Comparative Analysis of Deep Learning CNN Models and Traditional Machine Learning Approaches for Land Use Land Cover Classification Using Imagery

Apurwa Chaurasia[1], Ayush Chaurasia[2], Aditya Kumar Thakur[1], Nyenshu Seb Rehengma[3], Manohar Yadav[3], Pritipadmaja[1]

[1] Dept. of Geomatic Engineering, Indian Institute of Technology Roorkee, Uttarakhand, India - apurwa_c@ce.iitr.ac.in, aditya_kt@ce.iitr.ac.in, pritipadmaja@ce.iitr.ac.in

[2] Telgoo5, Noida, Uttar Pradesh, India -ayushnietian@gmail.com

[3] Geographic Information System (GIS) Cell, Motilal Nehru National Institute of Technology, Allahabad, India- nyenshu@gmail.com

Keywords: Land Use and Land Cover, Deep Learning, Machine Learning, sentinel 2, Convolutional Neural Network.

Abstract

An updated map of the area's land use land cover (LULC) is necessary for strategic planning and management of land use to shape the town sustainably. The advances in remote sensing imageries and artificial intelligence have facilitated the extraction of LULC classification. With the high number of studies on LULC mapping using various machine learning (ML) and deep learning (DL) algorithms incorporating imageries, no established algorithm shows stable results for all the datasets and study regions. Therefore, we used three robust machine learning algorithms, Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and four deep learning algorithms, Residual Network (ResNet50 and ResNet152) and Visual Geometry Group (VGG16 and VGG19), to understand which model can produce a highly accurate LULC map in the Indian context, which are inherently unplanned and unorganized using Sentinel 2 imageries. The results of these models were then comparatively analyzed statistically using Accuracy, Recall, Precision, F1-score, and Kappa coefficient. Although DL models require a large number of training datasets, they outperformed the ML algorithms with higher Kappa coefficient values (ResNET50 = 0.90, ResNET-152 = 0.91, VGG-16 = 0.94, VGG-19 = 0.94). VGG-19 has consistently given better performance in all accuracy metrics. Overall the study highlights the potential of deep learning models, particularly VGG-19, in generating highly accurate LULC maps for complex and unplanned urban environments in India. These findings underscore the importance of leveraging advanced AI techniques in remote sensing for effective land use planning and sustainable urban development.

1. Introduction

The land is a crucial natural resource, and a larger part of it has been utilized without proper planning, leading to irreversible degradation. If not managed effectively, this mismanagement negatively impacts both society and the environment. Therefore, the development of accurate and up-to-date land use land cover (LULC) maps is essential (Pallavi et al., 2022; Verma and Jana, n.d.; Yassine et al., 2021). LULC classification is the process of categorizing natural and artificial features on the Earth's surface within a specific time frame using scientific and statistical methods. These maps play a vital role in applications such as natural disaster monitoring, soil erosion estimation, environmental assessment, agriculture, and urban development. Access to updated LULC data facilitates sustainable planning and supports social, environmental, and economic development (Barakat et al., 2019; Boulila et al., 2021; Verma and Jana, n.d.).

LULC maps can be created through manual or modern techniques or a combination of both. Manual classification methods, such as field surveys, require significant human effort, making them time-consuming and costly. They rely on human interpretation and expertise, leading to varying levels of accuracy and scale (Carranza-García et al., 2019). Modern mapping techniques employ numerical, digital, and spectral-based classification methods. Numerical classification utilizes artificial intelligence, while spectral-based methods rely on calculated indices such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Soil-Adjusted Vegetation Index (SAVI)(Kalpana and Nandhagopal, 2021; Pallavi et al., 2022; Sathyanarayanan et al., 2020; Yassine et al., 2021).

Numerical and digital classification methods are further divided into hard and soft classification. Hard classification assigns each pixel to a single class, defining homogeneous land cover, whereas soft classification accommodates spatial heterogeneity and addresses mixed pixels. Hard classification techniques include traditional machine learning and advanced machine learning approaches. Traditional machine learning methods are categorized into unsupervised, semi-supervised, and supervised classification. Unsupervised classification does not require training samples and groups similar pixels automatically. Semi-supervised classification is applied when training samples are limited compared to the area of interest. Supervised classification relies on training samples and expert knowledge to classify images accurately (Alshari and Gawali, 2021). A significant number of studies have focused on LULC classification using machine learning algorithms applied to remotely sensed imagery. Researchers have compared and optimized different algorithms to identify the most accurate models for LULC mapping. The accuracy of these algorithms varies depending on factors such as spatial and temporal resolution and sensor characteristics (Kalpana and Nandhagopal, 2021; Sathyanarayanan et al., 2020). Studies indicate that Support Vector Machines (SVM) and Random Forest (RF) generally outperform other machine learning algorithms. Comparative analysis of multiple classifiers has shown that the RF algorithm achieves high accuracy, often exceeding 95% (Arfa and Minaei, 2024; Dewangkoro and Arymurthy, 2021).

Advancements in artificial neural networks (ANNs) have led to the evolution of deep learning (DL), which excels in complex feature learning and computationally intensive tasks. Deep learning benefits from high-performance computing resources such as Graphics Processing Units (GPUs) and large datasets. It achieves superior accuracy in LULC classification due to its ability to process large numbers of features and extract hierarchical representations from raw data (Gardner and Nichols, n.d.; Uba et al., 2016). Although DL models require longer training times compared to traditional machine learning optimization techniques such as max-pooling, batch normalization, and transfer learning can improve efficiency (Yassine et al., 2021).

Various deep learning frameworks, including TensorFlow, Keras, and PyTorch, facilitate DL model development. Pre-trained networks such as Convolutional Neural Networks (CNNs) have been widely used for image classification. CNNs, in particular, have demonstrated high accuracy in LULC classification by capturing spatial and temporal dependencies within images (Bhosle and Musande, 2019; Dewangkoro and Arymurthy, 2021). Popular CNN architectures include VGGNet and ResNet. Studies comparing different CNN models have found that architectures such as VGG19 and ResNet50 consistently achieve high classification accuracy, often exceeding 94% (Uba et al., 2016). Despite the extensive research on LULC classification using machine learning and deep learning, no single algorithm consistently delivers optimal results across all datasets. Most LULC analyses rely on well-structured test sites, whereas real-world datasets, particularly in regions with unplanned infrastructure, pose additional challenges. The selection of the best-performing model depends on dataset characteristics, parameter configurations, and hyperparameter tuning. Hyperparameters require expert knowledge and trial-and-error optimization to achieve the best model performance (Rousset et al., 2021; Sathyanarayanan et al., 2020; Yassine et al., 2021).

This study focuses on LULC classification using Sentinel-2 satellite imagery at 10m spatial resolution for the Lucknow district. The study employs three machine-learning techniques (RF, SVM, and K-NN) and four deep-learning CNN models (ResNet50, ResNet152, VGG16, and VGG19) to determine the most accurate method for generating high-precision LULC maps. By optimizing these models and analyzing accuracy statistics, this research aims to contribute to the effective application of Earth observation techniques for land use planning and management.

2. Methodology

2.1 Study Area

In this study, we selected the Lucknow district, the capital of Uttar Pradesh, the most populous state in India (Figure 1). According to the 2011 census, Lucknow is the eleventh-largest city in India, with a population of 4,589,838. In 2022, the estimated population was 5,178,766, based on adhaar (uidai.gov.in) data from December 2020. The geographical extent of the study area ranges between 26° 45' and 26° 55' N latitude and 80° 50' and 81° 5' E longitude in the northern hemisphere. It is situated in the core of the Gangetic plain, covering approximately 2,528 square kilometers (976 sq. Mi) at an elevation of about 123 meters (404 ft) above sea level (Shukla and Jain, 2019). LULC classification for Lucknow provides crucial data for environmental management, policymaking, and urban planning (https://lucknow.nic.in/). As one of India's most densely populated cities, Lucknow has undergone rapid and unplanned urban expansion, significantly altering its land cover (Salim et al., 2025; Shukla and Jain, 2019).The increasing conversion of land into residential zones has led to fragmented and unstructured urban development. Studies indicate a rise in built-up suburban areas and a decline in rural open spaces, driven by population growth and expanding human settlements (Rawat et al., 2020).

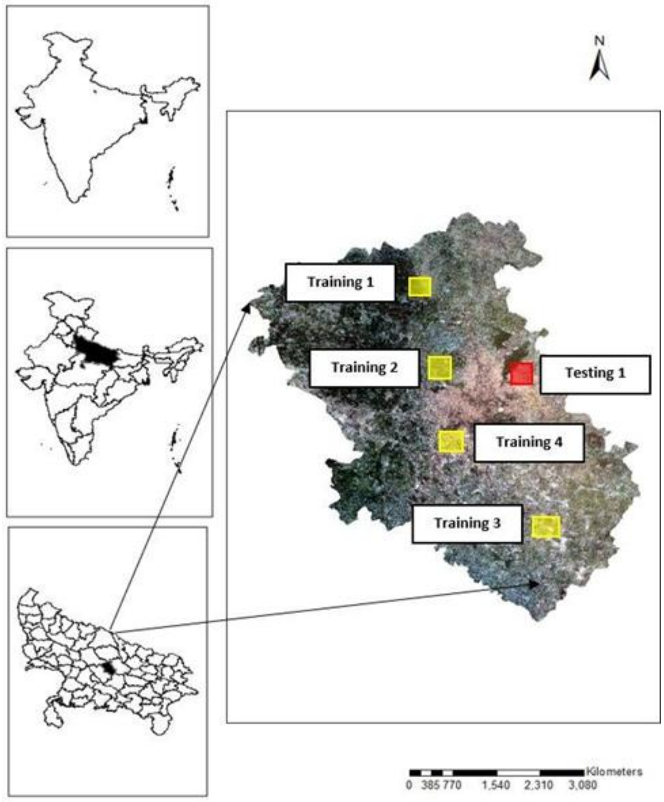

Figure 1: Sentinel 2A Satellite imagery of Study area Lucknow shows the four areas selected for the training (in yellow) and the area selected for the test (in red).

2.2 Dataset and Processing

Sentinel is a widely used dataset in multi-disaster assessment including land deformation, environmental monitoring, change detection, etc. (Boulila et al., 2021; Mohan et al., 2021; Salim et al., 2025; Srivastava et al., 2025; Thakur et al., 2025, 2024; Zope et al., 2017). For this study, sentinel-2 satellite imagery of the Lucknow district, dated September 15, 2023, was downloaded from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov). The sentinel-2 dataset comprises 13 spectral bands with varying spatial resolutions (10m, 20m, and 60m). In this study, we used three bands (R, G, B) at 10m spatial resolution. To minimize atmospheric effects, we selected satellite images with low cloud cover and performed atmospheric correction using QGIS software.

Five locations of interest in Lucknow district were chosen (Figure 1). These locations, spread across the district, represent diverse ecosystems, including built-up areas, barren land, vegetation, forests, water, and wetlands. The selection aimed to capture the area's landscape diversity. We generated approximately 2000 patches from the selected locations to create a comprehensive dataset. These patches were divided into training, validation, and testing sets, ensuring a balanced representation of all LULC classes.

The patches from four locations were used for training and validation, while patches from the fifth location were reserved exclusively for testing. This spatial segregation ensures that the model is evaluated on unseen data, enhancing its generalization ability.

The dataset was structured into patches, following a patch-based approach widely used in recent LULC classification studies (Carranza-García et al., 2019). This method involves extracting small, fixed-size three-dimensional patches centered at each pixel instead of using single-pixel data. Patches are used because nearby pixels often represent the same underlying material (Carranza-García et al., 2019). The accuracy of classification varies with patch size. After testing patch sizes ranging from 3 to 15, we found that a size of 5 performed best across all datasets.

Five LULC classes—barren land, built-up areas, forests, vegetation, and water/wetlands—were identified based on a literature survey (Rawat et al., 2020) and expert knowledge of the study area. Each class encompasses various subcategories; for example, the water and wetland class includes both flowing and stagnant water bodies, as well as wetlands. Similarly, the vegetation class includes scrub/shrubland, agricultural land, and urban parks, while the forest class comprises both dense and sparse tree cover. The built-up class includes human settlements and industrial areas. The correlation between these classes is generally low. To improve model performance and enhance dataset diversity, we applied data augmentation through rotation. Specifically, each patch was rotated seven times at 45-degree intervals. This approach introduces visual variability, helping the model learn different spatial features while also reducing overfitting (Azedou et al., 2023; Carranza-García et al., 2019).

2.3 Methods for Land Use Land Cover (LULC) Modelling and Optimization

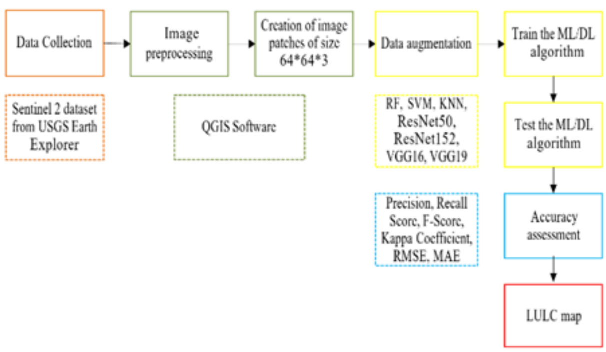

Figure 1:Methodological workflow depicting different steps involved in the study.

The LULC classification was performed using three widely used ML models—SVM, RF, and K-NN —along with four DL CNN models: ResNET (ResNET-50 and ResNET-152) and VGGNet (VGG-16 and VGG-19) (Figure 2). While both ML and DL models aim to learn from data, their approaches differ. ML models rely on identifying patterns within training data to make predictions, whereas DL models learn hierarchical features through artificial neural networks (ANNs), where each neuron in a layer is connected to some or all neurons in the subsequent layer. During training, weights and biases are adjusted to determine the influence of inputs on outputs, ensuring efficient feature extraction and classification (Boulila et al., 2021).

In this study, hyperparameter tuning was conducted to enhance the classification accuracy of ML and DL models. The optimization process involved grid search, where multiple hyperparameter values were tested to identify the best-performing configuration for each model. For ML models, RF was optimized by varying the number of decision trees (*n-tree*) and input features (*mtry*), while SVM was fine-tuned by selecting the most suitable kernel function and reclassification threshold. KNN was optimized for different *K-values*, distance functions, and leaf sizes. Similarly, DL models, including ResNet and VGG architectures, underwent optimization for dropout rate, learning rate, batch size, number of epochs, and activation functions. After testing multiple values, the most effective hyperparameter combination for each model was selected to improve overall performance. (Table 1).

3. Results and Discussions

3.1. Parameter Tuning

Table 1:Grid Search and Selected Hyperparameter Values

Model	Hyper-parameter	Parameter Grid Search	Selected Value
RF	mtry (input features)	{2,3,5}	3
	n-tree (decision trees)	{10,20,30,40}	20
SVM	Kernel function	{Radial basis, Polynomial, Sigmoid}	Radial basis function
	Pyramid reclassification threshold	{0.70, 0.80, 0.90}	0.90
KNN	K-value	{2,5,10,50,100}	50
	Distance function	{Euclidean}	Euclidean
	Leaf size	{20,30,50}	30
CNN (ResNet, VGGNet)	Dropout rate	{0.2,0.5}	0.2
	Learning rate	{0.1,0.01,0.001,0.0001}	0.00001
	Decaying learning rate	{True, False}	True
	Number of epochs	{20,50,80,100}	50
	Batch size	{32,16}	32
	Hidden layers	{3,5}	3

To improve the accuracy of LULC classification, hyperparameter tuning was conducted. For RF, different combinations of input features (*mtry*) and the number of decision trees (*n-tree*) were evaluated, revealing that an *mtry* value of 3 with 20 trees yielded the lowest out-of-bag (OOB) error rate of 8.4%, whereas increasing *mtry* to 5 resulted in a higher 9.4% OOB error rate. Therefore, *mtry = 3* and *n-tree = 20* were chosen as the optimal parameters. For SVM classifier radial basis function (RBF) kernel is selected, which

https://doi.org/10.5194/isprs-archives-XLVIII-G-2025-263-2025

efficiently handles non-linear relationships in high-dimensional data. The best-performing configuration included a gamma value of 1, a penalty parameter (C) of 100, a pyramid level of 1, and a pyramid reclassification threshold of 0.90, ensuring precise class separation. F or KNN, the model was fine-tuned by selecting K = 50, using the Euclidean distance function for similarity measurement, and setting a leaf size of 30 to balance accuracy and computational efficiency. In the case of DL models, including ResNet and VGGNet architectures, hyperparameter tuning was conducted to enhance feature extraction capabilities (Table 1). The optimal configuration consisted of a dropout rate of 0.2 to prevent overfitting, a learning rate of 0.00001 for stable convergence, an adaptive learning rate decay for dynamic weight adjustments, 50 training epochs, a batch size of 32, and three hidden layers to capture complex spatial patterns in Sentinel-2 imagery.

3.2. Evaluation of Classification

Table 2:Performance Comparison of ML and DL Models for LULC Classification.

Model	Accuracy	Precision	Recall	F1-score	Kappa Coeff.
RF	0.65	0.64	0.65	0.63	0.57
KNN	0.43	0.32	0.43	0.36	0.30
SVM	0.62	0.62	0.62	0.60	0.54
ResNet50	0.93	0.93	0.93	0.92	0.91
ResNet152	0.92	0.92	0.93	0.92	0.90
VGG16	0.95	0.95	0.95	0.94	0.94
VGG19	0.95	0.96	0.96	0.96	0.94

All DL-based CNN methods achieved accuracies above 92%, significantly outperforming ML models. Among the ML models, RF and SVM showed moderate accuracy levels of 65% and 62%, respectively, while KNN performed the worst with an accuracy of 43%. In contrast, DL models demonstrated superior performance, with VGG-16 and VGG-19 achieving the highest accuracy of 95%. Most models exhibited higher recall than precision, indicating that user accuracy was higher than the producer's accuracy. Furthermore, DL models outperformed ML models in terms of the Kappa coefficient, a statistical measure of classification reliability, with values reaching 0.94 for both VGG16 and VGG19 (Table 2). The ResNet50 and ResNet152 models also performed well, with Kappa coefficients of 0.91 and 0.90, respectively. The best-performing model, VGG-19, was further analyzed using a confusion matrix, as shown in Table 3. The matrix provides insights into class-wise performance, highlighting that the model achieved high classification accuracy across all LULC classes. Vegetation areas and water and wetland exhibited the highest classification accuracy at 97% and 98%, respectively, while other classes also showed strong performance, with minimal misclassification (Figure 3).

Table 3:Confusion matrix for the VGG19 model.

Predicted\ Actual	Barren Land	Built-up	Forest	Vegetation	Water and Wetland
Barren Land	0.90	0.00	0.00	0.01	0.002
Built-up	0.00	0.96	0.00	0.00	0.00
Forest	0.01	0.00	0.90	0.04	0.00
Vegetation	0.00	0.00	0.00	0.97	0.00
Water and Wetland	0.002	0.00	0.00	0.00	0.98

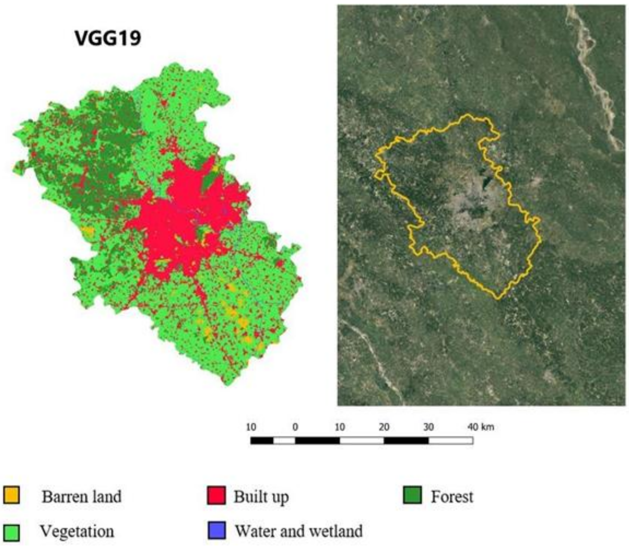

Figure 3:LULC classification using VGG19 model

3.3. Discussion

This study compares DL and ML models for LULC classification, highlighting the significant improvements offered by DL models. Patch-based labeling, which provides labeling captures spatial context by classifying groups of pixels together (Rousset et al., 2021), was used. Among all models, VGG-19 emerged as the best-performing DL model, demonstrating high accuracy, fast execution, and low CPU time consumption. A balanced dataset was used for training, ensuring all LULC classes were represented, while the Testing1 (Figure 1) dataset contained all possible labels to provide comprehensive validation. However, class imbalance was observed, with vegetation covering over 70% of the total area (Figure 3). Misclassifications, particularly between forest and vegetation, were attributed to spectral similarities, and the inherent imperfections. The distinction between forest and vegetation remains open to interpretation, as areas with dense trees in gardens may be misclassified as forests, emphasizing the need for on-the-ground verification. Performance metrics such as the Kappa coefficient, and confusion matrix analysis, revealed variations in classification accuracy across models, though differences among DL classifiers were minor but still significant for LULC mapping and planning. While deeper neural networks are harder to train, residual learning frameworks like ResNet facilitate training by learning residual functions instead of direct mappings. Empirical evidence indicates that ResNets benefit from increased depth but have fewer filters and lower complexity than VGG networks. Previous studies reported that LULC classification results vary across ML and DL models, with discrepancies influenced by atmospheric conditions, illumination, geometric distortions, and parameter optimization (Wawan Cenggoro et al., n.d.). Our study found less variation in class-wise LULC estimates for DL models compared to ML models, reinforcing their stability and reliability for large-scale mapping. VGG19 achieved the highest classification accuracy (96%) while KNN had the lowest accuracy (0.65). Though minor variations existed in the accuracy of SVM, KNN, RF, ResNet-50, ResNet-152, VGG-16, and VGG-19, VGG19 consistently outperformed all models based on the Kappa coefficient and confusion matrix analysis (Oikonomidis et al., 2023; Pallavi et al., 2022; Saleem et al., 2021).

Computational complexity in ML models depends on factors like the number of training samples, feature dimensions, and model-specific parameters, such as the number of decision trees in RF, the number of neighbors in KNN, and the number of support vectors in SVM. In contrast, DL models' complexity depends on training time, inference time, and hardware specifications, requiring extensive computations that are mitigated by parallel processing in deep neural networks. While DL models demand higher computational power, their superior accuracy and generalization ability make them the preferred choice for large-scale LULC classification.

4. Conclusion

This study aimed to generate an updated LULC map for Lucknow city and evaluate the performance of various ML and DL models using Sentinel-2 satellite imagery. The results demonstrated that classifier performance varies with dataset characteristics, with DL models showing minor accuracy variations that hold significant implications for LULC mapping and planning. Among the tested classifiers, VGG19 achieved the highest accuracy, as confirmed by the Kappa coefficient, confusion matrix analysis, Precision, Recall, and F1-score metrics. While previous studies have highlighted the effectiveness of RF, SVM, and ResNet50, our findings align with the literature suggesting VGG-19 or VGG-16 as the most reliable classifiers for LULC classification. The study also reinforces that LULC mapping accuracy is influenced by temporal and locational factors, necessitating future research across diverse morphoclimatic and geomorphic conditions. Moreover, integrating additional spectral indices such as NDVI, GNDVI, and BNDVI could further enhance classification accuracy. Regular updates to LULC maps are crucial for urban planning, environmental monitoring, and policy-making, and government agencies should prioritize maintaining up-to-date LULC datasets.

References

Alshari, E.A., Gawali, B.W., 2021. Development of classification system for LULC using remote sensing and GIS. Glob. Transitions Proc. 2, 8–17. https://doi.org/10.1016/j.gltp.2021.01.002

Arfa, A., Minaei, M., 2024. Utilizing multitemporal indices and spectral bands of Sentinel-2 to enhance land use and land cover classification with random forest and support vector machine. Adv. Sp. Res. https://doi.org/10.1016/j.asr.2024.08.062

Azedou, A., Amine, A., Kisekka, I., Lahssini, S., Bouziani, Y., Moukrim, S., 2023. Enhancing Land Cover/Land Use (LCLU) classification through a comparative analysis of hyperparameters optimization approaches for deep neural network (DNN). Ecol. Inform. 78. https://doi.org/10.1016/j.ecoinf.2023.102333

Barakat, A., Ouargaf, Z., Khellouk, R., El Jazouli, A., Touhami, F., 2019. Land Use/Land Cover Change and Environmental Impact Assessment in Béni-Mellal District (Morocco) Using Remote Sensing and GIS. Earth Syst. Environ. 3, 113–125. https://doi.org/10.1007/s41748-019-00088-y

Bhosle, K., Musande, V., 2019. Evaluation of Deep Learning CNN Model for Land Use Land Cover Classification and Crop Identification Using Hyperspectral Remote Sensing Images. J. Indian Soc. Remote Sens. 47, 1949–1958. https://doi.org/10.1007/s12524-019-01041-2

Boulila, W., Ghandorh, H., Khan, M.A., Ahmed, F., Ahmad, J., 2021. A novel CNN-LSTM-based approach to predict urban expansion. Ecol. Inform. 64. https://doi.org/10.1016/j.ecoinf.2021.101325

Carranza-García, M., García-Gutiérrez, J., Riquelme, J.C., 2019. A framework for evaluating land use and land cover classification using convolutional neural networks. Remote Sens. 11. https://doi.org/10.3390/rs11030274

Dewangkoro, H.I., Arymurthy, A.M., 2021. Land use and land cover classification using CNN, SVM, and Channel Squeeze & Spatial Excitation block, in: IOP Conference Series: Earth and Environmental Science. IOP Publishing Ltd. https://doi.org/10.1088/1755-1315/704/1/012048

Gardner, D., Nichols, D., n.d. Multi-label Classification of Satellite Images with Deep Learning.

Kalpana, Y.B., Nandhagopal, S.., 2021. LULC Image Classifications using K-Means Clustering and KNN Algorithm. Dyn. Syst. Appl. 30. https://doi.org/10.46719/dsa202130.10.07

Mohan, A., Singh, A.K., Kumar, B., Dwivedi, R., 2021. Review on remote sensing methods for landslide detection using machine and deep learning. Trans. Emerg. Telecommun. Technol. 32. https://doi.org/10.1002/ett.3998

Oikonomidis, A., Catal, C., Kassahun, A., 2023. Deep learning for crop yield prediction: a systematic literature review. New Zeal. J. Crop Hortic. Sci. https://doi.org/10.1080/01140671.2022.2032213

Pallavi, M., Thivakaran, T.K., Ganapathi, C., 2022. A Tile-Based Approach for the LULC Classification of Sentinel Image Using Deep Learning Techniques, in: 2022 International Conference for Advancement in Technology, ICONAT 2022. Institute of Electrical and Electronics Engineers Inc.

https://doi.org/10.1109/ICONAT53423.2022.9726030

Rawat, A.K., Banerjee, S., Roy, A.K., 2020. Assessment of Land Use/Land Cover Changes of potential growing fringe areas of Lucknow Using Remote Sensing and GIS, in: 2020 International Conference on Contemporary Computing and Applications, IC3A 2020. Institute of Electrical and Electronics Engineers Inc., pp. 254–259. https://doi.org/10.1109/IC3A48958.2020.233308

Rousset, G., Despinoy, M., Schindler, K., Mangeas, M., 2021. Assessment of deep learning techniques for land use land cover classification in southern new caledonia. Remote Sens. 13. https://doi.org/10.3390/rs13122257

Saleem, M.H., Potgieter, J., Arif, K.M., 2021. Automation in Agriculture by Machine and Deep Learning Techniques: A Review of Recent Developments. Precis. Agric. https://doi.org/10.1007/s11119-021-09806-x

Salim, M., Bhattacharjee, S., Sharma, N., Sharma, K., Garg, R.D., 2025. Spatial analysis and classification of land use patterns in Lucknow district, UP, India using GIS and random forest approach. J. Geogr. Cartogr. 8, 10230. https://doi.org/10.24294/jgc10230

Sathyanarayanan, D., Anudeep, D. V., Anjana Keshav Das, C., Bhanadarkar, S., Uma, D., Hebbar, R., Ganesha Raj, K., 2020. A multiclass deep learning approach for LULC classification of multispectral satellite images, in: 2020 IEEE India Geoscience and Remote Sensing Symposium, InGARSS 2020 - Proceedings. Institute of Electrical and Electronics Engineers Inc., pp. 102–105. https://doi.org/10.1109/InGARSS48198.2020.9358947

Shukla, A., Jain, K., 2019. Critical analysis of rural-urban transitions and transformations in Lucknow city, India. Remote Sens. Appl. Soc. Environ. 13, 445–456. https://doi.org/10.1016/j.rsase.2019.01.001

Srivastava, A., Thakur, A.K., Garg, R.D., 2025. An Assessment of the Spatiotemporal Dynamics and Seasonal Trends in NO_2 Concentrations Across India Using Advanced Statistical Analysis. Remote Sens. Appl. Soc. Environ. 101490.

Thakur, A.K., Attri, L., Garg, R.D., Jain, K., Kumar, D., Chowdhury, A., 2024. Temporal and Spatial Dynamics of Subsidence in Eastern Jharia, India, in: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Copernicus Publications Göttingen, Germany, pp. 349–356.

Thakur, A.K., Garg, R.D., Jain, K., 2025. An Assessment of Different Line-of-Sight and Ground Velocity Distributions for a Comprehensive Understanding of Ground Deformation Patterns in East Jharia Coalfield. Remote Sens. Appl. Soc. Environ. 101446.

Uba, N.K., Femiani, J., Razdan, A., Amresh, A., 2016. Land Use and Land Cover Classification Using Deep Learning Techniques.

Verma, D., Jana, A., n.d. LULC classification methodology based on simple Convolutional Neural Network to map complex urban forms at finer scale: Evidence from Mumbai.

Wawan Cenggoro, T., Isa, S.M., Putra Kusuma, G., Pardamean, B., n.d. Classification of Imbalanced Land-Use/Land-Cover Data Using Variational Semi-Supervised Learning.

Yassine, H., Tout, K., Jaber, M., 2021. Improving LULC classification from satellite imagery using deep learning - Eurosat dataset, in: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives. International Society for Photogrammetry and Remote Sensing, pp. 369–376. https://doi.org/10.5194/isprs-archives-XLIII-B3-2021-369-2021

Zope, P.E., Eldho, T.I., Jothiprakash, V., 2017. Hydrological impacts of land use–land cover change and detention basins on urban flood hazard: a case study of Poisar River basin, Mumbai, India. Nat. Hazards 87, 1267–1283. https://doi.org/10.1007/s11069-017-2816-4