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Land Feature Identification and Prediction of Burewala Using Machine Learning

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Abstract: Burewala's study area is made up of many geographical types with various attributes. There are various types of land based on features, such as agricultural land, urban land, river channel lands, roads, and suburban regions. between 30 and 43 years. The observed terrain features of Burewala differ from those of the native land. For instance, the development of towns and communities has event in the transformation of rural land into urban land (problem). Artificial neural networks, deep learning, regression analysis, and mathematical analysis are some of the machine learning approaches that we would be using. I use methods using the satellite photos to map the Burewala land based on features. I have created a map that displays the land characteristics of agricultural areas. Using features from 1980, I created a map that shows four to five distinct types of land. To lower the in accuracy, I would collect additional satellite pictures from 1990 of the same research region, with the same seasons and parameters applied. After ten years, I would remap all those chosen characteristics for the 1990. I would follow the same procedures and make new maps for the 2000 photos after ten more years of 2000.I would do the 2010 again. Lastly, I would make advantage of 2023. Options I would watch for changes between 1980 and 2023, both in terms of decreases and increases. Generally speaking, based on my observations—I reside in Burewala. I am aware of numerous instances when agricultural land has been converted into well-stalled urban areas. The impact that my work will ultimately have is on the decline of crop fields and the increase in urbanisation. It would expand the field of study and open up new avenues. Understanding the urban development factors and which businesses are suitable would be beneficial. My outcomes would be heavily reliant on machine learning techniques. I learned the results using machine learning. I would assess the numerical values of the areas that have changed over the course of 43 years. The outcomes of the machine learning test and judge. I went into the field, took a photo, and provided solid proof that the algorithm matched the data. If they did not match, I would use different machine learning approaches to determine the risk factors analysis.

Keywords: Machine Learning; Land Feature Identification; Satellite Imagery; Convolutional Neural Network; Remote Sensing; GIS; Burewala; Urban Planning; Agriculture; Environmental Monitoring.

1. Introduction

Burewala is a city located in the Vehari District of Pakistan. In recent years, the advent of machine learning techniques has revolutionized the field of remote sensing and geospatial analysis, offering powerful tools to automatically detect and classify land features from satellite imagery. My research aim is to explore the application of machine learning algorithms for the identification and classification of land features in Burewala. The advancement of machine learning techniques has revolutionized remote sensing and geospatial anal-ysis by enabling the automatic identification and classification of terrestrial objects from satellite photo-graphs. My project's goal is to find out how machine learning techniques may be used to recognize and categorize the terrain features of Burewala.Burewala presents interesting opportunities and challenges for land feature identification because of its unique topography and environment. Using machine learning, we can leverage the potential of large-scale data analysis to enhance our understanding of the land use and land cover changes in the region. Figure (2) illustrates how machine learning algorithms may automati-cally identify and categorize land units in Burewala using high-resolution satellite data. Models can be disciplined to separate between various piece of land types, such as vegetation, croplands, water bodies, and built-up regions, by use of the labelled data preparation performing.The application of ML proficiency, such as support vector machines (SVMs) and convolutional neural networks (CNN), will modify us to recognize land features with high quality (Rawat et al.,2015). Burewala is a city in the Vehari District of Punjab, Pakistan; it was one of the earliest places on the Indian subcontinent to be inhabited, having been a part of the Indus Valley Civilization for a very long time. Modern machine learning tech-niques are used to dissect satellite data and extract key information about the geographical characteristics in Burewala, such as water bodies, agricultural fields, urban areas, and more (Ahmad et al., 2012). Over the millennia, Burewala witnessed the rise and fall of numerous dynasties and empires, notably the Mauryan and Gupta Empires. It was influenced by a number of Islamic kingdoms during the Middle Ages, including the Delhi Sultanate and the Ghaznavids. Burewala joined the British Raj in the 19th century and, like many other parts of the Indian subcontinent, was heavily involved in the freedom movement. Burewala residents actively took part in the liberation struggle against British colonial control.

Burewala joined Pakistan in 1947 upon its independence, as seen in figure (1), and has since grown into a thriving metropolis with a diversified populace [3]. It is well-known for its agricultural pursuits, especially cotton production, which significantly boosts the regional economy. Burewala has undergone modernization and urbanisation recently, along with advancements in education and infrastructure. It continues to be a significant centre of culture and commerce in Pakistan's Punjab region. Total area of burewala is 1,313km2. The ratio of male is 70.42 % while female 57.26 % in burewala according to my literature review [4]. Burewala is predominantly an agricultural area, with a significant portion of land dedicated to farming. Crops such as cotton, wheat, sugarcane, and vegetables are commonly cultivated. Over the years, urbanization in Burewala has directed to the growth of inhabited, commercial, and industrial areas within the city limits. The growth of markets, residential neighborhoods, and businesses contributes to the urban landscape. The Sutlej River flows near Burewala, and while exact statistics on land adjacent to the river channel may not be available, these areas might be utilized for agricultural purposes or left undeveloped due to the proximity to the river. The water channel river is near to burewala is Sutlej River. It is crossing near the Kachi Pakki, Sahuka and Jamlera show in figure (3).

The Sutlej River [5] is one of the major rivers of the Indian subcontinent, originating from the Mansarovar Lake in Tibet. It flows through the northern region of India and into Pakistan, eventually joining the Indus River. The river holds historical significance, being mentioned in ancient texts and having played a role in the development of civilizations along its banks[6]. Over time, the Sutlej River's water flow has fluctuated due to a number of variables, including climate change, glacial melt, human construction projects like dams and diversions, and seasonal variations in precipitation. These variations have an effect on the aquatic life, the flora beside the river, and the biodiversity in general within the ecology of the river. Additionally, the Sutlej River's natural flow has been changed by the building of dams and hydroelectric projects nearby, which may have an impact on the river's path and cause biological changes. The Sutlej River faces numerous obstacles in the year 2023 flood. There are many areas of agriculture land and urbanization land effect[7].

These human interventions can disrupt the river's ecosystem, affecting sediment transport, fish migration patterns, and the livelihoods of communities dependent on the river for agriculture and fishing. Burewala is connected to major cities through highways, including the National Highway N-5. The land occupied by these roads and highways, as well as the surrounding areas for transportation purposes, contributes to the infrastructure and connectivity of the region. Burewala has been a crucial trade and travel route for centuries. In the pre-colonial era, the region had pathways and roads that connected it to significant trade centers and cultural hubs. These ancient routes facilitated the movement of goods, people, and ideas between Burewala and neighboring regions. During the colonial period, British rulers further developed these routes to serve their administrative and trade interests. Some of these routes were later expanded and upgraded, forming the basis of the modern road network in and around Burewala. One significant historical route was the Grand Trunk Road, built by Sher Shah Suri in the 16th century. This road, passing through Burewala, connected the eastern and western parts of the Indian subcontinent, fostering trade and cultural exchange[8]. The evolution of these historical highways laid the foundation for the modern road Infrastructure, including the National Highway N-5, which became a pivotal artery connecting Burewala to other major cities in Pakistan.

The development and expansion of these highways over time have contributed significantly to the economic and social development of the region. The suburban areas surrounding Burewala are a mix of agricultural fields, villages, and gradually developing residential zones [9]. These areas experience a blend of agricultural activities and the influence of urbanization due to the city's expansion. However, the time period of 1980 to 2023, it's reasonable to assume that urbanization and population growth might have led to changes in the suburban landscape. Agricultural lands might have experienced gradual transformation due to expanding residential areas, infrastructural developments, and commercial establishments. This transformation could have resulted in a decrease in agricultural land due to urban expansion and increased infrastructure, reflecting a shift from rural to suburban land use.

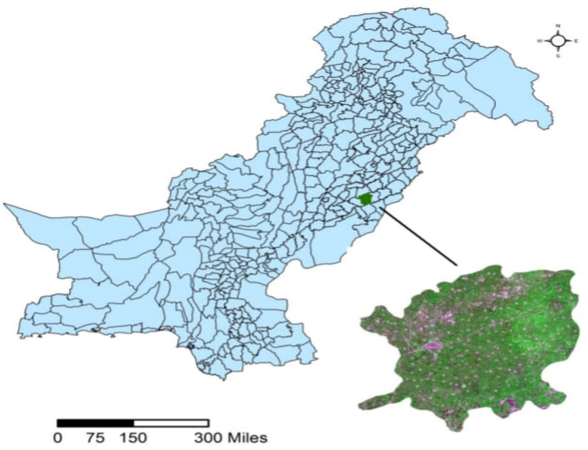


Figure 1. Location of tehsil Burewala

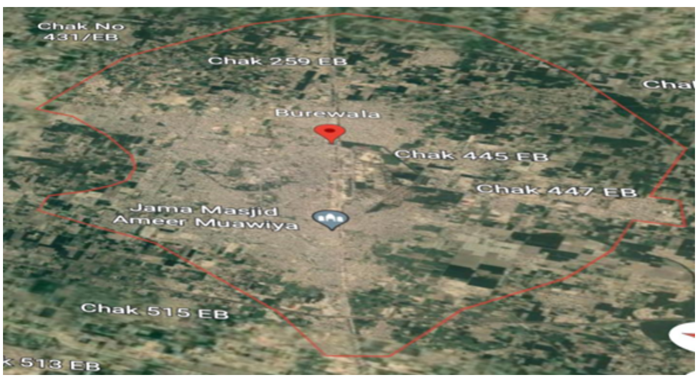


Figure 2. Latest area of burewala capturing by satellite

Figure 3. Capturing the Sutlej River images by satellite

2. Literature Review

Burewala is a city in Punjab, Pakistan, located on the banks of the Sutlej River. It has a hot desert climate with hot summers and mild winters[52]. I live in burewala according to my knowledge burewala is 5th largest city of Pakistan in population. The population of Burewala has increased per year. The population is increasing then the agriculture land is converting to urbanizations. The people are cutting down the agriculture land and making a building for living. The agriculture land used in some build a mall for business. According to my study the barren area is converting to urbanizations. In 1981 to 2017 the growth of population increased by almost 19% according to per 10 years. The transformation of rural areas into developed areas, which are consequently converted into cities with roads and infrastructure, has taken place at a remarkable speed. However, relatively little attention has been paid to the environmental issues of the city that may be among the factors in pervasive environmental problems (frequent flooding events, growing slums, mismanagement of resources, utilization of available land areas) across the city [10]. Due to the focus of the present study on using remote sensing for monitoring LULC, it is necessary to have review on the remote sensing analysis and related methods. Some satellites with different sensors have been launched in recent eras for remote sensing purposes reviewed by [11]. It's also important to mention that we used metaheuristic optimization to find the agricultural lands. Nonetheless, these techniques may be equally effective in identifying urban regions. Tehsil has a hot summer climate and a cold winter climate. The tehsil maximum and lowest temperatures are 35.5°C in June and 12.8°C in January, respectively, with 60mm of rain on average. Burewala is the second-largest tehsil in Punjab in terms of land and ranks 31st among all the cities in Pakistan in terms of population. The goal of land use classification, on the other hand, is to specify the use of the area, such as agriculture, recreation, or wildlife habitat. [12]. Notably, these data-location applications depend on the land cover and use, which differ from location to location due to issues with unauthorized use or eradication, particularly in coastal locations. Some prior research classified images as object-based, but the majority employed pixel-based satellite photos to learn Land Use/Land Cover (LULC) classifications. To create a high-performing classification model, vector data are utilized in this study as an object-based "polygon" and raster data as a point-based "pixel." Global developments, the effects of LULCC on ecosystem sustainability are becoming more and more significant. The largest changes in the current national of the earth's shallow look to be caused by human activity. Changes in the surface cover affect the local, regional, and global energy, water, and geochemical flux balances. These changes will unavoidably have an impact on the sustainability of natural resources and socioeconomic activities. [13]. Yonder the current state of the art, we suggest a deep neural network that uses patch normalization, convolutional, and BILSTM layers to capture all spatial, spectral, and temporal information at pixel-by-pixel granularity. This opens the door to the possibility of forecasting applications built on top of our rice mapping system. [14]. There is now a shift towards more regular and dependable monitoring and demonstrating of land use/land cover trends because to the development of high spatial resolution satellite images, more sophisticated image processing, and GIS technology. Updating land use/cover maps has been a common use of remote sensing, and it has grown to be one of the most significant uses of the technology [15]. A novel weight feature value convolutional neural network (CNN) model CNN (WFCNN) was created to segment far-off sensing photographs and citation more detailed information about land usage from the pictures. It included five semantic feature tiers obtained using the encoder, a classifier, a collection of ethereal features, and an encoder. An adjustment layer was used to fine-tune the models hierarchically merged semantic attributes for best outcomes. The model used linear fusion to do this [16] [17]. A novel weight feature value convolutional neural network (CNN) model CNN (WFCNN) was created to segment far-off sensing photographs and citation more detailed information about land usage from the pictures. It included five semantic feature tiers obtained using the encoder, a classifier, a collection of ethereal features, and an encoder. An adjustment layer was used to fine-tune the models hierarchically merged semantic attributes for best outcomes. The model used linear fusion to do this [37] .

Table 1. Literature review of previous studies

Study	Publication year	Approaches /Technology Inculcated	Goals
[13]	2017	PCA and NDVI, Image classification, Supervised learning Unsupervised learning was generated using ArcGIS version 9.1 software.	The municipal growing development of a Saudi Arabian metropolis is the aim of this study. In light of the growing urbanisation).
[55]	2018	Spaceborne sensors Optical imaging sensors, Thermal IR imaging sensors Radar imaging sensors.	hopeful provision for the merger of multiple sources of remote sensing data.
[26]	2017	NASA-GLCF (Global Land Cover Facility), Landsat TM (Thematic Mapper) and USGS (United States Geological Survey) for Landsat8 OLI-TIRS (Operational Land Imager/Thermal Infrared Sensor).	Sense LULCC in CWS with the goal of responding the question of how the land use has been transformed in CWS in the year 2005, 2010, and 2015.
[38]	2020	SPOT-4 and SPOT-5 satellites, Sentinel-1A, Landsat OLI and TRIS (Landsat 8), Thermal In-175, fared Sensor (TRIS).	paddy fields at the pixel level for an total year and for each temporal instance.
[37]	2023	Heuristic Models, Artificial Neural Networks, LULCRV model, convolutional neural network (CNN) model.	Meant to recognise the ideal deep learning configuration for LULC charting in New Caledonia's complicated subtropical climate.

In this table (1) shows that the literature review related to burewala after and before working. Addressing these research gaps would have required interdisciplinary collaboration between remote sensing scientists, machine learning experts, and domain specialists familiar with Burewala's landscape. Future research directions will likely focus on overcoming these challenges to improve the accurateness, reliability, and applicability of machine learning-based land feature identification methods in Burewala.

3. Materials and Methods

3.1 Study Area

East of Tehsil Vehari, at 30.16°N 72.67°E, is anywhere you'll discovery Tehsil Burewala.. Its borders are Sahiwal to the north, Vehari to the west, and Pakpattan to the east. It is in the southeast of the Tehsil Bahawalnagar district and forms the southeast border of the Sutlej River. Situated on the important Burewala Multan Road, it is 35 kilometre's easts of District Capital Vehari. The tehsil's total area is 1603.14 km^, or 160314 hectares), and it is made up of numerous tiny towns and villages, with Burewala serving as the primary urban centre. Burewala is the second-main tehsil in Punjab in terms of land and the thirty-first-prime city in Pakistan in terms of population. Burewala is crossed by the Sutlej River close to the southern towns of Jamlera and Sahuka [20]. The forest covered the southern portion of the tehsil, and over time, the Langrial clan from the area humanised it. Due to the Pakpattan Canal's operation in this region, people began to settle in settlements and the forest was transformed into agricultural land [21].

3.2. Data collection

USGS (United States Geological Survey) online service provides ANN (artificial neural network) satellite data that are used to analyze changes in the tehsil's land features. ERDAS was used to process four multi-date satellite pictures from the years 1981, 2000, 2010, and 2023. Consider examining the study area's land use fluctuations across time (Fig 2) [22]. Masking operations in eras are used to prepare a subset of the Tehsil Burewala. Spatial and spectral twin augmentation techniques are used to progress the visual understanding of various land use classifications in the photos once the research area has been prepared. It is crucial to identify and classify land use according to objectives before beginning any change detection process [23]. This study divides land use into four categories for analysis: constructed land, greenery, open/barren land, and bodies of water in 1981 toward 2023 show in table (2). in the respective years burewala development plans are changed in 1981 to 2023 the small towns are converted to cities and the urban growth of increase per year. The people are changed to agriculture land into built-up land show in table (3).

Table 2. Land uses area (%) in 1981 to 2023 [46]

Land uses	1981 Area (%)	2001 Area (%)	2011 Area (%)	2023 Area (%)
Water	4.02	3.34	2.84	2.34
Barren	26.2	11.57	11.24	10.91
Built-up	3.3	4.2	4.73	5.43
Vegetation	66.3	80.90	81.19	81.69

Table 3. Land uses categories of burewala development plans in respectively years (%) & hectors in 1981 to 2023 [46]

Land uses categories	1981		2001		2011		2023	
	ha+	Area (%)	ha+	Area (%)	ha+	Area (%)	ha+	Area(%)
Residential	230.3	29%	658.4	53%	847	62%	1052	65.9%
Commercial	11.2	1.4%	19.3	1.5	50	3.6%	85	5.3%
Public building	37.3	4.6%	57.5	4.6%	90	6.5%	130	8.1%
Education	12.9	1.6%	13.7	1.1%	52	4%	92.5	5.7%
Parks	7	0.8%	19.4	1.5%	17.6	1.2%	20.5	1.2%
Graveyard	17.5	2.1%	26.7	2.1%	28	2.1%	31.2	1.9%
Industrial	39	5%	86.9	7%	86	6.3%	84.5	5.2%
Disposal	0.47	.06%	10.2	.02%	3.4	0.25%	2.3	0.1%
Open land	442.3	55.4%	369.6	29.5%	191.2	14%	98	6.1%
Total land areas	798	100	1251	100	1365	100	1596	100

Historical land use data spanning the years 1981, 2001, 2011, and 2023 will be sourced from reliable and authoritative sources. This dataset will encompass detailed information on land area (ha) and the corresponding percentage (%) allocated to various land use categories. These categories encompass a wide range of urban and natural settings, including residential areas, commercial zones, public buildings, educational facilities, parks, graveyards, industrial sectors, disposal sites, and open lands, as outlined in this figure (4). The examination of data from geographical information systems (GIS), such as maps of land cover, elevation models, and satellite images. This improves model accuracy and the extraction of spatial features.

An essential tool for assessing supervised machine learning algorithms is the confusion matrix, especially when it comes to classification problems. By showing a figure(5) of projected versus actual classifications, it offers a thorough analysis of a classification model's performance.

3.3. Important Elements of a Confusing Matrix:

- **True Positives (TP):** The model accurately forecasts a favourable result are known as True Positives (TP)—for example, correctly classifying residential regions as residential shown in figure (5).
- **True Negatives (TN):** The model accurately predicts a negative result are known as True Negatives (TN)—for example, correctly classifying non-residential areas as non-residential showns as the figure (5).

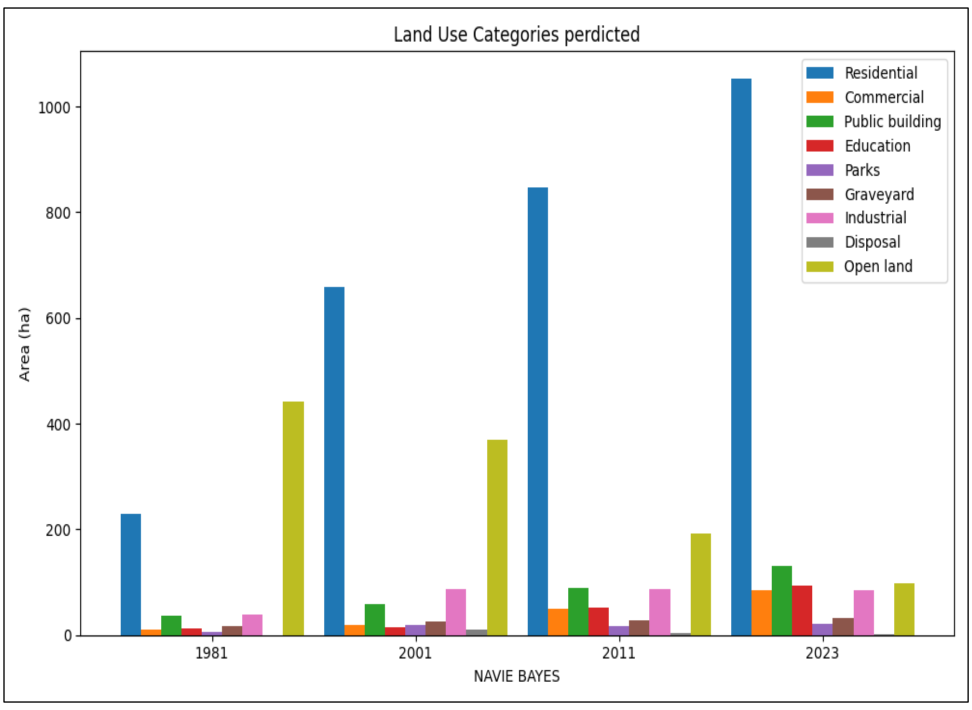


Figure 4. Applied machine learning algorithms in land uses categories

- **False Positives (FP):** False Positives (FP) are situations in which the model predicts a positive result wrongly (e.g., misclassifying non-residential regions as residential) show the figure (5).
- **False Negatives (FN):** False Negatives (FN) are situations in which the model predicts a negative result inaccurately (e.g., misclassifying residential regions as non-residential) as show figure (5).

Confusion matrices help academics and practitioners optimise model performance for particular applications by improving the transparency and dependability of machine learning models.

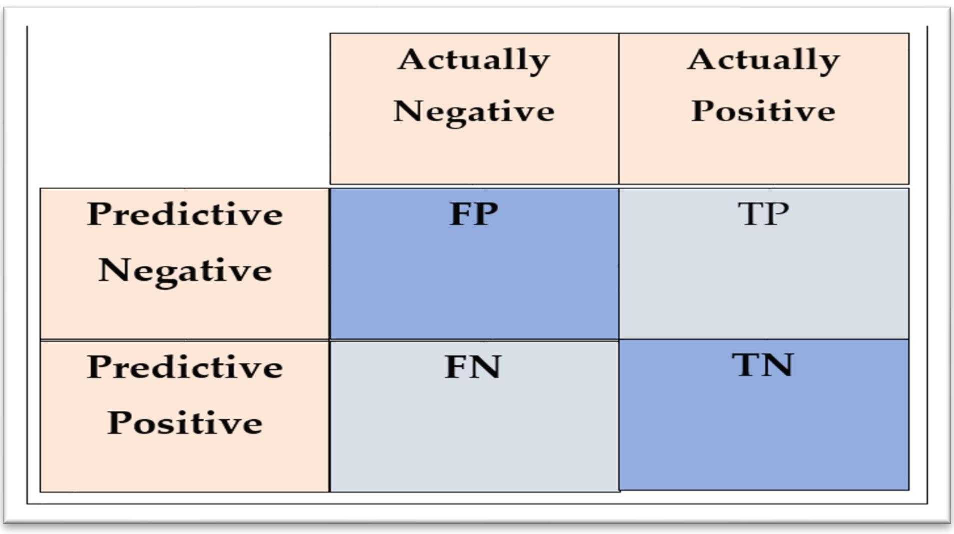


Figure 5. Confusion matrix [40]

There is no predetermined classification for the dataset. Rather, the categories are determined manually depending on the knowledge of experts. The suggested five classes are shown in Table (4) along with a description and definition with an example of each subclass within the primary class for the characteristics of land use and land cover (LULC) [24]. The model is created using an ArcGIS desktop and the open-source QGIS programming, and the whole process is carried out.

Table 4. The land-uses / land cover LULC classes identified

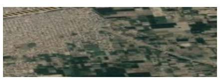
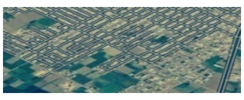
Class Name	Class Description	Class Description Example
Water channel area	Area covered by water	
Barren land area	large spaces with minimal to no vegetation	
Built-up area	Region encompassed by settlement, road	
Vegetation	Area covered by forest, sparse trees,	
Fallow land	Area without vegetation	
Agricultural land area	Area covered by agricultural crops	

Table 5. Historical growth of population in Burewala

Years	Population
1951	15,383
1961	34,237
1972	57,741
1981	86,311
1998	152,097
2019	231,797
2023	253,879

4. Results and discussion

Burewala land use shift is examined via supervised classification. Tehsil Burewala land cover and land use were determined by supervised classification. Table (3) displays the region used for respectively type of land routine group within the tehsil. The total land Burewala decreases per year because the population growth is increased in per 10 years show in table (5). Then the population is increased the agriculture land is decreased. And then some peoples belong to villages moving to city then the city land of agriculture are divided in built-up land [25]. The areas of land are less than per year according to my study. In this figure (6) show that the land uses area of vegetation is Burewala 1981 is 67.14 % and then 2001 in 57% then vegetation of 2011 was decrease 10% and almost the vegetation of 2023 is 44.37%. The need of water is because the population of Burewala is per year increase then water requirements increase but the dirty water increase, and the pure water is less than show in figure (6). The barren area of Burewala is decrease according to 1981 to 2023 in 1981 is 16.22% and 2023 is 12.43% [26]. According to my study the barren area of burewala was covered the buildings and malls. My knowledge of burewala because I live in burewala and using the supervised learning method the urban growth is increasing then the built-up land is increased. Because is increasing urbanizations and then decrease the agriculture land. The graph 1.1show that the land uses area of burewala are used or not used. The urbanized the area is intensification in per year in 1981 century the area in built is 16.14% but the same as the 2001 the built is increasing to 16.49% almost 1% increase in 20 years but the same as the after 10 years the built-up is increasing the 29% the per 10 years the built-up increasing show in table (6). The urban growth decreased in 2011 to 2023 1.9% show in table (7). According to supervised learning techniques. In 2024 and upcoming years the water is less required of water in other years for pure drink. Determining the area of Burewala using machine learning datasets typically involves utilizing geospatial data and algorithms, rather than machine learning specifically for area measurement. Geospatial information from satellite imagery or GIS datasets can be processed to calculate the area accurately. One method involves using GIS software to overlay the boundary of Burewala onto geo referenced satellite imagery or digital maps [27] [28].

With this, GIS tools can calculate the area within the defined boundaries. Machine learning can complement this process by aiding in the classification of land cover kinds within Burewala, This is thereafter applicable in GIS analyses to segment and calculate areas of different land use categories. However, the direct application of machine learning solely for area measurement might not be the most effective approach, as area calculation primarily relies on geospatial analysis techniques within GIS environments. The datasets, tools, and methodologies used in the analysis while conducting geospatial measurements and analyses of Burewala area [29].

Five different metrics are used to assess classification accuracy: precision, recall, f-score, kappa index, and misperception matrix. True positive (TP) for predictable items, false negative (FN) for non-detected ones, and false positive (FP) for erroneously identified objects are how they are defined and computed. For a given class, the recall, accuracy, and f-score statistics range from 0 to 1, where 1 represents excellent identification and 0 represents poor identification [33].

Table 6. The land uses categories in 1981 to 2023 [46]

Land uses categories	Change detection			Rate of urban growth		
	1981-2001	2001-2011	2011-2021	1981-2001	2001-2011	2011-2023
Built-up	13.86 6.16		6			
Vegetation	-10.1 2.48		-10	4.2%	1.9%	2.0%
Barren	-4.06 3.75	4.03	-			
Water	0.47 0.01		-0.5			

Land uses categories	1981		2001		2011		2023	
	hac+	area %	hac+	area %	hac+	area %	hac+	area %
Water	20	.50%	39	0.97%	41	1.02%	45	1.12%
Barren	652	16.22%	489	12.16%	651	16.19%	500	12.43%
Built-up	649	16.49%	1206	30%	1444	36%	1692	42.08%
Vegetation	1699	67.14%	2286	16.49%	1884	47%	1784	44.37%
Total	4020	100	4020	100	4020	100	4020	100

Table 7. Change detection and Rate of urban growth in 1981 to 2023 (M. malik et al.,2020)

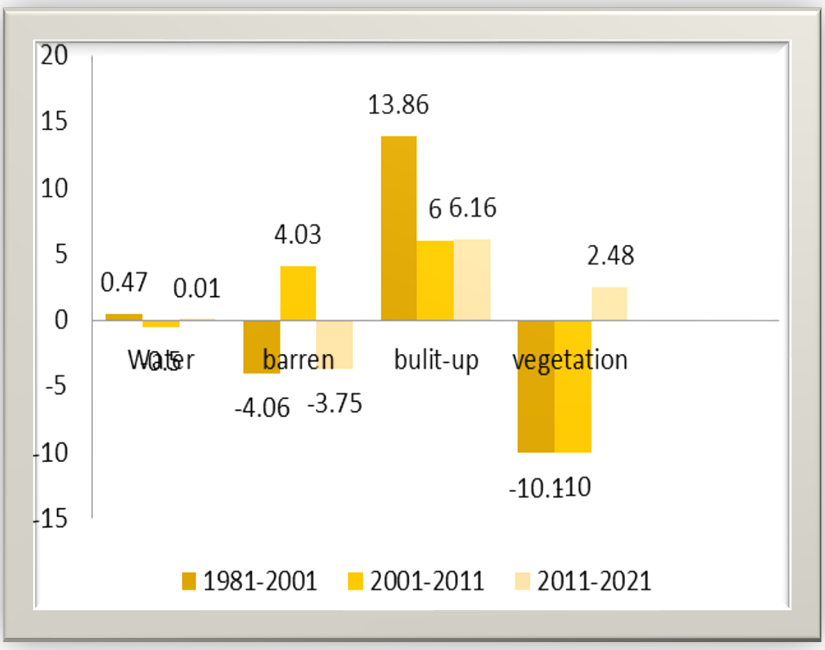


Figure 6. Change detection of Burewala in 1981 to 2023

Five different metrics are used to assess classification accuracy: precision, recall, f-score, kappa index, and misperception matrix. True positive (TP) for predictable items, false negative (FN) for non-detected ones, and false positive (FP) for erroneously identified objects are how they are defined and computed. For a given class, the recall, accuracy, and f-score statistics range from 0 to 1, where 1 represents excellent identification and 0 represents poor identification.

Precision=TP/TP+F (1)

Recall=TP/TP+FN (2)

f-score=2×precision×recall/precision+ recall (3)

SVM is a machine learning method that is applied to LULC classification[14][15]. The SVM algorithm locates a hyperplane that maximises the separation between the various classes in the data based on the properties or features of the data. Because the SVM technique can handle complex, non-linear interactions between the classes and features, it is a strong choice for LULC classification tasks.

4.1. ANN (artificial neural networks)

We used Artificial Neural Networks (ANNs), a broad class of machine learning models, to classify LULC. The forward pass of a feed forward ANN is represented by this general equation:

$Y = f(W2 \times f(W1 \times x + b1) + b2$ (4)

The model's requirements are five nodes in the hidden layer, training with 1000 reiterations, and classifications into eight distinct classes. The variables in Equation (4) are represented by the weight matrix W1, which has dimensions of 5 ×n, where n is the total number of input features included in the model. The weight matrix W2, on the other hand, has dimensions of 8 × 5 and is associated with the output layer.The result is a vector with eight elements, one for each class of land cover, where x is the input [37]. An LULC map is generated and predicted using the proposed LULC is land uses area are show in table (8) illustrates this process.

Table 8. Area of tehsil Burewala LULC

Tehsil	Land area	Cultivated Area	Uncultivated Area a
Burewala	3,25,474	2,84,790	40,684

Applied machine learning algorithm in different methods but the ANN algorithm are appling showns as the figure (7) . calculate the total land uses categories in ANN and train the machine learning model into 1981 to 2023 as showns as the the figure (7). According to my study the totally change of burewala city is almost then 75% to 80%.

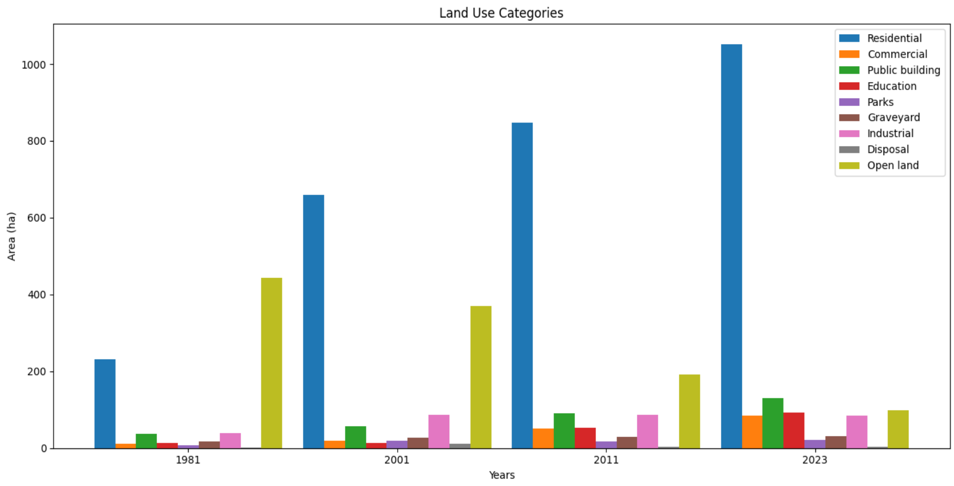


Figure 7. Used Machine Learning algorithm ANN

5. Conclusion

This study uses high-resolution satellite photos and machine learning techniques to create a prediction model for land use and land cover classes. The purpose of this study, which focuses on small tehsils in Punjab, is to provide evidence that urban growth is not limited to Pakistan's largest cities but is also expanding geographically in small cities and towns because of rising population pressure and infrastructural development. Small towns are becoming cities, and cities are becoming metropolitan areas. Burewala is among the medium-sized cities that are experiencing daily development because of population pressure. A reliable method of calculating changes in land cover and the rate of urban growth is to use remote sensing analysis. According to the data, the city is growing on its northeast and southeast sides. The growth of the city's road network, educational institutions, and commerce were key factors in its urbanization. A GIS-based study of the land use plan backed the city's built-up growth as it resulted in the creation of new frame civilizations [52] [54]. The growth of small-scale companies also improved job prospects for migratory workers seeking permanent settlement. Empirical evidence of the city's urban growth is provided by remote sensing and GIS analysis, and this unchecked city growth in all directions explains why peri-urban agricultural has been converted into developed land. Thus, the local government must be heavily elaborate in the management of normal resources such as vegetation and agricultural land, particularly when it comes to urban development, within the boundaries of the municipality. Population migration in quest of work and better possibilities for living sounds wonderful, but the region's rural scenery may benefit from increased living standards and the availability of essential services. It has been noted that ANN outperforms the others in accuracy measurements.

Author's contribution: The main concept was proposed by Iqra Irfan Rana, who was also involved in the write-up. Sidra Habib and Sidra Saeed Rana helped establish the sequence stratigraphy of the sections. Huma Irfan collected data in different areas. Dr. Rana Muhammad Saleem and Dr. Jahangir Khan provided a scientific discussion and proof read of the manuscript.

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