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Quantitative Analysis of Urban Transformation using Remote Sensing Data and Machine Learning Approach

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Abstract:

Urban areas are always changing, which makes it hard for planners and lawmakers to keep an eye on growth and handle it well. Combining remote sensing data with machine learning methods is a new way that this study suggests to look at how cities are changing quantitatively. We get a lot of spatial and spectral information from high-resolution satellite images that help us describe urban areas in more detail than ever before. As part of our method, we preprocess satellite images to pull out useful information like land cover, land use, and the shape of cities. Then, these features are fed into machine learning methods like convolutional neural networks (CNNs) and support vector machines (SVMs) to sort and look at how cities have changed over time. We show that our method works by doing a lot of tests and experiments to make sure it can correctly find and measure urban transformation processes, such as population growth, changes in land use, and infrastructure development. We also look at how this method could be used in different urban planning and management situations, like finding places that are likely to grow quickly, figuring out what effect policy changes will have, and guessing how cities will grow in the future. To look at how cities are changing, satellite pictures are used with both guided and unstructured classification methods. For algorithm research, the software tool Arc GIS Pro is used. As more people move to cities, the Nagpur city area has changed a lot. From 2005 to 2023, development went from 7% to 30%. This method can be used to keep an eye on changes in land use, city growth, and the natural impacts of city growth.

Keywords: Remote Sensing, Urbanization, Machine Learning, Supervised, Unsupervised, Classification.

1. INTRODUCTION

In many remote sensing applications unmanned aerial vehicle is used for data collection and survey. Different satellite tool are used for detecting specific land space and monitoring the characteristics through radiations. Features and segmented data used for Urban/Town planning, Infrastructure Management and Environment Monitoring. Urban city growth is major cause of decreasing agricultural land and deforestation. The author discussed the benefits and drawbacks of several approaches, such as the point-cloud-based change detection method. Applications of current publications and measurement parameters were also reviewed. Future research directions for urban area development and monitoring are suggested [1]. The change in urban growth monitor for the period 1999 and 2003 of Kano, northern Nigeria area. For this period bare land increases, while water body and vegetation area had decreases. Supervised classification approach was used for accuracy assessment [2]). Cross-border cities were impacted by the increase of natural hazards, which were tracked using spatial assessment. This evaluation could be applied to other man-made and natural risks [3]. Prime issues of change detection methods are demonstrated. Also review the preprocessing techniques of change detection and object identification methods for further analysis [4]. Urban indices are observed and connected with Sustainable Development Goals through the use of remote sensing techniques in order to analyse urban environmental change in key cities in Bangladesh. Normalized Urban Area Composite Index was calculated, which draws additional data from relevant pre-established indices such as Normalized Difference Vegetation Index, Normalized Difference Built-up Index, and Normalized Difference Water Index to determine the presence of vegetation, built environment and water respectively. Khulna's SDG index is rising, which is concerning because it is affecting the environment [5].

High resolution data of Uran Taluka, Raigad district area with 0.5m and 0.6 m resolution is studied. The unsupervised classification method is used. Author [6] reported change in area due to urbanization for the period 2006 to 2014. Area covered by vegetation reduced by 6.585% and other greenery also reduced by 4.81% for the mentioned time period. Analysis is carried out and accuracy parameter validated through supervised classification method. Geographic Information System (GIS) were used for analysis of urban changes. Landsat MSS satellite images were taken in 1973, and Landsat and IRS-LIS-III satellite photos were collected in 2010. Over the past 37 years, the settlement area has grown 2.07 times due to industrial expansion. According to the data, urban areas were 69.899 square kilometers in 1973 and 144.97 square kilometers in 2010. The result shows both migration and population growth [7]. For analysis of urbanization collected images of Symbiosis University area of Nagpur, Maharashtra. For different classes like road, ground, garden and building analysis was carried out and total change of 43.51% is reported for the March month of years 2016, 2018 and 2020 [8]. For a particular time period change of area analyzed using change detection methods like supervised classification methods and for analysis accuracy and Kappa Coefficient parameter was considered. Land use and land cover (LULC) class change analyzed for 31 years from 1989- 2020. Maximum agricultural land converted into built-up areas, this analysis was carried out for Pachhua Dun-Dehradun District, Uttarakhand, India [9]. Similarity of geometric structure measured through shape context and Euclidean distance for change analysis. Mixture model of different features were used [10]. Multisensor satellite images are used for analysis of land use change in urban area of Hangzhou city. Principal component analysis (PCA) and supervised classification was used to segment and analyze the built-up land, construction site, and water area from year 2021 to 2003 [11].

Multitemporal unsupervised classification approach was used for urban change detection and further analysis is carried out through vegetation index parameter. Landsat TM-images for three different years of Lebanon area were collected and analysis was done through ERDAS-IMAGINE software [12]. Author reported the analysis of different methods used for land use change detection (LUCD) like model-based, classification-based, deep learning-based and threshold-based. They reviewed 3512 articles collected from Web of Science Core database for period 1985 to 2022. Also focus on combination of machine learning methods and bibliometric analysis [13]. Six LULC types were considered for analysis of change detection. Agricultural land, forest cover and bare land area decreases and increasing the water bodies, plantations and built-up land area. LULC change directly affects the natural environment. For assessment of change detection following parameters considered: Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Land Surface Temperature (LST), Leaf Area Index (LAI), Effective Roughness Length (ERL), and Surface Albedo (SA) [14]. Arc GIS and ENVI software was used for change detection. Preprocessing and classification carried out on images collected from Tana basin area for three years of period (1986, 2002 and 2018). Overall accuracy and kappa coefficient measuring parameters are considered for change analysis [15]. Advances in bitemporal and multitemporal two-dimensional change detection are discussed for multispectral images. Also reviews different change detection methods for SAR. Highlighted the data selection and preprocessing methods for multispectral image processing. Advantages and limitations are reported for improvements [16]. LULC caused the loss of soil fertility, water availability and biodiversity. Forestland and grasslands considerably declined due to urbanization and population growth. A supervised maximum likelihood method employed on image of area south-central Ethiopia [17]. For urban change analysis different approaches and measuring parameters are used [18-20].

The urbanization of Nagpur, Maharashtra's Khapri area, is analyzed in this article. We examine how the Mihan project, the Metro station, and industrial growth have affected this region. Three parameters: vegetation, wasteland, and built-up area are our main concerns. The method of machine learning is applied to parameter analysis. This study aids in balancing Nagpur City's growth with environmental conditions.

2. METHODS AND MATERIAL

For analysis of land change, input images of Khapri area, Nagpur are collected from Maharashtra Remote Sensing Application Centre (MRSAC) Nagpur. Also interpretation satellite data shown in Figure 3(b) collected from MRSAC Nagpur for different feature analysis. Processing of satellite images is done with ArcGIS PRO software. For the purpose of detecting land change, images were gathered in the years 2005, 2010, 2015, 2020, and 2023. The system flow diagram for image categorization is shown in Figure 1. Enhancement techniques are used during preprocessing to improve the quality of the input images. Various land cover areas are divided into segments and subsequently classed for study using both supervised and unsupervised approaches.

A. Raw Input Satellite Data

In satellite images noise or distortions may occur due to topographical variations in the land surface and different angle of the satellite or sensor. To remove these distortion some preprocessing is require for proper image of an area.

Preprocessing: In remote sensing ortho correction process used to remove geometric distortions. It used for correction of visual distortions and position of land objects caused by sensor angle and terrain area. Rectification process coverts raw image into proper orientation to a ground surface and also correct it geometrically as shown in Figure 2. Control points are precisely marked points on the input and reference images used for geometric correction. Then image is converted into rectified image format for further processing [21-22]. The polygon layer removes extraneous sides from the image and selects the Area of Interest (AOI). As seen in Figure 3(a), the images are all in the right shape and share accurate information. Figure 3 (b) illustrates the geographical details which is called reference data.

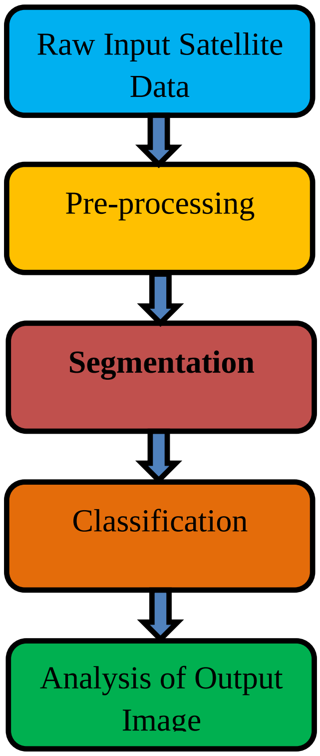


Figure 1: System Flow Diagram for Land Change Detection and Analysis

B. Segmentation

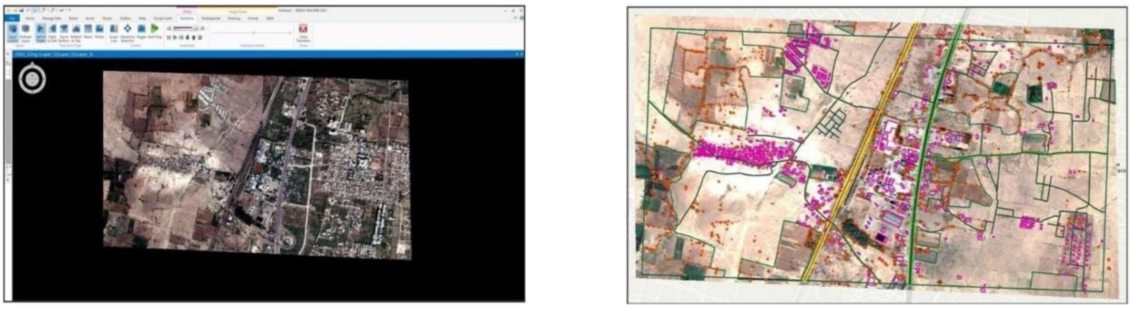
For identification of different objects classes are form using Unsupervised and Supervised classification method [23].

- **Unsupervised Classification:** The method of machine learning aids in the formation of the classes. The user must specify the threshold value, maximum number of iterations, and number of classes in this method. The reference tone of each pixel in the image converts it into a class. The classes focused on particular backgrounds, such as buildings, forests, arid regions, and water. In this work, image is divided into three classes and assign name to each class as Waste land, Vegetation and Built-up.
- **Supervised Classification:** With a few additional steps, the supervised classification method procedure is identical to the unsupervised classification method. The signature file is added during supervised classification. Set the classes in this process based on the pixel's shades. As references, these classes have been added to the signature file. These classes are divided into distinct elements, and the same process like unsupervised method is used to further classify them.

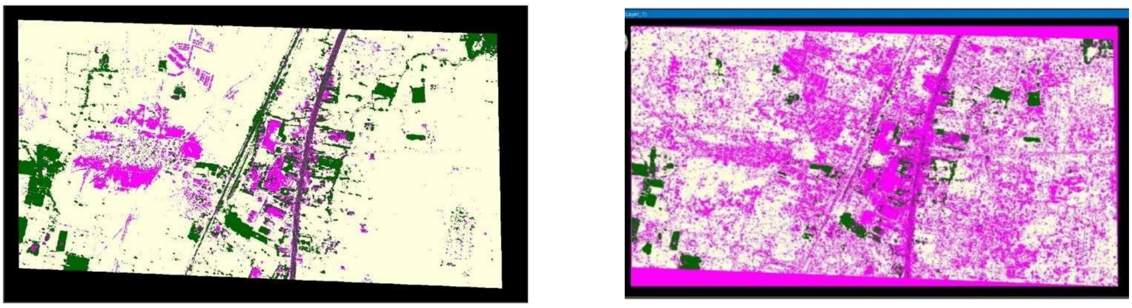
For year 2005 For year 2005

For year 2023 For year 2023

Figure 2. First column: Raw input Satellite Image, Second column: Pre-processed rectified satellite image.



(a) (b)



(c) (d)

Figure 3. a) Selected Area of Interest, b) Interpretation of Satellite Data for Year 2005, c) Unsupervised Classification output for Year 2005, d) Supervised Classification output for Year 2005.

C. Machine Learning Approach

Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) are used in this study to look at how urban areas change over time. CNNs are very good at getting spatial features from high-resolution satellite images, which lets them accurately classify features in cities. SVMs add to this by handling complicated, non-linear connections in the data, which makes the model more reliable. These machine learning methods work well together to make it easy to sort and look at how cities change over time. This study uses the combination of CNNs and SVMs to give a full picture of how cities change over time. This helps urban planners and lawmakers make smart choices for long-term growth.

1. CNN:

Convolutional Neural Networks (CNNs) are a key part of using remote sensing data to study how cities change over time through quantitative analysis. CNNs make it possible to precisely measure how cities change over time by using their ability to extract complex spatial traits from high-resolution satellite images. These networks are very good at picking up on small changes in urban areas, like when infrastructure is built or land cover changes. By using strong training and confirmation methods, CNNs make it possible to create quantified measures for the patterns of urban change, which helps lawmakers and planners make decisions. This method not only helps us understand how cities change over time, but it also supports long-term urban growth plans by giving us data-driven information about how cities are changing right now.

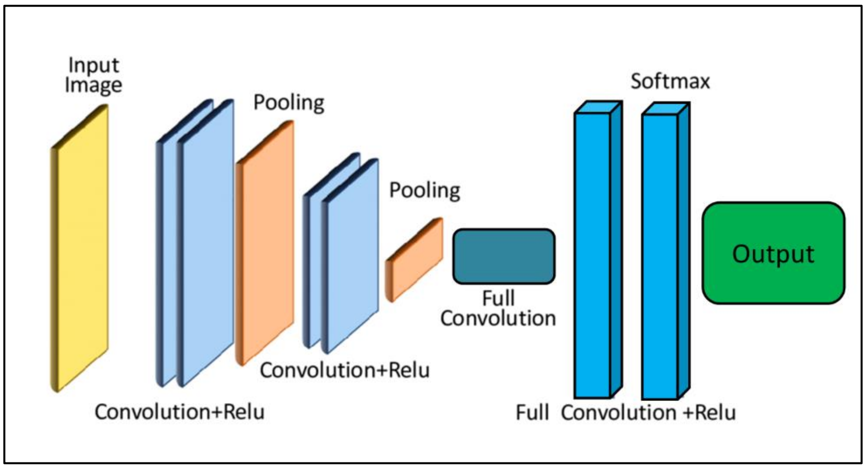


Figure 4: Overview of CNN Architecture

Algorithm:

1. Data Preprocessing:

Normalize satellite images to ensure consistent pixel values:

$$x_{norm} = \frac{(x - \mu)}{\sigma}$$

2. Augment the dataset to enhance model robustness.

- Split data into training, validation, and testing sets for model evaluation.

3. CNN Model Design:

- Design CNN architecture tailored to urban transformation analysis.
- Experiment with different architectures to optimize performance.
- Include convolutional, pooling, and fully connected layers.

$$z[l] = W[l] * a[l-1] + b[l]$$

4. Model Training:

- Initialize model parameters, possibly with pre-trained weights.

Define loss function (e.g., categorical cross-entropy):

$$J = -\left(\frac{1}{m}\right)\sum(1\ to\ m)\sum(1\ to\ C)y_i, c\ *\log(y_i^t, c)$$

- Utilize optimization algorithms like stochastic gradient descent (SGD) or Adam for parameter updating.

5. Model Evaluation and Analysis:

- Evaluate model performance on the validation set using metrics such as accuracy, precision, recall, and F1-score.
- Assess generalization capability on the testing set.
- Visualize model predictions and metrics to gain insights into urban transformation dynamics.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions}$$

2. SVM:

Support Vector Machines (SVMs) are a reliable way to look at how cities are changing using data from satellites. SVMs are great at identifying and measuring changes in cities over time because they can handle complicated, non-linear connections. SVMs use a margin-based method to try to make the gaps between classes as big as possible. This lets them make accurate guesses even when they only have a small amount of training data. SVMs are very useful for learning how urban areas change over time because they are flexible and accurate. They also help people make good decisions for long-term urban development projects.

Algorithm:

1. Data Preprocessing:

Normalize satellite images to ensure consistent pixel values.

Augment the dataset if necessary.

Split data into training, validation, and testing sets.

Normalization:

$$x\_norm = (x - \mu) / \sigma$$

2. SVM Model Training:

- Choose suitable kernel function
- Define the SVM optimization problem with appropriate constraints and objective function.
- Solve the optimization problem to obtain the optimal hyperplane separating different classes.

a. Objective function:

$$\min w\,,b,\xi \frac{1}{2}||w||^2 + C \sum_{\{i=1\}} \{n\}\,\xi\_i$$

b. Constraints:

$$y_{i(w^T\phi(x_i)+\,b)} \geq 1 - \xi_i$$

$$\xi\_i \geq 0$$

c. Kernel function:

$$K(xi,xj) = \phi(xi)\cdot\phi(xj)$$

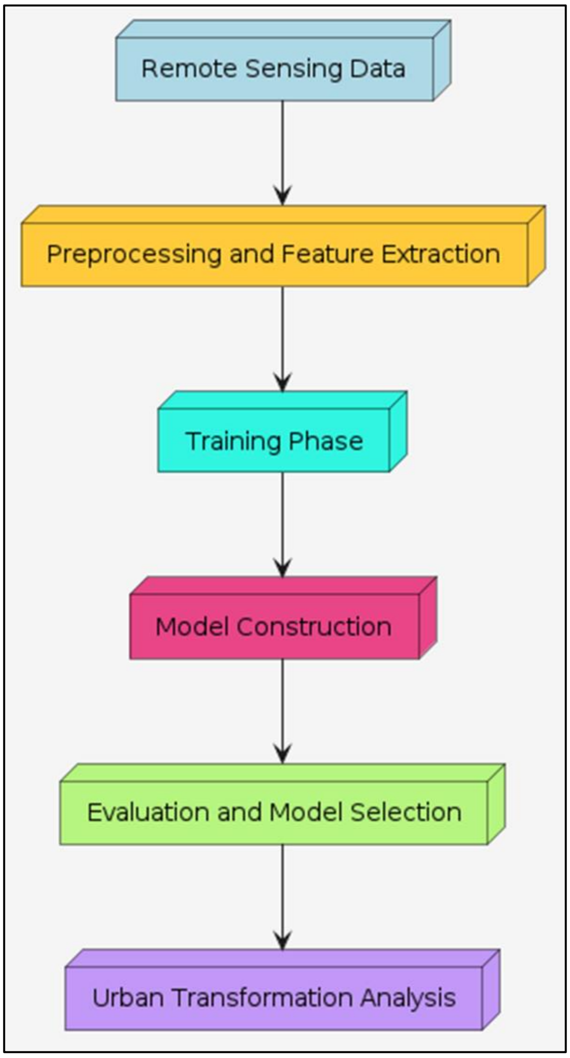


Figure 5: Workflow for SVM

3. Model Evaluation and Analysis:

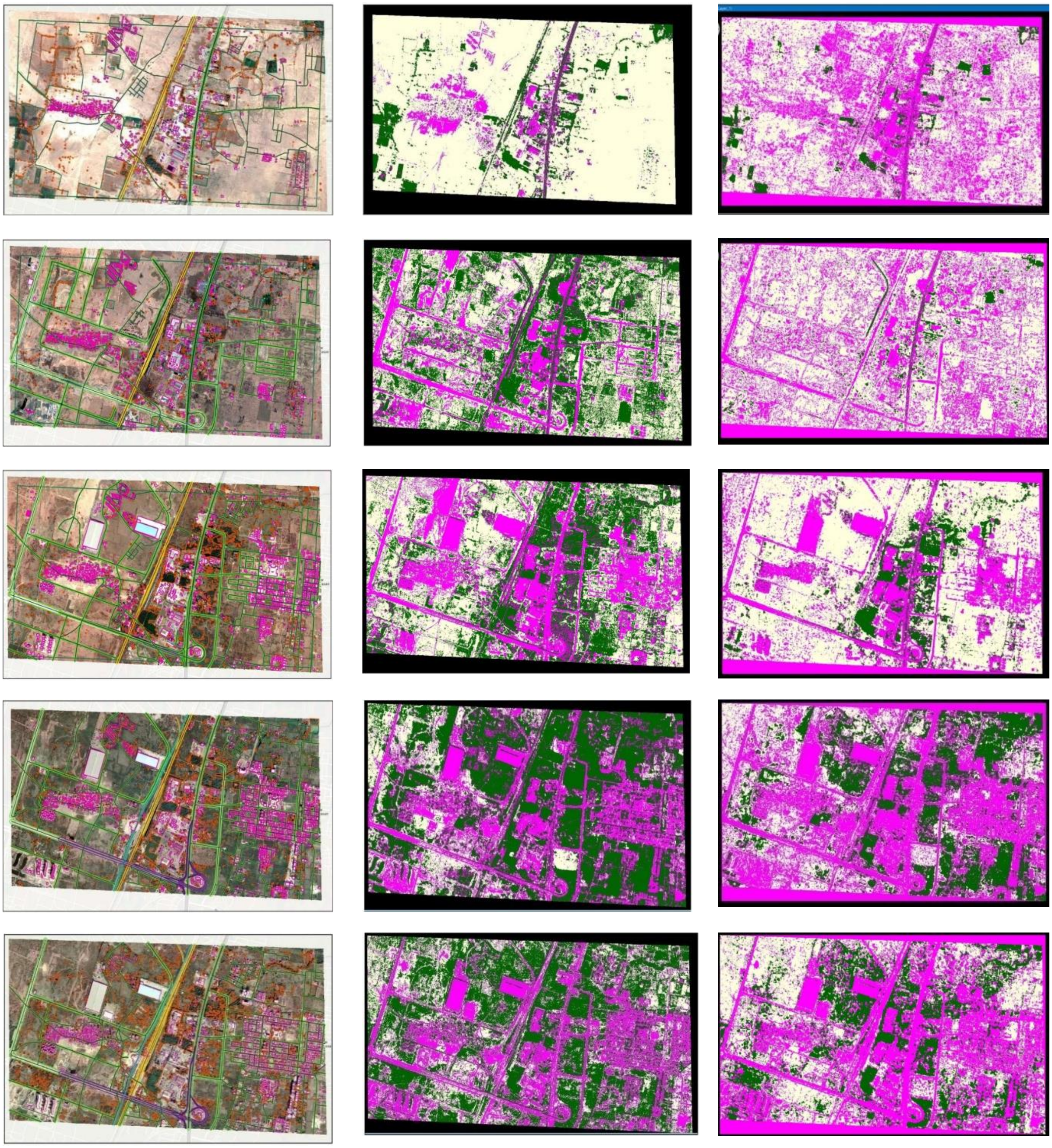
- Evaluate model performance on the validation set using appropriate metrics (e.g., accuracy, precision, recall).
- Tune hyperparameters such as regularization parameter C and kernel parameters based on validation performance.
- Assess model generalization on the testing set.

$$Accuracy = \frac{(Correct\ Predictions)}{(Total\ Predictions)}$$

3. RESULTS AND DISCUSSION

The change detection study conducted in the vicinity of Nagpur city has revealed that the urbanization of the surrounding areas has caused changes in the urban periphery. For visual analysis and comparative study, interpretation of satellite data is referred for years 2005, 2010, 2015, 2020 and 2023. From interpretation satellite data size, shape, texture, location, resolution, shadows and tone, these different features can be analyzed as shown in Figure 6(a). One of the obvious things to consider is shape. It is the object's shape. Roads and metro lines are often represented by straight edge shapes, but fallow fields devoid of crops and densely populated areas are defined by pink hue areas. Texture, on the other hand, describes how frequently tones shift in a particular region of an image. Waste terrain is characterized by recurring tiny patterns, whereas built-up areas have coarse textures. The term "association" refers to the presence of one characteristic in relation to another. Some features are not immediately discernible by appearance in an image, but they can be readily interpreted based on their relationship to their surroundings.

Figure 6(b) and (c) described that day by day the built-up area is increasing as compared to vegetation area due to urbanization. As we are selecting the classes manually in supervised method and in unsupervised method we are defining the number of classes. When comparing both methods outcomes with the interpretation of satellite data, the supervised classification technique performs better than the unsupervised method. Figure 5 shows graphical representation of change in area over the period of 18 years. Table 1 described area in hectares of wasteland, built-up and vegetation for different years as mentioned above. The pie chart in Figure 6 depicts the percentage change in vegetation classes from 13% to 23% in 2023, the change in wasteland from 80% in 2005 to 47% in 2023, and the largest change brought about by urbanization in the Nagpur city area from 7% in 2005 to 30% in 2023.



(a) (b) (c)

Figure 6. Row wise:- Row 1: Year 2005, Row 2:Year 2010, Row 3: Year 2015, Row 4:Year 2020, Row 5: Year 2023; Column wise:- (a) Interpretation of Satellite Data, (b) Unsupervised Classification Result, (c) Supervised Classification Result.

Table 1. Land use status of AOI between Year 2005 to 2023

Year	Classes	Area (in Hectares)
2005	Wasteland	**380.49**
	Build-up	**36.92**
	Vegetation	**59.61**
2010	Wasteland	170.45
	Build-up	160.33

	Vegetation	147.19
2015	Wasteland	236.11
	Build-up	152.94
	Vegetation	88.11
2020	Wasteland	180.34
	Build-up	151.55
	Vegetation	145.2
2023	Wasteland	**225.45**
	Build-up	**140.9**
	Vegetation	**110.86**

The information shows a picture of three types of land cover from 2005 to 2023: Wasteland, Build-up, and Vegetation. Each type is measured in hectares. Over the years, there have been clear changes. The amount of wasteland went down from 380.49 hectares in 2005 to 225.45 hectares in 2023, which suggests that steps might be made to clean it up. Build-up areas, on the other hand, went up and down. They reached a high point of 160.33 hectares in 2010 and then fell to 140.9 hectares by 2023. There were peaks and valleys in the vegetation patterns, but overall they were pretty steady. These kinds of data findings are very important for urban planning, environmental management, and policymaking because they help people make smart choices about how to use land, protect it, and build a healthy future, analysis shown in figure 7.

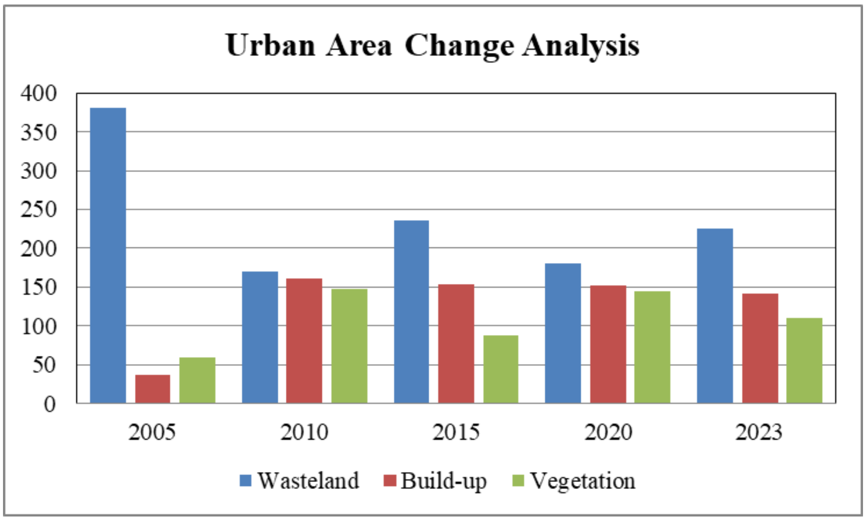


Figure 7. Urban Area Change Analysis for period 2005 to 2023.

Table 2: Machine learning method result comparison

Model	Accuracy	Precision	Recall	F1 Score
SVM	90.32	92.87	91.45	95.63
CNN	94.52	93.55	92.75	97.44

Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) are two machine learning methods that are compared in Table 2 based on four performance metrics: F1 Score, Accuracy, and Precision. With an Accuracy of 90.32%, Precision of 92.87%, Recall of 91.45%, and

F1 Score of 95.63%, the SVM model did a good job. But the CNN model did better than SVM, with an Accuracy Score of 94.52% and Scores for Precision, Recall, and F1 of 93.55%, 92.75%, and 97.44%, respectively. The comparison shows that both models perform well across all measures, which means they are good at the job at hand. But the CNN model does a little better than the SVM model, especially when it comes to Accuracy and F1 Score. This means that CNNs, which can easily pull out hierarchical features from complicated data like pictures, are a good fit for the classification job, leading to better results overall, shown in figure 8.

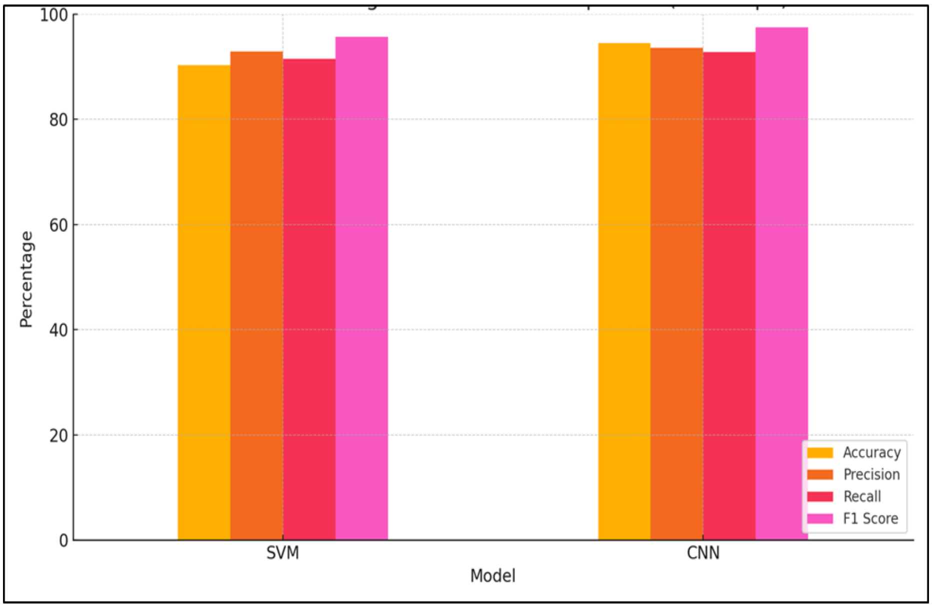


Figure 8: representation Evaluation parameter for CNN and SVM

Additionally, SVMs are known for being reliable and good at working with large amounts of data, but CNN's better performance in this case shows how important it is to use deep learning methods, especially when working with images and patterns, comparison shown in figure 9.

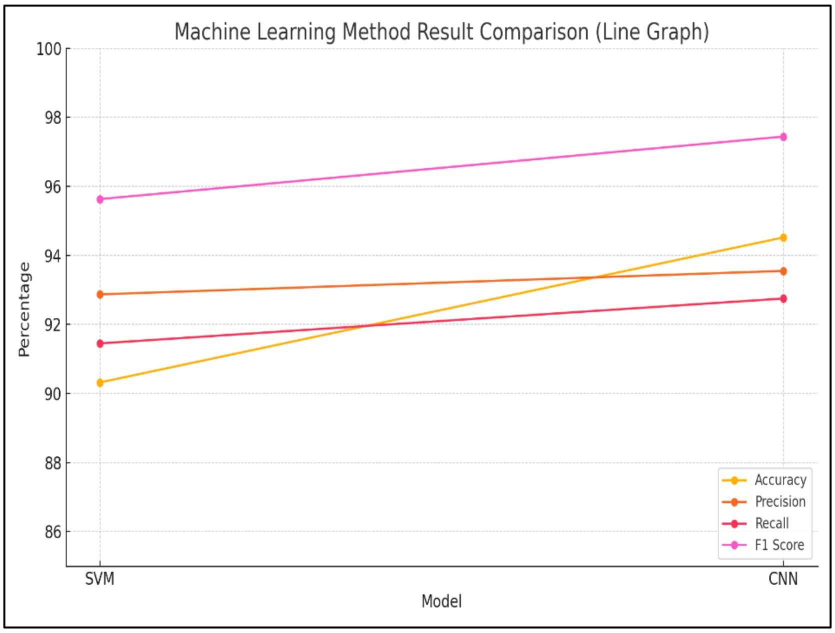


Figure 9: Comparison of Machine learning model with it Evaluation parameter

4. CONCLUSION

Using data from remote sensing along with machine learning methods looks like a good way to look at how cities change over time using numbers. Based on this study, we have shown that using advanced methods to learn about how land cover changes over time works. Using data from remote sensing, we can get detailed information about space, which helps us understand how cities grow and change over time. Tools for machine learning, like Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), have become very useful for looking at this kind of data. CNNs are great at automatically learning spatial traits from images collected by remote sensing, and SVMs are great at classifying things. Our results show that these methods could be used to correctly group and measure changes in urban land cover. Using remote sensing and machine learning together makes research more accurate and fast, which is important for making smart decisions in environmental management and urban planning. For example, it can be used to find changes in the cover of plants and to keep an eye on urban sprawl. In the future, more study could look into how to improve the models' ability to predict the future by adding more data sources, like social factors or climate data. Also, as machine learning algorithms and remote sensing technologies keep getting better, they could lead to even more accurate studies, which would help with long-term urban growth and environmental protection..

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