelated design rather than traditional colors and patterns only. Digital camouflage patterns are typically created by overlaying a series of small, random shapes or pixels of various colors in a way that helps to break up the outline of the wearer or equipment and make it harder to spot (Jia et al., 2020; Merilaita et al., 2017; Mortlock, 2018; Toet & Hogervorst, 2020; Xue et al., 2016; Yu & Hu, 2012).

One of the main advantages of digital camouflage is that it is more versatile than traditional camouflage patterns. Digital camouflage patterns can be created for a wide range of environments, and they are not as affected by changes in lighting or background as traditional patterns. This makes them more effective in a variety of different situations.

Another advantage of digital camouflage is that it is more difficult for the enemy to identify the wearer or equipment from various distances. These patterns are less affected by factors like change in background and lightning conditions, making them more effective at longer distances. Digital camouflage patterns are a relatively recent innovation in defence, and they offer a number of advantages over traditional camouflage patterns, including increased versatility and effectiveness at longer distances.

There is a need for a digital method to generate camouflage textures for the defence sector to improve the effectiveness of camouflage patterns. A digital method to generate camouflage textures would allow the defence sector to quickly and easily create custom camouflage patterns for specific environments and make changes to existing patterns as needed. This would help improve camouflage's effectiveness in various situations, making it harder for the enemy to spot soldiers and equipment.

1.6. Camouflage texture effectiveness parameters

Several parameters should be considered when creating digital camouflage patterns for the defence sector (Jia et al., 2017; H. Yang & Yin, 2015; X. Yang et al., 2021). These include :

- *Environment & Background:* The camouflage pattern should be designed to match the specific environment in which it will be used. This may involve using colors and patterns that mimic the natural surroundings, such as trees, rocks, or grass. It should be effective against various backgrounds, including natural and man-made surfaces. This may involve using a combination of different colors and patterns in order to blend in with the surroundings.

- *Distance:* The camouflage pattern should be effective at different distances, including both close range and long range. This may involve using a combination of different colors and patterns to break up the outline of the wearer or equipment.
- *Lighting:* The camouflage pattern should be effective in a variety of lighting conditions, including both daylight and low light. This may involve using colors and patterns less affected by lighting or background changes.

1.7. Plan of thesis

This research aimed to provide a technique for generating camouflage texture considering perceived visual characteristics of the battlefield or the terrain of deployment. This study explored the approaches adopted by bio-species taxonomy to obtain camouflage, also known as natural camouflage and various techniques to generate artificial camouflage textures. Evaluating the artificially generated camouflage texture is very important to ensure whether it can blend the object with its surroundings. The degree of concealment, similarity to the surroundings, visual attention, and human psychology all play vital roles in examining the effectiveness of artificial camouflage patterns. Therefore, this work includes a section covering evaluation parameters and techniques for artificially created camouflage textures. The research work reported in this thesis comprises the following chapters -

Section 1: Introduction and Organization of Thesis

This section introduces camouflage, including examples from the natural world and the defence sector. In addition, a summary of the proposed study can be found in this section.

Section 2: Literature Survey

This section of the report provides a review of the significant prior research literature. Classification of the battlefield and the creation of camouflage texture are the two sub objectives of the proposed work. The literature survey includes these area and other relevant factors for the research study.

Section 3: Methodology & Implementation

This section detail the methodology proposed for generating the pixelated camouflage textures, including all the algorithms and techniques employed. The concept development, research methodology, and implementation of each module are covered in this section.

Section 4: Experimentations, Results and Discussion

This section compiles and presents the experimentations and analysis of experimental results done over resultant camouflage textures. It presents the generated pixelated camouflage textures and evaluate their effectiveness through various metrics. It also includes the discussion about the analysis of the experimental results and assessment comparison with the findings from the literature review.

Section 5: Conclusion and further scope of work

This section summarizes the main contributions of this study and highlight its implications for future research and applications.

CHAPTER - 2

LITERATURE SURVEY

2. LITERATURE SURVEY

2.1. Overview

The aim of this chapter is to specify context for the current study by highlighting the work done in the field and to state the gaps in the existing research that the current study aims to address. This has been accomplished by highlighting the work done in classification of terrains, digital camouflage texture generation and their assessment methods. This chapter aims to present the literature review for the three critical aspects of the proposed research activity.

- Digital camouflage texture generation
- Scene classification
- Camouflage texture assessment techniques

This research requires a battlefield classification similar to that employed in scene classification applications in computer vision (CV). This chapter includes an outline of many methods and structures developed by researchers for scene classification in a wide range of domains. The several approaches proposed for creating digital camouflage textures have also been studied. Measuring the effectiveness of artificial camouflage patterns requires considering several factors, including the degree of concealment, the degree of similarity to the surroundings, visual attention, and human psychology. Hence, this study also includes evaluation parameters and procedures for gauging the efficacy of digital camouflage textures.

2.2. Digital camouflage texture generation

Since the Second World War, defence forces have used camouflage textures (Thornley, 1940). Since then, numerous efforts have been made to improve camouflage efficiency. There are two ways to generate camouflage textures: manual and computer-generated patterns. Many approaches for generating camouflaged textures for military forces have been offered by researchers working in this field, including image processing techniques (Abdi & Safabakhsh, 2022; Alfimtsev et al., 2019; Jia et al., 2020; Pei et al., 2023; Yu & Hu, 2012), machine learning (ML) (Gan et al., 2022; Wei et al., 2020; H. Xiao et al., 2020), and deep learning (DL) (H. Xiao et al., 2020; X. Yang, Xu, Jia, & Li, 2020)techniques. This section contains a literature survey on computational methods proposed by researchers, academicians, and industrialists to generate textures for camouflaging. Researchers have tried various computational methods to construct camouflage textures, as shown in Figure 2-1 and further précised in Table 2-1.

2.2.1. Image processing & Computer graphics based techniques

Image processing (IP) is an area of study in computer science (CS) which deals with manipulating and analyzing digital images. It involves techniques such as filtering, edge detection, and segmentation to extract useful information from images and to enhance their visual quality (da Silva & Mendonca, 2005; Gonzalez & Woods, n.d.). Computer graphics also an interesting field of CS related to generating and manipulating images and graphics using computers. It includes rendering, shading, and compositing techniques to create realistic images. Fractal geometry is a branch of mathematics that studies geometric shapes that exhibit self-similarity, meaning that they can be split into parts that are exact copies of the whole. It has applications in image processing and computer graphics, particularly in generating realistic textures and patterns (Boiangiu et al., 2015; Falconer, 2013; Widodo, 2019). Morphological operations are image processing techniques that involve the modification of the shape or structure of objects in an image. Morphology often used in with image processing methods to extract features from images and enhance their visual quality (Hu et al., 2013; Jia et al., 2017b). These fields are relevant to the generation of camouflage textures, as they provide the tools and techniques for manipulating and analyzing images and creating realistic patterns and textures.

2.2.1.1. Fractal geometry

Benoit Mandelbrot devised and developed "fractal geometry" (Mandelbrot & Wheeler, 1983) to offer a mathematical description of complicated structures that defy easy description using traditional Euclidean geometry. Texture can be described using fractal geometry. In-variance, also known as "statistical self-similarity," is typically found in "fractal objects" when viewed at varying

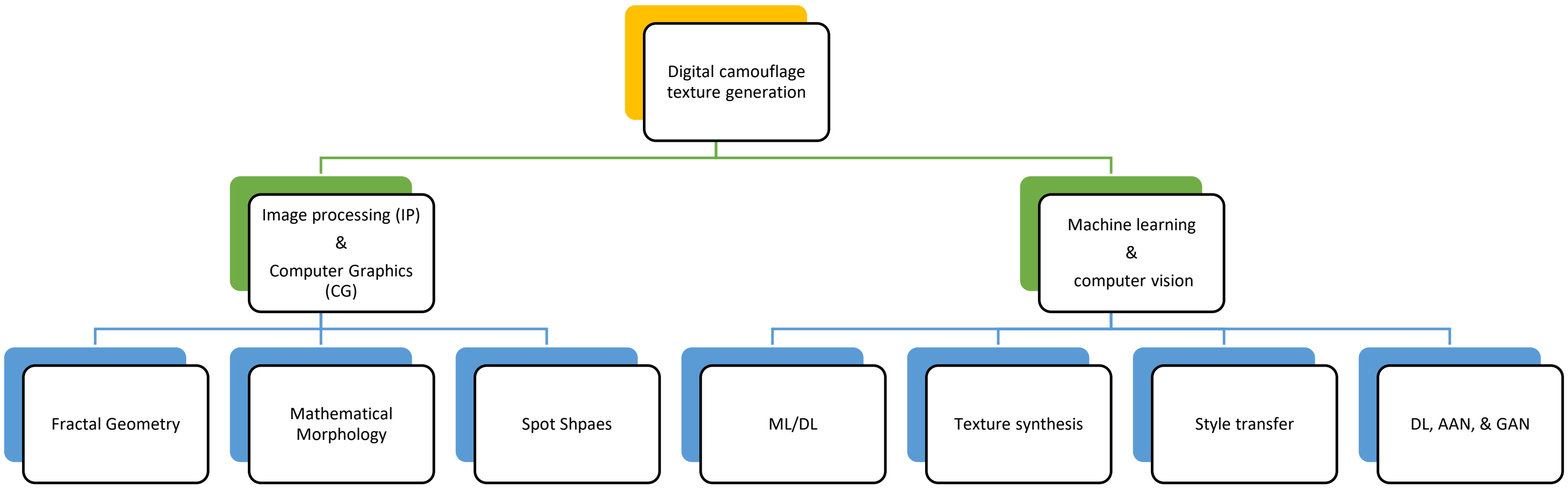
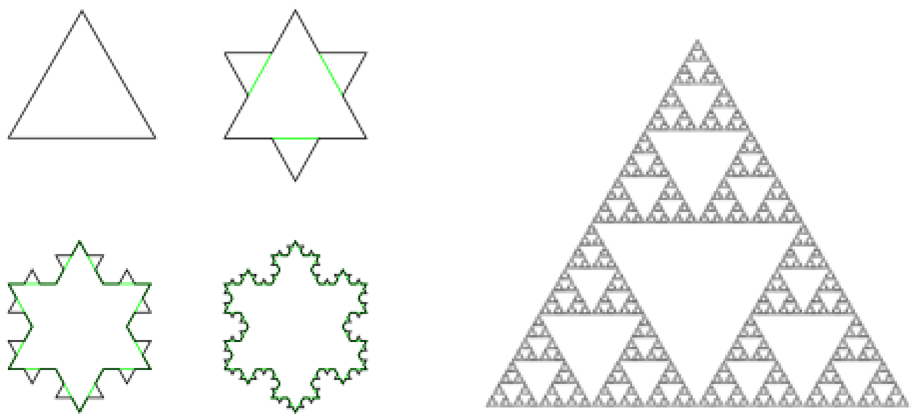


Figure 2-1: Digital Camouflage Texture Generation Techniques - Literature

magnifications. Fractal objects follow the statistical principle that they are "self-similar," meaning they are statistically very similar to themselves (Falconer, 2013; Mandelbrot & Wheeler, 1983; Schowengerdt, 2007). In statistical terms, the thing seems the same at any scale. The object's "fractal dimension," a measure of its complexity, can be calculated using this feature. Classical Euclidean geometry has four topological dimensions: 0 for points, 1 for lines, 2 for planes, and 3 for solids with volume, such as cubes and spheres. A larger fractal dimension typically results in a sharper and "rougher" texture (Schowengerdt, 2007). Some example fractals in nature are shown in Figure 2-2.



(a) Koch snowflake after 4 iterations (*Koch Snowflake - Wikipedia*, n.d.)

(b) A Sierpinski triangle, after 7 iterations. (Khovanova et al., 2014)

Figure 2-2: Fractals

In addition to its theoretical applications, fractal mathematics has many other application areas in real-world, such as in the creation of visually impressive and factual computer graphics, in textile designs (Tian et al., 2019; Wang et al., 2019), in file compression mechanisms, in the design of the internet's underlying network infrastructure, in the diagnosis of certain diseases (Baumann et al., 1998), and in defence industry to generate camouflage patterns (Defense Industry Daily staff, 2006; Miyashita et al., 1991; Pleşa et al., 2016; Ramli et al., 2012; Vancouver, 2007).

Guy Cramer, President/CEO of HyperStealth Biotechnology Corp. and the creator of the Passive Negative Ion Generator, started developing new military camouflage based on mathematical fractals in 2002. This project moved camouflage into a field of science that had been recommended by experts but that no one had been able to build. The fractal design is known as C2G, which stands for Camouflage Designated Enhanced Fractal Geometry. It is a multi-fractal that employs 4-6 colors in a camouflage texture to fool or deceive the brain into overlooking the pattern, hiding the troops' real shape (Defense Industry Daily staff, 2006).

To create a method for making camouflage textures for urban environments, (Friškovec et al., 2010; Friškovec & Gabrijelčič, 2010), researched several features of military camouflage. The researchers looked at several theoretical aspects, including the proportions of the human visual field, fractal geometry, and the effectiveness of camouflage patterns. The images were processed to remove unnecessary details and simplify the surface features and contours, allowing the researchers to extract representative forms and sequences. Then, three different approaches to pattern design were created and analyze, with the former two including the random and the latter the deliberate synthesis of forms and sequences. Compositional and graphical evaluates of reduced digital images, a theory of the vision and psychological perception of forms and sequences, principles of fractal sequences, and knowledge of the visual and optical impacts of shapes and repetitions were all part of the process for designing patterns. The Slovenian Ministry of Defense and Armed Forces approved the findings of the study, which defined a recommended method for digital camouflage pattern creation. This study was limited to designing the camouflage pattern for Slovenian urban environment.

The methodology presented by (Pleşa et al., 2016) is a fractal-based method for producing patterns and colors that are comparable to those observed in nature. Fractals employed in the replication process were generated by repeating indefinitely a specified generation rule. Artificially intelligent application programming techniques that can determine colors, geometric shape, and their arrangement from a digital image set the basis of the replication model for natural colors and forms presented in this study. The model has three components, an interior, the construction rule, and the generation process. An initiator is typically a simple geometric shape or figure like a line, square or triangle representing the geometric shape from which fractal generation begins. The construction law provides the fractal generation method specifying what changes while iteration from one to the next and the generation process by which the fractal is created from its initial shape and colors. After each cycle, a new fractal crowd is defined. Using the same pattern across different observation scales is a benefit of the established replication model. The spatial frequencies and repeating patterns of the forms are developed to replicate the target area with good accuracy. This system uses RGB values without considering brightness and orientation in camouflage texture.

Fractal geometry has applications and past work to generate camouflage textures due to its ability to generate highly complex and realistic patterns. Fractal patterns often have a high degree of self-similarity, meaning that they can be scaled up or down without losing their overall structure or visual quality, which can be useful in camouflage applications where the texture needs to be effective at different distances and scales. Additionally, fractal patterns can be generated algorithmically, allowing for customization and modification to suit different requirements.

However, some potential drawbacks exist to using fractal geometry for camouflage texture generation. The mathematical algorithms used to generate fractal patterns can be computationally intensive, which can be a limitation in applications where real-time processing is required. Fractal patterns may not be suitable for all camouflage applications, as they may not effectively mimic the specific patterns and textures in the camouflaged environment. Additionally, the appearance of fractal patterns may be too regular and structured, which could make them more easily detectable by certain observers. It is significantly important to sensibly consider the pros and cons of using fractal geometry in camouflage texture generation and to choose the most appropriate approach based on the specific requirements and constraints of the application.

2.2.1.2. Mathematical morphology

It is a field of mathematics that uses set theory norms to define morphological processes, where sets of points represent the images under consideration (Hu et al., 2013). Geometric shapes and structures may be expressed statistically using mathematical morphology, which also encompasses the study of algebraic structures, topologies, probability, and basic geometry. This technique uses an appropriate kernel to extract geometric properties from pixels using logical correlations rather than mathematical ones (Shih, 2010).

An innovative method for creating a digital pattern was introduced by (Bian et al., 2010). The technique employs morphological procedures and fuzzy c-means (FCM) color clustering to produce distracting patterns. The initial step of this process involves using the HSV color space to perform histogram color quantization and color matching between the military standard and the actual background colors. Then, morphological operations like opening and closing operations in conjunction with FCM clustring were used to suppress the camouflage pattern. Moreover, a tank was digitally camouflaged in a new scene. Finally, some widely used edge detectors were used to provide an impartial assessment of the digital camouflage pattern painted on the target in a simulated camouflage environment.

A technique that integrates the notions of mathematical morphology and camouflage was described by (Hu et al., 2013). The method produces prominent color patches of the background for colorful pictures using fundamental morphological operations like erosion and dilation that may then be used to create camouflage patterns. In this experiment, background images from aerial photography were utilized. The method has the ability to filter out small spots, roughness, and acute angles. It can smooth out the defects and preserve the essential characteristics of the forest background only.

(Jia et al., 2017b) also presented an approach to use erosion and dilation operations of mathematical morphology to generate the design for color spots. The method avoids the use of small spots in the resultant camouflage texture.

Mathematical morphology involves the modification of the shape or structure of objects in an image. It offers various techniques for manipulating and modifying images, which can be useful in creating realistic camouflage textures. It can also be relatively simple and computationally efficient which makes it appropriate for applications where real-time processing is required. It's evident that the researchers relied on mathematical morphology and associated procedures to isolate the shapes from their surroundings. It can extract and enhance specific features or patterns in an image, which can be useful in creating camouflage textures that effectively mimic the specific patterns and textures found in the camouflaged environment. However, there are also some potential drawbacks to using mathematical morphology for camouflage texture generation, such as its limitations in dealing with more complex or realistic textures and the sensitivity of the outcome to the choice of parameters and settings. Segmentation can potentially cause a loss of an object's proper form in its natural context. And no studies have disclosed a method for arranging these shapes and background colors in the final pattern.

2.2.1.3. Spot shapes-based techniques

Spots of camouflage texture should be similar in appearance to those of preexisting structures in the area. Researchers (Jia et al., 2020; Xue et al., 2016, 2018; Yu & Hu, 2012) used this strategy by breaking the procedure down into two phases:

1. Color separation and distribution in the final texture
2. The development and spreading of a database of spot form templates for use in texture generation

Over the decade, researchers and scholars have examined and developed strategies for distributing spots of varying sizes and shapes to produce a pattern. Based on prior knowledge, digital camouflage should be designed.

A technique was put forth by (Yu & Hu, 2012) that measures the size of the mosaic block first before filling it with the extracted colors. The process begins by quantifying the hue, saturation, and intensity (HSI) color space, then chooses the dimension of a mosaic block, fills in the primary colors in the spots, and then creates a digital camouflage pattern.

(Xue et al., 2016) developed a method wherein template distribution was used to iteratively overlap pattern templates of varying sizes in order to meet the spot shape and size restrictions. According to the size of the spot, the pattern templates used in this method were separated into two categories, A (big) and B (smaller), as depicted in Figure 2-3. In the phase of spreading, several sorts of templates serve various purposes. Pattern A was used to create large spots and conceal the target's true shape, and template B was utilized to adorn these large spots and enhance the camouflage's visual hierarchy. The researchers completed the spot distribution using a greedy technique. This procedure ensures that the final camouflage pattern has neither large patches nor excessively long stripes. It is possible that the overlapping patterns will lower production efficiency and increase implementation costs.

In addition, a spot combination method was presented to build the camouflage texture (Jia et al., 2020). With the support of artists and digital image processing (DIP) software, the researchers built a database of shapes. The original shapes were replaced by square patches as shown in Figure 2-4. Variable sized patches of various shapes were stored in the database. The technique generates the camouflage texture by combining spot shapes from the dataset. The placement of the spots and colors in a camouflage pattern conveys the design's texture. It's therefore crucial to carefully consider the pattern templates for the camouflage.

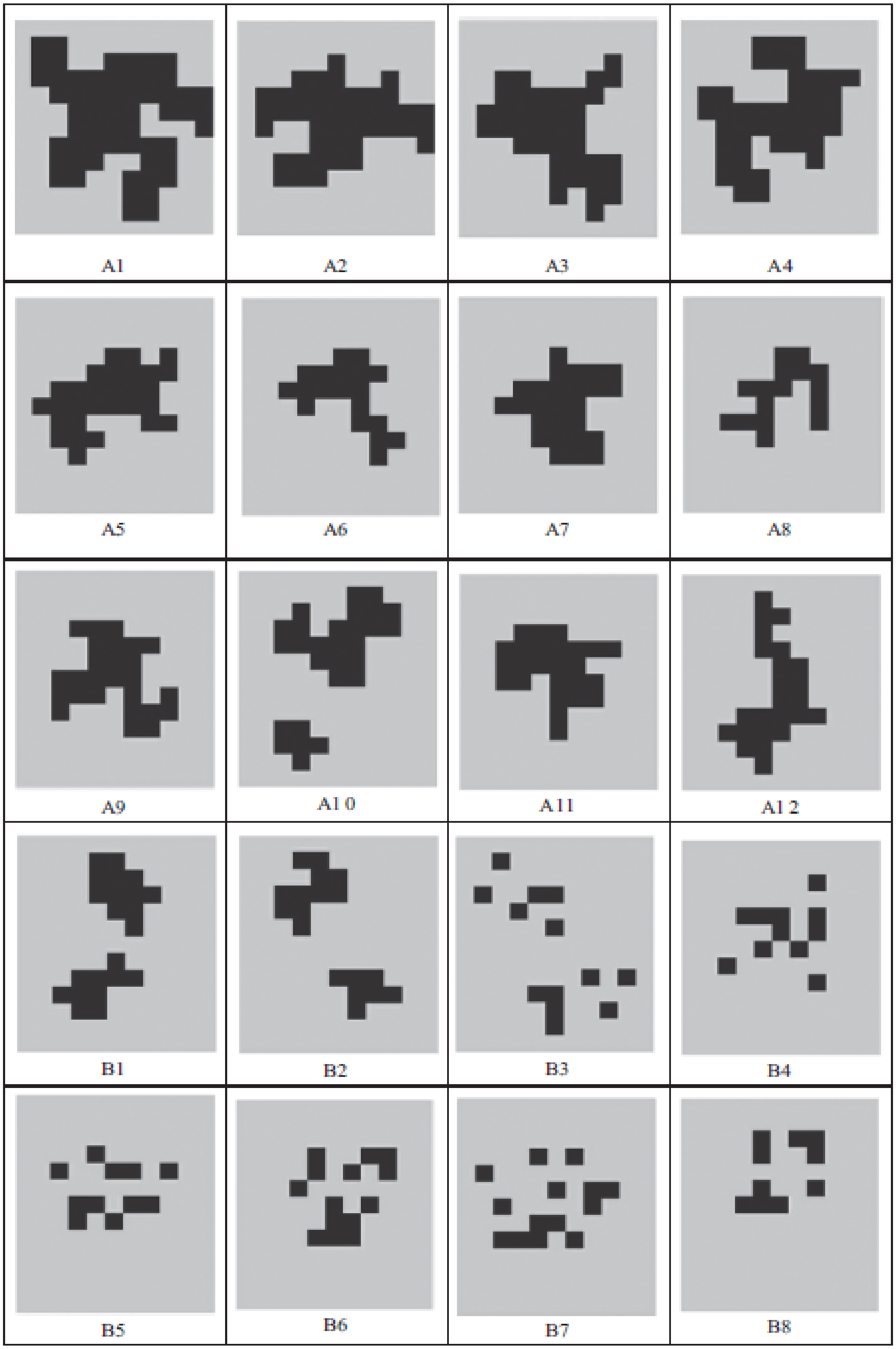


Figure 2-3: Spot shape dataset in paper (Xue et al., 2016)

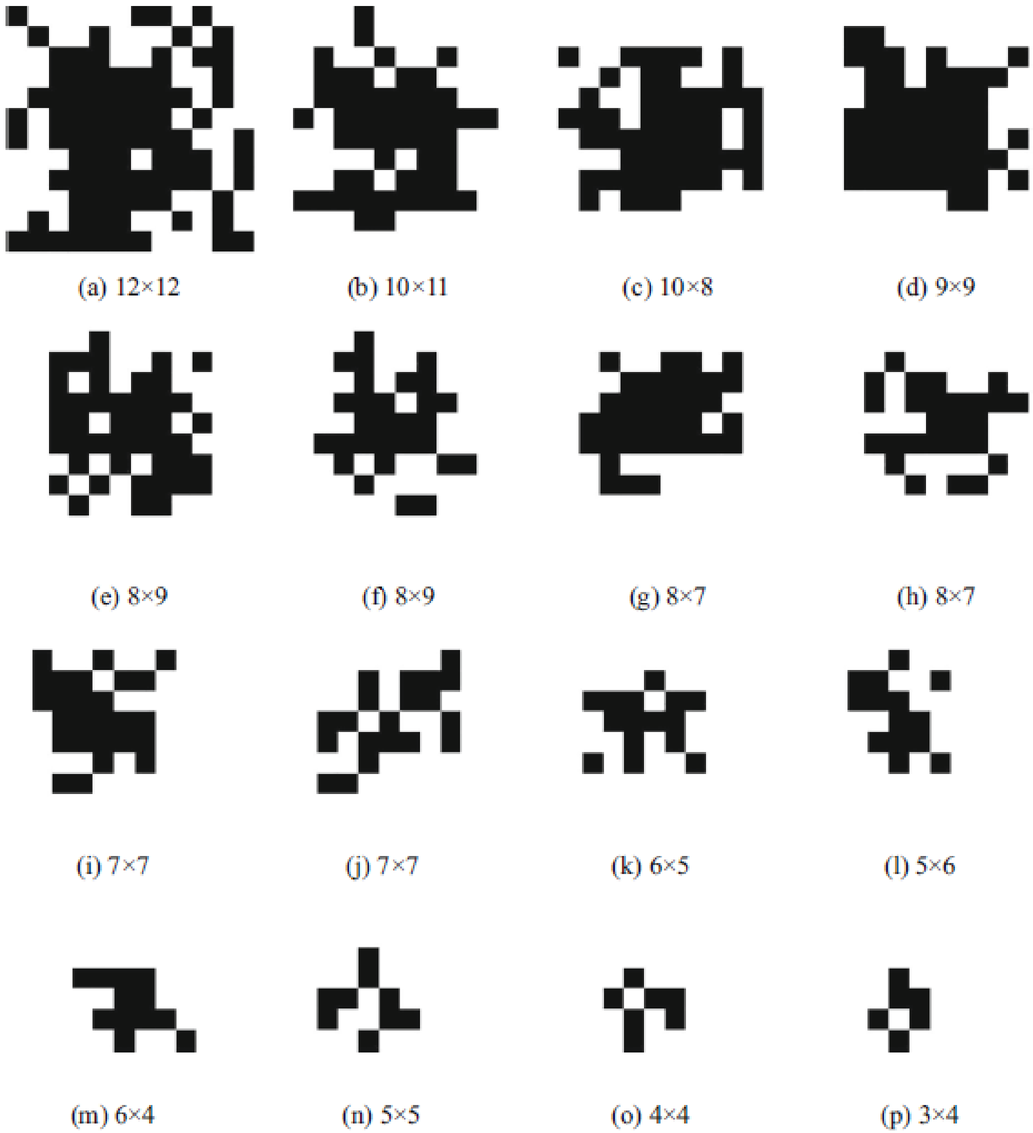


Figure 2-4: Spot shape examples from paper (Jia et al., 2020)

Spot shapes are a type of camouflage pattern that is made up of irregularly shaped spots or splotches of color. They are often used in nature-based camouflage schemes, as they can mimic the shapes and patterns found in natural environments. In the context of camouflage texture generation, spot shapes can be useful for creating realistic and effective camouflage patterns. Spot shapes can be effective at breaking up the overall shape and outline of an object, making it more difficult to detect. It can be used to mimic the patterns and textures found in natural environments, making them suitable for nature-based camouflage schemes. It can be customized and modified to suit different requirements, such as the specific environment being camouflaged or the specific characteristics of the object being camouflaged. Correctly placing spot shapes in a camouflage pattern can be a key factor in the effectiveness of the pattern, as it can help to break up the outer shape line of the object, mimic the patterns and textures of the environment, provide sufficient detail and structure, and avoid regularity and predictability. The methods proposed in literature lack with the technique or algorithm to place the spot shapes effectively while generating the camouflage texture. Additionaly, these methods are not capable of identifying the type of terrain for which camouflage is needed.

2.2.2. Machine learning (ML) & computer vision (CV) based approach

Because of the significant advancements that have been made in artificial intelligence (AI) over the course of the past few years, ML and CV are technological sectors that is advancing at a rapid rate. Traditional methods, such as image thresholding, filtering, and edge detection (Ansari et al., 2017; Jiang et al., 2009), are being supplemented by machine & deep learning approaches . ML & CV have a broad variety of applications, some of which include the following: medical applications (Barıs¸kayalıbay et al., 2017; Z. Fu et al., 2022; Rastogi et al., 2021; Yi et al., 2019), agricultural applications (Rußwurm et al., 2019; Santos et al., 2019; Talaviya et al., 2020), the recognition of violent activity (Pollok et al., 2019; Shah et al., 2021; Stec & Klabjan, 2018; Ying et al., 2021), the classification of scenes (King et al., n.d.; Rout & Bagal, 2017, 2018; Supriya R Iyer, 2020; Vasudevan et al., 2013; Zhou et al., 2014, 2018), defence (Bistron & Piotrowski, 2021; Johnson, 2019; Romstedt et al., 1985; Srivastava, 2021; X. Yang, Xu, Jia, & Li, 2020), and so on.

ML and CV techniques can be used to generate camouflage textures automatically. This can be done by training a ML model on a large dataset of camouflage textures and then using the trained model to generate new textures. These models can be trained using various techniques: supervised, unsupervised, or reinforcement learning, depending on the specific problem at hand. CV can be used to analyze and understand the visual characteristics of the camouflage textures in the dataset, which can then be used to guide the generation of new textures.

Here you can find a review of the research on camouflage texture generation using ML and CV methods.

2.2.2.1. Texture synthesis

Texture synthesis (Gatys et al., 2015; Schreiber et al., 2017) is a technique for generating new textures that are similar to a given example texture. There are several approaches that can be used for texture synthesis, including statistical methods, signal processing techniques, and machine learning approaches such as deep learning.

Texture synthesis can be a useful approach for generating camouflage textures. One approach that is to train a Convolutional Neural Network (CNN) on a dataset of real camouflage textures and then use the trained network to generate new textures by sampling the latent space of the network. (Pezeshkian & Neff, 2012) suggested a technique for creating adaptable camouflage that was ecologically inspired. This could produce high-quality, photorealistic camouflage textures that are similar to the ones in the training dataset. The procedure involves utilizing a camera to capture the environment, synthesizing the camouflage pattern, and replicating it on color electronic paper. Electronic paper is a thin low-power reflective display that is used as robot's outside enclosure surface. The method proposed by (Pezeshkian & Neff, 2012) concentrates on the first two parts of the process. After that modifying a gray-level texture generation technique that makes use of gray-level co-occurrence matrices, color-camouflage-synthesis was made possible. Conditional probability restrictions were used to ensure statistical equality in color-proportion.

A technique for producing dynamic camouflage was presented by (Wei et al., 2021). In this article, the author offered a technique for creating dynamic camouflage patterns by reconstructing texture characteristics offline and filling color features in accordance with the live combat scenario. First, the technology replaces the traditional irregular textures and regular pixel blocks of digital camouflage patterns with texture features designed using convolutional transfer networks, increasing the adaptability of camouflage designs. To extract deep texture features, 3x3 convolutional kernels and 2x2 max pooling were utilized. The submitted battlefield photographs' color distribution and reconstruction were extracted using a clustering-based method.

There are a number of potential benefits to using texture synthesis to generate camouflage textures, including the creation of high-quality, photorealistic patterns that are similar to real camouflage, the creation of a wide variety of patterns tailored to specific environments, and the creation of patterns in real-time for adaptive camouflage. However, there are also various disadvantages to this method, such as the fact that it could be less effective at disguising the movement of an object, and less effective at disguising the shape or silhouette of an object.

2.2.2.2. Neural style transfer

Neural style transfer (Daneshvar et al., 2022; Gatys et al., 2016; Jing et al., 2017) is a machine learning technique that allows to transfer the style of one image to the content of another image. It is based on the idea of using a CNN to decompose an image into its style and content components, and then recombine the content of one image with the style of another image.

(Q. Zhang et al., 2020) came up with an innovative neural style transfer strategy to building camouflage images, which makes use of the visual perception process to hide objects more effectively and with a more natural appearance. To eliminate the visual breaks between the concealed objects and the background, the authors created a naturalness regularization to bind the concealed objects to the manifold structure of the concealed backdrop.

Though it might not be the best method, neural style transfer could be used to generate camouflage textures. The fundamental issue with neural style transfer as a means of generating camouflage textures is that it is primarily intended to transfer the style of one image to the content of another image, rather than generating new textures from start. Therefore, it is expected to be challenging to apply neural style transfer to develop a large variety of camouflage patterns that are adapted to varied surroundings.

In addition, neural style transfer is more commonly utilized to create creative effects or improve the aesthetics of a picture than it is to blend in with a particular setting. While it's feasible to construct visually appealing camouflage patterns via neural style transfer, whether or not they'd be useful at disguising an object in the real world is questionable.

Overall, while neural style transfer might be able to generate some interesting and visually appealing camouflage textures, it is unlikely to be the most effective approach for generating functional camouflage patterns. Other techniques such as GANs or CNNs trained on a dataset of real camouflage patterns are likely to be more effective at generating camouflage textures that are tailored to specific environments and are effective at disguising objects.

2.2.2.3. Deep learning (DL) based approaches

Deep learning is a subfield of machine learning that involves using neural networks with many layers (hence "deep") to learn patterns and relationships in data, particularly large and complex datasets (Alzubaidi et al., 2021; Elgendy, 2020; Guo et al., 2016; He et al., 2016; Schmidhuber, 2015). DL techniques can be used for camouflage texture generation by training a generative model on a dataset of camouflage textures. The model could be a CNN or a generative adversarial network (GAN) variant.

Utilizing DL can make it possible to learn representations of data and features that have varying degrees of abstractness. For prey, predators, or the military, avoiding detection can be extremely advantageous for survival; on the other hand, increasing visibility would be beneficial for signaling. An animal's color in relation to its surroundings is one straightforward indicator of detectability. However, choosing the best color to reduce detectability in a specific natural setting is challenging, in part due to the characteristics of the perceptual space. (Fennell et al., 2019) developed a way to determine the best color that either decreases visibility using image processing techniques to embed targets into realistic surroundings, psychophysics to quantify detectability, and deep neural networks to interpolate between sampled colors.

For the next generation of adaptive optical camouflage, (H. Xiao et al., 2020) suggested a fast-self-adaptive digital camouflage design method based on deep learning. A YOLOv3 (Redmon & Farhadi, 2018) model that could recognize four typical military targets was first trained by the authors. YOLOv3 is based on a deep CNN that is trained to detect objects in images and videos. It is able to process images in real-time, making it suitable for use in a wide range of applications, including self-driving cars, surveillance systems, and robotics. The initial camouflage texture was created using a pre-trained deepfillv1 (Yu et al., 2018) model. Deepfill1 is a feed-forward, fully convolutional neural network technique based on a deep generative model that can not only synthesis new image structures, but also directly use surrounding image characteristics as references in network training for improved prediction accuracy. The k-means method was used to standardize the initial camouflage texture. The target image dataset used in the research was very limited.

Another approach that can be used is to train a Generative Adversarial Network (GAN) (Aggarwal et al., 2021; Goodfellow et al., 2014) on a dataset of real camouflage textures. A GAN consists of two networks: a generator network and a discriminator network. The generator network is trained to generate new data that is similar to a training dataset, while the discriminator network is trained to distinguish between real and synthesized data. GANs can be used for camouflage texture generation is by training a GAN on a dataset of images that contain a wide range of camouflage patterns. The generator network can then be used to generate synthetic camouflage patterns that are similar to the patterns in the training dataset. These synthetic patterns can be used to camouflage objects in images or videos. By training both networks together, the GAN can learn to generate new camouflage textures that are similar to the ones in the training dataset.

In order to model the evolutionary arms race between the camouflage of a synthetic prey and its predator, CamoGAN makes use of Generative Adversarial

Networks. It is an unsupervised method proposed by (Talas et al., 2020) to generate biologically equivalent camouflage stimuli. Validation with human visual predators showed that the evolving patterns provided progressively more efficient hiding.

One potential advantage of using GANs for camouflage texture generation is that they can generate a large number of patterns quickly, allowing for the rapid exploration of different design options. In addition, GANs can learn to generate patterns that are similar to those in the training dataset, but that are not necessarily identical, which can allow for the creation of novel camouflage patterns.

There are some possible difficulties of employing camouflage textures created by deep learning or GAN. DL and GANs are complex techniques that require specialized knowledge and resources to implement. This can make it difficult for some organizations or individuals to use these techniques to generate camouflage textures. Implementing these systems can be expensive, particularly if it requires a large amount of data to train the model or if specialized hardware is needed. These techniques rely on large amounts of data to learn and generate outputs. This means that the quality and effectiveness of the generated camouflage textures may be limited by the quality and diversity of the data used to train the model.

2.2.2.4. Other

Adaptive electronic camouflage (Pezeshkian & Neff, 2012; H. Yang & Yin, 2015a; Yao et al., 2019) is a technology that uses electronic displays to display a pattern that blends in with the surrounding environment, making an object appear to disappear or become hard to detect.

Table 2-1: Summary of SOAT for digital camouflage texture generation

SOAT	Key points	Findings (Pros and cons)	Example studies
Image processing and computer graphics			
Computer Graphics	Image transformation techniques	Pros: • Cost effective, Cons:	(Abdi & Safabakhsh, 2022; McREYNOLDS

	applied to augment shapes	• Spot shapes are not inspired from nature, • irregular patterns, • Form sharp edges and outlines	& BLYTHE, 2005)
Fractal Geometry	Fractal patterns to replicate shapes in environment	Pros: • Inspired from natural fractals • High degree of similarity Cons: • Fractal patterns may be too regular or similar • May not effectively mimic the specific pattern • Required high computation	(Boiangiu et al., 2015; Defense Industry Daily staff, 2006; Mandelbrot & Wheeler, 1983; Miyashita et al., 1991; Pleşa et al., 2016; Widodo, 2019)
Mathematical morphology	Segment shapes and patterns from natural scene	Pros: • Shapes inspired from nature • Easy to manipulate and modify shapes to improve effectiveness Cons: • Limitations with complex textures	(Hu et al., 2013; Jia et al., 2017b)

		• Studies lack the method to spread/use shapes in camouflage texture	
Color clustering and random patterns	Considering color as most dominant feature Color clustering: K-means, Fuzzy c-means Use of random patterns filled with extracted colors to generate camouflage texture	• Color as the primary parameter in camouflage texture • K-means color clustering gives better color set extraction then fuzzy-c means and other • Colors should be standardized before using it for texture • Effect of other environmental features should be considered along with colors	(Cuthill et al., 2005; Ghodeswar et al., 2017; Lin et al., 2019; Martin et al., n.d.; Price et al., 2019; Wei et al., n.d.; H. Yang & Yin, 2015a; Y. Zhang et al., 2013) (W. Xiao et al., 2021)(Ding et al., 2019)
Spot shape based	Generating spot shapes based on natural objects appearance and human psychology	Pros: • Cost effective • Work for different distances • Help to break outline Cons: • Fixed set of spot shapes have been used by researchers	(Jia et al., 2020; Pei et al., 2023; Xue et al., 2016; X. Yang et al., 2021b; X. Yang, Xu, Jia, Li, et al., 2020)

		• Spot shapes need refinement and standardization as per industry standard and terrain	
Machine/deep learning			
Texture synthesis	Creating synthetic texture using structural information of small digital sample	Pros: • Good quality, photo realistic patterns • Good for Replicating a small segment of whole scene Cons: • High computation • Less effective for disguising movement and shape of an object	(Pezeshkian & Neff, 2012; Wei et al., 2021)
Neural style transfer	Mimic the visual style of training images	Cons: • Artificial style • Transfer the style of one image to another which will not be realistic	(Daneshvar et al., 2022; Q. Zhang et al., 2020)
CNN & Deep learning	Background features learning Self-adaptive camouflage	Pros: • Learn representations of data and features that have varying degrees of abstractness.	(Wei et al., 2020; H. Xiao et al., 2020)

		• Good results for a particular object to be camouflaged at a fixed location Cons: • Have low adaptability for changeable environmental features • Less concealability for moving object • High computation • Require large dataset for training	
Generative adversarial network (GAN)	Generation of deformation camouflage patches using GAN	Pros: • Generate shapes that can be further used in camouflage textures • Can generate large amount of patterns quickly Cons: • High computational need • Expensive • Specialized hardware needed • Effectiveness of camouflage textures	(Alfimtsev et al., 2019; Talas et al., 2020; X. Yang et al., 2021b; X. Yang, Xu, Jia, & Li, 2020; X. Yang, Xu, Jia, Li, et al., 2020)

		may be limited by the quality and diversity of the data used to train the model	
Oher computational techniques			
Biased Random Walk	Biased Random Walk	Biased Random Walk	(Gan et al., 2022)
Particle Swarm optimization (PSO)	Optimized color designs using metaheuristic and PSO	Optimized color designs using metaheuristic and PSO	(Lin & Prasetyo, 2019)
Cellular automata	Distributed camouflage algorithm, Adaptive camouflage	Distributed camouflage algorithm, Adaptive camouflage	(Y. Li, 2019)
Adaptive camouflage	Camouflaging the object through LEDs by perceiving environmental coloration	LED arrays as the outer surface of an object Light has illumination which will make object easily noticeable	(Pezeshkian & Neff, 2012) (Cho et al., 2013) (Kumar et al., 2015) (Gnaniar et al., 2016) (Y. Li et al., 2017) (Warang et al., n.d.), 2017

2.3. Scene classification techniques

In order to generate effective camouflage textures, it is important to first identify the battlefield terrain and background features of the environment in which the camouflage will be used (*Camouflage, Concealment, and Decoys*, 2010; D.-P. Fan et al., n.d.; Lv et al., n.d.). This may involve analyzing the imagery, or extracting the background features through image processing or some computation tools. Once these features have been identified, the camouflage texture can be designed to blend in with the surrounding environment, making it more difficult for enemies or other observers to detect the objects or individuals being concealed.

In order to achieve various goals, a large amount of research has previously been done in this area. To categorize scenes into their appropriate classifications, researchers employed a variety of approaches from image processing, computer vision, and machine learning. The numerous scene classification models proposed by researchers for a variety of applications (L. Chen et al., 2021; Cireşan et al., 2011; Gangopadhyay et al., 2015; Herranz et al., n.d.; Krizhevsky et al., 2017; P. Li et al., 2017; Majumdar et al., 2008; Rout & Bagal, 2017; Vandapel et al., 2004; Walas, 2015; Zhou et al., n.d.) have been examined and summarized in this section.

Terrain classification methods aim to identify and distinguish different types of land cover and land use within an area. There are several approaches that have been developed for this purpose, including visual interpretation, image processing, geospatial analysis and machine learning.

- *Visual interpretation:* This involves manually examining aerial or satellite imagery to identify and classify different types of terrain (Chakraborty et al., 2017; Coyle, 2010; Oliva & Torralba, 2001; Vasudevan et al., 2013). This method is subjective and can be time-consuming, but it is useful for small-scale projects and for identifying unique or complex features.
- *Image processing:* This involves using computer algorithms to analyze digital imagery and extract information about the terrain. Techniques such as texture analysis, image segmentation, and feature extraction can be used

to classify terrain based on various characteristics, such as color, shape, and texture.

- *Geospatial analysis:* This involves using geographic information systems (GIS) to analyze and classify terrain based on spatial patterns and relationships. This can include techniques such as overlaying maps, performing spatial analysis, and using statistical models (Bourissou et al., n.d.; Lazebnik et al., n.d.; Müller-Budack, n.d.).
- *Machine learning:* This involves training a computer to recognize patterns in data and make predictions based on those patterns. Machine learning algorithms can be used to classify terrain based on various features, such as elevation, slope, and land cover (Alzubaidi et al., 2021; Buscombe & Ritchie, 2018; J. Chen et al., 2017; Cireşan et al., 2011; Parikh et al., 2018; Simonyan & Zisserman, 2015; Zhou et al., 2018).

Overall, the choice of terrain classification method will depend on the specific goals of the project, the availability of data, and the resources and expertise available. Table 2-2 shows some applications of scene classification. However, it can be observed from literature that CNNs and machine learning can be effective techniques for terrain or scene classification, as they can automatically learn and extract features from data for classification purposes. In comparison to traditional image processing techniques, CNNs and machine learning may have several advantages, including improved accuracy, automation and adaptability to new data and changing conditions.

Table 2-2: Literature survey: Scene classification

Author and year	**Focused area**	**Objective of research**
(L. Yang et al., 2021)	DCNet, CNN, GCNN	Semantic scene image segmentation
(Lima et al., 2017)	CNN, fine tuning a series of transfer learning	Ocean front detection using deep learning methods.

(J. Chen et al., 2020)	CNN	Classification of remote sensing scenes.
(Zhou et al., 2014)	Deep CNN, Places dataset	Scene classification for broad range of categories in Places dataset
(Vasudevan et al., 2013)	Spatial pyramid matching (SPM) algorithm, SIFT descriptors	Classification of natural scenes based on both temporal and spatial data extracted from videos.
(Lazebnik et al., n.d.)	Spatial Pyramid Matching	Training of a support vector machine (SVM) for multi-class classification of scenes.
(Oliva & Torralba, 2001)	Principal Components Analysis (PCA) and Fourier Transform (FT)	This study developed a computational model for real-world scene classification that does not need segmentation or processing of specific items or areas.

2.4. Camouflage texture assessment

The need for camouflage texture assessment arises when it is important to determine whether a particular camouflage pattern is effective in a given environment. This could be done in order to improve the effectiveness of the camouflage, or to compare the effectiveness of different camouflage patterns. This section of the thesis include an overview of the various techniques that have been used in the past to assess camouflage patterns, as well as a summary of their strengths and limitations. Camouflage assessment techniques and methods from literature are listed in Figure 2-5. Numerous researchers have contributed towards the development of digital camouflage texture generation techniques and assessed the outcomes of their proposed approaches. Table 2-3 lists the evaluation methodologies employed by these researchers.

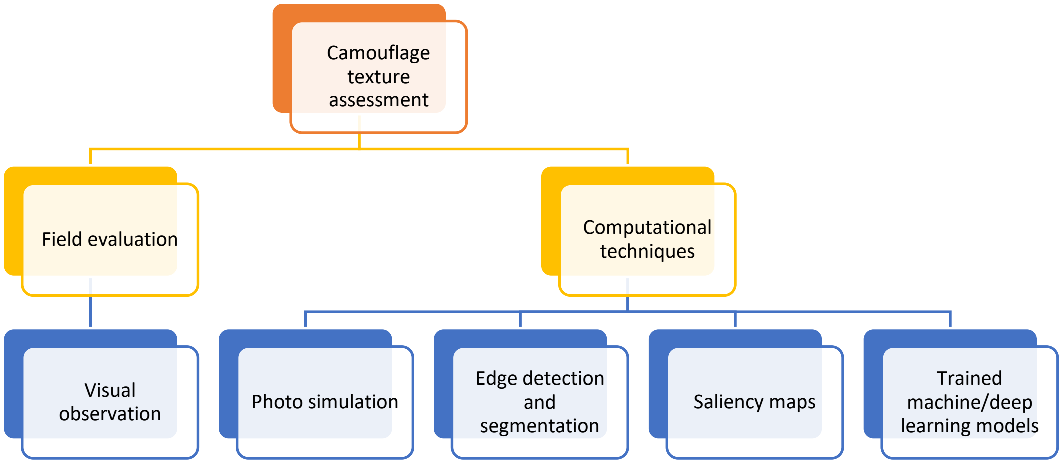


Figure 2-5: Techniques and methods for camouflage texture assessment

Table 2-3: Camouflage assessment techniques used in past research work

Author & Year	**Camouflage texture generation – Past work**	**Method used for evaluation**
(W. Xiao et al., 2021)	Implementation of Fuzzy C-Means (FCM) Clustering Based Camouflage Image Generation Algorithm	Edge detector-canny and sobel
(Wei et al., 2021)	A Novel Method for Automatic Camouflage Pattern Synthesize	Eye movement tracking, Photo simulation
(X. Yang et al., 2021b)	A small-spot deformation camouflage design algorithm based on background texture matching	Canny edge detection
(Jia et al., 2020)	Design and evaluation of digital camouflage pattern by spot combination	Saliency map
(Wei et al., 2020)	An Automatic Design of Camouflage Patterns Based on CNNs	Photo simulation
(Fennell et al., 2019)	Optimizing colour for camouflage and visibility using deep learning: The effects of the environment and the observer's visual system	Human eye observation
(Jia et al., 2019)	Intelligent design of gradual disruptive pattern painting and comparison of camouflage effectiveness	Photo simulation

(H. Yang & Yin, 2015a)	A digital camouflage generation algorithm using color similarity	Prewitt edge detector
(H. F. Yang & Yin, 2013)	An adaptive digital camouflage scheme using visual perception and K-mean clustering	Edge detector

2.4.1. Field Evaluation

The term "field evaluation" is used to describe the process of testing and assessing camouflage in a real-world or field environment. This can be done by evaluating how well the camouflage pattern conceals the individual or an object and how well it blends in with the environment. The kind of terrain, vegetation, lighting conditions, as well as the wearer's motions and activities, may all be taken into account during a field evaluation for camouflage assessment (Rao, 1999).

In theory, human target recognition performance may be tested in field experiments adopting carefully controlled scenarios and well observed settings (Toet & Hogervorst, 2020). The reports (Arseneau & Emond, 2003; Peak et al., 2006) details best practices for conducting field trials for assessing camouflage with human observers, including how to select a background, when to conduct the trials, what procedures to use, how many observers are needed, and how to analyze the data they collect.

Each observer in a field camouflage testing is taken out to the field and given the chance to look for targets. Field tests may be conducted in a number of different ways. It's possible, for instance, to transport observers to strategic points and then let them roam free in order to locate potential prey. On the other hand, the NATO SCI-095 Camouflage Assessment Trial also tried out having observers check for targets from a cable car as they descended (Peak et al., 2006). Camouflage evaluation often involves gathering data on three types of ranges: initial detection, recognition, and final identification. A key element in the analysis of camouflage data is that the sort of analysis to be performed affects how the data must be treated. In practice, two types of analysis are used: cumulative frequency distribution and descriptive analysis with the median and first percentile reports (Arseneau & Emond, 2003; Peak et al., 2006). Table 2-4 presents a format for collection of raw data from human observers during field trials. The data will be then adjusted and sued for analysis purpose.

Table 2-4: Observation sheet to record raw data in field trial

Camouflage Net A			Camouflage Net B		
Observer Session	Age	Detection Range (m)	Observer Session	Age	Detection Range (m)

The field evaluation for camouflage assessment using observers can be time-consuming and costly, especially if a large number of observers are needed to cover a wide area or a large number of different environments. Additionally, the presence of observers may alter the behavior of the wearer, which could affect the results of the evaluation.

2.4.2. Computational technique

Camouflage texture assessment using a computation approach involves the use of computer algorithms and image processing techniques to analyze and evaluate the effectiveness of camouflage patterns.

2.4.2.1. Photo-simulation

The ability of human vision to recognize and detect objects is exceptional. The primary function of the human eye is to concentrate our gaze on interesting items (Y. Li et al., 2022). Neurons initially adjust to basic visual cues such size, position, color, orientation, and eye movement speed. Based on human visual system (HSV) photo-simulation is the tried-and-true method of assessing camouflage effectiveness. It is a method in which images are perceived by human observers to detect any conceal object (Lin, Chang, & Lee, 2014).

In a conventional photo-simulation trial, analogue captured images were presented to observers as color slides in a lab environment. The field test should be configured to allow for the planned photo-simulation evaluation and to enable the extraction of the desired data. The photo-simulation is carried out in a room that is completely dark and has enough room for the projector, projection screen, and observers to be installed properly. The lighting in the space should not interfere with viewing the screen (Peak et al., 2006; Toet & Hogervorst, 2020). An observer views slides from a fixed, predetermined distance, a_2, which is determined by the formula Equation 2-1:

$$a_2 = (a_1 \times f_1)/f_2 \qquad \textit{Equation 2-1}$$

where, a_1 represents the distance between the projector and screen, while f_1 and f_2 respectively denote the focal lengths of the camera and projector.

At order to maintain its position constant throughout the picture simulation, an observation chair is placed in the predicted location and secured to the ground. The use of two data recorders ensures a more thorough and precise experiment by allowing results to be evaluated and confirmed. The photo simulation supervisor arranges one or more test runs to check the process and guarantee ideal circumstances after the room has been set up (Peak et al., 2006; Toet & Hogervorst, 2020).

Defense began utilizing digital imagery in a traditional photo simulation after realizing that current digital technology is quickly catching up to the quality of photographic slides. The available slides were first digitalized, and a computer with monitor were used in place of a projector and screen. Possibilities exist to make data collecting simpler by displaying the photos on a computer monitor as shown in Figure 2-6. Similar to the traditional photo-simulation experiment, imagery can be shown to the participants using a computer. The observer distance to the image does not need to be regulated as in the traditional experiment because computer monitors have a lesser resolution than slide projections. Each observer can choose their own viewing distance from the monitor as a consequence. The observers were told to use the pointer to highlight any prospective military targets they noticed in the photos and, whenever it was possible, to give the target's name (Peak et al., 2006).

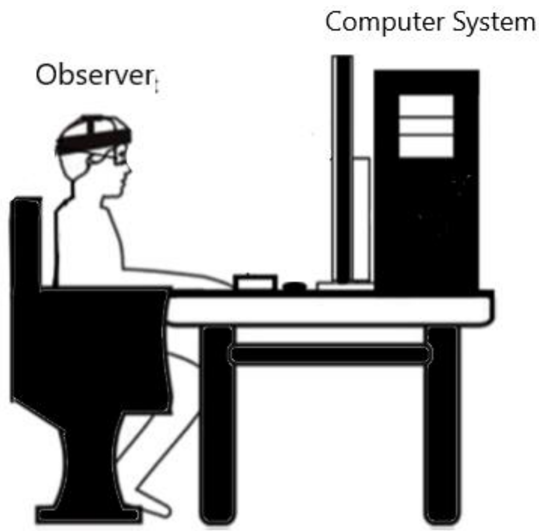


Figure 2-6: Photo-simulation setup

2.4.2.2. Edge detection and segmentation

Edge detection is a popular image processing technique that identifies and locates sharp changes in an image's intensity. These variations, known as edges, usually correspond to object borders or regions of interest in an image. Edge detection approaches include the Sobel operator, the Canny edge detector, and the Laplacian operator.

The detection of camouflaged objects in images is a critical application of edge detection. Camouflaged objects blend in with their surroundings, making them difficult to distinguish from the background. It is possible to highlight the edges of an object and make it more noticeable by using edge detection techniques. This technique is especially useful in the military and surveillance domains, where it is critical to detect things that are attempting to blend in with their environment.

2.4.2.3. Saliency maps

Saliency maps are frequently utilized in computer vision to identify objects in an image. It is a 2D scalar map used to depict visual prominence regardless of the primary area's characteristics in an image. Each pixel in an image possesses its own saliency. Creating a saliency map of an image enables observer to concentrate on the image's essential attributes. They are a sort of visual representation that draws attention to the key elements in an image or video, making them useful for object detection and tracking. Saliency maps make it simpler for humans to recognize things in an image by allowing us to concentrate on the crucial components of an image while ignoring the unimportant elements.

Many object classification and detection systems make heavy use of saliency maps , and they have also been employed in studies to locate camouflaged objects in the scene (D. P. Fan et al., 2020, 2021; Feng et al., 2015; Jia et al., 2016; Le et al., 2019, 2022; Lin, Chang, & Liu, 2014).

The initial step in creating a saliency map of an image is to extract its fundamental elements, such as color, orientation, and intensity. Then, a features map is made from adjusted images using Gaussian pyramids. The saliency map is then created by averaging all of the feature maps.

2.4.2.4. Pre-trained machine/deep learning models

Active research fields include camouflage object detection (COD) and segmentation (COS) utilizing machine learning (ML) and deep learning (DL). The human visual sensory system comprises a large dataset of semantic knowledge, which is the basis for (Zheng et al., 2019) 's proposed dense de-convolution network (DDCN) to extract and fuse the multi-scale semantic features in deep CNN to detect camouflaged people in an image.

The detection of camouflaged objects has a long history in ecology, art, and defence and it has had a considerable impact on our knowledge of visual perception. Unfortunately, due to a lack of a suitably large dataset, research into recognizing concealed objects is limited. Fan et al. solved issue by assembling the first-of-its-kind COD-specific dataset, COD10K (D.-P. Fan et al., n.d.), and building an easy-to-use and highly effective framework, SINet. SINet is a deep learning network that was trained and verified on the COD10K dataset to detect hidden objects in an image.

(Le et al., 2019) presented ANet for camouflage segmentation, which used a pre-trained model with dilated convolutions to learn from existing dataset attributes. The model was trained on two datasets of camouflage and tested on a range of other datasets. On the camouflage segmentation task, ANet produced cutting-edge results.

In conclusion, research in camouflage object detection and segmentation using ML and DL is motivated by the fact that the human visual sensory system contains a massive library of semantic knowledge. Many models, including DDCN, SINet, and ANet, have been created by researchers to solve the issues of recognising and segmenting camouflaged objects. However, due to the scarcity of datasets, additional study is required to increase the accuracy and resilience of these models.

Table 2-5 presents the evaluation techniques utilized to evaluate the efficiency of camouflage, their corresponding metrics, and a selection of sample studies.

Table 2-5: Camouflage evaluation methods, metrics and example studies from literature

Camouflage assessment methods	**Metrics/Evaluation measure**	**Example studies**
Field Evaluation	-Detection range -Recognition range	(Singh et al., 2013; Toet & Hogervorst, 2020)
Photo-simulation	- Hit rate - Detection time - Difficulty ratings	(Lin, Chang, & Lee, 2014) (Toet & Hogervorst, 2020) (Peak et al., 2006)
Edge detection and segmentation	Segmentation of object dissimilar to the background image	(Singh et al., 2013) (Bian et al., 2010; H. F. Yang & Yin, 2013)
Saliency maps	Local image distinctness maps	(Skurowski & Kasprowski, 2018)(K. Fu et al., 2013; Jia et al., 2020; N. Li et al., 2018; Ren et al., 2014; Xue et al., 2015, 2016)(Wei et al., 2021) (M. M. Cheng et al., 2015; J. Liu & Wang, 2015) (Achanta, 2011)

Pre-trained machine leaning models	Accuracy metrics	(D. P. Fan et al., 2021; Kamran et al., 2022; Sun et al., 2009; Yan et al., 2021) (L. Cheng et al., 2022; D. P. Fan et al., 2020; Le et al., 2019; Zheng et al., 2019)

2.5. Research gap

- Graphic designers typically paint graphic representations of camouflage textures over the object's surface. Although several techniques have been created to computerize the process of creating visual patterns, the majority of them only offer some assisting tools for the designers and are unable to suggest an automatic strategy. Since the objects move and their backgrounds may vary significantly, it is essential to generate multipurpose camouflage patterns with appropriate performance in various backgrounds (Abdi & Safabakhsh, 2022; Hejrandoost & Safabakhsh, 2011).
- Traditional camouflaging methods have several drawbacks, such as irregular patterns, shapes, and poor color combinations (Xue et al., 2016).
- The fixed camouflage pattern have low adaptability and concealability for changeable battlefields (Wei et al., 2021).
- The ability to detect an object in the environment depends on the difference in texture, color, brightness and distance from which it is being observed. Motion is considered an essential feature to detect an object (Pezeshkian & Neff, 2012).
- The usage of classic digital camouflage for only one background and location at a time is a common practice (W. Xiao et al., 2021). This camouflage is effective at the specified time and location; but, if the location, time, or season are altered, the camouflage will lose a significant amount of its effectiveness.

2.6. Problem Definition

Understanding the real environment in which the military forces are deployed is critical. For self-defence and greater concealment, they should camouflage themselves. The industry demands an intelligent system that can categorize and extract features of the terrain before generating texture for camouflaging their assets and objects, allowing them to adopt the conspicuous features of the scene. The gap is a technology that can deal with the real-time scenarios and requires a technology, which can instantly adjust to varying features of the environments.

2.7. Objective

The primary objective of this research work is to design & implement a model that can generate the pixelated camouflage pattern in real time for a particular environment.

2.7.1. Sub-Objectives

To achieve the proposed objective following sub objectives have been framed:

1. Implementation of a model for the classification of battlefield terrain.
2. Design & implementation of an algorithm for generating pixelated camouflage patterns for the particular terrain considering its background features.
3. Assessment of resultant camouflage textures

2.8. Summary

The aim of this study is to develop a novel approach for generating pixelated camouflage textures that effectively conceal objects or surfaces from visual detection. The study aims to address the limitations of previous methods and to improve the quality and diversity of the generated textures. In this chapter, the background and significance of the study were discussed, and the motivation for conducting this research was presented. The chapter provides a comprehensive overview of the current state of the art in pixelated camouflage texture generation and highlights the gaps that this study aims to fill.

By conducting an extensive review of the existing literature, the problem definition has been formulated. This chapter also defines the main objective along with the supporting sub-objectives of this study.

CHAPTER - 3

METHODOLOGY AND IMPLEMENTATION

3. METHODOLOGY AND IMPLEMENTATION

3.1. Overview

In the previous chapter, the literature survey highlighted the requirement to introduce a system that could generate effective camouflage textures for real time environment. Such methodology will help to get an effective camouflage pattern that can help an object to blend in the surrounding. This study aims to provide a method for creating camouflage textures that take into account actual battlefield conditions. This chapter projects the detailed methodology to achieve every objective associated with this research work.

3.2. Modules in proposed system

The proposed method utilizes a combination of CNN and image processing techniques to detect and interpret environmental features and generate a pixelated texture that blends in with the background. The generated texture is then applied to an object, such as a horse, vehicle, equipment or a human body, to camouflage and make it be concealed effectively. The approach can be utilized for different type of environments, including the desert, a snowy area, and forest.

A complete flow chart of the proposed system has been depicted in Figure 3-1. The system takes an image of the background environment as input. It consists of two major modules: a system that can identify the type of battlefield or terrain that requires a camouflage texture and a second module to generate effective pixelated camouflage textures for that environment considering primary background features. The generated textures are then assessed using photo-simulations and saliency maps to test the effectiveness.

Following modules have been implemented in this research work as shown in Figure 3-2:

- *Module I:* Input image, feature extraction and color clustering to extract primary colors from background image. Standardization of colors and its proportions.

- *Module II:* A Convolutional Neural Network model (TerrainCNN) to classify the environment into three classes: Forest, Desert and Snow land.
- *Module III:* Camouflage texture generation module

Module IV: Assessment of generated texture

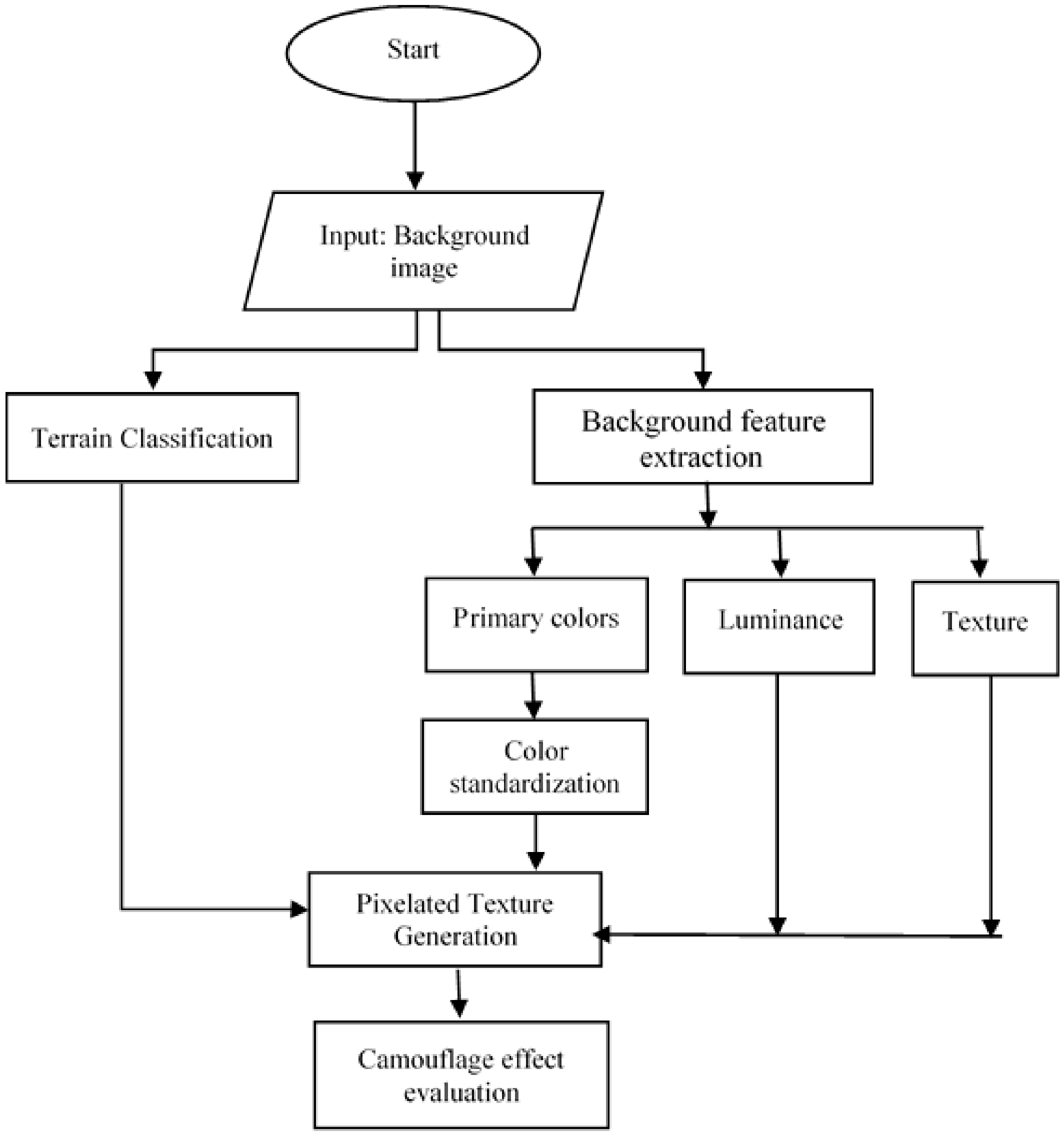


Figure 3-1: Flow chart of proposed system

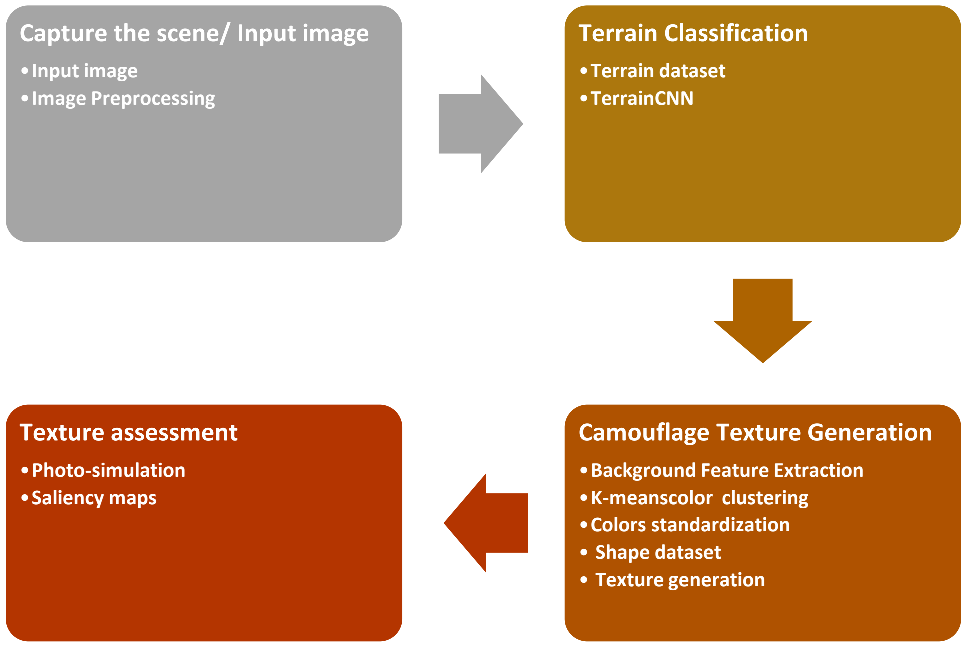


Figure 3-2: Modules in proposed system

3.3. Module 1: Input and pre-processing

This module consists of employing a high-resolution camera to capture an image of the actual environment or to upload it from the secondary drive. The captured image is subsequently subjected to pre-processing procedures like image de-noising and HSV color model conversion.

Different kinds of noise may be present in the image obtained from numerous sources or captured by the camera. The source of this noise may be electronic, read-out noise when reading data from camera, or cable noise when moving image from source of data to the computer (Booth & Schroeder, 1977; Shih, 2010). Noise could cause the loss of important data and features in the image (Ram & Choudhary, n.d.). Noise filtering method has been used to remove the noises from the input image. Two kinds of filters are heavily in use in image preprocessing: linear and non-linear (Distante & Distante, 2020; Gonzalez & Woods, 2018, n.d.). Linear filter does not affect the brightness of an image while reducing noise level that is why linear median filter has been used in this step(Bovik & Acton, 2009).

A linear median filter is a type of filter used to reduce noise in an image captured by a camera. It works by replacing the value of each pixel with the median value of the neighboring pixels in a defined window around that pixel (Dhruv et al., 2018; Gonzalez & Woods, 2018). This helps to remove random fluctuations and produce a clearer, more visually appealing image.

The equation for a simple linear median filter can be expressed as, Equation 3-1:

$$Y(i,j) = median(I(i-m:i+m, j-m:j+m)) \qquad \text{Equation 3-1}$$

where:

$Y(i,j)$ is the filtered pixel value at position (i,j)

$I(i,j)$ is the original pixel value at position (i,j)

m is half the size of the filter window, typically a square of size $3 \times 3 \ or \ 5 \times 5$

$median(I(i-m:i+m, j-m:j+m))$, represents the median value of the pixels within the filter window.

This filter is more robust than simple average-based filters because it replaces the pixel value with the median, which is less sensitive to outliers or extreme values. As a result, the median filter can provide a better representation of the underlying image and preserve important details while reducing noise. Figure 3-3 results of applying median filter over the input image.

3.4. Module 2: Terrain classification

Information about the terrain is important for making a good camouflage texture because it lets the pattern blend in with the environment. Knowing the terrain can help to figure out what kind of shapes, and patterns will work best in concealment of an object in that area. It is important to make sure that the camouflage texture is made to fit the environment in which it will be used. For instance, a camouflage pattern that works well in a forest might not work as well in a desert.

To achieve the objectives of proposed research work three kinds of terrains have been taken into consideration: desert, forest or woodland and snow fields. The entire process, from data collection to TerrainCNN model training and evaluation, is depicted in Figure 3-4. The processing stage includes gathering datasets for multiclass learning. A data set “Terrain” of a wide range of desert, forest and snow lands images has been created. It is a customized dataset and build utilizing the web as the primary source.

Figure 3-3: Results of applying median filter over input image

A common type of neural network (NN) for image classification problems is the convolutional neural network (CNN) (Gurney & York, 1997). Image classification is the process of analyzing the data and grouping it based on similarity (Elngar et al., 2021; P. Li et al., 2017). It relies heavily on the independent variables or properties of a dataset. A multiclass terrain classification model, "TerrainCNN," as shown in Figure 3-8 has been trained over the “Terrain” dataset. Multiclass classification refers to a classification task with numerous classes (more than two). In this research work "TerrainCNN" model is responsible for learning the features of the input background image and to classify the battlefield or military object deployment terrain into one of the specified category. The outcome is then used to produce a camouflage texture that will successfully help an item blend into that environment.

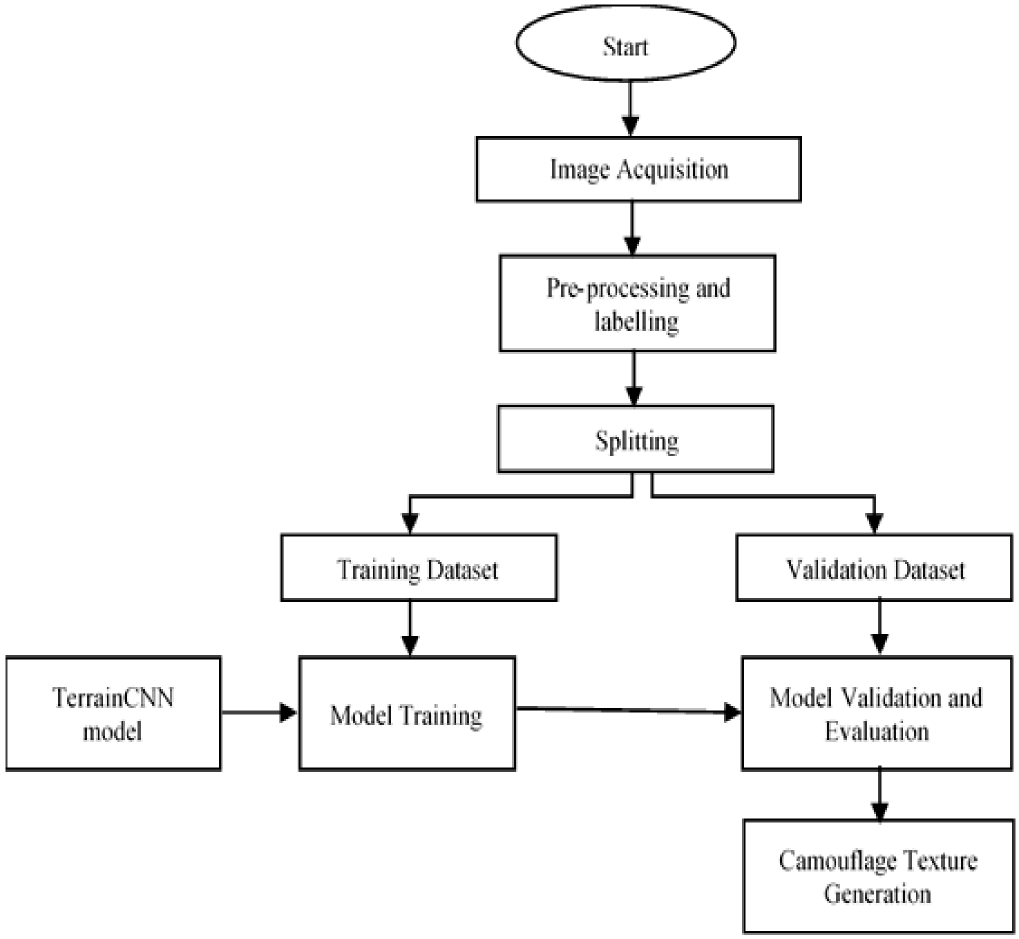


Figure 3-4: Terrain Classification using TerrainCNN

3.4.1. "Terrain" dataset formation

The model, TerrainCNN takes a set of images as training dataset representing different types of terrain and is trained to classify them into one of the three categories. The training process involves using a dataset of labeled images, where each image is assigned a label corresponding to its terrain category. This research work has produced a dataset titled "Terrain" featuring images of forests, deserts, and snow-covered areas. The dataset contains practically a diverse range of images that fit into one of these categories. Figure 3-5 depicts the procedure followed to create the dataset.

A detailed explanation of steps followed while creating the "Terrain" dataset is as follows:

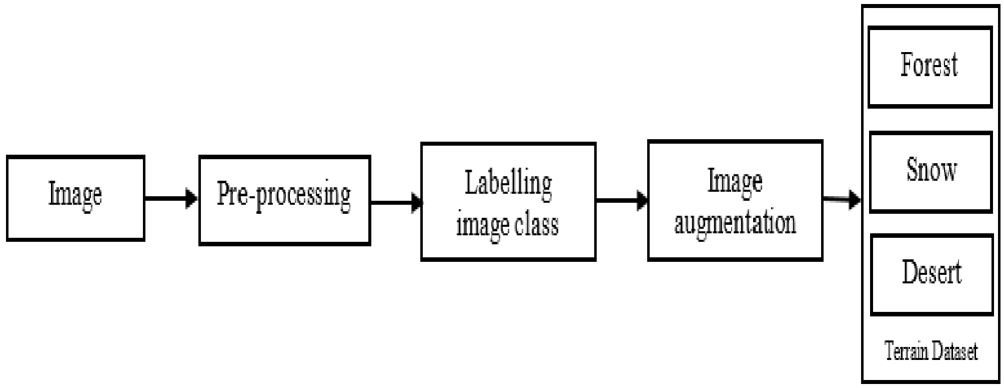


Figure 3-5: "Terrain" dataset formation

1. Image Acquisition

The process of acquiring digital images for use in a variety of applications, including computer vision, machine learning, and image processing, is referred to as image acquisition (DAVIES, 2005; McREYNOLDS & BLYTHE, 2005). Images may be downloaded from online sources, photographed using cameras, scanned from real documents or film, or both. Here, the images of the terrain where the defense force may operates have been downloaded from various online search engines (Bing Images, Google Images, etc.) after applying the filter on images having common creative license.

2. Pre-processing and augmentation

Image or data pre-processing is an important step before creating a dataset because it ensures that the images are in a consistent format and of high quality (Gonzalez & Woods, n.d.; Goyal et al., 2020; Nixon & Aguado, 2020), which can improve the performance accuracy of the CNN model will be trained on the dataset (Elgendy, 2020).

Noise in an image can cause false classifications, which can lead to inaccurate results. Linear and nonlinear noise filters are both commonly used to remove noise from images, but they have different advantages and disadvantages. The edges and minute features of an image are better preserved by linear filters than by nonlinear ones. Important characteristics in an image are less likely to be blurred or smoothed out by linear filters because they only react to minor variations in intensity. It does not affect the brightness of an image while reducing noise level which is why a linear median filter has been used while creating this dataset (Bovik & Acton, 2009; Dhruv et al., 2018).

In order to make data more processing-friendly, it is typically necessary to normalise it in some way before feeding it into a neural network. In this work, pixel values of images are normalized to binary. Images of the same size are required for both training and validation in machine learning models. All images in this dataset have been resized to 512×512 pixels.

Augmentation is a practice used to artificially expand the number of images in using numerous image transformations techniques to the existing images (Mikołajczyk & Grochowski, 2018; Shorten & Khoshgoftaar, 2019). Training the neural network model on a large dataset will yield more efficient models. In this work, the dataset augmentation has been done using some image transformation techniques like rotation, scaling, and flipping.

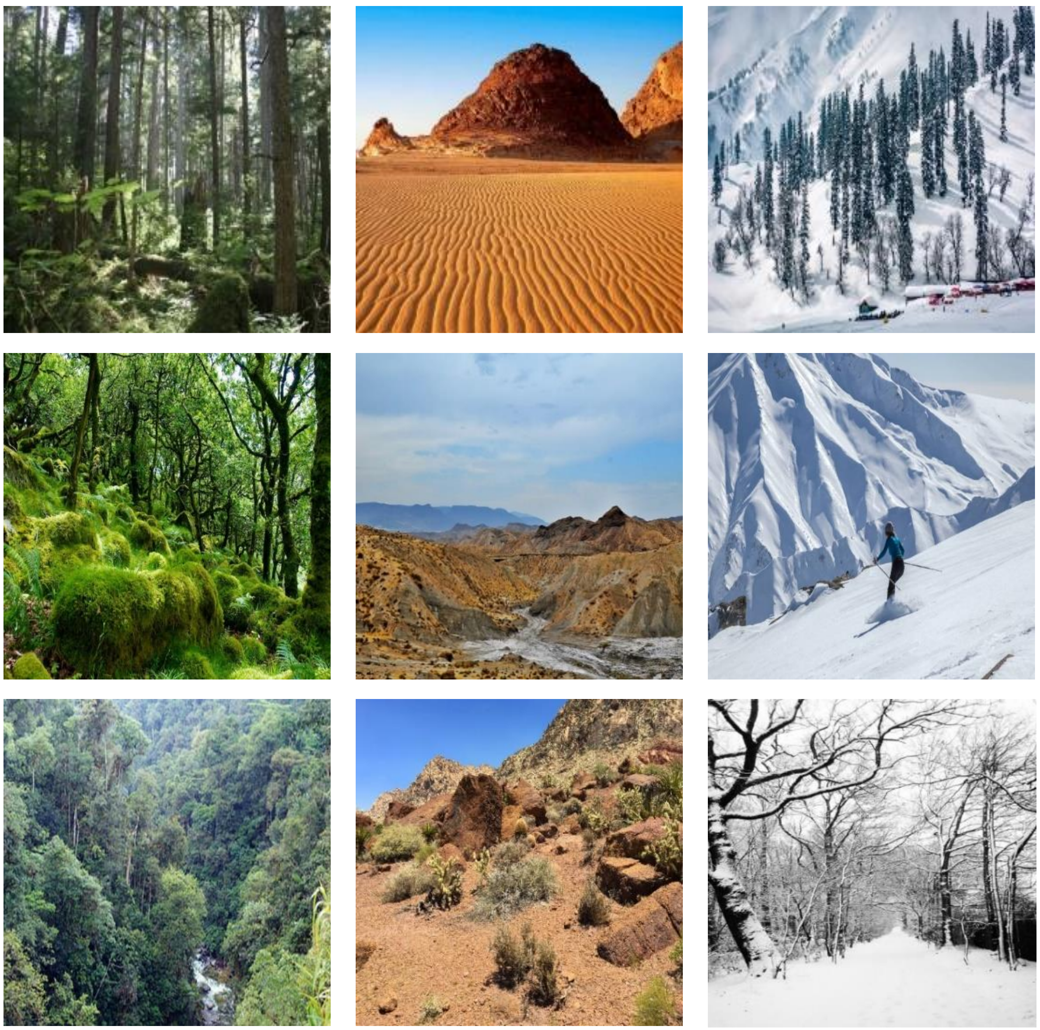
3. Labelling image class

Semantic classes of terrain are defined according to their appearance and human intelligence. The class label represents the type of environment of the image in the dataset. The initial version of the dataset has three categories designated as snow field, forest area, and desert land. Figure 3-6 contains sample images of different classes in the terrain dataset.

The dataset "Terrain" has been divided into two subset: training and validation. One portion is used for training, and the other is used for testing. To train the CNN model, 80% images were used from the dataset, while 20% images were used for validation. The set of images have been categorized into snow area, forest area, and desert land. The number of images grouped to each class group is displayed in Table 3-1 along with the details of the training and validation segmentation of the images for each class.

Table 3-1: Classes in Terrain dataset

<table>
<tr><th>Class labels</th><th>Number of images</th><td rowspan="5">Training: 80%
Validation: 20%</td></tr>
<tr><td>Forest</td><td>974</td></tr>
<tr><td>Snow</td><td>958</td></tr>
<tr><td>Desert</td><td>808</td></tr>
<tr><td>Total</td><td>2740</td></tr>
</table>



a) Forest area **b) Desert land** **c) Snow Field**

Figure 3-6: Sample images from "Terrain" dataset

3.4.2. Implementation of “TerrainCNN” model

Identifying the type of terrain is important before generating a camouflage texture because different terrain types have different visual characteristics and require different camouflage patterns to be effective. This section describes the proposed "TerrainCNN" a Convolutional Neural Network (CNN) model for the classification of terrain into following classes: desert, forest area & snow field. The CNN architecture is chosen for its ability to extract characteristics and learn characteristics from image automatically (Choudhary et al., 2022; Elgendy, 2020).

TerrainCNN is a CNN model designed to predict the class of landscape images amongst desert land, snow field, and forest area. The model consists of multiple layers, including convolutional, pooling, and fully connected layers. The convolutional layers are responsible for learning features, while the pooling layers reduce the dimensionality of the feature maps. The fully connected (dense) layers gives the predicted class as an output based on the probability calculation. The model is trained on a dataset of images labeled as desert, snow, or forest, and uses a supervised learning approach to learn the features and patterns that distinguish each class. Once trained, the model is used to classify new images of landscapes into the appropriate class based on their visual characteristics.

The layered architecture of proposed “TerrainCNN” model is depicted in Figure 3-8 and after training model summary is shown Figure 3-7. It consists of three convolution layers (Conv2D), an average pooling layer attached to each convolution layer, followed by a flat layer and two dense layers. It is trained for 12 epochs on NVIDIA GeForce GTX 1650.

The selection of the epoch count was based on observing the validation loss to identify when it stabilizes during training. Additionally, the implementation includes early stopping to automatically halt training if the validation loss ceases to improve or begins to deteriorate.

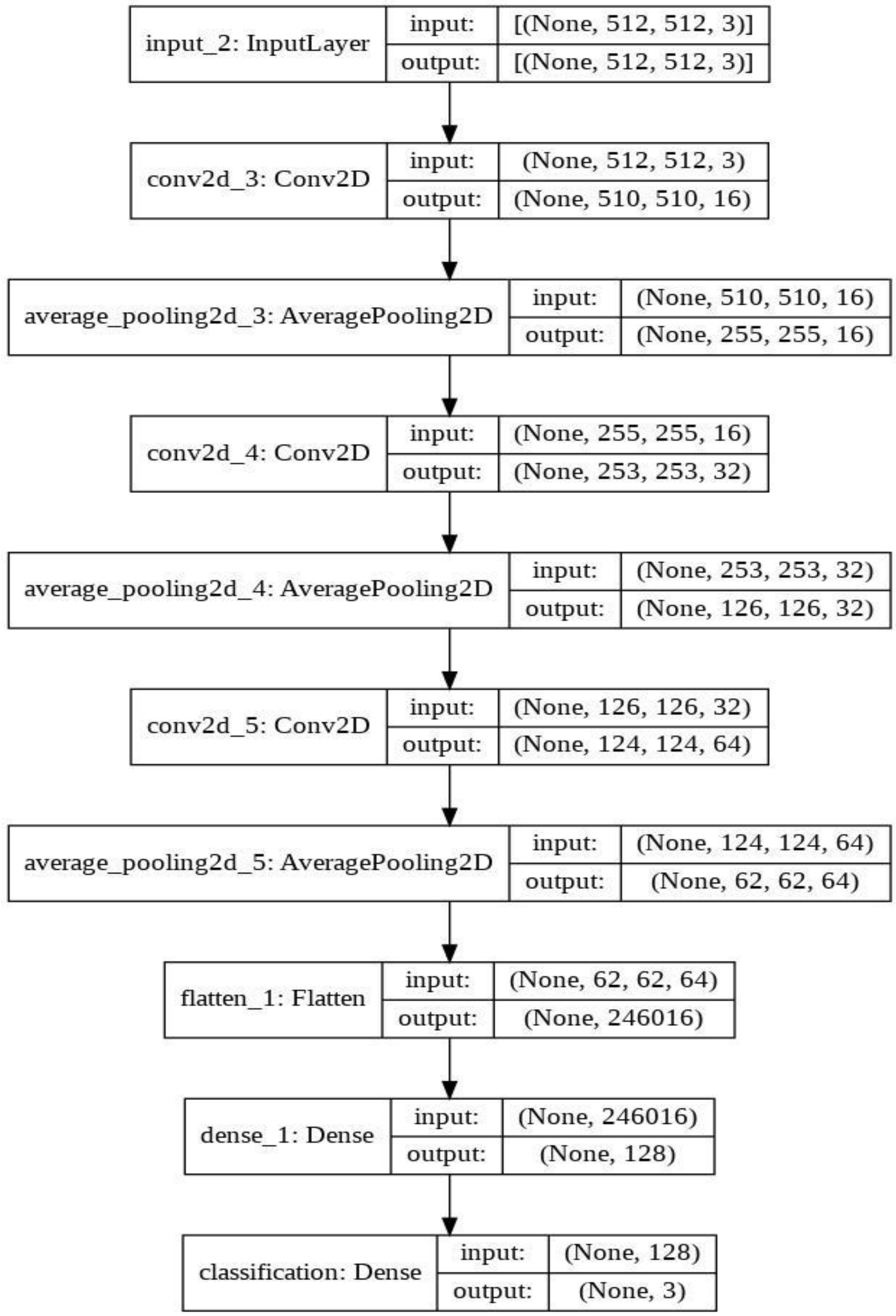


Figure 3-7: TerrainCNN model summary

Description of layers are as follows

1. All convolutional layers are having 3x3 kernel-sized filters and ReLU as an activation function. ReLU is used in hidden layers because it trains faster than tanh and sigmoid activation functions (Fred Agarap, 2018; Hara et al., 2015). Equation 3-2 represents the ReLU activation function:

$$f(x) = \max(0, x) \qquad \text{Equation 3-2}$$

2. All average pooling layers are having 2×2 pool size. It down samples the input values by calculating the average value of its input.
3. Flatten layer flattens the dimension volume $62 \times 62 \times 64$ to 1×246016 and the last dense layer classify the input landscape image to one of the specified class.

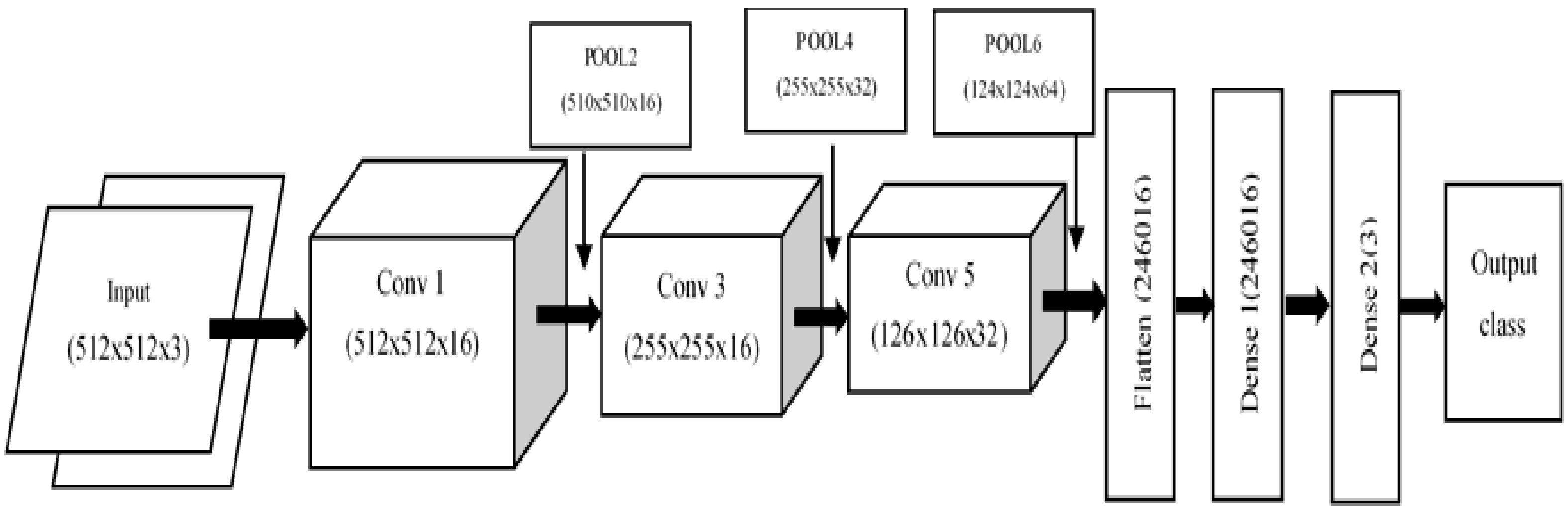


Figure 3-8: Layered Architecture of "TerrainCNN"

3.5. Module 3: Camouflage texture generation

Camouflage texture generation is a technique for creating patterns that blend into the background, making objects harder to distinguish. After identifying the type of terrain for which camouflage texture is required, the next step is to generate a texture that can resemble the background environment. Different environments have different visual characteristics, such as color, lighting, and texture, and these factors have been taken into account while generating camouflage textures. This section provides a detailed explanation of the proposed method of generating pixelated camouflage textures. It involves the use of terrain relative spot shapes, standardized set & proportion of colors, intensity, orientation, and other textural features.

The main topological elements are used in the texture generation process for camouflage, as seen in Figure 3-9, and the produced texture is then subjected to a pixalization effect. The produced texture should imitate the landscape's most notable features and be interpreted as terrain itself. The camouflage pattern of a landscape should not only resemble the surrounding environment, but also perform at any distance. Therefore, the disruptive digital pattern should mimic the background environment's hues, brightness, and textural pattern. The texture's pixilation will prevent its detection not only from close range, but also from a greater distance.

Figure 3-11 shows the complete process of generating camouflage texture that will blend effectively in the background environment. The procedure begins with a blank canvas of a predetermined size $(w \times l)$. The diverse shapes from “Shape” dataset are then dispersed throughout the canvas to match the camouflage texture to the background environment. The specific camouflage texture of the terrain will be derived using primary topological features. These features will be kept in the generated texture, and texture pixilation will aid in improving concealment and preventing prey’s observation. The generated texture will be then passed to the next module for effectiveness evaluation and assessment.

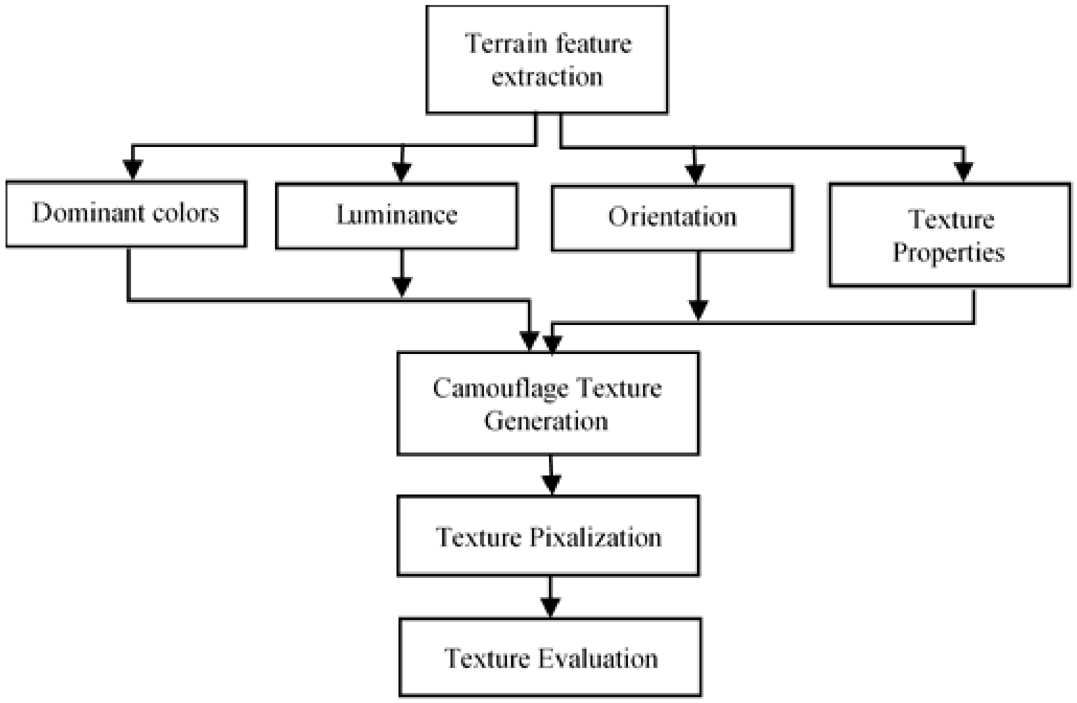


Figure 3-9: Camouflage texture generation steps

3.5.1. Parameters for texture design

The basic purpose of camouflaging anything in the surroundings is to conceal it by replicating background features and preventing recognition. To achieve this purpose, it is necessary to incorporate a wide range of natural environmental elements into camouflage texture (Jia et al., 2017b; H. Yang & Yin, 2015a). According to the literature, color values and intensities, as well as ambient texture, dominate the major design concepts. Aside from them, light, object's physical properties, and the surrounding environment all influence how far humans can see with their eyes (Miao & Shaohui, 2017).

This section addresses the many aspects that should be present in a camouflage texture to improve concealment. The parameters are as follows (*Finding Objects of Interest in Images Using Saliency and Superpixels*, n.d.; Y. Li & Correll, 2018; Merilaita et al., 2017; Rao, 1999; TAYLOR, 1959):

1. Terrain-specific characteristics

Background features, among other aspects, are critical for camouflage textures to accurately match objects to their surroundings. Landscape, vegetation, man-made objects, light, shadows, and colors all help to disguise backgrounds. Blending is just matching as many of these qualities as possible while eliminating as many conflicts as possible. Apart from that, geographical factors have a huge impact. The light, for example, influences the brightness factor. Another example is the formation of dense shadows in desert areas. Deserts and snow terrain are typically desolate, necessitating extra effort when creating camouflage textures. Forest habitats, which are mostly vegetated and densely forested, give more effective camouflage with less manufacturing work than snow or desert land.

2. Characteristics of light

Light is the most important factor in generating a picture on the retina, mirror, or lens. As a result, the capacity to detect an object in a scene is heavily reliant on light qualities. Color, optical texture, brightness, and shadow generation should all be considered when constructing the texture for an object to be hidden.

3. Texture characteristics

These qualities fall within the broad group of those that influence visible-range object recognition. The physical qualities of an object, such as its external shape or structure, dimension, colors and intensity, and orientation patterns, contribute in recognition and identification.

4. Movement

When using camouflage, it is essential to make sure that the object remains stationary or moves as needed, as movement makes the thing more visible. The best technique to conceal a moving object is to match its colors and texture to the background or to break up its outline.

3.5.2. Background feature extraction & standardization

The ability of the human visual system to detect camouflaged objects in a scene depends on several factors, including the background, the type of camouflage pattern, and the individual's attention and perception. In general, the human visual system is more likely to detect a camouflaged object if it is in contrast with its surroundings, has a noticeable shape, or is in an area of the scene that the observer is looking at. However, if the camouflage is effective in blending the object into the background, it can be difficult for the visual system to detect it.

As previously stated in section 1, the background features of a terrain image can include various elements such as color, texture, pattern, brightness, and clutter-ness. The background features can influence the perception and detection of objects in a scene by creating a context for the objects and affecting the overall visual salience. For example, a cluttered background with many elements can make it more difficult to detect an object, whereas a simple, uniform background can make an object stand out. The background features can also interact with the features of the object, such as its color and shape, to determine how well it blends into the scene and how easily it can be detected by the human visual system.

Background feature extraction is a key step in the process of generating camouflage textures. The goal of this step is to analyze the background features of an image and then use this information to synthesize a camouflage texture that will effectively blend the target object into the background.

3.5.2.1. Intensity and texture

The intensity of a pixel in an image is typically represented as a single numerical value, which can be calculated as a weighted sum of its RGB (Red, Green, Blue) values. The Equation 3-3 used for calculating the intensity of a pixel is (Gonzalez & Woods, n.d.):

$$I = 0.299 \times Red + 0.587 \times Blue + 0.114 \times Green \qquad \text{Equation 3-3}$$

I in Equation 3-3 represent intensity value of each pixel in the image. It is a common way to calculate grayscale intensity from a color image using the given weights for the red (R), blue (B), and green (G) channels. These weights, 0.299, 0.587, and 0.114, respectively, are derived from the relative luminance of each color channel to mimic the human perception of brightness in a grayscale image. The human eye is more sensitive to green light, followed by red and then blue. This formula is based on the fact that the human eye perceives different colors differently. The values in this formula reflect the relative sensitivity of the human eye to different colors (Feng et al., 2015).

Generating a camouflage texture relies also on the textured elements of the background image because texture is crucial in blending in with the environment to avoid detection. To extract textural features of the terrain image computer vision technique, texture analysis using Gabor filter (Ansari et al., 2017; Jiang et al., 2009; Mehrotra et al., 1992) has been used.

The Equation 3-4 for a 2D Gabor filter for texture analysis is as follows:

$$G(i,j) = \exp\left(-\frac{i^2+j^2}{2*\sigma^2}\right) * \cos(2*\pi*f*i) \qquad \text{Equation 3-4}$$

where:

- i and j are the coordinates in the image.
- σ is the standard deviation of the Gaussian envelope, which determines the size of the filter.
- f is the frequency of the sinusoidal component, which determines the orientation of the filter.
- exp is the exponential function.
- cos is the cosine function.

3.5.2.2. Extraction and standardization of dominating colors

In camouflage texture generation, the selection of colors is a primary requirement as it plays a crucial role in achieving the desired blending effect with the surrounding environment. In a terrain or scene image, the colors present can vary greatly depending on the environment and the lighting conditions. In order to generate a camouflage pattern, it is often necessary to simplify the color palette and select a smaller set of colors that represent the dominant colors in the scene. Color quantization (Frackiewicz et al., 2019; Hou et al., n.d.; Papamarkos et al., 2002; Ramella, 2020) can help to reduce the complexity of the image and make it easier to select the colors for the camouflage pattern. By quantizing the image to a smaller number of colors, the dominant colors in the scene can be more easily identified, and a smaller set of colors can be selected that best represent the dominant colors in the scene. This research work uses the K-means quantization, the technique which uses K-means clustering algorithm (Celebi, 2011; Dhanachandra et al., 2015; Maruyama, 2006; Wei et al., n.d.)to group similar colors together and map them to a smaller set of colors, Algorithm 3-1.

There are a number of potential drawbacks to creating camouflage textures by utilizing extracted dominant colors. One problem is that the extracted set of colors may have less diverse colors and belongs to same family of colors and potentially less effective final texture. Also, the colors that are extracted might not match the colors of the environment or the standards of the industry, so the final texture might not fit in well. Furthermore, the luminance values of the extracted colors may not match the environment, leading to a texture that is noticeable or stands out, making it less effective at hiding the object it is meant to camouflage. In conclusion, using the extracted dominant colors of an image directly without further processing may lead to limitations and possible errors that can make the final texture less effective.

Algorithm 3-1: K-means color clustering algorithm

Algorithm 3-1

KMeansColorClustering()

It is a popular method for color quantization in scene images. The basic steps of k-means color clustering are as follows:

Step 1: [Initialization]

K:= number of clusters

Centroid of K-clusters: Random initialization

[The centroids represent the center of the clusters and will be updated during the iterations of the algorithm.]

Step 2: [Repeat the following steps until convergence or a maximum number of iterations is reached:]

2.1: [Assign each pixel to a cluster: For each pixel in the image, calculate the Euclidean distance between the pixel color and the centroids of each cluster. Assign the pixel to the cluster with the closest centroid.]

for each pixel (x_i):

for each centroid (c_j),

calculate d_{ij} = dist(x_i, c_j)

assign x_i to the cluster with the minimum d_{ij}

2.2: [Update centroids: Calculate the mean color of all the pixels assigned to each cluster. Replace the current centroids with the mean color of each cluster]

for each cluster (c_j):

calculate the mean color m_j of all the pixels assigned to the cluster

update c_j= m_j

In this research, the extracted set of dominant colors has been standardized (Algorithm 3-2) before being used to generate camouflage textures, to ensure that the final texture will blend in well successfully with the environment and meet the industry standards. The standardization process involves matching the colors with the set of industry standard colors, discarding non-standard colors, and normalizing the luminance values to match the environment. By standardizing the colors, the final texture will be consistent with the industry perspective and have improved accuracy, reducing color discrepancies and ensuring better matching with the environment.

Algorithm 3-2: Algorithm to standardize the set of of colors for camouflage texture

Algorithm 3-2

Standardize_colorset()

The steps followed to standardize the set of colors for a camouflage texture.

Step 1: Extract dominant colors from image

input = Terrain_image

dominant_colors = KMeansColorClustering (input)

irrelevant_colors=#list of hexadecimal values as per assumptions listed below

Step 2: Match with industry standard colors

industry_standard_colors = IndustryStandardColors(terrain_class) #list

standardized_colors = [] #empty list

for color in dominant_colors:

```
                matched_color = MatchColor(color, industry_standard_colors)   #calculate
Euclidean distance
            if matched_color is not None:
                  standardized_colors.append(matched_color)
Step 3: Discard non-standard colors
            final_colors = []
            #Following assumptions mentioned below
            for color in standardized_colors:
                  if color in industry_standard_colors and not in irrelevant_colors:
                       final_colors.append(color)
Step 4: Repeat step 1 with K=K+3 if final set of colors is less than 3
Step 5: Find the proportion of each standardized color in the input image
            color_proportion = []
            for color in final_colors:
                    proportion = CalculateProportion(input, color)
                         color_proportion.append(color, proportion)
Step 6: Normalize luminance values
            normalized_colors = []
            environment_luminance = EnvironmentColorLuminance()
            for color in final_colors:
                         normalized_color=NormalizeColorLuminance(color,
environment_luminance)
                         normalized_colors.append(normalized_color)
```

Following assumptions not limited to have been made in this process:

- The set of colors finalized for the camouflage texture must accurately reflect the colors present in the target environment.
- The finalized set of colors should diverse, well- balanced and not too strong, as this may make the camouflage less effective.
- The brightness or luminance of the colors should fit to the environment and make the texture fit in with its surroundings.

- The colors should be standardized against the industry standard colors used by the Defense Force or other relevant organizations to ensure consistency and compatibility with existing equipment.
- Bright and vibrant colors such as hot pink, bright yellow, or red does not typically belong to camouflage textures for any kind of terrain.
- Black is not a color created by nature, usually it is the effect of the shade of trees, hills, mounds etc. Color black attracts human visual attention very easily. Therefore, if there are darker shades of black in the list of primary colors, it will be removed.
- If the image of the area is taken as the front view, the colors of the sky and clouds will be on the list of dominating colors. Hence, blue and white colors for desert land and forest area will not be considered. In the case of snow region, it has been seen that white snow has the effect of the color of the sky. So, some ranges of blue can be considered for the snowfield.

If any color in the primary color list has a larger difference in HSV values than the standard colors as shown in Table 3-2, that color will be removed from the final list. The Euclidean distance, Equation 3-5 can be used to calculate the difference in the HSV of the extracted primary color and the corresponding standard color.

$$\mathrm{Dist}(\mathrm{C}, \mathrm{S}) = \sqrt{(Hc - Hs)^2 + (Sc - Ss)^2 + (Vc - Vs)^2} \qquad \text{Equation 3-5}$$

Table 3-2: Standard set of colors for specific terrain (Dugas et al., n.d.)

Terrain	Standard colors
Dense forest land	Tan, Brown (different shades), Green (different shades), Khakhi,
Forest/woodland	Tan, Brown, Green,
Snow field	White, Dark green, brown, Sky blue
Dessert land	Tan, Brown (different shades),, Khaki, Dark Tan or Tan, Brown (different shades),, Light Grey, Dark Tan

3.5.3. Spot dataset formation

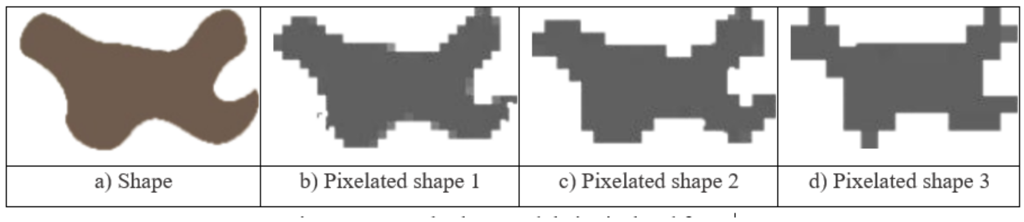
The need for a spot shape dataset to generate camouflage textures is driven by the requirement for creating realistic and effective camouflage patterns. Spot shapes are the basic elements of the pattern, and can be squares, rectangles or any other shapes. These shapes are positioned and sized to achieve the desired effect. The size and placement of the spot shapes can be adjusted to create a range of different textures, from tight, geometric patterns to more organic, irregular patterns.

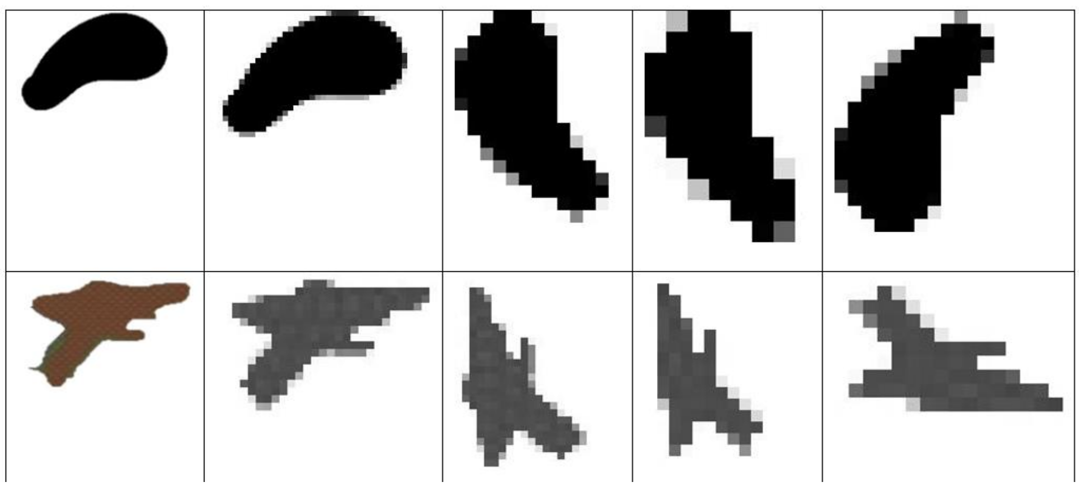
In this research work a systematic approach has been used to create a dataset of spots and shapes to generate camouflage textures that involves defining the parameters of the spots and shapes, collecting and categorizing sample images, generating a large number of spots and shapes, and testing and refining the dataset. The resulting dataset is then used to generate a range of camouflage textures that are well-suited to different environments.

The defence sector already employs a wide range of classic forms and designs in its uniforms, weapons, and hardware. For example, the chocolate chip pattern is popular among armies for use in deserts, while the tiger stripe pattern and the woodland pattern are preferred for use in dense forests. A dataset with a lot of variety in shape and pattern has been built for this research. This data set is composed of numerous geometric forms that were motivated by the patterns used by defence industry worldwide. This dataset shows the relative sizes of a variety of landscapes, including forests, deserts, and snow lands. Different morphological processes have been used in this. As pixelated shapes can help to conceal objects or surfaces from visual detection by breaking up their outlines and making them less recognizable, the shapes were pre-processed and then pixelated in different pixel dimensions. The dataset was augmented using various transformation techniques. Pixelated version of some shapes in different pixalization level are shown in Figure 3-10.

3.5.3.1. Morphology and shape segmentation

Morphology is a branch mathematics and have applications in image processing that deals with the shape, size, and structure of objects in an image. It provides a set of mathematical operations that can be used to extract shapes from images, analyze their properties, and modify their appearance. By using morphological operations, it is possible to extract shapes from images, separate objects from their background, and analyze their properties (Hu et al., 2013; Jia et al., 2017b; S. Liu et al., 2009). This can be particularly useful in fields such as computer vision, where it is important to recognize and classify objects in images. Morphological operation boundary extraction is used to extract the boundaries of shapes in an image.





a) Original Shape	b) Pixalization	c) Pixalization and 90^0 left rotation	d) Pixalization and 90^0 left rotation	e) Pixalization and flip vertical

Figure 3-10: Sample shape with various pixilation effect

Boundary Extraction

Morphological boundary extraction is a process used in image processing to extract the boundaries of objects in an image using morphological operations. The goal is to identify the contours of the objects and represent them as a set of points or curves. The basic idea behind morphological boundary extraction is to subtract the image from its erosion. The resulting image represents the boundaries of the objects in the image. Mathematically, the morphological gradient of an image I by a structuring element S can be expressed as in Equation 3-6:

$$I_{\mathrm{Boundary}} = I - I_{Erode} \qquad \text{Equation 3-6}$$

Erosion

The erosion operation works by removing pixels from the boundaries of objects in an image. It is performed by sliding a structuring element (a small binary shape) over the image and replacing each pixel with the minimum value of the pixels covered by the structuring element. Mathematically, the erosion of an image I by a structuring element S can be expressed as in Equation 3-7:

$$I_{Erode=}I \ominus_b S \qquad \text{Equation 3-7}$$

$$I \ominus_b S = \{\mathrm{x} \in E^N \mid x + s \in I \; for \; every \; s \in S \qquad \text{Equation 3-8}$$

In Equation 3-8 E^N is the set of all the points $p = (x_1, x_2, x_3, \ldots \ldots, x_N)$ in N-dimensional Euclidean space. I and S belongs to E^N having set elements $i = (i_1, i_2, i_3, \ldots \ldots, i_N)$ and $s = (s_1, s_2, s_3, \ldots \ldots, s_N)$ respectively.

3.5.4. Pixelated camouflage texture generation

This section provides a complete flowchart as shown in Figure 3-11 and algorithms for creating camouflage texture that will effectively blend an object in the background environment.

Basic steps followed to create the camouflage pattern are, Algorithm 3-3:

Algorithm 3-3: Camouflage texture generation algorithm

Algorithm 3-3

CamouflageTexture()

Step 1: Initialize the canvas dimensions $W \times H$

Step 2: Divide the whole canvas into smaller sections of varying sizes

Step 3: Initialize an empty list of shapes

Step 4: Extract shapes from Shape dataset for classified terrain

Step 5: For each extracted shape:

a. Calculate shape perimeter, P

$$P = \sum_{i=1}^{N} len(side_i)$$

Where:

i is the number of sides in the shape

$len(side_i)$ calculates the length of side i

b. Add shape to the list of shapes

Step 6: For each section in the canvas:

a. Select a shape from the list of shapes matching section dimension

b. Place the shape in the current section

Step 7: For each shape in the canvas:

a. Select a color from standardized color set

b. Fill the shape with the selected color

Step 8: Repeat step 5 and 6 until all the sections in canvas get filled

Step 9: Return the camouflage pattern on the canvas

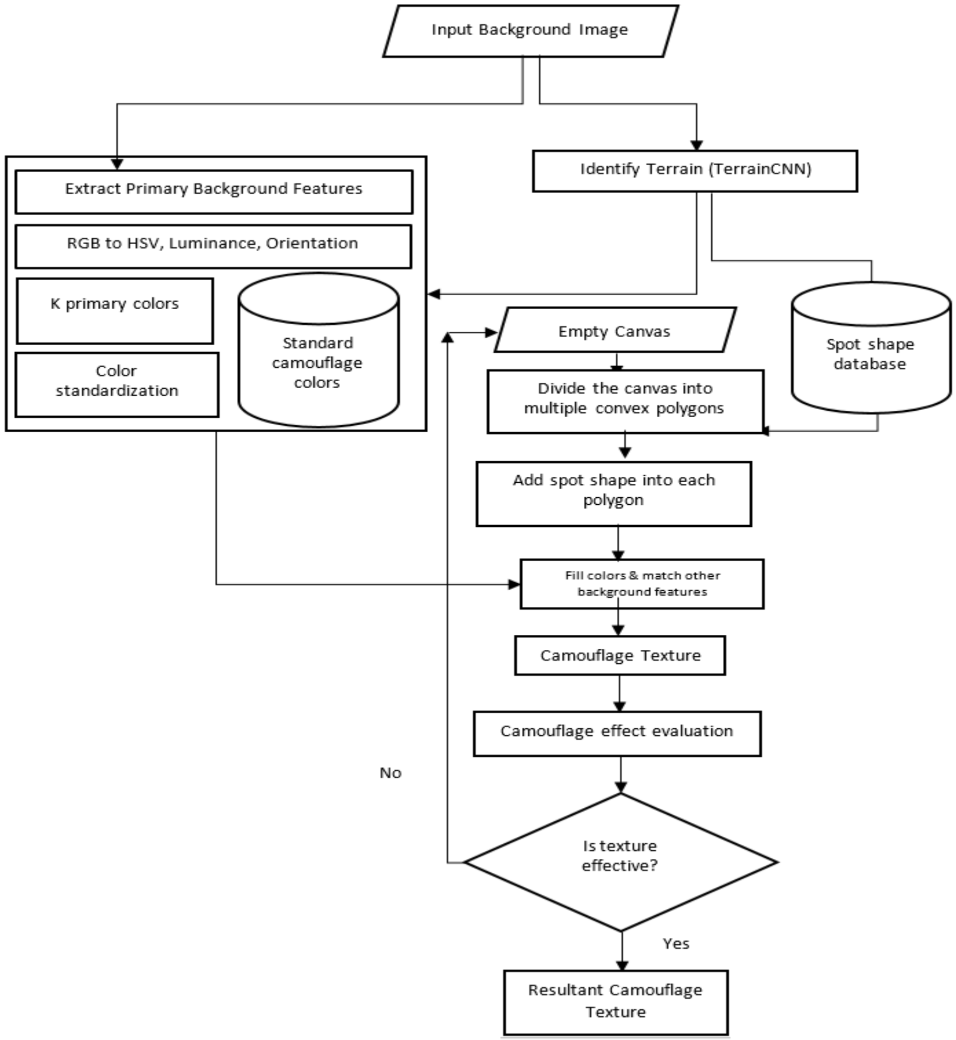


Figure 3-11:Flowchart for pixelated camouflage texture generation

The pseudocode shapeExtraction() shows the step-by-step process for the selection of shapes, and textureGenerate() shows the process for generating the final camouflage texture for the input background image.

Pseudocode textureGenerate()

Input: Empty canvas of the dimension $(WxH) and\ colors[]$

Output: Textured Canvas

textureGenerate() // **Function use to generate textures**

$\boldsymbol{Begin}$

Step 1: $Canvas(W, H)$ // **Creation of an empty canvas**

Step 2: $subSectionList = Add(subSection, edge\_coordinates)$ // **Divide the canvas into sub sections of different dimensions**

Step 3: $perimeterList = addPerimeter(subSection, calcPerimeter(subSection))$ // **calculate perimeter of each sub section**

Step 4: $shapes = shapeExtraction(Terrain, W, H)$ //**Extract shapes from shape dataset**

$sort(shapes)$ //**sorting of shapes on the basis of perimeters**

Step 5: $For\ i\ in\ subSectionList$

$if\ (shapePerimeter\ <=\ perimeterListi)$ //**Spread multiple shapes into the subsection i**

$\{$

$shapeList\ =\ addShape(shapes, subSection)$ //**add shapes into subsections of canvas**

$Canvas = append(shapeList)$

$\}$

Step 6: $For\ i\ in\ shapeList$

$If\ (shapeListi.color\ ==\ None)$ && $(shapeListi.neighbor.color! = Color)$ // **Select color and its proportion**

$fillColor(shapeListi, Color)$ // **spread color**

$\boldsymbol{else}$

$Repeat\ step\ 6$

Step 7: $Return\ textured\ canvas$

$\boldsymbol{End}$

Pseudocode: shapeExtraction()

shapeExtraction() //**Function use to extract shape**

Input: Terrain, Shape_dataset(S),w, h //**Terrain image, dataset of shapes, width & height**

$\boldsymbol{Begin}$

Step 1: $Select\ S$ // **Select shape dataset $\boldsymbol{S}$ for specific terrain**

Step 2:

$P =\ calcPerimeter(w, h)$ //**calculate perimeter and assign to $\boldsymbol{P}$**

$Shape\_list = []$ // **initially Shape list is empty**

$Edge\_list = []$ //**Initially Edge list is empty**

Step 3: $Select\ RS\ \in D$ //**Select a random shape from dataset**

$S = random\_shape(Shape\_dataset)$ //**Assign randomly chosen shape to S**

$SP\ =\ calcPerimeter(W_S, H_S)$ //**calculated perimeter of shape assign to $\boldsymbol{SP}$**

$If\ (P >\ SP)$

```
      {
  Add_shape(Shape_list, (S, SP))
  Edge_list(S, list(E))
     P −= SP
    }
Repeat Step 3
Step 4: Return (Shape_list, Edge_list) //Return the list of shapes with edges
End
```

3.6. Module 4: Camouflage texture assessment

Digital photo simulation (Lin, Chang, & Lee, 2014; Y. Li et al., 2022; Peak et al., 2006; Toet & Hogervorst, 2020) and saliency maps (M. M. Cheng et al., 2015; Feng et al., 2015) have been used in this research work to see how well the created camouflage texture can blend the object into the surrounding environment. This sub section provides the description of experimental setup used to conduct photo simulation and different ways to generate saliency maps for assessing camouflage texture's effectiveness.

3.6.1. Photo-simulation

The efficiency of various camouflage patterns can be tested in a simulated, digital environment using a photo simulation experiment. The procedure is divided into two steps: The first step is to compile a database of landscape photographs that include camouflaged objects. The second is to conduct experiments with observers in a controlled room to locate camouflaged objects in the image.

Experimental Setup: In this experiment, a personal computer with a digital imaging system and an assistant are provided to each observer. In addition, the experiment's methodology and examples are described before starting the experiment.

Table 3-3 represents the format used to record data in this experiment. The copy of this sheet is provided to each associated assistant to record the observations. The following presumptions and restrictions about the input background image are taken into consideration while conducting the experiments:

- It might or might not have a concealed object in it.
- It might have more than one item covered with camouflage.

Each observer's task is to find the object(s) concealed in the background image. The assistant keeps track of how long it takes observer to find a concealed object, how many concealed objects are found, and the time when the observer declares that the scene is complete and no more items are present.

Average hit rate, average detection time, and difficulty level are commonly used assessment parameters to evaluate the performance of camouflage texture in a scene (Lin, Chang, & Lee, 2014; Lin, Chang, & Liu, 2014).

Average hit rate refers to the proportion of camouflaged objects correctly detected by the observers, and it is typically expressed as a percentage, Equation 3-9. A low average hit rate indicates that the camouflage texture is performing good to blend the object in the scene (Lin, Chang, & Lee, 2014; Lin, Chang, & Liu, 2014).

Average detection time refers to the amount of time taken by the observers to detect a camouflaged object once it is present in the scene Equation 3-10. A higher average detection time is preferred, as it means that the camouflage texture is able to hide the object effectively in the background environment (Lin, Chang, & Lee, 2014; Lin, Chang, & Liu, 2014).

Difficulty level refers to the complexity of the camouflage texture with reference to background scene. Observers had to give a difficulty rating to textures (1 to 5, 1 weak and 5 very good) according to their perception of how effectively it would work in a real environment. A higher difficulty level indicates that the camouflaged object is harder to detect due to its similarity with the background.

$$Average\ Hit\ rate\ (\%) = \frac{True\ positive\ events}{Number\ of\ observers} \times 100 \qquad \text{Equation 3-9}$$

$$Average\ detection\ time\ (s) = \frac{\sum detection\ time}{Number\ of\ observers} \qquad \text{Equation 3-10}$$

Table 3-3: Format to record data from photo simulation experiment

<table>
<tr><td colspan="2">Observer name:</td><td></td><td></td><td colspan="5">Distance from computer:</td></tr>
<tr><td colspan="2">Age:</td><td></td><td></td><td colspan="5">Date of experiment:</td></tr>
<tr><td colspan="2">Eye sight:</td><td></td><td></td><td colspan="5"></td></tr>
<tr><th rowspan="2">S.No.</th><th rowspan="2">Input Image Id</th><th rowspan="2">No. of objects detected</th><th rowspan="2">Total time used for observation</th><th colspan="3">Detection time (Seconds)</th><th rowspan="2">Difficulty level
Rate (1 to 5: 1=min, 5=max)</th><th rowspan="2">Remark (if any)</th></tr>
<tr><th>1</th><th>2</th><th>3</th></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
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</table>

3.6.2. Saliency maps

A saliency map is a visual representation of an image that highlights the most salient or attention-grabbing regions. These regions are typically those that stand out from their surroundings, such as objects with dissimilar contrast, colors or orientation (Borji et al., n.d.; Itti, 2001; Itti et al., 1998; Itti & Koch, n.d., 2000, 2001). This is useful in fields such as image processing, computer vision, and object detection, where identifying and locating objects in an image is crucial (Achanta, 2011; Achanta et al., n.d.; Borji et al., n.d., 2019; Gold, 2001; Ren et al., 2014; Skurowski & Kasprowski, 2018; L. Xu et al., 2014)By using a saliency map, it is possible to locate concealed or camouflaged objects in an image, as they will appear as distinct regions in the map.

It is a 2-dimensional scalar map used to represent visual saliency regardless of the features of the main area. Evaluation of camouflage texture using saliency map is based on mechanisms of the human visual attention system. This technique compares different features between the foreground object and the background scene (Feng et al., 2015).

Two types of saliency maps are taken into account for locating the objects those have properties different from the background image. The saliency maps have been generated using region contrast based (M. M. Cheng et al., 2015) and histogram contrast based method (M. M. Cheng et al., 2015; Feng et al., 2015).

3.6.2.1. Global Contrast (GC) method

A global contrast-based saliency map is a type of saliency map that is generated by comparing the contrast of different regions in an image. This is typically done by computing the difference between the mean intensity of the region and the mean intensity of the entire image. The regions with the highest contrast will be highlighted in the saliency map, making it easier to identify and locate objects in the image. This method is commonly used in object detection and image processing applications because it is efficient and easy to implement.

Global contrast (GC) based method (M. M. Cheng et al., 2015) differentiate an object from its surroundings by creating clear saliency values around object edges. This model compares between all pixels/regions in the whole image. The results of the comparison are then accumulated. The advantages of using global contrast (GC) method is: 1) it produces high saliency and 2) highlights all saliency areas by distributing the same saliency values in equal areas. For the calculation of GC based saliency, histogram contrast (HC) method has been widely used. In this, the saliency value of a pixel can be calculated using the color contrast of all the pixels in the image.

Equation 3-11 is used to calculate the saliency value of a pixel (I_k) in an image (I),

$$S(I_k) = \sum_{i=1}^{N} D(I_k, I_i) \qquad \forall I_i \in I \qquad \text{Equation 3-11}$$

where, N is the number of pixels in the image (I). $D(I_k, I_i)$ is the color distance metric between pixels I_k and I_i in the L*_a*_b* color space for perceptual accuracy, Equation 3-12.

$$D(I_k, I_i) = |I_k - I_i| \qquad \text{Equation 3-12}$$

This can be observed from Equation 3-12 that pixels having same color will produce same saliency. Therefore, in order to minimize the computational cost, pixels with the same color value are grouped together in C_j. Saliency value of each color $S(I_k)$ is calculated using Equation 3-13 as:

$$S(I_k) = S(C_k) = \sum_{j=1}^{n} P_j D\left(C_k, C_j\right) \qquad \text{Equation 3-13}$$

Here, n is the number of discrete colors $[0{,}255]$, C_k is the color value respective to pixel I_k. P_j is the probability of color C_j in the image (I).

3.6.2.2. Region contrast (RC) method

A region contrast-based saliency map is a type of saliency map that is generated by comparing the contrast of different regions in an image with respect to their surrounding regions. This is typically done by computing the difference between the mean intensity of a region and the mean intensity of its surrounding region. The regions with the highest contrast will be highlighted in the saliency map, making it easier to identify and locate objects in the image. This method is commonly used in object detection and image processing applications because it takes into account the context of the region, which allows for more accurate object detection.

To generate the saliency map the region contrast based approach has been used in this research work. The prominence of an area is usually higher than that of the surrounding areas as compared to the far-flung areas. Since computing the contrast difference between each neighboring pixel is computationally expensive, (M. M. Cheng et al., 2015) introduced region contrast (RC) based method for contrast analysis. In this method, to calculate the color contrast of each region, the image is first divided into N regions $\{R_1, R_2, R_3, \dots \dots, R_N$. Saliency of any region R_k can be calculated using Equation 3-14:

$$S(R_k) = \sum_{R_K \neq R_i} W(R_i) Dr(R_k, R_i) \qquad \text{Equation 3-14}$$

Here, Dr is the color distance metrics for region R_k & R_i. $W(R_i)$ is the total count of pixels in R_i also known as "weight for region R_i". It can be calculated using Equation 3-15 as:

$$Dr(R_x, R_y) = \sum_{i=1}^{n_x} \sum_{j=1}^{n_y} P(C_{x,i}) P(C_{y,j}) D(C_{x,i}, C_{y,j}) \qquad \text{Equation 3-15}$$

Where, $Dr(R_x, R_y)$ is color difference matric between region R_x, R_y. $P(C_{x,i})$ is probability of color 'i' in region R_x for all n_x colors. Visual distinctiveness is an important indicator of low-level saliency with respect to high contrast comparable with specific image areas. The distinctiveness of any field can be improved by adding spatial weighting to the Equation 3-15 (Cheng et al., 2013, 2015). The modified Equation 3-14 can be re-written as Equation 3-16:

$$S(R_k) = W_s(R_k) \sum_{R_K \neq R_i} e^{\frac{D_s(R_k, R_i)}{-\sigma_s^2}} \; W(R_i) Dr(R_k, R_i) \qquad \text{Equation 3-16}$$

Where, D_s represents a spatial distance between two regions R_k and R_i. In this work, Euclidean distance has been considered for the calculation of D_s. W_s is the number of pixels in R_k called as spatial weight for region R_k. Here, σ_s^2=0.4 has been used to moderate the effect of W_s. This helps to calculate saliency of a region with effects of contrast of farther regions (M. M. Cheng et al., 2015).

3.7. Summary

The chapter includes three sub-sections: terrain classification, camouflage texture generation, and camouflage texture effectiveness assessment.

- Terrain classification: The proposed technique of identifying and classifying the type of terrain of an input image is described in this subsection. Convolutional neural network (CNN) model is used to do this.
- Camouflage texture generation: This sub-section describes the methods proposed to create camouflage textures that can be applied to objects to make them blend in with the surrounding terrain.

- Methods for Camouflage texture effectiveness assessment: This subsection discusses the techniques used to test the effectiveness of the resultant camouflage textures. Several criteria are used to measure the effectiveness of the camouflage textures, as explained.

CHAPTER - 4

EXPERIMENTATION, RESULTS AND DISCUSSION

4. EXPERIMENTATION, RESULTS AND DISCUSSION

4.1. Overview

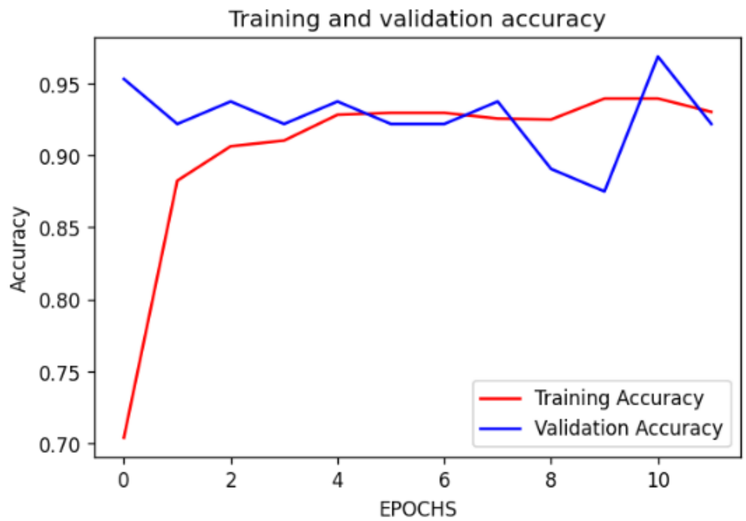
This study focused on two main parts: classification of terrain that requires a camouflage texture, and the design of a camouflage texture that resembles the background by combining essential background elements. This chapter includes experimentations, findings from experiments, analysis and interpretation of results, comparison with previous research and summary of findings.

4.2. Performance of "TerrainCNN"

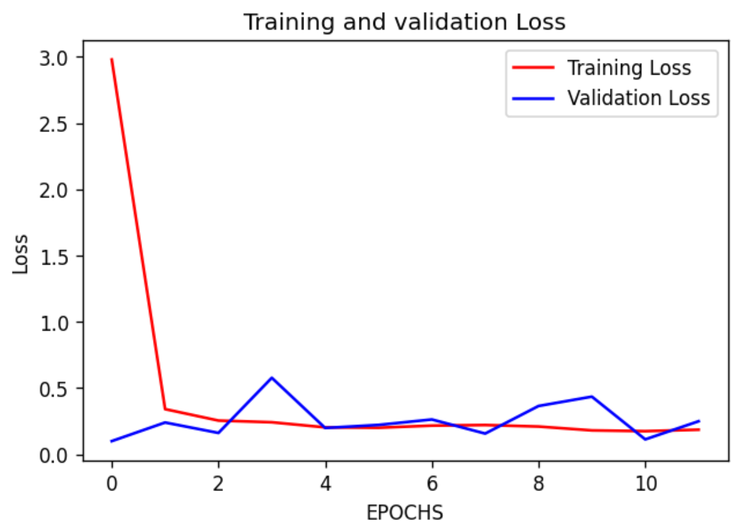
Performance of CNN model refers to how well the model is able to accurately classify or predict the class for a given set of input and test data. The performance of an image classification model is often quantified in terms of classification accuracy, that is the proportion of properly categorized images to the total number of images in the test set.

The performance of TerrainCNN on the "Terrain" dataset is really good. The TerrainCNN's accuracy is assessed 93.03% & loss is assessed 18.55% during training phase. The validation accuracy is assessed at 92.12% and validation loss is 24.92%. Figure 4-1 gives a graphical representation of the accuracy & loss incurred during training as well as validation phase. The performance curve for training accuracy shows a good increase in initial epochs, which shows the network is learning fast. After that, the training accuracy goes flat, which shows that not too many epochs are required to train the model. The validation accuracy plot has ups and downs due to the diverse set of images in the dataset. A good fit can be seen in the plot of learning curves as the plots of training loss and validation loss go down to a stable point. It can be observed that the plot of validation loss has a small gap with the training loss plot.

The performance of a CNN model is a combination of its accuracy, efficiency and ability to generalize to unseen data. Precision, recall, and F1-score are the measures that have been used to assess the performance accuracy of TerrainCNN.



(a)



(b)

Figure 4-1: Training and validation curves: (a) Accuracy & (b) loss of TerrainCNN on Terrain dataset

Precision is the ratio of true positive (TP) predictions (accurately classified as positive) to total positive predictions predicted by the pre-trained mode, Equation 4-1. It calculates the percentage of positive predictions that are true.

$$\text{Precision} = \frac{(\text{True Positives})}{(\text{True Positives} + \text{False Positives})} \qquad \text{Equation 4-1}$$

Recall is the proportion of true positive (TP) predictions to the total number of positive cases in the dataset, Equation 4-2. It quantifies the proportion of true positives correctly predicted by the model.

$$\text{Recall} = \frac{(\text{True Positives})}{(\text{True Positives} + \text{False Negatives})} \qquad \text{Equation 4-2}$$

The F1-score is the harmonic mean (HM) of precision value and recall value, and can be used to balance the precision-recall trade-off, Equation 4-3. It is a single value that represents the model's performance by taking precision and recall into consideration.

$$\text{F1} - \text{score} = \frac{2 * (\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \qquad \text{Equation 4-3}$$

Where:

True Positives (TP): number of test cases that are correctly predicted as positive.

False Positives (FP): number of test cases that are incorrectly predicted as positive.

True Negatives (TN): number of test cases that are correctly predicted as negative.

False Negatives (FN): number of test cases that are incorrectly predicted as negative.

Figure 4-2 shows the confusion matrix which includes the values of precision, recall, and F1-score. The confusion matrix shows a high precision values with respect to each class which means the model is performing good at identifying positive instances. The recall values are also good which means that the model is performing well at finding all positive instances. The F1-score is a metric used when the balance of both precision and recall metrics is important. It can be seen that the F1-score is also higher in this case. Therefore, TerrainCNN is showing good accuracy results when classifying landscape in one of the terrain classes: desert, forest and snow. Apart from this the computation time for different test images have been recorded and the average time computation time of TerrainCNN model is 0.11090 seconds.

```
['Desert', 'Forest', 'Snow']
              precision    recall  f1-score   support

      Desert       0.96      0.88      0.92       351
      Forest       0.94      0.96      0.95       440
        Snow       0.96      0.94      0.95       452

   micro avg       0.95      0.93      0.94      1243
   macro avg       0.95      0.92      0.94      1243
weighted avg       0.95      0.93      0.94      1243
 samples avg       0.93      0.93      0.93      1243
```

Figure 4-2: Confusion matrix: TerrainCNN on Terrain Dataset

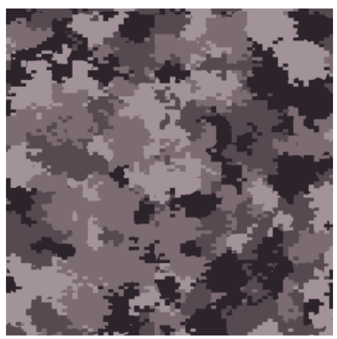
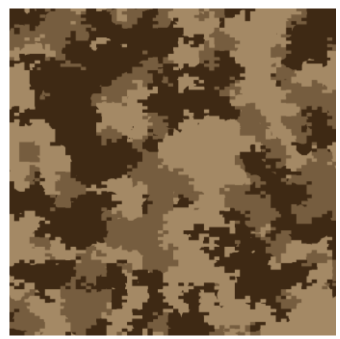
4.3. Experimental results of camouflage texture generation

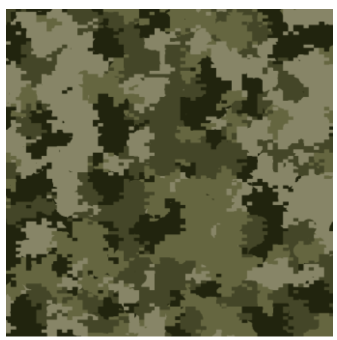
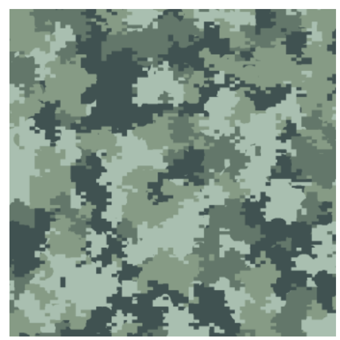
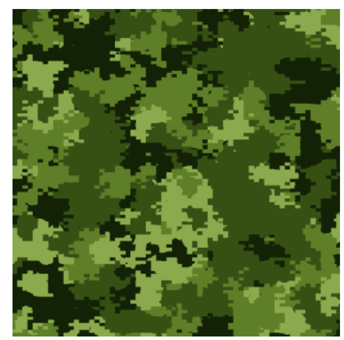
This section includes details on the methods and metrics used for the evaluation, the experimental setup, and the results obtained. The performance of the proposed method for generating real time camouflage textures is assessed and analyzed using a variety of metrics, and it is contrasted with current state-of-the-art techniques in this section.

4.3.1. Resultant camouflage texture

In this research work, a technique for generating a camouflage texture is proposed to create a pattern that resembles the features of the terrain it is intended for. After getting the type of the terrain of the input image the texture is generated by dividing the canvas into smaller sections, extracting shapes from a shape dataset, calculating the perimeter of each shape, and placing the shapes in the canvas. Then, each shape is filled with a color from a standardized color set. The Algorithm 3-3 repeats this process until all sections in the canvas are filled, and the final camouflage pattern is returned on the canvas. The parameters considered for the camouflage object detection, such as color, size, and shape, are taken into account to create a pattern that resembles the terrain and is perceived as the environment itself. The resultant textures are the combination of different shapes of various size that makes it less noticeable from different distances. The colors used are dominating colors of the input image, its HSV values are maintained in the output texture to resemble the lightning conditions of the background image. It helps in increased effectiveness of the resultant texture.

Experiments have been conducted on a wide variety of terrain images using the proposed technique. Figure 4-3 depicts some sample experimental results. Test terrain images for experimentations are shown Figure 4-3, row (a). Three examples from each category (desert, forest, and snow field) are presented. An effort has been made to display the outcomes for a variety of terrain images belonging to each category. Figure 4-3, row (b) displays the predicted classes of input images generated by the TerrainCNN model. In Figure 4-3, row (c), the clustered dominant colors of the corresponding terrain images are depicted using the K-means color clustering algorithm, with a value of K=5. Figure 4-3, row (d) shows the standardized color bar, which will be utilized in the camouflage texture generation process. Finally, Figure 4-3, row (e) displays the resultant camouflage textures in pixelated form. These resultant textures are then further passed to the assessment module for effectiveness evaluation. The effectiveness of a camouflage texture refers to how well it blends into the surrounding environment and makes the object it is applied to difficult to detect. The effectiveness evaluations focuses on various assessment factors and the observer's perception of the object. Additionally, the texture must be able to disrupt the object's outline and shape, making it blend in and appear as a natural part of the environment.

Desert images			
a. Terrain Image			
b. Predicted Terrain	[1,0,0] (Desert)	[1,0,0] (Desert)	[1,0,0] (Desert)
c. Dominant colors, K=5			
d. Standardized colors, K=3 to 5			
e. Resultant texture			

Forest images			
a. Terrain Image			
b. Predicted Terrain	[0,1,0] (Forest)	[0,1,0] (Forest)	[0,1,0] (Forest)
c. Dominant colors, K=5			
d. Standardized colors, K=3 to 5			
e. Resultant texture			

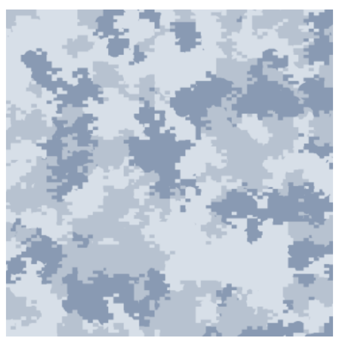
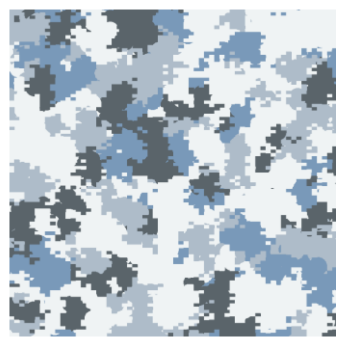
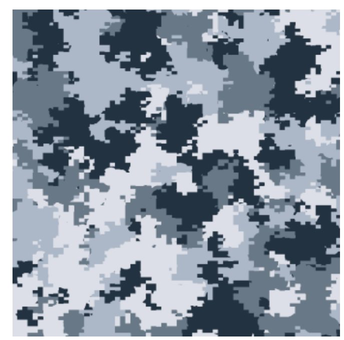
Snow land images			
a. Terrain Image			
b. Predicted Terrain	[0,0,1] (Snow land)	[0,0,1] (Snow land)	[0,0,1] (Snow Land)
c. Dominant colors, K=5			
d. Standardized colors, K=3 to 5			
e. Resultant texture			

Figure 4-3: Resultant camouflage textures for different input terrain image

4.4. Performance evaluation

The performance of proposed system for "Real-time camouflage texture generation" has been evaluated based on the following metrics:

- Generation time: The amount of time proposed system takes to generate a camouflage texture for a real environment in real time.
- Quality: Quality of the generated texture in terms of resembling the environmental features of the terrain such as color, texture and intensity.
- Realism: The ability of the generated texture to blend an object in the environment.
- Pixalization effect: The effect of pixalizing the texture to get the final texture, which will be capable of hindering the human visual attention from diverse distances.

4.4.1. Generation time

The generation time here is the amount of time the proposed technique takes to produce a texture. It is a parameter used to evaluate the process of camouflage texture generation because it directly influences the efficiency and practicality of the generation process. If the generation time is too long, it may not be practical for real-world applications, especially in situations where time is a critical factor, such as in military operations. The time utilized by proposed technique to generate the camouflage texture for a specific terrain has been recorded.

This experiment was carried out in two stages, with each phase comprising a fresh collection of terrain images containing a variety of desert, snow land, and forest areas. During the first round of testing, a total of 60 images were taken, with 20 images belonging to each terrain type. Color clustering was performed using K=5, and a standardized color set was generated with colors from 3 to 5. Figure 4-4 depicts the time taken by the proposed method to generate camouflage texture for several scenes of various terrain classes with K=5. It can be seen that the amount of time needed to create a camouflage texture for any scenario is extremely low, ranging from 0.10 to 0.26 seconds.

In another round of testing, a larger number of images were considered (50 from each terrain type, for a total of 150). Figure 4-5 displays the time required by the proposed technique to generate camouflage texture for each of these images. Graph indicates that the generation time vary between 1.3 sec to 5.3 sec. Since the generation time is not excessive, the proposed technique can be used for the real time terrain. Table 4-1 shows the average time taken by the system to create a camouflage texture for a certain type of terrain in each of the two phases of testing.

Table 4-1: Average camouflage texture generation time

	Average Texture Generation Time (Sec)		
Terrain class	**– Desert**	**– Forest**	**– Snow land**
• Color clustering (K=5) • Standardized color (C=3 to 5) • Number of images N=20	2.4	2.1	2.1
• Color clustering (K=7) • Standardized color (C=3 to 5) • Number of images N=50	2.3	3.7	2.5

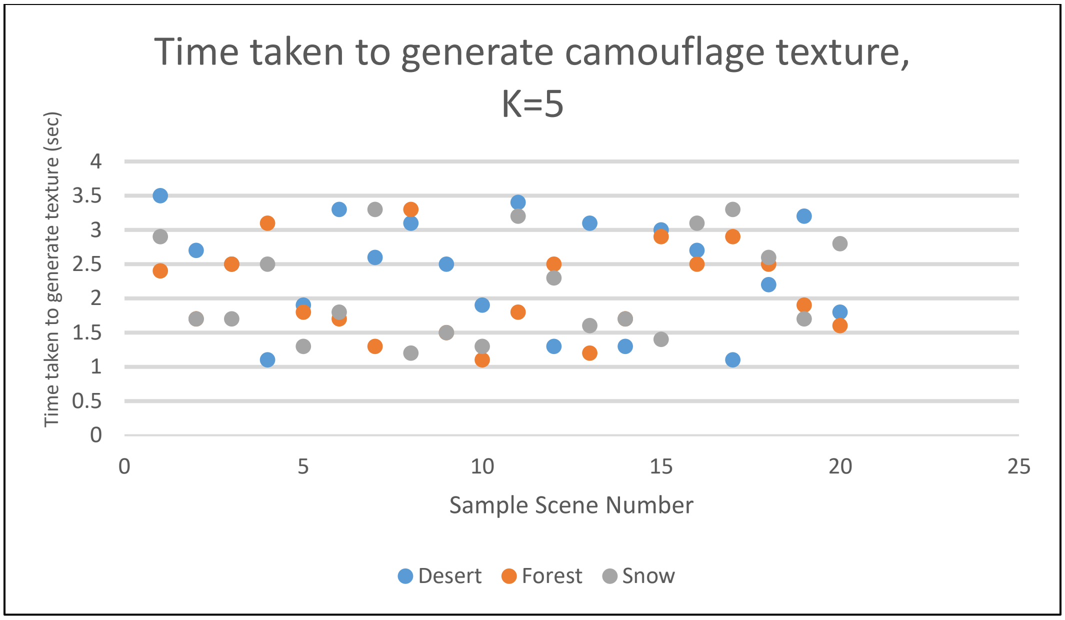


Figure 4-4: Camouflage texture generation time, keeping K=5 in color clustering

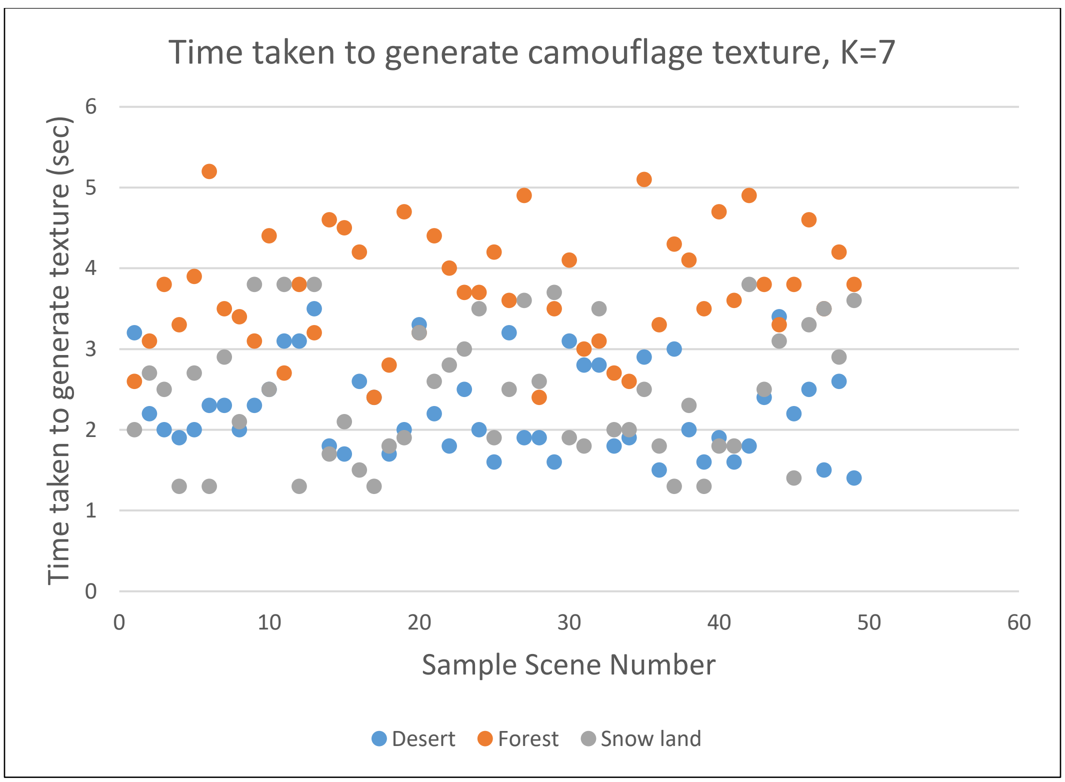


Figure 4-5: Camouflage texture generation time, keeping K=7 in color clustering

4.4.2. Camouflage texture assessment for quality and realism

The defence industry relies on camouflage texture assessment to make sure that the camouflage patterns used on its uniforms and equipment are of the finest quality and are realistic. In order to conceal or blend in their personnel, vehicles, and equipment in various environments and terrains, the defence industry uses camouflage, which is essential for military operations. It helps soldiers and equipment blend into their surroundings and remain undetected by the enemy. If the camouflage patterns used by the army are not of high quality and realism, then soldiers or equipment may be easily spotted by the enemy, putting them at risk of being attacked or captured.

Therefore, it is crucial to conduct camouflage texture assessments to ensure that the camouflage patterns are effective and provide the necessary level of concealment. In this section, various parameters and evaluation methods are used to evaluate the generated camouflage textures.

4.4.2.1. Dataset for assessment

A dataset has been created to evaluate the resultant camouflage texture, as shown Figure 4-6. he procedure entails applying the resulting camouflage texture for a specific terrain onto an object and then placing the camouflaged object somewhere within the input terrain. The following images are included in the dataset:

- Terrain images without camouflaged objects
- Terrain images with camouflaged object(s), including:
    - Object(s) camouflaged with the texture featuring extracted dominating colors from the input image
    - Object(s) camouflaged with the texture featuring standardized colors and HSV values
    - Object(s) camouflaged with the texture featuring standardized colors, HSV values, and maintained proportion of colors from the input image

This dataset has been utilized for experimental purposes in photo simulation and saliency maps to detect camouflaged objects within an image.

The camouflage texture assessment was done using photo simulation technique and different types of saliency maps. Figure 4-7 includes images of some of the terrain that were used in these assessment and evaluation. The set of images displayed in Figure 4-7 (a) corresponds to three different terrain classes: desert, forest, and snow land. This set of images showcases various terrain types that were used to test the proposed methods, providing a comprehensive representation of the landscapes studied in the photo simulations and saliency maps presented in the section 4.4.2.2 and 4.4.2.3. On the other hand, Figure 4-7 (b) showcases the textures that were generated using the proposed methods and used to conceal the objects shown in Figure 4-7 (c). These textures are designed to blend in with the surrounding terrain, and to effectively hide the object from observer's view. By utilizing these textures, the object can be concealed without being easily detected, which can be useful in various applications.

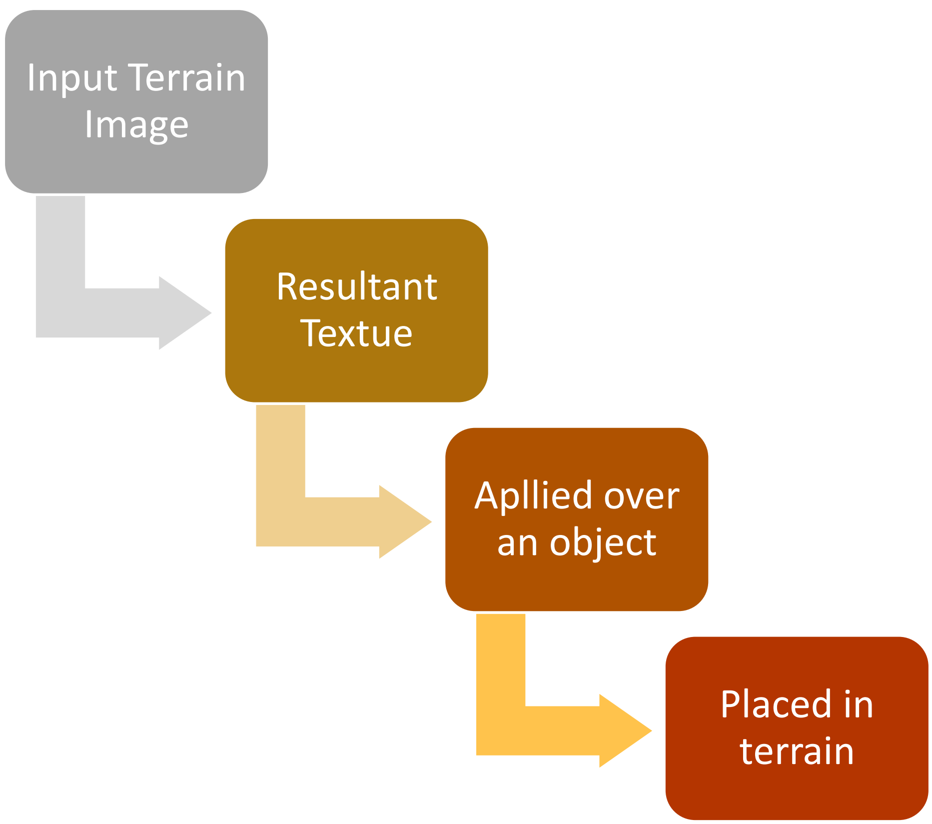


Figure 4-6: Dataset formation for camouflage texture assessment

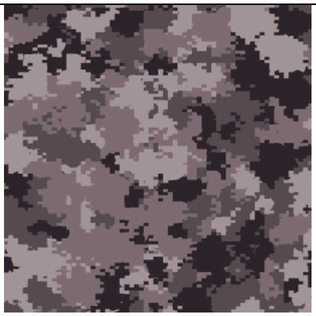
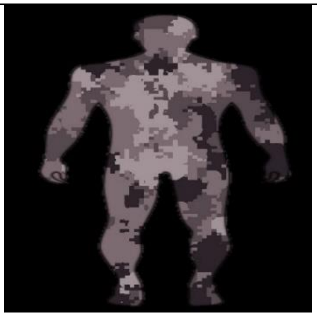
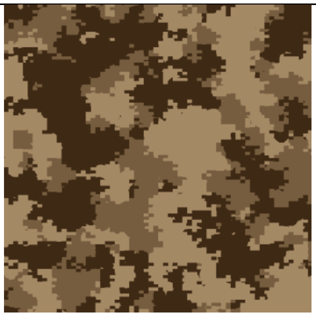
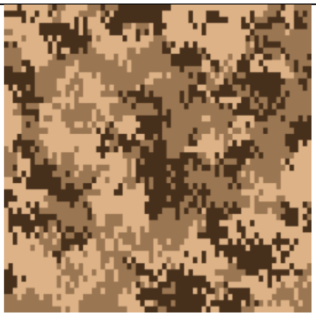
Image name	Terrain Type	a) Input terrain image	b) Resultant texture	c) Camouflaged object	d) Camouflaged object hidden in the terrain
D1	Desert				
D2	Desert				
D3	Desert				

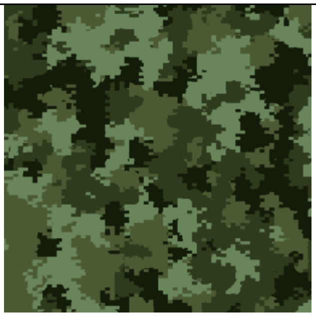
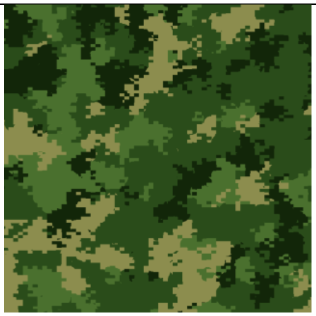
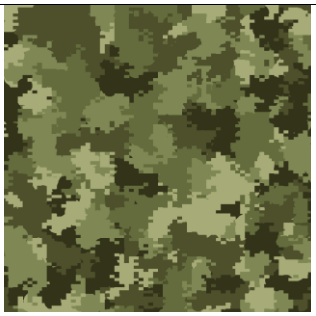
Image name	**Terrain Type**	**a) Input terrain image**	**b) Resultant texture**	**c) Camouflaged object**	**d) Camouflaged object hidden in the terrain**
F1	Forest				
F2	Forest				
F3	Forest				

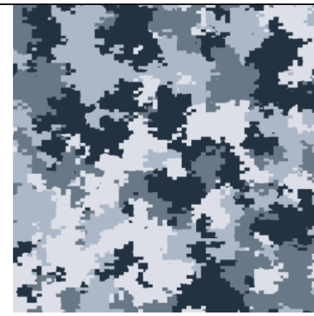
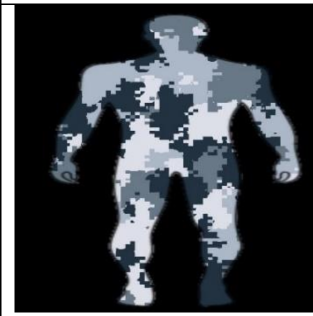
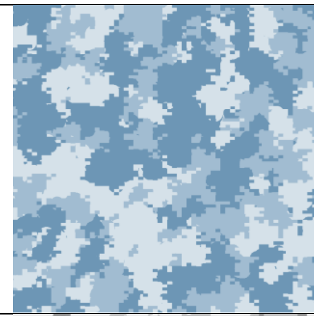
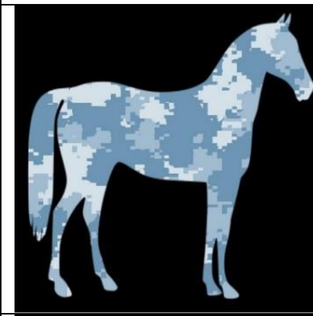
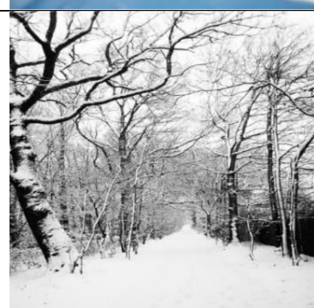
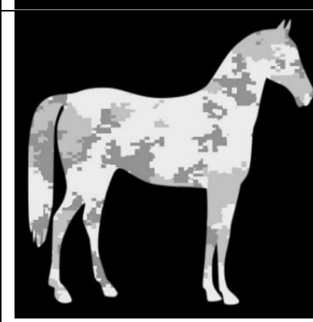
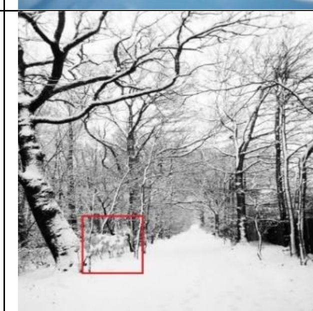
Image name	Terrain Type	a) Input terrain image	b) Resultant texture	c) Camouflaged object	d) Camouflaged object hidden in the terrain
S1	Snow				
S2	Snow				
S3	Snow				

Figure 4-7: Example input images used in photo simulation for camouflaged object detection

4.4.2.2. Assessment using photo simulation

Section 3.6.1 of this report outlines the methodology for conducting photo simulations, including a description of the experimental setup and assessment parameters. As part of this experiment, both target object localization and the level of difficulty in detecting camouflaged objects were observed and recorded by 35 observers. The results of the photo simulation experiment for the terrain images included in Figure 4-8 are presented in Table 4-2. This table is compiled based on the experimental data collected from the human observers during the experimentation phase. The analysis of the data has been done over three parameter: average hit rate, average detection time and texture difficulty rating.

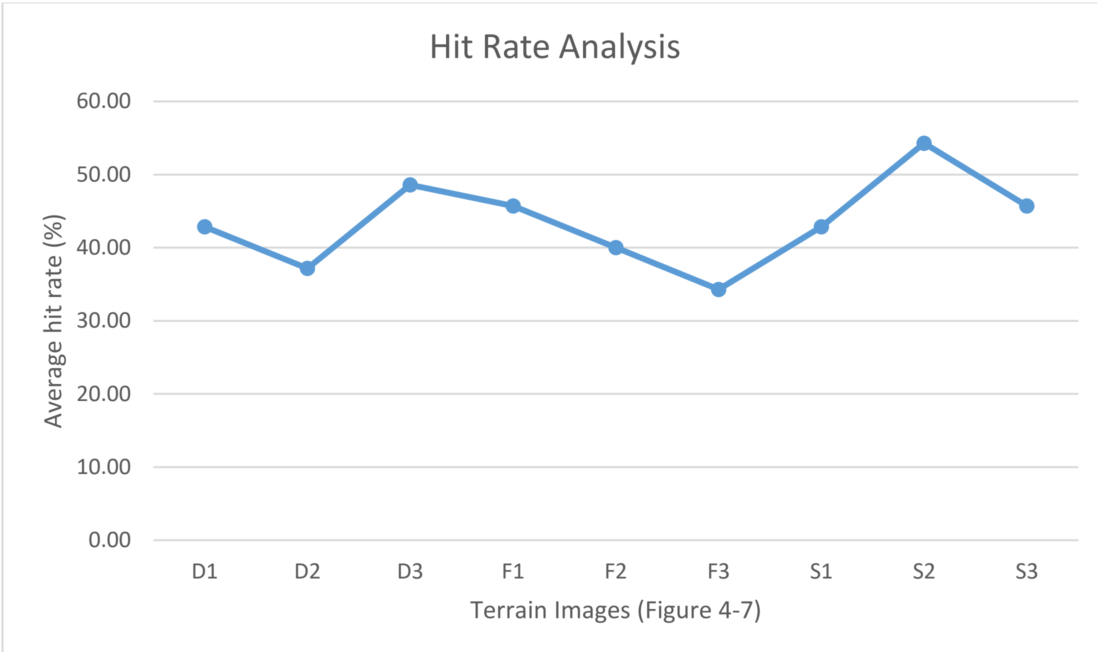
The graphical representation of the photo simulation results are depicted in the Figure 4-8. Figure 4-8 (a) depicts the results of average hit rate for the dataset of images shown in Figure 4-7 (d). In the experiment of photo simulation for camouflaged object detection with multiple observers, the hit rate is the percentage of correctly identified camouflaged objects by all observers, out of the total number of camouflaged objects presented in the set of simulated images. The results in Figure 4-8 (a) indicate that the detection of a camouflaged object using texture generated by the proposed technology is quite difficult, as the average hit rate lies in the range of 30% to 55%. A low average hit rate suggests that the camouflage texture is performing well in blending the object in the scene. It is important to note that the average hit rate for the camouflaged object in forest and desert areas is lower than that in snow areas. This means that the camouflage technique is more effective in forest and desert areas compared to snow areas. This can be attributed to the fact that in snow fields, the dominant colors belong to the white cluster, and other environmental factors such as luminance, reflection of the sky, and shadows of trees and mountains have a significant impact on the HSV factors of the actual dominating colors in the real environment. Although, it can be concluded that the performance of resultant textures on concealing an object is good and effective.

The analysis of the average detection time (Figure 4-8 (b)) for a camouflaged object in different terrain categories yields promising results. The graph presents the analysis using the average value, harmonic mean, and geometric mean of the detection time taken and the rating given by multiple observers. The harmonic mean (HM) and the geometric mean (GM) are both averages in statistics. The HM is the reciprocal of the mean of the reciprocals of the numbered data, while the GM is mean that shows the central tendency of a dataset of numbers. The results demonstrate that the detection time for the camouflaged object is reasonable and the proposed technique is effective. The HM and GM values show that the detection time is distributed among the observers, indicating that the observers are consistent in detecting the camouflaged object. The results suggest that the proposed technique can be applied in various environments to improve camouflage effectiveness.

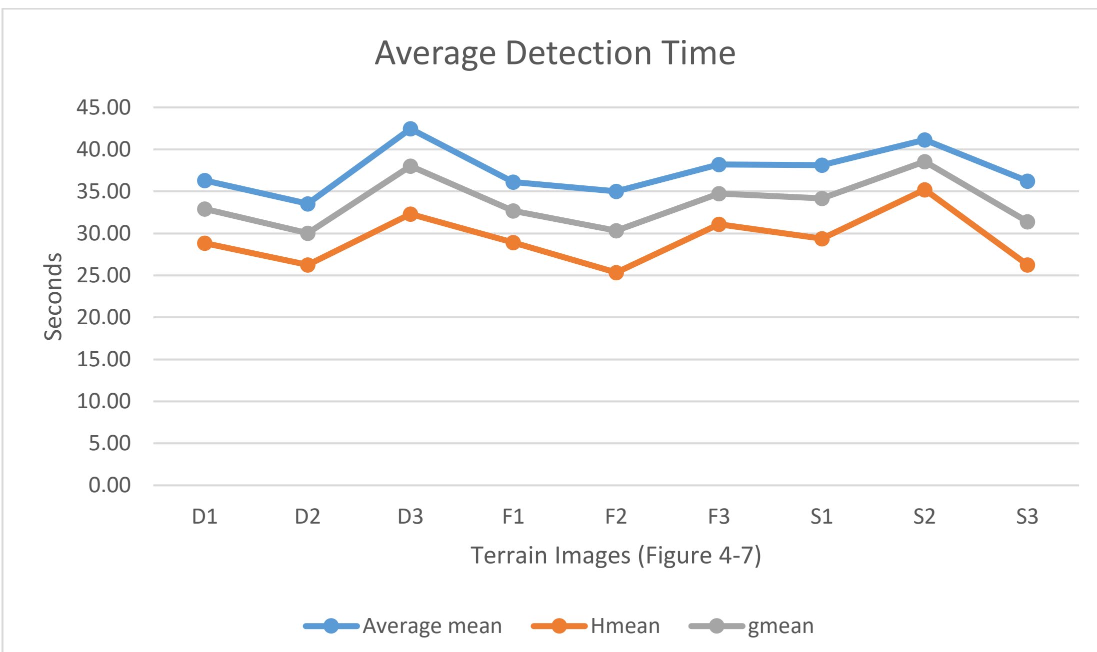
In addition to the average hit rate and detection time, the observer's difficulty rating was recorded on a scale of 1 to 5 to assess the generated camouflage texture's effectiveness. The difficulty rating indicates how challenging it was for the observer to detect the camouflaged object in the given environment. The texture difficulty ratings for various terrains show that the camouflage texture was highly effective in blending the object into the environment. The difficulty rating provides valuable information about the observer's perception of the effectiveness of the generated camouflage texture. The higher the difficulty rating, the more effective the camouflage texture is in blending the object into the environment. This parameter provides a more subjective assessment of the camouflage texture's performance, which is essential in evaluating the proposed technique's real-world application. The graph depicted in Figure 4-8 (c) analyses the difficulty rating for different terrain categories. The results indicate that the camouflage texture generated by the proposed technique is effective.

Table 4-2: Results of photo simulation for camouflaged object detection

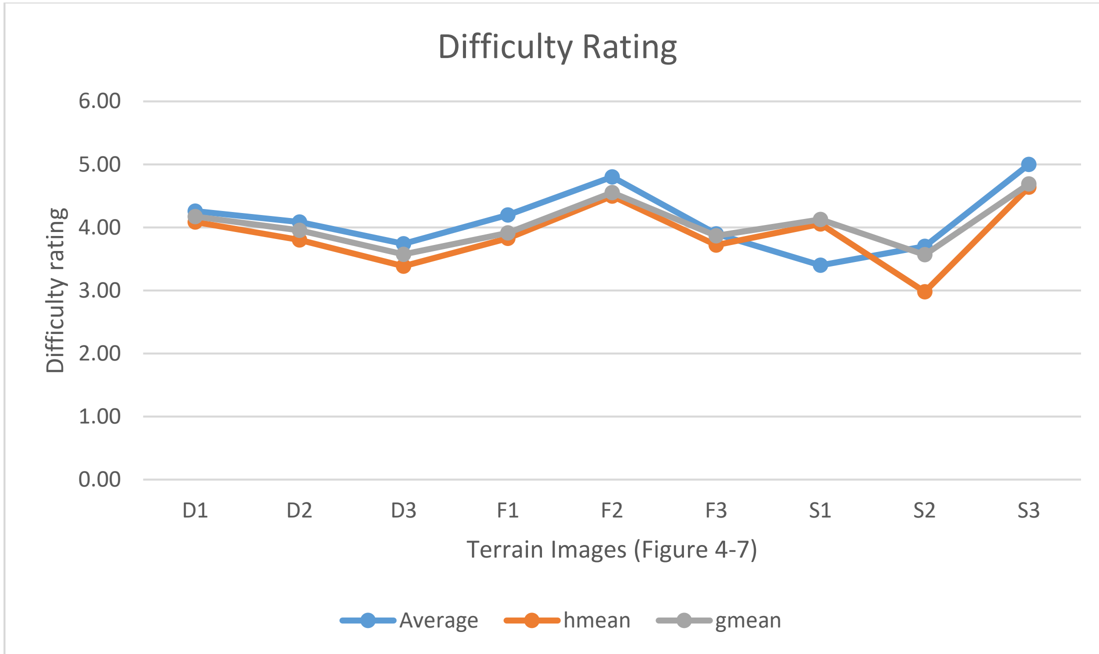
	Hit rate analysis (%)	**Detection time analysis (Sec)**			**Difficulty rating analysis**		
Terrain image	**Average hit rate**	**Average mean**	**Harmonic mean**	**Geometric mean**	**Average mean**	**Harmonic mean**	**Geometric mean**
D1	42.86	36.29	28.84	32.92	4.26	4.09	4.17
D2	37.14	33.54	26.25	30.03	4.09	3.80	3.95
D3	48.57	42.46	32.31	38.02	3.74	3.39	3.57
F1	45.71	36.13	28.91	32.68	4.20	3.83	3.91
F2	40.00	35.00	25.34	30.31	4.80	4.50	4.55
F3	34.29	38.22	31.09	34.76	3.90	3.72	3.87
S1	42.86	38.13	29.39	34.18	3.40	4.05	4.13
S2	54.29	41.14	35.22	38.56	3.70	2.98	3.57
S3	45.71	36.21	26.27	31.40	5.00	4.64	4.69


Hit Rate Analysis
60.00
50.00
40.00
30.00
20.00
10.00
0.00
Average hit rate (%)
D1
D2
D3
F1
F2
F3
S1
S2
S3
Terrain Images (Figure 4-7)

(a)


Average Detection Time
45.00
40.00
35.00
30.00
25.00
20.00
15.00
10.00
5.00
0.00
Seconds
D1
D2
D3
F1
F2
F3
S1
S2
S3
Terrain Images (Figure 4-7)
Average mean
Hmean
gmean

(b)



(c)

Figure 4-8: Result analysis of photo simulation experiments: (a) Hit Rate Analysis, (b) Average Detection Time, and (c) Difficulty rating

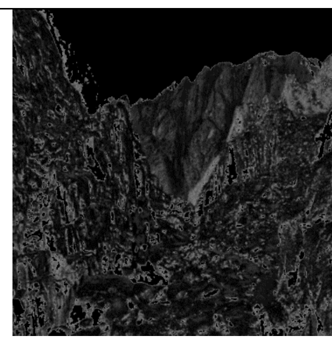
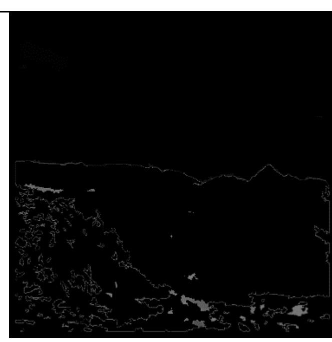
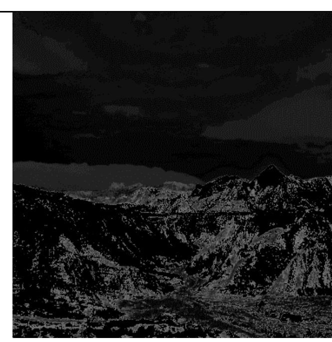
4.4.2.3. Saliency maps

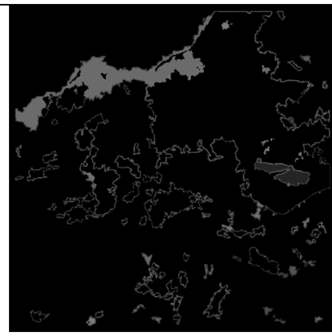
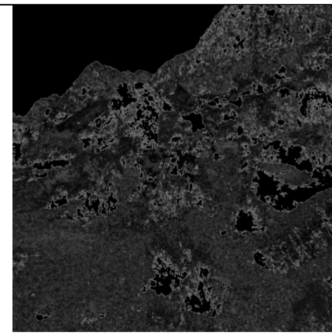
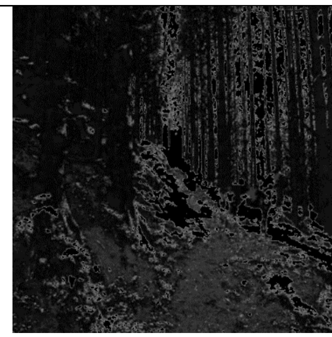
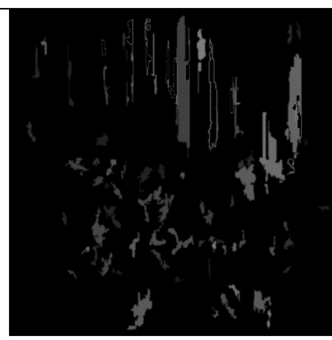
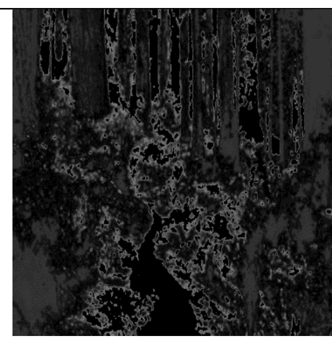
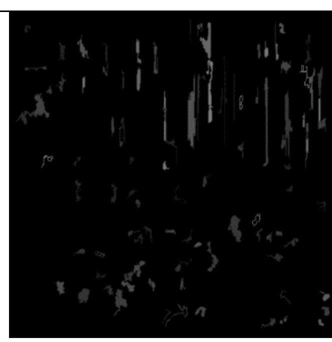
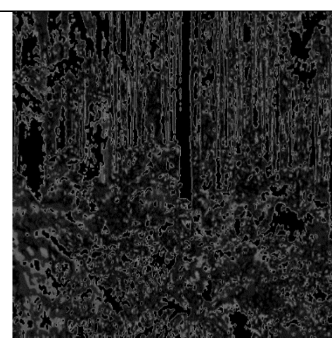
Saliency maps are derived from computational models that mimic human visual attention and identify the most important regions in an image. It is a useful technique for detecting camouflaged objects in a scene. It can help detect the most visually distinct regions in an image that stand out from the rest. These visually distinct regions are likely to correspond to objects in the scene and can be used to detect camouflaged objects that may be difficult to detect using traditional techniques. It can be challenging to spot a camouflaged object in an image because of how well it blends in with the background. A saliency map, on the other hand, can assist in locating the areas of an image that are the most visually striking and may be suggestive of the presence of a concealed object. In the methodology chapter, two types of saliency maps are discussed for detecting camouflaged objects: region contrast based and histogram contrast based. The region contrast based method involves segmenting the image into N regions and computing the color contrast of each region. The saliency is calculated as the weighted sum of the contrast of each region with respect to all other regions. The histogram contrast based method compares all the pixels/regions in the whole image and accumulates the comparison results. The saliency maps generated for terrains with hidden items are displayed in

Figure 4-9. These saliency maps show how a camouflage pattern affects the appearance of a natural object.

Figure 4-9 (a) presents the natural terrain images with the location of camouflaged objects. On the other hand,

Figure 4-9 (b) and (c) show the saliency maps generated using the region contrast (RC) based and histogram contrast (HC) based methods, respectively. Although the saliency maps are designed to highlight the most visually distinct regions, it is evident that the intensity and highlighted regions are unable to effectively segment the camouflaged object. This implies that the camouflaged objects blend in so well with the background features that they are challenging to detect.

a) Camouflaged object hidden in the terrain	**b) Saliency map using RC method** (M. M. Cheng et al., 2015)	**c) Saliency map using HC method** (Feng et al., 2015)
		
		

a) Camouflaged object hidden in the terrain	**b) Saliency map using RC method** (M. M. Cheng et al., 2015)	**c) Saliency map using HC method** (Feng et al., 2015)
		
		
		
		

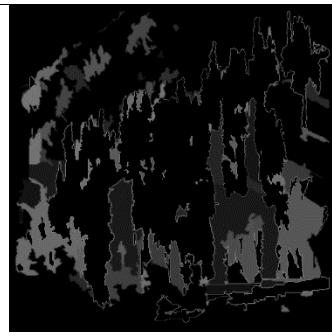
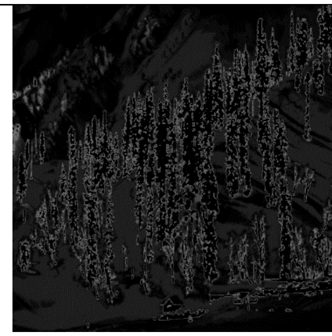
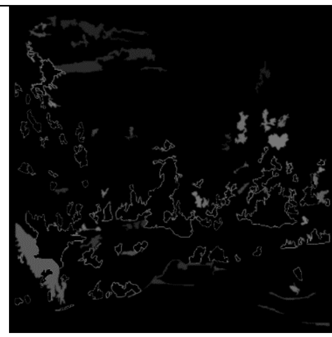
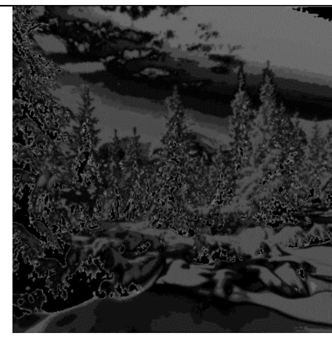
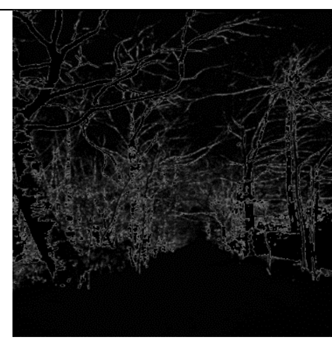
a) Camouflaged object hidden in the terrain	**b) Saliency map using RC method** (M. M. Cheng et al., 2015)	**c) Saliency map using HC method** (Feng et al., 2015)
		
		
		

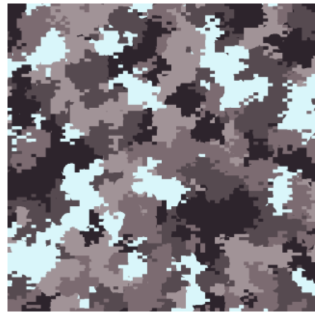
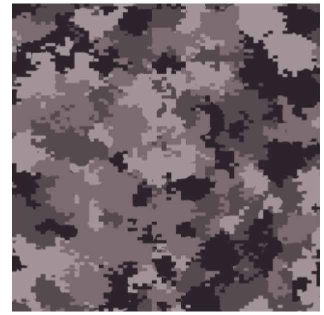
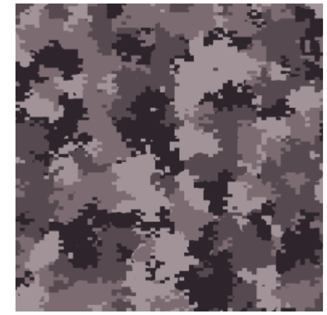
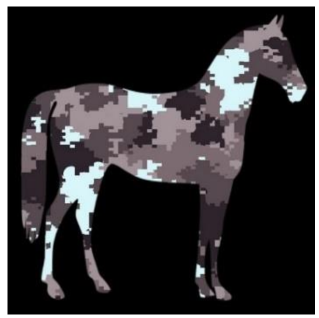
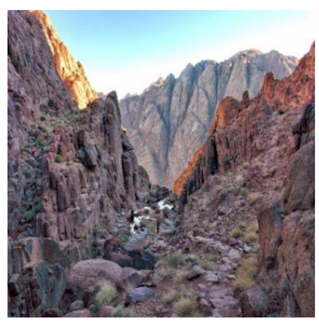
Figure 4-9: Camouflage texture effect evaluation using saliency maps

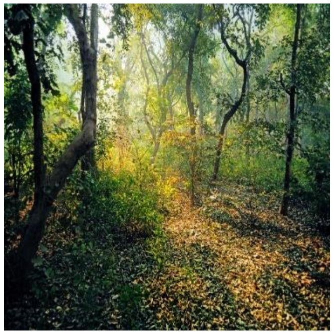
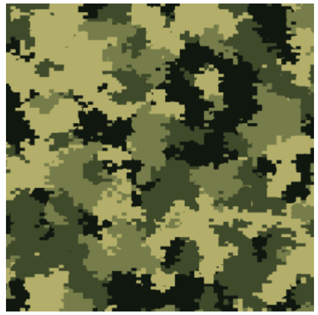
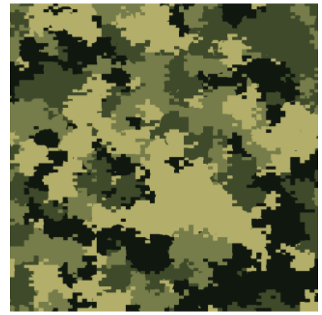
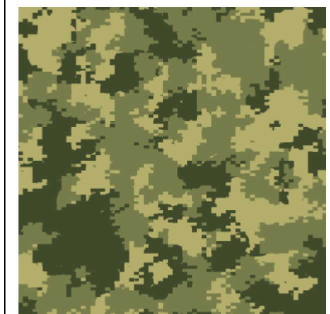
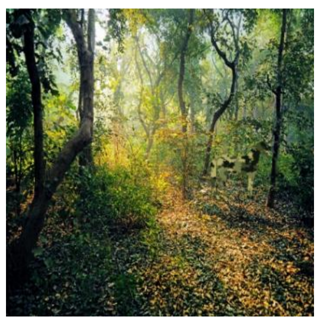
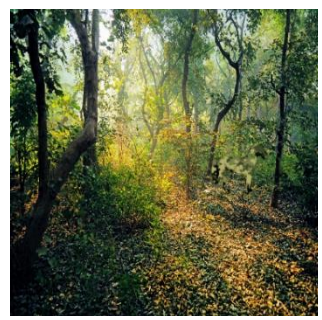
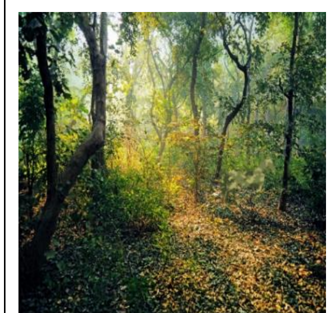
4.4.3. Effect evaluation of dominant colors standardization

There are a number of ways in which the effectiveness of a camouflage texture can be enhanced by standardizing the set of dominant colors in a scene according to human visual perception and industry standards before generating camouflage texture. Firstly, it ensures that the colors used in the camouflage texture blend in seamlessly with the colors present in the scene. This makes the object less noticeable to the naked eye because it blends in with its surroundings. Secondly, it will also ensures that the colors used in the camouflage texture are visually dominant in the scene. This means that the colors used are more likely to be noticed by the human eye than other colors in the scene. Using visually dominant colors, the camouflage texture can effectively hide the object by drawing attention away from it. Finally, standardization helps to ensure that the colors used in the camouflage texture are consistent with industry standards. This can help ensure the camouflage texture is effective across different environments and conditions, improving its overall performance.

Figure 4-10 illustrates the impact of standardizing the color set on generating a camouflage texture for different types of terrain, including desert, forest, and snow. The methodology section 3.5.2 explains that the standardization is not limited to color but also includes other environmental features. Figure 4-10 (a) displays the test terrain images that were used in the experiment. Figure 4-10, Column (b) shows the effect of generating a camouflage texture using the dominant colors in the input image without any further processing. The dominant colors in the input terrain and the corresponding camouflage texture are shown in cell (b.1) of Figure 4-10. Column (c) of Figure 4-10 displays the results of generating a camouflage texture using standardized colors that take into account human vision and industry standards. The corresponding texture is shown in Figure 4-10, cell (c.1). Column (d) of Figure 4-10 shows the texture created using standardized colors that maintain the proportionate distribution of colors as well as other environmental features including intensity, gradient and texture as in the input image. The corresponding texture is shown in Figure 4-10, cell (d.1). The objective of this experiment is to analyze the impact of the color standardization process on the camouflage texture and its blending capabilities.

Figure 4-10 (b.2, c.2, and d.2) demonstrate the objects with camouflage textures DCT1, DCT2 and DCT3 for desert FCT1, FCT2, and FCT3 for forest and SCT1, SCT1, and SCT1 for snow terrain respectively. These objects are then blended into the input terrain image, which is shown in Figure 4-10 (b.3, c.3, and d.3). The results are assessed using photo simulation and camouflage object segmentation using a saliency map (Feng et al., 2015). Figure 4-11 displays the observations recorded on the photo simulation for average hit rate, average detection time, and average difficulty rating. Camouflage textures with optimized color, contrast, size, and texture (Figure 4-10 (d.1)) for each terrain type have a longer average detection time and lower average hit rates than other textures (Figure 4-10 (b.1, c.1)). They also have a higher difficulty rating than the other textures. So, it can be concluded that the standardization of perceived dominating features in an environment have significant impact on the effectiveness of camouflage textures and its capabilities.

(a) Terrain Image (DC1) 	(b.1) Texture with Extracted colors (dCT1) 	(c.1) Texture with standardized colors (DCT2) 	(d.1) Texture with standardized colors & other features with proportion (DCT3) 
	(b.2) Camouflaged object with (DCT1) 	(c.2) Camouflaged object with (DCT2) 	(d.2) Camouflaged object with (DCT3) 
	(b.3) DCT1 in the terrain 	(c.3) DCT2 in the terrain 	(d.3) DCT3 in the terrain 

(a) Terrain Image (FC1) 	(b.1) Extracted colors & respective texture (FCT1) 	(c.1) Standardized colors & respective texture (FCT2) 	(d.1) Standardized colors with proportion & respective texture (FCT3) 
	(b.2) Camouflaged object with (FCT1) 	(c.2) Camouflaged object with (FCT2) 	(d.2) Camouflaged object with (FCT3) 
	(b.3) FCT1 in the terrain 	(c.3) FCT2 in the terrain 	(d.3) FCT3 in the terrain 

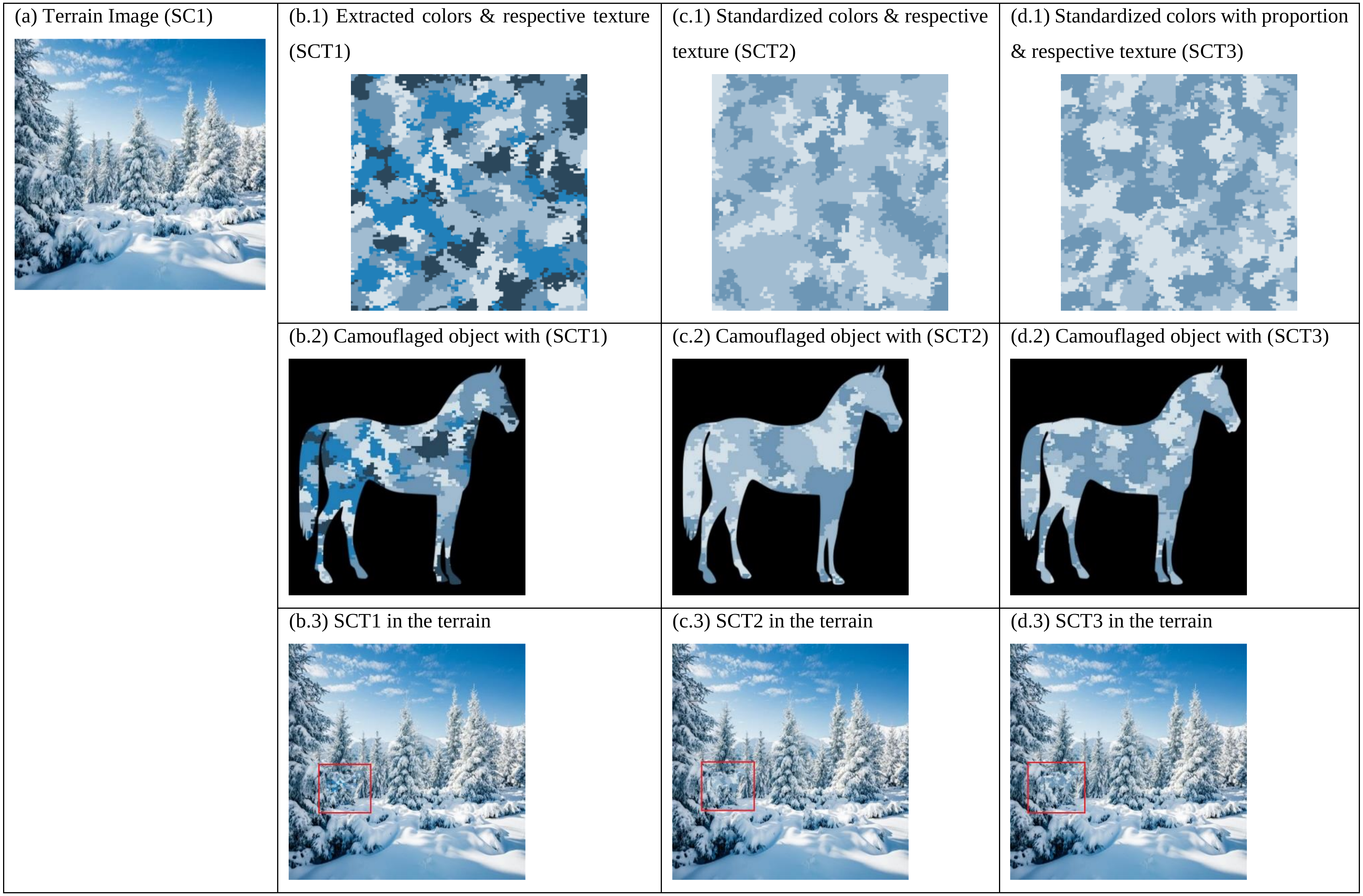
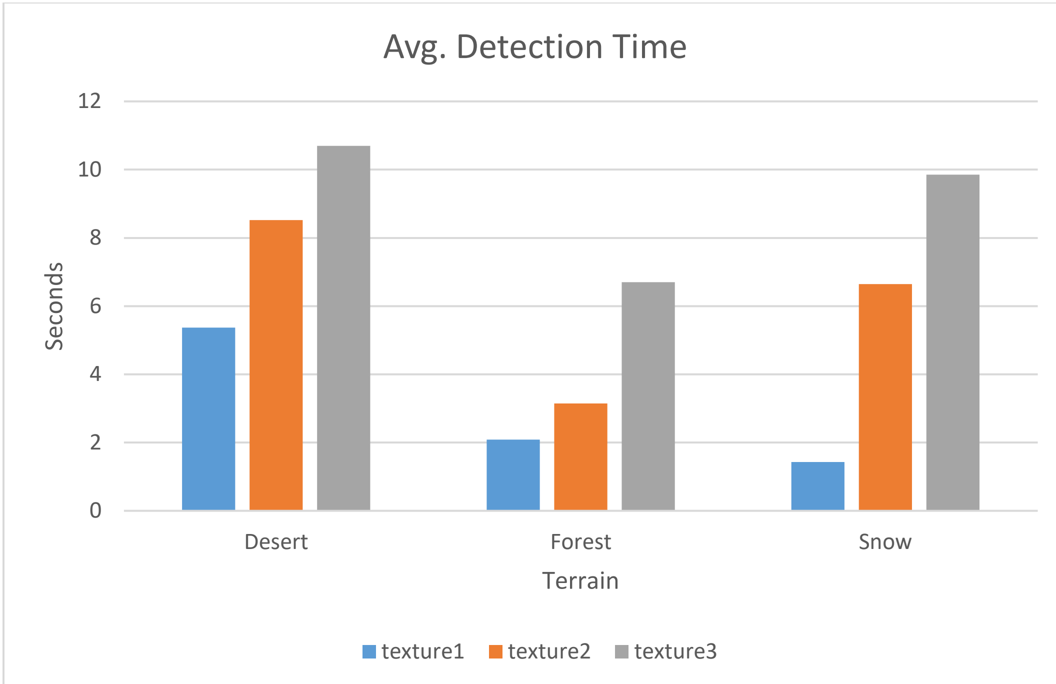
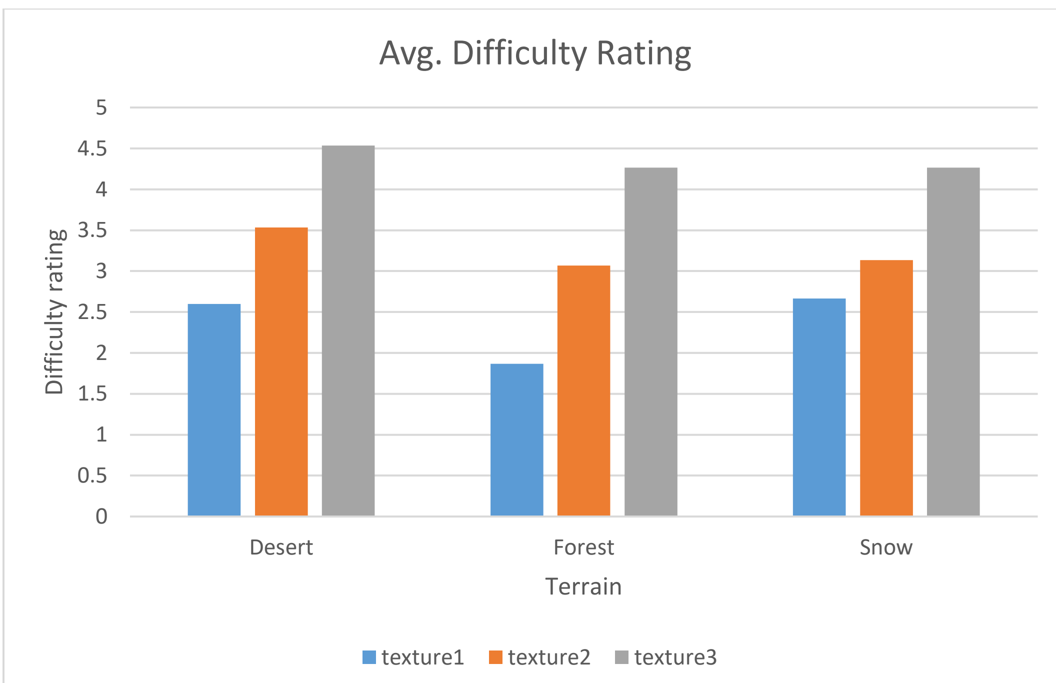


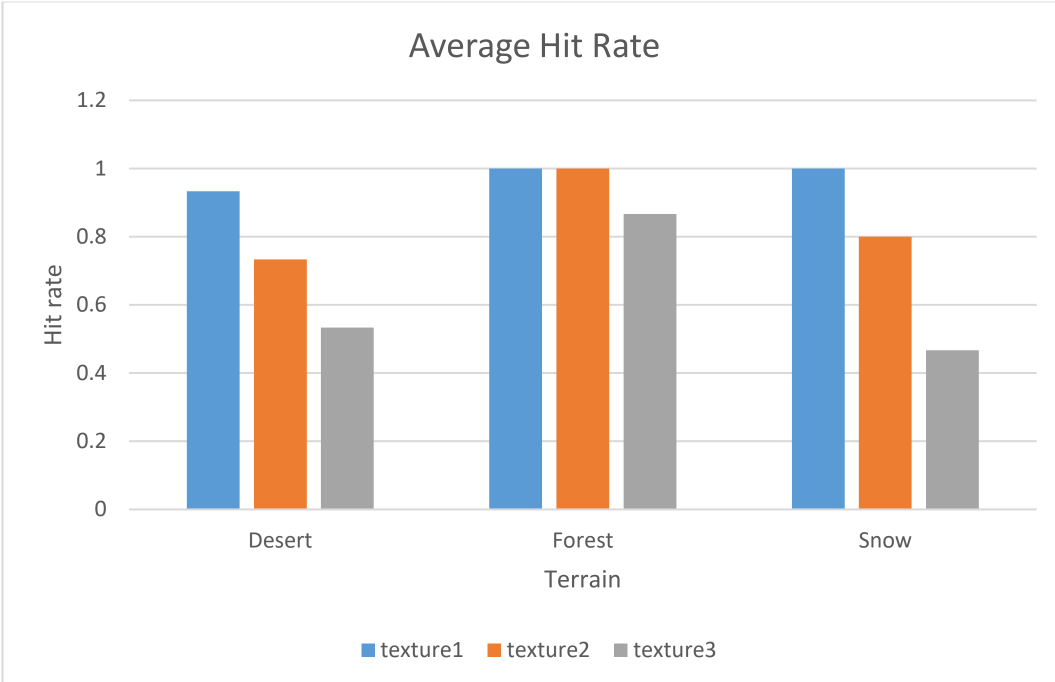
Figure 4-10: Effect of color set standardization in camouflage texture


Avg. Detection Time
12
10
8
6
4
2
0
Seconds
Desert
Forest
Snow
Terrain
texture1
texture2
texture3

(a)


Avg. Difficulty Rating
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Difficulty rating
Desert
Forest
Snow
Terrain
texture1
texture2
texture3

(b)



(c)

Figure 4-11: Analysis of photo simulation results of different textures for the same terrain

4.5. **Comparison with State of Art method** (Xue et al., 2016)

In this section, a comparison of two methods for producing camouflage textures is presented. The first method, which generates the textures by recursively overlapping patterns, was proposed by (Xue et al., 2016). The results of this technique are shown in Figure 4-12, which includes scenes with objects, colors extracted from the scene, camouflage texture generated using recursive overlapping of patterns, and a scene having camouflaged objects. On the other hand, the proposed methodology generates camouflage textures by standardizing the color set, many environmental features and shapes of industry standards. The results of this technique are shown in

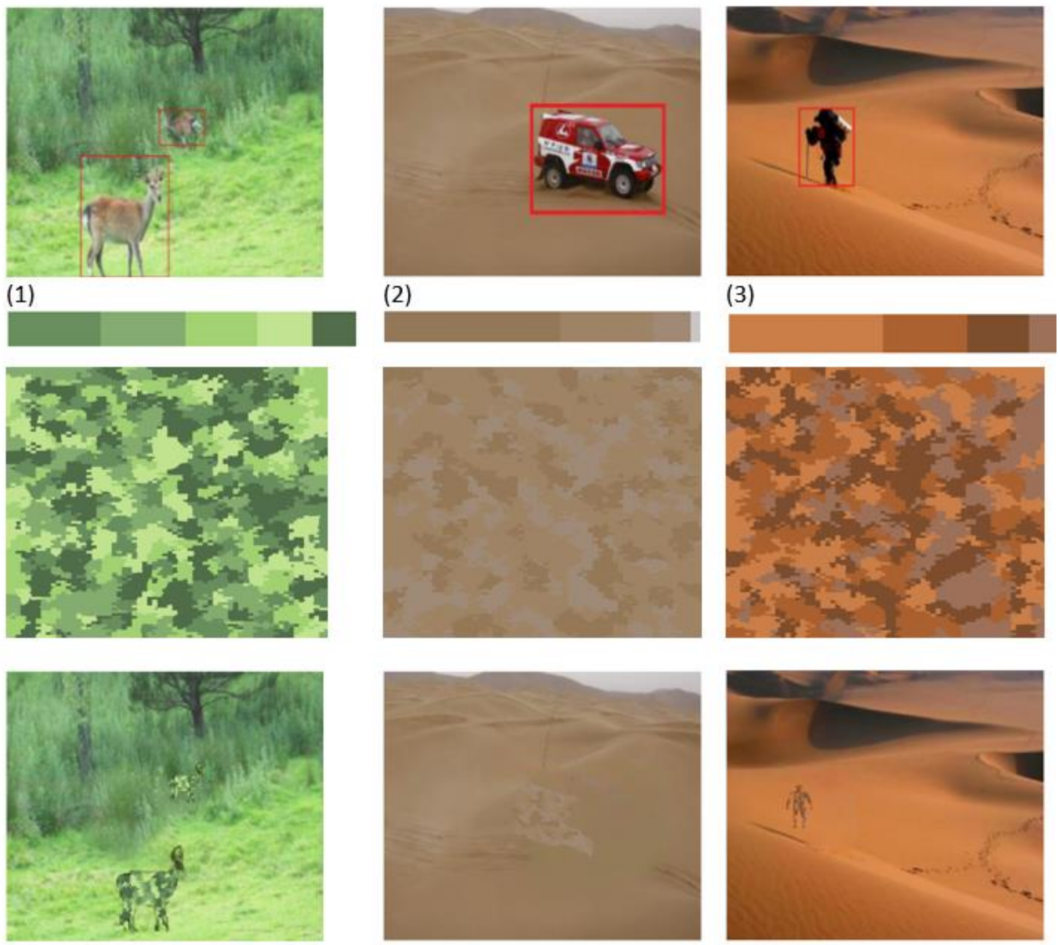


Figure 4-13, which includes the same set of input terrain images as used in Xue et al.'s technique. The objective of this comparison is to analyze the effectiveness of the proposed technique in generating better camouflage textures than the previous technique.

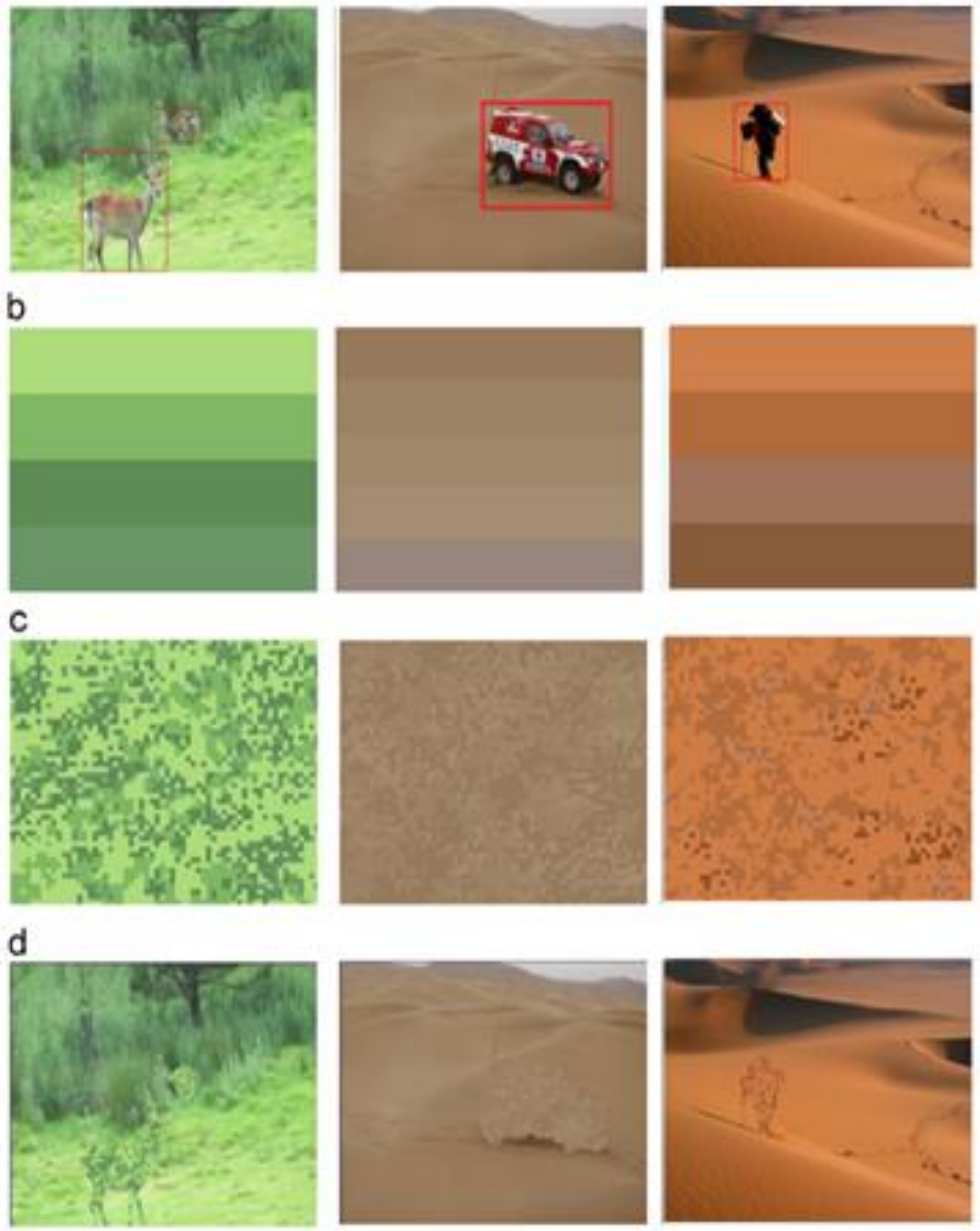


Figure 4-12: Results of (Xue et al., 2016)

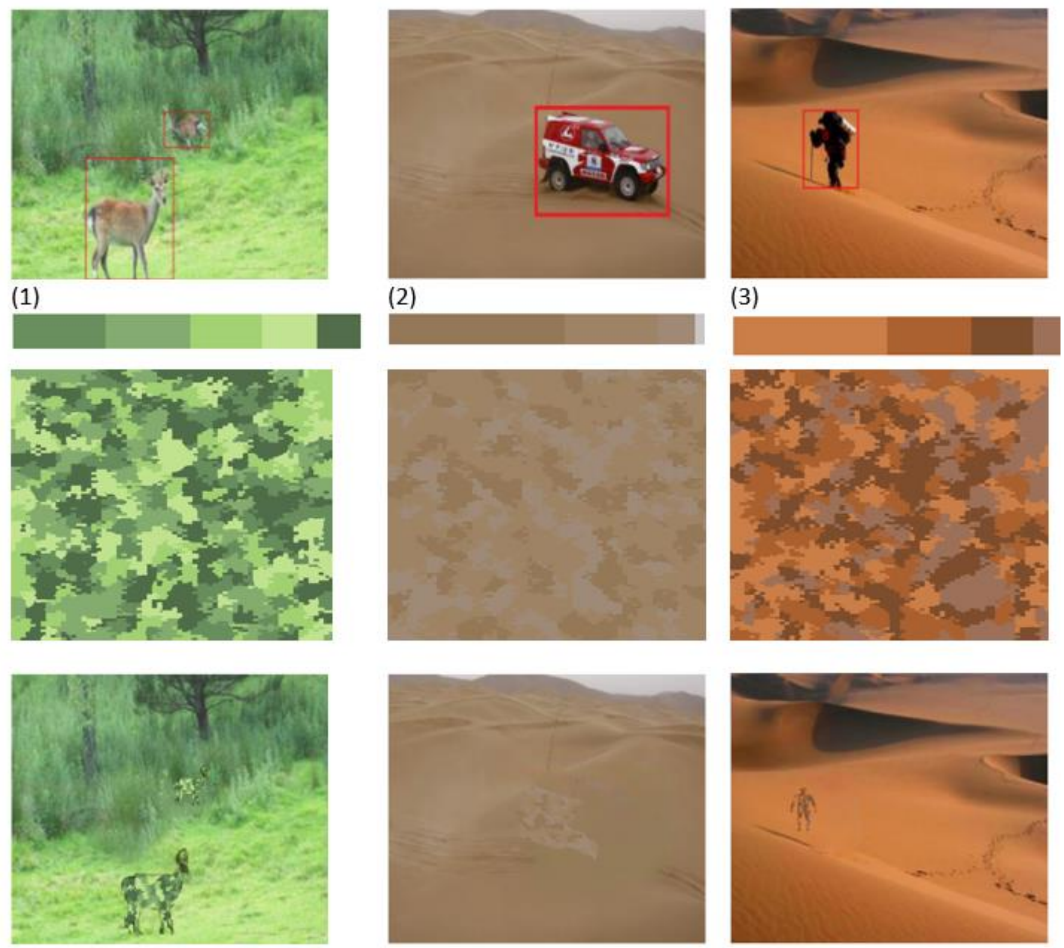


Figure 4-13: Results of proposed technique for the terrain images used in (Xue et al., 2016)

In order to evaluate the effectiveness of the proposed technique for generating camouflage textures, a photo-simulation experiment was conducted. The results of this experiment are compared with those obtained using the technique proposed by Xue et al. in 2016. The comparison is based on several parameters, including the technique used for terrain classification, extraction of colors, standardization of colors, properties of resultant textures, detection time for camouflaged object in the scene (photo simulation), and results of saliency maps.

The results of the experiment are presented in Table 4-3, which clearly shows that the proposed technique outperformed the technique proposed by Xue et al. in terms of overall performance.

Table 4-3: Detection time of camouflaged objects using texture generated by (Xue et al., 2016) and proposed method

	Related work		Proposed work	
Scene	**Detection time for natural images (s)**	**Detection time for camouflaged images (s)**	**Detection time for natural images (s)**	**Detection time for camouflaged images (s)**
(1)	0.28	0.84	0.25	2.1
(2)	0.31	1.22	0.29	2.8
(3)	0.1	0.19	0.1	0.59

In addition, saliency maps were generated for the image containing the camouflaged object, as shown in Figure 4-15. Two techniques are used to generate the saliency maps (Feng et al., 2015; Itti & Koch, 2001), which are then compared with the results obtained by Xue et al. in 2016, Figure 4-14.

The observations and were listed in Table 4-4. The comparison is done based on the parameters mentioned above. The results showed that the proposed technique performed better than the SOAT proposed by Xue et al. in 2016, as it achieved better terrain classification, improved color extraction and standardization, produced more realistic textures, reduced detection time for camouflaged objects in the scene, and generated more accurate saliency maps.

The textures generated using the proposed methodology have a more natural appearance and blend better with the environment. This is because the proposed technique considers not only the colors but also other environmental features, which helps in achieving a more realistic texture.

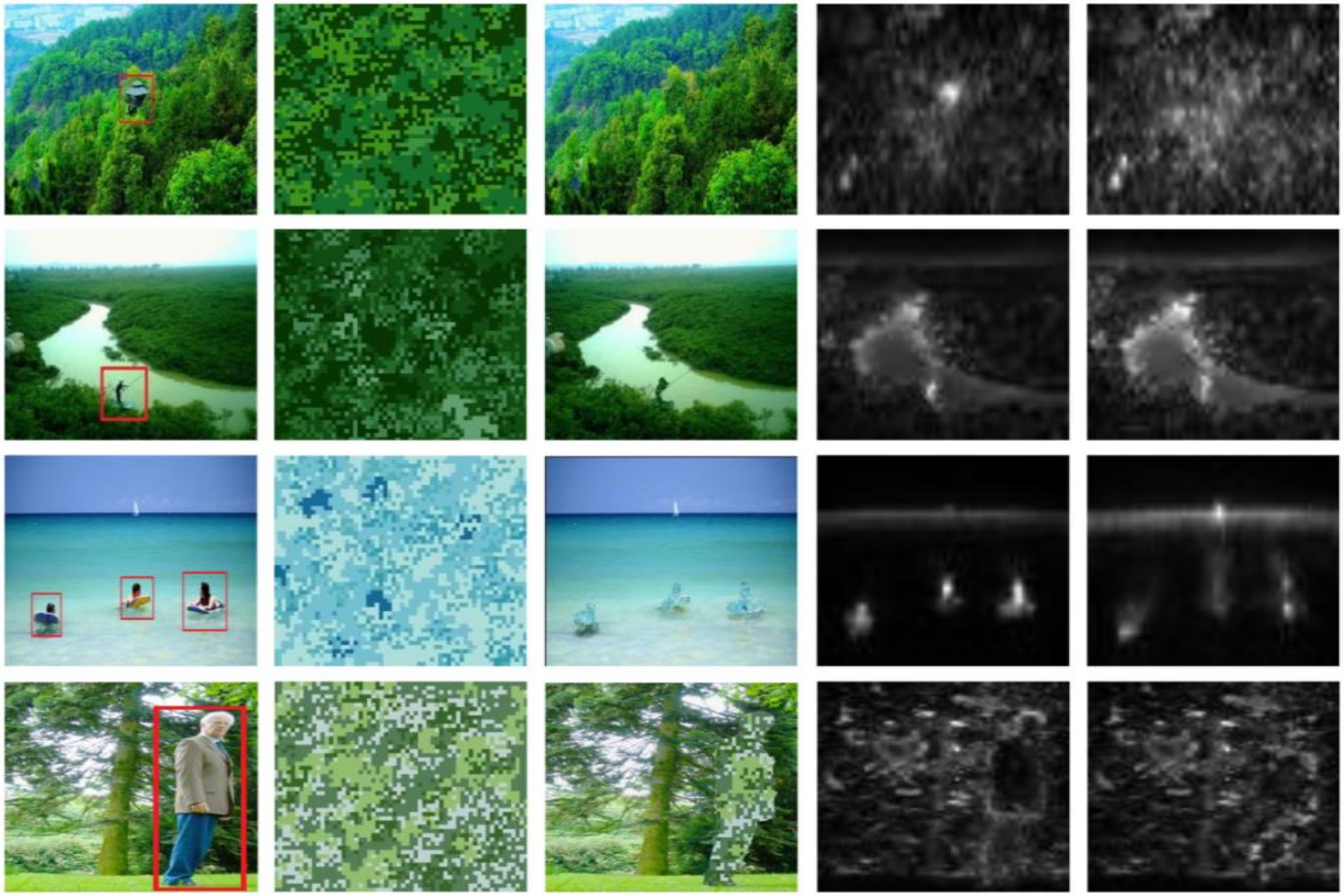


Figure 4-14: Results (Xue et al., 2016)*: Camouflaged object detection using saliency maps*

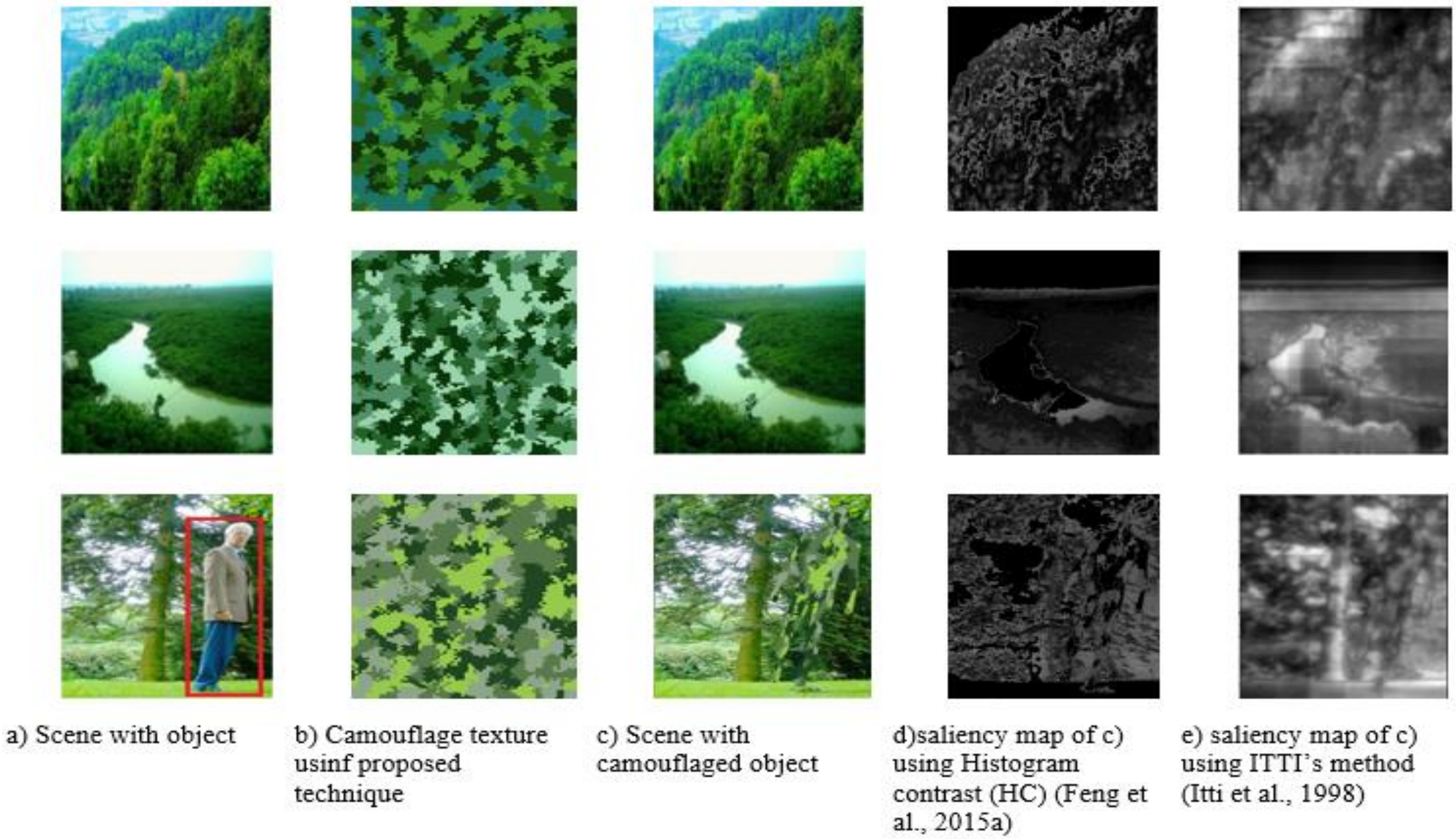


Figure 4-15: Results (Proposed technique): Camouflaged object detection using saliency maps

Table 4-4: Comparison of results: (Xue et al., 2016) and proposed technique

Comparison components/techniques	**SOAT** (Xue et al., 2016)	**Proposed technique**
Terrain Classification	NA	Capable of classifying the specific terrain into three classes: Desert, Forest, Snow
Extraction of Colors	Color clustering using K-Means	Color clustering using K-means color clustering.
Standardization of colors	NA	Standardization of colors have been done by removing colors those does not belongs to a specific terrain naturally and maintaining proportion in the resultant textures
Resultant texture	Recursive overlapping of micro and macro patterns.	Arrangement of pixalized forms of different military camouflage shapes with respect to terrain type.
Detection time for camouflaged object in the scene (Photo simulation)	Low: the camouflaged objects are easily locatable.	High: the time taken by observers to detect the camouflaged objects are comparatively high.
Saliency map	The saliencies of pixels having camouflaged objects are high and using those observers can easily identify the hidden object in a scene.	The saliency maps are not able to highlight the region of interest, as the resultant textures are not forming boundaries around the object.

4.6. Summary

This section of the report provides a comprehensive analysis of the research conducted, the results obtained, and their significance for the field. The experiments and findings of all the modules of the proposed work and comparison with state of art methods are covered in this section.

CHAPTER - 5

CONCLUSION & FURTHER SCOPE OF WORK

5. CONCLUSION & FURTHER SCOPE OF WORK

5.1. Conclusion

The design of a camouflage pattern for a specific terrain is still an essential requirement for the military globally. Traditional patterns have some drawbacks due to the standards in the set of colors and patterns. Here, efforts are made towards generating pixelated camouflage texture for a terrain image. The ability to detect an object in the environment depends on the difference in texture, color, brightness and distance from which it is being observed. Therefore, the predominant colors in the background image, their HSV values and proportions, shapes of different sizes, overlapping of smaller shapes over larger ones and pixilation of texture have been considered as key design parameters. Standardizing the set of perceived dominating colors in a scene helped to improve the effectiveness of the camouflage texture by ensuring that it blends in seamlessly with the environment, draws attention away from the object, and is consistent with industry standards.

Apart from the colors, the size of the various elements of the texture is of more importance than the particular shape. The larger the object with the contrast value, the easier it is to detect. Therefore, to get better results in a texture smaller patterns were inserted inside larger patterns to make it work for respective terrain and different distances.

After generating camouflage textures for the set of terrains, data for the effectiveness assessment were collected. Average hit rate, detection time, difficulty level in locating the target object in the background scene have been considered as performance measures for the effectiveness assessment of camouflage textures.

The average hit rate which is below 50% indicate that the proposed camouflage texture generation technology performs well in blending the object in the scene. A low average hit rate suggests that the camouflaged object is difficult to detect, which is desirable for effective camouflage. Moreover, the results also suggest that the performance of the camouflage texture varies depending on the environment. The technique works better in forest and desert areas compared to snow areas.

Therefore, the proposed technique can be a promising solution for achieving effective camouflage in different environments.

The average detection time (>40 seconds) which is quite higher for all three categories of terrain confirms that the proposed technology can aid in camouflaging objects effectively. The technique's performance is consistent among observers, and the harmonic and geometric means provide additional insights into the data distribution.

The difficulty rating parameter (>4 out of 5), combined with the average hit rate and detection time, provides a comprehensive assessment of the generated camouflage texture's effectiveness. The high difficulty rating indicates that the proposed technology can create highly effective camouflage textures that can be applied in various environments.

In addition to performance metrics, saliency maps have also been used to highlight different textures in the image. The saliency maps generated using the region contrast and histogram contrast based methods were not able to effectively segment the camouflaged object in the terrain image. This indicates that the camouflaged objects blend in well with the background features and are difficult to detect without assistance.

As the objective is to generate real time camouflage texture, the technique should take the lesser time for generating the texture. The average computation time of the TerrainCNN model is 0.11090 seconds and the time taken to generate the camouflage texture varies from 1.3 sec to 5.3 sec depending on the value of K (number of colors) and terrain type. Since the generation time is not excessive, the proposed technique can be used for the real time camouflage texture generation.

The generated patterns can be used in uniforms, to paint vehicles and weapons. This work can also be used to obtain camouflage patterns in real-time for a particular terrain. It can help hide surveillance robots, CCTV cameras, sensors, military vehicles, personnel or other military-related objects in a military-prone area.

5.2. Further scope of the work

There has been a lot of progress in this area over the past few decades, but there is still room for improvement. Researchers consider the form and scale of camouflage textures while proposing new approaches to prevent sharp and starry lines in digital designs. There are several potential future directions for the development of digital camouflage texture generation techniques. Some of the most promising areas of research and development include:

- Improved realism: One of the major challenges in digital camouflage texture generation is generating textures that are realistic and effective at hiding objects in a variety of environments. In the future, researchers may focus on developing techniques that can better replicate the natural variations and irregularities present in real-world environments to create more realistic camouflage textures. Counter-shading can be used in conjunction with camouflaging to evade detection of 3D objects (Cuthill, 2019). If the backdrop environment is subject to dynamic or natural change, such as lightning or weather, the final camouflage texture should be as effective as possible.
- Addition of more parameters: Position, size, shadow, texture, colors, tone, motion, and brightness are the eight identification criteria (Manual, 1959) (Army, 2010). Any of these variables should not reveal the placement of a camouflaged object.
- Movement: Movement is the adversary of camouflage because the overall consequence of moving features generates a pop-out of the figure from the ground and can help in object identification (Cuthill et al., 2019). Psychologists define "attention" as the act of focusing one's attention on one item while disregarding or dismissing the attention of others.
- Improved control: Researchers may also focus on developing techniques that offer more control over the characteristics of the generated camouflage textures, such as size, shape, and color. This could be particularly useful in

applications where it is important to tailor the camouflage texture to specific environments or requirements.

The primary objective of this research is to develop camouflage textures for the defence sector, to fulfill the concealment requisites crucial in military scenarios. The selection of parameters and considerations have been carefully aligned with military requirements. The categories of terrains (Forest, Desert land and snow field) have been considered in direct accordance with defence prerequisites.

The study could be made more flexible by fine-tuning some parameters and adding a few more groups to the "Terrain" dataset. Adding more groups like "Urban and Rural Areas," "Ocean," and "Indoor Living Spaces" and then retraining the "TerrainCNN" model could lead to camouflage textures that are useful for civilian uses. Such changes open up interesting possibilities for using camouflage schemes in fields other than the military.

When it comes to e-commerce, adding digital camouflage patterns to different areas can give them a new and interesting look. Digital camouflage designs can be used in a variety of ways in e-commerce, including Fashion and Apparel, Activewear and Sportswear, and Backpacks and Bags, among others.

The future of digital camouflage texture generation looks bright, and there are numerous opportunities for researchers and practitioners to explore and develop new and improved techniques in this exciting and important field.

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7. PUBLICATION DETAILS

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1. Choudhary, S., & Sharma, R. (2022). Terrain Specific Real-Time Pixelated Camouflage Texture Generation and its Impact Assessment. *Defence Science Journal*, *72*(6). https://doi.org/10.14429/dsj.72.17599 **[SCIE]**
2. Choudhary, S., & Sharma, R. (2023). CNN-based battlefield classification and camouflage texture generation for real environment. *International Journal of Computational Science and Engineering*, *26*(3), 231-242. https://doi.org/10.1504/IJCSE.2023.131514 **[SCOPUS]**
3. Choudhary, S., & Sharma, R. (2023). Camouflaged object segmentation using saliency maps-a comparative study. International Journal of Computational Vision and Robotics, 13(4), 359-377. https://doi.org/10.1504/IJCVR.2023.131987. [SCOPUS]

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BOOK CHAPTER

1. Choudhary, S., Sharma, R., & Sharma, G. (2022). Object Detection Frameworks and Services in Computer Vision. In *Object Detection with Deep Learning Models* (pp. 23-47). Chapman and Hall/CRC. https://doi.org/10.1201/9781003206736