Pixels in Focus: Deep Learning's Breakthrough in Remote Sensing Built-up Segmentation

Dhiroj Kumar Behera[1*], Pondari Satyanarayana[2], Rajiv Kumar[2], & K. Sreenivas[3]

National Remote Sensing Centre, ISRO, Hyderabad, India
**Corresponding author: dhirojkumar_behera@nrsc.gov.in*

Abstract

Land Use and Land Cover (LULC) constitute paramount expression of terrestrial ecosystems, exerting profound impacts on biodiversity, carbon cycles, hydrological processes, and human livelihoods. Automated LULC classification has become a fundamental task in remote sensing and geospatial analysis in recent times. The rapid urbanization and expansion of built-up areas have emerged as real challenges faced by urban planners and policymakers worldwide. Accurate and timely mapping of built-up areas is essential for effective urban management, resource allocation, and sustainable development This study focuses on the extraction of built-up areas using a deep learning segmentation method applied to Sentinel-2 multispectral satellite data with high spatial and spectral resolution, enabling detailed analysis of urban landscapes. The proposed approach leverages the semantic segmentation-based labelling of objects into built-up and non-built-up categories in a vast landscape of selected Agro-ecological zone (AEZ-4) of the nation covering approx. 34Mha. The segmentation model is trained on a labelled dataset containing diverse urban scenes, enhancing its ability to generalize across different urban environments. The research methodology involves pre-processing of Sentinel-2 data, including atmospheric correction, radiometric calibration, and mosaicking. Subsequently, the preprocessed data are used to train and fine-tune the deep learning segmentation model by using U-net architecture with resnet-50 as encoder. Performance evaluation of the model includes quantitative assessment using accuracy metrics, such as precision, recall, F1-score, and intersection over union (IoU), as well as visual comparison with ground truth data. This study demonstrates the effectiveness of the proposed approach in accurately identifying and delineating built-up areas within urban regions. The deep learning segmentation method exhibits a high potential for capturing complex spatial patterns and improving the mapping accuracy compared to traditional classification methods. The study contributes to the field of remote sensing and urban planning by providing a robust methodology for automated extraction of built-up areas, thereby facilitating informed decision- making for sustainable urban development. The best model shows an IoU of 0.62 in the validation set for predicting Built-up class after 100 epochs which used for prediction in test sites later. The results of this study showcase the effectiveness of deep learning-based semantic segmentation, underscoring its potential as a powerful tool for automating LULC classification tasks. This research contributes to the advancement of remote sensing applications, providing a reliable framework for informed decision-making in fields such as agriculture, urban planning, conservation, and resource management.

Keywords Deep Learning, IoU, LULC, Resnet-50, Semantic segmentation, U-net.

Introduction

Urbanization and associated need for resources for humanity have led to an increasing demand for accurate and efficient methods to extract land use land cover information from satellite imagery. Remote sensing technologies provide a valuable means to monitor and analyze these dynamic landscapes. With the advent of deep learning, particularly convolutional neural networks (CNNs), there has been a paradigm shift in automated image analysis, showing great promise for applications in semantic segmentation tasks. The task of characterisation of land cover and use is critical for planning, environmental monitoring, and disaster management. Accurate delineation of built-up areas is essential for understanding urban sprawl, assessing environmental impact, and facilitating disaster response planning. Deep learning models have demonstrated remarkable capabilities in image segmentation tasks, offering the potential for automated and accurate extraction of built-up areas from satellite imagery. Land Cover and use related changes are very dynamic in nature, which need to be monitored on the basis of spatial and temporal changes (Turner et al.,1994).

Technology domains ranging from visual interpretation (Liu et al., 2010), semi – automatic OBIA (Mohit et al.,2018) to deep learning (Zhang et al., 2016) has been explored in extracting the image information. Traditional pixel-based approaches often face challenges in dealing with the inherent heterogeneity and complexity of remote sensing data. They fail to capture the spatial context and relationships among neighbouring pixels, limiting their ability to extract high-level features and accurately classify land cover and land use (LULC) categories. In contrast, Object Based Image Analysis (OBIA) exploits the spatial and contextual information provided by image objects, resulting in improved classification accuracy and more robust analysis. Various segmentation algorithms have been proposed, ranging from region-based methods such as mean-shift and graph cuts to edge-based methods like watershed and morphological techniques. These algorithms aim to delineate objects based on spectral, spatial, and textural characteristics, effectively capturing the inherent heterogeneity of remote sensing imagery. The object-oriented image analysis using remotely sensed data was introduced in early 2000. Object-oriented classification pattern is in high demand due to involvement of image segmentation technique (Yongxue et al., 2006). The first step in this process is image segmentation (Ganguly et al., 2016), which involves grouping of pixels into homogenous regions based upon various features of image such as texture, shape, colour, and etc. The purpose of the process is to analyse feature selection in the generation of rule-based image classification.

It is well established that the artificial neural networks are apt for Land Use Land Cover (LULC) classification using remotely sensed data (Henry et al., 2019). The deep learning has provided resources with respect to theory, tools, and challenges for the classification technologies (Ball et al., 2017). The fundamental unit of deep neural networks is called an artificial neuron/perceptron. The first step towards building a neural network requires the user specific training of network structure and set the learning parameters (Marmanis et al., 2016). The cell in neuron network gives out a binary state – zero or one, on or off. The inputs provided is being carried out as a binary signal and more importantly the value number of the binary number as 0 or 1. The requirement of the model is that the neuron shall capture all of its properties and behaviour which will be enough to capture its computation performance. So, the new aspects being studied is to follow the hierarchy of image classification by simply identify a single LULC class at a time using attribute parameters. Residual networks (ResNets) have been a significant advancement in deep learning. Residual Network (ResNet) is a Convolutional Neural Network (CNN) architecture that overcame the “vanishing gradient” problem, that occurs due to backpropagation. It has helped to construct networks with up to thousands of convolutional layers, which outperform shallower networks. (https://www.run.ai/guides/deep-learning-for-computer-vision/pytorch-resnet). These networks have shown promise in various computer vision tasks, including image classification. Adapting ResNets for remote sensing data can enhance feature extraction for built-up area identification (He, K. et al., 2016).

Need for approach using artificial intelligence and machine learning:

Satellite remotely sensed data comprises of various land cover and land use (LULC) class information which needs to be extracted using advanced technologies (Singh et al. 2022; Kumar et al. 2023; Ahire et al. 2022). LULC changes are very dynamic in nature, which needs to be monitored regularly and prediction will help in better planning through different approaches (Turner et al. 1994; Singh et al. 2017; Behera et al. 2022). Conventional pixel-based approaches have dissatisfaction in dealing with the inherent heterogeneity and complexity of remote sensing data. Further, pixel-based methods failed to capture the spatial context and relationships among neighbouring pixels, which limit their ability to accurately extract high-level features (Gamanya et al. 2009). However, object-based image analysis (OBIA) is closer to real human perception (Baatz et al. 2004) and used the spatial and contextual information provided by image objects, resulting in improved classification accuracy and more robust analysis (Blaschke, 2010). The OBIA has a key component as image segmentation, which partitions an image into homogeneous and coherent objects (Blaschke et al. 2014). Various segmentation algorithms have been proposed (Ezzahouani et al. 2023), ranging from region-based methods such as mean-shift (Chandra & Vaidya, 2022) and graph cuts to edge-based methods (Sakshi, & Kukreja, 2023) like watershed (Wu & Li, 2022) and morphological techniques (Wang et al. 2008).

Methods ranging from visual interpretation (Liu et al. 2010; Shimrah et al. 2019; Boloorani et al. 2023; Zhou et al. 2023), semi–automatic OBIA (Mohit et al. 2018; Detka et al. 2023; Ponsioen et al. 2023) to deep learning (Zhang et al. 2016; Khlifi et al. 2023; Han et al. 2023) have been used in extracting the image information. The OBIA using remotely sensed data was introduced in early 2000. Object-oriented classification pattern is in high demand due to involvement of image segmentation technique (Liu et al. 2006). The first step in this process is image segmentation (Ganguly et al. 2016), which involves grouping of pixels into homogenous regions based upon various features of image such as texture, shape, colour, and etc. The purpose of the process is to analyse feature selection in the generation of rule-based image classification (Blaschke et al. 2014). The features are extracted ranging of values in distinct variations.

Various techniques have emerged to effectively map LCLU at different scales, ranging from local to global. These approaches can be broadly categorized into data-centric and model-centric strategies, or often employed in conjunction to achieve comprehensive LCLU classification. Data-centric approaches emphasize on the pre-processing and utilization of multi-sensor and multi-temporal remote sensing data (Hermosilla et al., 2018, 2022). In this approach, the emphasis is given on deriving textural information from the images, data fusion techniques like principal component analysis to capture the more variance and relevant information from image, spectral indices to highlight land cover features and normalization of data cube to enhance LCLU classification. Model-centric approaches, on the other hand, focus on developing and applying classification algorithms to categorize LCLU patterns (Alem & Kumar, 2022; Park et al., 2020; Yuh et al., 2023). These algorithms range from traditional statistical methods to advanced machine learning techniques, such as support vector machines (SVMs), Random Forest (RF) and deep learning models like Convolution Neural Network (CNN), Multi-Layer Perceptron (MLP) and Transfer Learning (TL). The synergistic integration of data-centric and model-centric approaches has proven to be particularly effective in LCLU classification (Hosseiny et al., 2022; Mahamunkar & Netak, 2022). Data-centric preprocessing ensures the high quality of input data for the models, while model-centric algorithms provide the analytical power to extract meaningful LCLU information which led to significant advancements in LCLU mapping, enabling researchers and policymakers to better understand and manage LCLU dynamics.

Deep learning and beyond:

Several studies have explored the application of deep learning models in remote sensing tasks, demonstrating their effectiveness in various domains. For instance, the work of Chen et al. (2017) showcased the use of CNNs for land cover classification in remote sensing imagery, while Zhang et al. (2019) presented a comprehensive review of deep learning applications in remote sensing data analysis. Despite this progress, there remains a need for a focused comparative analysis of specific architectures for the task of built-up area extraction.

Two prominent deep learning architectures, U-Net and 3D CNN, have emerged as powerful tools in image segmentation and volumetric data analysis, respectively. U-Net, introduced by Ronneberger et al. in 2015, has proven effective in biomedical image segmentation tasks due to its unique architecture, its distinctive U-shaped structure, consisting of a contracting path followed by an expansive path, enables the model to capture both local and global features efficiently. We discuss the adaptation of U-Net for built-up area extraction and highlight its ability to preserve spatial information through skip connections. Combining a contracting path to capture context and an expansive path to enable precise localization. In this paper, we conduct a study of U-Net model, tailored for the extraction of built-up areas from remotely sensed datasets. We aim to provide insights into the performance, strengths, and weaknesses of these models, considering factors such as spatial and temporal dependencies, computational efficiency, and generalization across diverse datasets. This research contributes to the ongoing efforts in leveraging deep learning for accurate and efficient built-up area extraction, ultimately benefiting urban planning and environmental monitoring.

In this paper, studies carried out to classify selected land cover categories employing advanced segmentation techniques, feature extraction methods, and classification algorithms are aggregated. Studies related to detection and mapping of urban are employed to demonstrate the application potential of Deep Learning approach. We evaluate the performance of the proposed framework using a representative dataset and compare it with other state-of-the-art approaches. Our results demonstrate the effectiveness and efficiency of DL based segmentation and classification in accurately characterizing and classifying LULC categories from remote sensing imagery. By leveraging the spatial context and semantic information captured by image objects, segmentation offers new opportunities for improved understanding and analysis of remote sensing datasets, contributing to a wide range of applications in environmental monitoring, urban planning, natural resource management, and beyond.

Materials and Methods

Studies presented herewith focus on applying AI and ML based methods for delineating regional level built up area. Following sections detail the study sites as well as brief of methods adopted.

Regional level delineation of built-up areas:

Land Use and Land Cover (LULC) are influenced by a multitude of factors, including terrain characteristics and a variety of human and environmental drivers. India is divided into 20 Agro-ecological zones (AEZ) by National Bureau of Soil Survey & Land Use Planning (NBSS&LUP) after considering climatic condition, soil, and topographic factors that influence agricultural practices and land use (Fig. 1). Categorisation aims to delineate regions with similar environmental conditions and agricultural potential to assist in land management, crop selection, and agricultural planning. Pattern of land use within the zone is assumed to be characteristic as influenced by biophysical features. AEZ-4 (TGA: 33.9 Mha) which is highlighted in green star mark (Fig. 1) being the largest out of 20 is selected for the first category of Built-up extraction which is hot semi-arid ecoregion with alluvium-derived soils in nature. The diversity in the class including major cities, clusters of villages, hamlets and isolated habitations with other dominant LULC classes helps invalidating the robustness of the model. The research focuses on two different types of terrain and landscape together for the selected land cover/land use studies. Following are the details for specific target LULC categorization studies: i) Built-Up extraction for Agro ecological Zone - 4 (AEZ4) ii) Extraction of shifting cultivation in parts of Nagaland and Arunachal Pradesh for shifting cultivation.

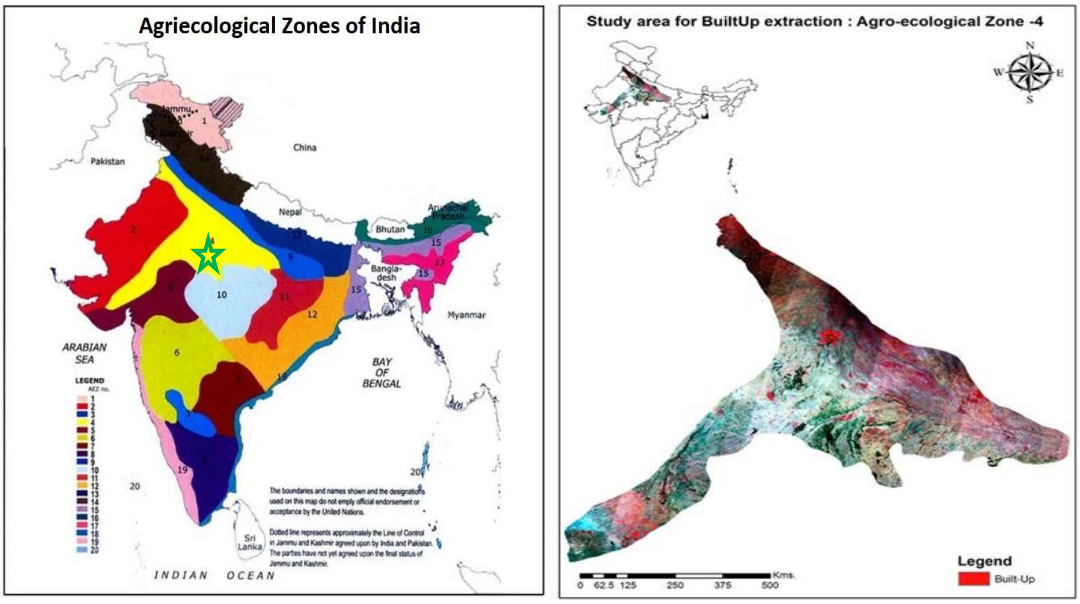

Fig. 1 Study Area location map (AEZ-4) for Built-up Extraction.

The main objective of the research is to obtain a methodology for automation of image classification. Data pre-processing involves the preparation of training samples and their labels from existing available datasets e.g., LULC 1:50K (2015-16) (available at: https://bhuvan-app1.nrsc.gov.in/thematic/thematic/index.php) by NRSC under Natural Resources Census (NRC) and World settlements footprints prepared by DLR (https://geoservice.dlr.de/web/maps/eoc:wsf 2019). Different type of indices of vegetation, Built-Up, Waterbody etc. like NDVI, NDWI, NDBI are generated and given as additional bands to a supervised machine learning algorithm. Random Forest classifier is used to classify Built-Up and Non- Built-up pixels in the whole study area. The classification involves the hyper-parameter tuning of the particular RF algorithm in terms no. of trees, tree depth, number of features and criterion etc. to obtain the best overall classification accuracy. Leveraging the feature importance from the RF classifier, most important contributing bands to the model are noted and used for the following process in the methodology. U-net (Fig. 2a) architecture is considered for semantic segmentation of the sentinel-2 (10m.) satellite data with 3 bands (SWIR, NIR & R) FCC with respective labels of particular categories viz Built-up and Shifting cultivation. The different type of loss and accuracy metrics e.g., IoU and Dice coefficients (Fig. 3) are tracked throughout the training process. Overall methodology flowchart (Fig. 2b) describes the detailed approach for the above study.

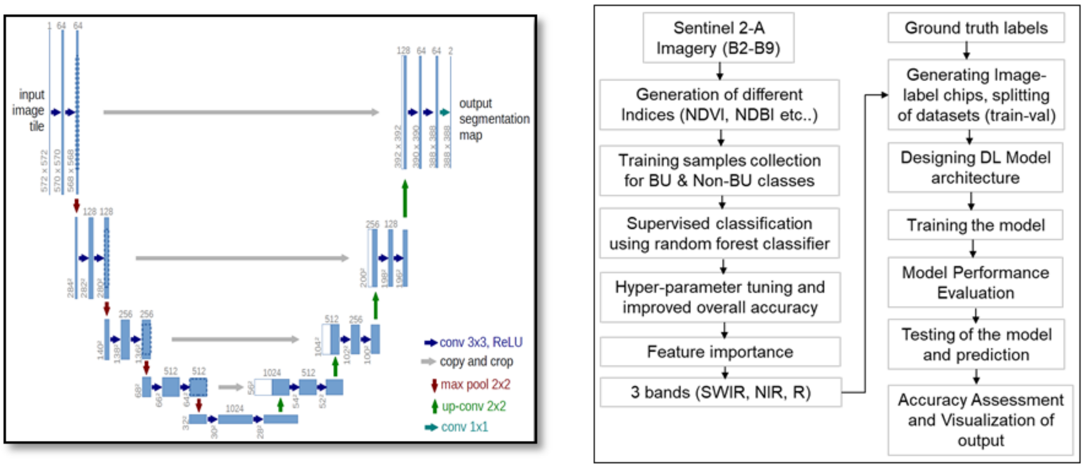

Fig. 2 (left) U-Net architecture (right) Overall Approach for the study.

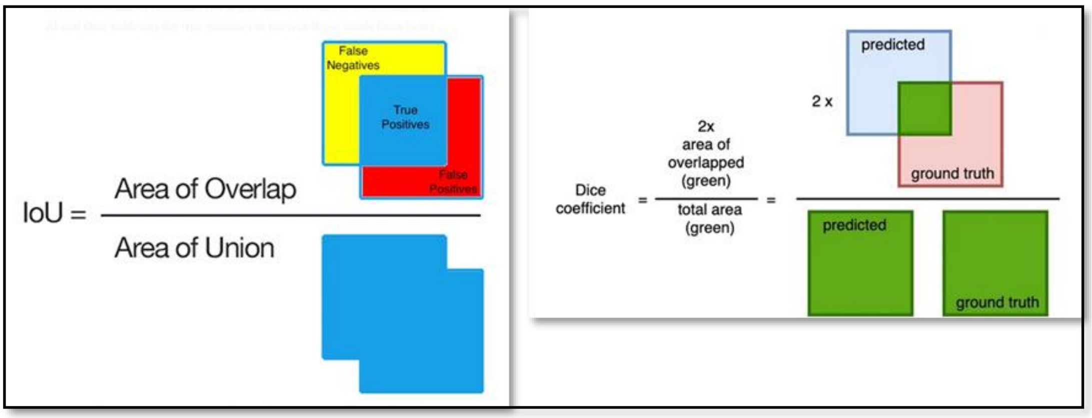

Fig. 3 Different metrics (IoU and Dice score) to evaluate the performance of model.

Results & Discussions

U-Net based analysis: The results indicate that both U-Net model exhibit commendable performance in accurately delineating built-up areas from remotely sensed imagery. However, the choice of model may depend on specific dataset characteristics, such as resolution, temporal variability, and spectral diversity. U-Net, with its emphasis on spatial relationships through skip connections, demonstrates superior performance in scenarios where spatial features play a critical role. Both models showcase varying degrees of generalization across diverse datasets. U-Net's ability to adapt to different spatial characteristics of remotely sensed imagery makes it a versatile choice, in real-world applications, considerations such as model interpretability, training data availability, and computational efficiency become pivotal. Researchers and practitioners should weigh these factors alongside model performance to make informed decisions about model selection and deployment.

Detection of urban surface indicates high confidence extraction of land cover classes from remote sensing images of large geographic coverage as well as inherent spectral variability due to fuzzy nature of reflectance patterns. Sentinel datasets available as open-source imagery processed using Google Earth Engine based implementation of U net architecture shows the strength of transfer learning. Deep learning approach preserves the learning enabled through labelling following optimal cessation of epochs, which in turn will effectively classifies similar image without supervision. Both urban surface and shifting cultivation patches in 'testing sets' cases illustrate such transfer learning.

Utilization of the Dice coefficient and IoU in our research not only facilitated a more thorough evaluation of our binary image classification model but also highlighted the model's capacity for accurate and precise predictions. As we continue to advance in the field of computer vision, these metrics prove to be invaluable tools for researchers and practitioners alike, providing a deeper understanding of model behaviour and enhancing the interpretability of classification results. Furthermore, the incorporation of these metrics into our accuracy assessment allowed for a more nuanced understanding of model performance beyond traditional accuracy measures. While accuracy provides an overall evaluation of classification correctness, the Dice coefficient and IoU offer a more fine-grained analysis, particularly beneficial when dealing with imbalanced datasets or when precise delineation of object boundaries is crucial.

Some of the samples test sites of model predicted Built-Up class area are illustrated in the below Figure 4, 5. The deep learning model based on U-net produced an IoU of 0.62 in Built-up prediction by U-Net architecture after iterating through 100 epochs (Fig. 6). Detailed model performances by U-net based deep learning architecture for Built-Up is tabulated in Table 1.

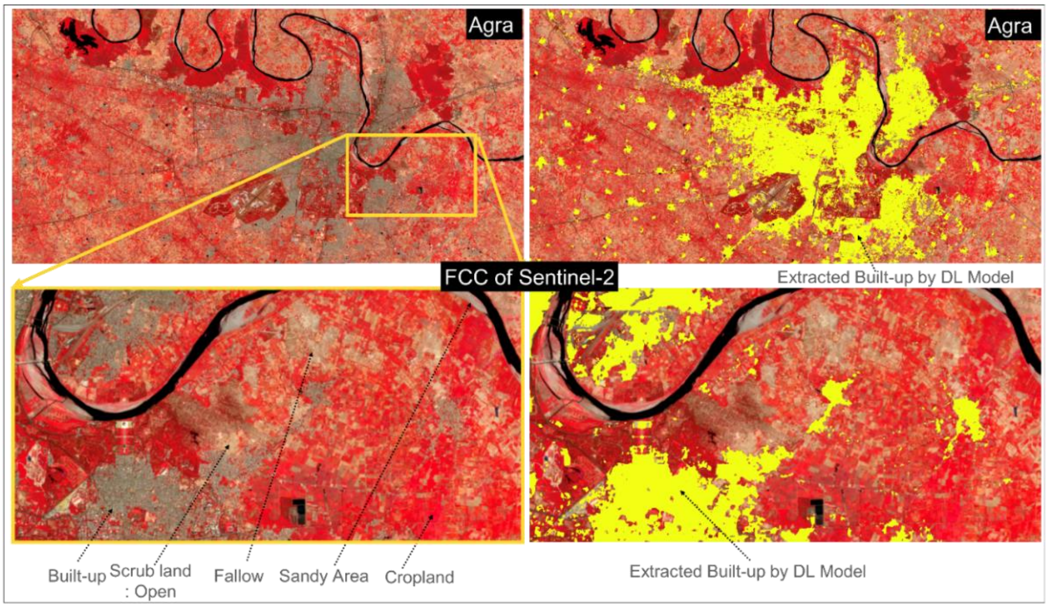

Fig. 4 Extracted Built-up area by the designed deep learning model (U-net) from Validation set.

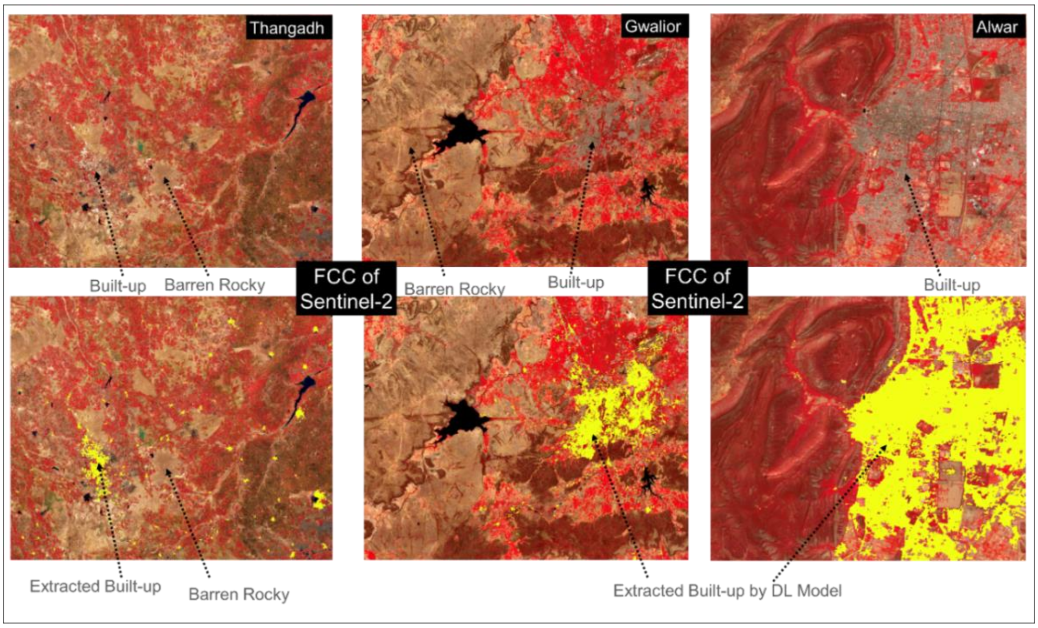

Fig. 5 Predicted Built-up area by the designed deep learning model (U-net) from testing sets.

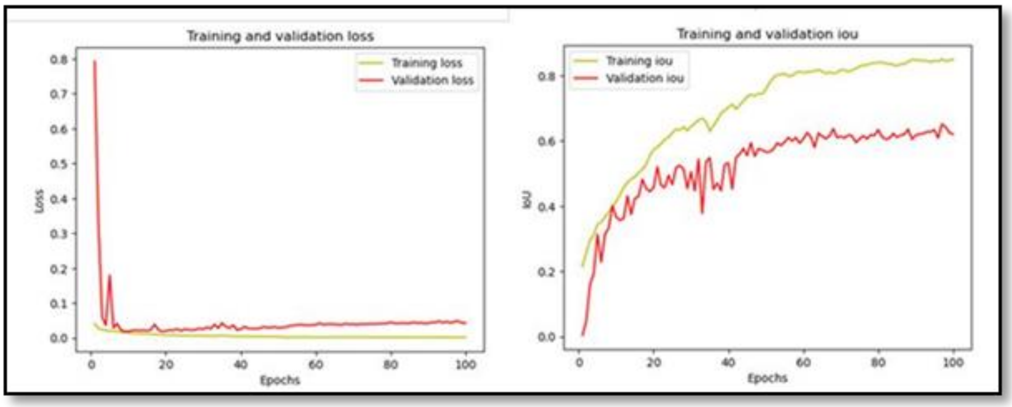

Fig. 6 Loss, IoU and Dice vs Epochs graph for Built-Up Extraction.

Table 1 Detailed Model performance in Built-Up and Shifting Cultivation Extraction by U-Net.

Model	Extracted Class	Validation IoU/Dice	Precision	Recall	F1-score
U-Net with Resnet50	Built-Up	60.2%	63%	65.4%	63.6%

Conclusion

Study results provide valuable insights for researchers and practitioners seeking to leverage deep learning for accurate and efficient extraction of land cover fractions from diverse remote sensing datasets. They contribute to the on-going advancements in remote sensing applications, promoting informed model selection and deployment strategies for specific environmental monitoring and urban planning tasks. Important approaches such as machine learning and deep learning have advantage of incorporating expert knowledge to function as independent unsupervised algorithms. Nuanced understanding gained from this comparative analysis can guide researchers and practitioners in selecting the most suitable model for their specific use cases, advancing the capabilities of remote sensing applications in urban planning, environmental monitoring, and disaster management.

In this study, we presented an evaluation of our binary image classification for both Built-Up and Shifting cultivation class using the dice coefficient and Intersection over Union (IoU) metrics in a U-net based deep learning model. These metrics, commonly employed in remotely sensed image segmentation tasks, provided valuable insights into the model's performance and its ability to accurately classify binary images. Our results demonstrated that the Dice coefficient and IoU are robust measures for assessing the overlap between predicted and ground truth regions. The high values obtained for these metrics indicate the model's proficiency in capturing the relevant features and accurately classifying positive instances. The model's ability to achieve a substantial Dice coefficient and IoU emphasizes its effectiveness in delineating the boundaries of the target class in binary images.

The findings presented in this study contribute to the ongoing discourse on robust evaluation methodologies for binary image classification, paving the way for further advancements and improvements in model performance in real-world applications.

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