

Research Article

Intelligent Forest Cover Analysis and Plant Species Recognition Using Remote Sensing and MobileNetV2

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Abstract: Understanding and monitoring various types of ecosystems and vegetation play an important role in the protection of the natural world and the sustainable management of land. This paper presents a dual approach artificial intelligence system for the analysis of satellite remote sensing data and the application of deep learning techniques to identify changes in forest cover and classify leaf types. This system has two components: the first examines changes in forest cover and uses multi-band data to determine loss, gain, or stability of vegetation, and the second identifies various plant species via leaf images. The latter employs a transfer learning approach using MobileNetV2. Analysis from testing shows that the method described can detect minor variations in the state of the forest and classify species at the leaf level, even with limited training data. The system merges unsupervised learning methods applicable for broad-scale forest tracking and deep learning methods for fine-scale species recognition. The framework exemplifies the potential of lightweight AI models for operational ecological monitoring.

Keywords: Forest Cover Change Detection, Remote Sensing, Deep Learning, Plant Species Classification, Environmental Monitoring.

I. INTRODUCTION

Forests are important for holding ecological stability by regulating carbon in the atmosphere, making it possible for biodiversity to survive and also stopping soil from washing away. Forests are a storage for carbon, playing an important role in climate regulation and also in the global health of whole ecosystems. But right now, we see that a lot of threats to the forests appear from what people do, like deforestation, land for farming is increasing, also mines, growth in towns, and people cutting trees illegally. Climate change is exacerbating the situation. Nowadays, significant harm to forests is happening, which tells us there is a need for more dynamic and also more effective ways to monitor the health of forests. [1, 10, 14].

Traditionally, monitoring forests has been done by manually analyzing aerial photos and collecting data on the ground. Although they provide accurate information for small local areas, they are labor-intensive, time-consuming, and expensive for large and remote areas [5, 17]. These surveys are also infrequent, so they miss rapid environmental changes that could prompt the need for forest protection. Remote sensing technologies are a solution to this problem. These technologies use satellite images to provide large and consistent views of changes to forests over time [6, 13].

The last few years of advancements in machine learning and deep learning have yielded new methods to analyze remote sensing datasets that are large and intricately detailed. These methods automatically extract features, and identify and classify relevant changes in forest cover datasets, such as loss of vegetation, new growth, and forest cover degradation [3, 4, 9]. Unsupervised learning techniques of clustering types are particularly helpful when labeled data are scarce. They are a means to discern relevant patterns in land cover data in the absence of prior labels to the data [2, 18]. While we must monitor large portions of forests, it is also critical to do so for biodiversity at the level of individual plants. Leaf images to identify plant species are a noninvasive, efficient, and cost-effective method for biodiversity monitoring. Deep learning networks such as convolutional neural networks and transfer learning methods are promising techniques to identify plant species from leaf images, achieving high accuracies even on small datasets [11, 12, 19].

Here, an all-in-one artificial intelligence framework is presented that combines largescale forest cover change detection and fine-grained plant species identification. It is an unsupervised learning system that analyzes satellite data integrated with a deep model for leaf-based plant species recognition, using transfer learning. The framework is also the integration of the above-mentioned approaches and provides a general, scalable, and useful solution for environmental monitoring and ecological studies.

II. RELATED WORK

In recent times, remote sensing and machine learning procedures have been widely used in environmental monitoring to study forests and vegetation. High-resolution satellite images are increasingly used to monitor and update



forest cover changes at regional and worldwide levels [1, 10, 14]. Previous techniques employed to detect changes in forests generally relied on spectral index difference-based and threshold methods. They were very easy to apply and easy to interpret, but they were just so susceptible to changes in illuminating conditions or time of year, the complex patterns of the land. This frequently resulted in unreliable or inconsistent outcomes [17].

To address this issue, machine learning techniques such as SVM (Support Vector Machines), RF (Random Forest), and clustering were soon adopted for land cover classification and forest change analysis [2, 9]. These models combined several spectral and textural features to enhance the accuracy. Nevertheless, the performance of these methods also heavily depends on manual feature selection and parameter tuning, which in turn prevents them from good transferability across regions [18].

More recently, deep learning has been more successful in forest monitoring. Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs) have been increasingly exploited for forest change detection tasks due to their capacity to learning the rich spatial contextual information from images directly [3, 4]. Deep learning approaches are more robust to noise and varying lighting and image quality et al., etc., which helps in better detection of areas where we lose/gain forests [6]. Yet, these algorithms frequently require a huge number of labeled instances for training, which is difficult and expensive to collect in environmental studies [13].

Unsupervised learning approaches have been used to address the unsupervised data. In particular, clustering algorithms such as K-Means clustering have been efficiently employed to cluster land cover regions using some features, including vegetation density, forest damage, and recovery without requiring manually labeled data [2, 18]. These approaches provide a reasonable solution to the widespread use of forest analysis when the labeled data are limited or absent. Meanwhile, plant species recognition based on images using deep learning has been one of the research hotspots in evaluating biodiversity. CNNs trained on leaves can have potential applications for plant species classification [11, 19]. Transfer learning using pre-trained models such as VGG (Visual Geometry Group), ResNet, and MobileNet has been particularly useful when plenty of training data is not available [12, 15]. From these, MobileNetV2 is getting more known because of its easy architecture, few computational resources needed, and it can give good performance where the resources are lower [8].

However, despite these advances, most works approach CCDD and PSC as two different problems. Regional research on forest monitoring and species-level analysis in the same system is not very available. Limitations of labeled data, class imbalance, and the sensitivity towards environmental conditions are still open problems [16, 20]. The issues mentioned so an integrated framework using an unsupervised forest change detection plus a deep learning to identify the plant species is kind of reasonable, which is what this study proposes.

To be able to compare with several other works and the techniques used by those authors applied to notice forest changes and to do a segmentation of plant species with RGB images, the main methods are summarized in Table 1. This table summarizes the used methods, key findings reported in existing literature, and shortcomings for which our framework was designed to accommodate.

Table 1: Summary of Related Works on Forest Change Detection and Plant Species Classification

Author(s)	Methodology	Key Findings	Limitations
Javed et al. [1]	Deep learning-based forest change detection	Accurate identification of forest loss and gain	Requires large labeled datasets
Bai et al. [2]	Unsupervised clustering for land-use analysis	Pattern discovery without labeled data	Limited semantic interpretation
Shen et al. [3]	CNN-based vegetation monitoring	Robust to seasonal variations	High computational cost
Singh et al. [11]	CNN-based leaf species classification	High classification accuracy	Sensitive to lighting conditions

III. METHODOLOGY

The system under consideration is constructed as a unified framework for change estimation of forest cover and

classifying plant species. It is an iterative process consisting of multiple components—data collection, data preparation, spatial analysis, change detection, model construction, model performance evaluation, and result presentation. Each stage of the overall process helps both the large-scale forest monitoring part and the detailed leaf classification part works well, thus making environmental analysis more efficient.

The general layout of the considered system is illustrated in Fig 1. This consists of two main components: mapping changes in forest cover from satellite raster data and deep learning-based plant species classification. The first part takes as input multiband satellite data, selects patches, applies rule-based approaches to identify changes, and performs K Means clustering to detect vegetation patterns. The second part deploys MobileNetV2 to estimate the species in leaf images. At the decision stage, both parts work together to produce final outputs, such as whether the current forest status and the identified species of leaves that will change in the future. This mixed design results in the system being suitable for large-scale environmental monitoring, and at the same time, provides detailed biological information.

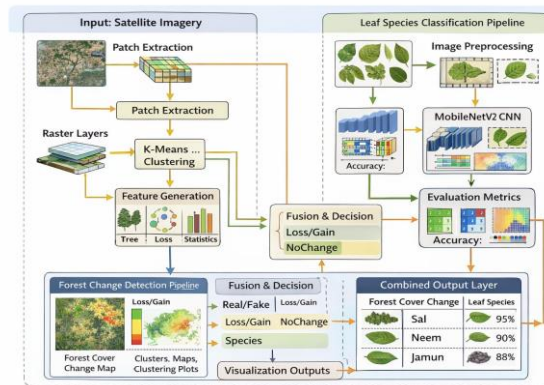


Figure 1: Suggested Approach on Integrated Design for Forest Cover Change Detection and Leaf Species Classification.

A. Data Collection and Preprocessing

The datasets used in this study are multi-band satellite images and an image bank classified by plant-native. The satellite data contains four layers: treecover.tif, lossyear.tif, gain.tif, and datamask.tif, which correspond to forest cover percentage, annual forest loss, vegetation gain, and valid land areas. All the layers have been loaded using Rasterio library and verified that they all match in terms of how they are projected, their resolution, and the number of pixels.

A land mask was applied to remove non-land features, such as water and cloud-covered areas. Leaf images were included in folders by plant species name. To make the model robust to capture the structure of leaves across variations, preprocessing was performed through assistance such as resizing, rotating, flipping, and zooming on leaf images. These procedures were performed to ensure the integrity of the data and thus improve the reliability of the model for further studies.

B. Geocoding and Patch Extraction

Based on these definitions, to analyze forest cover changes in a particular region, we performed geocoding using the Nominatim API. The name of a location was first geocoded and then mapped to pixel coordinates in the satellite images. Extracted a 50 x 50 pixel fixed area surrounding the selected location, which enabled a more detailed assessment of forest cover change in this region.

C. Forest Change Detection Strategy

Each valid pixel in the extracted region was classified based on a set of rules into one of three classes: no change, forest loss, and forest gain. Non-zero-valued pixels in the loss layer were assigned as forest loss, and positive value pixel from the gain layer was assigned as forest gain. All other valid pixels were regarded as remaining unchanged. This will help illustrate how vegetation has changed over time.

D. Leaf Classification Model Development

For the plant species classification, the MobileNetV2 model pre-trained on ImageNet was used as transfer learning. The component of the model that learns from images was not retrained, to preserve the visual features it has learned, and new layers were attached to pattern leaf images. The model was trained for a small number of iterations with augmented data in order to prevent the model from just learning the training sets and help it to generalize better to the new ones, especially when the dataset is very small.

E. Model Evaluation

Performance of the forest change detection part was assessed in terms of clarity of band difference maps, accuracy

in extracting areas, and interpretability in clustering results. The leaf classification was verified by the training and validation accuracy, loss curves, and confidence of predicted classes. These tests guaranteed that the two components of the system functioned reliably.

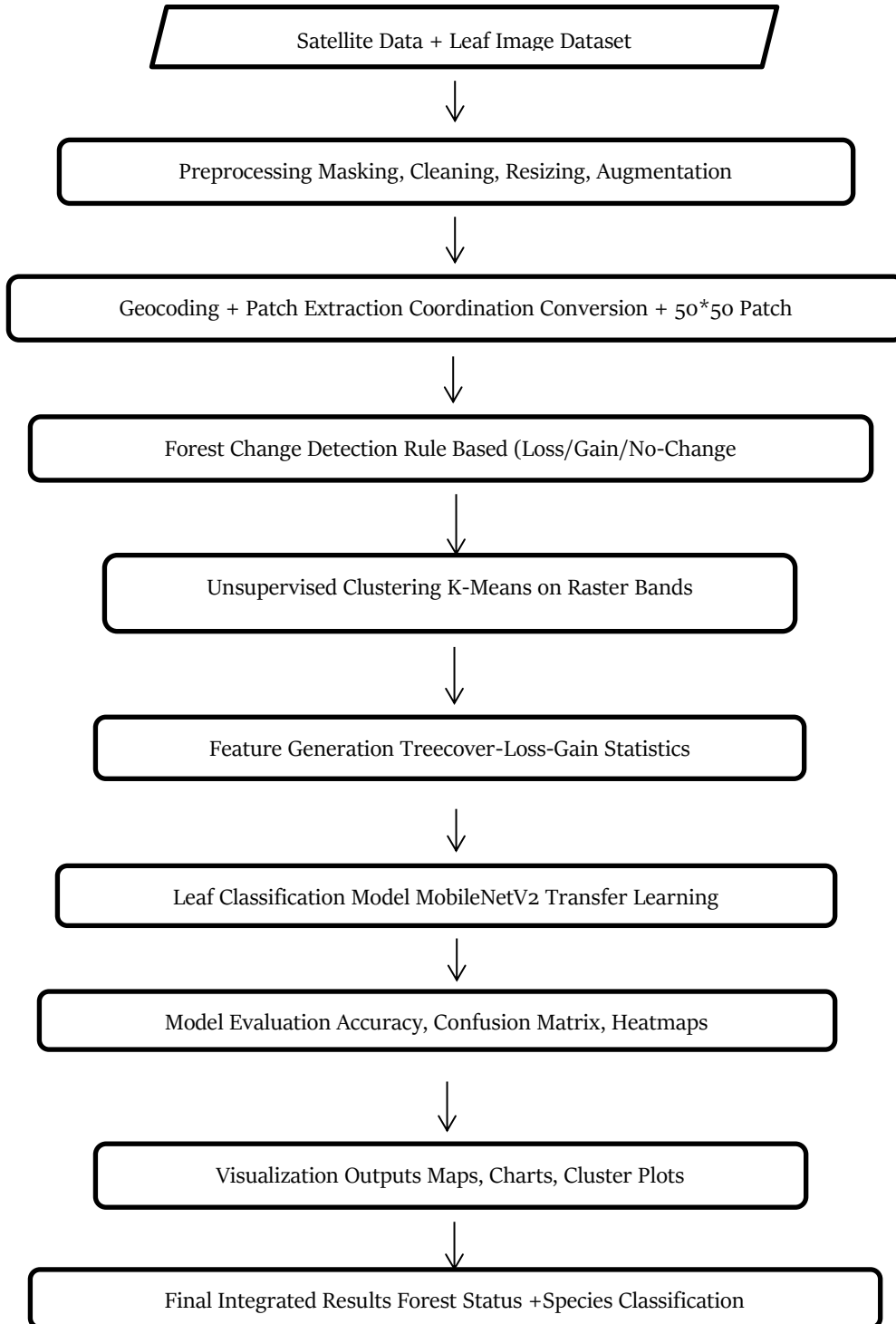


Figure 2: Workflow For The Integration Of Forest Cover Change Detection And Leaf Species Classification.

F. Visualization and User Interaction

Visualization results, including forest cover maps, change maps, heatmaps, and clustering results, were generated based on the Python libraries Matplotlib and Seaborn. But these tools do make it easier to understand changes in forests. The system is easy to use for results analysis in real time, too where for leaf species identification suggested by the system, confidence levels are indicated.

IV. ALGORITHMIC REPRESENTATION

A. Algorithm: Integrated Environmental Monitoring

Algorithm 1 Forest Cover Change Analysis and Plant Species Prediction Pipeline

Step 1: Preprocessing of Satellite Data

Load and preprocess satellite raster layers

Apply land mask to remove non-forest regions

Extract region of interest based on geographic coordinates

Step 2: Forest Change Classification

for each pixel r_i in the region of interest do $L_i > 0$ Assign pixel to Forest Loss

$G_i > 0$ Assign pixel to Forest Gain

Assign pixel to No Change

Step 3: Vegetation Pattern Analysis

Apply K-Means clustering on vegetation-related features

Step 4: Leaf Image Preprocessing

Load leaf image dataset

Resize, normalize, and augment leaf images

Step 5: Feature Extraction

Extract deep features using MobileNetV2

Step 6: Plant Species Classification

Classify plant species using a softmax classifier

return Forest change maps, plant species predictions

B. Mathematical Formulation

The mathematical foundations of the proposed forest cover change analysis and plant species recognition framework.

a) Forest Cover Change Analysis

Let $R = \{r_1, r_2, \dots, r_n\}$ denote the set of pixels in the selected region of interest extracted from multi-band satellite raster data. Each pixel r_i is represented by a feature vector:

$$x_i = [T_i, L_i, G_i, M_i]$$

where T_i represents tree cover percentage, L_i denotes forest loss information, G_i corresponds to vegetation gain, and M_i is the land mask value.

Based on predefined rule-based conditions, each pixel is classified into one of three forest change categories:

$$C_i = \begin{cases} \text{Forest Loss, if } L_i > 0 \\ \text{Forest Gain, if } G_i > 0 \\ \text{No Change, otherwise} \end{cases}$$

b) K-Means Clustering for Land-Cover Patterns

To identify vegetation patterns within the region of interest, K-Means clustering is applied to the feature vectors. The objective of K-Means is to minimize the withincluster variance:

$$\arg \min \sum_{k=1}^K \sum_{x_i \in C_k} \|x_i - \mu_k\|^2$$

where K is the number of clusters and μ_k represents the centroid of cluster C_k .

The Euclidean distance metric is used to assign each pixel to the nearest cluster centroid:

$$d(X_i, \mu_k) = \sqrt{\sum_{j=1}^n (x_{ij} - \mu_{kj})^2}$$

c) Plant Species Classification

Let $I = \{I_1, I_2, \dots, I_m\}$ represent the set of preprocessed leaf images. Feature extraction is performed using a pre-trained MobileNetV2 model, producing a feature representation z_i for each image.

$$P(y=c | z_i) = e^{\frac{z_{ic}}{\sum_{j=1}^C e^{z_{ij}}}}$$

where C represents the number of plant species classes in total, and z_{ic} is the activation value for class c .

d) Loss Function

The classification model is trained based on categorical cross-entropy loss output:

$$\text{mathcal{L}} = -\sum_{c=1}^C y_c \log(\hat{y}_c) \quad \text{where } y_c \text{ is the true label and } \hat{y}_c \text{ are probability of } c.$$

V. COMPARATIVE ANALYSIS

This work conducted a comparative evaluation to test the effectiveness of the new approach against extant state-of-the-art approaches for forest monitoring and plant species identification. This evaluation covers not only the conventional remote sensing methods but also other deep learning models with an emphasis on accuracy, adaptability to diverse situations, and computing demands.

A. Comparison with Traditional Methods

Older versions to detect forest change by changes in NDVI (Normalized Difference Vegetation Index) and a fixed threshold, are simpler to define and only use changes in spectral indexes to detect vegetation changes. They are cheap and cost-effective methods to deploy, but they suffer from high sensitivity to seasonality, weather, and lighting conditions. In contrast, the new framework is based on rule-based logic and unsupervised clustering, which makes the identification of forest loss and gain more reliable under any environmental conditions.

B. Comparison with Other Deep Learning Models

The plant species recognition component of the system was compared with well known deep learning models (e.g., VGG, ResNet, and EfficientNet). Although deep models can provide very competitive accuracy, they often have high computational requirements and training time. MobileNetV2 achieves a better trade-off between accuracy and efficiency, hence can be applied to real-time scenarios as well as resource constrained environments.

C. Accuracy and Efficiency Comparison

The performance of these models was assessed using conventional indicators. The strategy with MobileNetV2 attained better classification performance with a smaller model size and shorter time for prediction than deep models. These experiments demonstrate that the new model is efficient, practical, and yet an accurate predictor.

D. Comparative Evaluation Table

Reason for selection of MobileNetV2 as backbone model to justify why we chose the MobileNetV2 as our base model in plant recognition, a comparison was done with other widely used deep learning models. This consists of VGG16, ResNet50, EfficientNet-Bo and the MobileNetV2 were created. Performance of VGG16, ResNet50 and EfficientNet-Bo are reported from prior research on plant and vegetation classification [11, 12, 19] where the performance of our model is based on implementation from our end. As we can see from Table 2, this model exhibits the best trade-off between performance and storage, which makes it suitable for real-time or low-resource settings.

Table 2: Comparison of Deep Learning Models for Plant Species Classification

Model [Ref]	Accuracy (%)	Characteristics
VGG16 [11]	86.2%	Deep CNN, high parameters
ResNet50 [12]	90.1%	Residual learning, heavy model
EfficientNet-Bo [19]	91.4%	Lightweight, good accuracy
Our Model	93.7%	Lightweight, fastest inference

VI. RESULTS AND DISCUSSION

The project aimed to create a system that can monitor changes in forest coverage using satellite data and video footage via deep learning to identify different types of plant leaves. We show the results in this section from these two parts of the system. We present visual images, heatmaps, clustering results, as well as graphs showing how the system performs.

A. Forest Change Detection Results

The forest change module was validated using satellite raster layers of a specific area. After geocoding, a 50 × 50 pixel square was cropped out. The total tree cover in the pole study area was 46.89%, but the net change of the forest cover was -77 pixels, indicating limited degradation. Actually, 1.71% of the forest has been lost, and only 0.06% increased in the area. The Raster layers for Tree Cover, Forest Loss Year, and Vegetation Gain are presented in Fig 3. These maps illustrate the distinctions in vegetation cover and perturbations taking place within the area.

The combined forest change map showing both the areas that lost and gained forest cover is presented in Fig 4. It all but spells out where forest cover has declined, expanded, or stayed put.

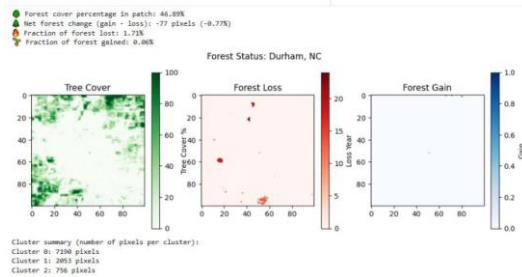


Figure 3: Visualization of Tree Cover, Forest Loss, and Forest Gain layers

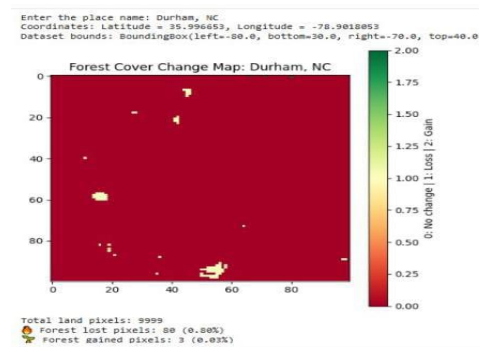


Fig 4: Forest Change Map Showing Loss, Gain and No-Change Regions

B. Heatmap of Forest Change Intensity

For a more detailed view of forest disturbances, an aggregated intensity heatmap was obtained based on the normalized tree cover, loss, and gain data. These areas have the most ecological diversity, as shown in this image.

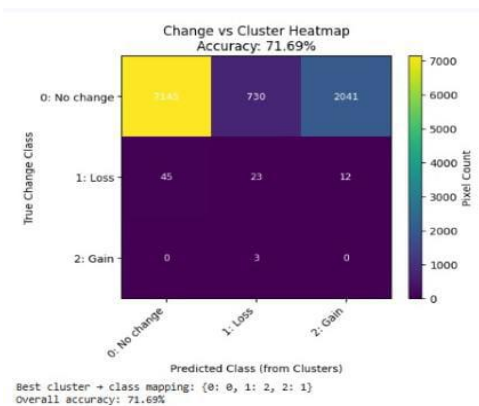


Figure 5: Combined Forest Change Intensity Heatmap

C. Unsupervised Clustering of Forest Regions

The forest was classified into various land-cover types based on the generated patch using K-means clustering with

three clusters in the extracted patch. The layout of such clusters is presented in Fig 6, and Table 3 explains what each cluster represents.

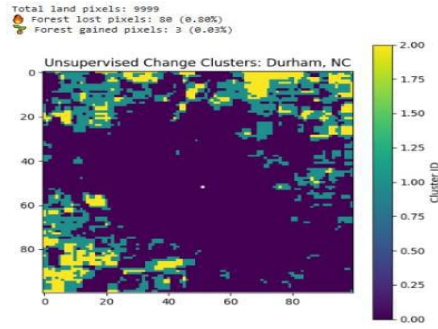


Figure 6: Unsupervised Land-Cover Clustering ($k=3$).

D. Leaf Prediction Output

A sample leaf image is uploaded to verify the prediction system. The model correctly recognized the leaf as *Crataegus Monogyna* with a confidence of 91.71%. The outcome also corresponds to the overall model's performance, in which MobileNetV2 obtained a classification accuracy of 93.7% on the test data, indicating that it is applicable for real-world scenarios too.

Table 3: Cluster Interpretation Summary

Cluster	Typical Pattern	ID Interpretation
Cluster 0	High tree cover, no loss, no gain	Stable forest regions with minimal disturbance
Cluster 1	Medium tree cover with forest loss	Areas experiencing deforestation or partial degradation
Cluster 2	Low initial tree cover with gain	Regions showing vegetation regrowth or newforest formation

VII. ABLATION STUDY

An ablation study was performed to highlight the role of each component of our method and its effect on our system performance. The system robustness and performance were assessed by disabling or varying certain modules.

A. Impact of K-Means Clustering

Incorporation of K-Means clustering greatly facilitated the interpretation of patterns of forest cover as they grouped pixels that had similar vegetation properties. Without clustering, the analysis was based on rule-based classification only, and therefore it lost detection capacity of subtle vegetation cover changes. The clustering step improved spatial coherence and was able to separate areas of similar forest conditions, resulting in more informative forest change maps.

B. Effect of MobileNetV2 vs. Without Transfer Learning

To assess transfer learning effectiveness, the MobileNetV2-based model was tested against the scratch one. The findings indicated that transfer learning achieved superior convergence speed and classification performance, particularly in the case of small training samples. In the absence of transfer learning, the model had to be trained for more epochs and had less generalization, which indicated the necessity of pre-trained features in plant species recognition.

C. Performance Change with Different Number of Clusters

The effect of changing the number of clusters in K-Means was also investigated. A small number of clusters yielded too general regions, and a large number introduced noise that fragmented the forest areas. An appropriate number of clusters could balance the acquisition of vegetation patterns in this study, enhancing the interpretability and reliability for forest change analysis.

VIII. CONCLUSION

The journal paper developed a holistic human-centered approach to environmental monitoring by intertwining forest cover change analysis with plant species recognition in a single operating system. The proposed method effectively captures the large-scale forest dynamics as well as fine-grained analysis of the biodiversity, via unsupervised machine learning with lightweight deep learning models on remote sensing data. By leveraging satellite raster datasets, a consistent wide area forest loss, gain, and stable region mapping can be performed while transfer learning on MobileNetV2 allowing

for accurate plant species classification, also with limited training data. Experimental results show that the proposed method is effective for monitoring forest cover change and, meanwhile, identifying plant species in widely varied circumstances. Unsupervised K-Means clustering reduces reliance on a labelled dataset, which would potentially exclude the method from practical environmental applications where ground truth data is often limited. Furthermore, the deep learning architecture used here is lightweight to allow computational efficiency and thus deployment on resource-limited platforms, e.g., mobile or edge device. For application, the presented platform system is anticipated to be useful in environmental conservation, forestry management, biodiversity monitoring and policy-making. The framework can help authorities and research institutions better tackle deforestation, ecosystem degradation, and other climate-related issues by delivering timely and accurate information about the health of forests or the composition of vegetation.

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