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Convolutional Neural Network Methods for Detecting Land-Use Changes

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Abstract: As the demand for reliable, up-to-date information about natural and manmade environments has risen, so has attention to this problem. Due to urbanization, it must contend with rapid climatic changes. To lower the urban heat island, both existing and rising cities require accurate land cover classification, which enables changes in settlement distribution, bodies of water, and vegetation index to be recognized. Images from space and the air are gathered from different sources and categorized by characteristics. Further research is needed on convolutional neural networks (CNN), which have been implemented progressively in land-use classification. CNN approaches are tested for land classification and land use (LU) change detection in this study. To solve a practical challenge caused by a shortage of data, the CNN and faster recurrent neural network (R-CNN) models were trained utilizing data from two sources. The statistics showed that while green spaces and low-density residential areas diminished over time, residential areas with higher densities rose with time, indicating the pattern of LU community transformation in Nagpur's study area and the technique's accuracy of 98.86%.

Keywords: *Land use Land cover changes, Convolutional neural networks (CNN), remote sensing, Discrete Wavelet Transform (DWT), Satellite Image Classification, Urbanization.*

1. Introduction

Recent years have brought focus to the effects of changes in land use and land cover (LULC) on ecological processes. Keeping an eye on these changes can help with planning for cities and rural areas, figuring out how temperatures change and keeping an eye on the environment. Natural changes in land cover have the most important effect on how climate and biogeochemistry are spread out around the world. The Earth's surface has a big effect on the hydrologic cycle, biogeochemical cycles, strength balance, etc. In turn, the Earth's surface has a big effect on these cycles and also leads to affect the strength balance. Human-induced activities, such as entrapment, overgrazing, and baring, and to a lesser extent human-induced activities leads to climate change. The earth's surface is altering gradually, however certain changes in land cover are triggered by regular processes as the evolution of morphology and the change of vegetation kinds or by climate change brought on by orbital mechanics. The scientific community is aware of the necessity of charting, monitoring, and evaluating the effects of changes in the physical characteristics of the Earth's surface (Shi et al. 2021a). The term land use (LU) refers to how a region's inhabitants put their land to use in the marketplace as well as for other social and cultural functions, such as entertainment and conservation. The term land cover (LC) is used to describe the percentage of Earth's land area that is covered by various types of vegetation, water, forests, and other natural features. The rising need for shelter, food, resources, and services, among other things, is only one example of how the world's population boom in the modern era has posed serious problems for society and the environment. These factors have led to shifts in land use as well as land cover (LULC), which had detrimental effects on the environment. Effective land use planning and management are becoming more important, not only to reverse the unfavorable results of previous LU choices but also to ensure the long-term health and sustainability of future nations. Port, home, highway, farmland, and park are all examples of land-use scenes since each one illustrates a different situation via its combination of elements (Cao et al. 2019). Present techniques for updating urban land-use maps need the arduous and time-consuming analysis of aerial photographs and field surveys. The term change detection refers to the method of comparing two or more states of an item, scene, or phenomenon across many time intervals. Detecting changes in remotely sensed images requires expertise in geomatics, analytics, and information science. In recent years, high-resolution (HR) image studies for land cover

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have gained a lot of traction in the area of remote sensing thanks to the proliferation of several optical satellite sensors capable of taking such pictures (Wang et al. 2020). Understanding the interrelationships between humans and their natural environments is aided by the ability to detect changes on the Earth's surface (Shi et al. 2021b) The land resource is crucial to the development of a region's economy, society, and ecological health as a whole and must be taken into account in any discussion on environmental sustainability since it provides the material foundation for economic growth and social activity.

Understanding place, natural processes, the environment's influence, and people are the four major tenets of sustainable design. Connecting with nature is also made possible by adopting co-creative design approaches. Understanding place aids in determining design practices, knowledge of natural processes aids in establishing goals for eradicating depletion, knowledge of management and economics' impact on the environment enhances design outcomes, and knowledge of people is essential for accounting for the diversity of cultural practices and human behavior. Indirectly or directly, the release of industrial effluent, waste gas, and waste residue during the construction process causes soil contamination, degradation of land structure and fertility, salinization, acidification, and hardening of the soil (Liu et al. 2020). Many methods have been developed to assess and simulate LUC for sustainable land use management and decision-making since it is a dynamic process with major effects on the environment. Unchecked, the stresses on the natural environment brought on by land use change (LUC) as a consequence of urban development can cause irreparable harm (Shi et al. 2021c). The categorization of land use provides useful information for monitoring and predicting urban growth, managing and planning land resources, and maintaining natural systems by identifying land cover characteristics and reflecting local human behavior and socioeconomic changes in a region. Given the wealth of spatial and structural information, it provides about ground objects, remotely sensed photos are often employed for land-use categorization. A prominent area of study in the study of remote sensing, land-use categorization entails assigning semantic labels to extracted areas that include several land-use classifications. Since deep learning models have shown great feature representation capabilities in a variety of applications, they are now widely used in feature learning to produce robust, powerful, and discriminative features. Although the degree of variability differs from one area to another, there are similarly mixed conclusions in the literature concerning impact fees (Evans-Cowley and Lawhon, 2003). In particular, deep convolutional neural networks have shown effectiveness for various remote sensing image processing applications, such as item recognition and land-use scenario categorization, thanks to their capacity to collect both local and global data, as shown in Figure 1(Liang et al. 2020). An accurate estimation of the productivity of earthmoving equipment is one of the conditions for project control and planning. An ANN model that predicts equipment productivity is being created and tested in this project. Neural networks are proposed in this study to improve productivity estimation models due to their inherent ability to capture non-linearity and the complexity of the dynamic environment of each project. In light of the findings, it seems that the non-linear ANN acts as a tool for bettering the estimating model for equipment productivity. Taxes are price-based instruments that include direct payments for each unit used or polluted. To regulate the type of use, various land uses are taxed at various rates. Real estate taxes, land taxes, and split-rate taxes are a few examples of various taxes relating to land use. (Banzhaf et al. 2010).

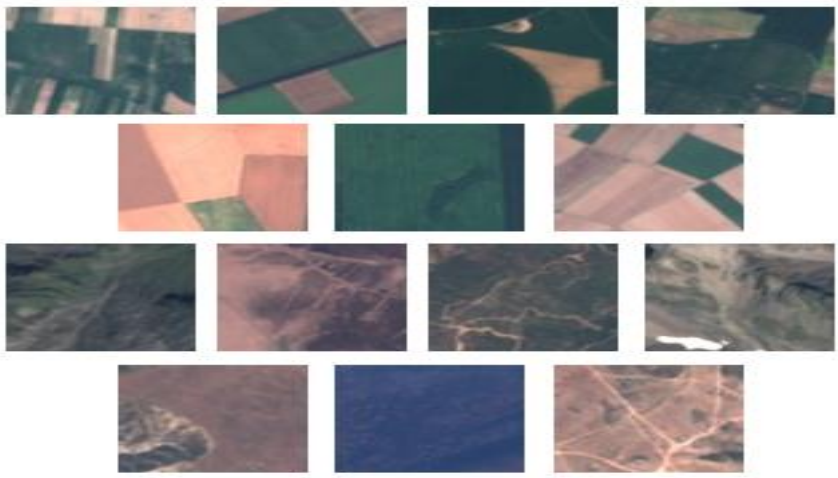


Fig 1. Land classification and different measures of occupied spaces

In recent decades, the world's land cover has been rapidly replaced by a wide range of land use types. Changes in land use and land cover are two distinct but related terms that are often interchanged when discussing global environmental shifts. Understanding LULC and its effects are crucial for effective resource management and long-term planning. Ecological factors, altitudes, ecological structure, all have a responsibility in deciding land use and cover, with technical, socioeconomic, and institutional frameworks (Mishra et al. 2020). Similarly, using two-stage probit and neural network models to examine land 6 development trends in and around the city of Knoxville,Tennessee, Cho et al. (2007). Spectral variance is amplified by differences in plant species, growth phase, canopy cover, soil type, moisture, and weather. The degree to which the results from the various methods are adequate for a given task varies (Berberoglu et al. 2009). The human-environment interaction that gives birth to land use change (LUC) is still in its infancy, and as a result, around 39% of Earth's land has never been utilised by people in any way (Cao et al. 2019).

2. Literature Review

A wide range of authors have worked in the same direction, and after conducting a literature review, the following are the findings of their work.

Sedighkia et al. (2022) analyze how well the hybrid machine learning approaches perform in processing remote sensing data to spot changes in land usage, particularly as they pertain to agricultural fields. The machine learning model was trained and tested using two different Landsat 8 spectral pictures. A feed-forward neural network filter was used as the ML model, with swarm optimization and intrusive weed optimization as the evolvable training methods, respectively. Therefore, BFGS quasi-Newton back propagation (BFG) or Levenberg–Marquardt back propagation (LM) is the finest technique to discover the agricultural fields now. When compared to the LM approach, BFG is more reliable. Due to its low computing complexity, however, LM could be favoured for use in projects.

Das et al. (2021) determine that the study utilises remote sensing data to analyse the LULCC dynamics in the Barrackpore Subdivision region, India, and finds that it is closely tied to the expansion of the city. The land use and land cover maps were created using multi-temporal Landsat imagery and the Maximum Likelihood Classifier (MLC) technique. The ‘from-to’ change matrix identifier was used to analyse the spatial and temporal adjustments made to the land. Variation in the expansion of human settlements was also found. Given the positive relationship between population and built-up land expansion, it can be concluded that population pressure has accelerated the expansion of developed areas in the region under consideration.

Wang et al. (2020) discovered that the Kathmandu district lost 9.48% of its forests, 9.85% of its agricultural area, and 76% of its water bodies during 20 years (from 1990 to 2010). Rapid urbanisation, which has increased by 53.47% since 1970, has absorbed a significant portion of these declines. Forest, agricultural, and aquatic body areas are all expected to shrink by an additional 14.83%, 17.67%, and 26.83%, respectively, by 2030, according to projections of land use and land cover change. In urbanised regions, growth is anticipated to be greatest in 2030, at 18.59 percent. Loss of ecosystem services will hurt city dwellers as a result of these alterations. It is advised that urban planners include ecosystem-based adaptation and mitigation into their designs, backed by sound legislation and enough funding. Planning for a sustainable future is made easier with the use of techniques like remote detection and geographic information systems, which have been used for years to analyse land use and land cover changes.

Zhai et al. (2020) developed a CNN-variable correlation analysis (VCA) model that uses Utilising convolutional neural networks (CNNs), can extract the high-level characteristics of the driving variables inside a neighbourhood of an irregularly shaped cell and discover the correlations between numerous land use changes and driving factors at the neighbourhood level. China's Shenzhen was used as a test case for the suggested model, which simulated urban land use changes. The suggested CNN-VCA model out performed numerous previous VCA models trained with various machine-learning techniques (figure-of-merit = 0.361). Based on the findings, it seems that the CNN-VCA model is a useful tool for learning more about the morphological features of land parcels and revealing the influence of numerous neighbourhood-level driving variables on development potential. In addition, to aid in urban planning decisions, simulations of land use patterns in 2020 and 2025 under a natural management approach were conducted.

Alawamy et al. (2020) focus on the value of GIS (Geographic Information System)-assisted satellite digital image processing in mapping and identifying LULC shifts. By using a maximum likelihood supervised classification of Landsat TM5 (Thermomix5), ETM+7 (Embedded Trace Macrocell), and OLI8 (Operational Land Imager) data followed by a post-classification comparison technique, reasonably accurate maps of LULC changes can be predicted and obtained. Overall, the LULC classifications produced in this study show promising levels of accuracy and kappa coefficient values. Natural Mediterranean Forest has been drastically decreasing while other land uses, including orchards, rain-fed agriculture, irrigated crops, urban and built-up regions, and barren and low vegetation, have been increasing (BLV).

Garca et al. (2019) suggested a generic deep learning framework for categorising land use and land cover using multi-source remote sensing images (in this case, radar and hyperspectral datasets). In this paper, a convolutional neural network has also been validated by comparing its results to those of more traditional ML methods like support vector machines (SVM), random forests (RF), and k-nearest neighbours (KNN). When the results of cross-validation trials were statistically analysed, the expected convolutional neural network outperformed the other models studied in terms of overall accuracy and accuracy per class.

Hussain et al. (2019) use 40 years' worth of Landsat photos to look for trends in LULC, Naturalistic Development Behavioural Interventions (NDBI), and Normalised Difference Vegetation Index (NDVI) in Pakistan's Lodhran area. The four main LULC categories that will be used are as follows: bodies of water, urbanisation, wilderness, and vegetation. Because the maximum likelihood technique in Earth Resource Data Analysis System (ERDAS) envision 15 is not intuitive, authors used supervised classification to discover LULC shifts in the Lodhran area. The majority of farmers in the Lodhran area (47.6%) believe that significant shifts in temperature and planting season timing, as well as decreased precipitation amounts, have occurred in recent years.

Cao et al. (2019b) tries to figure out how well CNN approaches work for land categorization and LU change detection. Concerning RS information for LU scene categorization, three pre-qualified CNN models (Alex Net, Google Net, and VGG Net) were used to do a thorough analysis of eight imported CNN-based models. The accuracy of categorization for all models is between 94% and 99%, with the transferred CNN model paired with a support vector machine (SVM) as an attribute classifier (CNN-SVM) being the best method. The findings obtained showed that residential areas were growing via the development of higher-density regions, with the concurrent decline of open spaces and low-density neighbourhoods precisely indicating the pattern of LU change in the Cloverdale neighbourhood.

Storie et al. (2019) study explores the use of a deep learning neural network (DLNN) for satellite image processing, with an emphasis on land use and land cover map creation. Over the last several years, DLNNs have achieved significant advancements in the realms of pattern recognition and machine learning. Their use in remote sensing, however, is still in its infancy since the technique was created for conventional images rather than satellite pictures. The purpose of this project was to construct a DLNN to produce land use and land cover maps of the southern agricultural area of Manitoba, Canada. Once the DLNN is fully trained, the findings show a significant reduction in processing time compared to a human-based semi-automated procedure.

Karimi et al. (2018) analysed the LULC shifts in Ravanssar between 1992 and 2015 utilising spatial analytic techniques. Cellular automata (CA) models, such as the CA-Markov model, are suitable for precise resolution modelling and simulating dynamic spatial processes, and hence a broad variety of approaches and models have been created to identify and anticipate these variations. Finally, the spatial pattern improvements of LULC until 2030 were simulated using the CA-Markov model. According to the findings, the proportion of this region that is urbanised and used for agriculture (both aquatic and non-aquatic) has grown significantly between 1992 and 2015, whereas the proportion that is used for gardening, grazing, and bare land has shrunk.

Helber et al. (2018) focus on how to use Sentinel-2 satellite images to classify land uses and land covers. The author tests how well the best deep convolutional neural networks (CNNs) work on this new dataset with many different wavelengths. Also, compare the results from deep CNNs with those from remote sensing datasets that have already been published. Overall classification accuracy was 98.67% using the unique dataset suggested. The suggested study might pave the way for new kinds of Earth observation applications thanks to its proposed categorization system. It shows how the categorization scheme could be used to enhance existing maps of the world.

Nataly et al. (2017) demonstrate the effect of land use changes on groundwater quality in Northern Kelantan, Malaysia, where widespread deforestation has occurred in recent decades. This study makes use of 25-year records of nitrate concentrations (from 1989 to 2014). Nitrate (NO3-N) concentrations rose dramatically over 25 years, with increases of 8.3% and 3.88% per year in agricultural and domestic wells, respectively, according to findings from the combination of time series data and geospatial modelling. The autoregressive integrated moving average (ARIMA) theory predicts that nitrate pollution will increase by 2.4 and 3.8 percent yearly in agricultural and urban regions, respectively, until 2030.

Hua et al. (2017) used LULC shifts to determine whether the Malacca River's water quality has changed. Analysis of Variance (ANOVA), Principal Component Analysis (PCA), Controller of Certifying Authorities (CCA), Human Critical Area (HCA), National Hearing Conservation Association (NHCA), and LULC are all used in this approach. Principal component analysis was used to confirm dissolved solids, electrical conductivity, salinity, turbidity, total dissolved solids, dissolved organic carbon, biological oxygen demand, metals (As, Hg, Zn, Fe, E. coli), and total coliform. CCA checked 14 variables in a few groups. The first group is about household and business activities. The second group is about farming, sewage treatment, and raising livestock. The results of the study helped policymakers figure out where pollution comes from and how LULC affects the quality of water in rivers.

The provided Table 1 is a summary of the reviewed literature from different authors.

Table 1. Summary of Literature Review.

Authors	Methods	Outcomes
Sedighkia et al. (2022)	BGM and LM	The study also revealed substantial variations in the growth of metropolitan regions.
Das et al. (2021)	MLC	According to the findings, BLV land is on an unstable upward trend that has averaged around 53% growth over the last several years.
Wang et al. (2020)	Geographic Information System (GIS) and Remote Sensing	This was determined to be the most helpful resource for understanding the physical characteristics of property parcels and how local context affects development possibilities.
Zhai et al. (2020)	CNN-VCA	The results show that the percentage of land that is barren or has very little vegetation has been steadily rising over the last several decades, having grown by roughly 50% in most cases.
Alawamy et al. (2020)	GIS and Remote Sensing	The results show the radar and hyperspectral datasets for land use and cover categorization used to evaluate convolutional neural network.
García et al. (2019)	Deep-Learning	The study will assist policymakers in properly managing land resources by providing a key monitoring base for ongoing studies of changes in land management.
Hussain et al. (2019)	GIS	All transferred models successfully classified land use with an accuracy of 95.0% or higher, as shown by the results.
Cao et al. (2019)	CNN and SVM	Pattern recognition and machine learning are used to describe a Deep Neural Network (DLNN) for making land use and land cover maps of the southern agricultural region.
Storie et al. (2019)	DLNN	Between 1992 and 2015, data show that more of this area was built on or used for farming, while less of it was used for gardening, grazing, or just being left empty.
Karimi et al. (2018)	CA-Markov model	The results of the experiment show that by using the unique dataset that was suggested, it was possible to get a total classification accuracy of 98.05%.
Helber et al. (2018)	Deep CNN	Based on the ARIMA model, nitrate pollution is expected to rise by around 2.64 and 3.9% each year until 2030 in rural and urban areas, respectively.
Naraly et al. (2017)	ARIMA	The results helped policymakers figure out where pollution came from and what the relationship was between LULC and the quality of river water.
Hua et al. (2017)	LULC, PCA, CCA, HCA, NHCA, and ANOVA	The study also revealed substantial variations in the growth of metropolitan regions.

3. Background Study

This paper uses a convolutional neural network model to describe the spatial and temporal hierarchy of LC and LU. Both LC and LU classification schemes were employed to fit the complicated, nonlinear relationships, and their predictions were utilised to update each other in an iterative process that approximated the ideal answers. Inherently hierarchical, LC and LU cover the same contiguous geographical region at varying scales and semantic depths. A completely generalizable method would be developed and implemented, thereby strengthening the accuracy evaluation framework. Using the JDL (Joint Deep Learning) framework to identify and simulate LC and LU changes over time is also relevant. There is a need for further exploration into the potential of CNNs, which have seen increased application in numerous land-use categorization assignments. The main goal of this study is to assess how well CNN techniques can classify land and detect land-use (LU) shifts (Cao et al. 2019c).

4. Problem Formulation

For this study, a convolutional neural network (CNN) model was designed to describe how LC and LU are related spatially and in terms of hierarchy. The images are preprocessed by setting an atmospheric correction value and applying a stack of hyperspectral images. Dimensionality reduction is carried out after the data has been preprocessed. To achieve dimensionality reduction, the discrete wavelet transform (DWT) is used. DWT compresses information into a suitable quantity of bands by applying a two-dimensional wavelet stream. The data is divided into coarse and fine granularities. To create the dimensionally reduced data set with d-bands, it joins the estimate and detail matrices together. Dimensionality reduction with DWT is followed by the application of machine learning classifiers to assign images to predetermined groups. In this work, a faster region-based convolutional neural network (Fast R-CNN) is employed for picture classification. R-speed CNNs have been increased thanks to enhancements made to the CNN Classifier. After quickly classifying images using Faster R-CNN, it conducts in-depth analyses of land use, climatic change, and geographical shifts. LULC considers the deforestation that has occurred over the past decade. Spatial change analysis, a type of trend surface analysis, provides insight into the geographical context of a phenomenon. When all is said and done, a confusion matrix is used to assess the model's precision.

In Google Earth Engine (GEE), the accuracy of image classification is measured and analyzed with the help of a confusion matrix.

5. Research Objective

- To determine the efficacy of CNN-based categorization models and discover instances of land-use change in the past.
- Classifying and mapping land use using orthophotos of the study region using the highest-performing transferable CNN-based model as a classifier.
- For the best results, it is important that all transferred models give reliable results for categorising land use.

6. Research Methodology

The current research focuses on the discovery of convolutional neural network methods for detecting land-use changes.

6.1 Technique Used

6.1.1 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) is an improved version of Yann LeCun and his colleagues' neural network (Razmjooy et al. 2018). CNN can be used with a number of mathematical learning methods, such as regularisation, backpropagation, and gradient descent. The fully connected layer, the convolutional layer, and the pooling layer are all components of CNN (Acharya et al. 2018).

- ***Convolutional layer***

In the convolutional layers of a deep CNN, adjustments are made to the source image or other feature maps using filters. This is where the advantage of user-specified network settings resides. The two most essential factors are the number of kernels and their size.

The purpose of the convolution layer is to transform the input picture using a convolution layer to extract features. This transformation involves convolving the picture with a kernel (or filter). The height and breadth of a kernel matrix are less than the picture to be convolved. A convolution matrix is also known as a convolution mask.

Pooling in convolutional neural networks is a method for generalising features recovered by convolutional filters and assisting the network in recognising features regardless of their position in an image.

There are several types of pooling layers in CNN, as follows:

- ***Max pooling***

The filter's feature map region takes up a big chunk of the feature map area, so the max-pooling algorithm chooses the biggest element from that area. So, if the max-pooling layer is used for the feature mapping project, the best leading elements from the previous feature map will be used.

- ***Average pooling***

Using an average pooling method, the parts of the feature map that were changed by the filter are added together to get a mean value. Consequently, As opposed to max-pooling, average pooling creates a statistical average of the features present in a region of the feature map. Using pooling layers to reduce the dimensionality of feature maps. Consequently, there is less processing and less learning required by the network result. The pooling layer, a convolution layer, can summarize a section of the feature map created by the convolution layer.

- ***Fully connected layer***

Fully Connected Layer neural networks are essentially feed-forward networks. The last few network levels are known as Fully Connected Layers (FCL). Finally, the flattened output of the final Pooling or Convolutional Layer enters a full-link layer.

Convolutional layers apprehension the complex operation to produce feature-map array $Y \in R^{M' \times N' \times P}$ (M', N' and P is the number of height, width, and channel/depth of Y) from the input image array $X \in R^{M \times N \times D}$ (M, N, and Dare the number of height, width, and channel/depth of X) for feature origin. One feature map $Y^P \in R^{M' \times N'}$ is calculated as:

$$Y^P = f(\sum_{d=1}^{D} W^{p,d} \otimes X^d + b^P) \qquad (1)$$

Where $X^d \in R^{M \times N}$ is one of the response image arrays. $W^{p,d} \in R^{m \times n}$(1 ≤ d ≤ D, 1 ≤ p ≤ P, 1 ≤ m ≤ M, 1 ≤ n ≤ N) denotes one means of the convolutional kernels and b^P is the subsequent diagonal term. The convolutional operation is signified as ⨂. For feature reduction, down-sampled feature-map arrays are generated by pooling layers using either max-pooling or mean-pooling, as represented as:

$$Y_{m,n}^d = \max_{i \in R_{m,n}^d} x_i \ or \ \frac{1}{|R_{m,n}^d|} \sum_{i \in R_{m,n}^d} x_i \qquad (2)$$

where $Y_{m,n}^d$ is the output of X^d , which signifies an input sub-section with a size of m × n. $R_{m,n}^d$ is a set of the index number of X^d and x_i is the value of the i^{th} pixel in X^d . That is $|R_{m,n}^d|$ =m×n. The result is obtained by computing nonlinear functions in fully linked layers (Kattenborn et al. 2020).

6.1 Faster Region Convolutional Neural Network (Fast R-CNN)

The faster version of the recurrent neural network (R-CNN) is a two-stage detection network that is often used to identify medical images. The Faster R-CNN is made up of several primary components, including a characteristic extractor, region proposal network (RPN), ROI pooling, and classifier. It could be roughly divided into two halves. The RPN is one such component; it is a fully convolutional network (FCN) used to generate item recommendations for use in the second stage of the system. The second is a detector called Fast R-CNN, whose goal is to improve the suggestions and the rough detection processing map. It is important to note that fast R-CNN saves time by sharing the convolutional layers. High-quality region suggestions are produced for detection, while object limits and saliency scores are predicted for each picture concurrently (Seydi et al. 2020).

6.2 Land Use Change Analysis

The Land-Use Change Analysis System (LUCAS) is an experimental software programme that combines ecological and socioeconomic data. It is used to find adaptive ways to manage landscapes. How human actions affect the long-term viability of ecosystems and natural resources The model assumes that market mechanisms, social structures, the expertise of landowners, and natural procedures all play a role in shaping landscape features, including fragmentation, connectedness, spatial subtleties, and degree of the supremacy of habitat types. Thus, including human and ecological processes in environmental sustainability models of human-dominated settings is advantageous. The LUCAS programme is a computer programme developed to combine existing and prospective data to (1) provide a platform for modelling across disciplines to investigate land-use effects, (2) Make use of adaptive management techniques to answer landscape impact assessment management questions.

6.3 Spatial Analysis of Land Change

The spatial analysis of land use and change is shown in Figure 2**.**

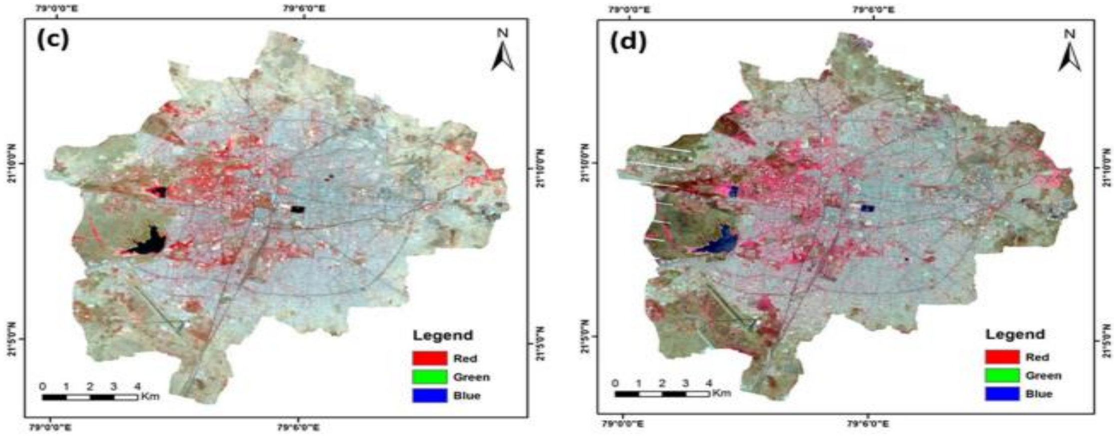


Fig 2. Land change description of images from 2010 to 2016 (Ma et al. 2020).

Accelerating urbanization and deforestation are driving forces behind shifts in land use. Figure 2 shows the spatial analysis of land change in Nagpur city from 2010–2016, during which time the city's built-up area increased while the share of undeveloped land decreased, followed by the share of forested land, agricultural land, and bodies of water. The various land-use classes have been shown in Figure 3.

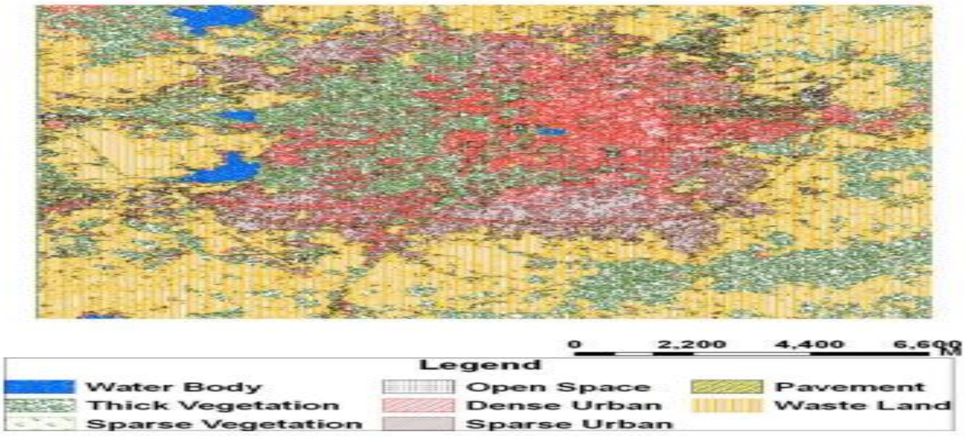


Fig 3. Division of various land use categories.

7. Proposed Methodology

Step 1: Data collection and acquisition

In this study, the dataset was taken using the GIS tool of the Nagpur Region. The year of acquisition for the data is 2020.

Step 2: Data pre-processing (Hyperspectral Image Stack, Atmospheric Correction)

In this step 2, the data that was collected in step 1 is pre-processed for evaluation in a later process. In this regard, the data is pre-processed based on two parameters: the hyperspectral image stack and atmospheric correction.

Step 3: Dimensionality reduction by using Discrete Wavelet Transform

After data pre-processing, the dimensionality reduction is performed on the pre-processed data. In this study, the dimensionality reduction is performed by using Discrete Wavelet Transform (DWT). Using a two-dimensional wavelet filter, the DWT approach condenses the data down to the appropriate number of bands.

It does a decomposition on the supplied data, creating an approximation matrix and a detailed matrix. After that, the dimensionally shortened data set with d bands are formed by first concatenating estimation and detail matrices into a single matrix. The mathematical expression of DWT is shown below:

$$a_{j+1}[p] = \sum_{n=-\infty}^{\infty} h[n-2p]a_j[n] \quad (3)$$

$$d_{j+1}[p] = \sum_{n=-\infty}^{\infty} g[n-2p]a_j[n] \quad (4)$$

where a_j are the estimated coefficients at scale 2^j , a_{j+1} and d_{j+1} are separately the estimate and describe components at scale 2^{j+1}.

***Step 4: Image classification using machine learning classifier*.**

After the dimensional reduction using DWT, in this step, the image classification is performed using a machine learning classifier. In this study, Faster Region-based Convolutional Neural Network (Fast R-CNN) is used as a classifier to classify the image. It is an improved version of the Convolution neural network (CNN) classifier. Then classification function is solved by the eq. 3 that are given below:

$$maximise : \sum_{u=1}^{f} \alpha_u - \frac{1}{2}\sum_{u=1}^{f}\sum_{v=1}^{f} \alpha_u \alpha_v y_u y_v K(x_u, x_v) \quad (5)$$

$$subjectto : \sum_{u=1}^{f} \alpha_u y_u = 0 \ and \ 0 \leq \alpha_u \leq C \quad (6)$$

Here, α_u and α_v are Lagrange multipliers. K is the kernel and C is a positive constant, (x_u, x_v) is the kernel function.

Step 5: Change Analysis

In this step after classifying the image by using Faster R-CNN the Land Change -Land Use (LULC) change and spatial change analysis are performed. In LULC change, it considers the change such as forest change to non-forest places or vice-versa in the last decade. Spatial change analysis refers to the change in the place, it is a comprehensive trend surface analysis highlighting the spatial increment of the state transition inside a given place.

Step 6: Multi-layer perception neural network and Markov chain (MLP -MC) techniques analysis

In step 6, a Multi-Layer Perception neural network and Markov Chain (MLP-MC) methods are used to detect and predict land use and land changes. The MLP-MC approach, like with other spatial models, generally included uncertainty regarding the data, the model, and the future predictions. The Markov chain analysis is represented as:

$$S(t, t+1) = P_{ij} \times S(t) \quad (7)$$

Where, $S(t)$ is the order status at time of t, $S(t+1)$ is the system status at time $t+1$; P_{ij} is the transition possibility matrix.

Step 7: Accuracy assessment using a Confusion matrix

In this last step, the accuracy of the proposed model is evaluated using a confusion matrix. An integral part of Google Earth Engine (GEE), the confusion matrix checks and measures how well the photos categorize. The formula for determining the Overall Accuracy (OA) is as follows:

$$OA = \left(\frac{p_c}{p_n}\right) * 100 \quad (6)$$

where p_c is the value of pixels categorized accurately and p_n is the total value of pixels.

Step 8: Prediction of LULC map

This is the last step of the proposed methodology, in this step the LULC map is predicted using MLP-MC analysis based on earlier LULC changes and spatial trend changes. It is clearly shown that the non-forest area and deforestation area increases at a high rate.

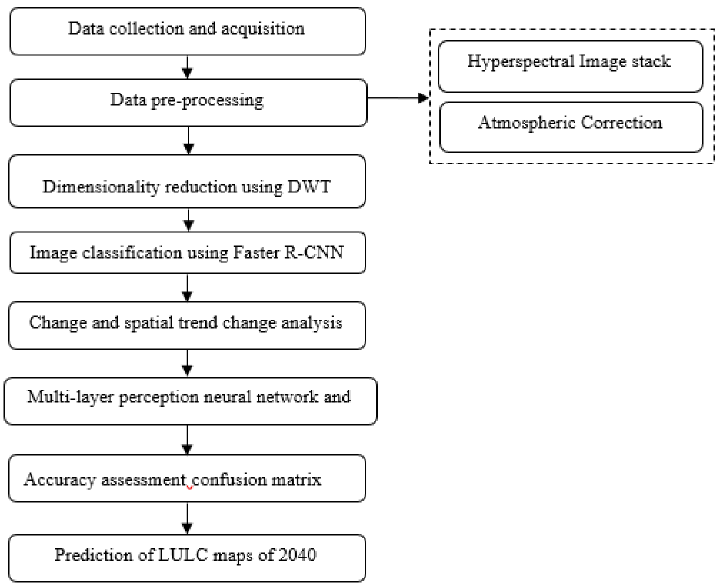


Fig 4. Methodology step by step.

7.1 Proposed Algorithm

Start

ALGORITHM:	Detect & Predict Land-Use Change using Multi-layer Perception Neural Network and Markov Chain

Start

Phase I : Data Collection *and* Acquisition.

Phase II : IMAGE PRE-PROCESSING *from* Step **1 → 2.**

Step 1: Load hyperspectral image stack
→ image_stack ← load_hyperspectral_image_stack('file_path')
Step 2: Apply atmospheric correction
→ atmosphere_parameters ← get_atmospheric_parameters('image_stack')
→ corrected_image_stack ← apply_atmospheric_correction('image_stack', atmosphere_parameters)

Phase III : DIMENSIONALITY REDUCTION *using* **DWT** *from* Step **3 → 5.**

Step 3: Apply DWT
→ dwt_image_stack ← apply_dwt('corrected_image_stack', wavelet_type, levels)
Step 4: Apply thresholding
→ thresholded_image_stack ← apply_thresholding('dwt_image_stack', threshold)
Step 5: Apply inverse DWT
→ reconstructed_image_stack ← apply_inverse_dwt('thresholded_image_stack', wavelet_type)

Phase IV : SPATIAL TREND CHANGE analysis *from* Step **6 → 10.**

Step 6: Apply noise reduction
→ denoised_image_stack ← apply_noise_reduction(reconstructed_image_stack')
Step 7: Apply spectral resampling
→ resampled_image_stack ← apply_spectral_resampling('denoised_image_stack', target_resolution)
Step 8: Apply spatial filtering
→ filtered_image_stack ← apply_spatial_filtering('resampled_image_stack', filter_size)
Step 9: Apply feature extraction
→ feature_image ← extract_features('filtered_image_stack')
Step 10: Compute spatial trend change
→ trend_change ← compute_spatial_trend_change('change_map', window_size, trend_type)

Phase V : IMAGE CLASSIFICATION *using* Faster **R-CNN** *from* Step **11 → 16.**

Step 11: Initialize the Faster R-CNN model
→ model ← initialize_faster_rcnn_model()
Step 12: Define the classes to be detected
→ classes ← ['Annual Crop', 'Forest', 'Herbaceous Vegetation', 'Highway', 'Industrial', 'Pasture', 'Permanent Crop', 'Residential', 'River', 'SeaLake']
Step 13: Load the dataset
→ dataset ← load_dataset()

Step 14: Split the dataset into training and testing sets
→ train_set, test_set ← split_dataset(dataset)
Step 15: Train the model on the training set
→ trained_model ← train_model(model, train_set)
Step 16: Evaluate the model on the testing set

→ evaluation_metrics ← evaluate_model(trained_model, test_set)

Phase VI : DETECT & PREDICT LAND-USE CHANGE *using* **MLP-MC** *from* Step **17 → 28.**

Step 17: MLP-MC : Multi-layer Perception Neural Network and Markov Chain

Multi-layer Perception Neural Network

Step 18: Initialize weights and biases for each neuron in the network
Step 19: Input the training data and their corresponding labels
Step 20: ***for*** each input data, calculate the output of each neuron using the sigmoid activation function:

- Multiply the input data by its corresponding weights and add the bias
- Pass the result through the sigmoid activation function
- Calculate the error between the predicted output and the true label using a loss function such as mean squared error
- Update the weights and biases using backpropagation:
  - Calculate the derivative of the loss function with respect to each weight and bias
  - Update each weight and bias using the derivative and a learning rate

Step 21: Use the trained MLP to predict the labels of new data

Markov Chain

Step 22: Define the states of the Markov Chain, which in this case are different land-use types

Step 23: Create a transition matrix that describes the probabilities of transitioning from one state to another

Step 24: Input the initial land-use distribution

Step 25: until the distribution stabilizes

| Multiply the initial distribution by the transition matrix
| obtain the distribution after one time step

Step 26: Use the final land-use distribution to detect changes from the initial distribution.

Step 27: Use the trained model for prediction on new images
→ image ← load_new_image()
→ predicted_classes, confidences, bounding_boxes ← predict_classes(trained_model, image)
Step 28: Visualize the predicted classes and bounding boxes on the image
visualize_prediction(image, predicted_classes, bounding_boxes)

Phase VII – PERFORMANCE EVALUATION *from* Step **29** – **31**.

Step 29: Provide classification report.
Step 30: Calculate the best **A**ccuracy, **P**recision, **F**1 – **S**core, and **R**ecall.
Step 31: Faster R-CNN and Muti-Layer Perceptron extract both spatial and temporal characteristics, which led to a considerable improvement in the minute changes in Lands based on classes over year to year.

End

8. Implementations and Results

8.1 Dataset description

The high-resolution images of land use shown in the Land Use Dataset span 10 different classifications. Each image has a ground sampling distance of 10 metres and a size of 64x64 pixels. In this study, geospatial images of 10 distinct classes are presented to classify land use. The Sentinel Dataset is the source of the RGB images included here. This dataset contains ten distinct classes that fulfil the need for a more comprehensive dataset containing land-use characteristics from various locations and provinces. Land-use categories such as farmland, buildings, and road networks were not comparable to the images in the inspection dataset, so physically experimented images were used instead. All these images originated from the Sentinel-2 satellite, as shown in Figure 5.

All these images originated from the Sentinel-2 satellite as shown in Figure 4.

The directories contain the following datasets fields:

1. Annual Crop

2. Forests

3. Herbaceous Vegetation

4. Highway

5. Industrial

6. Pasture

7. Permanent Crop

8. Residential

9.River

10. Sea & Lakes

Fig 5. Datasets field used the study- images by satellites.

In this study, the dataset and manually sampled digital orthophotos were used to look at a wide range of land-use characteristics and how they were grouped. The images were made with a 15-cm resolution and 650 pixels on each side. The photos in the dataset are 64*64 pixels in size and have a 10-centimeter resolution. The resulting photographs cover essentially the same area from both perspectives. Image characteristics representing different land-use types (including farms, cities, and highway systems) were manually classified to create the sample set used for the manual categorization. Classification and analysis were performed using the ten land-use categories. A total of 2520 and 1080 images were used for each land-use class's model, using a random proportion of 70% (280 photos) to 30% (120 images) for training and testing.

8.2 Location of Research and Primary Data

Nagpur city has been analyzed for studying Land use land cover change as it is the geographic center of India; the region under study is in the city's northeastern sector (Figure 5). Nagpur was selected as the ideal region to detect LU change by DL approaches because of its rapid development of residential areas and its experience of transformation from a rural agricultural community to a prosperous city. The LU classification was applied to data in form of orthophotos drawn from the city database of Maharashtra. As the classification of each orthophoto required an average of 4 hours, the authors only processed the best of a lot of images. A few images of the LULC transformation are depicted in Figure 6.

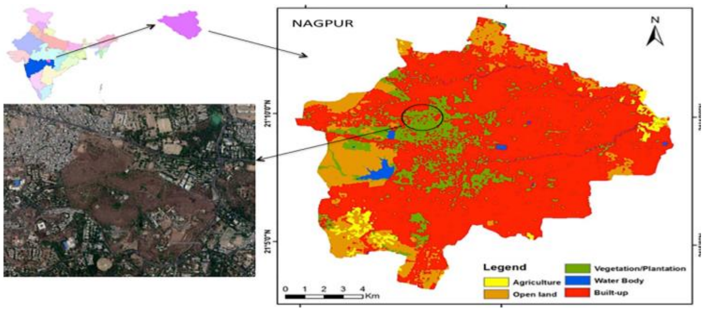


Fig 6. Location Research of Nagpur land use and change.

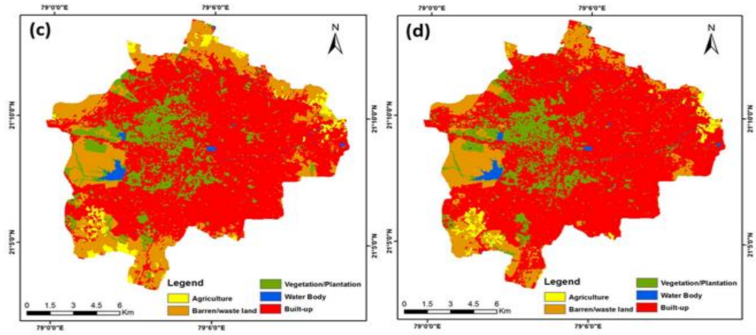


Fig 7. LULC Scenario of 2010 to 2016 (Sakhre et al. 2020).

8.3 Growth Rate Prediction of 2010 to 2016

8.3.1 Highway Growth Rate:

The Highway representation transformation from the year 2010 to 2016 is shown in Figure 8.

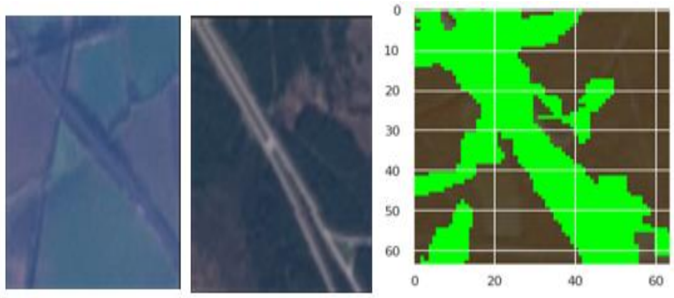


Fig 8. Represents the highway transformation from 2010 to 2016 and the graph of Growth Rate.

8.3.2 Industrial Growth Rate:

The Industrial Growth Rate transformation from the year 2010 to 2016 is shown in Figure 9.

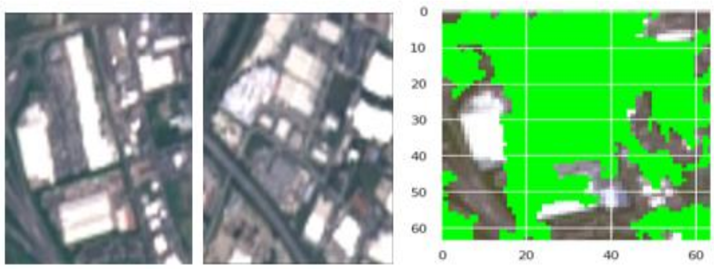


Fig 9. Represents the Industrial transformation from 2010 to 2016 and the graph of Growth Rate.

8.3.3 Pasture Growth Rate:

The Pasture growth Rate transformation from the year 2010 to 2016 is shown in Figure 10.

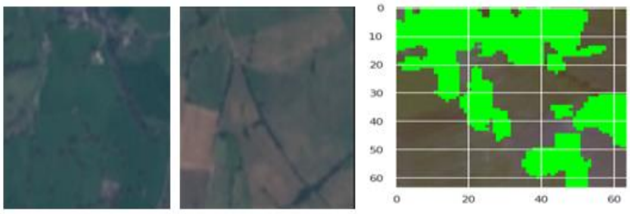


Fig 10. Represents the Pasture transformation from 2010 to 2016 and the graph of Growth Rate.

8.3.4 Permanent Growth Rate:

The Permanent Growth Rate transformation from the year 2010 to 2016 is shown in Figure 11.

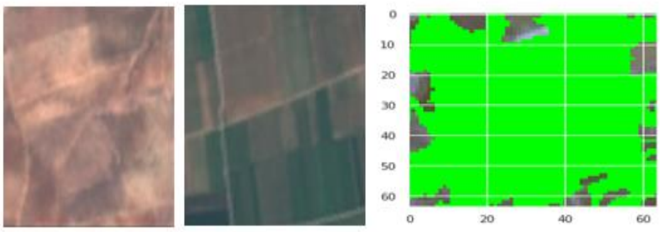


Fig 11. Represents the Permanent transformation from 2010 to 2016 and the graph of Growth Rate.

8.3.5 Residential Growth Rate:

The Residential Growth Rate transformation from the year 2010 to 2016 is shown in Figure 12.

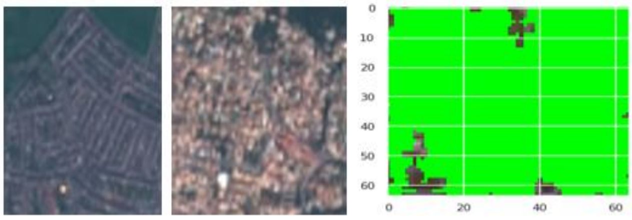


Fig 12. Represents the Permanent transformation from 2010 to 2016 and the graph of Growth Rate.

8.3.6 River Growth Rate:

The River Growth Rate transformation from the year 2010 to 2016 is shown in Figure 13.

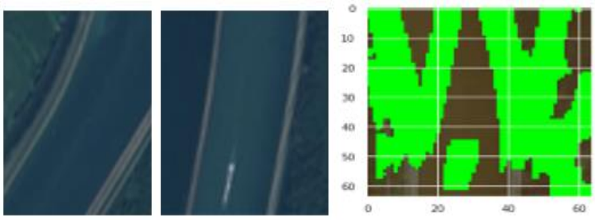
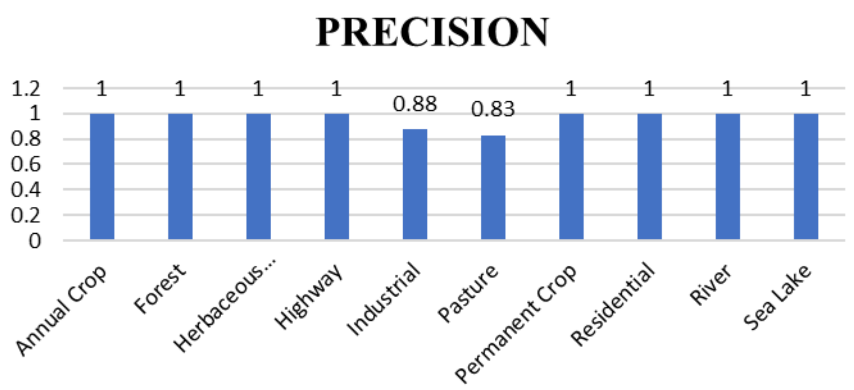


Fig 13. Represents the River transformation from 2010 to 2016 and the graph of the Growth Rate.

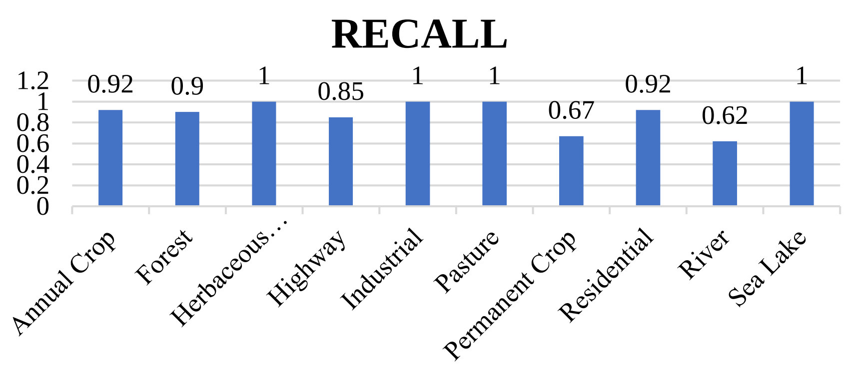
The digital orthophoto of the study area is compared to the map in Table 2 which shows how the land is used. In the final land-use map, the division between various land-use categories was well delineated. Precision, recall, and F1-score analysis were all covered here in figure 14.

Table 2 Analysis Table of Comparison measures.

Classification Report	Precision	Recall	F1-Score
Annual Crop	1.00	0.92	0.96
Forest	1.00	0.90	0.95
Herbaceous Vegetation	1.00	1.00	1.00
Highway	1.00	0.85	0.71
Industrial	0.88	1.00	0.93
Pasture	0.83	1.00	0.91
Permanent Crop	1.00	0.67	0.80
Residential	1.00	0.92	0.96
River	1.00	0.62	0.76
Sea Lake	1.00	1.00	1.00



(a)



(b)

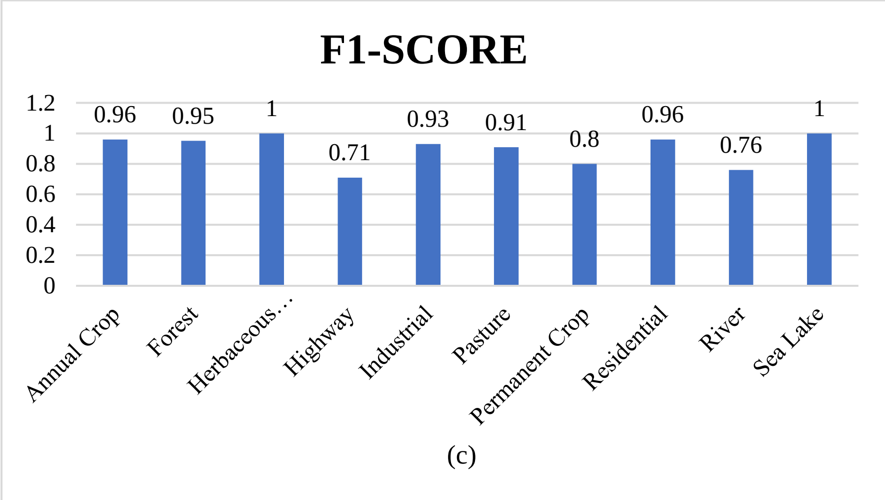


Fig 14. Contains the comparative graph for better understanding of the measures value. (a) Shows Precision graph (b) Shows Recall graph (c) Show F1-Score graph.

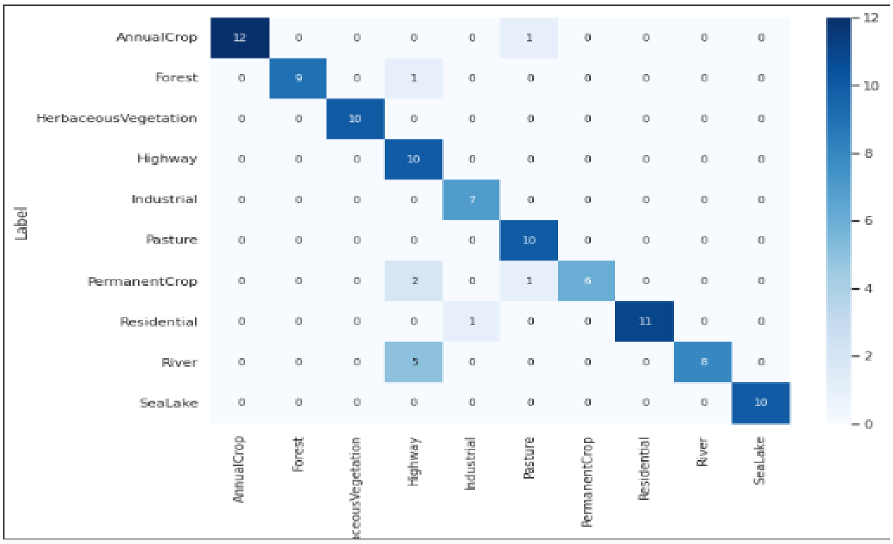


Fig 15. Confusion matrix of studied measures.

The following is a graph of Comparison measures shown in figure 14 above. There was not a massive discrepancy in precision. The time effectiveness of employing the assigned standards, mainly the CNN models, is shown by the confusion matrix for the best-performance metric, shown in Figure 15.

9. Conclusion and Future Scopes

This study shows how machine learning can be used to classify land use and land cover using remote sensing images from various sources, especially radar and hyperspectral datasets. In addition, authors demonstrated a validation process for evaluating the convolutional neural network's efficacy. Statistical examination of cross-validation studies conducted with all approaches across many datasets showed that the projected convolutional neural network outperformed the other models studied, both in terms of overall and per-class accuracy. Classifying and mapping land use from orthophotos of the study region is the primary emphasis of this investigation, which has included the assessment of faster CNN-based models for this specific purpose.

All of the presented models (CNN and Faster R-CNN) were able to correctly classify land use with an accuracy of at least 98.86%, as shown by the findings. In the end, the research proved that machine learning is an extremely strong way out of the issue of LULC classification since it provided favorable results for all the photos investigated, even though they are from diverse sources and have unique properties. In addition, the paper attempted to demonstrate the need for a unified approach for validation, that could be used to rate the merit of fresh suggestions for the remote sensing sector.

A further, in-depth investigation of the setup of the network's architecture and characteristics is required for future efforts along this line of research. Additionally, research into the use of advanced post-processing methods to enhance output quality might be undertaken. Finally, a nobler long-term goal could be to modify the system so that it can process data that has been fused from a variety of sources and sensors.

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Conflicts of interest

The author has disclosed no possible conflicts of interest (s).

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