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SatelliteChangeNet: Deep Learning approach for Detection & Prediction

Dr. Sharda Chhabria, Mr. Aditya Bhagwat, Ms. Monali Patle, Mr. Om Barde
Artificial Intelligence Engineering
G. H Raisoni Institute of Engineering and Technology, Nagpur, India

Abstract: *In geoscience, Detection is a useful method for analyzing land surface changes using data from Earth observation and for uncovering links between human activities and environmental phenomena. Detection in remote sensing is a rapidly evolving area of interest that is relevant for a number of fields. Recent years have seen a large number of publications and progress, even though the challenge is far from solved. This review focuses on deep learning applied to the task of Detection in multispectral remote-sensing images. In this work, SatelliteChangeNet addresses the growing need for an accurate and effective method to monitor and predict changes in satellite imagery, which is important for many purposes such as environmental monitoring, urban planning, and agriculture and disaster management. The changes always aim to show the struggle with the body and its different structures and lead to the search for a deep learning process. The program focuses on the use of satellite data for exploration of new areas, urban development analysis, environmental management damage, and change and prediction with important applications in agriculture. Water resources and farmland provide a lot of information about our planet. Analyzing these changes over time is important for understanding land use, environmental change, and natural hazards*

Keywords: Satellite imagery, detection, Prediction, Deep learning, Bi-temporal analysis, Environmental monitoring, Semantic segmentation, Object detection, Feature extraction, Pattern recognition, Sustainable development

I. INTRODUCTION

SatelliteChangeNet lies in the growing demand for accurate and efficient methods to monitor and predict changes in satellite imagery. Satellite data plays a crucial role in various fields, including environmental monitoring, urban planning, agriculture, and disaster management. Traditional Detection methods often struggle with complex spatial and temporal patterns, motivating the exploration of advanced deep learning techniques. Detection and prediction using satellite data have significant applications in various domains such as new build-up area detection, urban development analysis, disaster management, and agriculture.

1.1 Overview:

By utilizing multi-temporal remote sensing imagery, dynamic changes on the Earth's surface can be detected automatically. In this process, land cover changes on temporal imageries are identified in the same geographical area. Automatic Detection is widely used for both civil and military applications, such as environmental monitoring, disaster evaluation, urban expansion monitoring, and reconnaissance. In general, The Detection process is composed of three steps: pre-processing, feature extraction, and classification. Pre-processing corrects radiometric and geometric distortions and performs image registration.

1.2 Problem Statement:

The project aims to tackle the significant challenge of accurately detecting and predicting the satellite imagery, a task critical for a multitude of applications spanning disaster response, land cover monitoring, and environmental assessment. With the rapid advancements in satellite technology, there is a growing demand for robust and efficient algorithms capable of analyzing vast amounts of satellite imagery data to extract meaningful insights. This research proposes practical applicability of the proposed SCN, a comprehensive comparative analysis will be conducted against existing algorithms, including U-Net, R-CNN, and YOLO. This research contribute to the advancement of the field of satellite image analysis by introducing a state-of-the-art deep learning solution capable of addressing the complex challenges associated with detection and prediction.

1.3 Research Objectives:

The main objectives of the research are: -

- Analyze and compare three state-of-the-art algorithms (U-Net, R-CNN, and YOLO) to assess their effectiveness in addressing challenges related to Detection in satellite images.
- Evaluate the performance of U-Net, R-CNN, and YOLO algorithms used considering metrics such as accuracy, and computational efficiency.
- Utilize bi-temporal high-resolution satellite images to train and validate the SCN, enhancing its capability to accurately identify and predict changes over time.

Scope of the Research:

Change detection and prediction using satellite imagery are critical for numerous applications, including urban planning, environmental monitoring, and disaster response. The advent of deep learning has significantly enhanced the capabilities of these tasks, enabling more precise and efficient analyses. This literature review integrates insights from several seminal works, focusing on the methodologies, results, and limitations of state-of-the-art approaches.

II. RELATED WORK

Recently, there has been a lot of research focusing on creating automated systems for detecting signatures and photos in documents using AI and OCR technologies. This review covers various studies that discuss important findings, methods, and progress in this area. Change detection and prediction using satellite imagery are critical for numerous applications, including urban planning, environmental monitoring, and disaster response. The advent of deep learning has significantly enhanced the capabilities of these tasks, enabling more precise and efficient analyses. This literature review integrates insights from several seminal works, focusing on the methodologies, results, and limitations of state-of-the-art approaches.

Automatic Change Detection Methods In "An Approach Automatic Change Detection Method for Satellite Images," the authors present a framework for automatic change detection that leverages both pixel-based and object-based techniques to improve accuracy [1]. This approach typically involves preprocessing steps such as image registration to align multi-temporal images accurately, followed by change detection algorithms that may include image differencing, rationing, or machine learning-based classification. The effectiveness of this method lies in its ability to minimize false positives caused by sensor noise or atmospheric conditions, providing a robust solution for large-scale change detection tasks.

Deep Convolutional Spiking Neural Networks (DCSNN) and Enhanced Elman Spike Neural Networks (EESNN) The paper on "Land use/land cover change classification and prediction using DCSNN and EESNN" delves into the use of spiking neural networks for temporal data analysis [2]. Spiking neural networks (SNNs) are particularly advantageous for processing time-series data due to their event-driven nature and temporal coding capabilities. The authors demonstrate that DCSNN and EESNN can effectively capture and predict land cover changes by learning temporal dependencies in the data, leading to high classification accuracy. This work highlights the potential of SNNs in modeling complex temporal patterns inherent in satellite imagery.

Review of Deep-Learning Methods for Change Detection "A Review of Deep-Learning Methods for Change Detection in Multispectral RemoteSensing Images" offers a comprehensive overview of deep learning techniques applied to change detection [3]. The review covers various architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models. It emphasizes the advantages of deep learning, such as automatic feature extraction and scalability, while also discussing challenges like the need for large annotated datasets and computational resources. The synthesis of these findings underscores the transformative impact of deep learning on change detection, enabling more accurate and automated analyses.

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Genetic Algorithms for Change Detection In "Change detection in satellite images using a genetic algorithm approach," the authors propose using genetic algorithms (GAs) to optimize change detection processes [4]. GAs are effective in exploring large search spaces and finding optimal or near-optimal solutions for complex problems. This paper demonstrates how GAs can enhance the performance of traditional change detection algorithms by optimizing parameters such as thresholds and feature selection. The use of GAs helps in addressing issues related to noise and varying illumination conditions, making the change detection process more robust and adaptable to different scenarios.

Block Adjustment of High-Resolution Satellite Images The study "Block Adjustment of High-Resolution Satellite Images Described by Rational Polynomials" addresses the challenge of geometric correction in satellite imagery [5]. Accurate geometric correction is crucial for reliable change detection, as misaligned images can lead to erroneous results. The authors introduce a method using rational polynomials for block adjustment, improving the alignment and spatial accuracy of higher solution satellite images. This methodological enhancement ensures that subsequent change detection analyses are based on accurately aligned data, thereby increasing their reliability and precision.

In summary, the studies reviewed here contribute valuable insights and methodologies to the field of satellite image analysis and remote sensing. By addressing key challenges and leveraging innovative techniques, these studies advance the state-of-the-art in change detection, land cover classification, disaster detection, and image processing, thereby enhancing our understanding of Earth's dynamic surface.

III. METHODOLOGY

The research paper outlines a Methodology for detecting and predicting changes using Sentinel imagery. By following Algorithm used, users can detect changes, train deep learning models for future predictions, and validate the results to ensure accuracy and reliability. We explore three deep learning algorithms for Detection & Prediction.

U-Net:

U-Net is a popular architecture for semantic segmentation. It consists of an encoder-decoder structure with skip connections, allowing it to capture both local and global context.

It consists of a contracting path and an expansive path. The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for down sampling. At each down sampling step we double the number of feature channels.

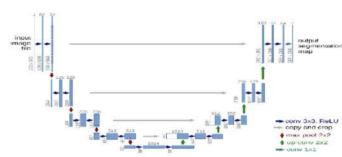

Figure 1: Architecture of Unet

R-CNN (Region-based Convolutional Neural Network):

R-CNN is a two-stage object detection framework. It first generates region proposals and then classifies objects within those regions.

This R-CNN architecture uses the selective search algorithm that generates approximately 2000 region proposals. These 2000 region proposals are then provided to CNN architecture that computes CNN

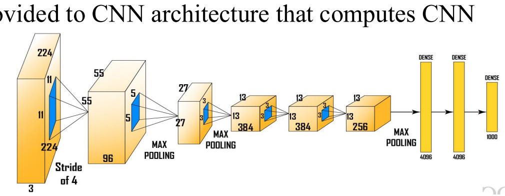

Figure 2: Architecture of RCNN

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YOLO (You Only Look Once)

YOLO is an efficient real-time object detection algorithm. It divides the image into a grid and predicts bounding boxes and class probabilities directly.

This architecture uses Leaky ReLU as its activation function in whole architecture except the last layer where it uses linear activation function.

We extend YOLO to handle Detection by training it on pairs of satellite images. YOLO's speed and accuracy make it suitable for large-scale applications.

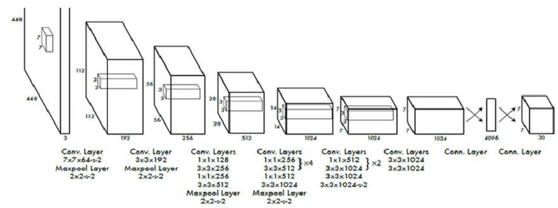

Figure 3: Architecture of YOLO

IV. IMPLEMENTATION

This implementation framework for change detection and prediction using Sentinel in Google Earth Engine involves several critical steps, including data acquisition, preprocessing, change detection, model training for prediction, and post-processing. Each step is designed to ensure that the data is accurately processed and analyzed, leading to reliable detection of changes and predictions of future changes.

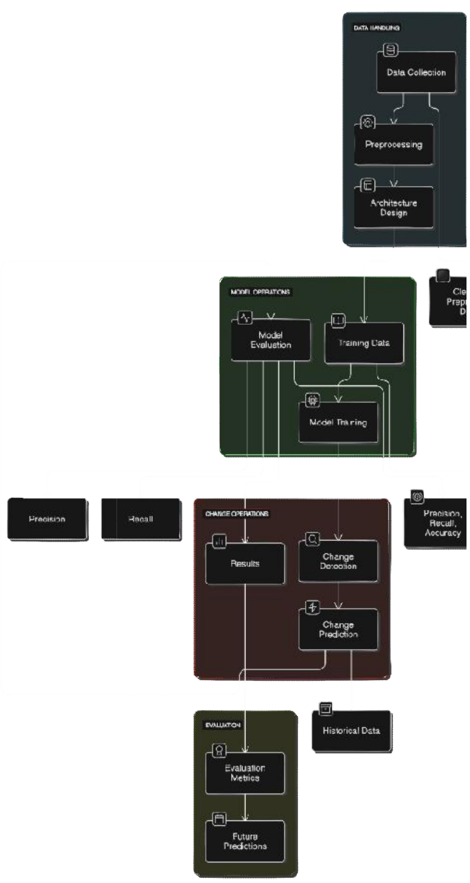

Figure.4: Flowchart of the project

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1. Data Acquisition

Objective: Collect Sentinel-1 SAR imagery for the study area. We have taken Semantic segmentation dataset, the dataset consists of aerial imagery of Dubai obtained by MBRSC satellites and annotated with pixel-wise semantic segmentation in 6 classes

Process:

- **Access Data Source**: Utilize Google Earth Engine (GEE) to access the Sentinel-1 image collection, which provides radar images with frequent revisits and reliable coverage.
- **Define Region of Interest (ROI)**: Identify and delineate the geographic area that will be the focus of the analysis.
- **Select Time Periods**: Choose appropriate dates for the "before" and "after" periods to capture the time span during which the changes are expected to have occurred. This involves filtering the Sentinel-1 image collection to include images from the specified dates.

2. Pre-processing

Objective: Prepare the data by applying necessary corrections and filtering to enhance the quality and comparability of the images.

Steps:

- **Radiometric Calibration**: Convert the raw SAR data to backscatter coefficients to make the pixel values physically meaningful and comparable across images.
- **Speckle Filtering**: Apply speckle noise reduction techniques to mitigate the granular noise inherent in SAR images. Common filters include the Lee filter or the Gamma MAP filter.
- **Geometric Correction**: Correct geometric distortions caused by the sensor's viewing geometry and the Earth's curvature to align the images accurately with the ground coordinates.
- **Terrain Correction**: Use Digital Elevation Models (DEMs) to correct for terrain-induced distortions, ensuring that the images accurately represent the surface of the Earth.

3. Change Detection

Objective: Identify changes between two time periods by comparing the pre-processed images.

Techniques:

- **Image Differencing**: Subtract pixel values of the before image from the after image to create a difference image that highlights areas where changes have occurred.
- **Thresholding**: Apply a threshold to the difference image to classify areas as changed or unchanged. The threshold value is chosen based on the specific characteristics of the data and the type of changes being detected.
- **Visualization**: Display the original images, difference image, and thresholder change map to visually inspect and interpret the changes.

4. Prediction using Deep Learning

Objective: Predict future changes using machine learning models trained on historical data**.**

Steps:

- **Prepare Training Data**: Collect and label data representing different land cover types or change/no-change classes. This involves creating training samples from the Sentinel-1 images and associating them with known changes (ground truth data).
- **Feature Extraction**: Extract relevant features from the SAR data that will be used as input for the deep learning model. These features could include backscatter coefficients, texture measures, or temporal statistics.
- **Model Training**: Choose a suitable deep learning algorithm (Neural Networks) and train the model using the prepared training data. The model learns to differentiate between changed and unchanged areas based on the features provided.

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5. Post-Processing and Validation

Objective: Refine the detected changes and validate the results to ensure their accuracy and reliability.

Steps:

- **Morphological Filtering:** Apply morphological operations to the change detection results to remove noise and small artefacts, thus refining the change map. This could involve operations like erosion, dilation, opening, and closing.
- **Accuracy Assessment**: Validate the change detection results using ground truth data or high-resolution imagery. This involves comparing the detected changes with known changes to assess the model's performance. Confusion Matrix: Create a confusion matrix to evaluate the accuracy of the change detection. Metrics such as overall accuracy, user's accuracy, producer's accuracy, and the Kappa coefficient are calculated to quantify the performance of the detection and prediction models.

V. VISUALIZATION

For U-Net, the training loss graph illustrates a consistent decline over the epochs, indicating that the model progressively improves in fitting the training data. The validation loss, while also decreasing, does so at a slower rate compared to the training loss.

Unets:

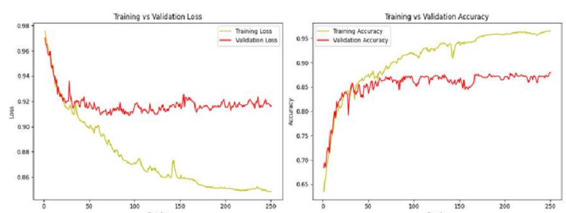

Fig. 5. U-net Graph for Training vs Validation loss & Training vs Validation accuracy

RCNN demonstrates a rapid initial decrease in training loss which then stabilizes, reflecting effective learning from the training dataset. However, the validation loss exhibits occasional fluctuations, suggesting potential overfitting as the model starts to learn more complex features.

RCNN:

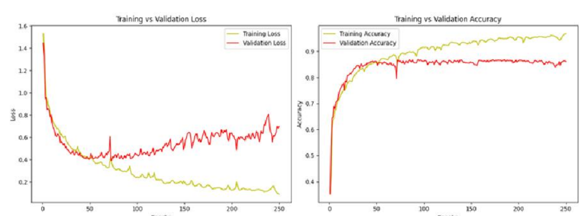

Fig. 6. RCNN Graph for Training vs Validation loss & Training vs Validation accuracy

YOLO, known for its efficiency in object detection tasks, exhibits a steep drop in training loss early in the training process, which then plateaus, indicating quick convergence. This rapid decrease signifies YOLO's ability to learn from the training data swiftly

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YOLO:

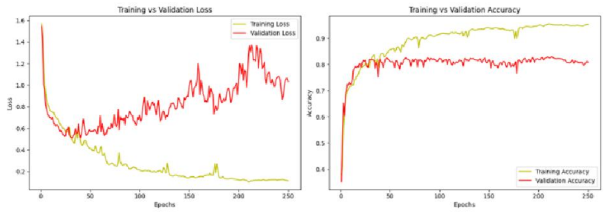

Fig. 7. YOLO Graph for Training vs Validation loss & Training vs Validation accuracy

VI. RESULTS

Our experiment demonstrates the effectiveness of the three algorithms:

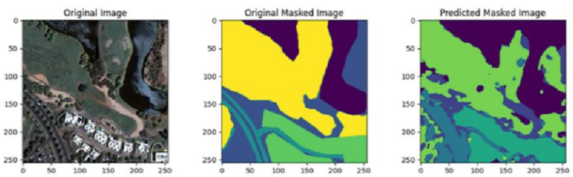

Fig. 8. U-net Comparison on Training and Predicted image

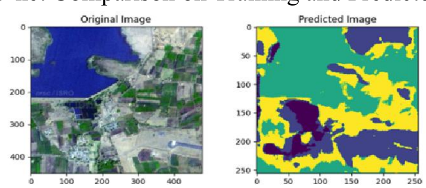

Fig. 9. Image in Real Time (U-Net)

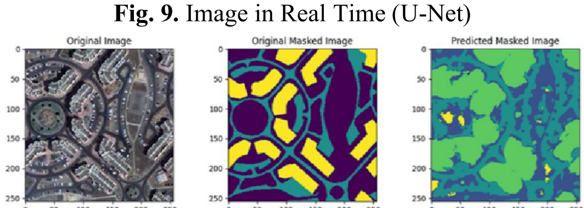

Fig.10. RCNN Comparison on Training and Predicted image

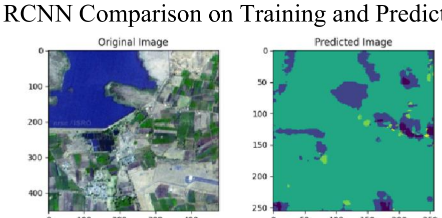

Fig. 11. Image in Real Time (RCNN)

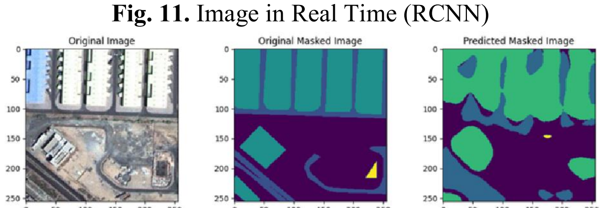

Fig. 12. YOLO Comparison on Training and Predicted image

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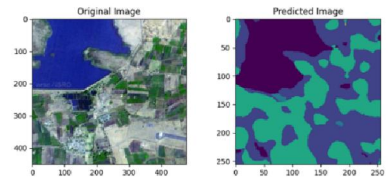

Fig. 13. Image in Real Time (YOLO)

The results highlight the effectiveness of deep learning techniques in addressing the challenges of Detection in satellite imagery. The comparison between existing algorithms (U-Net, R-CNN, and YOLO) revealed the advantages of U-Net in terms of accuracy and computational efficiency.

VII. CONCLUSION

This project evaluates the performance of U-Net, R-CNN, and YOLO. Findings highlight the strengths and limitations of each algorithm.

Algorithms	Conclusion	Accuracy
U-Net	fine-grained Detection	85%
R-CNN	precise localization	83%
YOLO	large-scale monitoring	88%

Table. 1. Accuracy Comparison

U-Net achieves higher accuracy in Detection compared to R-CNN and YOLO due to several key architectural features and design principles. While R-CNN and YOLO have their strengths in object detection tasks, they may not perform as well in Detection scenarios where pixel-level accuracy and detailed segmentation are crucial. R-CNN's region-based approach and YOLO's grid-based prediction may struggle to capture fine-grained changes effectively, especially in regions with complex textures or overlapping objects. Overall, U-Net's architectural design, skip connections, and suitability for pixel-wise segmentation make it a strong choice for Detection tasks, often resulting in higher accuracy compared to R-CNN and YOLO in this specific context.

VIII. ACKNOLEDGEMENT

We express our profound gratitude to Dr. Sharda Chhabria, Associate Professor, Artificial Intelligence department, G. H Raisoni Institute of Engineering and Technology, Nagpur, India for her invaluable insights, guidance, and constant encouragement throughout the course of this research. Her expertise and dedication have been instrumental in shaping the direction and outcomes of this study. Special thanks for her mentorship and guidance throughout this research endeavor

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