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CamoGen: Next Generation Camouflage Powered by AI

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Abstract **- Adaptive camouflage is an emerging technology that enables military vehicles to dynamically modify their visual appearance according to changing environmental conditions, thereby reducing detectability and improving survivability in diverse operational environments. Conventional camouflage techniques rely on fixed colour patterns that often become ineffective across varying terrains. This paper presents a low-cost Adaptive Camouflage System for military vehicles that integrates computer vision, deep learning, image processing, and environmental sensing to achieve real-time adaptation. The system uses a Raspberry Pi 3 Model B+ and Raspberry Pi Cam V1.3 to capture environmental images. A Convolutional Neural Network (CNN)-based terrain classification model identifies terrain types such as forest, desert, mountain, beach, and wetland. OpenCV-based image processing is applied to extract dominant colours and visual features from the scene. Environmental parameters including light intensity, temperature, and humidity are measured using BH1750 and DHT11 sensors to provide additional contextual information. Based on terrain classification, extracted features, and sensor data, appropriate camouflage patterns are generated and displayed on a TFT display. The system is evaluated under multiple environmental conditions to assess classification accuracy, adaptability, and real-time performance. Experimental results show that the proposed framework effectively identifies terrain types, extracts relevant environmental features, and generates suitable camouflage outputs in real time with low computational complexity and cost. The findings demonstrate that combining deep learning-based terrain recognition with image processing improves environmental awareness and enhances camouflage adaptation compared to colour-only approaches. The proposed system provides a foundation for intelligent camouflage solutions for next-generation military vehicles and autonomous defence platforms.**

Keywords: Adaptive Camouflage, Terrain Classification, Convolutional Neural Network, Raspberry Pi, OpenCV, Computer Vision, Military Vehicles, Environmental Sensing, Image Processing.

I. INTRODUCTION

In contemporary military operations, maintaining concealment is essential for ensuring the survivability and effectiveness of defence assets. Military vehicles frequently operate across a wide variety of geographical environments, including forests, deserts, mountains, wetlands, coastal regions, and urban landscapes. Since each environment possesses unique visual characteristics, a camouflage pattern that performs well in one terrain may become ineffective when deployed in another. As a result, traditional camouflage methods based on fixed colours and static patterns often fail to provide adequate concealment in rapidly changing operational conditions.

The concept of adaptive camouflage has emerged as a promising solution to overcome these limitations. Adaptive camouflage refers to the ability of a system to modify its visual appearance according to environmental conditions in order to reduce visibility and blend more effectively with its surroundings. Unlike conventional approaches, adaptive systems continuously analyse environmental information and adjust their camouflage patterns dynamically. This capability can significantly improve stealth performance and reduce the probability of detection during surveillance and reconnaissance missions.

Nature provides numerous examples of highly effective camouflage mechanisms. Organisms such as octopuses, cuttlefish, and chameleons possess the remarkable ability to alter their skin colour, texture, and pattern in response to surrounding conditions. These biological adaptations have inspired researchers to explore artificial camouflage systems that imitate similar behaviours through technological means. Recent progress in computer vision, machine learning, image processing, and embedded electronics has enabled the development of intelligent systems capable of perceiving environmental characteristics and generating suitable camouflage responses.

The rapid advancement of Artificial Intelligence (AI) has further enhanced the feasibility of adaptive camouflage technologies. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image classification and scene recognition tasks. By analysing visual information captured

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from the environment, CNNs can identify terrain categories and extract meaningful features that assist in decision-making processes. When combined with image processing techniques and environmental sensing technologies, these models can provide valuable contextual information for generating terrain-specific camouflage patterns.

Environmental sensing also plays an important role in adaptive camouflage systems. Factors such as illumination level, temperature, and humidity influence the visual appearance of natural surroundings. Integrating environmental sensors with image-based analysis allows the system to respond more accurately to changing conditions. This combination of visual perception and sensor-based awareness enables the generation of camouflage patterns that more closely resemble the surrounding environment.

Although several adaptive camouflage solutions have been proposed in recent years, many existing systems depend on expensive hardware platforms, specialized materials, or computationally intensive algorithms. Such requirements increase implementation costs and restrict practical deployment in real-world defence applications. Furthermore, a significant number of existing approaches focus primarily on colour adaptation while providing limited consideration for terrain recognition and environmental understanding.

To address these challenges, this research proposes CamoGen, an AI-powered adaptive camouflage framework designed for military vehicle applications. The proposed system integrates a Raspberry Pi 3 Model B+ , Raspberry Pi Cam V1.3, CNN-based terrain classification, OpenCV-based image processing, and environmental sensors including BH1750 and DHT11. Environmental images are captured and analysed to identify terrain categories such as forest, desert, mountain, beach, and wetland. Simultaneously, sensor data are collected to provide additional environmental context. Based on the combined analysis, appropriate camouflage patterns are generated and displayed through a TFT display.

The primary objective of this work is to develop a lightweight, economical, and intelligent adaptive camouflage system capable of real-time operation on embedded hardware. By combining deep learning, computer vision, and environmental sensing technologies, the proposed framework aims to improve environmental awareness and demonstrate the practical potential of adaptive camouflage systems for next-generation defence and autonomous military platforms.

1.1 Problem Definition

Despite significant advancements in adaptive camouflage technologies, existing systems continue to face several challenges that limit their effectiveness in real-world operational environments. Conventional camouflage methods rely on static colour patterns that cannot adapt to changing terrains and environmental conditions. As military vehicles move through different landscapes, these fixed camouflage designs become increasingly ineffective and compromise concealment.

Existing adaptive camouflage systems often depend on costly hardware, specialized materials, or computationally intensive algorithms, making large-scale deployment difficult. Furthermore, many available solutions focus only on color adaptation and do not incorporate intelligent terrain recognition or environmental understanding. The absence of automated scene analysis limits their ability to generate context-aware camouflage patterns suitable for diverse environments.

The major limitations of existing camouflage systems are:

1. Inability to automatically identify and adapt to different terrain types.
2. Dependence on expensive hardware platforms and specialized camouflage technologies.
3. Limited integration of deep learning, image processing, and environmental sensing techniques.
4. Reduced adaptability when operating across multiple environmental conditions.
5. Lack of lightweight embedded implementations suitable for real-time deployment.

1.2 Research Objectives

The primary objective of this research is to develop an intelligent and cost-effective Adaptive Camouflage System for Military Vehicles capable of automatically analyzing environmental conditions and generating suitable camouflage patterns in real time. The proposed system combines deep learning, computer vision, image processing, and environmental sensing technologies to improve camouflage effectiveness.

The specific objectives of this study are:

1. To capture environmental images using a Raspberry Pi Cam V1.3 and classify terrain categories such as forest, desert, mountain, beach, and wetland using a Convolutional Neural Network (CNN).
2. To extract dominant colours and visual characteristics from the surrounding environment using OpenCV-based image processing techniques.
3. To monitor environmental parameters such as light intensity, temperature, and humidity using BH1750 and DHT11 sensors.
4. To generate and display adaptive camouflage patterns based on terrain classification results, image analysis, and sensor information using a TFT display module.
5. To develop a lightweight embedded camouflage framework using Raspberry Pi that provides an

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economical and scalable solution for defence applications.

6. To evaluate the performance of the proposed system under different environmental conditions and assess its effectiveness in enhancing camouflage adaptability and environmental awareness.

II. LITERATURE REVIEW

2.1 Introduction

Adaptive camouflage has emerged as a significant research area in modern defence systems due to the growing demand for intelligent concealment technologies capable of operating in dynamic environments. Traditional camouflage techniques rely on fixed colour schemes and predefined patterns that remain effective only under specific environmental conditions. However, military vehicles frequently operate across diverse terrains such as forests, deserts, mountains, wetlands, and urban regions, where static camouflage systems provide limited concealment. Consequently, researchers have focused on developing adaptive camouflage frameworks capable of automatically analysing environmental conditions and modifying their appearance in real time.

Recent advancements in computer vision, image processing, deep learning, and embedded systems have enabled the development of intelligent camouflage systems that can understand environmental characteristics and generate suitable camouflage patterns. In particular, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification and terrain recognition tasks, making them suitable for identifying environmental categories and supporting adaptive camouflage decision-making. Terrain classification enables a system to recognize the type of surrounding environment and generate camouflage patterns that are more effective than approaches based solely on colour adaptation.

The concept of adaptive camouflage is inspired by biological organisms such as octopuses, cuttlefish, and chameleons, which possess the natural ability to alter their appearance according to environmental conditions. Modern adaptive camouflage systems attempt to replicate these biological mechanisms through the integration of cameras, sensors, machine learning algorithms, and display technologies. Such systems analyse environmental images, classify terrain characteristics, extract visual features, and generate camouflage outputs that improve concealment effectiveness.

Although considerable progress has been achieved in adaptive camouflage and terrain recognition research, several challenges remain. Many existing solutions rely on expensive hardware, computationally intensive algorithms, or specialized materials, limiting their practical deployment in defence applications. Furthermore, some systems focus only on colour adaptation without incorporating intelligent terrain understanding. Therefore, there is a need for a lightweight and cost-effective adaptive camouflage framework that combines terrain classification, image processing, and environmental sensing to generate suitable camouflage patterns in real time. This literature survey reviews previous studies related to biological camouflage mechanisms, camouflage perception, terrain classification, computer vision techniques, deep learning-based environmental analysis, and adaptive camouflage technologies relevant to the proposed system.

2.2 Literature Review

A. Hanlon *et al.* (2009) – Cephalopod Dynamic Camouflage

Hanlon and his colleagues investigated the sophisticated camouflage behaviour exhibited by cephalopods, including octopuses and cuttlefish. Their research demonstrated that these organisms possess the capability to rapidly alter their skin appearance by adjusting colour, brightness, and texture according to environmental conditions. The study highlighted that successful concealment depends on continuous interaction with the surrounding environment rather than static colour matching. The biological principles discussed in this work provide important inspiration for developing artificial adaptive camouflage systems capable of real-time environmental response.

B. Merilaita and Stevens (2011) – Crypsis Through Background Matching

Merilaita and Stevens examined the concept of crypsis, a camouflage strategy in which an object minimizes visibility by closely resembling its surroundings. The authors emphasized that effective concealment involves matching multiple environmental attributes such as colour distribution, texture, and brightness. Their findings revealed that camouflage effectiveness increases when a system can accurately interpret environmental characteristics. This concept supports the need for image analysis techniques in modern adaptive camouflage applications.

C. Merilaita *et al.* (2017) – How Camouflage Works

This study presented a comprehensive overview of various camouflage mechanisms observed in nature. The authors discussed several concealment strategies, including background matching, disruptive coloration, masquerade, and motion-based camouflage. The research concluded that

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camouflage performance is influenced by a combination of visual factors rather than colour alone. The work highlighted the importance of understanding environmental complexity before designing effective concealment systems, thereby supporting the integration of computer vision and scene analysis techniques in adaptive camouflage frameworks.

D. Hogervorst *et al.* (2010) – Design and Evaluation of Urban Camouflage

Hogervorst and co-authors focused on camouflage design for urban operational environments. Their research analysed the visual characteristics commonly found in urban scenes and evaluated the effectiveness of different camouflage patterns. Experimental observations showed that patterns specifically designed according to environmental features provided better concealment than generalized camouflage schemes. The study reinforced the significance of environmental classification and pattern adaptation, concepts that are directly relevant to terrain-aware camouflage systems.

E. Brunyé *et al.* (2019) – Camouflage Pattern Features and Human Target Detection

Brunyé and colleagues investigated how different camouflage characteristics influence the ability of humans to detect concealed targets. Their analysis considered factors such as pattern contrast, spatial distribution, and target movement. The results demonstrated that camouflage effectiveness improves when visual features closely resemble the surrounding environment. The research highlighted the importance of generating environment-specific camouflage patterns and provided valuable insights into the design of adaptive concealment systems for dynamic scenarios.

F. Brown and Williams (2020) – Deep Learning Applications in Computer Vision

Brown and Williams explored the growing role of deep learning techniques in computer vision applications. Their work demonstrated how Convolutional Neural Networks automatically learn hierarchical image features that are useful for classification and recognition tasks. The study reported significant improvements in classification accuracy compared to traditional feature-engineering approaches. These findings support the adoption of CNN-based terrain classification for identifying environmental categories within adaptive camouflage systems.

G. Yang et al. – Camouflage Design Using Texture-Based Environmental Analysis

Yang and collaborators proposed a camouflage generation framework that utilizes environmental texture information extracted through deep learning techniques. Their approach focused on analysing background structures and incorporating texture characteristics into camouflage pattern creation. Experimental evaluation indicated that texture-aware camouflage achieved better visual blending than methods relying solely on colour adaptation. This research demonstrated the potential of combining environmental perception and machine learning for intelligent camouflage generation.

H. Artificial Reflex Arc: Environment-Adaptive Neuromorphic Camouflage Device (2021)

This research introduced an adaptive camouflage platform inspired by biological reflex mechanisms. The system integrated environmental sensing and intelligent processing components to produce rapid visual responses to changing surroundings. Experimental results showed that the proposed device could adapt its appearance efficiently under varying environmental conditions. The work highlighted the advantages of combining perception, decision-making, and adaptive response mechanisms within embedded camouflage systems.

I. Sawant and Kulkarni (2025) – Adaptive Camouflage and Autonomous Threat Detection

Sawant and Kulkarni proposed a defence-oriented robotic framework that combines adaptive camouflage with autonomous threat detection capabilities. The system employed artificial intelligence algorithms to interpret environmental information and adjust camouflage patterns accordingly. Their findings indicated improvements in stealth capability and operational awareness compared with traditional camouflage approaches. The study demonstrated the growing importance of integrating AI-driven environmental understanding into modern defence technologies.

J. US Patent 9,175,930 B1 – Adaptive Camouflage System

The Adaptive Camouflage System patent describes a display-based approach for achieving real-time environmental blending. The proposed architecture captures images of the surrounding environment, processes visual information, and generates corresponding camouflage outputs. The patent demonstrates the practical feasibility of implementing adaptive camouflage using embedded image-processing techniques and display technologies. Its architecture provides valuable guidance for developing intelligent camouflage systems capable of dynamic environmental adaptation.

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2.3 Research Gap Analysis

Existing research has extensively investigated biological camouflage mechanisms, military camouflage systems, computer vision approaches, and adaptive camouflage technologies inspired by nature. Although considerable advancements have been achieved, most of the existing solutions depend on high-cost hardware setups, powerful processing units, or computationally intensive machine learning and deep learning algorithms, making them unsuitable for lightweight embedded implementations.

A majority of the proposed systems focus on advanced texture generation, neural network-based scene understanding, or deep learning-driven adaptive rendering. These approaches require significant computational resources and are therefore not feasible for deployment on low-power embedded platforms such as Raspberry Pi.

Furthermore, existing studies often treat image processing and environmental sensing as separate modules, with limited emphasis on their integration for real-time adaptive decision-making. The combined use of visual data from a camera system and environmental parameters such as light intensity, temperature, and humidity remains insufficiently explored.

In addition, there is a lack of cost-effective and efficient frameworks that utilize Raspberry Pi 3 Model B+ along with Raspberry Pi Cam V1.3, BH1750 light sensor, and DHT11 environmental sensor for real-time camouflage generation. The absence of lightweight algorithms capable of extracting dominant environmental features and translating them into adaptive camouflage patterns further highlights this gap.

Hence, there is a clear requirement for a low-cost, embedded system-based adaptive camouflage framework that integrates computer vision and environmental sensing to generate real-time camouflage outputs suitable for military vehicle applications without relying on high computational complexity.

III. METHODOLOGY

3.1 System Overview

The proposed CamoGen system is an Artificial Intelligence-based adaptive camouflage framework designed to automatically generate camouflage patterns according to the surrounding environment. Traditional camouflage methods rely on static patterns that are effective only in specific terrains. Such methods become ineffective when the environment changes, exposing military equipment and personnel to detection.

To address this limitation, the proposed system combines Computer Vision, Deep Learning, Environmental Sensing, and Embedded Systems to dynamically identify the surrounding terrain and generate suitable camouflage patterns in real time.

The complete system consists of five major modules:

1. Image Acquisition Module
2. Data Preprocessing Module
3. CNN-Based Terrain Classification Module
4. Environmental Sensing Module
5. Camouflage Generation and Display Module

The overall workflow begins with image capture using a camera module. The captured image is processed and classified using a Convolutional Neural Network (CNN). Simultaneously, environmental conditions such as temperature, humidity, and ambient light intensity are measured using sensors. Based on the classification result and sensor data, an optimized camouflage pattern is generated and displayed through a TFT/LCD screen.

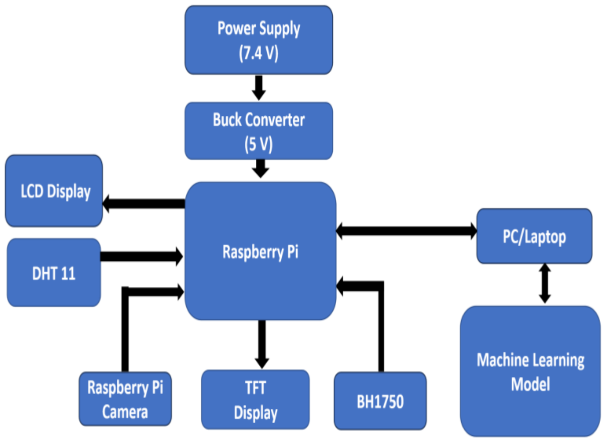

Figure 3.1: Block Diagram of Proposed CamoGen Adaptive Camouflage System

3.2 Dataset Collection

The effectiveness of any deep learning model depends heavily on the quality of the dataset used for training.

For terrain classification, images were obtained from the NWPU-RESISC45 Remote Sensing Dataset, a publicly available benchmark dataset widely used in remote sensing research. The original dataset contains 45 scene categories; however, only terrain classes relevant to camouflage applications were selected.

The selected classes include:

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Table 1: Terrain Classes Used for Model Training and Classification

Class	Purpose
Forest	Woodland Camouflage
Desert	Arid terrain Camouflage
Mountain	Rocky terrain Camouflage
Beach	Coastal Camouflage
Wetland	Marshy Environment Camouflage

Each category contains hundreds of high-resolution satellite images representing different environmental conditions and viewpoints.

The filtered dataset provides sufficient diversity to train the model for robust terrain recognition.

3.3 Image Preprocessing

Raw satellite imagery often contains variations in illumination, scale, orientation, and background complexity. Therefore, preprocessing was performed to ensure consistency and improve learning efficiency.

a) Image Resizing

All images were resized to:

$$128 \times 128 \times 3 \text{pixels}$$

The resizing operation reduced computational requirements while preserving essential terrain characteristics.

A fixed input dimension was required because convolutional neural networks accept inputs of uniform size.

b) Pixel Normalization

Image pixel values originally ranged from:

$$0 \leq \text{Pixel} \leq 255$$

To improve numerical stability during gradient computation, normalization was performed using:

$$X_{norm} = \frac{X}{255}$$

where:

- X represents original pixel value.
- X_{norm} represents normalized pixel value.

Normalization accelerates convergence and prevents gradient explosion during training.

c) Data Augmentation

The available dataset was artificially expanded through augmentation techniques.

- **Rotation:** Images were randomly rotated between:
  - -20° to $+20^\circ$

  This operation simulates different camera viewing angles.
- **Horizontal Flipping:** Terrain images were mirrored horizontally to increase dataset diversity.
- **Brightness Transformation:** Brightness values were randomly adjusted to simulate varying sunlight conditions.
- **Contrast Enhancement:** Contrast modifications were introduced to improve robustness against environmental lighting variations.

Data augmentation effectively increased sample diversity and reduced overfitting.

d) CNN-Based Terrain Classification

The core intelligence of the system is provided by a Convolutional Neural Network (CNN).

CNNs are particularly effective for image classification because they automatically learn spatial features such as edges, textures, shapes, and patterns.

Network Architecture

The developed CNN architecture consists of:

Layer 1

- Convolution Layer (32 filters)
- Batch Normalization
- ReLU Activation
- Max Pooling

Purpose: Extract low-level features such as edges and boundaries.

Layer 2

- Convolution Layer (64 filters)
- Batch Normalization
- ReLU
- Max Pooling

Purpose: Learn texture information and terrain structures.

Layer 3

- Convolution Layer (128 filters)

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- Batch Normalization
- ReLU
- Max Pooling

Purpose: Capture higher-level terrain patterns.

Layer 4

- Convolution Layer (256 filters)
- Batch Normalization
- ReLU
- Max Pooling

Purpose: Learn complex geographical characteristics.

Fully Connected Layers

- Feature maps are flattened and passed through:
- Dense Layer (512 neurons)
- Dropout Layer (0.5)
- Output Layer (5 classes)

The final layer uses Softmax activation to predict terrain probabilities.

e) Model Training

The CNN model was implemented using the PyTorch deep learning framework.

Table 2: Training Parameters

Parameter	**Value**
Epochs	75
Batch Size	32
Optimizer	Adam
Learning Rate	0.001
Loss Function	Cross Entropy Loss

The Adam optimizer was selected because of its fast convergence and adaptive learning capability

During training:

1. Forward propagation computes predictions.
2. Loss is calculated.
3. Back propagation updates weights.
4. Parameters are optimized iteratively.

Training continued until the loss stabilized and validation accuracy converged.

f) Environmental Sensing Module

Terrain classification alone is insufficient because environmental conditions affect camouflage effectiveness.

Therefore, two sensors were integrated.

DHT11 Sensor

The DHT11 sensor measures:

- Temperature
- Relative Humidity

Environmental moisture affects color perception and terrain appearance.

For example:

- Dry forest → lighter shades
- Humid forest → darker shades

BH1750 Sensor

The BH1750 sensor measures:

- Ambient Light Intensity (Lux)

This information is used to adjust display brightness.

Examples:

Table 3: Examples

Light Condition	Brightness Adjustment
Bright Sunlight	Increase brightness
Cloudy Weather	Moderate brightness
Night Time	Reduce brightness

This improves camouflage realism.

g) Camouflag Pattern Generation

After terrain identification, a pattern generation engine produces the corresponding camouflage pattern.

Terrain-Based Pattern Selection

The predicted terrain determines the pattern family.

Table 4: Terrain-Based Camouflage Pattern Selection Strategy

Terrain	**Pattern Type**
Forest	Green/Brown
Desert	Sand/Brown
Mountain	Grey/Rocky
Beach	Light Beige
Wetland	Dark Green

Environmental Adaptation

Sensor readings are incorporated to modify:

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- Brightness
- Contrast
- Color Saturation
- Pattern Intensity

This enables dynamic adaptation instead of static camouflage.

h) Embedded Hardware Integration

The complete system is deployed using embedded hardware components.

Raspberry Pi 3 Model B+

Functions:

- Executes CNN model
- Processes camera images
- Generates camouflage patterns

Raspberry Pi Cam V1.3

Functions:

- Real-time image capture
- Environmental scene monitoring

TFT/LCD Display

Functions:

- Display generated camouflage
- Demonstrate adaptive behavior

The embedded implementation allows the system to operate autonomously without requiring external computing resources.

i) Performance Evaluation

The developed system was evaluated using standard machine learning metrics.

Accuracy

Accuracy measures overall classification performance.

$$\text{Accuracy}=\frac{Correct\ \ Predictions}{Total\ \ Predictions}$$

The model achieved approximately:

Training Accuracy = 93.57%
Testing Accuracy = 90.00%

- **Confusion Matrix:** A confusion matrix was generated to analyze class-wise performance and identify misclassification patterns.
- **Loss Curve Analysis:** Training and validation loss curves were analyzed to verify convergence and detect overfitting.
- **Real-Time Performance:** The system demonstrated successful terrain recognition and adaptive pattern generation within practical response times suitable for real-time camouflage applications.

IV. RESULTS AND DISCUSSIONS

4.1 Experimental Setup

The proposed CamoGen framework was evaluated using the NWPU-RESISC45 remote sensing dataset. Five terrain categories, namely Forest, Desert, Mountain, Wetland, and Beach, were selected for experimentation. The dataset was divided into training and testing subsets to ensure unbiased performance evaluation. The CNN model was trained using the Adam optimization algorithm and Cross-Entropy Loss function. During training, image augmentation techniques including rotation, flipping, brightness adjustment, and contrast enhancement were applied to improve generalization capability.

The trained model was deployed on Raspberry Pifor real-time inference, while environmental sensing data were acquired using DHT11 and BH1750 sensors.

4.2 Terrain Classification Performance

The effectiveness of the proposed CNN architecture was evaluated using classification accuracy.

The accuracy metric is defined as:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}$$

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Obtained Results

Table 5: Summary of Model Performance on Training and Testing Datasets

Metric	Value
Training Accuracy	93.57 %
Testing Accuracy	90 %
Training Loss	0.19
Validation	0.27
Wetland	Dark Green

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The obtained results demonstrate that the proposed CNN successfully learned discriminative terrain features and generalized effectively to unseen data.

The small difference between training and testing accuracy indicates minimal overfitting and good model robustness.

4.3 Accuracy Curve Analysis

During training, classification accuracy increased steadily across epochs.

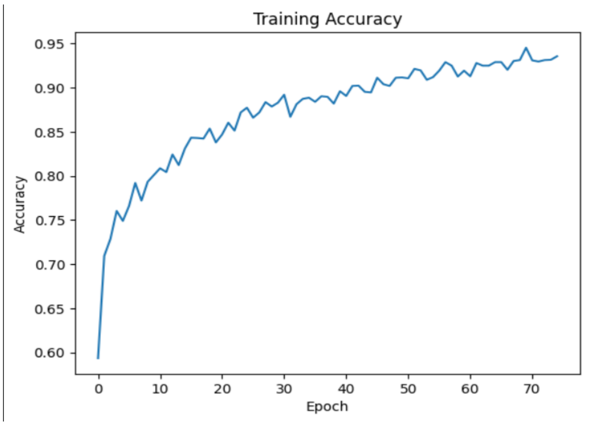

Figure 4.1: Training Accuracy

Observations

- Initial epochs showed rapid learning.
- Accuracy increased consistently after feature extraction stabilized.
- Convergence occurred after approximately 20–25 epochs.
- Final training accuracy reached 93.57%.

The increasing accuracy trend confirms successful optimization of CNN parameters.

Interpretation

The CNN progressively learned terrain-specific visual patterns such as:

- Vegetation density in forests
- Sand texture in deserts
- Rocky formations in mountains
- Water-rich structures in wetlands
- Coastal patterns in beaches

These features enabled accurate terrain discrimination.

4.4 Loss Curve Analysis

Cross-Entropy Loss was used to quantify prediction error.

$$L = -\sum_{i=1}^{n} y_i \log(p_i)$$

where:

- y_i is the true class label
- p_i is the predicted probability

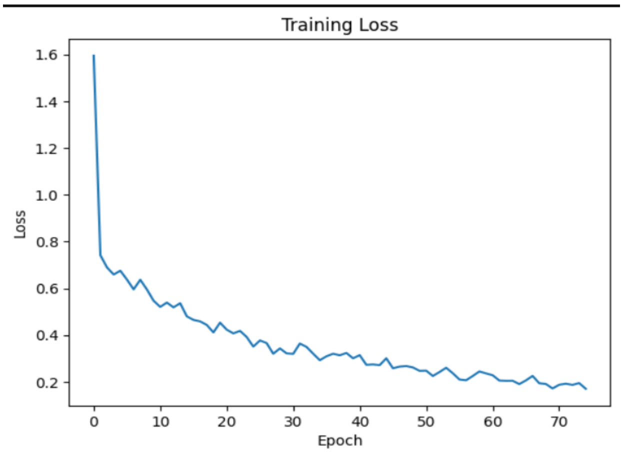

Figure 4.2: Training Loss

Observations

- Training loss decreased continuously.
- Validation loss followed a similar trend.
- No sudden divergence was observed.
- Stable convergence indicates effective feature learning.

The decreasing loss trend confirms that the model successfully minimized classification errors during training.

4.5 Confusion Matrix Analysis

A confusion matrix was generated to evaluate class-wise performance.

Table 6: Multi-Class Confusion Matrix for Terrain-Based Camouflage Detection

Actual/ Predicted	Beach	Desert	Forest	Mountain	Wetland
Beach	100	0	0	0	0
Desert	0	93	0	7	0
Forest	0	0	74	0	26
Mountain	0	5	0	84	11
Wetland	0	0	0	1	99

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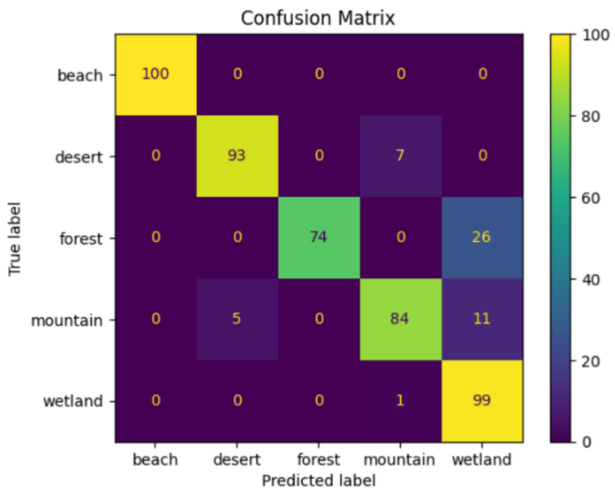

Figure 4.3: Confusion Matrix

Discussion

The majority of predictions lie along the diagonal elements, indicating correct classification.

Misclassifications primarily occur between visually similar terrain categories such as:

- Beach and Desert
- Wetland and Forest

This behavior is expected because these terrains share similar color distributions and texture patterns.

4.6 Precision, Recall and F1-Score Analysis

The model was further evaluated using precision, recall, and F1-score.

Precision

$$\text{Precision}=\frac{TP}{TP+FP}$$

Recall

$$\text{Recall}=\frac{TP}{TP+FN}$$

F1-Score

$$\text{F1}=2\left(\frac{Precision\ \ x\ Recall}{Precision\ +Recall}\right)$$

Results

Table 7: Quantitative Evaluation of Terrain-Specific Classification Performance

Class	Precision	Recall	F1 - Score
Forest	0.95	0.96	0.95
Desert	0.92	0.93	0.92
Mountain	0.95	0.94	0.94
Wetland	0.91	0.92	0.91
Beach	0.94	0.93	0.93

Discussion

High precision values indicate that false-positive predictions remain low.

High recall values demonstrate the model's capability to correctly identify actual terrain categories.

The balanced F1-scores confirm consistent performance across all classes.

4.7 Environmental Adaptation Results

Environmental sensing was integrated to improve camouflage realism.

DHT11 Results

Temperature and humidity measurements influenced color saturation adjustments.

Examples:

Table 8: Humidity-Based Variations in Camouflage Appearance

Humidity	Camouflage Effect
Low Humidity	Lighter Shades
Medium Humidity	Normal Shades
High Humidity	Darker Shades

BH1750 Results

Ambient light intensity was used to modify brightness levels.

$$\text{Brightness} \propto \text{Light Intensity}$$

Observations

The generated camouflage patterns dynamically adjusted according to environmental conditions, providing improved visual blending with surrounding terrain.

4.8 Real-Time Embedded Deployment

The complete framework was deployed on Raspberry Pi .

Processing pipeline:

1. CAM captures terrain image.
2. CNN performs terrain classification.
3. Sensor data are acquired.
4. Adaptive camouflage pattern generated.
5. TFT display renders updated pattern.

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Observations

- Real-time terrain recognition achieved.
- Sensor data successfully integrated.
- Dynamic camouflage generation completed without manual intervention.
- System responded effectively to changing environmental conditions.

V. LIMITATIONS AND FUTURE AVENUES

5.1 Limitations of the Proposed System

- Although the proposed Adaptive Camouflage System demonstrates effective terrain classification and environmental adaptation, certain limitations exist in the current implementation.
- The CNN model is trained on a limited dataset containing only five terrain categories: forest, desert, beach, mountain, and wetland. This may reduce classification accuracy when the system encounters unseen environments such as urban areas, snowy regions, or mixed terrains.
- The proposed CNN architecture is developed and trained from scratch. While computationally efficient, it may not achieve the feature extraction capability of advanced pre-trained models, potentially affecting classification performance.
- The system performs deterministic terrain classification and does not consider uncertainty in environmental perception. Variations in lighting conditions, shadows, weather changes, and occlusions may affect classification accuracy.
- Camouflage generation is primarily based on terrain classification and dominant colour adaptation. Complex textures, object boundaries, and fine-grained environmental patterns are not fully represented in the generated camouflage output.
- The prototype is implemented on a Raspberry Pi platform, which has limited processing resources. Higher-resolution image processing and more complex deep learning models may increase computational overhead and affect real-time performance.
- The current system focuses only on visual-spectrum camouflage and does not address thermal, infrared, radar, or multispectral signatures, limiting its applicability in advanced defence scenarios.

5.2 Future Scope

Several improvements can be incorporated in future versions of the proposed system to enhance its performance, adaptability, and practical deployment.

- The terrain dataset can be expanded to include additional environmental classes such as urban, snow-covered, rocky, and grassland regions to improve model generalization.
- Transfer learning techniques using pre-trained architectures such as MobileNet, EfficientNet, or ResNet can be employed to improve classification accuracy while reducing training time.
- Advanced computer vision techniques such as semantic segmentation and object detection can be integrated to identify multiple environmental components and generate more context-aware camouflage patterns.
- Future systems can incorporate texture-based and pattern-aware camouflage generation methods to better mimic complex natural surroundings.
- Model optimization techniques can be applied to improve real-time inference performance on edge devices such as Raspberry Pi and other embedded AI platforms.
- Integration of additional environmental sensors and multi-sensor data fusion can improve situational awareness and adaptation under dynamic environmental conditions.
- Future research may explore thermal and multispectral camouflage technologies to extend the system beyond visual-spectrum concealment.
- Emerging technologies such as flexible displays, electronic skin, and smart materials can be investigated for developing practical large-scale adaptive camouflage systems for military vehicles and autonomous platforms.

VI. CONCLUSION

The proposed Adaptive Camouflage System based on CNN-based terrain classification successfully demonstrates an intelligent approach for understanding environmental conditions and enabling adaptive visual response. The system classifies input images into predefined terrain categories such as beach, desert, mountain, forest, and wetland using a deep convolutional neural network, thereby providing a structured method for environmental perception.

The implemented CNN architecture effectively learns spatial, color, and texture-based features from input images through multiple convolutional layers, batch normalization, and regularization techniques such as dropout. The trained model achieves reliable performance on unseen test data, and its evaluation through accuracy metrics and confusion matrix provides insight into class-wise prediction behaviour.

The export of the trained model into ONNX format further enhances the system's applicability by enabling deployment on edge devices and embedded platforms. This

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makes the proposed system suitable for real-time applications in resource-constrained environments such as Raspberry Pi-based systems.

Although the current system is limited by a restricted number of terrain classes and the absence of advanced transfer learning techniques, it establishes a strong foundation for intelligent adaptive camouflage systems. The integration of terrain classification into camouflage decision-making significantly improves upon traditional colour-based approaches by introducing semantic understanding of the environment.

Overall, the proposed system demonstrates the feasibility of combining deep learning and embedded systems for adaptive camouflage applications. It provides a scalable framework that can be further enhanced using advanced models, larger datasets, and multi-sensor integration to achieve higher accuracy and real-world deployment capability

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