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Infrastructure Change Detection from Satellite Imagery Using Deep Learning Techniques

[1]Dr. D. V. Lalitha Parameswari, [2]Konga Mamatha, [3]Andamdas Tejeshwini, [4]Ganjikunta Sai Vyshnavi, [5]Cheekati Veena

[1,2,3,4,5]Department of CSE, G. Narayanamma Institute of Technology and Science (For women), Shaikpet, Hyderabad, Telangana-500104, India

E-mails: [1]dvlalitha@gnits.ac.in, [2]kmamathak9@gmail.com, [3]andamdaastejeshwini@gmail.com, [4]vyshnaviganjikunta31@gmail.com, [5]cheekativeena@gmail.com

***Abstract* - Satellite remote sensing imagery is crucial in monitoring and evaluating urban and rural area changes. The conventional machine learning techniques applied to analyze such images tend to have limitations, such as high computational costs and the requirement of a large amount of labelled data. Deep learning offers a strong alternative, with the ability to extract features automatically and identify intricate patterns from large datasets. Convolutional Neural Networks (CNNs), including U-Net, have gained general acceptance for alleviating these shortcomings. The balanced encoder-decoder structure of U-Net architecture and skip connections make it well-suited to semantic segmentation as well as detecting changes in remote sensing images. The use of residual connections is helpful in the preservation of key information during the training process and improves model performance.**

A deep learning system that detects infrastructure changes through time utilizes satellite pictures and spatial data for time-specific identification with precision. STANet serves as the integration framework within the system because it unites spatial with temporal attention methods for detecting minute changes between satellite images. The spatial component of attention allows the model to concentrate on critical changing areas yet the temporal aspect enhances time-based change identification. The system integrates satellite images and different global infrastructure labeling data to detect infrastructure changes with high precision. Advanced image processing along with deep learning models including U-Net, FCNs, and STANet creates an improved system for change detection which leads to better urban planning and disaster management and infrastructure maintenance capabilities.

Keywords: Remote sensing, Satellite imagery, Deep learning, Convolutional Neural Networks (CNNs), Change detection, Urban planning.

1. INTRODUCTION

Satellite technology development at rapid pace brought enhanced capabilities to study Earth's surface through time-based observations of land use alterations and infrastructure and environmental changes. Because of high-resolution multispectral imagery Sentinel-2 serves as a leading satellite system that provides essential support for planning cities and managing disasters and monitoring environmental changes. The increased importance of accurate and reliable change detection emerges from the ongoing city growth and transformations to landscapes and natural environmental modifications. The monitoring of transformations requires remote sensing techniques that focus on change detection through satellite imagery.

The process of detecting changes through satellite imagery remains difficult to accomplish. The process of accurate change detection faces obstacles from different illumination conditions and misaligned images and minimal image variations. Traditional methods consisting of image differencing and machine learning techniques experience difficulties when detecting modifications when small-scale changes occur in imbalanced datasets that have less altered area than unchanged parts. The current detection methods need to be enhanced through advanced methods to achieve better detection precision.

The implementation of deep learning models using spatial-temporal attention mechanisms and pixel-level segmentation addresses problems related to change detection. The proposed solution employs STANet and U-Net architectures to boost the detection of changes. STANet employs attention models to detect pivot areas of alteration while U-Net provides exceptional segmentation accuracy which makes it efficient for infrastructure along with land use change detection. The system utilizes these innovative approaches to establish a powerful method for satellite-based infrastructure monitoring which enhances accessibility of computation to all sectors.

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II. RELATED WORK

The process of monitoring changes across different times in remote sensing operations defines the fundamental task known as change detection (CD). Multiple traditional change detection approaches utilized pixel-wise comparison and statistical analysis along with manual features yet they struggled because of differences in light levels and sensor disruptions and geographical change. Thresholding methods together with clustering algorithms were used early by machine learning methods to improve accuracy however they needed manual tuning adjustments because of their limitations in handling complicated environments. The revolution in change detection became possible through deep learning when convolutional neural networks (CNNs) brought the capability of automated feature extraction along with representation learning. FCN along with U-Net architecture succeeded in performing spatial hierarchy capture yet they presented insufficient models for processing temporal relationships effectively. Twin networks in the Change Detection Network (CDNet) used Siamese-based architecture to process before-and-after image pairs more effectively thus improving change localization. The models experienced difficulties with misalignment problems because they failed to integrate broad contextual relationships between different areas.

Attention mechanisms integrated into deep learning models guide feature representation improvements which lead to better detection accuracy in changed areas. Spatial attention methods concentrate on essential regions to improve recognition of changed and unchanged regions and self-attention models use Transformers to establish relationships within long sequences. Recent developments utilize spatio-temporal attention systems to let networks direct their focus toward meaningful changes throughout multiple time durations. Through its attention-based framework the Spatio-Temporal Attention Network (STANet) effectively combines spatial with temporal features for precise detection of changes. STANet utilizes attention mechanisms to merge features more effectively while eliminating false detections and adapting to various change detection situations thus achieving state-of-the-art performance in remote sensing applications.

III. LITERATURE SURVEY

A hybrid method to predict and classify land use and land cover (LULC) change through deep convolutional neural networks has been proposed by J. Jagannathan et al. [6]. A hybrid hot encoding VGG19 approach along with transfer learning using the ResNet50 model, on satellite as well as aerial images, has been used by their study. The data were pre-processed using image augmentation to improve classification accuracy. The model attained a remarkable 98.5% accuracy in classifying changes in urban areas, water bodies, and vegetation, proving to have the capability of accurate urban planning and mitigation measures, for example, mitigating the urban heat island effect. Future use of the technique may be employed by government agencies for better city planning and environmental conservation.

Yangpeng Zhu et al. [9] presented a new deep learning paradigm for land cover change detection with limited training samples from heterogeneous remote sensing images (Hete-CD). It integrates a multiscale network and a kernel-attention module together with a non-parameter sample-augmented algorithm, which selects potential samples according to the Pearson correlation coefficient. This iterative method showed competitive precision on four sets of actual High-Resolution Satellite Images from Landsat-5, Radarsat-2, and Sentinel-2, outperforming conventional and state-of-the- art deep learning techniques by 3.38% and 1.99%, respectively. The simplicity of the framework and low parameter needs make it amenable to real-world applications, with further research aimed at increasing the dataset and multiclass change detection.

Oliver Sefrin et al. [7] conducted a research on land cover classification and change detection with multitemporal and multispectral Sentinel-2 satellite imagery. He utilized fully convolutional networks (FCN) with long short-term memory (LSTM) networks to efficiently process both monotemporal and multitemporal data. The research emphasizes the importance of pre- processing operations, including shoreline masking and class exclusion, which enhanced water classification and ensured dataset integrity. Results indicated that multitemporal LSTM methods performed better than the FCN model by 3 to 5 percentage points in land cover change detection. Future work will involve applying the LSTM methods to different image sequences and assessing ground truth quality to improve change detection ability.

Hao Chen et al. [4] introduces a Siamese-based spatial-temporal attention neural network for remote sensing image CD capable of handling illumination changes and misregistration discrepancies in bitemporal images. The method incorporates a change detection self-attention mechanism into feature extraction, enabling attention weights to be computed between pixels in terms of time and space, which enables discriminative feature enhancement. Chen introduces the LEVIR-CD dataset, significantly larger than existing datasets, with 637 image pairs and over 31,000 labeled change instances. The attention module improved the F1-score of the baseline model from 83.9 to 87.3 while maintaining manageable computational overhead. The study highlights the method's superior performance compared to state-of-the-art approaches and outlines future directions for enhancing spatial-temporal dependency modeling.

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Waleed Alsabhan et al. [8] conducted a study on Automatic Building Extraction Method From ResNet50 enhanced U-Net architecture for high-resolution satellite images. Rethinking Cities Housing: The research examines the challenges of urban settlements wherever they emerge, rather especially in high-density areas, such as Boston. A comprehensive analysis The analysis is carried out on the Massachusetts building dataset, consisting of buildings, mostly residential buildings. U-Net: A U-Net Model to Perform ControlExp Data Imputation and Translation | The U-Net Model The introduced U-Net model is capable of achieving an Intersection over Union (IoU an F1 score of 0.9 and accuracy of 82.2%, with overall accuracy being 90% in image segmentation. Abstract Over the last few years there has been a rise in the use of Deep learning techniques for predictive modelling. in facilitating building mapping in urban areas which helps better city planning based on precise satellite image interpretation. The study demonstrates robustness of the U-Net- ResNet50 model quantitatively by showing accurate building footprints, which is essential for urban growth management.

Harshika A. Kaul et al. [5] published a article regarding LULC mapping in Jalgaon. District, March and November IRS P-6 LISS III satellite images Supervised classification in 2007 It recognizes seven LULC classes from the research. And utilize accuracy assessment with an error matrix and a Kappa analysis of errors. The results suggested that the land cover in Land cover in 49.43% was agricultural land in November, strongest increase in agricultural areas compared to pre-monsoon (9.02% increase) to post-monsoon. For March, the global classification rate is 89% and 111.09% for regional November, suggesting effectiveness of the methodology, at least for the regional level LULC assessments. This study showcases the application of remote sensing Approaches for monitoring changes in land cover/use, and the promise they have for Utilisation of Spatial Data For Efficient Management of Irrigation Projects.

Yi Liu et al. [10] propose a dual task constrained deep Siamese convolutional network (DTCDSCN) model for object change detection in remote sensing imagery. The model integrates a change detection network and two semantic segmentation networks, improving both feature discrimination and providing comprehensive change detection maps. This is achieved with the help of the dual attention module (DAM), which enhances feature representation by exploiting the dependencies between channels and spatial locations. Thus, by modifying the focal loss function, the model can solve sample imbalance problems. The experimental findings on the WHU building dataset suggest that the DTCDSCN outperforms other methods in all aspects including precision, recall, F1-score, and intersection over union for building change detection.

Haixu He et al. [3] introduced the Temporal Semantic Segmentation Change Detection (TSSCD) model that applies deep learning to detect urban land cover changes by jointly modeling spatial (where), temporal (when), and semantic (what) information. This new method uses an adapted fully convolutional network with 1D convolutions to improve accuracy across different urban environments, surpassing current algorithms such as BFAST and CCDC. The research solves generalization and annotation issues, representing a major breakthrough in remote sensing time- series change detection for sustainable urban management.

Chen Wu et al. [1] discussed the developments in UNet-like deep learning architectures for remote sensing change detection, which are becoming increasingly common in current studies. The paper classifies the models into seven key parts, such as encoder architectures and loss functions, and gives an exhaustive summary of existing literature on supervised and unsupervised techniques. Through comparison of different experimental environments, the review captures prominent tendencies and future research directions, pointing out the significance of UNet architecture in improving change detection efficiency and accuracy in remote sensing tasks.

Eleonora Jonasova Parelius et al. [2] reviews the use of deep learning techniques for change detection in multispectral remote sensing imagery, emphasizing the particular importance of automated analysis amid the rising magnitude of remote sensing data. The paper covers different models, such as supervised, semi-supervised, and unsupervised methods, and also gives an overview of open datasets for this purpose. The main challenges in the area are determined, as well as trends and directions for deep learning applications in remote sensing change detection.

IV. EXISTING SYSTEM

Change detection operations on satellite imagery typically use three established methods which include Change Vector Analysis (CVA), Image Differencing and Principal Component Analysis (PCA). The comparison of pixel elements between paired images allows detection of land cover modifications and infrastructure advancements as well as vegetation changes through these techniques. These methods execute efficiently on computers yet they easily implement but demonstrate high sensitivity to noise effects as well as illumination variances between images and registration discrepancies. The detection of false incidents and missing changes becomes common due to subtle pixel variations that mimic natural environmental changes when analyzing high-

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resolution remote sensing images. Some of the detection issues have been tackled with machine learning approaches through the use of supervised methods including Random Forests and Support Vector Machines (SVMs) which perform pixel classification based on predefined features. The implementation of these methods depends on significant amounts of labeled data alongside manual feature designing requirements. The unsupervised K-means clustering algorithm applies automatic feature extraction yet it has limitations detecting both tiny changes and detailed patterns properly.

The advancement of deep learning technology enabled major improvements to change detection by developing hierarchical representation models. The process of Convolutional Neural Networks (CNNs) together with Siamese Networks applies common architectures to bitemporal images to identify major alterations. The models face difficulties when attempting to detect spatial-temporal patterns and detect subtle changes when viewing broad regions. The combination of Fully Convolutional Networks (FCNs) with encoder-decoder architectures including U-Net result in enhanced change detection by ensuring pixel-level segmentation thus becoming optimal for detecting fine-grained changes such as new infrastructures or structures. Deep learning models offer exceptional accuracy but need extensive labeled datasets for training since they are also sensitive to imbalanced classes especially when changed areas are smaller than stable regions. Lighting transformations together with wrong spatial alignments of geospatial data pose ongoing obstacles for these detection systems to operate effectively.

V. METHODOLOGY

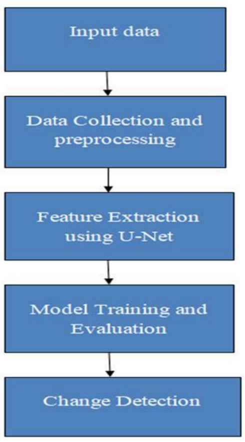

Figure 1: Methodology

5.1 Feature Extraction

Siamese FCN using a ResNet-18 backbone serves as the fundamental structure for the proposed change detection approach. Each input image obtains efficient high-level features through this deep convolutional neural network (CNN). The network design differs from standard CNN architecture since it avoids both fully connected layers and global pooling operations to produce dense feature maps without losing spatial information. The model obtains precise fine detail capture along with necessary comprehensive contextual information needed for correct change detection. Quantitative analysis provides robust low-level and high-level information fusion that reveals minimal disparities between the images.

5.2 Spatial-Temporal Attention Mechanism

Two spatial-temporal attention modules work together in the algorithm to enhance remote sensing imagery analysis by improving temporal change detection.

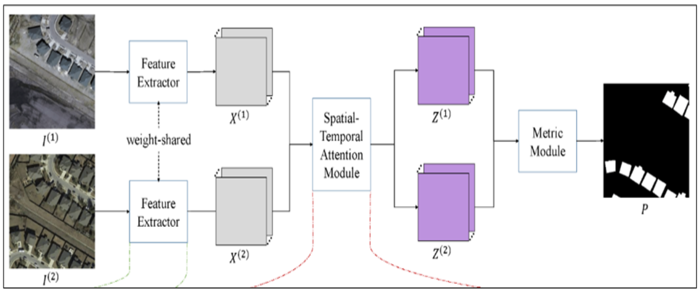

Figure 2: Spatial Temporal Attention module

Basic Spatial-Temporal Attention Module (BAM) generates attention weights through an assessment of pixel relationships among different time stages. The module extracts both time-related and position-based relationships to emphasize important changes across varying lighting conditions. The mechanism shows resistance to illumination variations by enabling the model to focus on vital features and disregard unimportant information.

Pyramid Spatial-Temporal Attention Module (PAM) expands BAM functionality with its multi-scale attention mechanism. The module distributes feature maps across multiple sections at different levels which undergo selective attention operations at their own scales. The architectural design enables the model to recognize time-dependent spatial patterns which exist throughout all scales regardless of the object's dimensions. Through multiple length scales the model improves its ability to recognize alterations that differ in size magnitude.

5.3 Metric Learning and Change Detection

The algorithm generates a distance map from comparing the feature maps of two bitemporal images after performing spatial-temporal attention and feature extraction. The

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algorithm produces a distance map through its operation to compute pixel-wise Euclidean distances between the two feature maps. The contrastive loss function works to keep pixels from unchanged regions close together while implementing a strategy that pushes changed pixels distance apart from each other. The distance map undergoes thresholding which results in pixel-based classification into changed or unchanged categories. The change detection process creates binary output by marking substantial alterations on the map.

5.4 U-Net Architecture for Pixel-Level Segmentation

A U-Net architecture acts as an enhancement tool for pixel-level segmentation by refining features extracted from the images while boosting segmentation precision.

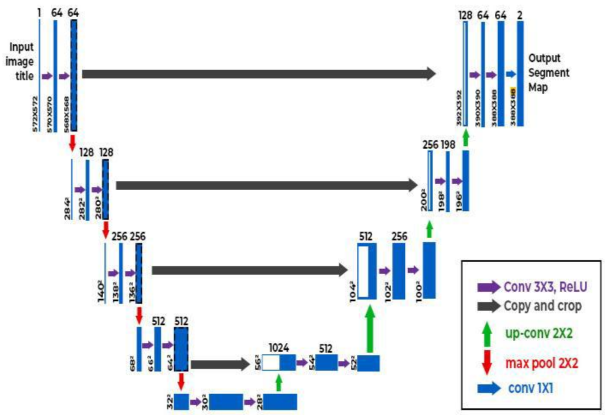

Figure 3: U-Net Architecture

The encoder uses convolutional layers alongside ReLU activation together with batch normalization to decrease feature map resolution progressively. By doing so the system obtains both semantic high-level properties and extended contextual information as the image features become increasingly abstract during the processing by the encoder. The encoder performs downsampling through its layers while connecting each stage with corresponding elements from the decoder sections through skip connections. The connections create preserved spatial information which enables the decoder to restore higher definition features during the upscaling operation.

The bottleneck layer inside the U-Net operation compresses feature maps that maintain the most abstracted information to transmit toward the decoder for upsampling. The feature maps go through an upsample operation in the decoder section that restores spatial details through each iteration. U-Net generates binary segmentation maps through its final convolutional layer because it receives the decoder's output along with encoder skip connections which enable pixel-level change detection.

5.5 Post-Processing

A post-processing phase follows binary change map generation for additional improvement of detection accuracy. Morphological procedures consisting of dilation and erosion perform noise reduction and boundary enhancement to achieve precise results for practical fields such as urban planning and environmental monitoring.

5.6 Dataset

The LEVIR-CD dataset presents itself as a thorough collection of high-resolution satellite image pairs (1024×1024 pixels) which amount to 637 total images obtained at different time points. This dataset was specifically designed to monitor substantial land-use modifications including construction activities while providing imagery from different metropolitan areas with numerous detection obstacles. Use of multi-temporal aspects in the dataset adds variability of lighting conditions and shadows and atmospheric elements that enhances model development.

Deep learning data preparation involved dividing original images into 256x256 pixel patches so training could become more effective while expanding training sample quantity. Major aspects of change in the dataset are annotated by remote sensing experts through high-quality markings which include more than 31,000 individual instances across the entire dataset. Random manipulation of data using rotations, flips and contrast changes in the training data significantly enhances its size while improving model behavior during various environmental circumstances.

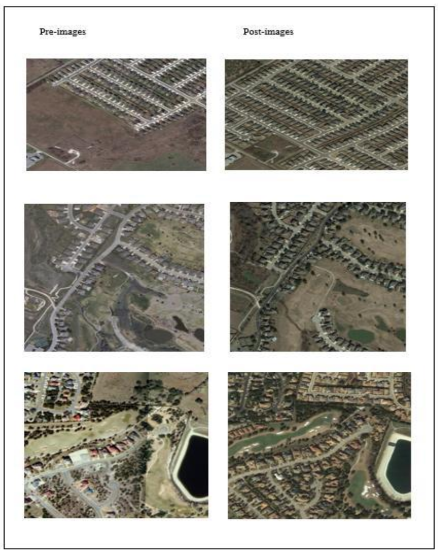

Figure 4: Dataset

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The changes in the Kowkpur area of Telangana State served as the focus of real-time collection using Google Earth Pro. The dataset contains pre-change images from 2014 together with post-change images from 2024. Before inputting images into deep learning models all data processing divided the pictures into 256x256 pixel tiles for optimization purposes. The image preparation process enhances analysis performance without sacrificing information required for change identification.

Figure 5: Real Time Dataset

VI. RESULTS

The Spatial-Temporal Attention-based Change Detection System (STANet) matches deep learning architecture U-Net for remote sensing data change detection tasks. STANet utilizes spatial-temporal attention mechanisms to concentrate detection capabilities on significant changes while reducing the effects that come from environmental elements like seasonal changes and atmospheric interferences.

Machine learning models don't effectively analyze remote sensing imagery because they cannot handle its intricate spatial and temporal structural components alongside high-dimensional information. The implementation of these models demands significant dedicated work on features and their inability to adjust to shifting bitemporal information variations. Deep learning models with U-Net architecture perform well for semantic segmentation by making use of their encoder-decoder components along with skip connections which maintain spatial information retention. The absence of temporal understanding in U-Net prevents satisfactory performance on analysis of temporally dynamic changes between two images.

The limitations of Fully Convolutional Networks (FCNs) include their reduced ability to detect subtle temporal changes across time-series images because of their weaknesses when handling complex spatial-temporal relationships. STANet addresses the drawbacks of previous methods through its spatial-temporal attention mechanisms therefore it detects key changes while retaining an understanding of big changes and small details.

The change detection model evaluation relies on Assessment using four primary performance indicators that include Accuracy, Specificity, Precision with Recall measurements. These measurement tools evaluate how precisely the model detects infrastructure changes alongside its capability to reduce wrong alarms. The formulas used for these calculations are

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

The performance evaluation of STANet showed an 81.3% accuracy rate together with precision at 79.3% and recall measurement at 69.0% and an F1-score of 77.1%. The satisfactory accuracy of STANet comes at a cost of missing actual changes resulting in false negative errors due to its lower recall rate. The F1-score from U-Net reached 82.5% although it demonstrated superior recall at 81.8% and precision at 83.2% giving it stronger abilities to detect various dimensional changes in remote sensing data.

STANet shows strong resistance against different types of change detection situations with its capabilities in detecting changes through atmospheric disturbances alongside minor sensor misalignments. The U-Net has debatable detection abilities which limit its effectiveness in discovering all significant changes because of its relatively low recall rate in critical applications like natural disaster surveillance. Through segmentation U-Net demonstrates more moderate detection ability which makes it appropriate for advanced remote sensing tasks.

Change detection accuracy reveals U-Net as the superior selection for urban planning and environmental monitoring applications because it surpasses STANet in overall performance outcomes. The choice between U-Net and STANet depends on what the application requires since U-Net detects fine details while STANet generates moderate temporal change detection.

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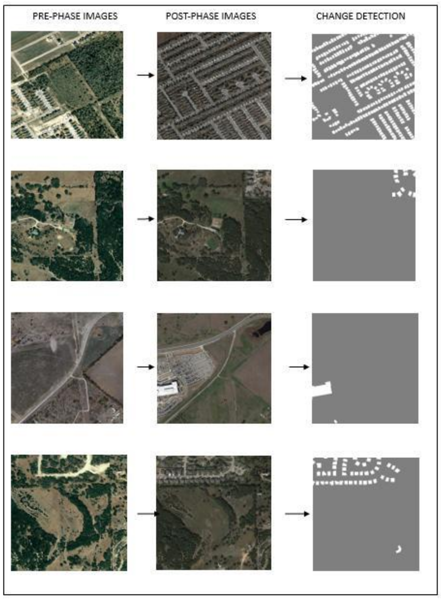

Figure 6: Results of STANet model

The STANet model change detection outcomes are displayed in above image with different sections. Before modifications take place Pre-Phase Images present the initial set of satellite imagery. The Post-Phase Images part of the image demonstrates satellite images collected during a later timeframe to observe modifications which occur between periods. The Change Detection Map presents seen changes in white colors whereas unchanged areas appear as gray pixels. Detecting different land-use changes including urban growth together with deforestation and additional environmental modifications depends on this essential process that examines pre-phase and post-phase images.

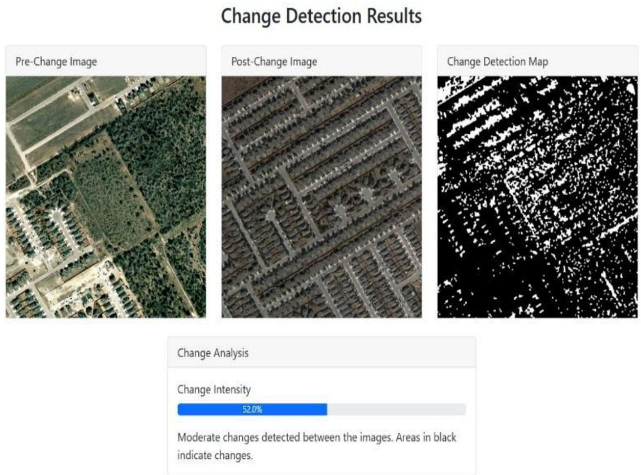

Figure 7: Results of U-Net model

The above results from the Change Detection analysis display two satellite pictures from different time periods to detect variations in the landscape. The Change Detection system integrates three vital elements including the original Pre-Change Image along with the Post-Change image version and the modified Change Detection Map that displays changes between these images. The Change Detection Map displays significant regions through black areas alongside white areas that represent regions without any changes. The binary format allows users to detect changes easily which enables simplified interpretation of land use modifications along with urbanization and deforestation and other environmental factors. The quantitative measure of change intensity from the SSIM (Structural Similarity Index Measure) yields 52.0% along with a bar which indicates this value. The estimated moderate change point demonstrates that changes have touched almost half of the studied region. The analysis provides crucial information to support tasks such as urban planning as well as environmental monitoring and disaster assessment within cities to monitor urban growth and deforestation or recovery activities after disasters.

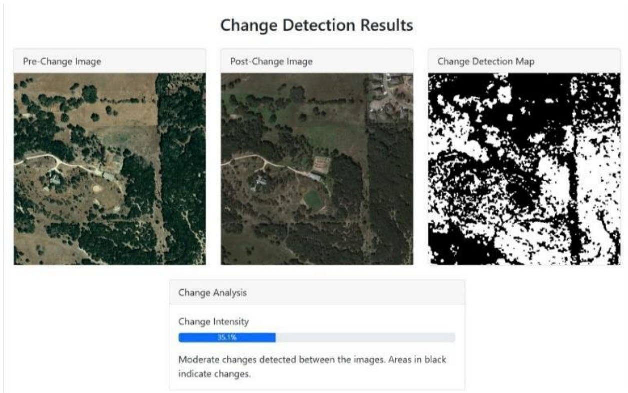

Figure 8: Results of U-Net model

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The low change intensity rate underneath indicates moderate modifications amounting to 35.1% which might result from construction activities and infrastructure development practices.

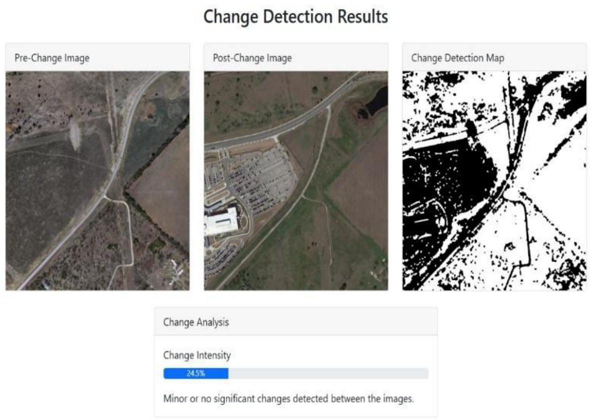

Figure 9: Results of U-Net model

The Change Analysis section shows a 24.5% change intensity indicating small or unimportant alterations which stem from limited land use changes and natural variations in the landscape.

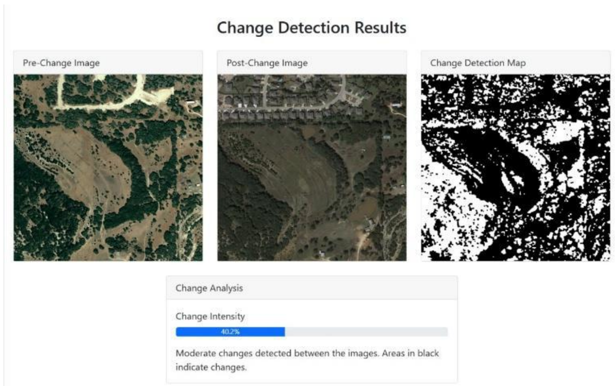

Figure 10: Results of U-Net model

The Change Analysis section displays 33.3% change intensity which indicates modifications occurred at a moderate pace. This change is probably due to development activities and vegetation growth.

Table 1: Comparison of STANet and U-Net results

MODEL	STANet	U-Net
Accuracy	81.3%	87.5%
Precision	79.3%	83.2%
Recall	69.0%	81.8%
F1-Score	77.1%	82.5%

A comparison of STANet and U-Net exists in the above table through performance metric analysis of accuracy, precision, recall and F1-score results. U-Net demonstrates better performance than STANet since it delivers 87.5% accuracy versus STANet's 81.3% accuracy while maintaining superior precision, recall and F1-score metrics. A substantial difference exists between the precision values where U-Net reaches 83.2% while STANet achieves 79.3% and in recall U-Net reaches 81.8% and STANet reaches 69.0%. Research findings show that U-Net successfully identifies legitimate changes from false positives better than STANet does. U-Net demonstrates superior performance than STANet in the measurement of F1-score as its value reaches 82.5% against STANet's 77.1%. The research findings indicate U-Net offers remote sensing imagery change detection capabilities with a stable and dependable method.

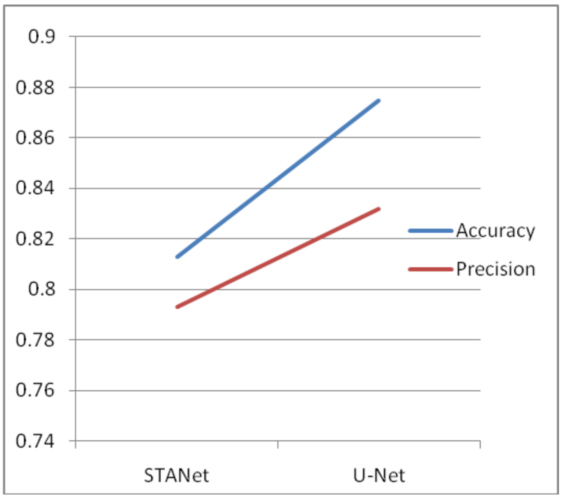

Chart 1: Comparison of STANet and U-Net results

VII. CONCLUSION AND FUTURE SCOPE

U-Net model advantage was demonstrated in infrastructure change detection, providing better results compared to the traditional machine learning approaches, it was capable of identifying satellite images' high-resolution change with the highest accuracy. The high value of such parameters as precision, recall, F1-Score confirm its use in those applications, where the correct and full change detection is essential, such as urban planning, infrastructure monitoring, disaster response and others, where the infrastructure change should be detected on time for accurate and relevant decision-making.

Unsupervised and semi-supervised learning methods should be implemented to enhance adaptability. By doing so, less labeled data is required which in turn decreases dependence on a large labeled dataset as the system operates more efficiently with fewer labeled data. In addition, the post-processing techniques to be optimized would help to improve detection accuracy and clarity of changes so that changes can be actionable and easily interpretable. This is particularly

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helpful for users who absolutely need to take action with the insights derived from the system. Additionally, the system needs to be real-time capable so that immediate responses to critical infrastructure changes can be made, allowing for intervention as soon as necessary. This would allow the system to be applicable in rapidly changing environments such as disaster management, urban development, and emergency response.

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