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Classification of Remote Sensing Dataset Imagery Using Deep Learning Techniques

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ABSTRACT

Integrating deep learning with remote sensing is contentious due to the disparity between natural and remote sensing images, raising the question of whether deep learning techniques can transform the remote sensing domain. This study covers prior research employing deep learning methodologies for land use and land cover categorization in the last five years. Our study is categorized into three groups based on the data type utilized in each analysis. The initial group comprised roughly 20 prior studies of multispectral data, the subsequent group contained 8 studies of hyperspectral data, and the final group encompassed 10 studies of aerial photos obtained via drones or radar. Each data type is physically distinct and serves a specific purpose. Furthermore, we chose one of the studies and implemented it with the specified data to categorize land cover with the CNN technique, employing a 4-band CNN patch size of 5x5. An accuracy of 95.0% was achieved, whereas a 4-band CNN with a patch size of 9x9 attained an accuracy of 91.5% on the training data for a region in Pakistan. The accuracy for the test data in Lahore City was 93.6% for the 4-band CNN with a patch size of 5x5 and 91.1% for the 4-band CNN with a patch size of 9x9.

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1. Introduction

1.1. Overview

In 1957, the inaugural satellite orbited Earth. Human capability has attained an extraordinary degree due to the significant advancement of Earth observation technology [1]. Addressing the population's demands and acquiring highly precise information is a primary function of remote sensing photographs, regarded as a crucial data source [2]. It provides effective information at a reduced cost [3-5]. The principal satellites utilized in remote sensing image categorization are radar (SAR), Google Earth Engine (GEE), unmanned aerial vehicles (UAV), Sentinel-1, Sentinel-2, and Landsat-8 [6]. Medium-resolution remote-sensing imagery is a crucial data source for producing land use and land cover (LULC) maps across extensive regions, owing to its capacity to deliver near-global high-frequency land

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surface coverage, such as every 5 or 8 days for Sentinel (-2a/2b) and Landsat (-8/-9) satellite data, respectively [7]. Remote sensing satellites with a spatial resolution below one meter have attained image quality akin to airborne photographs, owing to the swift advancement of remote sensing technology. Consequently, the volume of data has surged significantly due to the incessant functioning of sensing technologies over the week. Satellite-generated images differ in texture, shape, color, spectral information, scale, and other attributes; remote-sensing images display the following characteristics:

• Intricate spatial configurations. Remotely sensed images exhibit significant semantic variability, with common examples including agricultural, airport, business, and residential scenes.

• Minimal inter-class variance. Specific scene images exhibit similarities, such as agriculture, forests, densely inhabited regions, and residential areas. This attribute is designated as low intra-class variance. Attaining precise scene classification under these circumstances necessitates well-calibrated computer vision methodologies.

• Elevated intra-class variance. Images of the same type are generally captured from several angles, scales, and perspectives. The variation in images within the same category necessitates sophisticated computer vision methodologies capable of extracting consistent pattern elements from remotely sensed images, irrespective of their discrepancies.

• Noise: Remotely sensed images are captured under different weather conditions and in different seasons. Scene images may have variable lighting conditions and require robust feature-learning techniques for different weather conditions.

Deep learning (DL) methods are based on neural networks, which have long been employed in remote sensing [1]. It is a more complex subclass of machine learning, which uses different stacked layers of information to make repetitive decisions [9]. Deep learning classifiers may require longer training and classification times than machine learning classifiers, suggesting that slight differences in overall accuracy may not be worth the longer processing times[10]. This study provides a comprehensive overview of how to classify remote sensing data using deep learning, emphasizing the importance of data type, model selection, and patch size in achieving high classification accuracy. The main research gap addressed in this work is the need to develop more accurate and reliable deep learning models for land cover classification, with a focus on improving performance in classes that are difficult to distinguish, such as agricultural land and settlements. Through this research, the work seeks to provide innovative solutions that enhance the effectiveness of existing models, contributing to improving classification accuracy in remote sensing data.

1.2. Remote Sensing Datasets

Remote sensing facilitates spatial coverage across multiple scales, from meticulous analyses of individual assets to investigations spanning hundreds of square kilometers [11]. Numerous publicly accessible remote sensing databases exist for applications with deep learning techniques [12]. In remote sensing, picture preprocessing is a crucial initial phase, encompassing geometric rectification and image registration, radiometric normalization, cloud and cloud shadow identification, and atmospheric and topographic correction. Three techniques employed in remote sensing imaging are synthetic aperture radar (SAR), light detection and ranging (LiDAR), and photogrammetry. Landsat 5 and 8, as well as Sentinel-1 and -2, are satellites extensively utilized for image classification in deep learning [13]. Due to its superior spatial and temporal resolution, Sentinel-2 is the most prevalent satellite for remote sensing image categorization [14]. Satellite sensors catch the electromagnetic radiation reflected from or released by the Earth's surface, thereby acquiring data from satellites orbiting the Earth continuously throughout the week. Alterations in climate and land cover influence biochemical processes and cycles, nutrient loads, and water resources; thus, environmental factors, including cloud cover and meteorological conditions, also impact the quality of the collected data [15, 16]. QuickBird-2, GeoEye-1, WorldView-2, and WorldView-3 are sensors that acquire satellite imagery with a spatial resolution ranging from 0.3 to 1.4 million pixels. The attributes of these scenes The images consist of four corrected and augmented bands: blue, green, red, and near-infrared channels [17]. Deep learning methodologies have been employed to effectively associate image objects with their geographic components, leveraging their substantial modeling and learning capabilities and enabling enhanced knowledge regarding real-world changes[18]. Remote sensing systems utilized in aerial surveillance and agriculture can be categorized primarily by (a) the sensing platform and (b) the type of sensor. Recently, satellite-mounted remote sensing devices have been extensively employed in aerial surveillance of land cover, including drones and unmanned aerial vehicles (UAVs). Satellite-mounted sensors are crucial for obtaining real-world data and relaying it to applied reality, offering high-resolution details gathered by satellites at sub-meter precision. Multispectral remote sensing images comprise high-resolution, medium-resolution, and low-resolution data. The precision of land use and cover classification is influenced by sensor attributes and image data factors, such as spatial and temporal resolution, as well as processing software and hardware.

1.3. DEEP LEARNING Techniques

Diverse and comprehensive techniques have been employed in applying deep learning to remote sensing, resulting in the development of more adaptable models and derivative networks due to the widespread utilization of deep learning in this domain [21]. Learning representations constitute a way of deep learning within the remote sensing domain [22]. A node is the computational element constituting the neural network of a deep learning model. The neural network operates through multiple layers, beginning with the input layer and concluding with the output layer, interspersed with hidden layers. Neural networks are trained by executing linear transformations for each input, succeeded by a nonlinear transformation known as the activation function. This is referred to as deep learning. Neural networks are employed to extract spatial characteristics in the picture domain owing to their efficacy in images and are classified as a deep learning technique. Solar radiation and cloud cover significantly influence the performance and forecasting of any system. The selection of CNN for aerial cameras and satellite imagery is highly appropriate in this domain since notable advancements have been recorded in remote sensing. Nonetheless, extensive datasets are necessary for training CNNs, frequently presenting a significant obstacle because of the manual work required for data labeling [26, 27]. The most often utilized CNN architectures are ResNet, DenseNet, InceptionNet, and AlexNet [28]. Inputs to CNNs are consistently of a predetermined size, and sequential convolutional filters are utilized to produce learned features from these inputs. The pooling layer samples diminish the output size; however, certain issues arise during the classification of Land Use and Land Cover (LULC) using Convolutional Neural Networks (CNN). Specifically, CNNs require fixed-size inputs, leading to the convolutional filters' neglect of small LULC edges, resulting in the inclusion of extraneous inputs in the classification process [29]. Convolutional Neural Networks (CNNs) are considered potential methodologies for land cover categorization and enhancement, and they are assessed utilizing high-resolution time series imagery acquired from satellites, including Sentinel-2 [30].

1.4. RELATED WORK

Prior research in this survey categorized multiple categories based on the data type utilized for LULC classification. The initial group comprised roughly 20 prior studies on multispectral remote-sensing data, the subsequent group encompassed about 18 prior studies on hyperspectral remote-sensing images, and the final group consisted of 8 prior studies on remote sensing images obtained through aerial photography. Researchers analyzed multispectral remote sensing data with deep-learning methodologies to forecast the proliferation of forest fires. Mohammad Marjani developed an innovative deep learning model named CNN-BiLSTM, integrating convolutional networks (CNN) with binary long short-term memory (BiLSTM) units. The CNN-BiLSTM model was trained with the wideband visible infrared spectroscopy (VIIRS) network ensemble [31]. Antonio Rangel examined the latest deep-learning methods to enhance the precision and efficacy of LC analysis. He compared transformer-based methodologies with convolutional neural networks (CNNs) and employed EuroSAT, a patch-based land cover classification dataset sourced from Sentinel-2 satellite imagery, to achieve state-of-the-art results using pre-existing transformer models. [32].The Reham Gharbia Faster R-CNN technique was employed to delineate water bodies from remote sensing images, and the methodology was evaluated using about 3500 images from both Sentinel-2 and Landsat-8 (OLI) satellite imagery data [33]. Ali Asido executed LCLU. A DNN model using five spectral indices was employed to differentiate six land cover classes from Sentinel-2 satellite remote sensing pictures to classify the TNP [34]. Mohammad Al-Jibreen introduced a novel land use and land cover (LULC) classification approach termed LULCC-RFDADL, which employs a deep learning technique alongside the river formation dynamic algorithm to differentiate various land cover types in remote sensing imagery (RSI). EfficientNet's density-based feature extractor and RFDA-related hyperparameter optimization [35]. Qianxiong Xu proposed utilizing an incomplete-to-complete Two-Channel Network (P2CNet), comprising two primary components, for road extraction from satellite data and incomplete road maps. Missing Part Loss (MP) and Gated Self-Attention Module (GSAM) GSAM employs the gate module and the channel-level self-attention module to capture long-range semantics [36]. The first calibration of multiple advanced deep-learning models was conducted utilizing the multispectral Sentinel-2 dataset from BigEarthNet. The test encompasses traditional convolutional neural network architectures and non-convolutional methods, such as multilayer neural networks and vision transformers.[37] Kamran Ali conducted LULC categorization of semi-arid environments at three research sites in Pakistan, utilizing a CNN model with a predetermined architecture. The region encompassing the Pakistani cities of Gujranwala, Gujranwala Saddar, and Wazirabad functioned as a training site for CNN before deploying the advanced CNN at two undisclosed test sites [7]. Guillaume Rousset determined the most efficient deep learning configuration currently available for land use and land cover mapping in a demanding subtropical environment. A human operator designated five representative regions of New Caledonia to create a tailored dataset utilizing SPOT6 satellite data [38]. Sumaya Falih Hasan examined the impact of speckle filtering on land use and land cover, employing multispectral Sentinel-2B data and SAR Sentinel-1A (VH, VV) data collected in Kirkuk, Iraq. Datasets from Sentinel-1A with differing window sizes underwent multiple filtering approaches, including Boxcar, Frost, Gamma, and Lee filters, which were subsequently evaluated quantitatively using various performance measures. Kai Zhang proposed a land classification model utilizing remote sensing images based on deep learning for environmental resource utilization, incorporating feature-level image fusion techniques, processing DBN network models, and analyzing remote sensing image data acquired from the Gaofen-1 satellite in Jinfeng District, Yinchuan City, China, ascertain land type [40] accurately. Kunhao Yuan proposed a novel DCNN model, known as the Multi-channel Waterbody Detection Network (MC-WBDN), which comprises three innovative components: space-to-depth/depth-to-space operations, an advanced spatial hierarchical pooling module, and a multi-channel fusion module [41]. Xuedong Yao presented the Dense Coordinate Network (DCCN) to mitigate the loss of some spatial properties. In contrast, DenseNet was introduced to enhance spatial information by integrating coordinate data into feature maps [42]. Honsoo Song introduced a lightweight convolutional neural network (LCNN) that attains good accuracy without overfitting, even with limited training data, and it incurs lower processing costs due to its streamlined architecture relative to conventional convolutional neural networks. Each test site utilizes a single Landsat-8 image and a specific date to categorize land cover with medium accuracy [43]. Rafael Gaetano employed direct classification to utilize both PAN and MS images without any pre-sharpening or resampling of the images. The deep learning architecture he presented comprises two branches that extract features at the original resolution from each source [44]. Yunfeng Hu suggested a deep learning architecture that incorporates parameter pooling across successive channels and the intermediate pooling layer, utilizing Landsat-8 Operational Land Imager (OLI) pictures from Qinhuangdao City, Hebei Province [45]. Chunping Qiu categorized land cover derived from the LCZ by introducing a recurrent neural network (Re-ResNet), a deep learning model utilizing Sentinel-2 imagery that can assimilate both temporal and spatial features through the integration of ResNet and RNN into a unified architecture [46]. Atharva Sharma suggested a deep slice-based system tailored for medium-resolution satellite imaging data utilizing convolutional neural network technology. The system generates slice-based samples from multidimensional atmospheric reflectance data, with the test data representing the Everglades region of Florida [47].

Table 1 - Comparisons between previous studies and multispectral sensing data

Author	Methods/Technique	Advantage&disadvantage	Result
Mohammad Marjani et al (2024) [31]	CNN-BiLSTM	Adv: Improved near-term wildfire forecasting, enhancing fire management strategies Dis: Wildfires cannot be prevented entirely and the model relies on raw data that may not be	The validation set achieved an IoU score of F1 (0.58), and the training set achieved F1 (0.73).
Antonio Rangel et al (2024) [32]	(CNN and Transformer)	Adv: Improved accuracy and efficiency in land cover analysis using deep learning models. Dis: Traditional methods were labor-intensive and prone to human error, affecting results.	Achieved up to 99% accuracy with Transformer models. Transformer models outperformed CNN in some

			cases.
Reham Gharbia (2023) [33]	Faster R-CNN	Adv: Using satellite images, extracting water bodies will be accurate and efficient. Div: Relying on the quality of input images, training data must be available in large quantities and with high accuracy. May have difficulty identifying small water bodies.	Accuracy is 98.7% for Sentinel-2 data and 96.1% for Landsat-8 data. Faster R-CNN outperforms traditional CNN methods.
Ali Azedou et al (2023) [34]	(DNN) with (Hyperparameter Optimization)	Adv: Improved land use/cover (LCLU) classification to facilitate natural resource management. Dis: We need very large computational resources when applying deep learning techniques to satellite imagery.	Improved classification accuracy by 12.5%. Overall accuracy 94.5% kappa coefficient 93.4%
Mohammed Aljebreen et al (2023) [35]	LULCC-RFDADL	Adv: Improve classification accuracy in environmental applications and urban planning. Dis: To ensure very high performance across multiple geographies, we must provide very large and diverse training datasets when applying the LULCC-RFDADL algorithm.	Classification accuracy of 98.15%, F-score and G-measure around 90.76%
Qianxiong Xu et al (2023) [36]	(P2CNet) (GSAM) (MP).	Adv: Developing a method to extract roads from remote sensing images captured by satellites, increases road extraction accuracy and reduces the heavy reliance on manual data. Dis: Partial maps may be limited in areas where good data or partial maps are not available.	IOU scores of 70.71%), (75.52%) for both Space Net and OSM datasets
Ioannis Papoutsis et al(2022) [37]	CNNs and alternative methods such as Vision Transformers and MLPs.	Adv: Pre-trained data will provide us with a comprehensive set of deep-learning models. Div: The need for a large change in the trained data, can be a barrier to in limited data applications.	F1-Score (71.1%) for the SEN12MS dataset, with a 4.5% increase in classification accuracy when compared to the ResNet50 model.

Kamran Ali et al (2022) [7]	CNN	Adv: Increasing the classification of LULC use in semi-arid lands using satellite imagery. Dis: Semi-arid regions do not have previous studies using satellite image data	For Lahore city, the accuracy was 97.8% and 95.8%, respectively.
Guillaume Rousset et al (2021) [38]	Deep Learning techniques for (LULC) classification	Adv: Deep ground coverage using learning techniques helps in environmental planning. Did: Some results may be unexpected compared to traditional learning techniques, such as XGBoost in some cases	Comparative performance between deep learning techniques and XGBoost, with some results(81.41%)
Kunhao Yuan, (2021) [41]	MC-WBDN	Adv: Improving water detection accuracy using multispectral data. Dis: Multispectral data required, design complexity	mIoU reached 74.42%, a strong performance in changing conditions.
Sumaya Falih Hasan et al (2021) [39]	Boxcar, Frost, Gamma, Lee- Fusion using Gram–Schmidt- Classification using Random Forest	Adv: Provides accurate information on land use/cover Dis: Limited effectiveness of other filters; Frost filter was the best	Highest classification accuracy: 97.211% with Frost filter (9 × 9 window)
Kai Zhang et al (2021) [40]	Used Deep Belief Network (DBN)	Adv: Classifies all land for this proposed model. Dis: Complex parameter settings. Strong performance depends on the quality of the training samples and their quality.	It achieved an accuracy of 97.86% and an F1 value of 87.25%, respectively.
Xuedong Yao et al (2019) [42]	DenseNet architecture with (DCCN)	Adv: Improve land use classification accuracy and reduce spatial feature loss in remote sensing imagery. Dis: complex and requires high computational resources	(OA): 89.48% - Average F1: 86.89% - Building classification: 95.59%
Hunsoo Song, (2019) [43]	Convolutional Neural Network (LCNN)	Adv: Using a few training samples leads to high accuracy in land cover classification. Dis: Some experimentation and adjustment are required to achieve optimal	Achieved 13 out of 15 accuracy when applying the LCNN model compared to other techniques.

		performance.	
Chunping Qiu et al (2019) [46]	Re-ResNet	Adv: Improved urban land use classification using multi-season data from Sentinel-2 satellite imagery. Dis: The resulting maps are not fully reliable for local climate studies due to the variability of climate characteristics within the classifications.	Improved classification accuracy by about 7% when using temporal information with Re-ResNet.
Yunfeng Hu et al. (2018) [45]	(DCNN)	Adv: Increase the accuracy of LULC information for remote sensing images. Dis: Complex models may require large computational resources and are difficult to train	Overall accuracy 82.0% - Kappa coefficient 0.76 - 5% and 14% improvement compared to other methods
Raffaele Gaetano et al .(2018) [44]	(MultiResoLCC) utilizing (PAN) and (MS)	Adv: Increase the accuracy of LULC information for remote sensing imagery using multi-resolution data without the need for preprocessing. Dis: Limited reference data or noise in the data may be challenges that affect the classification accuracy in some cases.	Experiments have shown that the proposed method performs well in land cover classification.
Atharva Sharma et al.. (2017) [47]	Patch-based CNN	Adv: Improves image classification accuracy by leveraging spatial context Dis: Requires large training setup and accurate data	Improves classification accuracy by 24.36% compared to traditional networks

Researchers analyzed hyperspectral remote sensing data employing deep learning methodologies, with Tae-Ho Kim conducting the classification. Utilization of deep learning techniques and hyperspectral data for the analysis of green algae on artificial structures A ground-based hyperspectral camera was employed to analyze the spectral properties of green algae affixed to artificial structures [48]. Behnam Asghari Beirami introduced the recurrent convolutional neural network (ICNN), This innovative deep learning method successively integrates classifier probability maps and fractal spectral features to improve the precision of hyperspectral image classification [49]. Hongquan Cheng suggested a change detection framework utilizing high-efficiency distributed deep sensing in communication (CEDD-CD) founded on a synchronous update architecture to tackle the interconnected issues. By integrating change detection with efficient distributed gradient compression methods, CEDD-CD significantly reduces the data transmission volume. [50]. Jibo Yue proposed investigating and mapping the biochemical characteristics of winter wheat leaves and cover in Changping, Beijing, China LabTNet. A deep neural network and hyperspectral satellite imagery system were assessed utilizing field spectra of wheat during the winter across two growth seasons. [51]. The spectral fractional differentiation (SFD) technique for hyperspectral satellite imaging was developed to extract valuable attributes for the categorization of high-resolution satellite images (HRSIs).[52]. Bin Xia suggested a CNN-based method for classifying land resource utilization in satellite environmental imagery. A seven-layer CNN was constructed, and the output of the CNN training was enhanced by integrating the features from the two fully connected layers. [53]. Quanlong Feng suggested an adaptive integration of light detection and ranging (LiDAR) and hyperspectral imaging (HSI) data with a modified dual-branch deep convolutional neural network. To reduce network design time, the proposed model incorporates LiDAR and HSI branches that utilize identical network architecture. [54]. Ahram Song introduced the recurrent 3D full convolutional network (Re3FCN), which integrates the advantages of convolutional long short-term memory (ConvLSTM) with 3D full convolutional networks (FCN). The fundamental element of Re3FCN is a spatiotemporal spectral unit that concurrently extracts spatiotemporal characteristics from hyperspectral images utilizing a 3D convolutional layer [55].

Table 2 - Comparisons between previous studies for Hyperspectral sensing data

Author	Methods/Technique	Advantage&disadvantage	Result
Hongquan Cheng et al (2024) [50]	(CEDD-CD)	Adv: Improving communication efficiency in change detection systems using gradient compression and momentum compensation techniques. Dis: Some compression methods may result in the loss of important information, which affects the detection accuracy in some cases.	Effectiveness of CEDD-CD in reducing the size of transmitted data. Improved performance compared to traditional methods
Jibo Yue et al (2024) [51]	Hyperspectral Remote Sensing combined with Deep Learning	Adv: Accurate estimation of winter wheat biotic characteristics helps monitor crop growth and better manage crops. Dis: Reliance on limited field data may affect the accuracy of the model	Improved accuracy of estimating winter wheat biotic characteristics using the LabTNet model compared to traditional methods
Behnam Asghari Beirami (2024) [49]	(SF-ICNN)	Adv: Improved classification accuracy of hyperspectral images (HSI) using spectral and spatial features. Dis: Maybe more complex compared to traditional methods.	The overall accuracy of the Indian Pines dataset was (99.16%), while that of the Pavia dataset was (95.5%).
Tae-Ho Kim (2024) [48]	(CNN and DenseNet)	Adv: High accuracy in the classification of green algae: using spectral data and providing accurate information about different types of algae.	(SVM): Accuracy: 82%, Error Rate: 18% (CNN) Accuracy: 93%,

		Dis: The process may be complex, requiring special settings and large data.	Error Rate: 7% (DenseNet): Accuracy: 95%, Error Rate: 5%.
Jing Liu (2023) [52]	(SFD) (1DCNN and 3DCNN)	Adv: Improving terrain classification accuracy in high-resolution hyperspectral images Dis: Traditional methods may not be effective in all cases	SFD: 85% (1DCNN): 90%, 3DCNN achieved 92%.
Bin Xia et al (2022). [53]	(CNN) with PCA and SVM integration	Adv: Improved classification accuracy in remote sensing images, effective edge recognition Dis: Difficulty in integrating DL features and efficiency in processing large data	Classification accuracy: 0.9472, Error rate: 0.0528, Kappa coefficient: 0.9435
Quanlong Feng (2019) [54]	Two-Branch CNN	Adv: Increase the accuracy of urban LULC using multi-source data Dis: Results may not be generalizable to other regions	92% classification accuracy, 8% improvement over single-source data
Ahram Song (2018) [55]	(Re3FCN)	Adv: Improving the accuracy of detecting changes in spectral images using a deep network. Dis: Good training samples are required and are difficult to obtain in the real world, affecting effectiveness.	Change detection accuracy: 95.3% (compared to 89.2% for traditional methods)

Researchers analyzed remote sensing images obtained through aerial photography employing deep learning methodologies. Peiyan Jia emphasized the significance of semantic segmentation of satellite images in urban planning and land use. Utilizing imagery from the German cities of Vaihingen and Potsdam, he presents a novel deep neural network model that leverages band combination in remote sensing photography to enhance the efficacy and precision of semantic segmentation. He focuses on enhancing the segmentation capabilities of remote sensing imagery and applying this technology in urban planning and land use to promote sustainable development in smart cities. [56]. Muhammad Fayaz investigated the application of transfer learning with the Inception version 3 and DenseNet121 architectures to develop a robust LAC system for identifying urban land use types. The UC-Merced_LandUse dataset, comprising high-resolution aerial images across various land use classes, was utilized to develop an efficient and robust land cover classification system employing modified versions of the latest Inception-v3 and DenseNet networks, leveraging transfer learning. [57]. Ning Li proposes a novel framework for automated target identification in large-scale optical sensor imaging, encompassing the entire territory of Japan with high-resolution imagery from Google. The ongoing approach is the cascade technique , which enhances the precision of target extraction while maintaining elevated retrieval rates [58]. Naftaly Wambugu introduced CRD-Net, a hybrid network developed to address the challenge of identifying land use using very high-resolution images .He employed short, medium, and long-term semantic information at different stages of the network while preserving spatial details to provide robust feature descriptions [59]. Husam A. H. Al-Najjar concentrated on integration LU/LC mapping with DSM and UAV imagery, which is categorized into seven kinds.CNN was employed to delineate LULC classes from two separate datasets. 1) CNN was employed to categorize mosaic image data, and 2) CNN was utilized to classify both mosaic image and DSM data. [60]. Yue Zhu integrates spatiotemporal semantic segmentation with post-classification relearning; this hybrid system employs spatiotemporal semantics. Multiple CNN models were tested and assessed using two principal relearning strategies to leverage temporal dependence to extract of high-level dynamical characteristics [61]. Mohamed Marzhar Anuar explored Various (DCNN) models to find which one best detects faulty rice seedlings using drone images [62]. R. Ķēniņš deliberated. The process of training convolutional neural networks to classify land into specific cover types, such as grass, water, forest, and buildings, utilizing color infrared images of Ventspils city, is labor-intensive when performed manually; therefore, this segmentation is improved through automatic updating [63]. Chun Liu proposed a relation-reinforced multi-scale convolutional network (REMSNet) method, incorporating a dense connection pattern and parallel multi-kernel convolutional fusion to create a lightweight and diverse receptive field volume model, utilizing data from the ISPRS 2D semantic labeling competition in Vaihingen and Shanghai [64]. Manuel Carranza Garcia proposed a general CNN with fixed structure and parameters to achieve high accuracy in LULC classification on RS data from different sources such as radar and hyperspectral data. He introduced a framework for a thorough experimental comparison between our proposed deep learning approach and machine learning algorithms, including SVM, RF, and KNN [65].

Table 3 - Comparisons of previous studies of aerial imagery sensor data

Author	Methods/Technique	Advantage&disadvantage	Result
Muhammad Fayaz et al(2024). [57]	Deep Learning (CNNs: Inception-v3, DenseNet121)	Adv: Improved accuracy in urban land classification Dis: Traditional methods struggle with urban complexity	Accuracy was 92%, while precision (92%), F1 score (92%) for Inception-v3, when applying ResNet-50, the results were 91%, 91%, 90%, and 88%, respectively.
Ning Li et al (2024) [58]	An automatic labeling framework.	Adv: Effective and efficient for extracting object detection samples Div: May encounter low accuracy in some cases due to the similarity of targets and difficulty in distinguishing between them	58.9% increase in the number of automatic and uncertain labeling cases (F1) by 2.88% Resistant to advanced work
Peiyan Jia et al (2024) [56]	By using band combination in convolution operations	Adv Improving the accuracy and efficiency of LULC satellite image segmentation especially in urban planning. Dis: There may be limitations in model accuracy due to simplified calculations in some cases	82.43% segmentation accuracy for built-up surfaces and 76.54% for trees on the ISPRS dataset
Naftaly Wambugu et al (2021) [59]	(CRD-Net)	Adv: Provides accurate information on land cover, useful in agriculture, city management, and disaster monitoring Dis: Challenges in classifying high-resolution images require large computations and advanced tools, which can be expensive	(OA) 90.73% of the Potsdam dataset (OA) 90.51% of the Vaihingen dataset

Yue Zhu et al (2021) [61]	ConvLSTM.	Adv: Increased accuracy of LULC by exploiting the spatiotemporal relationships in remote sensing data. Dis: require large amounts of labeled data	The use of VHR images has proven to be effective in classifying complex multi-temporal LU
Chun Liu et al (2020) [64]	(REMSNet)	Adv: Increase LU classification using high-resolution urban aerial images. Dis: requires significant computational resources and may be complex to implement.	Vaihingen dataset, (OA) 90.46%. (mIoU) 0.8073. Vaihingen dataset, (OA) 88.55% . (mIoU)0.7394
R. Ķēniņš (2020) [63]	(U-net Convolutional Neural Network)	Adv: Topographic maps are updated and human errors in the classification process are reduced. Dis: The classification accuracy may be lower for some categories such as roads and buildings than for other categories.	(OA)82.9% Product accuracy for forest category: 87.4% Product accuracy for the water category: 89.0%
Husam A. H. Al-Najjar et al (2019) [60]	(CNN) to fuse Digital Surface Model (DSM)	Adv: Land use classification accuracy improved by merging data from different sources (DSM and UAV) using DL techniques. Dis: There are not enough previous studies on using DSM data merging with UAV data for land classification	The overall accuracy was 0.98, the average accuracy was 0.97, and the kappa index was 0.98
Manuel García et al (2019) [65]	CNN model	Adv: Increased accuracy of LULC Dis: Developing models that can be applied to satellite images requires	(CNN) outperformed traditional ML techniques such as SVM and RF, achieving accuracy ranging from 96.78% to 99.36%.
Mohamed Marzhar Anuar (2022) [62]	(DCNN)	Adv: Aerial photography increases the extraction of bad rice seedlings Dis: Focused on counting seedlings without pinpointing defective locations	Achieved a detection accuracy of 83% (F1-Score).

2. Experimental results

This section utilizes a significant prior study employing multispectral remote-sensing imagery. We have selected the study mentioned in the source [7]. Convolutional neural networks (CNNs) have been used in land use and land cover (LULC) classification to outperform traditional algorithms such as Random Forest and XGBoost. CNNs provide the ability to automatically learn features from data, reducing the need for manual feature extraction, which is required in traditional learning. CNNs are highly efficient when dealing with large amounts of data, and perform excellently in complex environments with similar spectral characteristics. Moreover, CNNs demonstrate higher classification accuracy compared to traditional algorithms. We employed the model referenced on GitHub [66,67] with the data presented in Table 4. This test evaluated the capacity of CNN to categorize semi-arid regions based on land cover patch sizes of 5x5 and 9x9. The CNN model was initially trained in Gujranwala, a semi-arid city in Pakistan. Subsequently, we implemented this model to evaluate its efficacy in LULC classification mapping of Lahore city, which will be elaborated upon in the following sections.

2.1. Study Area

The study area selected for this research consists of Gujranwala City and its surrounding urban areas, which are located in the Gujranwala district of Punjab, Pakistan (Figure 1). It has a semi-arid climate. The area comprises barren lands, settlements, vegetation, water bodies, and wastelands. As for the test area, a city in Pakistan, Lahore City, was considered for testing the DL models. This city has a semi-arid climate. It was considered a suitable location to test the performance of DL models trained on unseen semi-arid regions.

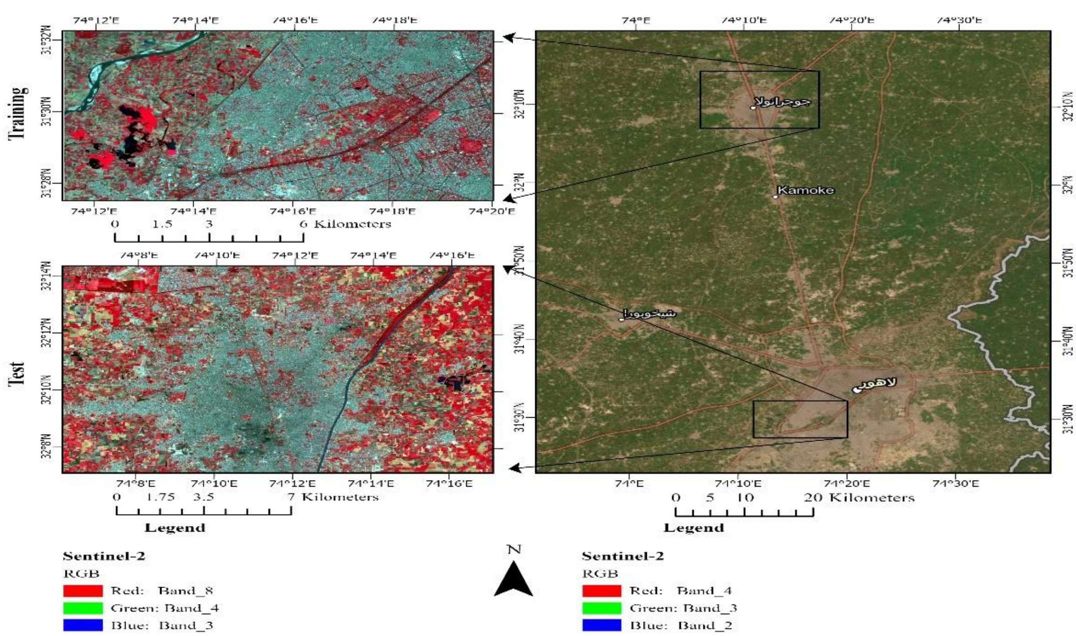

Fig. 1 - study area map.

2.2 Dataset

We trained the DCNN model with the training samples from the five classes of dimensions (9*9) and (5*5) that were previously produced and processed, resulting in the model: "Sequential" as presented in Tables (5) and (6). The maximum overall accuracy (OA) attained for the training dataset of size (5*5) was 95.0%, while the OA for the test dataset was 93.6. The results were derived utilizing four bands to implement the CNN model. For a size of 9x9, the maximum accuracy for the training dataset was 91.5, while for the test dataset, it was 91.1. Table 7 compares their accuracy, while the confusion matrix is displayed in Table 8. The classification of the test location for Lahore city is presented in Table (9). We acquired the loss curves for the training and test data.

Table 4 - Number of samples used for land cover classification

LULC Classes	Training Patches (5 × 5) Pixels	Training Patches (9*9) Pixels
Settlement	2400	2400
Barren land	474	812
Fallow land	2400	2400
Vegetation	2400	2400
Water bodies	754	723

Table 5 - the patch size (5*5) model "Sequential".

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 5, 5, 16)	272
patch_normalization (BatchNormalization)	(None, 5, 5, 16)	64
dropout (Dropout)	(None, 5, 5, 16)	0
conv2d_1 (Conv2D)	(None, 5, 5, 32)	2,080
max_pooling2d (MaxPooling2D)	(None, 5, 5, 32)	0
batch_normalization_1 (BatchNormalization)	(None, 5, 5, 32)	128
dropout_1 (Dropout)	(None, 5, 5, 32)	0
conv2d_2 (Conv2D)	(None, 5, 5, 64)	8,256
max_pooling2d_1 (MaxPooling2D)	(None, 1, 1, 64)	0

batch_normalization_2 (BatchNormalization)	(None, 1, 1, 64)	256
dropout_2 (Dropout)	(None, 1, 1, 64)	0
flatten (Flatten)	(None, 64)	0
dense (Dense)	(None, 64)	4,160
dropout_3 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 128)	8,320
dropout_4 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 5)	645

Total params: 24,181 (94.46 KB)

Trainable params: 23,957 (93.58 KB)

Non-trainable params: 224 (896.00 B)

Table 6- the patch size (9*9) model "Sequential"..

Layer (type)	Output Shape	Param #
conv2d_24 (Conv2D)	(None, 9,9, 16)	272
batch_normalization_24 (BatchNormalization)	(None, 9,9, 16)	64
Dropout_40 (Dropout)	(None, 9,9, 16)	0
conv2d_25 (Conv2D)	(None, 9,9, 32)	2,080
max_pooling2d_16 (MaxPooling2D)	(None, 4,4, 32)	0
batch_normalization_25 (BatchNormalization)	(None, 4,4, 32)	128
dropout_41 (Dropout)	(None, 4,4, 32)	0

conv2d_26 (Conv2D)	(None, 4,4, 64)	8,256
max_pooling2d_17 (MaxPooling2D)	(None, 2,2, 64)	0
batch_normalization_26 (BatchNormalization)	(None, 2,2, 64)	256
dropout_42 (Dropout)	(None, 2,2, 64)	0
flatten _8(Flatten)	(None, 256)	0
Dense_24 (Dense)	(None, 64)	16,448
dropout_43 (Dropout)	(None, 64)	0
dense_25 (Dense)	(None, 128)	8,320
dropout_44 (Dropout)	(None, 128)	0
dense_26 (Dense)	(None, 5)	645

Total params: 36,469 (142.46 KB)

Trainable params: 36,245 (141.58 KB)

Non-trainable params: 224 (896.00 B)

Table 7- OA (%), and training patch size ((5*5)- (9*9)) CNN model.

Model	OA
4- band CNN Patch size (5*5)	95.0
4- band CNN patch size (9*9)	91.5

DCNN model, learning rate set to 0.0001 and batch size set to 128. The model has three convolutional layers with 16, 32, and 64 filters, with kernel size (2, 2). ReLU activation function is used in the convolutional layers and Softmax in the final layer. Dropout techniques with rates of 0.2 and 0.5 were applied to avoid overfitting, as well as batch normalization to improve model stability and training speed. These parameters were chosen to improve performance and reduce overfitting .The images below illustrate the confusion matrix classification outcomes for the training site and the loss curves for the training data utilizing CNN with patch sizes of (5*5) and (9*9). Figure (2) presents the confusion matrix classification results for the training site utilizing a CNN with a patch size of (5x5), while Figure (3) displays the confusion matrix classification results for a patch size of (9x9). Regarding the loss curves, (Figure 4) illustrates the loss curves for the training data of the 5x5 patch, while (Figure 5) presents the loss curves for the training data of the 9x9 patch. The CNN model was implemented on unknown data, namely in Lahore city, and the results are displayed in Table 8. The confusion matrix for testing sites is illustrated in (Figure 6). Classification results of the confusion matrix for the training site utilizing a 5x5 patch size CNN, as depicted in Figure 7. Classification results of the confusion matrix for the training site utilizing a patch size of 9x9 in the CNN. The

Testing Data Loss Curves are illustrated in (Figure 8). Evaluating Data Loss Curves for a patch (5x5) and (Figure 9). Evaluating Data Loss Curves for a patch (9x9). (Figure 10) illustrates a map delineating the forecast groups for water, barren lands, semi-arid lands, structures, and vegetation.

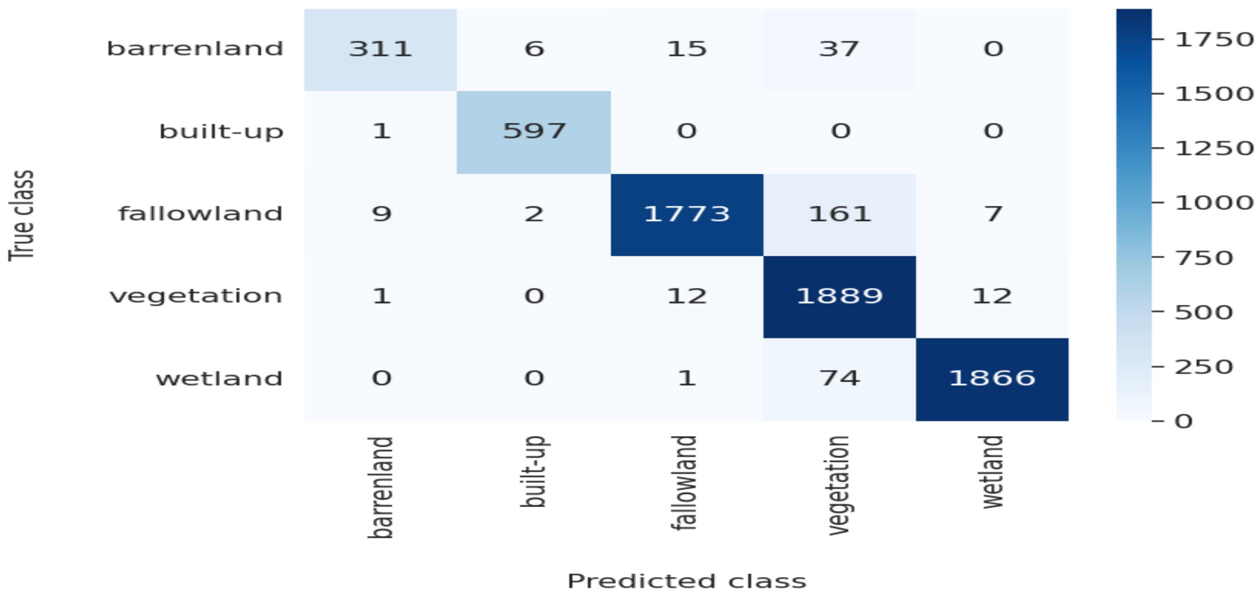

Fig. 2 - Confusion matrix classification results of training site using patch size (5*5) CNN.

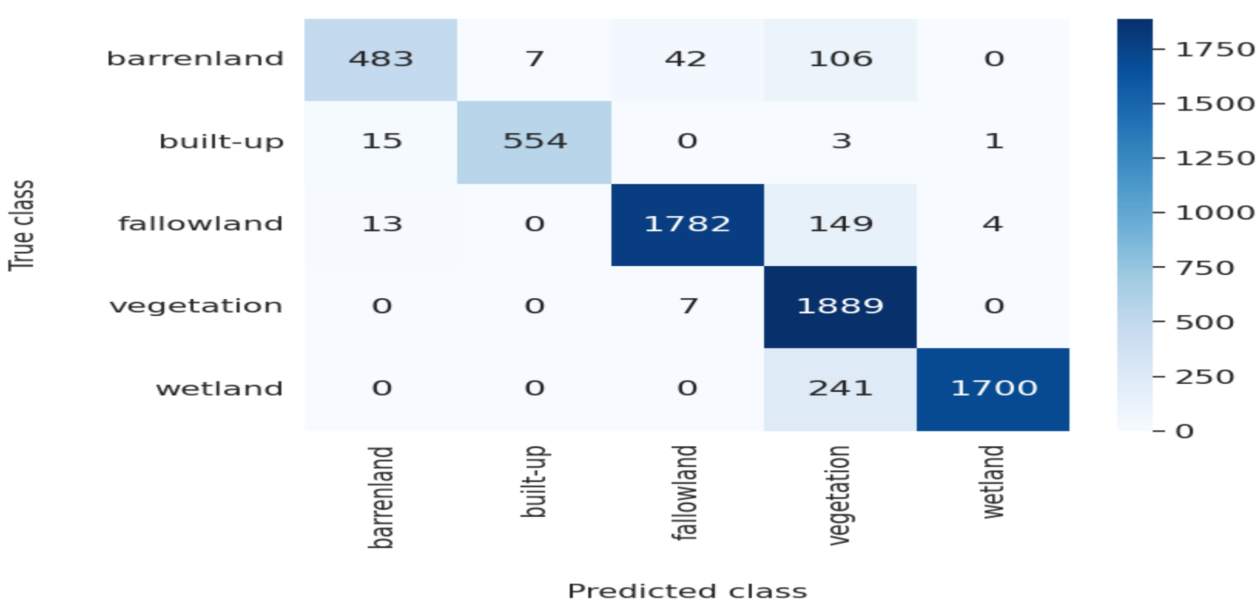

Fig. 3 - Confusion matrix classification results of training site using patch size (9*9) CNN.

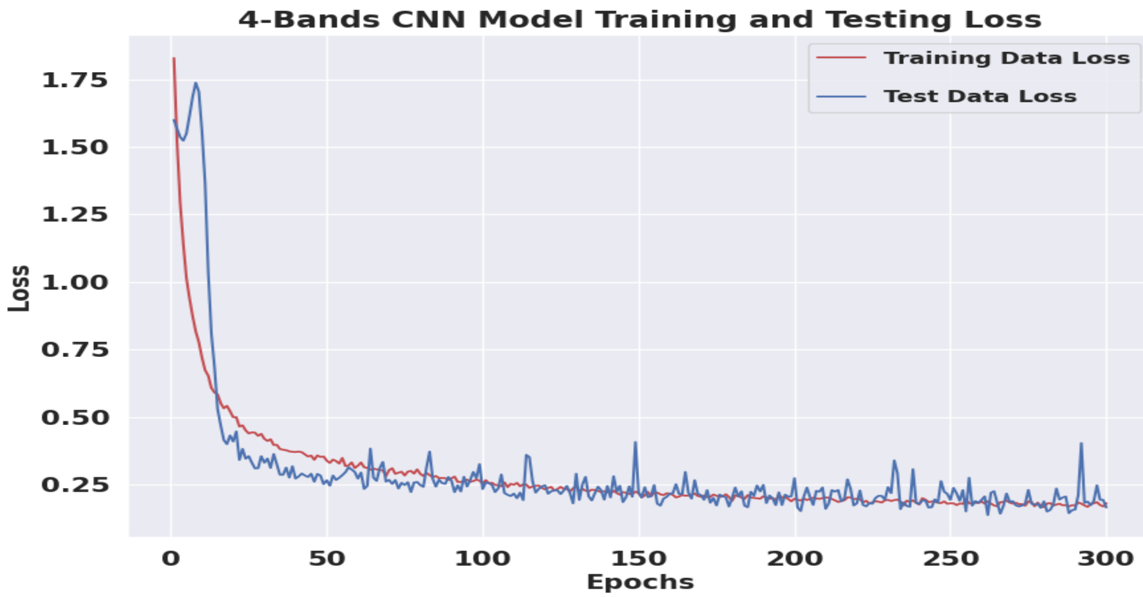

Fig. 4 - Training Data Loss Curves for patch (5*5) .

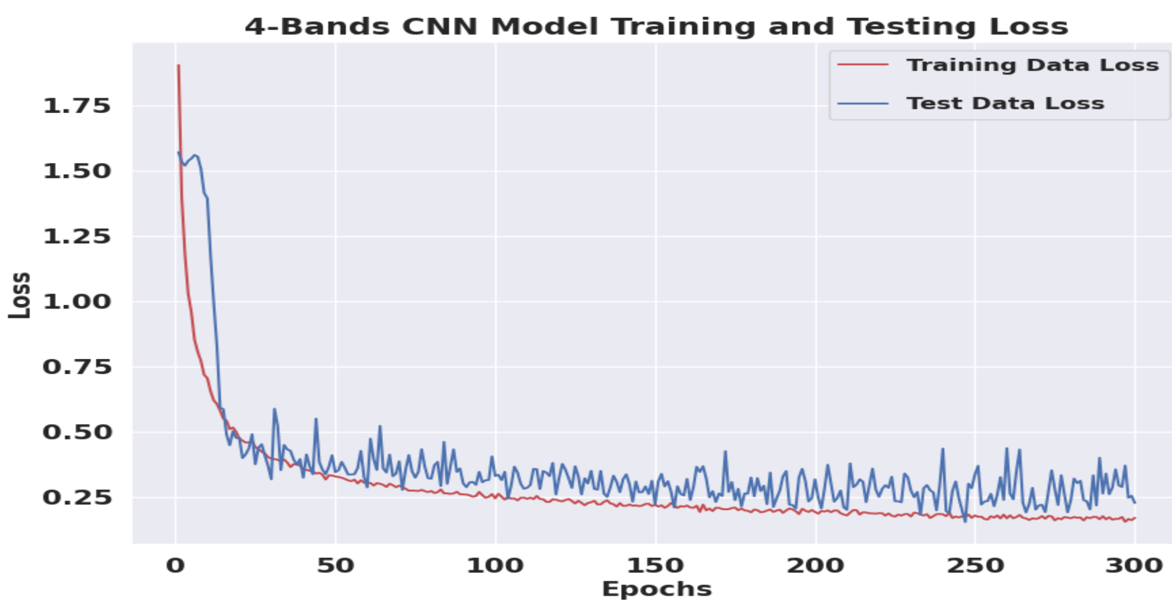

Fig. 5 - Training Data Loss Curves for patch (9*9) .

Table 8- OA (%), and testing CNN model for Lahore city

Testing sites	Model	OA
Lahore city	4- band CNN Patch size (5*5)	93.6
Lahore city	4- band CNN patch size (9*9)	91.1

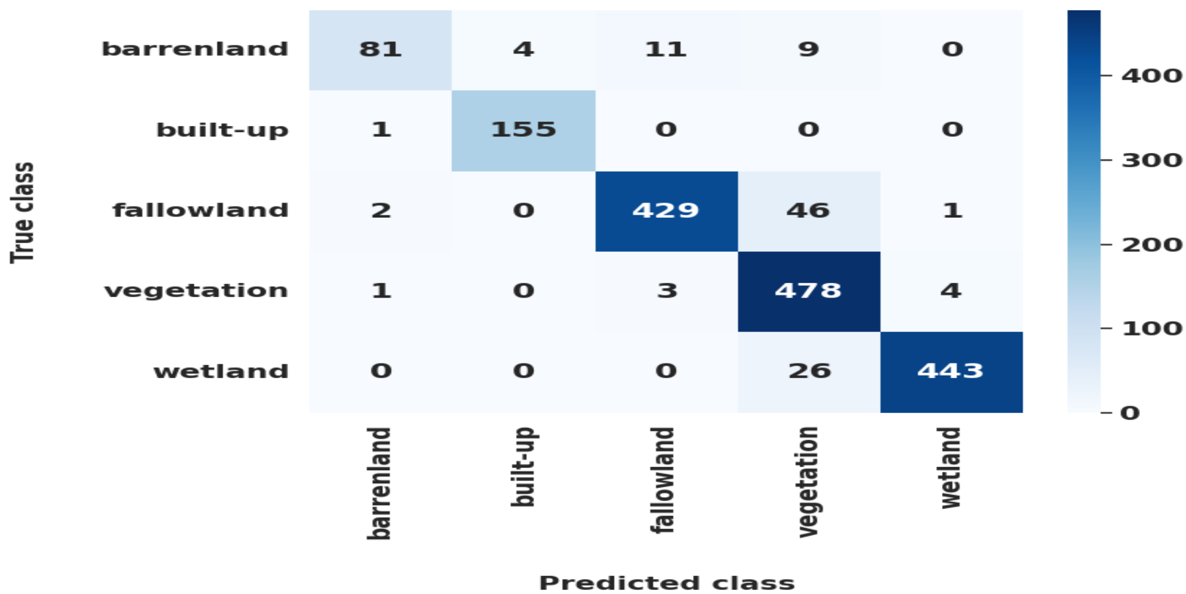

Fig. 6 - confusion matrix testing site (Lahore city) classification results 4-band CNN model patch size (5*5) .

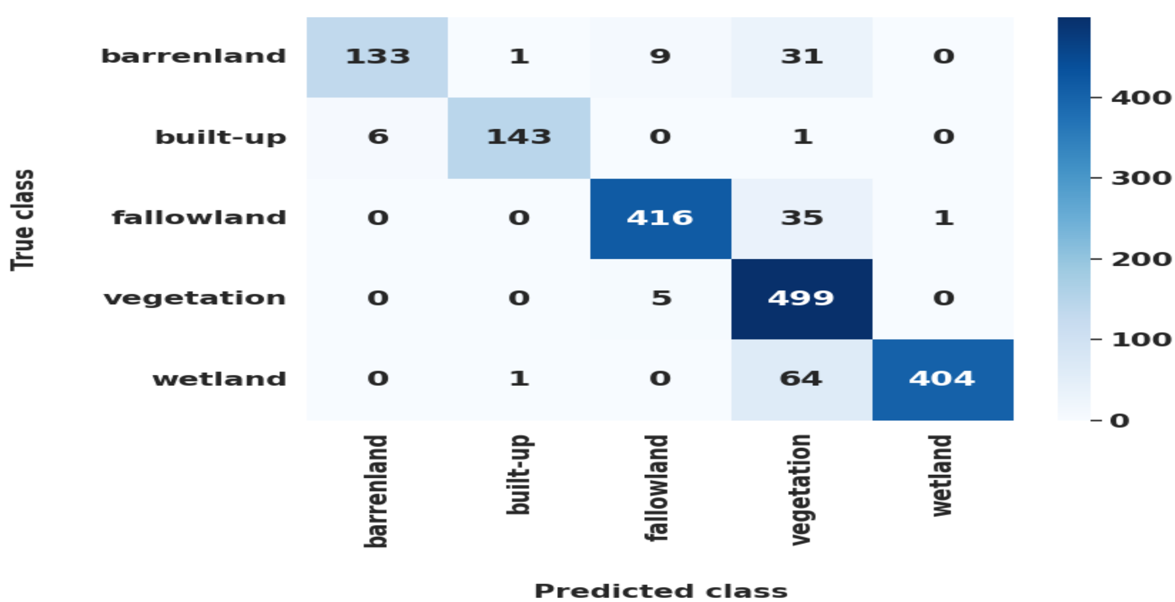

Fig. 7 - confusion matrix testing site (Lahore city) classification results 4-band CNN model patch size (9*9) .

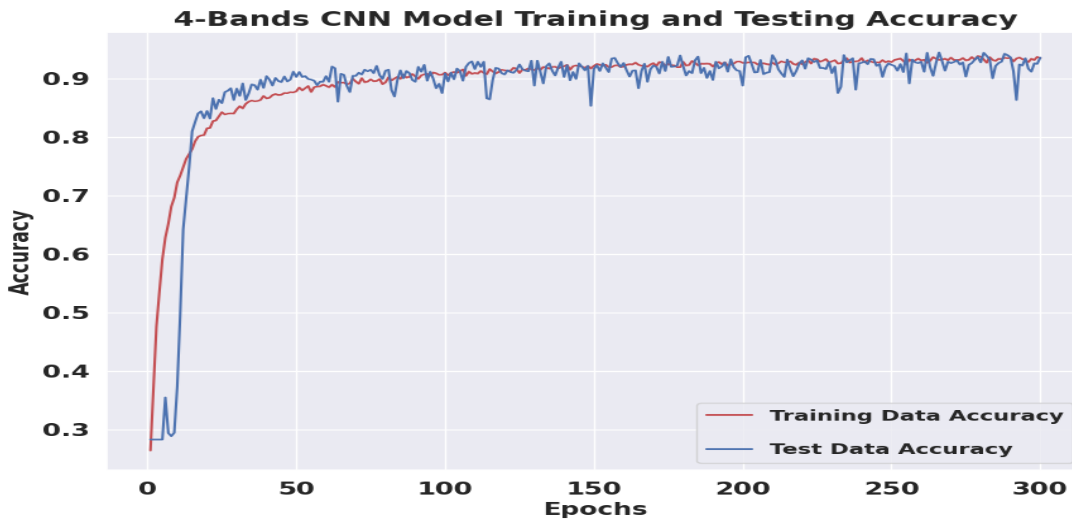

Fig. 8 - Testing Data Loss Curves for a patch (5*5) .

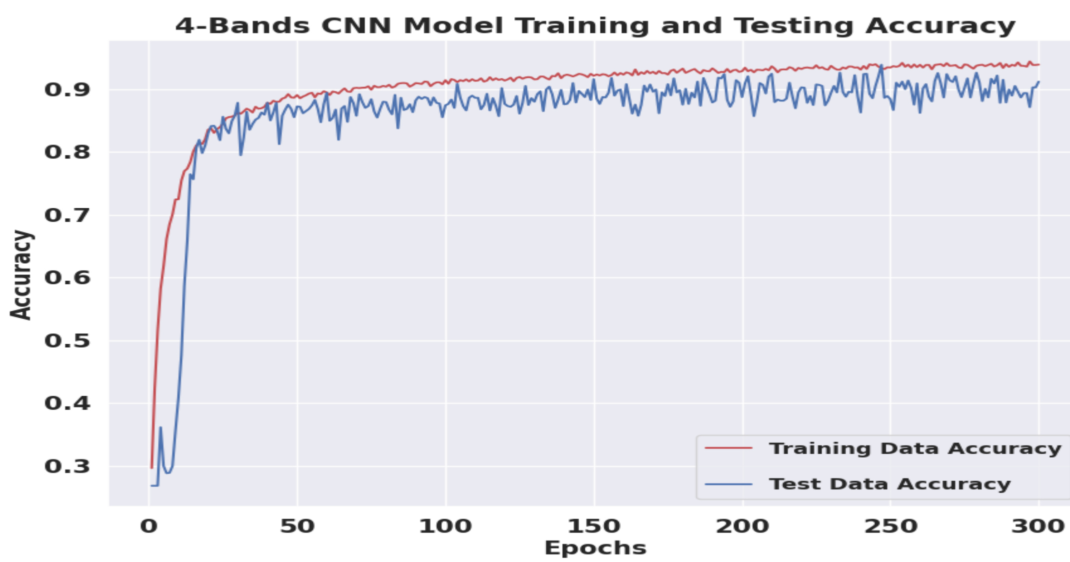

Fig. 9 - Testing Data Loss Curves for a patch (9*9) .

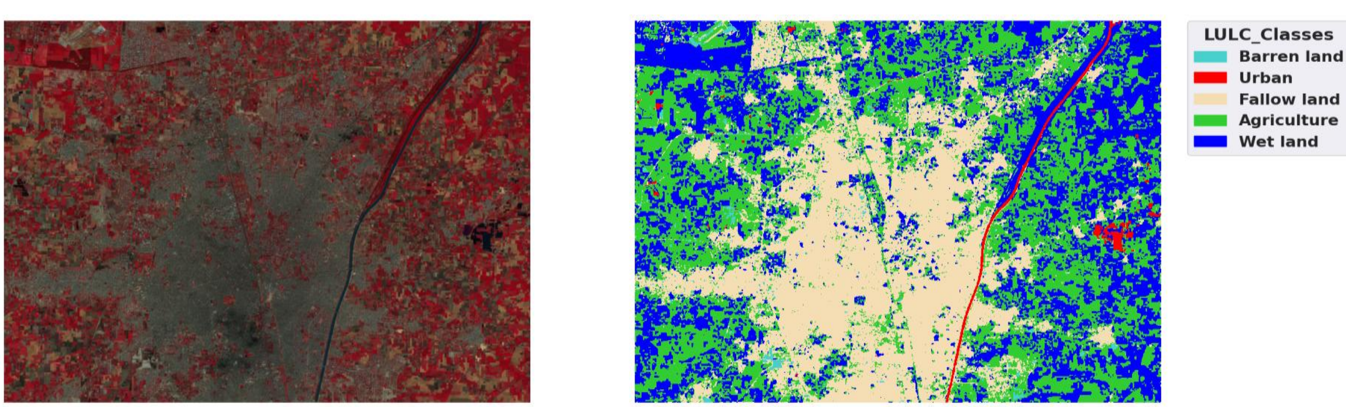

Fig. 10 - Predict new data.

2.3. Analysis of Results

The high accuracy in the different classes indicates that the model can distinguish between different types of land cover accurately, which reflects the effectiveness of the deep learning technique in processing remote sensing data. The smaller patch size (5x5) led to higher accuracy. This may be because smaller sizes capture finer details in the images, helping the model better understand nuances and distinguish differences between classes. This can be useful for classes with unique features, such as the boundaries between agricultural land and settlements. Conversely, a large patch size (9x9) may result in some loss of detail, as more information from larger areas is incorporated, leading to class overlap. In this case, the model may misclassify an area as vegetation due to the inability to see the nuances. Despite the positive results, the Config Matrix indicates some errors (False Positives and False Negatives). For example, the similarity between classes (such as agricultural land and settlements) can lead to misclassification. For settlements, the model achieved a high accuracy of 97.9%, meaning the error rate was 5.9%. This good performance is due to the model's ability to clearly distinguish settlements from other classes, as well as the diversity of the training data that contributed to the improved accuracy. For agricultural land, the model achieved an accuracy of 96.0%, with an error rate of 11.1%. This good performance is partly due to the clarity of the differences between this category and other categories, despite some challenges, such as the blurred boundaries between agricultural land and settlements. For water, the classification accuracy was 93.3%, indicating an error rate of 12.5%. This error is due to reflections on the water surface, which may negatively affect the model's ability to distinguish this category from surrounding areas. As for arid land, its accuracy was 88.9%, resulting in an error rate of 15.8%. This error is due to the similarity of arid land to settlements in some characteristics, making it difficult for the model to distinguish them accurately. The limited data available for this category also contributed to its low accuracy. The reasons for the misclassification of categories are due to the similarity between categories; some categories, such as vegetation and settlements, may show similar visual features, especially in medium-resolution images. For example, urban areas may contain plants and trees, which can make them appear similar to vegetation. In addition, differences in angles and lighting, images taken from different angles or in varying lighting conditions can affect how classes appear. This can lead to misclassification, as vegetation can be mixed in with cultivated or urban areas. These points can be considered limitations of the study, as they show that using larger plot sizes can lead to inaccurate classifications due to overlapping classes and loss of detail.

3. Conclusion

In this paper, the use of deep learning techniques in the classification of remote sensing data was explored, with a focus on land use and land cover classes. A comprehensive review of previous research that has used deep learning techniques in this field over the past five years is presented, and the studies are categorized into three main groups: multispectral data, hyperspectral data, and UAV images. A convolutional neural network (CNN) model was applied to a multispectral dataset with different cut sizes (5x5 and 9x9) to achieve high classification accuracy, achieving an accuracy of 95.0% on the training set and 93.6% on the test set for data from Lahore City. The results showed that using a smaller cut size (5x5) improves accuracy due to its ability to capture fine details. The results demonstrated the effectiveness of the deep learning model in processing complex and diverse data used in remote sensing, reflecting the potential of these techniques in real-world applications such as monitoring land use changes and natural resource management. In addition, current research gaps and the need to improve classification accuracy were identified, especially in hard-to-distinguish classes such as agricultural land and settlements. Therefore, a set of future actions, such as improving deep learning models, increasing data diversity, and applying unsupervised learning techniques, have been proposed to improve the performance of existing models.

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