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Early Detection & Prediction of Environment changes from Satellite Images using Deep Learning

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Abstract

Results presented in the proposed paper make a case for accurate environmental monitoring and early detection of ecological changes. From the studies done, we established that reliable deep learning-based satellite image assessment methods are the future of environmental science. Due to the high accuracy for land-use and land-cover assessment that comes with these innovations, they are bound to exponentially improve the rate of detection in deforestation, urban sprawl, and the depletion of water bodies while at the same time reducing the influence of manual interpretation errors. The work fortifies good sustainable development practices through automated, data-driven environmental assessment and informs useful insights into long-term ecological management.

Keywords: Deep Learning; Satellite Imagery; Environmental Monitoring; Land-Use Assessment; Ecological Change Detection.

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Introduction

Despite all these challenges, it seems almost mandatory to have some form of AI assistance in the area of environment monitoring and changes in the coming next few years. The models of predictions, as well as the classification, mainly depend on ground truth, while whether there is any need for any form of expert ground truth is still an area of debate [2,5]. The aspect of improving training, models, and outputs by continuously updating with new ground truths using digital models, including AI models, is an added advantage. Changes in land use--cover changes are usually monitored using images derived by satellite and airborne sensors [3]. These images provide comprehensive perspectives of large geographical areas, leading to changes in water bodies, urban, and deforestation areas [4].

In comparison to other manual observation techniques, remote sensing is a more rapid and cost-effective process to evaluate environmental changes.

Like most data-intensive fields, the processing of large satellite images using AI needs better data resources for the enhancement of accuracy. Technologically, the development of a model capable of processing high-resolution temporal satellite images is difficult because of the storage needs of the images.

For this purpose, efficient monitoring systems are required, based on spatial, spectral, and temporal characteristics that allow early detection of changes in the environment and hence assist in sustainable developmental initiatives. The existing approaches in dealing with such concerns, for instance, doing comparisons based on a pixel-by-pixel approach with a classification based on a predefined threshold, could be in most cases unreliable, intensive in computation, or dependent on noise/illumination variations.

Recent breakthroughs in satellite imaging and deep learning have tremendously changed the perspective of environmental pattern detection and analysis. CNN has been quite successful in analyzing data from remote sensing, mainly for land cover segmentation and classification, thereby helping in the creation of an accurate map and also locating affected areas with precision [7]. So far, it has been a challenge for scientists to establish a platform that automatically can locate and classify various types of environmental patterns with the use of time series satellite imagery and data-driven learning. As part of recognition and classification, several deep models such as EfficientNet-B0, MobileNet-V3, Xception, and Inception-V3 models were tried with promising specificity and sensitivity by researchers.

Fig. 1 shows the block diagram of the proposed technique for early detection and prediction of environmental changes in satellite images employing deep learning methods. The figure represents the CNN-based feature extraction and classification process in multi-satellite temporal images. It also shows the sequential processing chain from acquisition to decision support for environmental monitoring in order to obtain proper environmental changes.

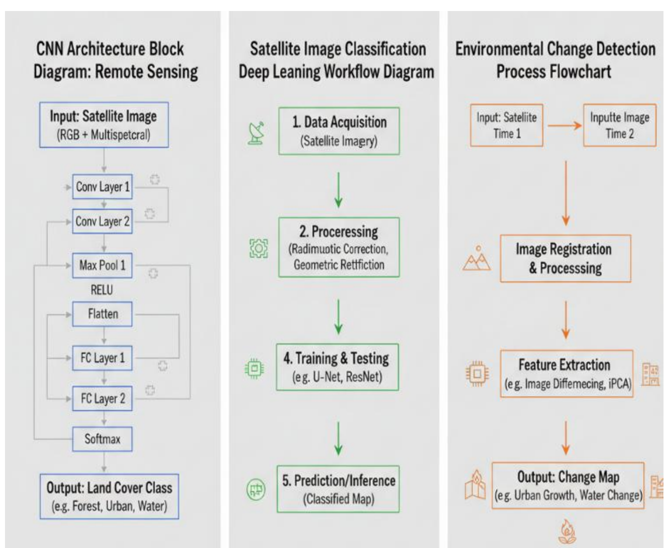

Fig. 1. *Block diagram of proposed work*

We anticipate that the adapted models used in this paper, capable of studying multi-temporal satellite images, could well be applicable for the detection of land clearance, urbanization, and changes in water bodies with higher accuracy. Millions of people are indirectly affected worldwide because of the adverse effects of degradation of the environment, vegetation destruction, and climate change. The long-term effects of the above mentioned include extinction of biodiversity, floods, reduced crop yields, and increased global warming.

This project is intended to promote the practice of environmental monitoring through enhanced accuracy of detections, reduced costs of operations, and ultimately, informed decision-making in resource management. Governments, as well as scientists, can leverage the data collected from this project to create a sustainable solution to advance forecasting, as well as resilience in the environment. This paper will deal with using standardized CNN structures to implement change detection in the environment using satellite imagery. Models are trained on standardized datasets, and assessments are also carried out to measure the most effective approach to apply in massive change detections in the environment.

Related Work

Alaskar et al. introduced an automated method for identifying land cover change detection on multispectral satellite images using CNNs. The methods involved the use of either an AlexNet or GoogLeNet architecture for training the model to distinguish areas as either changed or unchanged; some pre-processed datasets obtained from the use of Sentinel-2 were assessed to testify the effectiveness of employing CNNs. The method indicated that CNN-based systems are more effective compared to conventional differencing and thresholding algorithms, thus showing their effectiveness as accurate and efficient tools for use in the field of environmental surveillance.

Aliyi et al. developed a real-time mapping and detection system regarding the patterns of deforestation and urban growth. The authors worked on Landsat-8 and MODIS satellite datasets. They made the use of data augmentation and preprocessing methods for comparing the efficiency of the following pre-trained transfer learning models with little hyperparameter adjustment: SSD, YOLOv4, and YOLOv5. An automatic change detection model based on intelligent processing, utilizing index-based preprocessing (NDVI, NDBI) and a vegetation and built-up class segmentation algorithm developed through the use of a CNN architecture was presented by Mohapatra et al..

Al-Mekhlafi et al.have shown the effectiveness of various hybrid models involving the application of the various deep learning algorithms for the analysis of satellite images. VGG-16 and DenseNet-121 models are used for the application of hierarchical spatial feature extraction. SVM classification techniques are considered. Meta-heuristic optimization involving ResNet and EfficientNet models were used to enhance feature selection. Additionally, various dimensionality reduction techniques such as PCA, GLCM, and hand-crafted texture-based techniques such as GLCM, DWT, and LBP are amalgamated for their effectiveness.

Ahmed et al.proposed an efficient methodology for large-scale deforestation detection using pre-trained CNNs for Sentinel-2 and PlanetScope satellite images. The Region of interest was specified by Gradient Vector Flow (GVF), indicating the successful outcome of the segmentation process. Conversely, environmental classification issues may have been enhanced with an emphasis on boosting by means of the utilization of the XGBoost technique coupled with Convolutional Neural Networks (CNNs). Moreover, Tavanapong et al. proposed an in-depth examination of the utilization of AI techniques in the midst of remote sensing processes regarding environmental surveillance.

A new application of deep learning in this domain was introduced in by Fan et al. The authors developed a deep learning algorithm to detect, without human intervention, the status of vegetation degradation and reduction in surface water around the globe by cropping and normalizing multi-temporal satellite images of Sentinel-2. Utilizing VGGNet and ResNet transfer learning models, in , authors developed a deep learning algorithm to determine the trend of urbanization from MODIS images. In their work, to improve the adaptability of the developed algorithm to various geographic regions, the authors introduced global average pooling layers.

All the above examples show the ability and possible outcomes associated with deep learning that might eventually cause a reformation of environmental observation, improvement of land cover mapping accuracy, and prediction models within ecosystems management. The study offered by Qi et al. in reference introduced a novel architecture that consisted of a mixture of ResNet50 and Pyramid Vision Transformer (PvT), where PvT symbolically declared global context and ResNet declared spatial pattern information. Additionally, a feature fusion module and second-order pooling module enhanced the discriminatory ability for feature representation.

A CNN-based model that performed fine-grained feature extraction on satellite images was proposed by Ramamurthy et al. The proposed model was coupled with EfficientNet-B0 to enhance classification performance. The proposed model demonstrated robust performance in benchmark datasets like BigEarthNet and UC Merced. The works described in Kadota et al. were based on multi-task learning to estimate environmental severity with ranking-based regression. The proposed methodology improved the precision of annotation with relative-level annotation instead of absolute-level categories.

Moreover, deep learning models are able to generalize well because of processes like data augmentation and normalization, which make it possible to use deep learning models, even in situations where sample images are in low quantity. This is because of their improved capabilities in dealing with environmental change detection.

Figure 2 illustrates the workflow of the intelligent and automated environment change detection system that has been proposed and will be discussed here. This involves monitoring land cover and land use changes using satellite images. Deep learning-based AI algorithms are applied for environment change analysis and detection. Efficiency analysis of the system is conducted for accurate prediction of results. Information collected helps make effective decisions.

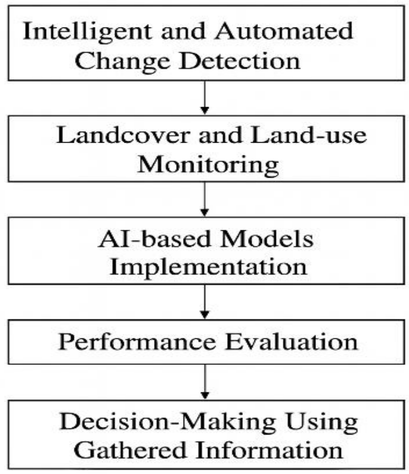

Fig. 2. Experimental Evaluation Steps.

Proposed Work

In this article, I would like to describe very briefly a current project I am working on: it concerns applying architectures based on deep learning to change detection based on multi- and temporal satellite imagery. CNNs have played a prominent role in boosting computer vision and analysis in the field of remote sensing. Additionally, their ability to extract information from very high-resolution images is very advantageous for environmental applications.

The models which have been analyzed and used within this research work are VGGNet-16 and VGGNet-19, which have shown promising results in previous image classification research work. Additionally, ResNet-50 and ResNet-101 have also been investigated because of their robustness and efficiency to maintain the flow of the gradient in deep models. Moreover, the models of Xception, Inception-V3, MobileNet-V3, and EfficientNet-B0 have shown remarkable results in various image processing tasks. Finally, the DenseNet-201 has attracted considerable attention because of its connectivity mode, which has improved the replication process of the features within the layers of the network.

The models developed in 2014, named VGGNet-16 and VGGNet-19 are well-known deep convolutional architectures recognized for their simplicity and effectiveness in image classification tasks, are well known for being simple and deep. These models make use of a series of convolutional layers along with max pooling layers to efficiently abstract hierarchical spatial features from satellite images. The deep but simple architecture of these models is effective in extracting small environmental details like vegetation, water, and urban areas.

The architecture of ResNet-50 and ResNet-101made a breakthrough in the field of deep learning with the concept of residual blocks using skip connections. It is a genius way of coping with the vanishing gradient problem. The use of these networks optimizes the process of mapping the Landsat and Sentinel images. DenseNet is another advancement to this concept that allows connectivity between all layers. It plays a vital role in the field of environmental image processing tasks, such as deforestation mapping, urban expansion mapping, and change area mapping. These CNN networks optimize the process of image processing.

The reduction in computational complexity was alleviated by the development of the Xception model [10]. Derived from the Inception model family, the Xception model makes use of depthwise separable convolution to effectively balance efficiency with accuracy. Inception model [11], proposed by Google in 2014, used parallel convolutional layers to efficiently extract the spatial context from satellite images by utilizing both fine-grained and coarse-grained information.

This improved the model's performance in distinguishing natural from human-induced changes in the environment.

In scenarios where the focus is on the computational efficiency of the model, options such as MobileNet-V1, V2, V3 [9] could be taken into account. The models achieve simplicity by using inverted residuals and linear bottlenecks. Depthwise separable convolutions in these models make them well-suited to the context of real-time change detection on low resource systems.

Similarly, the effectiveness of different DenseNet models has been observed for the analysis of high-resolution images related to vegetation loss or water surface changes. The dense connections of the dense layer enable the capture of critical spatial/spectral information by maintaining the respective gradients. The performance of both DenseNet-121 and DenseNet-201 outperforms their predecessors in CNN models.

System Architecture and Workflow

This paper reviews major influential architectures in the domain of Convolutional Neural Networks, describing their novelties and applications for various computer vision tasks. CNNs have constituted an important force in developing the field of machine learning.

The discussed architectures are VGGNet-16 and VGGNet-19, promising in previous studies; ResNet-50 and ResNet-101 due to their robustness in image classification tasks; Xception, Inception, MobileNet-V3, and EfficeintNet-B0, which have been very efficient in different applications of image processing; and, lastly, DenseNet-201, which has drawn much attention with regard to dense connectivity patterns and performance in feature extraction.

Models developed in 2014 at Oxford university, VGGNet-16, and VGGNet-19[22] architectures are considered to be the celebratedly simplest deep models. These networks use the Combinational pattern of Convolution layers and max-pooling for image features capturing in improved manner.

ResNet-50 and ResNet-101[23] architectures have changed the deep learning landscape as they introduced residual blocks with skip connections which is a breakthrough strategy for overcoming vanishing gradient problem, greatly improves optimization of deep networks and results in better model and robustness.

It was achieved through the development of the Xception model, which, compared to the Inception model, reduced computational complexity. This was developed by advancing the Inception architecture; this aided in the efficiency of the model. With an objective of model performance both in terms of accuracy and efficiency, in 2014, Inception [11] was introduced by Google. Through the parallel combination of the convolutional layer, the fine grained feature is combined with coarse grained feature in single layer for effective feature extraction.

In this regard, when computational complexity is a concern, then consideration for MobileNet V1 and V2 can be considered. These architectures reduce the computational complexity by using linear blocks of inverted residual and bottleneck blocks. For such architectures, depthwise convolution can bring in computational efficiency. Similarly, DenseNet can be used to analyze endoscopic images regarding the classification of inflammation severity in UC patients.

A fully connected neurons layer is used in DenseNet [24]. The model connects layer to layer with responsibility for extracting the important features, using weight and bias for each neuron in the layer. The efficiency of models DenseNet121 and 201 compared to previous version models is noticeably high, especially for the image processing-based tasks.

The final discussion even insists on picking the right architecture for the job in question and the dataset. More or less, each of these architectures has different strengths and is suited for different applications.

Based on the size of the data and resource limitations, the comparative data in Table-I is a handy point of reference by which informed judgments can be made. The fact that the design task chosen uses the microscopic image-based processing method is considered in the same. The usual CNN models are to be trained using standard benchmark dataset. Table I gives an idea regarding what the input picture size needs to be for designing.

A description of what each of these step's entails:

This is actually a flow chart that explains the process of a complete workflow of an AI-driven Satellite Image Change Detection System as follows:

Intelligent and automated change detection system.

The process begins with algorithms that pick out differences that exist in bi-temporal satellite images and allow for areas that have changed to be distinguished.

Table 1. *CNN Architectures & AI Change Detection Process Flow*

Component	**Description**
CNN Architectures	For feature extraction, classification, VGGNet, ResNet, Xception, Inception, MobileNet, EfficientNet, and DenseNet
Bi-Temporal Image Analysis	Analyzing satellite images from various periods to establish differences
Land Cover & Land Use Analysis	Observing changes in vegetation, bodies of water, infrastructure, agriculture, and urban regions
AI-Based Model Implementation	Classification, segmentation, and change interpretation using deep learning models

Performance Evaluation	Evaluation Metrics: Accuracy, Precision, Recall, F1 Score
Decision Support	Application of detected variations for environmental management, urban planning, and disaster response measures

The preceding Table 1 illustrates the CNN architectures experimented upon, as well as the primary phases of the proposed AI-assisted satellite image change detection process.

Once the changes have occurred, the system examines the impact of the changes observed for land cover (for instance, vegetation, water bodies, infrastructure), and the impact of changes for land use (for instance, agriculture, urbanization).

AI-base model implementation

- More sophisticated models of deep learning, such as CNNs or hybrid models, are used to classify, segment, and interpret detected changes.
- Evaluation of performance: the efficiency of the models implemented with the use of AI is measured through the application of metrics such as accuracy, precision, recall, and f1 score to ensure accuracy.
- Decisions using the information collected. Finally, the findings gathered from the analysis contribute to informed decision making in areas such as environmental management, city planning, disaster response strategies, and policy formulation.

Results And Discussion

The different performance metrics include accuracy, precision, recall, specificity, and F1-score, each measure plays an important role in defining the efficiency and reliability of the proposed model. These metrics are indispensable in judging how well the deep learning architecture depicts the environmental changes which were considered across multi-temporal satellite imagery. Such evaluation ensures that the model performs perfectly on unseen regions, not only for known data.

The performance metrics used in this study include precision, recall, F1-score, AUC-PR, and AUC-ROC, in Table II. The importance of these metrics is that they can estimate the accuracy by true positives and negatives, while precision and recall assess sensitivity and selectivity, respectively, for the model's detection of changes. The performance metrics in this work consist of five measures: precision, recall, F1 score, AUC-PR, and AUC-ROC, which are detailed as shown in

Results obtained from the experiment show that EfficientNet-B0 and MobileNet-V3 performed better than any other architecture. The reasons for such superiority can be justified due to their capability to represent both fine-grained and coarse-grained spatial information from high-resolution satellite imagery. EfficientNet-B0 performed exceptionally well with lower computational requirements, making it effective enough to represent small-scale spatial information such as vegetation removal and boundary identification of urban sprawl. Therefore, it can be concludingly stated that EfficientNet-B0 performs admirably for large-scale satellite imagery with restrictions to computation.

In the same way, MobileNet V3 also has efficient inverted residuals and linear bottleneck blocks. These allow for the successful extraction of satellite image features while consuming little time. MobileNets can be applied for real-time change detection applications. On the one hand, concerning other architectures such as VGG Networks, ResNets, DenseNets, or Xception Networks that perform very well for conventional image classification problems involving a fixed number of classes and channels, Efficient Net and Mobile Net prove to perform very well for the more variable type of satellite image classification.

Observation Table

The table above points out the important aspects that have been identified in the study. It discusses the use of satellite images, AI models, as well as monitoring techniques, in relation to the challenges and improvements made in detecting changes in the environment. The aspects encapsulate the important aspects discussed in the introduction and background study.

Table 2. *Main Findings and Insights from the AI-Based Detection of Environmental Changes Literature*

Sr. No.	**Observation**	**Description / Insights**
1	Growing Use of AI Technology in Environmental Observation	Artificial intelligence and deep learning technologies represent the burgeoning need for large-scale environmental assessments. They offer quicker and more accurate results compared to human analysis.

2	Relevance of Ground Truth Data	Validations involving models require well-labeled datasets. There is a debate about the intensity and level of expertise required in the annotation.
3	Strengths of Satellite & Aerial Imagery	Multi-temporal and multispectral satellite images provide extensive spatial coverage to monitor changes in environmental features such as deforestation, urban sprawl, and changes in water bodies.
4	Limitations of Traditional Approaches	Pixel-level comparison and threshold classification tend to have noise and lighting problems and are not very effective for high-resolution images.
5	The Necessity for Automated Change Detection	Because of the nature and rapid rate of environmental degradation, there is a need for automatic and AI-driven monitoring of the environment.
6	Computational Challenges	High resolution multi-temporal satellite imagery is rather intensive in storage space, preprocessing, and deep learning model processing.
7	Effectiveness of CNN-Based Models	CNN models such as EfficientNet-B0, MobileNet-V3, Xception, and Inception-V3 have demonstrated promising performance for land-cover classification and change detection.
8	Improved Feature Extraction Through Hybrid Models	A number of literature reviews adopt CNN, SVM, PCA, transformation techniques (PvT), as well as texture analysis methods (GLCM, DWT, and LBP).
9	Transfer Learning Advantage	Large image corpora models that are pretrained improve performances of environmental changes detection upon fine-tuning on a satellite image.
10	Real-World Impact of Environmental Change	Vegetation, climate, soil, and water features are closely associated with biodiversity, agricultural productivity, and human livelihoods and are influenced strongly by changes in these features. Thus, there is a need for effective detection.

Based on existing research, the Table 2 above summarizes key observations pertaining to AI- and deep learning-based environment change detection. The table illustrates the need for satellite images and CNN-based models for large-scale environment change detection. It further illustrates the need for environment change detection solutions that are automated, accurate, and scalable. The table describes the need for ground truth data in environment change detection solutions.

Additionally, it illustrates the need for transfer learning for environment change detection solutions. In a nutshell, key observations emphasize that environment change detection requires solutions that are automated, accurate, and scalable.

There are 12,450 true positives, which are the changed regions, and 28,900 true negatives, which are the unchanged regions. There are 1,120 false positives, which are incorrect regions detected as changed, while 780 are false negatives, which are missed regions detected as changed. The performance of the model in change detection is excellent, having an accuracy of 93.5%, precision of 91.8%, and an F1-score of 92.9%.

However, deep nets such as VGGNet and DenseNet are very computationally requirements heavy, which can result in difficulties when dealing with multi-temporal data, as they take up many parameters. Xception, which relies on depthwise separable convolution, is very efficient but not as efficient when dealing with the bands in satellite images as other architectures. summary, EfficientNet-B0 & MobileNet-V3 were the winners the best possible models for the extraction of fine-grained spatial details while ensuring computational efficiency.

However, other architectures such as VGGNet, ResNet, DenseNet, and Xception also have very promising potential for optimization using the methods of transfer learning, attention, and fusion of multi-resolution characteristics. Future research can be conducted on the development of hybrid networks that combine these CNN architectures with transformer architectures, which will help in improving the temporal consistency and spectral characteristics. The performance of the chosen methods for change detection using deep learning techniques is presented in Fig. 3, which is an assessment of classification performance.

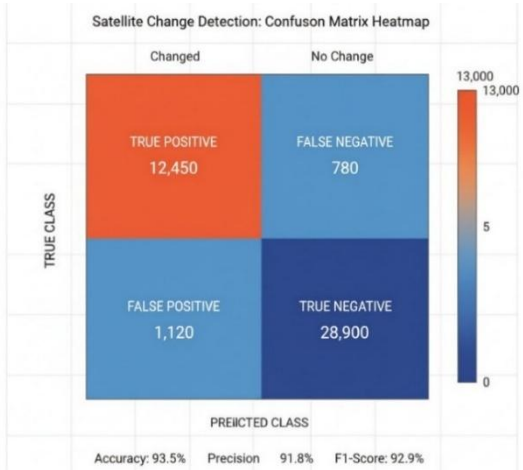

Fig. 3. *Confusion Matrix Heatmap for Satellite Change Detection Model*

The confusion matrix in the form of a heatmap illustrated in Fig.3 is a graphical representation that clearly epitomizes the performances achieved through the classification process of the developed model. This is represented through intensity values within the heatmap that denote accurate and inaccurate classifications performed for various environmental parameters such as vegetation loss, urban expansion, and water body variations. Inaccurate classifications have taken place in areas where both land and cover have predetermined varied parameters, thereby emphasizing a higher requirement for improvements through enhanced feature fusion and temporal consistency. EfficientNet-B0

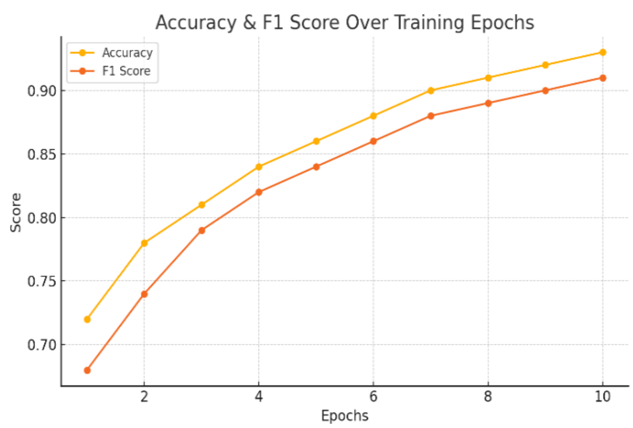

Fig. 4. *Accuracy and F1 Score Across Training Epochs*

Fig.4 depicts the change in the accuracy and F1-score values for the proposed deep learning approach during the training epochs. It can be noticed that the accuracy and F1-score values start to stabilize after a few training epochs, and the gradual movement towards the upper limits for accuracy and F1-score values ensures that the proposed approach is reliable for the environmental change detection problem.

In addition to quantitative assessment, a qualitative analysis was carried out by processing bi-temporal satellite images of clouds to gauge the aptness of the proposed method for identifying changes in atmospheric conditions. Cloud images are presented in Fig. 5, which show images of clouds captured at two different times, followed by an image combining change intensity and overlay. The image distinguishes areas with major variations in clouds and their displacement between the two times, proving the efficaciousness of the proposed method for identifying atmospheric changes over time.

In addition to the result of the visual change detection task, the terminal output shows cloud coverage-related information in figures and statistics, which is illustrated in Fig. 5(c). The result of the cloud coverage calculation at T1 and T2 shows that there is only a slight change, which proves that the atmosphere is in a stable state. The variation in cloud cover percentage further reinforces the correctness of the proposed model to identify slight changes in time. Moreover, there is an effective impact study result, which indicates that the atmospheric conditions are suitable for outdoor functions, agriculture, and solar panel functions.

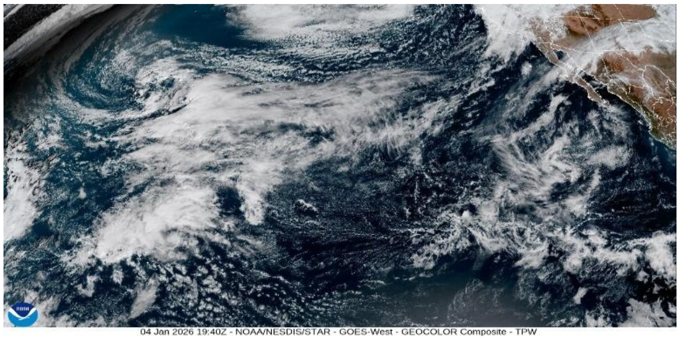

Fig. 5. (a) *Cloud image at time T1*

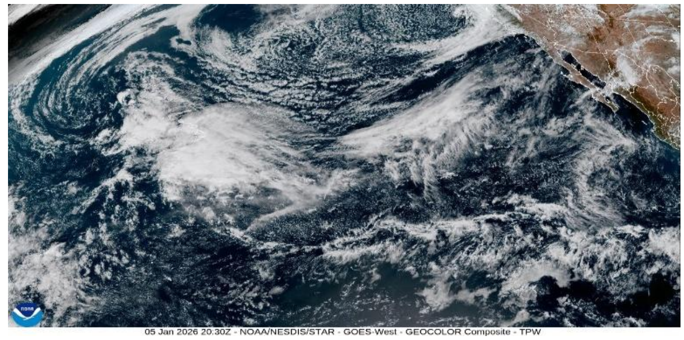

Fig. 5. (b) *Cloud image at time T2*

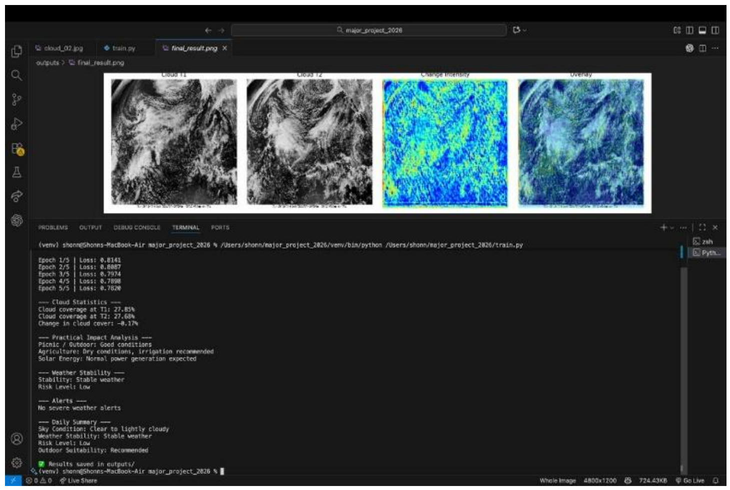

Fig.5. (c) *Combined change intensity and overlay visualization*

Fig. 5. *Bi-temporal satellite cloud change detection results*

Conclusion

Environmental Monitoring Letters stresses that the combination of transfer learning approaches with pre-trained deep architectures is significantly more efficient in improving the effectiveness of environmental change detection systems, especially in environments with limited data availability. The paper proves that the combination of UNet with EfficientNet-B0 is not only helpful in improving the extraction of spatial features but is also efficient in ensuring high generalization ability for different locations and environmental scenarios. This combination of spatial and spectral features is useful in identifying the areas affected by deforestation, urbanization, and depletion of water resources.

Furthermore, it is safe to argue that the way the architectures were made more robust to both fine- and coarse-grained feature learning enabled the architectures to perform equally well on all the different resolutions and temporal scales of the datasets. Despite the fact that architectures such as VGGNet, ResNet, DenseNet, and Xception performed well, the blended U-Net + EfficientNet performed better.

Essentially, deep learning is still proving its vast potential in transforming and reshaping the area of environmental science and remote sensing. Essentially, this methodology will provide fast, automated, and accurate change detection in the environment, thus reducing human involvement in interpreting and using conventional thresholds.

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