A LAND USE LAND COVER MAP GENERATION OF SATELLITE IMAGE USING DEEP LEARNING TECHNIQUES.

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Abstract

Land use land cover (LULC) usually alludes to the assortment and cataloging of certain activities carried out by humans together with the natural elements on the land. Sentinel satellite images are meant to obtain optical images at high spatial resolution say of about 10m. In this paper, LULC map generation approach using Sentinel satellite images is proposed. Our objective is to classify the entire sentinel image to generate LULC map, which can be further used for predictive analysis. Here, we have used three predominant bands namely NIR, Red and Green to classify the sentinel data with five classes namely Water, Forest, Vegetation, Urban and Open land of silicon city of India. For the proposed dataset, an inclusive exactness of 95% was achieved with neural networks and various deep convolutional neural network architectures.

***Keywords*: Sentinel images; deep learning Neural Networks; LULC; CNN.**

1. Introduction

Remote sensing is a common technique for gathering data about the Earth's resources and patterns of use. Information is captured without having any physical contact by sensing and recording reflected or emitted energy. This reflected energy is then sent to remote centers and further processed and finally converted to images. The broad division of sensors include passive and Active. Passive Sensors do not have its own source of illumination, they use sunlight to generate energy. Hence they can capture data only during day time. Unlike passive, active sensors have their own source of illumination like microwave, electromagnetic radiation and can be captured at any time. [1]. But Passive sensors are more feasible than active. The following Figure 1 shows how energy is generated by both active and passive sensors.

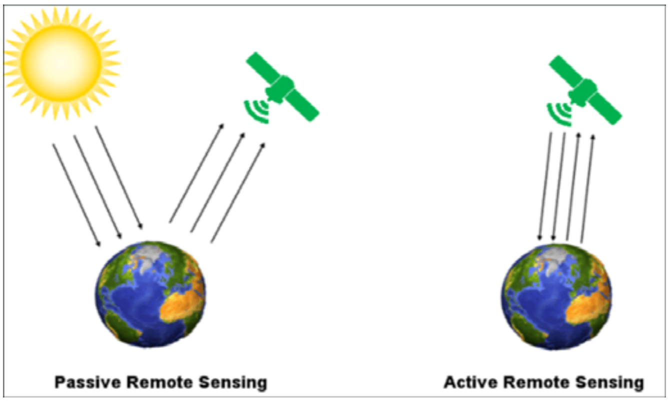

Fig. 1. Passive and Active Sensors [2]

The significant increase in satellite imagery has improved our understanding of the world. Due to recent improvements in computer vision, particularly with deep convolutional neural networks (CNNs), object detection in satellite images is attracting researchers. [1].In the last few years, researchers have become increasingly interested in deep learning. The CNN is an extensive structured training technique built in-order to address the various distinct issues. It circumvents the limitations of traditional machine learning techniques. The purpose of this research is to obtain information and expertise regarding CNN's aspects. [2] Scene classification in satellite imagery has got a lot of attention because it's important in different applications. Deep learning has also exploded in popularity in domains like computer vision and natural language processing [3].

In land change science, though the locutions land use and land cover [15] seem to be the same, their meanings differs. Land use describes 'human actions on and in connection to the land that are generally not visible from a picture,' whereas land cover is the material found physically on the surface of the earth and land use is an illustration of how people are carrying out different activities on the land. The land use and land cover matrix have ambiguous and unambiguous links to variety of geophysical and socioeconomic events.

Land use and Land cover maps (LULC) are the basic tools for decision making and planning. They mainly describe the features of the specific geographic location. Land Use (LU) in terms of human usage (such as farm, airport, road, etc.) and Land Cover (LC) in terms of physical/chemical substance (such as vegetation, bare soil, etc.). At various granularities, both LU and LC classes which are generally established in hierarchical schemes, play an essential role in planning and management of the natural and built environment.

Remotely sensed imagery is a main data source for creating LULC maps, as it may be used for either picture interpretation by a human operator or automated categorization using appropriate classification algorithms. Deep Learning has lately emerged as a very successful framework for automatic picture interpretation in comparisons of algorithms to categorize LULC from satellite imagery on different benchmark datasets. Deep Learning can extract incredibly complicated decision rules from vast volumes of training data. Deep learning is at the forefront of state-of-the-art semantic picture analysis in image processing aided substantially by the convolutional neural network’s unique design.

The goal of the LULC classification is to create uniform landform categorization at diverse scales. This type of categorization is necessary for the construction of standardized maps that aid decision-making and planning. Natural hazards mapping, agricultural production estimation, urban change detection, climate, and biodiversity have all been studied using LULC maps. The development of image categorization systems has been assisted by Earth observation datasets made available by numerous space agencies. The different peer pixeled image categorization or image differentiation tasks have been used for various parametric and non-parametric techniques[26] such as Maximum Likelihood (ML), Support Vector Machines (SVM), Random Forests (RF), and Artificial Neural networks (ANN)[8]. The spatial-spectral classification systems like Object-Based Image Analysis challenge the differentiation procedures which have been exclusively used. The OBIA-based study, on the other hand, has been limited to the few Very High/High Resolution (VHR/HR) image collections.

The classification task includes the usage of Landsat dataset series (Landsat 1-8) among the diverse earth observation datasets. The land cover classes which includes urban, vegetation etc are usually analyzed by the utilization of imager products which have a coarser spatial resolution. In order to analyze the intra urban characteristics by using Landsat and Sentinel products, improved classification algorithm have been used. [4].

An initial task in every classification study of LULC maps is to choose a classification system. To satisfy the user's needs as well as to improve the reproducibility at various scales, the classification algorithms are designed based on it. In-order to classify large images for monitoring land as well as for its analysis, various organizations [6] like UNESCO - United Nations Educational, Scientific, and Cultural Organization, FAQ - the Food and Agricultural Organization, FGDC - the Federal Geographic Data Committee, CEC - the Commission of the European Communities are used.

These systems use a variety of EO datasets to assess the differentiation for vegetation and broad land cover. Anderson [1] demonstrated a hierarchical LULC categorization system that may be created utilising various EO datasets as well as land use maps obtained through ground surveys at multiple levels of evaluation. Similar classification techniques have been used in urban development [6] and administration. The main groups in classification [6] such as residential, commercial, recreational, transportation, and industrial can further be classified into subgroups based on the layout of established structures, density and function.

Still, such categorization methods cannot be generalised because the governing body of the place in question controls the underlying definitions and rulesets for creating such classifications. The absence of exact class boundaries and definitions in the greater part of classification systems have enforced researchers to focus on the individual -requirement based classes to discover intra-urban features [16].

Multiple EO datasets were utilised to produce land use maps, and pattern recognition was used to find spatial patterns. Morphological features were employed to designate impervious surfaces building types, and pattern recognition was used to discover spatial patterns. The examination of the spatial form and its purpose serve an important theme of investigation in urban planning [15], configuration and finally its development. Due to the inadequate presence of uniformity or evenly approach and categorization systems, the classification maps prepared previously depended on uneven and had limited observations.

Image-based classification maps can be built using the WUDAPT - World Urban Database and Access Portal Tools [6]. This approach makes use of the plug-in related to GIS provided by the source, in-order to execute the various categorization algorithms. In-order to develop training examples for the chosen city, it is important to enlist the help of local experts. For picture classification, the open source SAGA GIS software employs Landsat data and an RF classifier. Various investigations or examinations in research have revealed the existence of samples which have been trained and those samples have then been transferred to conurbations, together with the utilization of data which is relevant to ASTER amidst LandSat and Sentinel-1 SAR data with multispectral Landsat data [1], as well as the detailed procedure for the construction of LULC maps [7].

Pixel-based classification algorithms are used in traditional image classification problems, which ignore the spatial information of surrounding pixels. In order to address the issue of intraclass spectral variations, contextual classification techniques use surrounding pixels. However, for image classification tasks, the bulk of regularly used classification approaches still rely solely on spectral characteristics. While contextual classification approaches have revealed splendid improvements in accuracy in hyper spectral datasets, few investigations have duplicated the approaches in EO datasets which includes Landsat and Sentinel.

ConvNet has made great progress in quality recognition and image categorization applications in recent years. CNN models can be used to learn how the satellite dataset's spatial and spectral variations are represented. The image and video analysis are the actual fields where maximum percentage of ConvNet models application cases lies on. In the field of remote sensing, certain studies have adapted and applied this principle. The investigations have largely focused on VHR/MR imaging types, similar to OBIA. With Medium Resolution satellite imagery, LULC classification using CNN has not been attempted. The exception is hyper-spectral image, in which CNN models outperform standard image classification approaches.

2. Dataset Acquisition

The city of Bangalore has been chosen to demonstrate the proposed methodology's findings. For this research, we used the sentinel level 2 dataset from March 2019. There are 13 spectral bands in the Sentinel dataset, each with a different spatial resolution (10, 20 and 60m). Panchromatic bands, which are typically utilised to improve the spatial resolution of bands with coarser resolution, are not included in the collection. Three fine (10m) resolution bands are used (8, 4, 3). 16-bit data format is used to encode the Sentinel picture dataset and data normalization can be achieved by splitting up each Digital Number (DN) [26] of the pixel by the dataset's maximum DNvalue.

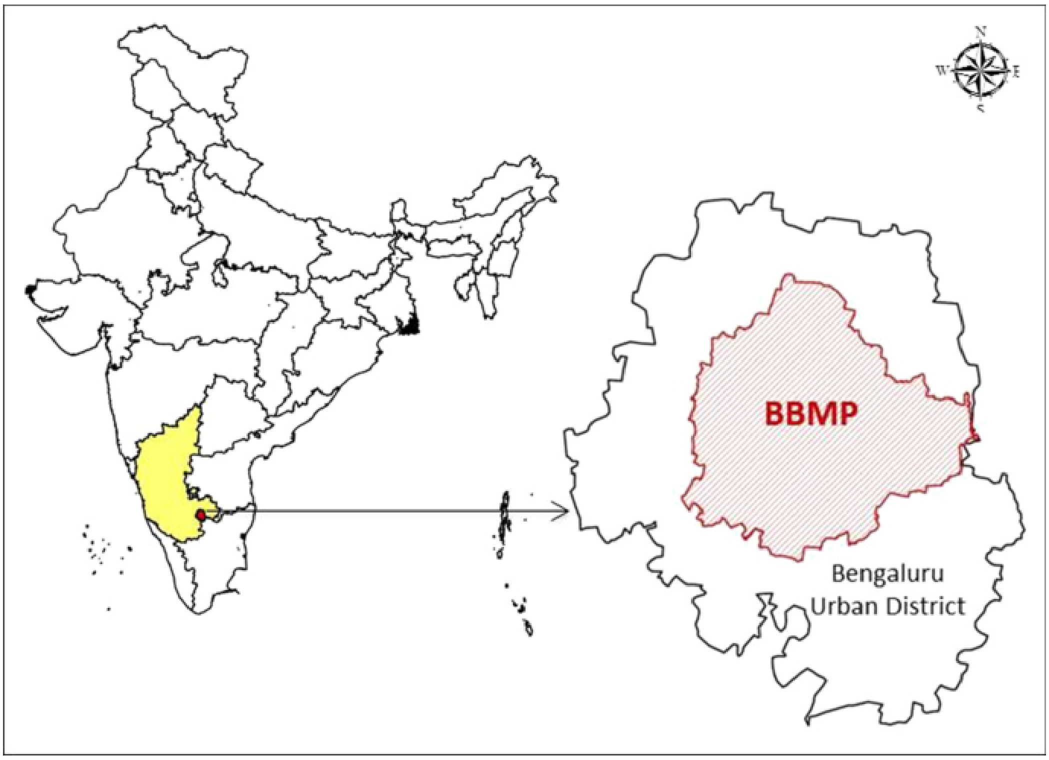

Fig. 2. Study area Bangalore with latitude and longitude of 12.9716° N, 77.5946° E respectively [28].

Bangalore is one of the metropolitan cities in India. It is popularly known as Garden and Silicon city. In a developing country like India, urbanisation is more difficult and unpleasant. Bangalore city is characterised by high population density, more traffic jams, high levels of pollution, unaffordable housing, forming slums, urban crimes, high cost of livings, and environmental degradation, and sanitation and water shortages as a result of rapid and uncontrolled development.

The district has an overall dimension of 2196 square kilometers and its population counts to 4381 persons. It is the smallest district in Karnataka in terms of territory but the largest in terms of population, and it has already reached its carrying capacity limit and is no longer viable. Continued Increased migration to metropolitan areas is exacerbating the problem. To present this problem and to create awareness about the conservation of natural resources, this is the first step taken and further analysis will be carried out on the same.

3. Methodology

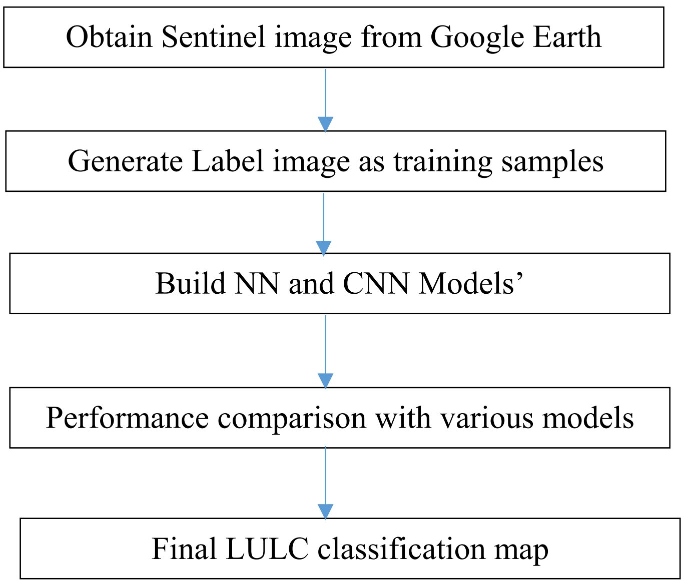

Fig. 3. Workflow of the proposed methodology.

At a spatial resolution of 10 meters, the proposed work presents a ConvNet-based classifier or extractor for urban area and natural regions classification. It creates training and testing datasets using 10-band Sentinel 2 level satellite images. We also compared the classification results with a variety of deep learning models and provided a method for creating a land use/land cover classification map.

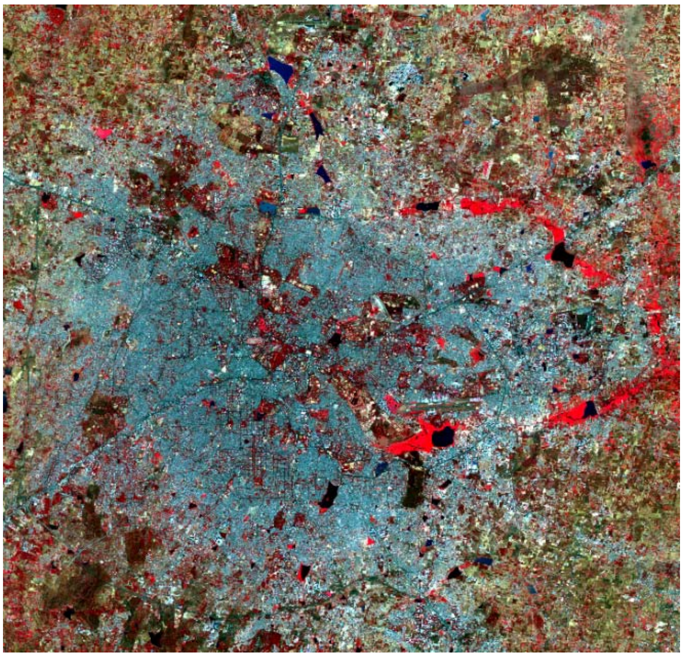

Fig. 4. Sentinel image of Bangalore BBMP limits obtained in 2019 [29].

We have used three Sentinel 2 bands namely 8, 4, 3 as features to predict Multi types such as forest, aquatic bodies, openland, urban, and vegetative land. For training and testing, multispectral Sentinel 2 data recorded in 2019 captured for the month of March of the Bangalore region and its related multi class's layer will be used. Finally, new projections will be made using muwltispectral Sentinel 2 data gathered in 2019 (April Month) of the same region. This is a supervised DL strategy because we are using tagged data to train the model.

We built a Neural Network using Google's Tensorflow library in Python (NN). Make that the raster and labelled multi class layer files have the same amount of rows and columns. We then divided the data into training and validation groups. This is done to ensure that the model has not been exposed to the test data and that it performs equally well with new data. Otherwise, the model will get overfit and will only function well on training data. The split ratio is 0.8. (80 percent of training and remaining 20 percent for test data). The vast majority of deep learning algorithms require standardised data. This implies that the histogram has been stretched and scaled to fit a specific range (here, 0 to 1). To meet this criterion, we'll standardise our features. The brief explanation of the proposed methodologies is as follows:

3.1. ***Neural Networks***

A data processing system comprising of a number of easy, highly associated components which are processed and arranged in a structure motivated by the cerebral cortex is known as neural network. As a result, neural networks are often capable of performing tasks which mammals excel at but the conventional computers might have scuffled with it. Neural networks have risen to popularity in recent years as a viable area for research, development, and application to a variety of real-world problems. In fact, it has become the tough approach having great traits and capabilities compared to others. [8]

MLP, which has multiple hidden layers and functions in a close bondage exists between the input, hidden, and output layers which forms the foundation for neural networks. Once the loss function has been defined, gradient descent renovates the parameters, and by multiplying or adding the function to obtain the step up parameters, the categorization needs of users may be exactly achieved by employing the correlated model of this optimal parameter. A single neuron in a complete Neural Network has architecture comparable to that of a logistic regression. [8]. Consider z to be an output of a neuron, and that z is merged with bias b and results of coefficient w with x as an input, and that δ(z) is the output of a sigmoid activation function translated by Bayes, which is formulated as shown in (1) and (2). [9]

$$z=\sum_i^n w_i x_i + b \qquad (1)$$

$$\delta(z) = \frac{1}{1+e^{-[(\sum_i^n w_i x_i)+b]}} \quad (2)$$

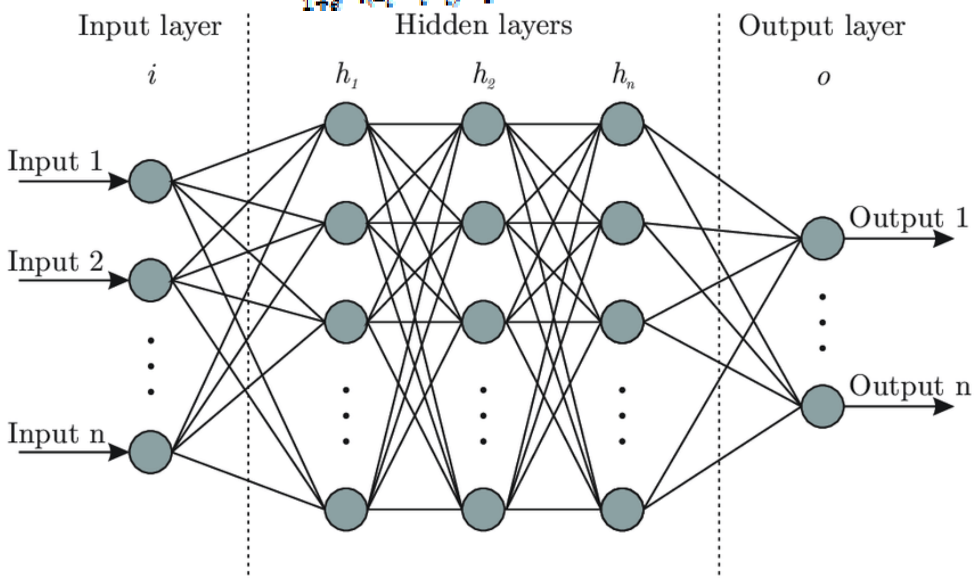

Fig. 5. Diagrammatic representation of Neural Network Architecture [10]

3.2. *Deep Convolutional neural networks*

Neural network is capable of acquiring knowledge to recognize patterns and representations so that classification of satellite images becomes easier. In neural networks, neurons are grouped into three tiers. Input layer nodes save the data features. Hidden layer is interlinked with the output layer, and each node is linked to it. The hidden and output layers are activated by the activation functions which are present. The function activated institutes inconsistency into the model by capturing subset of layer's nodes.

Weight is relevant to every node-to-node link. The loss in each iteration or stage can be examined using a loss function, and it is possible to modify the weights of each connection using the back-propagation method. The execution of the model takes place until the loss stabilises at a certain point. The outcomes of a new dataset can be predicted by a trained model. CNNs are a type of neural network that goes beyond what standard neural networks can do. The neurons in the CNN model are organised or arranged using X x Y x Z arrays, where X, Y, and Z are the length, breadth, and depth, respectively. The CNN model uses the bands 8, 4, and 3 with a depth of 3 as inputs.

In a Convolutional Neural Network (ConvNet/CNN) an image is considered as an input and various facets/objects in the image are focused, which can then be distinguished. Quantity of pre-processing needed by ConvNet is lesser when compared to various other differential algorithms. The basic techniques just need hand-engineering of filters, whereas with sufficient training ConvNets can explore the filters or characteristics.

Visual Cortex's organization has motivated a ConvNet's architectonics and this in-turn is found to be indistinguishable with that of pattern of Neurons interconnected in the Human Brain. Receptive Field is a tiny portion of the visual field and here only individual or single neurons can respond to the stimuli. Various differentiative fields can be stacked one upon another in-order to span the whole visual field. A neural network comprises of the convolution layer, unambiguity, pooling and sub sampling layer.

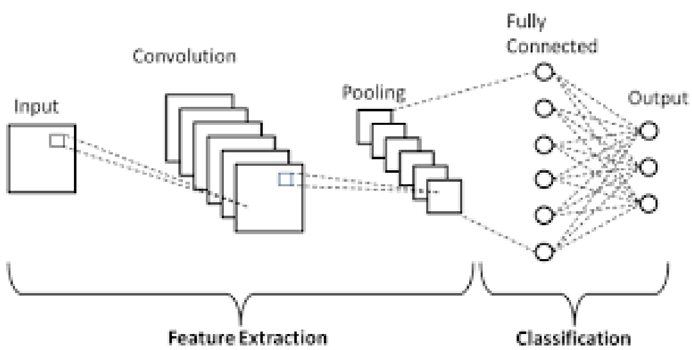

Fig. 6. General Structure of CNN [11].

Convolution layer: This is the first layer which extracts various features from the input image. For a given size of an input and a filter say MXM[4], the first layer carries out the convolution mathematical process. The information about the corners of the image and edges are depicted as the output of the feature map [3]. From an input image, various other attributes can be explored by passing the feature map onto the remaining layers.

Pooling Layer: Computational expenses can be reduced by lowering the size of the convolved feature. This is the major aim of the pooling layer. This can be achieved by minimizing the connections between layers and operating independently on each feature map. Different pooling methodologies exists which depends on the technique deployed. In Max Pooling, the largest element is derived from the feature map. In a predefined sized image segment, the mean or median of the elements can be calculated by using the concept of average pooling. Sum Pooling can be used in-order to determine the summation of components in the predefined section. The Convolutional and FC Layers can be linked by using the pooling layers.

Fully Connected Layer: The two layers here which includes weights and biases together with neurons are interconnected together by the fully connected layer. The output layer is frequently placed before the last few layers of a CNN Architecture. The FC layer receives the input images from the previous layers in this stage. The mathematical functional operations are generally carried out in the FC layer and this in-turn causes the flattened vector to be passed to it. The assortation process begins at this phase or stage [5].

Dropout: When all the picture characteristics are combined or integrated together into the FC layer, the training dataset is inclined to overfineness or overfitting. Whenever the model poses an excellent performance on the data which has been trained, but has a negative impact on the performance of the model when new data has been applied, then this scenario is known as overfitting. Dropout layer which is utilized to eliminate neurons from the neural network during the training phase is used to resolve this case. This in-turn results in a smaller model. For instance, a dropout of 0.3 constitutes to drop out of 30% of the nodes in the neural network.

Activation Functions: The most salient outlook in the ConvNet model is the activation function. Different types of uninterrupted and complex network variable-to-variable relationship can be explored and estimated with the use of these activation functions. The information to be launched in the progressive direction and which shouldn't be launched at the end of the network, are decided by this model. Randomness to the network model is added by this function. ReLU, Softmax, tanH and Sigmoid are some of the commonly used functions of activation. Each of these functions is useful in its own way. As it's a multiclass classification, softmax function is considered in the classification phase. CNN and the below mentioned models are implemented using pytorch as it's faster.

Considering the fact that Sentinel image's dimension is too huge (4126 X 4208) of three channels and thus requires enough memory and larger time for the computation, on an average of 30 epochs and learning rate of 0.001 and batch size of 128 were used to train the model. Pre-trained model is utilized to save the computation time. For rest of the CNN architectures, hyper parameters are bit modified and are specified in the later section.

CNN Models used in this work includes MobilenetV2, EfficientnetB0 and Resnet18.

3.3. *MobilenetV2*

MobileNetV2 is an augmented chronicle of MobileNet which extends the correctness considerably. There are 19 original basic blocks known as congestion residual blocks which form the MobileNetV2 network architecture as shown in the figure. A one-to-one convolution layer exists with an average pooling layer following these layers. The final layer of this model belongs to the categorization level. The MobileNetV2 [25] network was customised for our purposes. Size of the filter together with padding and changing the pace makes the network reliable or suitable for small images. In our research, the classification layer has been changed to permit the network to classify a greater number of classes (here, five).

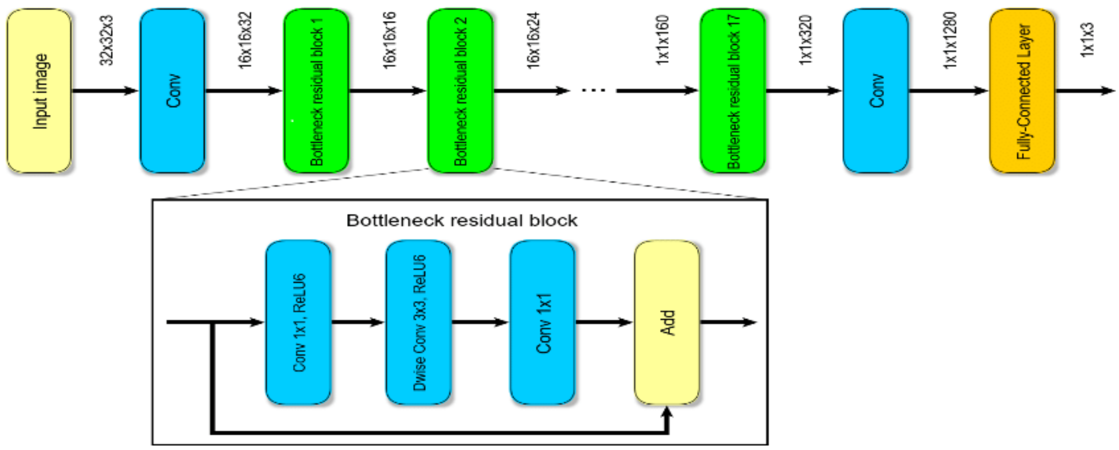

Fig. 7. MobilenetV2 Architecture [18].

3.4. *EfficientnetB0*

The last approach is based on the EfficientNetB0 [20] baseline model, which accepts an input image with a specific sentinel image dimension. The model gathers features throughout the layers by using multiple convolutional (Conv)[27] layers with a 3x3 receptive field and the mobile inverted bottleneck Conv (MBConv)[27]. Because of its balanced depth, width, and resolution, the EfficientNetB0 was chosen to create a scalable, accurate, and easy-to-deploy model. Unlike previous DCNNs, EfficientNetB0[17] scales each dimension using a specified set of scaling coefficients. This technique outperforms other state-of-the-art models trained on the standard ImageNet dataset.

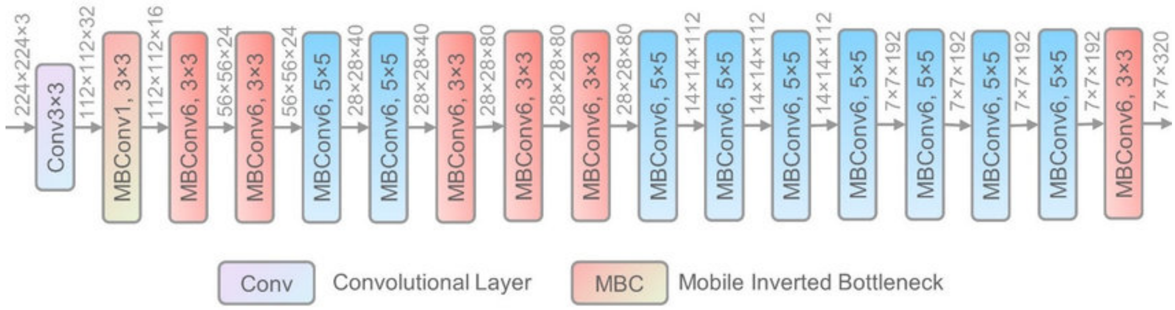

Fig. 8. EfficientnetB0 Architecture [14].

3.5. *Resnet*

The vanishing / expanding gradients problem affects traditional deep networks with several hidden layers. In the ILSVRC 2015 challenge, Kaiming He introduced the Residual Network (or ResNet) to solve the gradient loss problem. The winning ResNetis variant had 152 layers, whereas other variants had 34, 50, and 101 layers. Residual blocks allow the network to keep track of what it has already learned [24]. Resnet18 includes five convolutional layers, average pooling layer, full connected layer and a classification layer with softmax [12] at the end. To overcome exploding and vanishing gradient, skip connection layer is added.

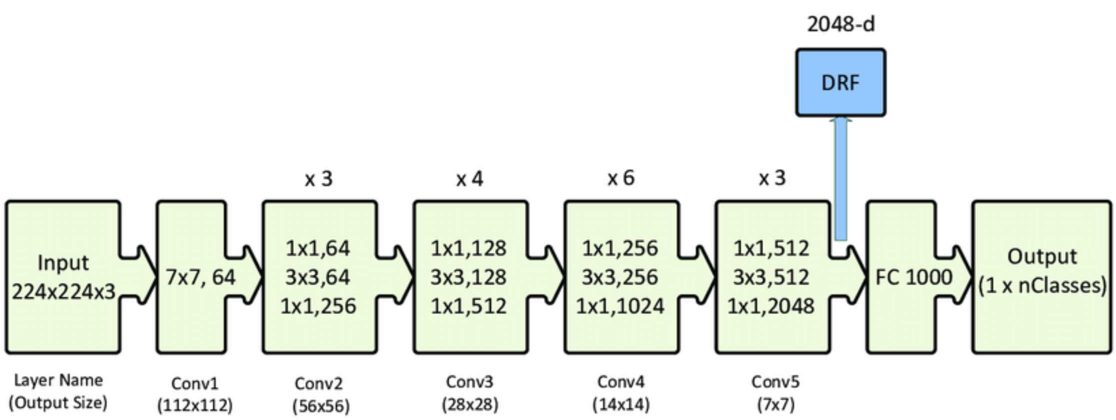

Fig. 9. Resnet Architecture [12].

4. Results and Discussion

The Retrieved data sets have already been geo-referenced obtained from the Google Earth engine. Both data sets were taught through visual interpretation after registration. To create label files, the determined classes were digitised by sketching polygons. Deep learning models were used to perform supervised classification based on the label file in order to generate the LULC maps [6].

Using the dataset presented in Section III, we trained the Neural Networks, CNN (base CNN, resnet [13], mobilenetv2, and efficientnetb0) from scratch. The training set and testing set can be divided as a ratio of 80:20. Initially, examined rate of 0.05, a [24] momentum of 0.9, and a weight decay of 0.001, the adam and SGD - stochastic gradient descent optimization technique were utilized for to train the network. The training was done with a batch size of 128 on an NVIDIA GeForce RTX 3090 128 GB GPU. During the training, we have limited the starting examined rate by a characteristic of ten every ten epochs. As the dataset is huge, small epochs are considered and to reduce the training time.

The below mentioned evaluation metrics on test data used in table 1.1 through table 1.5 are calculated using the following equations (1)-(4) [21]

$$\textbf{F1 Score} = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{1}$$

$$\textbf{Precision} = \frac{TP_m}{TP_m + FP_m} \tag{2}$$

$$\textbf{Recall} = \frac{TP_m}{TP_m + FN_m} \tag{3}$$

$$\textbf{Accuracy} = \frac{TP_m + TN_m}{TP_m + TN_m + FP_m + FN_m} \tag{4}$$

TP and TN [23] indicate correct classification, FP and FN represent misclassification when compared with actual class and model predicted class. Where m is considered to be total number of classes or labels for the classification, here m=5 (water, urban, forest, vegetation and openland).

The estimation of the information extracted or retrieved from the algorithms can be made using the metrics precision and recall. The metrics which are found to be derived such as F-score and precision–recall [21] curves can make use of these base metrics. Predictive analysis can be used for obtaining positive results [19]. The maximum number of objects which can be predicted can be calculated using the recall metric. Finally using these metrics that is precision and recall, we have calculated F1-score [19] metric. [21] Accuracy is the sum of measure of correct classifications to the total number of measures including correct and misclassifications.

Tables 1.1 till 1.5 provide the accuracy and other metrics assessment findings for the data set using the various neural networks such as DNN, CNN as follows.

	Precision	**Recall**	**f1-score**	**Support**
Water	1.00	0.99	1.00	86818
Urban	0.96	1.00	0.98	1315219
Forest	1.00	0.99	1.00	1166392
Vegetation	1.00	0.99	0.99	2204782
Openland	0.99	0.98	0.99	2171673
accuracy			0.99	6944884
macro avg	0.99	0.99	0.99	6944884
Weighted avg	0.99	0.99	0.99	6944884

Table 1.1 Classification report of deep neural networks.

	Precision	**Recall**	**f1-score**	**Support**
Water	0.90	0.87	0.88	108496
Urban	0.95	0.98	0.96	608984
Forest	0.99	0.98	0.99	492990
Vegetation	0.97	0.98	0.97	1419126
Openland	0.98	0.93	0.96	842846
accuracy			0.97	3472442
macro avg	0.96	0.95	0.95	3472442
Weighted avg	0.97	0.97	0.97	3472442

Table 1.2 Classification report of base CNN model.

	Precision	**Recall**	**f1-score**	**Support**
Water	0.88	0.87	0.88	108490
Urban	0.91	0.94	0.93	608980
Forest	0.92	0.92	0.93	492980
Vegetation	0.90	0.90	0.91	1419116
Openland	0.96	0.93	0.95	842946
accuracy			0.95	3472442
macro avg	0.95	0.95	0.95	3472442
Weighted avg	0.95	0.95	0.95	3472442

Table 1.3 Classification report of Resnet-18 CNN model.

	Precision	**Recall**	**f1-score**	**Support**
Water	0.87	0.87	0.88	108490
Urban	0.91	0.93	0.93	608980
Forest	0.92	0.92	0.93	492980
Vegetation	0.90	0.90	0.91	1419116
Openland	0.94	0.92	0.94	842946
accuracy			0.94	3472442
macro avg	0.94	0.94	0.94	3472442
Weighted avg	0.94	0.94	0.94	3472442

Table 1.4 Classification report of MobilenetV2 CNN model.

	Precision	**Recall**	**f1-score**	**Support**
Water	0.87	0.87	0.88	108490
Urban	0.92	0.92	0.92	608980
Forest	0.91	0.91	0.91	492980
Vegetation	0.92	0.92	0.92	1419116
Openland	0.95	0.93	0.94	842946
accuracy			0.94	3472442
macro avg	0.94	0.94	0.94	3472442
Weighted avg	0.94	0.94	0.94	3472442

Table 1.5 Classification report of EfiicientnetB0 CNN model.

Methods	**Accuracy**
Neural Networks	98.99
Convolutional Neural Networks	97
Resnet	95
MobilenetV2	94
Googlenet	94

Table 2. Overall accuracy of proposed methodologies

As per the results obtained from table 1 and 2, deep neural networks outperformed well and there are less misclassifications compared to Convolutional Neural Networks and its architectures. The following LULC maps are the predicted results of the above models for the Bangalore sentinel image captured during May, 2019. The saved models of Deep NN, CNN, Resnet18, MobilenetV2 and EfficientnetB0 were used to predict the LULC maps of Figure 10-14.

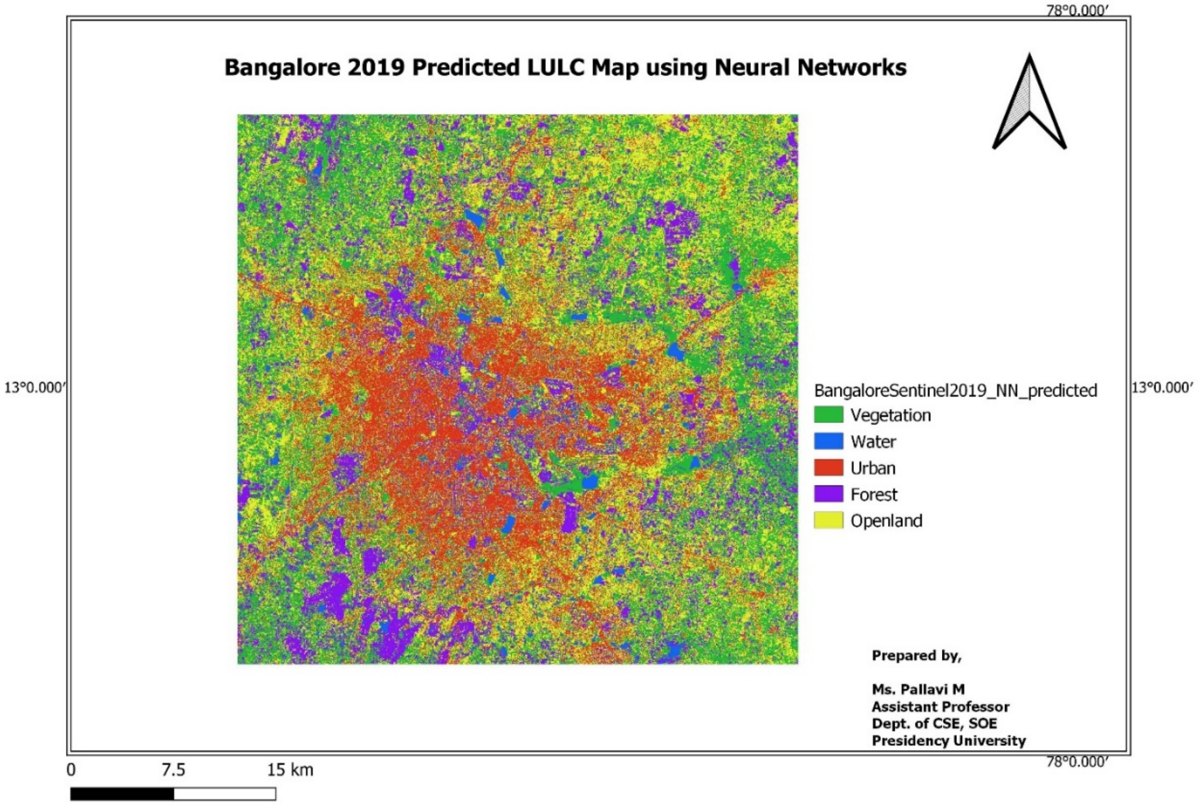

Fig. 10. LULC map predicted with deep neural networks model.

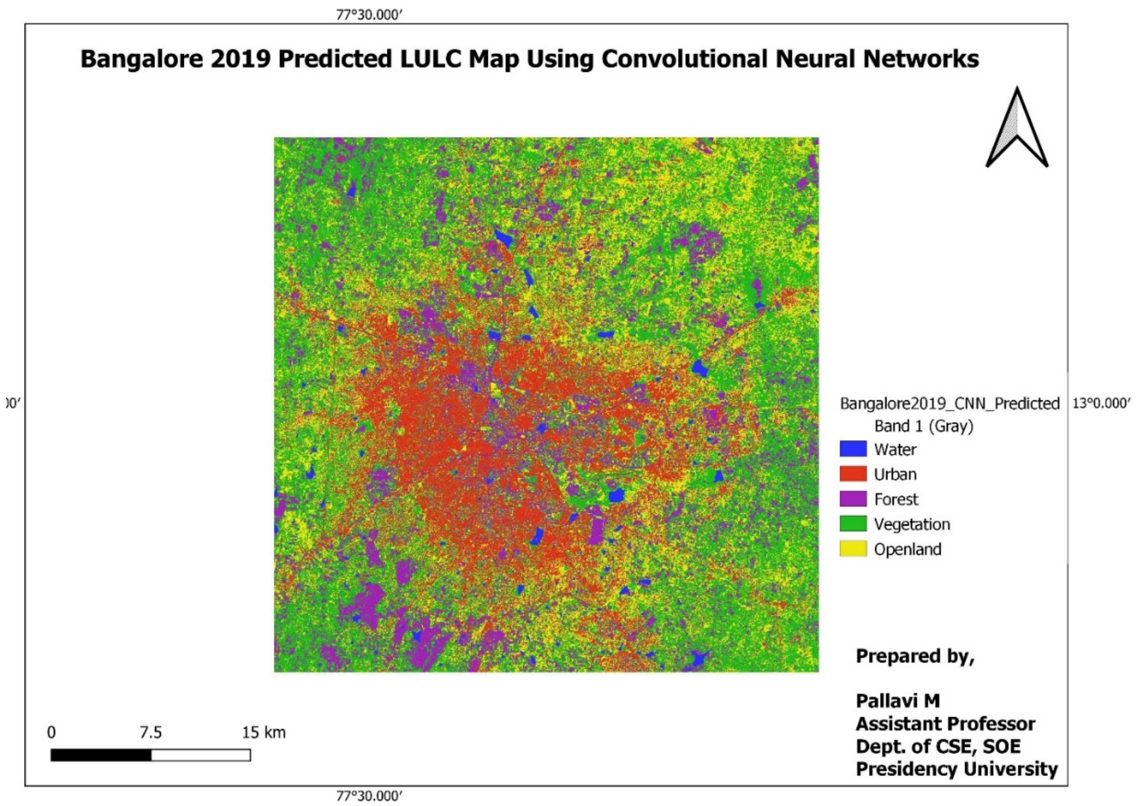

Fig. 11. LULC map predicted with deep convolutional neural networks model.

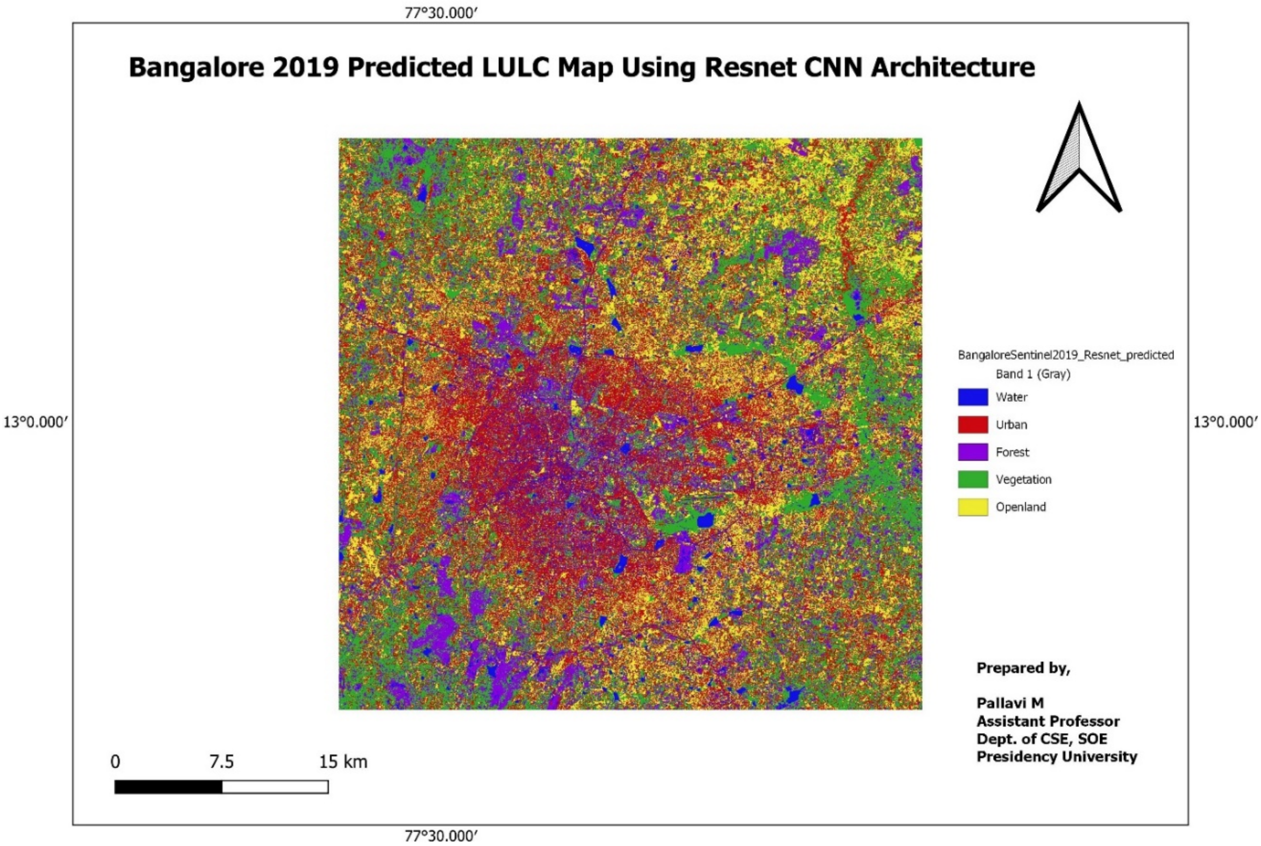

Fig. 12. LULC map predicted with deep convolutional neural networks Resnet18 model.

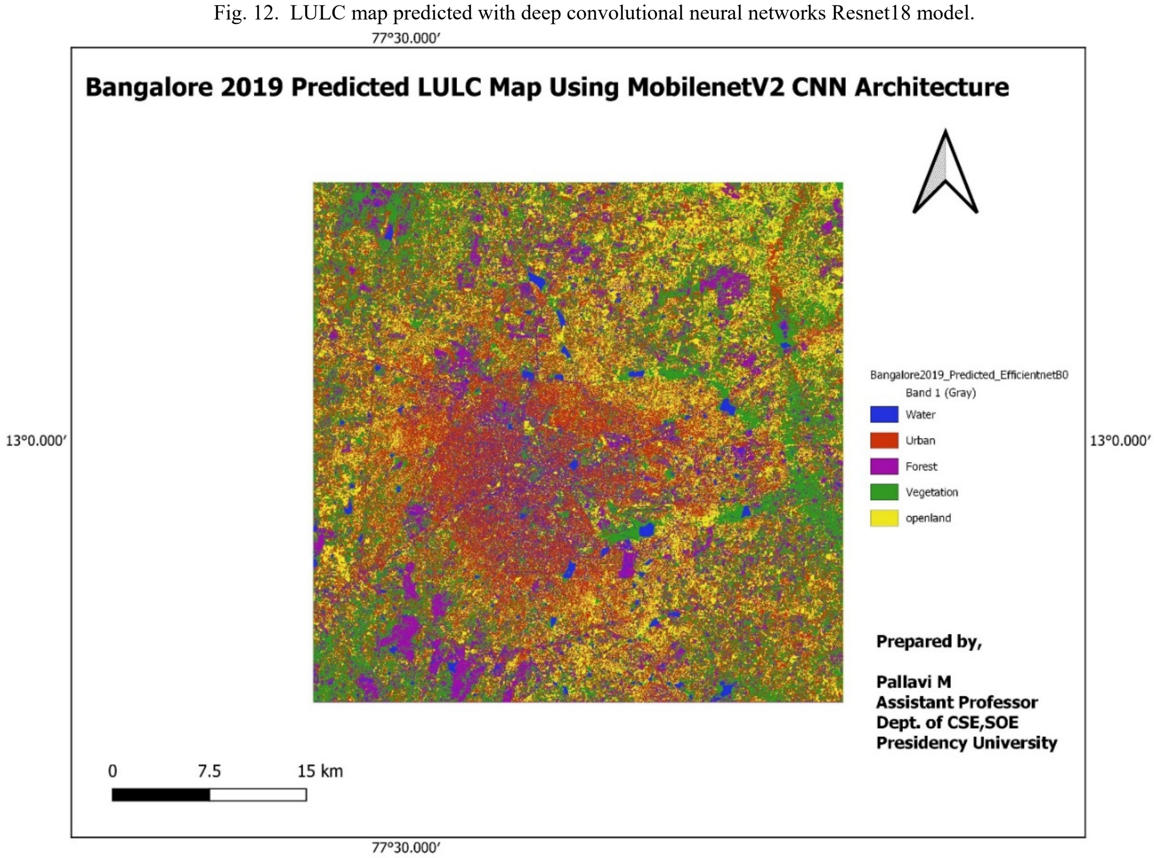

Fig. 13. LULC map predicted with deep convolutional neural networks MobilenetV2 model.

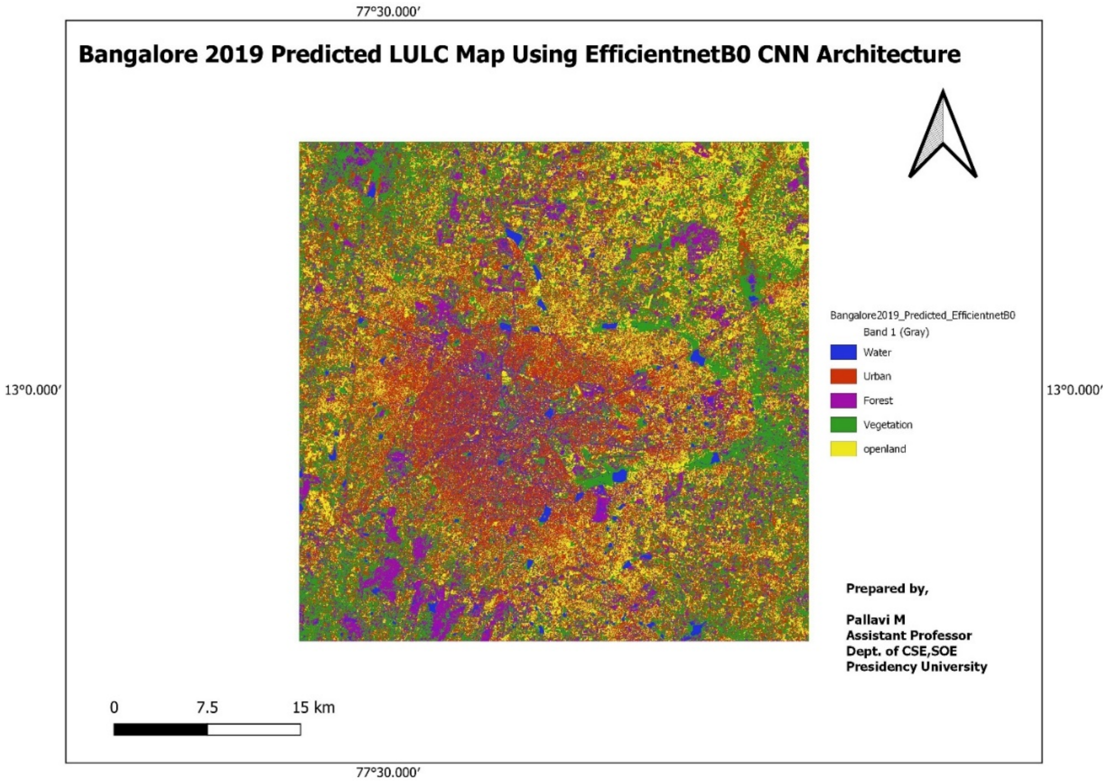

Figure 14. LULC map predicted with deep convolutional neural networks EfficientnetB0 model.

To the Predicted LULC maps, North Arrow, Latitude and Longitude values, Scale bar, labels and legends are added to match with the typical LULC maps using QGIS tool [22]. Deep Neural networks model yielded much less misclassifications among five unbalanced classes and hence gives more clarity in the LULC map also. CNN base model predictions are better compared to other architectures used in this research work. As more convolutional, average pooling layers and other optimization techniques are included, pixel based classification goes deeper and there would be more chances of misclassification. To avoid this, more epochs can be given but that might take days together to generate maps. Also, digitization of polygons can be improved.

5. Applications

During the exploration of regional, local, and global environmental changes, changes in land use/land cover marks a significant factor [2].On land, the human population has grown tremendously in the last 100 years, as has its influence. Land cover changes as a result of human modifications on the planet's surface.These changes have a profound impact on how the Earth system works (including the balance of energy, water, and soil). Furthermore, population growth adds onto the load which contributes towards changes in land surface cover. Forest degradation, agricultural amplification, globalisation, and urbanisation are among the primary causes of regional and worldwide LULC [6] shifts, according to the study. Significant changes in land cover are linked to biophysical features, global climate, and ecosystem activities. The LULC undergoes dynamic and continual changes. Factors like worldwide change [7], environmental monitoring, and the calculation of forest degradation, updated and accurate LULC maps all have a huge impact on the effective planning. Reports on changes in the LULC are essential for the effective use and management of natural resources.

Assessment of LULC has become significant in many aspects of the human and natural environment. Determination of land use and land cover is an important factor in-order to address a number of regional environmental challenges, including unregulated development, agricultural land loss, wetlands degradation, and wildlife habitat devastation. Furthermore, because of their frequently approaching negative influence on the state and integrity of ecosystem functioning, LULC alterations demand additional consideration in land management. LULC is particularly relevant to DRR - disaster risk reduction and changes in climatic adaptation plans, given the increasing demand on land resources as a result of population increase and extension of human settlement. [16].

6. Conclusion and Future Work

Land use and cover might be compared to the earth's top layer, which is constantly changing owing to natural and man-made forces [15]. It is possible to capture the changes with the help of remote sensing satellite sensors with varying spectral, geographical, and temporal resolutions. Land use/land cover (LULC) is crucial for planning and monitoring natural resource utilisation in response to today's ecosystem's progressive development in human demands. This research is primarily concerned with the application of deep learning convolutional neural networks to generate Land Use and Land Cover map of Bangalore BBMP limits of Karnataka, South India. Here the different models of convolutional neural networks are used to generate LULC map and they are evaluated with the appropriate metrics like accuracy, precision and recall. Further, deep neural networks would be fine-tuned and customized, then applied on different bands of sentinel image to generate improved LULC maps.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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