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Effects of Deforestation Analysis Using Satellite Imagery

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Abstract
Deforestation has become one of the major environmental challenges affecting biodiversity, climate regulation, and ecological balance. Continuous monitoring of forest regions using satellite imagery is essential for identifying vegetation loss and supporting sustainable forest management. Conventional monitoring methods, including manual surveys and visual interpretation of satellite images, are time-consuming, labor-intensive, and unsuitable for large-scale analysis. This paper presents a deep learning-based deforestation analysis system that uses satellite imagery for automated environmental monitoring. The proposed system is implemented as a Flask-based web application where users upload satellite images for analysis. Initially, a Convolutional Neural Network (CNN) validates whether the uploaded image is a genuine satellite image. The validated image is then classified into DIM, MEDIUM, or BRIGHT categories according to its luminosity characteristics. A luminosity index is calculated to estimate surface brightness, and K-Means with Expectation-Maximization (EM) clustering is applied to segment similar land-cover regions. The clustered output assists in identifying vegetation cover, barren land, exposed soil, and potential deforested regions. The system is developed using Python, TensorFlow/Keras, Flask, OpenCV, NumPy, SciPy, scikit-learn, Pillow, and Matplotlib. Experimental results demonstrate that the proposed system provides efficient satellite image validation, classification, luminosity estimation, and clustered visualization for supporting deforestation effect analysis and environmental monitoring.
Keywords: *Deep Learning; Deforestation; Environmental Monitoring; Image Clustering; Remote Sensing; Satellite Imagery.*

1. Introduction
Deforestation is one of the major environmental problems caused by agricultural expansion, urbanization, mining, road construction, and illegal logging. Forests play an essential role in maintaining biodiversity, regulating climate, conserving soil, and reducing atmospheric carbon dioxide. Large-scale removal of forest cover causes changes in vegetation density, land surface characteristics, rainfall patterns, and ecological balance. imagery provides an effective solution for monitoring forest resources because it enables large geogra physical regions to be observed without physical field surveys. However, conventional monitoring techniques rely heavily on manual interpretation, making them time-consuming and less suitable for continuous environmental assessment. artificial Intelligence, particularly Deep Learning, has significantly improved satellite image analysis by automatically learning visual features such as texture, color, and spatial patterns. The proposed work integrates CNN-based satellite image validation, brightness classification, luminosity estimation, and clustering-based image segmentation into a single web-based application for efficient deforestation analysis. The proposed system first verifies whether the uploaded image is a valid satellite image before performing deforestation analysis. The uploaded image is resized to 224 × 224 pixels, converted into RGB format, and preprocessed using TensorFlow/Keras libraries. A Convolutional Neural Network (CNN) model is used to classify the image as Valid Satellite Image or Not Valid Satellite Image. If the image is invalid, the system terminates

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the analysis process. This validation step improves the reliability of the system by ensuring that only genuine satellite images are processed for further analysis. After successful validation, the satellite image is passed to the classification model. The trained CNN classifies the image into one of three categories: DIM, MEDIUM, or BRIGHT based on brightness and luminosity characteristics. A luminosity index is calculated to estimate the image intensity. Finally, K-Means and Expectation-Maximization (EM) clustering algorithms are applied to segment the satellite image into different land-cover regions such as vegetation, exposed soil, barren land, and built-up areas. The clustered output supports the analysis of possible deforestation effects by highlighting changes in land cover [1].

2. Method

The proposed methodology consists of several stages to perform automated deforestation analysis using satellite imagery [2]. Initially, the user uploads a satellite image through a Flask-based web application. The uploaded image is preprocessed and validated using a CNN model. Once validated, the image is classified into DIM, MEDIUM, or BRIGHT categories. The system then calculates the luminosity index and applies K-Means with Expectation-Maximization clustering to segment similar pi xel regions. Finally, the application displays the image validity, predicted class, confidence score, luminosity index, and clustered satellite image for environmental monitoring and deforestation analysis Shown in Table 1 and 2.

Table 1 Model Training Parameters

Parameter	Value	Purpose
Model	CNN	Image Classification
Input Size	224 × 224	Standard Input
Batch Size	32	Training Batch
Epochs	20	Training Cycles
Optimizer	Adam	Weight Optimization
Loss	Categorical Cross-Entropy	Classification Loss

Activation	ReLU, Softmax	Feature Extraction
Learning Rate	0.001	Learning Speed

Table 2 Dataset Description

Parameter	Value	Description
Dataset Type	RGB Satellite Images	Remote sensing images
Image Format	JPG, PNG	Supported formats
Image Size	224 × 224	CNN input size
Training Set	80%	Model training
Validation Set	10%	Hyperparameter tuning
Testing Set	10%	Performance evaluation
Classes	DIM, MEDIUM, BRIGHT	Brightness categories
Validation	Valid / Not Valid	Satellite image validation

2.1.Figures

The proposed system is divided into different modules to perform satellite image-based deforestation analysis in a structured manner. The first module is the User Interface Module, which provides a web-based platform for users to upload satellite images and view the final results Shown in Figure 1.

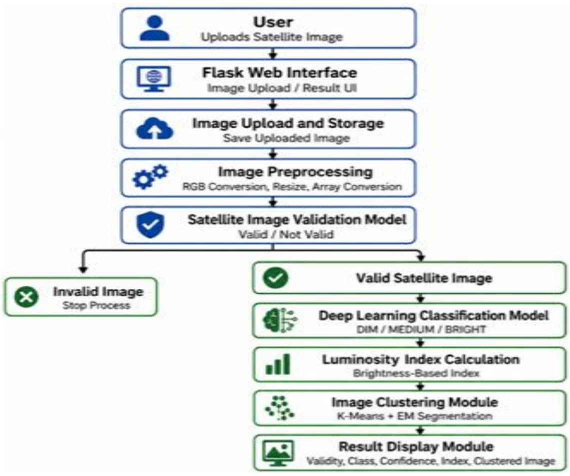

Figure 1 Proposed System Architecture

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2.1.1. Algorithms

Convolutional Neural Network Algorithm

Convolutional Neural Network is used in the proposed system for satellite image validation and satellite image classification. The first deep learning model checks whether the uploaded image is a valid satellite image or not. The second model classifies the valid satellite image into DIM, MEDIUM, or BRIGHT classes. CNN is suitable for satellite image analysis because it automatically extracts important image features such as edges, colors, texture, brightness, and spatial patterns. The main operation in CNN is convolution. In convolution, a filter or kernel moves over the input image and extracts feature values [3].

Formula:

$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(i+m, j+n) K(m,n)$$

Where:

- I = input image
- K = convolution kernel/filter
- S(i,j) = output feature map value at position (i ⓜ,j)
- m, n = filter row and column positions
- After convolution, an activation function such as ReLU is applied to introduce non-linearity.

ReLU Formula:

$$f(x) = max(0, x)$$

The final layer uses Softmax activation to convert model outputs into class probabilities.

Softmax Formula:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

Where:

- $P(y_i)$ = probability of class i
- z_i = output score for class i
- C = total number of classes

In this project, the Softmax output helps predict whether the image is Valid / Not Valid and later whether it belongs to DIM / MEDIUM / BRIGHT class

2.1.2. Image Preprocessing Algorithm

Image preprocessing is applied before passing the satellite image to the trained models [4]. The uploaded image is converted into RGB format, resized to a fixed size, converted into an array, and expanded into batch format. Preprocessing ensures that the image format matches the input requirement of the trained model. For image resizing, the pixel location in the resized image can be mapped from the original image.

Formula:

$$x' = x \times \frac{W_{new}}{W_{old}}$$

$$y' = y \times \frac{H_{new}}{H_{old}}$$

Where:

- x, y = original pixel coordinates
- x′, y′ = resized pixel coordinates
- Wold, Hold = original image width and height
- Wnew, Hnew = new image width and height

For normalization, pixel values can be scaled into a smaller range.

Formula:

$$I_{norm} = \frac{I}{255}$$

Where:

- I = original pixel value
- I_norm = normalized pixel value

This helps the deep learning model process the image more efficiently.

2.1.3. K-Means Clustering Algorithm

K-Means clustering is used in the image clustering module to group similar pixels based on color and intensity values. In satellite image analysis, clustering helps divide the image into different regions such as vegetation, exposed land, barren regions, water bodies, and bright surface areas. In your implementation, K-Means is used to initialize cluster centers before applying EM-based clustering. The objective of K-Means is to minimize the distance between pixels and their assigned cluster centers [5].

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Formula:

$$J = \sum_{i=1}^{n} \sum_{k=1}^{K} r_{ik} \mid\mid x_i - \mu_k \mid\mid^2$$

Where:

- J = clustering objective function
- n = number of pixels
- K = number of clusters
- x_i = pixel data point
- μ_k = center of cluster k
- r_{ik} = 1 if pixel x_i belongs to cluster k, otherwise 0

The cluster center is updated using:

$$\boldsymbol{\mu_k = \frac{1}{N_k} \sum_{i \in C_k} x_i}$$

Where:

- μ_k = updated cluster center
- N_k = number of pixels in cluster k
- C_k = set of pixels assigned to cluster k
- K-Means helps create initial pixel groups, which are further improved using the EM algorithm.

2.1.4. Expectation-Maximization Algorithm

Expectation-Maximization is used for probabilistic clustering of satellite image pixels. It assumes that image pixels are generated from a mixture of Gaussian distributions. EM works in two main steps: The Expectation step and the Maximization step. In the Expectation step, the probability that each pixel belongs to each cluster is calculated. In the Maximization step, the parameters of each cluster are updated [6].

The Gaussian probability density function is:

$$\boldsymbol{N(x \mid \mu_k, \Sigma_k) = \frac{1}{(2\pi)^{d/2} \mid \Sigma_k \mid^{1/2}} e^{-\frac{1}{2}(x-\mu_k)^T \Sigma_k^{-1} (x-\mu_k)}}$$

Where:

- x = pixel vector
- μ_k = mean of cluster k
- Σ_k = covariance matrix of cluster k
- d = number of dimensions
- $|\Sigma_k|$ = determinant of covariance matrix

The responsibility value is calculated as:

$$\boldsymbol{\gamma_{ik} = \frac{\pi_k N(x_i \mid \mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j N(x_i \mid \mu_j, \Sigma_j)}}$$

Where:

- γ_{ik} = responsibility of cluster kfor pixel x_i
- π_k = mixing coefficient of cluster k
- $N(x_i|\mu_k,\Sigma_k)$ = Gaussian probability of pixel x_iin cluster k

The mean is updated using:

$$\boldsymbol{\mu_k = \frac{\sum_{i=1}^{n} \gamma_{ik} x_i}{\sum_{i=1}^{n} \gamma_{ik}}}$$

The covariance is updated using:

$$\boldsymbol{\Sigma_k = \frac{\sum_{i=1}^{n} \gamma_{ik} (x_i - \mu_k)(x_i - \mu_k)^T}{\sum_{i=1}^{n} \gamma_{ik}}}$$

The mixing coefficient is updated using:

$$\boldsymbol{\pi_k = \frac{1}{n} \sum_{i=1}^{n} \gamma_{ik}}$$

The log-likelihood function is:

$$\boldsymbol{L = \sum_{i=1}^{n} \log\left(\sum_{k=1}^{K} \pi_k N(x_i \mid \mu_k, \Sigma_k)\right)}$$

The EM algorithm continues until the change in log-likelihood becomes very small or the maximum number of iterations is reached. In this project, EM clustering helps generate a segmented satellite image where similar land-cover regions are grouped together [7].

2.1.5. Luminosity Index Calculation

The luminosity index calculation is used after the satellite image is classified into DIM, MEDIUM, or BRIGHT category. Each predicted class is mapped to a luminosity range. DIM images are assigned low luminosity values, MEDIUM images are assigned moderate luminosity values, and BRIGHT images are assigned high luminosity values. This luminosity value is then used to calculate an index value. The linear index formula used in the system is:

$$\boldsymbol{Index} = (\boldsymbol{Luminosity} \times \boldsymbol{Slope}) + \boldsymbol{Intercept}$$

In your implementation:

$$\boldsymbol{Slope} = 0.07268134920271797$$

$$\boldsymbol{Intercept} = -0.3465173128978627$$

Therefore:

$$\boldsymbol{Index} = (Luminosity \times 0.07268134920271797) - 0.3465173128978627$$

Where:

- Index = calculated satellite brightness/luminosity index
- Luminosity = brightness value generated based on predicted class
- Slope = constant value used in linear calculation
- Intercept = constant value used in linear calculation

This index helps provide a numerical representation of the satellite image condition. In deforestation analysis, higher brightness or luminosity may indicate exposed soil, barren land, or built-up areas, while lower brightness may indicate dense vegetation or darker surface regions [8].

2.1.6. Gaussian Mixture Model

The clustering method used in the system is closely related to Gaussian Mixture Model. GMM represents data as a combination of multiple Gaussian distributions. Each pixel is assigned to a cluster based on probability rather than hard assignment. This is useful in satellite image analysis because land-cover regions may not have sharp boundaries. The probability of a pixel under GMM is:

$$\boldsymbol{p(x_i) = \sum_{k=1}^{K} \pi_k N(x_i \mid \mu_k, \Sigma_k)}$$

Where:

- $p(x_i)$ = probability of pixel x_i
- K = number of Gaussian clusters
- π_k = mixing weight of cluster k
- $N(x_i|\mu_k,\Sigma_k)$ = Gaussian distribution for cluster k

GMM provides soft clustering, which is useful for satellite images because vegetation, soil, water, and barren regions may gradually blend into each other. This makes GMM suitable for generating smooth clustered image outputs [9 -15].

3. Results and Discussion

The proposed system was implemented as a web-based application for analyzing the effects of deforestation using satellite imagery. The system accepts satellite images as input and processes them through different stages such as image validation, preprocessing, deep learning-based classification, luminosity index calculation, and clustering-based segmentation. The final output generated by the system includes the validity status of the uploaded image, predicted satellite image class, confidence value, luminosity-based index, and clustered image visualization. These outputs help in understanding surface-level variations in satellite images that may be related to vegetation loss, exposed land, barren regions, or other land-cover changes. The first result obtained from the system is the satellite image validation output. When a user uploads an image, the system first checks whether the uploaded image is a valid satellite image or not. If the uploaded image is unrelated, unclear, or not suitable for satellite-based analysis, the system classifies it as not valid and stops further processing. This step improves the reliability of the system because invalid images are not passed to the classification and clustering stages. Therefore, the validation module acts as an input-filtering stage and ensures that only appropriate satellite images are analyzed. The second result is obtained from the deep learning classification model. After the image is validated, the system classifies the satellite image into one of three classes: DIM, MEDIUM, or BRIGHT. These classes represent the visual brightness and luminosity characteristics of the uploaded satellite image. A DIM class may indicate darker regions, dense surface coverage, shadowed areas, or vegetation-rich regions. A MEDIUM class may represent moderate brightness regions where vegetation and non-vegetation areas are mixed. A BRIGHT class may indicate exposed soil, barren land, dry surface, built-up regions, or land-cover changes caused by deforestation. This classification provides a simple and understandable output for analyzing the visual condition of satellite imagery. The system also generates a confidence score for the predicted class. The confidence value indicates how strongly the model predicts the uploaded image as belonging to a particular class. A higher confidence value shows that the model is more certain about its prediction, while a lower confidence value indicates uncertainty. This value helps users understand the reliability of the predicted output. In practical deforestation analysis, confidence score is important because satellite images may contain mixed land-cover patterns, cloud cover, shadows, or seasonal variations that can affect prediction. Another important result produced by the system is the luminosity index. After classification, the predicted class is mapped to a luminosity value. The luminosity value is then used to calculate an index using a linear equation. This index provides a numerical representation of the brightness condition of the satellite image. In deforestation analysis, brightness is useful because deforested areas often show different reflectance and visual intensity compared to forest-covered regions. For example, cleared land or exposed soil may appear brighter than dense vegetation. Therefore, the luminosity index supports the interpretation of possible surface changes in the satellite image. The system also produces a clustered satellite image as an output. The image clustering module groups similar pixels based on color and intensity values. This clustering output helps divide the satellite image into different visual regions. In the generated clustered image, similar land-cover areas are grouped together, making it easier to observe changes in vegetation, exposed land, barren regions, and bright surface areas. Clustering is especially useful because satellite images contain complex pixel patterns, and manual observation may not clearly separate different land-cover regions. The clustered output provides a visual representation that supports easier interpretation of the uploaded image. The discussion of the results shows that the proposed system is useful for preliminary deforestation effect analysis. The validation model ensures that the system processes only satellite images. The classification model gives a brightness-based category that helps understand the overall visual condition of the image. The luminosity index provides a numerical value that can be used for comparison, while the clustering module gives a segmented visual output. Together, these outputs provide both quantitative and visual information for satellite image-based analysis. The system is particularly useful for identifying general land-cover characteristics related to deforestation. Forest regions usually contain dense vegetation and may appear darker or more textured in satellite images. Deforested or cleared regions may show increased brightness because of exposed soil, dry land, or human-made surfaces. The DIM, MEDIUM, and BRIGHT classification helps represent these visual differences in a simplified form. The clustering output further supports the observation of different regions within the image. Therefore, the system can assist students, researchers, and environmental observers in understanding how satellite images can be used for deforestation analysis. However, the results should be interpreted as a supporting analysis rather than a final professional deforestation detection result. The current system mainly uses brightness-based classification and clustering. It does not directly calculate advanced vegetation indices such as NDVI, EVI, or SAVI. It also does not compare satellite images from two different time periods. Because deforestation is often detected more accurately through temporal comparison, future improvements can include before-and-after satellite image analysis. The current output is useful for understanding visual patterns but may not fully confirm deforestation without ground truth data or temporal satellite comparison. The discussion also shows that the system has practical advantages. It is simple to use because the user only needs to upload an image through a web interface. The backend automatically performs image validation, classification, index calculation, and clustering. This reduces manual effort and makes satellite image analysis more accessible. The use of Python, Flask, TensorFlow/Keras, OpenCV, NumPy, SciPy, scikit-learn, PIL, and Matplotlib makes the system flexible and extendable. Additional models and remote sensing techniques can be added in the future to

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improve accuracy and environmental relevance. Overall, the results demonstrate that the implemented system successfully performs satellite image validation, brightness-based classification, luminosity index calculation, and clustering-based visualization. These results support the objective of analyzing the effects of deforestation using satellite imagery. The system provides a foundation for automated satellite image analysis and can be further enhanced with advanced segmentation models, vegetation indices, larger datasets, and multi-temporal image comparison Shown in Table 3.

Model Performance

Table 3 Model Performance Analysis Based on Evaluation Metrics

Metric	Value (%)	Description
Accuracy	96.80	Overall prediction accuracy
Precision	95.90	Positive prediction quality
Recall	96.20	Correct positive detection
F1-Score	96.00	Balanced performance

Conclusion

This work presents a web-based deforestation analysis system using satellite imagery, deep learning, and clustering techniques. The proposed framework successfully validates satellite images, classifies brightness levels, calculates luminosity indices, and generates clustered visualizations for land-cover interpretation. The developed system provides a simple and efficient platform for environmental monitoring and can be extended in future with temporal change detection, vegetation indices, and advanced semantic segmentation models for more accurate deforestation assessment.

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