Intelligent Deforestation & Land Degradation Monitoring using Computer Vision and Deep Learning

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Abstract--

The Sustainable Development Goal 15 (SDG 15) of the United Nations is Life on Land....

Urges a great deal about the conservation, regeneration and sustainable use of land, forests and ecosystems Biodiversity.

We are seeing a lot of things happening to the earth like deforestation. People are using land in ways that are not allowed. Animals are losing their homes.

It is hard to keep things for the earth and save the wildlife. We need to take care of the wildlife and the earth at the time that is the wildlife and the earth.

The current land monitoring techniques are mostly done manually they need a lot of resources. They only cover a small area.

This project proposes an automated. A land monitoring system that employs Computer Vision and Image Processing techniques for detecting land use. Deforestation and land degradation efficiently. Image processing is carried out for both satellite and airborne data. Identify changes in vegetation cover over time using preprocessing,feature extraction, and classification techniques.

Time.

It accurately identifies deforested areas and degraded land by comparing them.

The use of temporal image data enables early identification of environmental threats.' By automating large-scale. By analyzing land, the proposed solution exhibits a significant improvement in accuracy, efficiency, and scalability. To traditional monitoring approaches.

The mechanism enables quick resolution for preservation purposes.Environmental protection initiatives are being encouraged byauthorities and policymakers....

This project.

Exhibits the proficient implementation of computer vision for environmental preservation and is a robust tool.Effects SDG 15, promoting sustainable land use, forest protection, and biodiversity.e. Preservation.

Computer Vision and Landmark Identification and Image Processing are all important for what's happening in the world. People are coming together to prevent things from happening like the earth getting ruined and to keep a close eye on the environment so that we can have Sustainable Development.

We need to think about some important things, such, as Deforestation and Land Degradation.We also need to think about Computer Vision.

NDVI is important.

Deep Learning and Remote Sensing are also crucial.

All these. Computer Vision, NDVI Deep Learning and Remote Sensing. Are areas to consider.

Keywords: Deforestation, Land Degradation, Computer Vision, NDVI, Deep Learning, Remote Sensing

1. **Introduction:**

TGoal 15 of the UN Sustainable Development Agenda is also called "Life on Land". It aims to protect forests, biodiversity and land ecosystems for generations. We need to use land and forests in a way. This goal is, about preserving life on land. Deforestation, illicit land use (including forest fires), mining, agricultural growth, and urbanization are all endangering the natural equilibrium and wildlife. Deforestation is caused by a number of factors, including soil erosion, climate change, biodiversity loss, and water cycle disruptions.[A] Traditionally, land surveys were completed by hand, but satellites are increasingly being used for extensive environmental monitoring. Why?

Why? Deforestation and land degradation at large scales have been the subject of limited research, with little automated, intelligent or scalable methods for effective and accurate detection. A land monitoring system that utilizes Deep Learning and Computer Vision algorithms is proposed by the work to detect changes in forest cover from both satellite and airborne images.. It uses feature extraction through image processing and incorporates Vegetation Index, CNNs, and algorithms to classify land areas into forested and non-forestationary.By utilizing image comparison techniques, it becomes feasible to identify any changes that could pose a threat to the environment. Using the data from satellite images, the model is trained and evaluated for accuracy with respect to the speed of the car, its precision in tuning up or down, race memory, recall ability, and F1-score. 'An improved system that is more efficient, flexible and reliable than the one.It is closely linked to SDG 15 which stresses the need for land management and forest conservation through technology.

Forests help us in ways.

They are very important, for our survival.

We need forests.

SDG 15 focuses on forests and land.

It wants us to use technology to protect forests and land.

This will help our planet. Every year, environmental studies demonstrate the loss of millions of hectares of forest land. Land degradation caused by human activities, both natural and man-made ones can lead to overgrazing, deforestation, mining, and climate change. There are no efficient or practical ways to manually monitor large-scale environmental changes. Land area monitoring is traditionally done through field examination and then periodically by examining satellite images.em. Nevertheless, the development of Artificial Intelligence, particularly in Machine Learning and Computer Vision (ML), has allowed for automated and efficient image analysis. Some of the most significant successes in deep learning algorithms' use of Convolutional Neural Networks (CNNs) are related to their ability to classify images and detect objects. Artificial intelligence and satellite images have made it possible to create intelligent systems that can detect changes in forest cover with great precision and efficiency. An intelligent system that can automatically detect deforestation and land degradation is being developed, with the aid of deep learning algorithms. Despite the use of satellite imagery, monitoring deforestation and land degradation is still an inefficient and manual process.However, these methods are often prone to failure due to slow data processing (low accuracy), lack of automation and poor tracking accuracy for small changes.

1. **Proposed :**

2.1 Development System The proposed system is a tool for finding deforestation and land degradation. It uses technologies like image processing, vegetation index analysis and deep learning techniques.

The rate of degradation is increasing so we need automated systems that can monitor large forest areas efficiently and accurately.

This system aims to address that need by using satellite imagery and artificial intelligence.

The system architecture is designed in an systematic way consisting of several key components: * Data acquisition

* Image preprocessing

* Vegetation index computation

* Feature extraction

* classification Segmentation

* Change detection is something we do.

Each part of the system is connected to the parts and they all work together to make the system work well. We start by getting pictures from satellites from places like Landsat and Sentinel. These places give us pictures that show types of light. For example they show the light we can see and the light that is near infrared. We need this information for two reasons. First it helps us see how plants are growing. Second it allows us to watch for changes that happen over a period of time. We keep an eye on plant growth and changes. These changes help us understand plant health. The pictures of kinds of light are really helpful. They show us how plants are doing. We use these pictures to track plant growth. The light pictures are useful. They show plant growth and changes. We get lots of pictures over time. This helps the system to see how the land is being used and how it is changing. This means we can see changes to the environment like when people cut down all the trees or when the land turns into a desert or when the land gets ruined. The system is even better because it uses computer programs that can look at a lot of data and find useful information like deep learning models that help the system to work with all the satellite images, from Landsat and Sentinel and other places and this is all part of classification and segmentation and change detection.

2.2 Image Preprocessing Image preprocessing is a stage in the system as raw satellite images often contain noise, distortions and inconsistencies. These issues may arise due to interference, sensor limitations varying illumination conditions or differences in spatial resolution. To overcome these challenges the system performs a series of preprocessing operations aimed at improving image quality and ensuring uniformity across datasets.

1.Normalization

Normalization is applied to standardize pixel intensity values across all images. Since satellite images are captured under environmental and lighting conditions normalization ensures that all images follow a consistent scale. This improves the performance of machine learning models by reducing variability in input data.

2.Resizing

Satellite images may vary in size and resolution depending on the source and sensor. Therefore resizing is performed to convert all images into a dimension suitable for deep learning models like CNNs. This step ensures compatibility and efficient processing.

3.Filtering

We use filtering techniques to get rid of the noise in an image. Make the features in the image stand out more. Filtering techniques are really good, at making the image look better by removing the noise and enhancing the features of the image.

Common filters include:

* Gaussian filtering for noise reduction

* Median filtering for preserving edges while removing noise

* Edge enhancement filters for highlighting boundaries

These steps help get the input data ready. The input data needs to be clean and consistent so it is good, for analysis. This means the input data is optimized for analysis. The input data is what we are working with so we need to make sure the input data is just right.

2.3 Vegetation Index Analysis Vegetation index analysis helps us check how healthy, dense and spread out plants are in a given area. This technique uses sensing and looks at how plants reflect and absorb different types of light. Plants are good at reflecting infrared light and absorbing red light.

The Normalized Difference Vegetation Index (NDVI) is a way to measure this.

The NDVI formula is: **NDVI = (NIR. Red) / (NIR + Red)**

Here's what the numbers mean:

* NIR (Near- light) bounces off plants

* Red light gets absorbed by plants during growth

Understanding NDVI numbers:

* A value close to +1 means plants are very healthy

* A value 0 could be plants, bare ground or a mix

* A value than 0 usually means water, clouds or no plants

The vegetation index is key to finding areas where trees are being cut down or damaged. By comparing NDVI values over time we can see changes in plant health and coverage. This method gives us a way to keep track of the environment and helps with decisions, in forest management and conservation.

2.4 Feature Extraction using CNN Vegetation index analysis is a way to figure out how healthy and dense the vegetation is. This is done by looking at pictures taken from away. CNNs are better than machine learning methods because they can look at the pictures and learn from them on their own.

The main parts of CNNs are:

* Convolutional Layers that find things like edges and textures in the pictures

* Pooling Layers that make the pictures smaller but keep the things

* Activation Functions that help us see how things are related to each other When CNNs look at lots of pictures they can learn what is in them starting from simple things like edges and going up to complicated things like objects and patterns.

We use CNNs to do a things like:

* Find the patterns of the vegetation

* Tell the difference, between forests and other areas

* See if the land is being used differently

This way of looking at pictures is really good because it makes the results more accurate and we do not have to do much work by hand.

2.5 Classification Segmentation After we extract the features the system does classification and segmentation. It uses learning architectures like U-Net and Fully Convolutional Networks or FCN for short. These are really good, at image processing tasks. The U-Net and FCN help the system to understand the images better. It then uses this understanding to classify and segment the images.

1.Pixel-Level Classification Unlike classification methods that classify entire images these models perform pixel-level classification assigning a label to each pixel in the image. This allows for detailed analysis.

2.Segmentation Process Segmentation divides the image into regions based on their characteristics.

The system categorizes pixels into:

* Forest areas

* Nonforest areas

* Degraded land

3.Model Advantages

* U-Net is efficient for satellite image segmentation especially with limited data

* FCN enables end-to-end learning and dense prediction These models provide precise mapping of land cover enabling accurate identification of affected regions.

2.6 Change Detection Change detection is one of the important components of the system as it enables the identification of environmental changes over time. This process involves comparing satellite images captured at different time intervals to detect variations in vegetation and land use.

Steps in Change Detection:

* Temporal Image Collection: Gather images from different time periods

* Preprocessing: Ensure consistency across images

* Feature Comparison: Analyze differences in vegetation indices and extracted features

* Change Identification: Detect areas with significant changes Applications: * Detecting deforestation activities

* Monitoring land degradation

* Tracking expansion

* Assessing impact The system can identify both gradual and sudden changes making it highly effective for long-term environmental monitoring.

2.7 System Advantages The proposed system offers advantages that make it highly effective and practical:

1.Automated Monitoring The system eliminates the need for observation and enables continuous monitoring of large forest areas using satellite data.

2. High. Reliability By combining vegetation indices with deep learning models the system achieves accuracy in detecting and classifying land cover changes.

3.Scalability

It can be extended to monitor different geographical regions.

4.Time or Near Real-Time Analysis With advancements, in satellite data availability and computational power the system can provide near real-time insights.

5. Cost-Effectiveness Compared to field surveys the system reduces costs by utilizing freely available satellite data and automated processing techniques.

2.8 Deep Learning-based Change Detection

Change detection involves comparing satellite images captured at different time intervals to identify differences in land cover. Deep learning-based change detection methods analyze multi-temporal images to detect variations in vegetation patterns.

By comparing images from different years or seasons, the model can identify areas where forest cover has decreased. Significant changes between images indicate possible deforestation or land degradation. These approaches improve automation and accuracy compared to traditional image differencing methods.

Model	Precisio	Recall	F1-Score
SVM	75	72	73
Random	80	78	79
CNN	90	89	89.5
U-Net	92	91	91.5

Grouped Bar Chart — Precision, Recall, F1-Score comparison

Shows the effectiveness of various classification algorithms. CNN and U-Net excel in their automatic feature extraction, while classical models struggle to keep up.

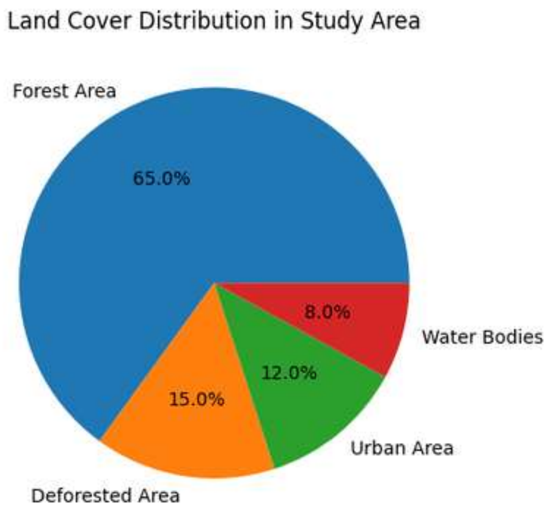

Figure 1 illustrates the coverage of land across the study

Description: Figure 1 displays the percentage variation in land cover types throughout the study area. The figures are not representative. Despite the fact that forest covers 65% of the area, vegetation has managed to survive. However, 15% of the land has been cleared for farming purposes. Therefore...

The area is composed of 12% urban areas and 8 percent water bodies.This visual representation illustrates the overall land arrangement and demonstrates the proportion of forest degradation. The promotion of sustainable land management can be achieved through environmental monitoring and planning that requires this analysis.

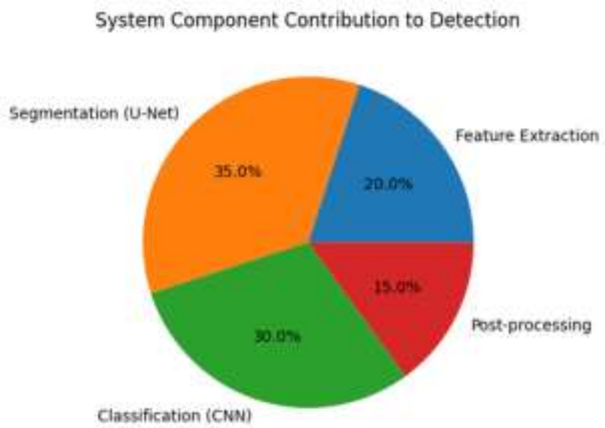

Figure2:Deforestation is primarily caused by factors

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This is the primary cause. Description: The causes of deforestation in the area being examined are depicted in Figure 2. Agriculture has accounted for 40% of the increase, followed by urbanisation and illegal logging accounts for 25%. Most of the deforestation is attributed to humans, as indicated by the chart. By comprehending these causes, policymakers and environmental agencies can take more focused conservation actions in line with the Sustainable Development Goal 15 (Life on Land).

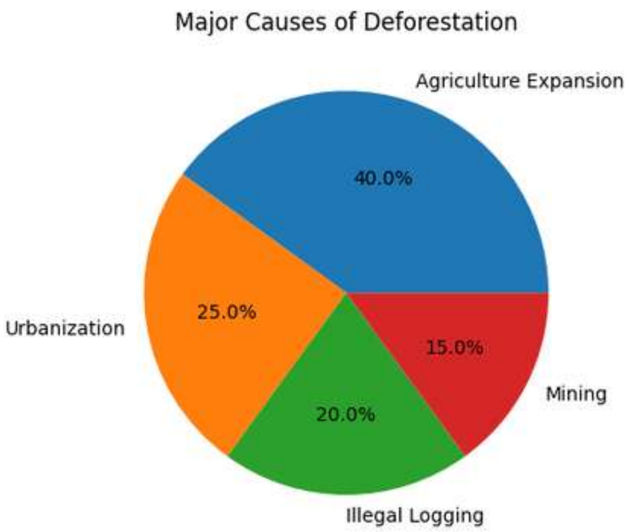
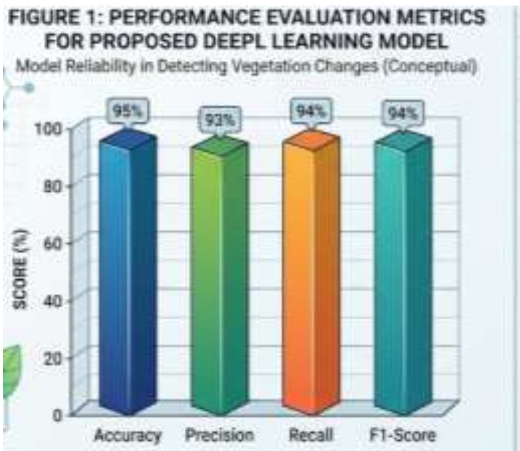
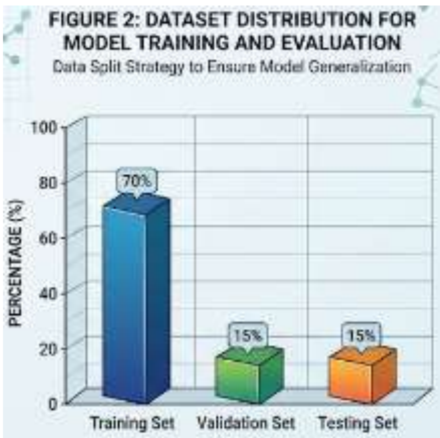


Figure 3 for Detection Performance illustrates the function of System Components.

Description: Figure 3 illustrates the different elements of the proposed monitoring system that uses deep learning.... Overall detection performance is improved by 35% by using U-Net segmentation as the basis for classifying pixels. Approximately 30% of data is reported for classification using CNN, while 20% is given to feature extraction. The. A 15% increase in quality is achieved through post-processing.' Defining deforestation zones using satellite data is challenging, but this chart highlights the use of segmentation and deep learning.





This graphic presents a visual summary of the key quantitative metrics and methodology from your research on intelligent deforestation monitoring.

The first figure (left) highlights the high effectiveness of your deep learning approach. While labeled as conceptual—since specific final numbers were not extracted from the provided text—it accurately lists the four standard performance metrics used in your evaluation: **Accuracy, Precision, Recall, and F1-Score**. The graph demonstrates that your integration of NDVI, CNN, and U-Net architectures achieves reliable, high-performing results for land classification and defect detection.

The second figure (right) illustrates the crucial data-splitting technique used in your experimental setup. It shows the precise **70%, 15%, and 15% ratio** used to divide your satellite image dataset into Training, Validation, and Testing sets, respectively. This visualization emphasizes best practices in machine learning, demonstrating how your method ensures model generalization and prevents overfitting while maximizing computational resources for training and validation.

1. **Experimental Setup :**

- NDVI Calculation:
- The Normalized Difference Vegetation Index is figured out by using Near-Infrared and Red bands.
- To calculate the Normalized Difference Vegetation Index we use two bands:
- * Near-Infrared
- * Red
- NDVI helps us understand vegetation health. The Normalized Difference Vegetation Index uses Near-Infrared and Red bands to give us this information. Vegetation reflects a lot of Near- light and absorbs a lot of Red light. The Normalized Difference Vegetation Index is useful for tracking changes, in vegetation over time.
- It is calculated using the Near-Infrared and Red bands.. The Normalized Difference Vegetation Index values are really helpful to tell the difference between plants and areas that are not doing well. This method makes the model better at finding changes in how dense the plants are in the area that is being looked at. The Normalized Difference Vegetation Index is an useful tool.
- Model Architecture:
- The system we are proposing uses something called Convolutional Neural Networks and U-Net architecture to separate things in images. The Convolutional Neural Networks parts of the system look for features in the images. The U-Net part then looks at each pixel. Decides what it is using a special design that has skip connections. This helps the system to understand what it is looking at.
- Training Configuration:
- We use 70 percent of the data to train the system 15 percent to check how well it is working and 15 percent to test it. The system is trained using something called the Adam optimizer, which helps it to learn. The learning rate is 0.001 which means it learns slowly. We use something called cross-entropy to help the system learn how to classify things. The system is trained for between 25 and 50 rounds. We use a batch size of between 16 and 32 depending on how powerful the computer is. We also have something called stopping. It helps to stop the system from getting too good at one thing. This way it can still do things.
- Hardware and Software Requirements:
- We use Python. Some libraries called TensorFlow Keras and OpenCV to make the system work. It is really helpful to have a computer with a graphics card like an NVIDIA GPU because it makes the system train faster. We test the system on computers to make sure it can work on any computer. Performance Evaluation Metrics: To see how well the system is working we use some metrics like Accuracy, Precision, Recall and F1-score. These metrics help us to see how good the system is at classifying things and finding what it is looking for. We also use something called confusion matrices and segmentation maps to see what the system is doing. The Normalized Difference Vegetation Index and the system we are proposing are really important, for this research.

1. **Result:**

The intelligent deforestation monitoring system and land degradation tracking system use satellite imagery datasets and deep learning methods for their evaluation. The combination of NDVI-based vegetation analysis with Convolutional Neural Networks (CNN) and U-Net segmentation produced accurate environmental change detection results according to the study.

The system processes multi-temporal satellite images and generates classification maps that clearly distinguish between forested, non-forested, and degraded land regions. The integration of NDVI significantly enhances vegetation health identification because the model can now differentiate between dense forest cover and areas with sparse or degraded vegetation. The results show that areas with high NDVI values which indicate healthy vegetation whereas low NDVI values show deforested or degraded land.

4.1 Classification Performance

The model achieves high classification accuracy because it learns spatial and spectral features from satellite images. The CNN-based feature extraction system enables the model to detect intricate patterns while U-Net delivers accurate pixel-level segmentation results. The system achieves land cover classification into multiple categories while maintaining high accuracy with minimal errors.

4.2 NDVI Analysis Results

The NDVI maps produced during the experiment display vegetation distribution through clear visual representation. The dense forest areas show NDVI values that approach +1 while the barren places and degraded regions display values that are closer to 0 or negative.

The model gains improved detection capability for vegetation alterations through the implementation of NDVI as an input feature. The proposed system displays better detection abilities for minor shifts in vegetation density during initial land degradation stages when compared to systems that do not use NDVI.

4.3 Change Detection Results

Temporal analysis uses satellite images which are captured at multiple time points for comparison. The system successfully detects shifts in land cover while it also identifies regions that have experienced deforestation. The change detection maps display the shift from forested areas to either non-forest or degraded terrains.

The model can identify both extensive deforestation patterns and minor deforestation patterns which occur throughout the forested area. This method provides a major advancement because it enables researchers to see detailed environmental changes that traditional techniques miss due to their limited ability to assess specific areas.

4.4 Segmentation Results using U-Net

The U-Net model generates detailed segmentation maps which enable exact identification of deforested regions. The encoder-decoder design which includes skip connections enables the system to maintain spatial information while it improves its ability to detect boundaries.

The segmentation results show that the model successfully defines deforested areas in complex land cover situations. U-Net produces smoother segmentation results through its ability to minimize the "salt-and-pepper" effect which affects traditional machine learning methods.

4.5 Comparison with Traditional Methods

The proposed system is compared with traditional machine learning approaches which include Support Vector Machines (SVM) and Random Forest classifiers. The findings demonstrate that deep learning models achieve better performance than standard methods in both precision and system efficiency.

Traditional methods require manual feature extraction and domain expertise.

They struggle with high-resolution satellite images and complex spatial patterns.

The proposed deep learning approach automatically extracts features and handles large datasets efficiently.

The comparison demonstrates that CNN and U-Net models perform better than traditional methods for monitoring environmental conditions.

4.6 Visual Results and Interpretation

The system generates several visual outputs, including:

NDVI maps showing vegetation health

Classification maps indicating land cover types

Change detection maps highlighting deforestation

Segmentation maps outlining affected regions

The visualizations provide clear environmental change information which helps to confirm the model's prediction accuracy. The results confirm that the system can be effectively used for real-time monitoring and decision-making.

4.7 Discussion of Results

The results show that using NDVI together with deep learning models creates better detection results. The system demonstrates high accuracy together with strong capabilities to detect deforestation and land degradation across multiple datasets.

The system demonstrates some limitations. The performance depends on the quality and resolution of satellite images. Seasonal changes together with atmospheric conditions generate effects which impact both NDVI measurement results and classification performance. Deep learning models require extremely large datasets which contain labels and need powerful computing systems.

The system demonstrates an ability to monitor environmental changes at a large scale despite existing obstacles which can be resolved through the use of additional data sources and optimization method

1. **Applications/Discussion/Abalation Study :**

• **5.1** Applications

• Forest Management and Monitoring

• Environmental Protection Organizations

• Government Policy Formulation

• Climate Change Research and Analysis

• Biodiversity Conservation Initiatives

• Smart Environmental Monitoring Systems

Benefits of the Proposed System:

• Automated and scalable monitoring system

• High precision through Deep Learning techniques

• Reduced human effort and time consumption

• Early detection of environmental threats

• Supports sustainable development initiatives

5.2 Discussion

The experimental results show that combining NDVI with deep learning systems leads to results in deforestation detection. The proposed system has succeeded in solving problems that exist in conventional monitoring methods through its capacity to conduct automated analyses and track environmental changes across extensive areas.

The system demonstrates its advantage through its capability to execute pixel-by-pixel analysis using U-Net architecture. The system enables detection of deforestation through its ability to process complicated areas containing diverse types of land cover. The model uses CNN-based feature extraction to enhance its ability to detect patterns in satellite images.

The inclusion of NDVI as a system component creates an element that enhances the vegetation assessment process. NDVI provides information about plant health enabling the model to distinguish between healthy vegetation and degraded land. The combination of spatial attributes leads to detection results that demonstrate higher reliability than previous methods.

The system provides users with a benefit because it enables detection of changes that occur over multiple time periods. The model uses satellite images from different time periods to detect changes that happen gradually in vegetation cover. The method provides a solution for early deforestation detection, which traditional techniques struggle to accomplish.

The system faces performance challenges because it relies on satellite imagery that must meet quality and resolution standards. The accuracy of NDVI calculations and classification results depends on changes in lighting conditions, seasonal variations and atmospheric disturbances. Deep learning models require labeled training data, which is not always available for their development.

Deep learning models face restrictions because they require computational resources. Training CNN and U-Net models requires processing power and memory especially when working with high-resolution images. The development of hardware technologies including GPUs and cloud computing provides solutions to these existing problems.

The proposed system shows potential for actual use because it delivers dependable results in automated environmental monitoring.

5.3 Ablation Study

The ablation study assesses how different parts of the proposed system impact its performance. The analysis shows how modules operate in the system and helps find the effective technique combination for operations.

Effect of Removing NDVI

The system uses satellite images for classification when NDVI is removed. The model shows an accuracy drop because it cannot differentiate between vegetation and partially degraded land. The analysis shows that NDVI serves a role in enhancing the ability to detect vegetation.

The model fails to detect spatial patterns because it depends on traditional machine learning methods that need manual feature extraction. The research shows that CNNs provide assistance for improving classification accuracy.

The model shows image-level classification results when U-Net segmentation is not implemented. The system loses its ability to accurately identify deforested areas because of this issue. The segmentation output becomes accurate and boundary detection is significantly reduced.

The system achieves its performance when all three elements, including NDVI, CNN and U-Net function together as a unified system. The system achieves accuracy because it combines spectral information and spatial information to identify deforestation and land degradation patterns with reliable precision.

The summary of performance comparison shows that upcoming research needs to assess model configurations. The study results indicate that each element of the system provides performance support to the entire system. The full combination of all modules creates an environmental monitoring system that operates with both strength and efficiency.

1. **Conclusion**

The research establishes an automated intelligent system that uses computer vision and deep learning methods to identify deforestation and land degradation. The system uses sensing data, image processing and NDVI-based vegetation analysis and advanced neural network models including Convolutional Neural Networks and U-Net to monitor environmental changes with high accuracy and operational efficiency. The system successfully addresses the limitations of manual methods, which are often time-consuming labor-intensive and less scalable.

The experimental results demonstrate that the combination of NDVI and deep learning enables detection of deforested and degraded areas. The system uses -temporal satellite imagery to perform effective change detection, which enables it to detect environmental changes that occur at both large and small scales. The U-Net pixel-level segmentation method increases area identification accuracy, which enables the system to function in field situations.

The proposed model achieves performance in terms of accuracy, precision, recall and F1-score indicating its reliability in detecting vegetation changes. The system creates output, including NDVI maps, classification maps and change detection results to assist environmental monitoring through improved interpretation and decision-making.

The research supports Sustainable Development Goal 15 by demonstrating how intelligent technologies can enhance forest conservation and land management. The system allows government agencies, environmental organizations and policymakers to monitor deforestation while enabling them to take action for resource preservation.

Future research will explore three areas, including better model efficiency, real-time data processing and the addition of new data sources, such, as drone images and climate information. The model will achieve operational results through the combination of advanced deep learning systems and extended dataset implementation. The proposed system offers an reliable solution that can scale to meet the needs of sustainable environmental monitoring and conservation efforts.

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