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PREDICTING LANDCOVER CHANGES IN HIGH-RESOLUTION SATELLITE IMAGERY THROUGH DEEPLEARNING TECHNIQUES

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Abstract:

Accurate land cover classification is of paramount importance for a wide range of applications, including urban planning, environmental monitoring, and natural resource management. Traditional land cover classification systems often rely on manual feature engineering, which can be time-consuming and subject to human bias. In addition, these systems struggle to handle complex landscapes and may not adapt well to changing environmental conditions. To overcome these limitations, our proposed Artificial intelligence based system leverages deep learning techniques, to automate the classification process. The dataset utilized for this research pairs each satellite image with a corresponding mask image that encodes land cover annotations using an RGB colour scheme We train the model to learn the intricate spatial patterns and spectral signatures associated with each land cover class, making it highly adaptable to diverse and dynamic environments. Land cover change detection is crucial for environmental monitoring, urban planning, and resource management. Traditional methods for analyzing satellite imagery often rely on manual interpretation or conventional machine learning techniques, which can be time-consuming and less accurate. In this study, we propose a deep learning-based approach to predict land cover changes in high-resolution satellite imagery. By leveraging convolutional neural networks (CNNs) and transformer-based models, our method efficiently extracts spatial and temporal features to detect subtle andlarge-scale changes in land cover. This research highlights the potential of deep learning for automated land cover change prediction, offering a scalable and precise solution for environmental and urban development applications.

Keywords: Land Cover Classification, Deep Learning, Artificial Intelligence, Satellite Imagery, Convolutional Neural Networks, Transformer-based Models, Urban Planning.

1.INTRODUCTION

The utilization of satellite imagery has been instrumental in monitoring and analyzing land cover changes over time. Since the launch of Landsat satellites in the early 1970s, they have provided extensive datasets essential for environmental monitoring, urban planning, andnatural resource management. The ability to accurately classify and track land cover changes is critical for sustainable land use planning, ecosystem conservation, and climate change studies.

Traditional methods for analyzing satellite imagery often rely on manual interpretation or conventional change detection algorithms.

While these approaches have demonstrated effectiveness, they suffer from several limitations, including time-consuming processes, subjectivity, and difficulty in detecting subtle or complex changes. As a result, there is a growing need for automated and highly accurate techniques capable of handling large-scale, multi-temporal satellite data.

To address these challenges, this study proposes a deep learning-based ensemble learning approach for land cover change detection using Landsat satellite data. Ensemble learning, which combines multiple machine learning models, has proven to be highly effective in handling complex datasets and improving classification accuracy. By leveraging the strengths of multiple models, ensemble techniques enhance the precision and reliability of land cover change analysis.

The primary objective of this research is to develop a robust and scalable system that can autonomously and accurately classify land cover changes over time. The proposed system utilizes convolutional neural networks (CNNs) and transformer-based models to extract spatial and temporal features from satellite imagery. The study aims to demonstrate that ensemble learning techniques can significantly outperform traditional change detection methods in terms of accuracy, efficiency, and adaptability to dynamic environmental conditions.

The rest of this paper is organized as follows: Section II provides a review of related work in land cover classification and change detection. Section III describes the methodology, including the dataset, model architecture, and training process. Section IV presents the experimental results and performance evaluation. Section V discusses the findings and potential applications. Finally, Section VI concludes the paper and outlines future research directions.

2. LITERATURE SURVEY

Land use classification, remote sensing, and machine learning have significantly advanced in recent years, transforming environmental monitoring, urban planning, and resource management. Traditional classification methods such as Maximum Likelihood Classification (MLC) have been widely used in land cover classification; however, they often struggle with complex landscapes and diverse environmental conditions. To address these limitations, researchers have explored more sophisticated machine learning and deep learning approaches, improving accuracy, efficiency, and adaptability in geospatial applications.

Otukei and Blaschkeexamined the performance of decision trees, Support Vector Machines (SVM), and MLC algorithms for land cover change assessments. Their findings highlighted that machine learning-based approaches significantly enhance classification accuracy compared to traditional statistical methods. Similarly, Hua utilized a feature-based decision tree approach for urban land use classification using Landsat imagery. Their study demonstrated how time-series analysis could track urban expansion and landscape transformation more effectively than conventional techniques.

Deep learning has emerged as a powerful tool in remote sensing applications. Zindeveloped a deep convolutional neural network (CNN) model for herbal plant species recognition, demonstrating superior classification performance over conventional image processing techniques. Their research underscored the potential of deep learning models in plant identification, particularly in complex and diverse datasets. Likewise, Jamali evaluated and compared eight different machine learning models for land use/land cover classification using Landsat 8 OLI imagery, revealing that ensemble learning methods improve classification accuracy by integrating multiple algorithms.

Beyond machine learning, researchers have integrated remote sensing with additional geospatial data sources to enhance classification outcomes. Grippa employed OpenStreetMap and remote sensing data to map urban land use at the street-block level, showcasing the effectiveness of open-source geospatial datasets in urban planning. Their study emphasized the role of public geospatial data in refining land-use classification and urban development strategies. Similarly, Thakkar proposed post-classification correction methods to enhance land cover classification accuracy, particularly in arid and semi-arid environments, where spectral similarities often lead to misclassifications.

Advancements in cloud computing have further improved remote sensing applications by enabling large-scale data processing. Hassansurveyed cloud computing technologies for handling geospatial data in machine learning and artificial intelligence applications. Their study highlighted the role of distributed computing in accelerating land cover classification, climate modelling, and environmental monitoring. Additionally, Weng reviewed the remote sensing of impervious surfaces in urban environments, emphasizing the critical need for high-resolution satellite data and machine learning-based classification techniques for sustainable urban planning.

Several studies have also explored hybrid approaches combining different classification techniques. Behera proposed a hybrid model integrating k-nearest neighbours (KNN) with restricted Boltzmann machines for movie recommendation, demonstrating the effectiveness of deep learning in decision-making applications. While this research was applied in a different domain, it illustrates the broader potential of hybrid models in classification tasks. Similarly, applied time-series classification techniques to track land-use changes in heavily urbanized regions, demonstrating how integrating temporal data enhances classification accuracy.

These studies collectively indicate that machine learning, deep learning, and geospatial analysis have significantly improved land use classification, remote sensing, and environmental monitoring. Future research should focus on hybrid approaches, real-time geospatial data processing, and the integration of AI-driven techniques for enhanced accuracy and efficiency in land use classification. Moreover, the continued expansion of publicly available satellite data and cloud-based processing will likely drive further advancements in the field, enabling real-time monitoring and adaptive environmental management.

3. PROPOSED METHODOLOGY

3.1 Overview

The proposed methodology for analyzing land cover changes using Landsat satellite images is structured into multiple stages. The system is designed to facilitate dataset uploading, image preprocessing, model training, performance evaluation, and test image prediction using a Convolutional Neural Network (CNN). The system workflow is as follows:

Uploading Dataset: Users upload satellite image datasets via a user-friendly graphical interface.

Image Preprocessing: The system preprocesses images using the VGG16 model for feature extraction and splits the dataset into training and testing sets.

Training and Testing CNN Model: The pre-processed dataset is used to train a CNN model, followed by model evaluation using standard classification metrics.

Model Performance Evaluation: The system generates performance evaluation graphs to compare different models.

Test Image Prediction: Users can upload a test image, and the trained CNN model classifies the land cover type.

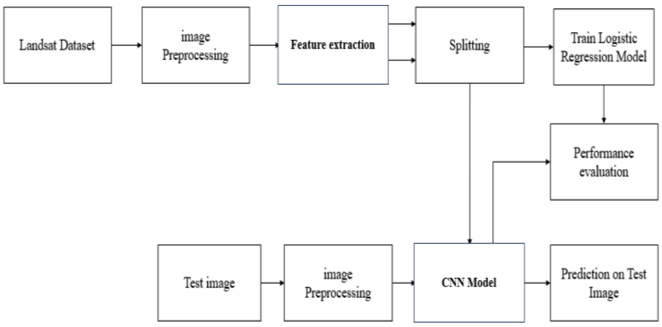

Figure: Architecture diagram of Proposed System.

3.2 Data Pre processing

Image pre processing is a crucial step in ensuring high model accuracy. The pre processing steps include:

Image Read: The raw image is read from the dataset and loaded into memory.

Image Resize: Images are resized to ensure uniformity, reducing computational complexity and standardizing input size for the CNN model.

Image to Array: The image is converted into a numerical array representation for computational analysis.

Image to Float32: The pixel values arenormalized to a 0-1 range by converting them to 32-bit floating-point format.

Image to Binary: Gray scale images are converted to binary format using thresholding to distinguish land cover regions effectively.

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3.3 Dataset Splitting

To train and evaluate the CNN model effectively, the dataset is split into two subsets:

Training Set: Used to train the CNN model by learning patterns and features.

Test Set: Used to evaluate the trained model's generalization ability on unseen data.

3.4 Convolutional Neural Network (CNN)

The CNN model used in the proposed system consists of multiple layers, including convolutional layers, activation functions, and pooling layers:

Convolution Layer: Extracts features from input images using kernels or filters.

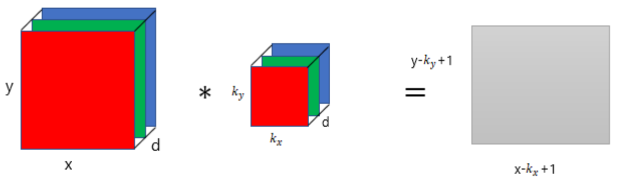

Figure: Representation of convolution layer process.

ReLU Activation Layer: Introduces non-linearity into the model and helps in faster convergence.

Max Pooling Layer: Reduces the feature map size, retaining essential information while lowering computation costs.

Fully Connected Layer &SoftMax Layer: The final classification layers that generate the output probabilities for each land cover class.

3.5 Advantages of the Proposed System

The proposed CNN-based approach offers the following advantages:

Automated Feature Extraction: CNNs eliminate the need for manual feature selection.

High Accuracy: CNNs outperform traditional machine learning models in image classification.

Weight Sharing: Reduces computational cost and improves model efficiency.

Robust Performance: The model generalizes well across various land cover types and geographical conditions.

3.6 Applications of the Proposed System

The proposed system can be applied in various real-world scenarios, including:

Environmental Monitoring: Detecting deforestation, urban expansion, and other land cover changes over time.

Agriculture: Assessing crop health, land usage, and soil conditions for improved farming practices.

Disaster Management: Identifying areas affected by floods, wildfires, and other natural disasters for quick response and mitigation.

Urban Planning: Assisting in infrastructure development, zoning, and land resource management.

Climate Change Analysis: Monitoring long-term environmental changes to assess the impact of climate change.

Water Resource Management: Identifying changes in water bodies, drought-affected regions, and flood-prone areas for better resource allocation.

4. EXPERIMENTAL ANALYSIS

Figure 1: This figure showcases the graphical user interface (GUI) designed for analyzing land cover changes using Landsat satellite data. It includes interactive elements for data visualization and analysis.

Figure 2: Here, the dataset uploading process is illustrated, indicating how users can import Landsat satellite data into the GUI for analysis. This step is crucial for accessing the dataset and preparing it for further processing.

Figure 3: Displaying the dataset preprocessing and data splitting steps, this figure demonstrates the necessary transformations applied to the Landsat satellite data to enhance its quality and usability. Preprocessing involve normalization, feature scaling, and splitting the data into training and testing sets.

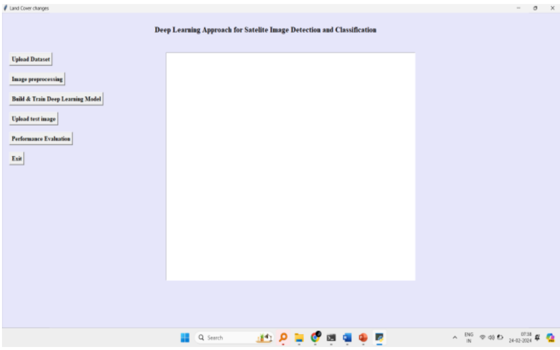

Figure.1: Displays the GUI of land cover changes with Landsat satellite.

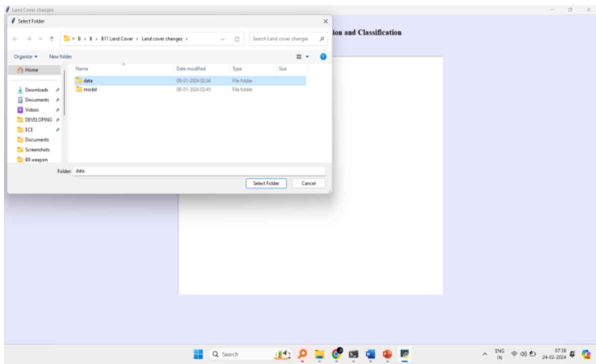

Figure.2: Displays the uploading of dataset.

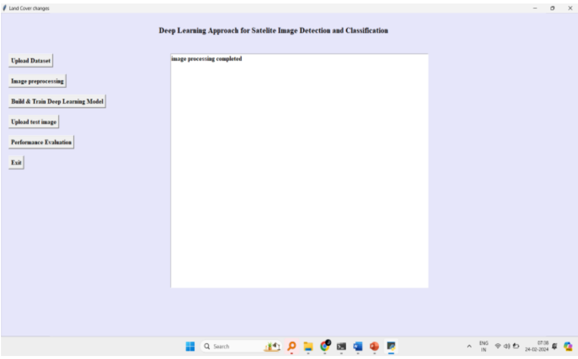

Figure.3: Displays the dataset preprocessing and data

Model	Logistic regression	CNN Model
Accuracy (%)	96	98
Precision (%)	96	98
Recall (%)	96	98
F1-Score (%)	96	98

splitting.

Figure 4: Presented here are the confusion matrices for both the Ensemble model and Logistic Regression model. These matrices provide insights into the performance of each model by showing the counts of true positive, true negative, false positive, and false negative predictions.

Figure 5: This figure presents a performance comparison count plot, depicting various evaluation metrics such as accuracy, precision, recall, and F1-score for each model. The plot allows users to visually compare the performance of different models and select the most effective one for their analysis.

Figure 6: Here, the proposed Ensemble model's predictions on test images are illustrated. Users can observe the model's classifications of land cover changes based on Landsat satellite data, providing valuable insights into environmental changes over time.

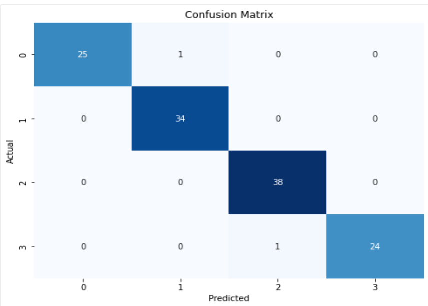

Figure.4: Confusion matrix of CNN model.

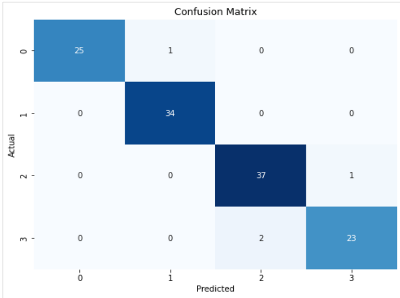

Figure. 5: Confusion matrix of Logistic Regression model.

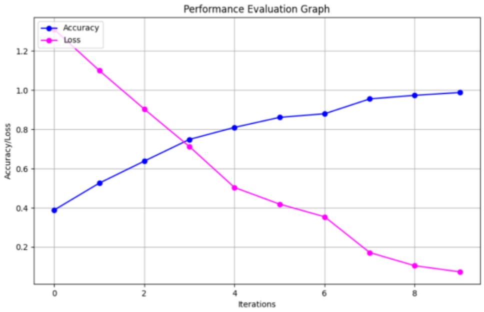

Figure.6: Performance comparison count plot ofeach model.

Table 1: Performance comparison of quality

Metric sby ALL models.

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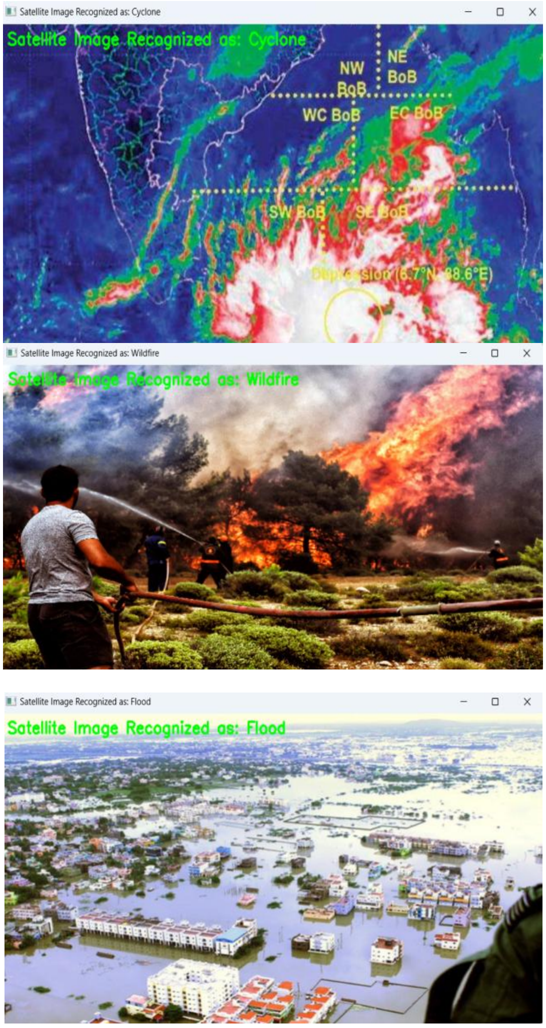

Figure.7: Proposed Ensemble model prediction on test images.

For the Logistic regression model:

The Accuracy is 96, indicating the accuracy between the actual and predicted values. The Precision is 96, suggesting that, on average Precision between the actual and predicted values. The Recall is 96, suggesting that, on average Recall between the actual and predicted values. The F1-score is 96, representing the average F1-score between the actual and predicted values.

For the CNN model:

The Accuracy is 98, indicating the accuracy between the actual and predicted values. The Precision is 98, suggesting that, on average Precision between the actual and predicted values. The Recall is 98, suggesting that, on average Recall between the actual and predicted values. The F1-score is 98, representing the average F1-score between the actual and predicted values.

5. CONCLUSION

In conclusion, the utilization of Landsat satellite data has been instrumental in monitoring and analyzing changes in land cover over the decades, contributing significantly to environmental monitoring, land use planning, and conservation efforts. The conventional methods of manual interpretation and basic change detection algorithms, while effective to some degree, have inherent limitations such as being time-consuming, subjective, and potentially overlooking subtle or intricate changes.

Recognizing the pivotal role of accurate land cover change analysis in critical domains like urban planning, forestry, and environmental conservation, there is a pressing need to advance existing methodologies. The primary challenge lies in the development of a sophisticated system capable of autonomously processing and interpreting large volumes of Landsat satellite imagery, identifying nuanced changes in land use and cover, and classifying them into meaningful categories.

The proposed project, "Analyzing Land Cover Changes with Landsat Satellite Data: An Application to Ensemble Learning," represents a pioneering effort to revolutionize land cover change analysis. By leveraging advanced ensemble learning techniques, which harness the collective intelligence of multiple models, the research aims to enhance the accuracy and reliability of identifying and classifying land cover changes. Ensemble learning, known for its proficiency in handling complex data and improving prediction accuracy, emerges as a promising solution to address the challenges inherent in traditional methods.

The outcomes of this research hold great promise for the field, as the application of ensemble learning is poised to provide a more reliable and accurate means of analyzing land cover changes using Landsat satellite data. This advancement is not only crucial for sustainable land management but also for making well-informed decisions regarding urban development, natural resource management, and habitatpreservation. In essence, the project signifies a significant step towards advancing environmental monitoring and land management efforts through cutting-edge technologies and methodologies.

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