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SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

SENIOR DESIGN PROJECT

Project report on

Vegetation Mapping using UAV

Submitted

in partial fulfillment of the requirements for the award of the degree of

Bachelor of Engineering

IN

COMPUTER SCIENCE AND ENGINEERING

Submitted By

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2024-2025

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CERTIFICATE

This is to certify that project entitled "Vegetation Mapping using UAV" is a bonafied work carried out by the student team Vibhashree BS 01FE21BCI003, Rohan Kolhar 01FE21BCI030, Konkathi Rithin Kumar 01FE20BCS008, Sandeep Angadi 01FE21BCS293, in partial fulfillment of the completion of 7th semester B. E. course during the year 2024 – 2025. The project report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above said course

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ABSTRACT

This project aims to develop a deep learning model that uses drone imagery to map and predict the percentage of vegetative land coverage across various landscapes. The primary goal is to establish a system that can monitor changes in vegetation over time, providing valuable insights for land management, environmental monitoring, and climate change analysis. The system will leverage advanced computer vision techniques to process aerial images, segment vegetation, and calculate the percentage of vegetative cover across different terrains. It is designed to efficiently handle large datasets of aerial imagery, incorporating features for preprocessing, segmentation, and coverage analysis. Ultimately, this project will provide a comprehensive tool for monitoring and assessing vegetation changes, which will be instrumental in detecting environmental risks, informing conservation efforts, and supporting improved decision-making in land use and management. By combining state-of-the-art deep learning methods with an intuitive user interface, the project ensures both technical accuracy and ease of use. This system is a valuable resource for addressing environmental challenges and enhances our understanding and management of vegetative resources in the context of changing climates and human impact.

Keywords :*Deep learning, Segementation, UAV, Machine learning.*

ACKNOWLEDGEMENT

The satisfaction and euphoria that accompany the successful completion of any task would be incomplete without the mention of a number of individuals whose professional guidance and encouragement helped me in the successful completion of this report work.

We take this opportunity to thank Dr. Ashok Shettar, Pro-Chancellor, Dr. P. G. Tewari, Vice-Chancellor and to Dr. Basavaraj Anami, Registrar, KLE Technological University, Hubballi.

We also take this opportunity to thank Dr. Meena S. M., Dean faculty, School of Computer Science and Engineering and Dr. Vijayalakshmi M., Professor and Head, School of Computer Science and Engineering for having provided us academic environment which nurtured our practical skills contributing to the success of our project.

We sincerely thank our guide Dr.Sharada K S Professor, Department of Computer Science and Engineering for her guidance, inspiration and wholehearted co-operation during the course of completion.

We sincerely thank our project co-ordinators Dr. P.G Sunita Hiremath for their support, inspiration and wholehearted co-operation during the course of completion.

Our gratitude will not be complete without thanking the Almighty God, our beloved parents, our seniors and our friends who have been a constant source of blessings and aspirations.

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Chapter 1

INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are utilized to capture aerial imagery of vegetation through advanced cameras and sensors, enabling the mapping of plant species, health assessments, and coverage analysis. By employing machine learning techniques to analyze these images, it is possible to accurately identify various types of vegetation and evaluate their condition across extensive regions. This approach offers high-resolution imagery, cost-effective data collection, and frequent monitoring capabilities, significantly benefiting sectors such as agriculture, forestry, and environmental management.

1.1 Motivation

Vegetation mapping is an essential tool for monitoring changes in forests, grasslands, and other plant-covered areas over time, especially in the context of challenges posed by climate change. It allows researchers, environmentalists, and policymakers to track shifts in vegetation patterns, which helps them understand the health and dynamics of these ecosystems. Similar to a GPS that guides us along the best route, vegetation maps provide crucial information for making informed and sustainable decisions about land use. These maps can identify areas at risk of degradation, enabling timely interventions to minimize harm to the environment. Moreover, vegetation mapping serves as a warning system by highlighting regions where plants and trees are disappearing. This signals potential environmental dangers, such as habitat loss, soil erosion, or decreased carbon sequestration. By offering insights into these changes, vegetation maps support efforts to protect biodiversity, manage natural resources responsibly, and mitigate the effects of climate change.

1.2 Literature Review / Survey

The data preparation process for the model involved several key steps, including data correction, augmentation, and labeling. For object detection, models such as YOLO, SSD, and Fast RCNN were employed, while segmentation tasks were handled using U-Net and SegNet architectures. For classification, VGG and ConvNet were utilized to analyze the data effectively. The model was trained on multi-temporal UAV red-green-blue (RGB) imagery, which provided comprehensive insights over different time periods. Experimental results demonstrated that this model outperformed others, achieving an impressive accuracy of 92.33 percentage and an F1 score of 90.37 percentage, indicating its superior performance compared to alternative models.

The LiDAR point clouds were collected from three distinct natural scenes to build 2D and 3D datasets for training vegetation classification models. These datasets were used to develop two deep learning models, with MrFSNet being proposed for 2D classification. The LiDAR data from various natural scenes, including the Karst wetland, played a key role in training the models. The performance of the MrFSNet model achieved an accuracy of 81.90 percent for vegetation classification in the Karst wetland, highlighting its effectiveness in processing and classifying complex LiDAR data for ecological analysis.

The research presents a semantic segmentation approach specifically designed for urban vegetation mapping using high-resolution true-color imagery. This method leverages a "labor-free" index-guided segmentation, which minimizes manual intervention by utilizing predefined indices or thresholds to automatically differentiate vegetation types. The high-resolution true-color imagery, which captures natural RGB colors, is commonly used in vegetation studies to provide detailed insights into urban environments. The main goal of this approach is to achieve accurate urban vegetation segmentation while reducing the need for manual labor, making the process more efficient and scalable for large-scale applications.

The data preprocessing involved the use of Sentinel-2 (S2) multispectral bands, vegetation indices such as NDVI and GNDVI, and texture features derived from the Gray-Level Co-Occurrence Matrix (GLCM). For feature extraction, principal component analysis (PCA) was conducted on the spectral bands, and four texture features—mean, homogeneity, correlation, and entropy—were extracted. The classification step combined 26 variables, including spectral bands, vegetation indices, and texture features, to perform random forest (RF) classification and categorize land cover into different vegetation classes. The dataset included S2 images from July 2020, resampled to a 10m resolution, and incorporated ten spectral bands, four vegetation indices, and twelve GLCM texture features. Reference data for training and validation were sourced from land use maps (COS2018), National Forest Inventory data, and Google Earth imagery. The classification achieved an accuracy of 90.9 percent, which increased to 92 percent when combining spectral bands and texture features. Key variables in the classification included the SWIR and Blue bands, along with specific texture features such as mean and correlation. This approach supports effective vegetation mapping, particularly for applications in biomass and wildfire management.

The study utilized a Deep Neural Network (DNN) for urban vegetation mapping, incorporating the SHAP (Shapley Additive Explanations) method to assess feature importance. The model took both spectral and textural features as input, passing them through seven hidden layers with dropout and regularization techniques to prevent overfitting. SHAP identified key features such as Hue, Brightness, and GLCM textures as significant contributors to classification accuracy. The dataset used consisted of three aerial images from the AIRS dataset, captured in Christchurch, New Zealand, with a resolution of 7.5 cm. The total dataset included 81,831 samples, which were split into training, validation, and testing sets for model training. By focusing on high-contributing features, the model achieved 94.44 percent accuracy and an F1 score of 92.66 percent, surpassing the 93.11 percent accuracy obtained using all features. This DNN-based approach demonstrated superior performance in urban vegetation classification, particularly in complex urban environments.

1.3 Problem Statement

Develop a deep learning model that uses drone imagery to accurately map and predict the percentage of vegetative land coverage.

Figure 1.1: Drone Capturing Images

1.4 Problem Analysis

The Problem Analysis section outlines the foundational design principles used in the project, emphasizing behavioral and structural patterns for efficient user interaction and system functionality. It also highlights the scope and significance of vegetation mapping in various domains while addressing key constraints like UAV capabilities.

1.4.1 Design principle 1

1 Behavioral Patterns – Best for Managing User Actions and States.

i Command Pattern:

a Encapsulates each action (displaying feed) as a separate command.

b Keeps user actions modular and easy to manage, allowing for easy addition of new actions if needed.

1.4.2 Design principle 2

1 Structural Pattern – Best for Simplifying UI and Backend Interactions.

i Facade Pattern:

a Simplifies the user interface by providing a clean interface, hiding backend complexities.

b Makes the UI more intuitive by presenting simple buttons for tasks, ensuring an easy and straight forward user experience.

1.4.3 Scope and Importance

i Agriculture: Accurate vegetation mapping enables farmers to monitor crop health, manage land resources efficiently, and plan irrigation systems. It allows for the timely detection of crop stress or disease, which can lead to improved crop yields.

ii Forestry: Vegetation mapping plays a crucial role in monitoring forest cover, detecting deforestation, and assessing biodiversity. It supports conservation efforts by identifying areas that need protection and by helping to understand forest dynamics.

iii Urban Planning: Mapping vegetation in urban areas provides valuable insights into the distribution of green spaces. This information is essential for planning sustainable cities, enhancing air quality, and reducing the urban heat island effect.

iv Environmental Monitoring: Accurate mapping is vital for tracking environmental changes over time, assessing the impacts of climate change, and managing natural resources more sustainably.

1.4.4 Constraints

i UAV Capabilities: - Assumption: The drone is capable of capturing high-quality aerial images of targeted vegetation areas. - Constraint: The drone's flight time and battery life may limit the duration and extent of data capture.

ii Environmental Factors: - Assumption: Weather conditions will be favorable for clear image capture (e.g., minimal rain, fog, or wind). - Constraint: Weather and lighting conditions can affect image quality, which may impact the accuracy of vegetation mapping.

iii Image Resolution: - Assumption: The captured images will have sufficient resolution to accurately identify vegetation. - Constraint: Limited image resolution may reduce the precision of vegetation segmentation, particularly in densely vegetated or mixed environments.

1.5 Objectives

i Use UAV to capture high-resolution images of the terrain, indicating the locations of plants and trees.

ii Preprocessing (such as resizing the images, data normalization etc) the UAV images so they are ready to be analyzed by the model.

iii Utilizing the Attention U-Net model to effectively detect and segment areas with vegetation from other regions of the land.

iv Finding out the percentage of the vegetation using the model's results.

Chapter 2

REQUIREMENT ANALYSIS

Unmanned Aerial Vehicles (UAVs) equipped with cameras and sensors capture high-resolution aerial images to monitor vegetation. They assess plant types, health, and coverage. Machine learning algorithms analyze these images to identify vegetation patterns and evaluate conditions over large areas. This approach offers a cost-effective, detailed, and frequent monitoring solution, which is valuable for agriculture, forestry, and environmental management. It supports sustainable practices and informed decision-making across ecosystems.

2.1 Functional Requirements

i The system shall capture aerial images of vegetation using a drone and provide a live feed to the user interface.

ii The system shall preprocess captured images to prepare them for segmentation.

iii The system shall apply image segmentation to identify vegetation coverage and patterns.

iv The system shall provide insights on vegetation coverage and other metrics based on segmented images.

2.2 Non Functional Requirements

i The system must support the processing and analysis of up to 500 high-resolution images per session to accommodate larger areas of vegetation.

ii The interface enables users to navigate and access stored images within 3 clicks.

iii Stored images are available for access or further processing every 1-2 seconds.

2.3 Hardware Requirements

- Processor: Intel Core i5 (10th Gen) or AMD Ryzen 5 or higher

- RAM: Minimum 8 GB (16 GB recommended for large datasets)
- GPU: NVIDIA GTX 1050 Ti or higher with CUDA support (recommended for TensorFlow)
- Storage: At least 20 GB free space
- Display: Full HD (1920x1080 resolution) or higher
- Internet Connection: Stable connection for downloading datasets and libraries

2.4 Software Requirements

- Operating System: Windows 10 / Linux (Ubuntu 20.04 or above) / macOS Monterey
- Programming Language: Python 3.8 or above
- Libraries and Frameworks:
  - TensorFlow 2.0 or above
  - NumPy
  - Pandas
  - Matplotlib
  - TQDM
- Development Tools:
  - Jupyter Notebook or Google Colab
  - IDE: PyCharm, VS Code, or any Python-compatible IDE

Chapter 3

SYSTEM DESIGN

The provided diagram3.1 outlines a vegetation analysis system using UAV (Unmanned Aerial Vehicle) and machine learning. First, the UAV captures aerial images of vegetation via its camera and sensor system, creating a live feed. Frames are extracted from this feed and passed through an image preprocessing pipeline, which resizes the images to 512x512 pixels and normalizes them.

3.1 System Design

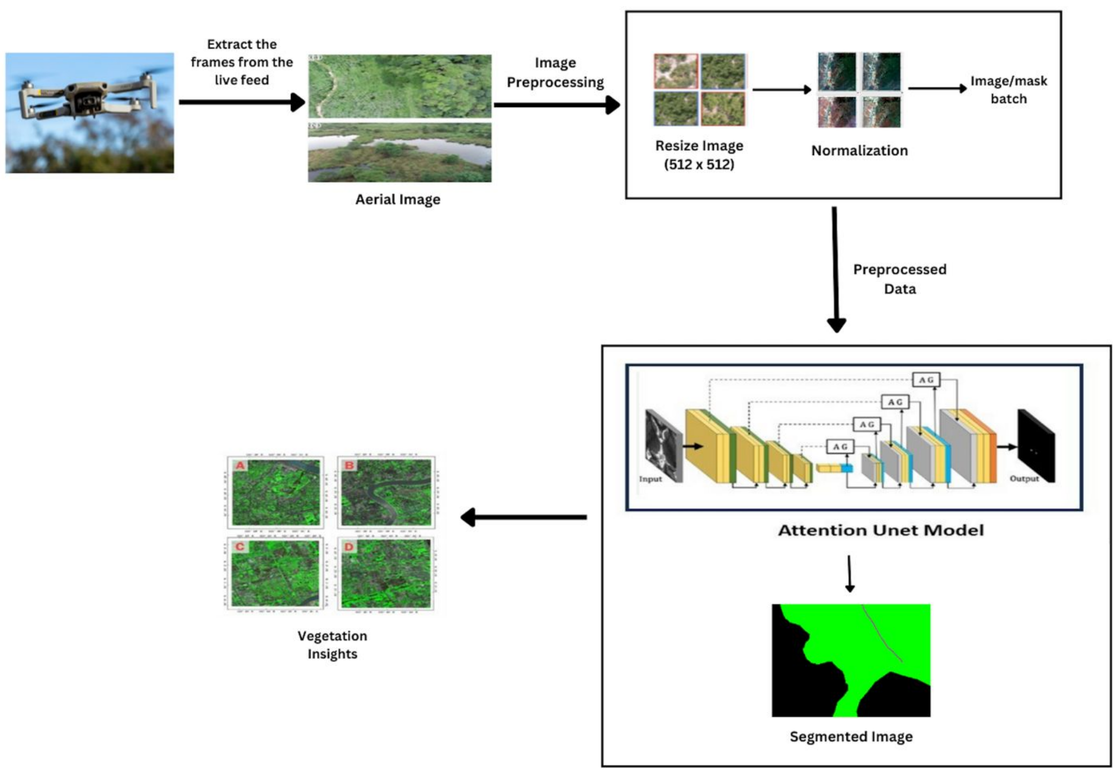

Figure 3.1: System Design

After preprocessing, the images are fed into an Attention U-Net model, a type of neural network designed for precise segmentation tasks. This model generates segmented images that highlight areas of vegetation. The segmented output allows further analysis, revealing insights into vegetation health, coverage, and types across regions. This workflow supports applications in agriculture, forestry, and environmental management, providing detailed and high-frequency monitoring of plant life.

Dataset (Aerial Images): The process begins with aerial images captured by drones. These images provide a high-resolution overview of different environmental features like vegetation, water bodies, and land areas, essential for ecological or geographical studies.

Data Preprocessing: Before analysis, the raw images go through a preprocessing phase to standardize and enhance the quality. This step may involve tasks like noise reduction, resizing, normalization, and color correction, ensuring that the images are optimized for analysis and consistent in quality. Preprocessing also adjusts the data into a uniform format, making it easier for the model to process varied environmental conditions.

Attention U-Net Model: The core of the analysis is performed by an Attention U-Net model, a neural network architecture tailored for image segmentation tasks, especially in complex landscapes. The U-Net model, with its encoder-decoder structure, isolates key features within images. The attention mechanism in this model further enhances the segmentation by focusing on the most relevant parts of the image, such as specific plant types, water bodies, or other land features. This allows the system to generate high-precision segmentations, even in challenging environments with varying patterns and textures.

The final output of the model is a set of segmented images, where environmental elements are highlighted and delineated. These processed images provide detailed visual insights, allowing for further interpretation and analysis, which can be valuable for applications in ecological monitoring, conservation, and land use planning.

This system architecture effectively integrates data collection, preprocessing, and advanced machine learning, creating a streamlined workflow from image capture to the generation of insightful, processed data ready for practical environmental applications.

3.2 Design Principles

3.2.1 Design Patterns

Design patterns are established templates used to address common design challenges in software development. They improve the robustness, maintainability, and scalability of a system. This project effectively utilizes the Command Pattern and the Facade Pattern to simplify functionality and provide a user-friendly experience.

3.2.2 Command Pattern

The Command Pattern encapsulates user actions and system requests as objects, promoting modularity and decoupling between the user interface and backend processes. In your project, actions like displaying the live feed, preprocessing images, and analyzing vegetation coverage are treated as separate commands. This method ensures that each action is modular and operates independently of others.

For example, a command object could be created to handle the "Start Analysis" action. This command would initiate a sequence that includes preprocessing the drone-captured images, segmenting vegetation, and calculating coverage percentages. The modular nature of this approach allows for new actions, such as exporting results or applying filters, to be added without impacting existing commands.

The Command Pattern enhances the system's flexibility by centralizing action management. A command manager can queue, execute, or log commands as necessary, making it easy to modify or extend functionality. This decoupling also simplifies debugging and maintenance, as changes to one command do not affect others.

3.2.3 Facade Pattern

The Facade Pattern simplifies complex subsystems by providing a unified interface for client interactions. In your project, this pattern serves as a bridge between the user interface and the intricate backend processes involved in vegetation mapping. While the backend performs tasks such as image preprocessing, segmentation, and vegetation analysis, the Facade presents a single, cohesive method for initiating these processes.

For example, when a user clicks the "Analyze Vegetation" button on the interface, the Facade manages all backend complexities seamlessly. It triggers preprocessing to standardize the drone images, applies segmentation to isolate the vegetation, and calculates the percentage of vegetative coverage. This abstraction enables non-technical users to interact with the system without needing to understand the technical details of each step.

Furthermore, the Facade Pattern enhances maintainability by separating backend logic from the user interface. Changes to any backend subsystem, such as updating the segmentation algorithm, can be implemented without impacting the interface. This design ensures that the system remains user-friendly while being able to adapt to evolving requirements.

Chapter 4

IMPLEMENTATION

This chapter gives a brief description about implementation details of the system by describing each component with its code skeleton in terms of algorithm.

4.1 Data Loading

This module loads and preprocesses image and mask data by reading, decoding, resizing, and normalizing them into tensors suitable for model input. It ensures all data is standardized to the required dimensions and formats.

Algorithm 1 Data Loading

```
Function load_image_and_mask(image_path, mask_path):
   Accept paths for an image and its corresponding mask.
   a.  Read the image and mask files:
      Use tf.io.read_file() to read the files.
   b.  Decode the files into tensors:
      Use tf.image.decode_jpeg() with appropriate channels.
   c.  Resize the tensors to predefined dimensions:
      Apply tf.image.resize().
   d.  Normalize the pixel values to [0, 1]:
      Use tf.clip_by_value() for normalization.
   e.  Return the processed image and mask tensors.
```

4.2 Dataset Preparation

The dataset consists of aerial images and their corresponding segmentation masks, organized in a structured directory format. The images represent various forest regions captured from satellites, with high resolution to capture intricate details of the terrain. Each image is stored in standard formats (e.g., .jpg or .png) and typically resized to dimensions of $160\times160\times3$ (height, width, and RGB channels). Alongside these images, the dataset includes corresponding segmentation masks, which are grayscale images where each pixel indicates whether it belongs to a forested area or not. These masks serve as ground truth for training machine learning models, ensuring pixel-wise accuracy in segmentation tasks. Both the images and masks are stored in separate directories, maintaining a clear structure for easy access and processing during model training. The images and masks are aligned, meaning each image has an exact corresponding mask of the same dimensions, typically resized to 160×160×1, and are prepared for machine learning workflows like supervised image segmentation.

Algorithm 2 Dataset Preparation

```
Function load_dataset(image_paths, mask_paths, split_ratio, batch_size, ...):
   a.  Preallocate space for storing images and masks as arrays.
   b.  Iterate through image-mask pairs:
      Use load_image_and_mask() to process each pair.
      Store the processed tensors in the preallocated arrays.
   c.  Create a TensorFlow dataset:
      Use tf.data.Dataset.from_tensor_slices().
   d.  Shuffle the dataset if needed.
   e.  If a split ratio is provided:
      i.  Split the dataset into training and validation parts.
      ii.  Batch and prefetch both subsets.
      iii.  Return the training and validation datasets.
   f.  If no split is needed:
      i.  Batch and prefetch the entire dataset.
      ii.  Return the complete dataset.
```

4.3 Visualization

Visualization displays images, their masks, and overlays to understand segmentation quality. When a model is provided, predicted masks and overlays are also shown to compare with ground truth.

Algorithm 3 Visualization

```
Function show_images_and_masks(data, n_images, model=None):
   a.  Extract a batch of images and masks from the dataset.
   b.  For each image in the batch:
      i.  Display the original image.
      ii.  Display the mask and image-mask overlay.
      iii.  If a model is provided:
         - Predict the mask using the model.
         - Display the predicted mask and overlay.
   c.  Use matplotlib to plot all visualizations.
```

Chapter 5

RESULTS AND DISCUSSIONS

The model achieved moderate segmentation performance, with a Dice coefficient of 0.6958 (training) and 0.7125 (validation), and exhibits reasonable segmentation capabilities. The Grad-CAM visualizations indicate the model's focus aligns well with forest boundaries and regions of interest, demonstrating its interpretability.

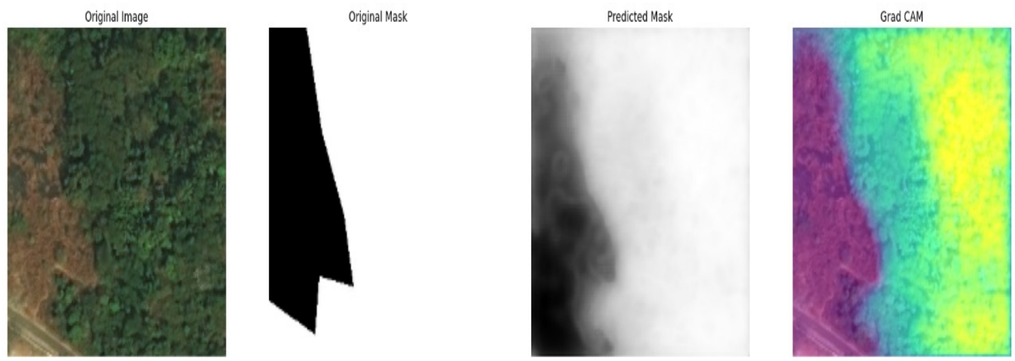

Figure 5.1: Trained Image of the Model

Original Image: The first panel showcases a satellite image of a forested area. This serves as the input to the segmentation model. The image demonstrates the complex textures and variations in vegetation, making it a challenging task for segmentation.

Original Mask: The second panel presents the ground truth mask, which represents the target segmentation for the model. The mask is binary, where white regions denote the areas of interest (e.g., deforested regions or specific forest cover), and black regions indicate the background or non-relevant areas.

Predicted Mask: The third panel displays the model's predicted mask. The grayscale intensities indicate the confidence of the model for each pixel's belonging to the region of interest. While the model captures the general area, the presence of gradient-like transitions suggests some uncertainty in its predictions.

Grad-CAM Visualization: The fourth panel provides the Grad-CAM (Gradient-weighted Class Activation Mapping) visualization. This heatmap highlights the regions of the image that the model considered most influential in making its predictions. Brighter areas (yellow) indicate high attention, while darker areas (purple) signify lesser attention.

5.1 Quantitve Metrics

The model's segmentation performance is reflected through key metrics. The Mean Intersection over Union (Mean IoU) was 0.2337 for training and 0.2032 for validation, indicating the model's ability to identify overlaps between predicted and actual regions, though these relatively low values suggest room for improvement, potentially due to task complexity or limited data diversity. The Dice coefficient values, 0.6958 for training and 0.7125 for validation, indicate moderate performance, demonstrating the model's capability to segment overlapping regions effectively, with higher values reflecting better quality. Loss values were 0.3784 for training and 0.3851 for validation, showing the model successfully minimized error during both phases and maintained stability. However, pixel accuracy was recorded as 0.0000e+00, suggesting no exact matches between predictions and ground truth, likely due to dataset imbalance or metric misalignment. Overall, the model demonstrates potential but requires enhancements to improve segmentation precision and accuracy.

Chapter 6

CONCLUSION AND FUTURE SCOPE OF THE WORK

Vegetation mapping using UAVs (Unmanned Aerial Vehicles) has revolutionized environmental monitoring by enabling high-resolution, cost-effective, and efficient data collection methods. UAVs offer precise mapping of vegetation structure, health, and biodiversity across diverse landscapes, such as agricultural fields and natural ecosystems. By integrating advanced sensors like multispectral, hyperspectral, and LiDAR, these systems enhance the accuracy of vegetation classification, biomass estimation, and stress detection.

Our project further leverages these advancements by utilizing UAVs to capture aerial images, preprocess them, and apply segmentation algorithms to extract meaningful vegetation patterns. The use of deep learning techniques improves classification accuracy, enabling detailed and automated insights into vegetation coverage and health. This system demonstrates flexibility in data acquisition, particularly for inaccessible or dynamic environments, supporting informed decision-making in land management, conservation, and precision agriculture.

Looking forward, the future of UAV-based vegetation mapping holds promising potential in several areas. First, ongoing advancements in AI and machine learning techniques will likely improve the automation of vegetation classification, reducing the need for manual intervention and enabling faster analysis. The integration of UAVs with Internet of Things (IoT) devices and real-time data transmission could facilitate continuous monitoring of vegetation health and environmental changes.

Moreover, as UAVs become more advanced in terms of flight time, payload capacity, and data processing capabilities, their use for large-scale, long-term vegetation monitoring projects will become more feasible. Further research into multi-sensor fusion, combining LiDAR, multispectral, and thermal imagery, will enhance the precision of vegetation monitoring. Additionally, the development of more robust regulatory frameworks for UAV use in environmental monitoring will ensure safe, ethical, and widespread application in vegetation mapping.

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Chapter 7

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Appendix A

Vegetation mapping using Unmanned Aerial Vehicles (UAVs) offers a high-resolution, efficient method for monitoring forest health and land cover changes. UAVs equipped with advanced sensors provide detailed imagery of forested areas, which can be processed using machine learning models for segmentation tasks, such as identifying deforested regions or classifying vegetation types. In this study, a segmentation model was trained to classify forested areas based on UAV imagery. The results showed a Mean Intersection over Union (Mean IoU) of 0.2337 for training and 0.2032 for validation, indicating moderate overlap between predicted and actual regions, though further improvements are necessary. The Pixel Accuracy was recorded as 0.0000, suggesting that no exact matches were found between predicted and ground truth pixels. The Dice coefficient was 0.6958 for training and 0.7125 for validation, demonstrating the model's moderate success in identifying overlapping regions. The loss values were 0.3784 for training and 0.3851 for validation, indicating stability in the model's learning process.