Asian Journal of Computer Science and Technology
ISSN: 2249-0701 (P); 2583-7907 (E)
Vol.14 No.1, 2025, pp.1-5

www.crijournals.org
DOI: https://doi.org/ 10.70112/ajcst-2025.14.1.4330

Comprehensive Study on Binary Classification for CNN-LNet Based Urban Change Detection Using Satellite Images

Jambukeshwar Pujari[1*], Javed Wasim[2], Aprna Tripathi[3] and Sudharani Bangarimath[4]
[1&2]Department of Computer Engineering and Applications, Mangalayatan University, Uttar Pradesh, India
[1]KIT's College of Engineering (Autonomous), Maharashtra, India
[3]Department of Data Science and Engineering, Manipal University Jaipur, Rajasthan, India
[4]D. Y. Patil Agriculture and Technological University, Maharashtra, India
E-mail: wasim.javed@mangalayatan.edu.in aprna.tripathi@jaipur.manipal.edu, rani.bangarimath@gmail.com
*Corresponding Author: 20221385_jambukeshwar@mangalayatan.edu.in
(Received 16 November 2024; Revised 23 December 2024, Accepted 22 January 2025; Available online 30 January 2025)

Abstract - **These days, a large array of images obtained from various satellites are available due to the rapid development of remote sensing (RS) technology. Change detection from remote sensing images is a crucial component of remote sensing analysis and is applied extensively in various fields, including catastrophe assessment, urban planning, and resource monitoring. Due to their practical applications, deep learning (DL) algorithms are now widely utilized in change detection processes. However, despite the substantial amount of raw satellite data currently available, the labels for various forms of land cover remain limited. Land cover labels, typically produced through labor-intensive manual processes, are essential for training and validating machine learning models. The effectiveness of statistical learning techniques heavily depends on the availability of extensive and accurately labeled datasets, making the lack of labeled data a significant challenge. Change detection refers to the quantitative evaluation and analysis of surface changes in objects or phenomena during two different time periods. The study presented in this paper demonstrates CNN-LNet-based change detection for binary classification in satellite images, achieving an accuracy of 95.24%, sensitivity of 97.7%, and an F1-score of 97.14% in identifying locations where significant changes have occurred.**
Keywords: **Remote Sensing, Change Detection, Deep Learning (DL), Land Cover Labels, CNN-LNet**

I. INTRODUCTION

The primary objective in the field of remote sensing is to identify land-cover characteristics from satellite imagery [1], [2]. The volume of remote sensing data is increasing at an unprecedented pace due to the rapid expansion of Earth observation satellites. This growing wealth of data presents a unique opportunity to leverage advanced statistical learning techniques to address various Earth observation challenges [3], [4]. These techniques significantly enhance the utility of large datasets, making vast amounts of satellite data valuable for applications such as urban planning and environmental monitoring. However, despite the availability of substantial raw satellite data, the number of labels for different land-cover types remains limited. Land-cover labels, typically produced through labor-intensive manual procedures, are essential for training and validating machine learning models [5]. This lack of labeled data poses a significant challenge, as the effectiveness of statistical learning techniques heavily relies on the availability of extensive and accurately labeled datasets. A critical issue in remote sensing is the disparity between the abundance of raw satellite data and the limited number of land-cover classifications. To fully exploit satellite imagery, there is an urgent need to develop more efficient methods for generating land-cover labels. Advances in automated labeling methods, transfer learning, and semi-supervised learning have the potential to bridge this gap, enabling better utilization of vast datasets. Addressing the challenge of obtaining sufficient land-cover labels is essential for advancing remote sensing technologies and applications. Refining labeling procedures can enhance the precision of land-cover classification and expand the scope of remote sensing insights across various domains [6].

Modern Earth observation and remote sensing systems integrate multi-temporal data from multiple satellites to extract critical information that supports land-cover classification and decision-making. Rapid land-cover changes, driven by natural forces and human activities such as natural disasters and urban expansion, are increasingly evident [7]. Monitoring these changes provides management authorities with crucial information about significant environmental issues and hazards, empowering them to take timely and appropriate actions.

Thus, accurate evaluation of land-cover maps and their changes is vital for effective natural resource management and continuous environmental monitoring [8]. For continuous environmental monitoring and efficient natural resource management, accurate evaluation of land-cover and land-use (LCLU) maps and their adjustments is essential. Complex LCLU monitoring models have been developed to track changes in land cover and usage patterns to meet this need. These models have numerous applications, including monitoring changes in wetlands and coastal zones. By offering a comprehensive understanding of land-cover and land-use changes over time, these models assist authorities in making informed decisions and implementing timely actions. Maintaining the accuracy of LCLU assessments not only supports resource management but also promotes proactive approaches to environmental challenges.

II. BACKGROUND

The basic architecture of the CNN model used for change detection is shown in Figure 1. CNN is a type of deep learning algorithm. Yann LeCun first introduced CNN in the late 1980s with the LeNet-5 model for handwritten digit recognition. As dataset sizes and processing capacities increased, CNNs began to demonstrate their powerful feature extraction and pattern recognition capabilities.

Convolution operations are performed at the Convolutional Layer, one of CNN's fundamental building blocks, which extracts features from the input data. Convolution can be considered a filtering process in which sliding filters scan the input data to produce local feature responses. The mathematical operation of convolution is represented as:

$$(f * g)(a, b) = \sum_{k} \sum_{m} f(k, m) g(a - k, b - m)$$

The input data is represented by f, and g denotes the convolution kernel, where (a,b) represents the position in the output feature map. Convolution layers often take into account factors such as padding, which adds zeros around the input data to preserve spatial dimensions after convolution. The stride specifies the distance the filter moves across the input data, and the kernel size determines the dimension of the sliding filters, impacting the network's ability to extract features of various scales. Activation Process: Activation functions, which map inputs to a new space and enable the network to learn complex characteristics, usually follow the convolutional layers. For the network to train and perform effectively, selecting an appropriate activation function- such as Sigmoid, Tanh, ReLU, or Softmax - is crucial. Pooling Layer: Pooling layers, also referred to as subsampling, reduce the number of parameters and data dimensions while preserving essential features, thus improving computational efficiency and reducing overfitting.

Pooling techniques such as max pooling and average pooling aggregate data within localized regions to produce a reduced feature map. Fully Connected Layer: Each neuron in this layer is connected to every other neuron in the preceding layer, forming a fully connected network. This layer combines the high-level abstractions of the network to generate intricate mappings of the input data. CNN layers are applied to produce optimized classification results [9], [10].

LSTM Integration: Long Short-Term Memory (LSTM) networks are well-suited for sequence prediction tasks as they effectively capture long-term dependencies. Due to their feedback links, LSTMs can process entire data sequences rather than individual data points [11].

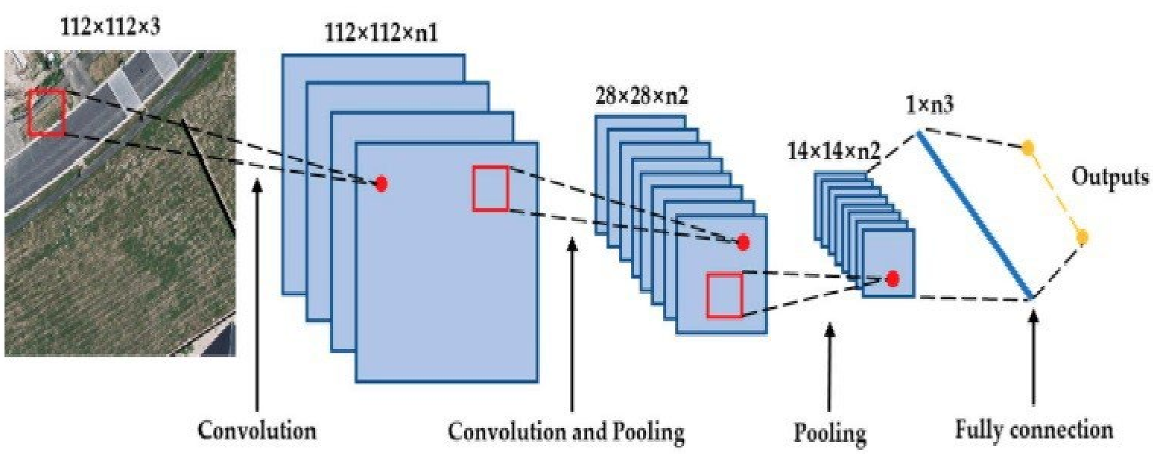

Fig. 1 CNN Architecture

III. REVIEW OF LITERATURE

In 2021, Indira Bidari *et al.,* [12] proposed an algorithm for classifying land cover and detecting changes using deep learning. This research introduced a 2D and 3D CNN technique, referred to as the Hybrid Spectral Net, for band-specific feature extraction and categorization. Additionally, a change detection method was implemented to provide binary classification using fully connected neural network layers and the Slow Feature Analysis (SFA) technique. In 2023, Ahmed Tahraoui *et al.,* [13] employed a Deep Neural Network (DNN) technique for detecting land cover changes in bi-temporal satellite images without requiring extensive prior knowledge about the study area. This approach enhances the automation of the change detection process during the training phase, eliminating the need for human intervention.

The DNN algorithm uses inputs such as recursively re-weighted multivariate alteration detection (IR-MAD) components and binary training data (change/no change). In 2023, Hong Fang *et al.,* [14] proposed a deep learning-based automatic binary scene-level change detection method. First, a scene-level pseudo-change map was generated using the pretrained VGG-16 model and change vector analysis for direct scene-level predetection. Second, another scene-level pseudo-change map and pixel-level classification were produced using a pixel-to-scene-level conversion approach with decision trees.

In 2024, He *et al.*, [15] introduced a deep learning approach for Temporal Semantic Segmentation Change Detection (TSSCD). This method captures the location, timing, and nature of changes simultaneously. The TSSCD model effectively bridges the gap between abrupt changes in remote sensing time series and land cover transformations by mapping spectral data to land cover types on a monthly basis.

In 2024, Sanchez *et al.,* [16] presented a computer vision-based methodology to extract land cover information from photos in the Land Use-Cover Area Frame Survey (LUCAS). The objective was to demonstrate how automatic photo classification can be utilized to create reference datasets for training and validating land cover products, among other applications. Critical information that supports land-cover classification and decision-making is extracted from multiple satellites using multi-temporal data integration techniques in modern Earth observation and remote sensing systems.

IV. METHODOLOGY

Rapid changes in land cover are caused by both natural and human-made forces, such as human activity and natural disasters. Monitoring these changes in land cover provides management authorities with crucial information about significant environmental issues and hazards, empowering them to take appropriate actions. Therefore, for the efficient management of natural resources and continuous environmental monitoring, it is crucial to accurately evaluate land-cover maps and their changes. To assess changes in land cover and usage patterns for various purposes, including tracking changes in coastal areas, land management, environmental protection, urban planning, and wetland zones, land-cover monitoring models have been developed. Using satellite images, deep learning-based segmentation for urban land-cover change classification involves multiple processing and analysis stages to identify changes in urban land cover over time.

A. Data Set

Satellite Images: High-resolution satellite images are collected over the study area at different time points. These images may come from sources such as the Nanjing dataset, the Onera Satellite Change Detection dataset (Sentinel-2), and the HRSCD Kaggle dataset. Fig. 2 illustrates
a) Indian dataset b) Dubai dataset

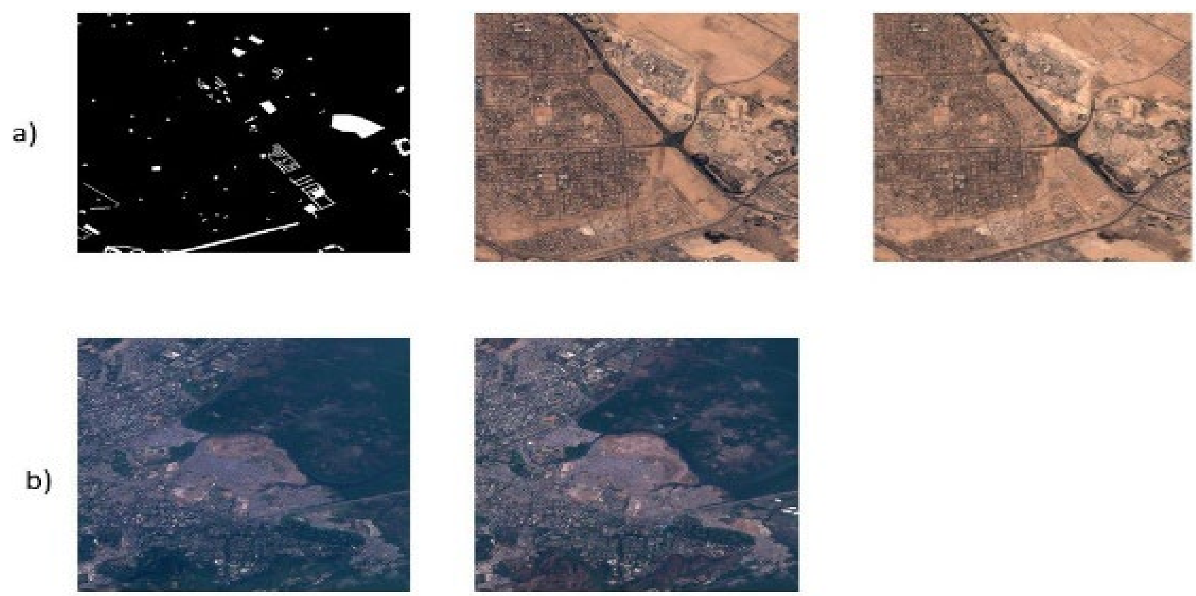

Fig. 2 Sample Dataset Images

B. Preprocessing

The raw satellite images undergo radiometric and geometric corrections to ensure consistency and alignment between images taken at different times. After collecting the satellite images, histogram equalization and normalization methods are applied to improve the quality of the images.

C. Change Detection

Change detection involves the quantitative analysis and assessment of surface changes in phenomena or objects over two distinct periods. A novel CNN-LNet + Image Transformer is applied to identify areas where significant changes have occurred. This step helps focus the deep learning model on regions of interest.

D. Segmentation

Semantic segmentation involves taking an image and assigning a specific class label to each pixel within the image. In this research, semantic segmentation is implemented using the Modified CNN-L-Net (LSTM-Net) architecture. Notably, encoder-decoder architectures are gaining popularity in semantic segmentation due to their high flexibility and performance.

The modified L-Net (LSTM-Net) architecture is enhanced by incorporating a decoding branch that performs additional semantic segmentation on the semantic categories available across the different input data.

E. Performance Metrics

The efficiency of the proposed method is assessed using numerous performance measures such as sensitivity, precision, recall, computational complexity, F-measure, specificity, and overall accuracy. In this paper, only accuracy, sensitivity, and F1-score are considered to measure the overall performance of the model.

F. Model Architecture

Figure 3 shows the overall model architecture. In this model, the change detection methodology is designed as a CNN + LSTM network. Change detection in the image is processed by the CNN, and the classification of change detection is carried out by the LSTM.

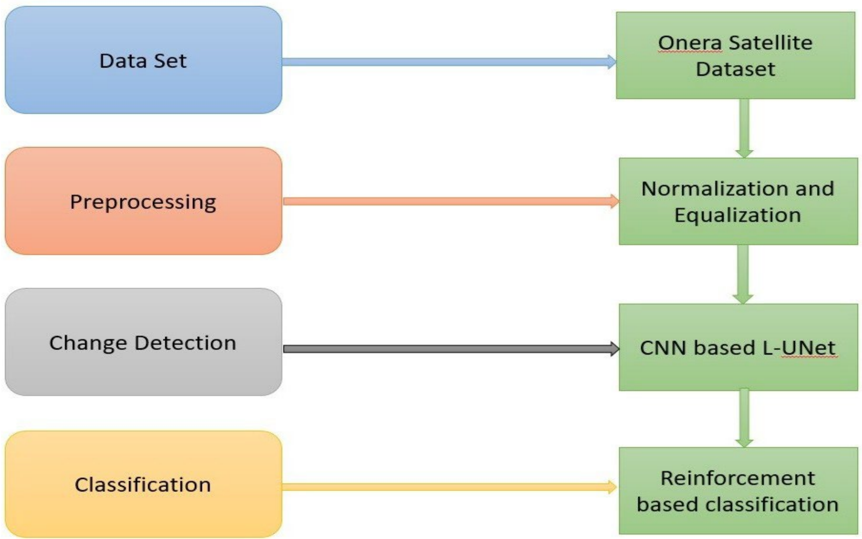

Fig. 3 Model Architecture

V. RESULTS AND DISCUSSION

The suggested CNN-LSTM architecture is used for classifying change detection in urban images. The CNN architecture correctly identified 85% of the images where changes were detected, while 15% were incorrectly identified by the suggested CNN-LSTM architecture. With better true positive and true negative values, and fewer false negative and false positive values, the suggested CNN-LSTM network was found to perform better than the competitive CNN network. As a result, the suggested approach can effectively identify binary classification in images, determining whether changes occurred in the original image compared to the updated image. The overall performance of the designed CNN-LNet, in terms of accuracy, sensitivity, and F1-score, achieved 95.24%, 97.7%, and 97.14%, respectively, for the satellite images.

TABLE I CONFUSION MATRIX

Predicted Class	**Actual Class**	
	Actual Positive	Actual Negative
Predicted Positive	85(TP)	03(FP)
Predicted Negative	02(FN)	15(TN)

The performance of the model is shown in Table I as the confusion matrix. A total of 100 images were considered, of which 85 are True Positives and 15 are True Negatives. The model predicted 2 images as False Negatives and 3 images as False Positives.

VI. CONCLUSION

The rapid growth of urban areas in many countries necessitates the identification of changes in these areas. Therefore, various proposed methods by different authors were studied, and a deep CNN-LSTM network was applied for binary classification in change detection (CD). In this approach, CNN is used as a feature extractor, and the LSTM network serves as a classifier for change detection.

The performance of the designed system is improved by combining the extracted features with LSTM, which differentiates between the original image and the updated (changed) image. The designed system achieved an accuracy of 95.24%, sensitivity of 97.70%, and F1-score of 97.14%. Both the designed CNN-LNet and competitive CNN architectures were applied to the Onera dataset. The experimental results revealed that the designed architecture outperforms the competitive CNN network. In the future, the model can be developed to identify exact changes in the updated images, and optimization algorithms can be developed to further improve accuracy.

VII. FUTURE SCOPE

The rapid growth of urbanization is making it increasingly challenging to detect changes in geographical areas, motivating researchers to develop new change detection algorithms. As deep learning technology is highly promising and multifaceted, it helps in the development of models that outperform previous ones. This paper outlines recently proposed algorithms by various researchers; however, significant challenges remain in achieving high accuracy, including F1 score, precision, and Kappa parameters. Additionally, most researchers have worked on specific datasets from particular geographical areas. In the future, there is a need for the preparation of datasets covering more countries or geographical areas. Furthermore, there is a need for the development of optimization algorithms to handle unclear data in images.

REFERENCES

[1] Q. Zhu, X. Guo, Z. Li, and D. Li, "A review of multi-class change detection for satellite remote sensing imagery," *Geo-spatial Information Science*, vol. 27, no. 1, pp. 1–15, 2024.

[2] S. Shah Heydari, J. C. Vogeler, O. S. Cardenas-Ritzert, S. K. Filippelli, M. McHale, and M. Laituri, "Multi-tier land use and land cover mapping framework and its application in urbanization analysis in three African countries," *Remote Sensing*, vol. 16, no. 14, p. 2677, 2024.

[3] A. Safonova, G. Ghazaryan, S. Stiller, M. Main-Knorn, C. Nendel, and M. Ryo, "Ten deep learning techniques to address small data problems with remote sensing," *International Journal of Applied Earth Observation and Geoinformation*, vol. 125, p. 103569, 2023.

[4] J. S. Babu and T. Sudha, "A novel remote sensing technology on land analysis use change detection," *Asian Journal of Computer Science and Technology*, vol. 8, no. 3, pp. 10–14, 2019.

[5] A. Vali, S. Comai, and M. Matteucci, "An automated machine learning framework for adaptive and optimized hyperspectral-based land cover and land-use segmentation," *Remote Sensing*, vol. 16, no. 14, p. 2561, 2024.

[6] S. Cao, Y. Tang, E. Yan, J. Jiang, and D. Mo, "Bridging domains and resolutions: Deep learning-based land cover mapping without matched labels," *Remote Sensing*, vol. 16, no. 8, p. 1449, 2024.

[7] B. R. Adhikari, S. Gautam, T. P. P. Sharma, and S. Devkota, "Land cover, land use change and its implication to disasters in the Hindu Kush Himalayan region," in *Surface Environments and Human Interactions: Reflections from Asia*. Springer, 2024, pp. 7–27.

[8] R. Mostafazadeh and H. Talebi Khiavi, "Landscape change assessment and its prediction in a mountainous gradient with diverse land-uses," *Environment, Development and Sustainability*, vol. 26, no. 2, pp. 3911–3941, 2024.

[9] S. Singh et al., "Fruit disease detection using convolution neural network approach," *Asian Journal of Computer Science and Technology*, vol. 7, no. 2, pp. 62–65, 2018.

[10] T. D. Singh and R. Bharti, "Detection and classification of plant diseases in crops (Solanum lycopersicum) due to pests using deep learning techniques: A review," *Asian Journal of Computer Science and Technology*, vol. 12, no. 2, pp. 39–47, 2023.

[11] Y. Kumar and V. Singh, "A comprehensive hybrid model for language-independent defect prediction in microservices architecture," *Asian Journal of Computer Science and Technology*, vol. 12, no. 2, pp. 48–65, 2023.

[12] I. Bidari, S. Chickerur, A. Kulkarni, A. Mahajan, A. Nikkam, and S. Akella, "Change detection and classification using hyperspectral imagery," in *2021 2nd International Conference on Range Technology (ICORT)*, IEEE, 2021, pp. 1–6.

[13] A. Tahraoui, R. Kheddam, and A. Belhadj-Aissa, "Land change detection in Sentinel-2 images using IR-MAD and deep neural network," in *2023 International Conference on Earth Observation and Geospatial Information (ICEOGI)*, IEEE, 2023, pp. 1–6.

[14] H. Fang, S. Guo, X. Wang, S. Liu, C. Lin, and P. Du, "Automatic urban scene-level binary change detection based on a novel sample selection approach and advanced triplet neural network," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–18, 2023.

[15] H. He, J. Yan, D. Liang, Z. Sun, J. Li, and L. Wang, "Time-series land cover change detection using deep learning-based temporal semantic segmentation," *Remote Sensing of Environment*, vol. 305, p. 114101, 2024.

[16] L. Martinez-Sanchez, L. See, M. Yordanov, A. Verhegghen, N. Elvekjaer, D. Muraro, R. d'Andrimont, and M. Van der Velde, "Automatic classification of land cover from LUCAS in-situ landscape photos using semantic segmentation and a random forest model," *Environmental Modelling & Software*, vol. 172, p. 105931, 2024.