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Deforestation Detection and Alert System Using Deep Learning

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Abstract—Deforestation is a major environmental challenge that contributes to biodiversity loss and climate change. Conventional forest monitoring techniques rely on manual surveys or delayed analysis of satellite imagery, which limits timely detection of illegal forest clearing. This research proposes a deep learning-based system for automated deforestation detection using satellite imagery. The proposed approach utilizes transfer learning with the ResNet50 convolutional neural network combined with a spatial attention mechanism to improve the identification of deforested regions. The system is implemented within a web-based platform consisting of a React frontend, a Flask backend, and a deep learning inference module. Experimental evaluation using satellite image datasets demonstrates that the proposed model achieves approximately 88% classification accuracy while maintaining an average inference time of less than two seconds per image. Additionally, an automated alert module notifies users when deforestation is detected with high confidence. The results indicate that the proposed framework can support large-scale environmental monitoring and assist authorities in identifying deforestation activities more efficiently.

Keywords—Deforestation Detection, Deep Learning, ResNet50, Satellite Imagery, Environmental Monitoring

I. INTRODUCTION

A. Background and Motivation

Forests play a critical role in maintaining global ecological balance by supporting biodiversity, regulating climate systems, and acting as major carbon sinks. Approximately 31% of the Earth's land surface is covered by forests, making them one of the most important natural resources for environmental sustainability [1]. However, large-scale deforestation caused by agricultural expansion, illegal logging, and infrastructure development continues to threaten forest ecosystems worldwide. According to global environmental assessments, millions of hectares of forest are lost each year, significantly impacting biodiversity, carbon storage, and regional climate stability [2].

Monitoring forest loss effectively is therefore an essential requirement for environmental conservation. Traditional monitoring approaches rely heavily on **ground surveys and manual inspection**, which are expensive, time-consuming, and limited in geographical coverage. As a result, deforestation activities are often detected only after substantial environmental damage has already occurred.

Satellite remote sensing has significantly improved large-scale forest monitoring by enabling the observation of vast geographic regions through high-resolution imagery [3]. However, conventional satellite-based analysis often depends on **manual interpretation or delayed processing pipelines**, which limits the ability to respond rapidly to illegal forest activities.

Recent advancements in **machine learning and deep learning** have provided new opportunities for automated environmental monitoring. Convolutional Neural Networks (CNNs) have demonstrated strong capabilities in image classification and land-cover analysis tasks by learning hierarchical spatial features directly from raw image data [4]. These techniques enable faster and more scalable analysis of satellite imagery compared to traditional rule-based methods.

B. Problem Definition

Despite recent progress, several challenges still limit the effectiveness of automated deforestation monitoring systems.

First, satellite monitoring requires processing **large volumes of imagery**, which demands efficient algorithms capable of handling large datasets. Second, satellite images often contain **environmental noise**, including cloud cover, shadows, atmospheric distortion, and seasonal variations that can affect classification accuracy. Third, timely detection is essential for conservation efforts, as delayed identification of forest loss can allow illegal activities to continue undetected.

Furthermore, many existing deep learning approaches focus primarily on **offline analysis of satellite datasets**, rather than real-time operational monitoring systems. Developing efficient models that can perform accurate detection while maintaining fast inference time remains an important research challenge.

C. Proposed Approach: ResNet50 + Attention Framework

To address these challenges, this study proposes a **deep learning-based deforestation detection system** that integrates transfer learning with an attention mechanism to improve classification accuracy and interpretability.

The proposed framework utilizes **ResNet50**, a deep residual neural network architecture that has been widely adopted for image recognition tasks due to its ability to learn complex hierarchical features [5]. By leveraging transfer learning, the model can utilize pre-trained feature representations learned from large image datasets and adapt them to the task of deforestation detection using a relatively smaller training dataset.

To further enhance detection performance, a **spatial attention mechanism** is incorporated into the architecture. The attention module enables the model to focus on image regions that are most relevant to deforestation patterns while suppressing irrelevant background information. This mechanism improves classification reliability and helps reduce false detections caused by environmental noise.

The proposed system also integrates a **web-based platform** consisting of a React.js frontend and a Flask backend, allowing users to upload satellite images and obtain automated deforestation predictions in near real-time.

D. Contributions

The main contributions of this research are summarized as follows:

1. Development of an automated deforestation detection framework using transfer learning and attention mechanisms.

2. Integration of a ResNet50-based deep learning model optimized for satellite image classification.

3. Design of a web-based monitoring platform enabling real-time deforestation detection and alert generation.

4. Evaluation of the proposed system on a multi-region satellite image dataset to assess classification accuracy and operational performance.

II.RELATED WORK ON DEFORESTATION DETECTION

A. Traditional Remote Sensing Approaches

Early research on deforestation monitoring primarily relied on **remote sensing techniques combined with manual interpretation of satellite imagery**. Analysts examined aerial photographs and satellite images to identify changes in forest cover over time. Although these methods provided reliable observations, they were labor-intensive and difficult to scale for large geographic areas [1].

To improve efficiency, vegetation indices such as the **Normalized Difference Vegetation Index (NDVI)** were introduced to estimate vegetation density and detect changes in forest cover using spectral information from satellite data [2]. These techniques allowed automated identification of vegetation loss but remained sensitive to atmospheric disturbances, seasonal variations, and sensor noise.

Subsequent studies adopted **change detection algorithms**, which analyze satellite images acquired at different time intervals to identify land cover changes. Techniques such as image differencing, principal component analysis, and change vector analysis have been widely applied in forest monitoring applications [3], [4]. However, these approaches often require complex preprocessing steps and may be affected by environmental variability such as illumination changes or seasonal vegetation cycles.

Large-scale monitoring initiatives have demonstrated the potential of satellite-based forest observation. Global forest monitoring datasets derived from Landsat imagery have enabled long-term analysis of forest loss patterns and provided valuable insights into deforestation dynamics worldwide [1].

B. Deep Learning for Remote Sensing

Recent advancements in **deep learning** have significantly improved the ability to analyze satellite imagery automatically. Convolutional Neural Networks (CNNs) have become a widely used approach for image classification and land cover analysis because they can learn hierarchical features directly from raw pixel data [5], [6].

Several studies have applied deep learning techniques to environmental monitoring tasks. CNN-based models have shown strong performance in land cover classification, demonstrating higher accuracy compared to traditional machine learning methods [7].

More specialized research has explored CNN architectures for detecting deforestation from satellite images. For example, convolutional neural networks have been used to identify forest loss patterns in tropical regions using Landsat imagery, achieving promising results for large-scale monitoring applications [8]. Transfer learning approaches have also been applied to improve model performance when training data is limited, enabling models trained on large image datasets to adapt to remote sensing tasks [9].

In addition, some studies have investigated combining multiple remote sensing data sources to enhance detection performance. Integrating optical satellite images with radar or thermal data can improve reliability in situations where cloud cover or atmospheric conditions affect image quality [10].

C. Attention Mechanisms in Environmental Monitoring

Attention mechanisms have emerged as an effective technique for improving deep learning models by allowing networks to focus on **important spatial features within images**. These mechanisms help models emphasize relevant regions while suppressing background information.

One widely used attention technique is the **Convolutional Block Attention Module (CBAM)**, which incorporates both channel attention and spatial attention to enhance feature representation within convolutional networks [11].

Such mechanisms have been successfully applied in various computer vision applications.

For environmental monitoring tasks, attention mechanisms can help highlight areas where deforestation is likely to occur, such as exposed soil regions, clearing boundaries, and irregular vegetation patterns. Recent studies indicate that integrating attention modules into CNN architectures can improve detection accuracy while also providing interpretable visualizations of model predictions [12].

D. Operational Monitoring Systems

Although many studies focus on improving detection algorithms, relatively fewer works address the **practical deployment of deforestation monitoring systems**. Real-world monitoring systems must balance detection accuracy with computational efficiency to process large volumes of satellite imagery in a timely manner.

Recent research has evaluated various deep learning architectures for large-scale environmental monitoring, emphasizing the trade-off between model accuracy and inference speed [13]. Some approaches utilize cloud-based geospatial platforms to process satellite data efficiently and support global-scale environmental analysis [14].

However, many existing systems require specialized technical expertise and complex workflows, which can limit accessibility for conservation organizations. To address these limitations, the system proposed in this study integrates a **deep learning detection model with a web-based interface and automated alert mechanism**, enabling users to analyze satellite imagery and receive deforestation alerts through an accessible platform.

III. DATASET DESCRIPTION

A.Data Sources and Composition

The dataset used in this study consists of satellite and aerial images categorized into two classes: **Forest** and **Deforested**. Images labeled as *Forest* represent regions with intact vegetation cover, while images labeled as *Deforested* correspond to areas where forest cover has been removed or significantly degraded.

The dataset was compiled from publicly available satellite imagery sources, including open datasets commonly used for land-cover classification research [7]. These images represent diverse environmental conditions and geographical regions, enabling the model to learn different patterns of forest cover and deforestation.

The collected dataset includes images representing multiple deforestation scenarios such as **clear-cutting, agricultural land conversion, and logging activities**. Including these variations improves the model's ability to generalize to real-world environmental monitoring applications.

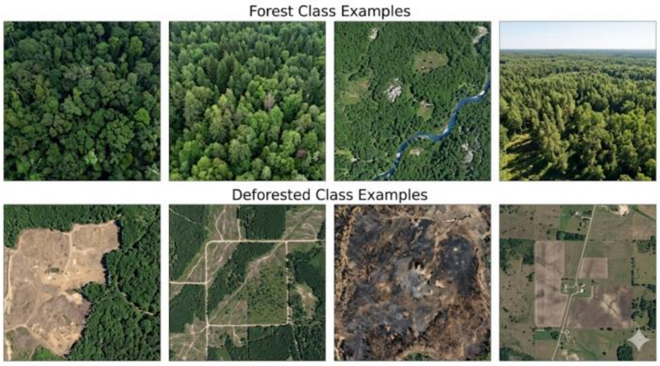

Figure.1. Dataset samples showing forest (top) and deforested (bottom) satellite images.

B. Dataset Characteristics

The final dataset contains approximately **5,000 labeled images** distributed equally between the two classes. Maintaining a balanced dataset helps prevent bias during model training and improves classification stability.

Each image represents an approximate **1 km² geographic area**, capturing spatial patterns of vegetation and land-use changes. The dataset contains substantial variability in terms of:

- Vegetation density (sparse vegetation to dense forest canopy)
- Illumination conditions due to seasonal changes**Test set**: 15% (750 images) held out for final performance evaluation
- Atmospheric effects such as haze or shadows
- Different levels of deforestation severity

This diversity ensures that the model can perform reliably across different environmental conditions and geographic regions.

C. Preprocessing Pipeline

Before training the deep learning model, all images undergo a series of preprocessing steps to ensure consistent input data:

1. **Image resizing:** All images are resized to 256 × 256 pixels to match the model input requirements.
2. **Normalization:** Pixel values are scaled from the range [0, 255] to [0, 1] to stabilize model training.
3. **Color standardization:** Images are converted to a standard RGB representation to ensure consistent input format.

These preprocessing steps help improve model convergence and reduce variations caused by differences in image resolution or sensor characteristics.

D. Data Augmentation

To increase model robustness and prevent overfitting, several data augmentation techniques are applied during training. These transformations artificially expand the dataset and expose the model to a wider range of visual conditions.

The augmentation techniques include:

- Random rotations
- Horizontal and vertical flipping
- Random zoom scaling
- Brightness adjustments
- Contrast modifications

Applying these augmentations improves the model's ability to generalize to unseen satellite imagery.

E. Dataset Split

The dataset is divided into training, validation, and test subsets using stratified random sampling to maintain equal class distribution.

- **Training set:** 70% of the dataset (3,500 images) used for model training
- **Validation set:** 15% (750 images) used for hyperparameter tuning
- **Test set:** 15% (750 images) used for final performance evaluation

This partitioning ensures that the model is evaluated on data that was not used during training, providing a reliable assessment of generalization performance.

IV. METHODOLOGY

A. Transfer Learning with ResNet50

Deep convolutional neural networks have demonstrated strong performance in image classification tasks; however, training such models from scratch typically requires large annotated datasets. In remote sensing applications, collecting and labeling large-scale datasets can be expensive and time-consuming. To address this limitation, **transfer learning** is commonly used to adapt pre-trained models to new tasks with limited training data [9].

In this study, **ResNet50** is adopted as the backbone architecture for feature extraction. ResNet50 is a deep residual neural network that introduces skip connections to allow effective training of very deep networks while mitigating the vanishing gradient problem [15]. The network was originally trained on the ImageNet dataset, which contains millions of labeled natural images.

Instead of training the model from scratch, the pre-trained ResNet50 weights are used as initialization. Early convolutional layers are kept frozen to preserve general image features such as edges and textures, while the deeper layers are fine-tuned to adapt to satellite imagery representing forest and deforested regions.

This approach significantly reduces the amount of training data required while maintaining strong feature extraction capabilities.

B. Attention Mechanism Design

Standard convolutional neural networks process all spatial regions of an image equally, even though only certain regions may contain meaningful information related to deforestation. To improve detection performance, a **spatial attention mechanism** is incorporated into the model architecture.

The attention module enables the network to identify and emphasize regions that are more likely to represent deforestation patterns, such as exposed soil, vegetation boundaries, or irregular canopy structures. By assigning higher weights to relevant regions and suppressing background features, the attention mechanism improves classification accuracy and reduces false detections.

Attention mechanisms have been widely applied in computer vision tasks and have shown effectiveness in improving feature representation within convolutional networks [11].

C. Classification Architecture

The complete model architecture consists of a **ResNet50 feature extractor followed by fully connected classification layers**.

The main components of the architecture include:

1. **Input Layer:** Accepts RGB images with dimensions 256 × 256 × 3.
2. **ResNet50 Backbone:** Extracts hierarchical feature representations from satellite imagery.
3. **Attention Module:** Enhances spatial feature representation by highlighting relevant image regions.
4. **Global Average Pooling:** Reduces feature maps into a compact feature vector.
5. **Fully Connected Layers:** Dense layers with ReLU activation used to learn classification patterns.
6. **Dropout Layers:** Applied to reduce overfitting during training.
7. **Output Layer:** A softmax layer producing probabilities for the two classes: Forest and Deforested.

This architecture allows the model to capture both low-level texture features and high-level spatial patterns relevant to deforestation detection.

D. Training Configuration

The model is trained using the **Adam optimizer**, which adapts learning rates during training and improves convergence speed. The main training parameters include:

- **Optimizer**: Adam with β_1=0.9, β_2=0.999
- **Learning rate**: 0.0001 with exponential decay (0.95 per 10 epochs)
- **Batch size**: 32 images per gradient update
- **Loss function**: Categorical cross-entropy
- **Epochs**: Maximum 50 with early stopping based on validation loss
- **Early stopping patience**: Stop if validation loss does not improve for 10 consecutive epochs

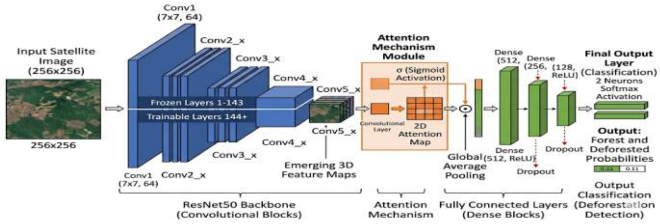

Figure.2. ResNet50-based architecture with attention mechanism for deforestation detection.

Early stopping is applied to prevent overfitting by terminating training when validation performance stops improving.

E. Inference and Alert Generation

During inference, new satellite images are processed using the same preprocessing pipeline applied during training. The trained model generates class probabilities for each image, identifying whether the region corresponds to **forest or deforested land**.

To support environmental monitoring, the system incorporates an **alert mechanism**. If the predicted probability of the deforested class exceeds a predefined confidence threshold, the system automatically generates an alert containing the detected image and associated prediction score.

These alerts can be used by monitoring authorities to identify potential deforestation activities and initiate further investigation.

V. SYSTEM ARCHITECTURE

A. Overview

The proposed deforestation detection platform is implemented using a **three-tier architecture**, consisting of a frontend interface, backend processing layer, and deep learning inference module. This architecture enables efficient interaction between users and the machine learning model while maintaining scalability and modular system design.

The system allows users to upload satellite images through a web interface. These images are transmitted to the backend server where preprocessing and model inference are performed. The prediction results are then returned to the frontend interface, where users can visualize classification outcomes and receive deforestation alerts.

This modular design allows each system component to be updated independently without affecting the overall functionality.

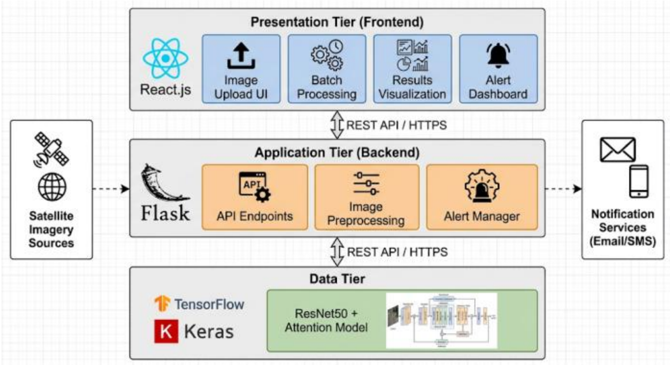

Figure.3. Three-tier system architecture integrating React frontend, Flask backend, and TensorFlow model.

B. Frontend Implementation

The frontend of the system is developed using **React.js**, which provides a responsive and interactive user interface. The interface allows users to upload satellite images and view prediction results generated by the deep learning model.

Key frontend functionalities include:

- Image upload through a simple web interface
- Visualization of classification results and prediction confidence
- Display of attention heatmaps highlighting detected deforestation regions
- Dashboard for monitoring detected events

The frontend communicates with the backend through RESTful API requests.

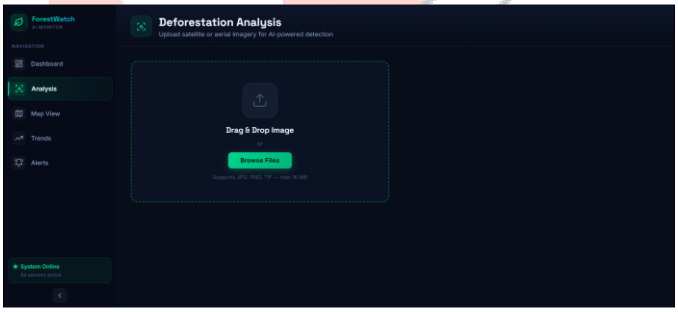

Figure.4. frontend design to upload image

C. Backend Implementation

The backend is implemented using **Flask**, which serves as the middleware between the frontend interface and the machine learning model. The backend handles image processing, model inference, and system communication.

When an image is uploaded, the backend performs the following steps:

1. Image preprocessing and resizing
2. Normalization of pixel values
3. Model inference using the trained deep learning model
4. Generation of prediction results and confidence scores

The backend returns the processed results to the frontend, where they are presented to the user.

D. Model Integration and Deployment

The trained deep learning model is integrated into the backend environment for real-time inference. The model processes incoming satellite images and classifies them into two categories: **Forest** and **Deforested**.

To improve system efficiency, prediction requests are processed sequentially, and frequently accessed results may be cached to avoid redundant computations. This architecture ensures stable system performance when multiple users access the platform simultaneously.

The modular structure of the system also allows the model to be retrained or replaced without modifying the frontend interface.

VI. EXPERIMENTAL SETUP

A. Implementation Environment

The proposed system was implemented using a Python-based machine learning environment. The backend components were developed using **Python and Flask**, while the deep learning model was implemented using **TensorFlow and Keras** frameworks. The frontend interface was developed using **React.js** to provide an interactive web-based environment for image upload and prediction visualization.

Model training and evaluation were conducted on a system equipped with GPU acceleration to improve computational efficiency during training. GPU-based training significantly reduces training time compared to CPU-only execution, allowing faster experimentation and model optimization.

B. Performance Metrics

To evaluate the effectiveness of the proposed deforestation detection model, several standard classification metrics were used, including **accuracy, precision, recall, and F1-score** [16].

- **Accuracy**: Measures the proportion of correctly classified samples.
- **Precision**: Indicates the proportion of predicted deforestation instances that are correctly identified.
- **Recall**: Represents the ability of the model to detect actual deforestation cases.
- **F1 Score**: The harmonic mean of precision and recall, providing a balanced performance measure.
- **Confusion Matrix**: Displays the distribution of true positives, false positives, true negatives, and false negatives.

Among these metrics, recall is particularly important for deforestation monitoring, as missing true deforestation events may allow environmental damage to continue undetected.

In addition to classification metrics, **operational performance metrics** were also evaluated:

- **Inference time**: Time required for the model to process a single image and produce a prediction.
- **API response time**: Total latency between image upload and result delivery.
- **Throughput**: Number of images that can be processed per second.

These measurements help determine the practicality of deploying the system for real-time environmental monitoring.

C. Baseline Comparisons

To demonstrate the value of transfer learning and attention mechanisms, we compare our approach against several baselines:

1. **ResNet50 (without attention) [17]:** Transfer learning model without the attention module.
2. **ResNet50 (trained from scratch):** Model trained without pre-trained weights.
3. **VGG16 (transfer learning) [18]:** Alternative convolutional neural network architecture.
4. **Simple CNN:** A lightweight convolutional model with fewer layers.

All models use the same training data, preprocessing pipeline, and evaluation protocol to ensure fair comparison.

D. Ablation Studies

To understand the contribution of individual components in the proposed architecture, several ablation experiments were conducted.

These experiments evaluate the impact of:

- The attention mechanism on classification accuracy
- Transfer learning compared with random weight initialization
- Data augmentation techniques used during training
- The number of frozen layers in the ResNet50 backbone

Ablation analysis helps determine which design choices contribute most significantly to the model's performance.

VII. RESULTS AND DISCUSSION

A. Classification Performance

The proposed **ResNet50 with attention mechanism** model was evaluated on the test dataset to assess its effectiveness in distinguishing between forest and deforested areas. The model achieved an overall **accuracy of 88.3%**, demonstrating strong performance in satellite image classification tasks.

The detailed evaluation metrics obtained from the test dataset are as follows:

- **Accuracy**: 88.3%
- **Precision**: 86.7%
- **Recall**: 89.1%
- **F1 Score**: 87.9%

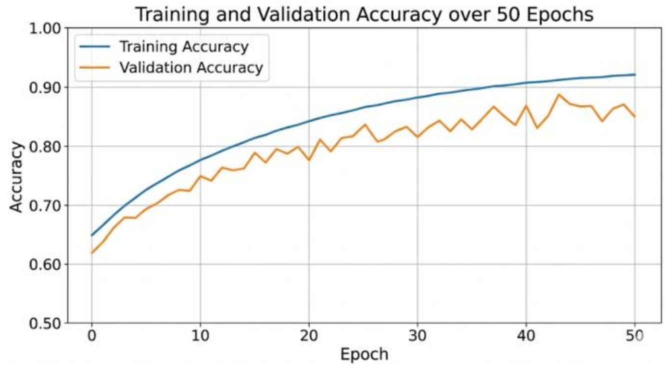

Figure.5. Training curves showing 88.5% validation accuracy with minimal overfitting.

The relatively high recall value indicates that the model effectively identifies deforestation events, which is particularly important in environmental monitoring applications where missing true deforestation cases may delay intervention.

The confusion matrix analysis shows that the model correctly identifies most forest and deforested regions, with a limited number of misclassifications. False positives primarily occur in regions with sparse vegetation or natural canopy gaps, while false negatives are often associated with small or partially obscured deforested areas.

- True Positives (correctly identified deforestation): 425
- False Positives (forest incorrectly classified as deforestation): 48
- True Negatives (correctly identified forest): 464
- False Negatives (deforestation incorrectly classified as forest): 63

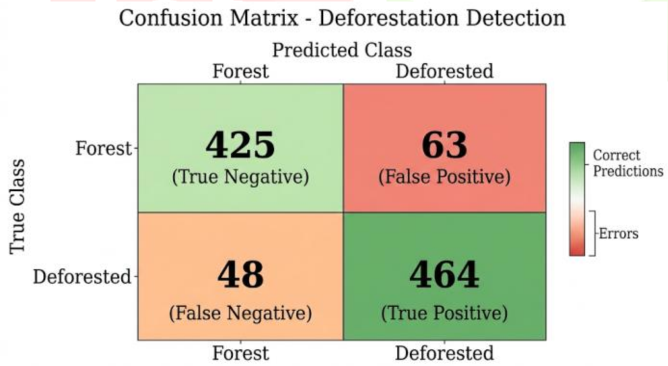

Figure.6.Confusion matrix demonstrating 88.5% classification accuracy on test data.

These results indicate that deep learning–based approaches are effective for land-cover classification tasks, consistent with findings reported in previous remote sensing studies [6].

B. Inference Speed

In addition to classification accuracy, the operational performance of the system was evaluated to determine its suitability for real-time monitoring applications.

The average **single-image inference time** was approximately **1.82 seconds**, measured across multiple test samples. When images were processed in batches, the average processing time per image decreased due to improved computational efficiency.

The **API response time**, including image upload, preprocessing, model inference, and result transmission, was approximately **2.14 seconds**. This latency is sufficiently low for interactive use within the web-based monitoring platform.

These results indicate that the system is capable of processing satellite imagery efficiently while maintaining reliable prediction accuracy.

C. Attention Visualization

To better understand the model's decision-making process, attention heatmaps were generated to highlight image regions that influenced the classification results.

For correctly classified deforestation images, the attention maps typically focused on **clearing boundaries, exposed soil patches, and irregular vegetation patterns**. In contrast, for forest images, attention weights were distributed more uniformly across the vegetation canopy.

These visualizations provide interpretability by demonstrating that the model focuses on meaningful environmental features rather than unrelated background patterns. Visualization techniques for deep learning models have been widely used to interpret neural network predictions in computer vision applications [19].

D. Limitations

Despite achieving promising results, several limitations remain in the current system.

First, the model performs **binary classification**, distinguishing only between forest and deforested regions. It does not currently identify specific types of deforestation activities such as selective logging or agricultural conversion.

Second, satellite imagery affected by **dense cloud cover** may reduce detection accuracy, even after preprocessing. Additional data sources such as radar imagery could improve reliability under such conditions.

Finally, the dataset used in this study contains a limited representation of some geographic regions, which may affect model generalization across different forest ecosystems.

Addressing these limitations could further improve the robustness and applicability of the proposed monitoring system.

VIII. FUTURE DIRECTIONS

A. Multi-Class Classification

The current system performs **binary classification**, distinguishing only between forest and deforested regions. Future work could extend the model to support **multi-class classification** that identifies different types of deforestation activities.

Possible additional classes may include:

- Selective logging (partial canopy removal)
- Clear-cutting (complete forest removal)
- Agricultural conversion (replacement with crops)
- Natural disturbance (fire, wind damage)

Such classification could provide more detailed information for environmental monitoring agencies and improve decision-making for forest conservation strategies.

B. Predictive Modeling

Beyond detecting deforestation events after they occur, future systems could incorporate **predictive models** that estimate the likelihood of deforestation in specific regions. Machine learning techniques can analyze historical land-use patterns and environmental variables to identify areas at higher risk of forest loss.

Factors that may contribute to predictive modeling include:

- Distance from roads and human settlements
- Historical deforestation patterns
- Climate conditions and drought risk
- Proximity to protected areas

Predictive monitoring approaches have been explored in environmental analysis and could support proactive conservation strategies [6].

C. Edge Computing

Another promising direction is the deployment of deforestation detection models on **edge devices or distributed monitoring platforms**. Techniques such as model compression, pruning, and quantization can reduce model size while maintaining acceptable performance levels.

These optimizations would allow models to operate on resource-constrained devices such as drones or field monitoring systems. Edge-based analysis could reduce dependency on cloud infrastructure and enable **faster detection in remote forest regions**.

Lightweight deep learning models have shown potential for deployment in real-time environmental monitoring applications [13].

IX. CONCLUSION

We This study presented an automated **deforestation detection system** based on deep learning and satellite image analysis. The proposed framework integrates **transfer learning using the ResNet50 architecture with a spatial attention mechanism** to improve the detection of deforested regions in satellite imagery.

Experimental results demonstrate that the proposed model achieves strong classification performance, with an overall **accuracy of 88.3%**, while maintaining efficient inference time suitable for real-time monitoring applications. The attention mechanism further enhances model interpretability by highlighting image regions that contribute most significantly to classification decisions.

The developed web-based platform enables users to upload satellite images and obtain rapid predictions through an integrated **React–Flask architecture**, making the system accessible for environmental monitoring applications.

The results indicate that deep learning techniques can significantly improve the efficiency of large-scale forest monitoring systems, supporting earlier identification of deforestation activities and facilitating timely environmental intervention. Similar deep learning approaches have demonstrated strong potential for remote sensing applications involving land-cover classification and environmental monitoring [6].

Overall, the proposed system demonstrates that combining **transfer learning, attention mechanisms, and web-based deployment** provides a practical framework for automated deforestation detection. Future improvements may focus on incorporating multi-class classification, additional satellite data sources, and predictive monitoring techniques to further enhance system capabilities.

X.REFERENCES

[1] M. C. Hansen et al., “High-resolution global maps of 21st-century forest cover change,” *Science*, vol. 342, no. 6160, pp. 850–853, 2013.

[2] Food and Agriculture Organization, “Global Forest Resources Assessment 2020,” FAO, Rome, Italy, 2020.

[3] R. B. Wulder et al., “Fifty years of Landsat science and impacts,” *Remote Sensing of Environment*, vol. 280, p. 113195, 2022.

[4] P. Coppin, I. Jonckheere, K. Nackaerts, B. Muys, and E. Lambin, “Digital change detection methods in ecosystem monitoring: A review,” *International Journal of Remote Sensing*, vol. 25, no. 9, pp. 1565–1596, 2004.

[5] A. Huete et al., “Overview of the radiometric and biophysical performance of the MODIS vegetation indices,” *Remote Sensing of Environment*, vol. 83, no. 1–2, pp. 195–213, 2002.

[6] L. Ma et al., “Deep learning in remote sensing applications: A meta-analysis and review,” *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 152, pp. 166–177, 2019.

[7] P. Helber et al., “EuroSAT: A novel dataset and deep learning benchmark for land use and land cover classification,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 12, no. 7, pp. 2217–2226, 2019.

[8] X. X. Zhu et al., “Deep learning in remote sensing: A comprehensive review and list of resources,” *IEEE Geoscience and Remote Sensing Magazine*, vol. 5, no. 4, pp. 8–36, 2017.

[9] S. J. Pan and Q. Yang, “A survey on transfer learning,” *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 10, pp. 1345–1359, 2010.

[10] A. Krizhevsky, I. Sutskever, and G. Hinton, “ImageNet classification with deep convolutional neural networks,” *Advances in Neural Information Processing Systems*, vol. 25, 2012.

[11] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, pp. 436–444, 2015.

[12] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

[13] O. Russakovsky et al., "ImageNet large scale visual recognition challenge," *International Journal of Computer Vision*, vol. 115, no. 3, pp. 211–252, 2015.

[14] S. Woo, J. Park, J. Lee, and I. S. Kweon, "CBAM: Convolutional Block Attention Module," *European Conference on Computer Vision (ECCV)*, 2018.

[15] J. Hu, L. Shen, and G. Sun, "Squeeze-and-Excitation networks," *IEEE Conference on Computer Vision and Pattern Recognition*, 2018.

[16] P. P. de Bem et al., "Change detection of deforestation in the Brazilian Amazon using Landsat data and convolutional neural networks," *Remote Sensing*, vol. 12, no. 6, 2020.

[17] A. Alzu'bi and L. Al-smadi, "Monitoring deforestation using deep semantic segmentation with satellite imagery," *Ecological Informatics*, vol. 70, 2022.

[18] G. Fodor and M. V. Conde, "Rapid deforestation detection using deep multimodal learning on satellite imagery," *IEEE CVPR Workshops*, 2023.

[19] R. R. Selvaraju et al., "Grad-CAM: Visual explanations from deep networks via gradient-based localization," *IEEE International Conference on Computer Vision*, 2017.

[20] N. Gorelick et al., "Google Earth Engine: Planetary-scale geospatial analysis for everyone," *Remote Sensing of Environment*, vol. 202, pp. 18–27, 2017.