Visualizing Rural and Urban Landscapes

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***Abstract*– A ml-based method for categorizing snapshots into rural and urban areas is presented in this work. The system trains different classifiers using a tagged dataset of photos by utilizing supervised learning techniques. Using the BRISK technique, the methodology first extracts features. Next, it uses algorithms like KNN, SVM, DTs, RFs , and LR for classification.**

Experiments show that when the number of clusters, K, is set to 3, the KNN classifier achieves a noteworthy accuracy of 98%. The suggested approach has potential for real-world use in a variety of fields, such as disaster relief, land-use planning, and environmental monitoring. The system offers insightful information to researchers and policymakers on the distinctions between rural and urban areas, which helps them make well-informed decisions about resource allocation and land use.

***Keywords:* Rural and Urban identification, BRISK, ML Classifiers.**

I. Introduction

Computer vision algorithms have advanced quickly in recent years, and thanks to advancements in remote sensing technology, it is now feasible to distinguish between rural and urban environments autonomously with great efficiency and accuracy. Planning land use, environmental monitoring, disaster relief, and public health are just a few of the many real-world uses for this.

This paper reviews the traditional feature-based methods used for rural-urban identification, which have several limitations, including low accuracy and time-consuming processing. Then it introduces ML methods, which have been shown to provide higher accuracies and faster processing times. We look at the difficulties and possibilities facing this study area, including the requirement for extensive and varied datasets, the interpretability of models, and the ethical issues surrounding the application of such technology.

The development of ML algorithms has opened up new possibilities for effective and automatic rural-urban classification. ML algorithms are very effective and precise at distinguishing between rural and urban environments because they can automatically extract features from massive amounts of mentioned data. This paper provides an overview of the most advanced ML classifiers for classifying rural and urban areas using remote sensing images.

II. Literature Review

This paper is a review of the research trends in the field of evaluation of a city area using google map images. The authors summarize the main methods used to analyze street view images, including computer vision techniques, deep learning algorithms, and geographical information systems (GIS). They also highlight the challenges and limitations of using pictures from street view of cities regions assessment and provide suggestions for future research[1].

This study introduces a novel method for identifying land uses based on gray-level vector reduction and frequency-based contextual categorization. The authors' goal is to improve land-use categorization's accuracy by incorporating contextual information and reducing the size of the input data. The method uses frequency-based contextual analysis to extract relevant information from the input data, followed by a gray-level vector reduction to simplify the data. The reduced data is then used to train a ML approach for. The authors demonstrate that their method is more accurate and effective when the findings are contrasted with those from other cutting-edge land-use identification techniques. The study analyses the significance of this findings for future land-use identification studies[2].

A deep learning strategy for recognising metropolitan regions from remote sensing photos is presented in this study. The authors' objective is to use deep learning algorithms to improve the precision and efficacy of urban area identification. The suggested technique analyses the attributes of remote sensing photos and identifies metropolitan regions based on patterns and characteristics in the data using a deep neural network. When compared to other cutting-edge techniques, the method's results are evaluated, and the authors show that their method is more accurate and efficient. The paper concludes with an explanation of how this work may be interpreted for future study in the field of urban area identification using remote sensing images [3].

Using Google Earth Engine's pixel-based picture categorization, this study gives a dataset for identifying the borders of metropolitan areas in India. The authors aim to provide a high-quality and reliable dataset for researchers and practitioners working towards a profession in urban area identification. The dataset was created for the study of geographic data and visualization using cloud base platform Google Earth Engine. The authors proposed a combination of satellite imagery and other data resources to create the dataset, and applied a pixel-based image classification algorithm to identify urban surroundings. The dataset and the procedures used to create it are described in great length in the research, and highlights the key features and limitations of the dataset. The authors also describe some initial results using the datasets, and discuss the potential applications and future directions for research using this dataset [4].

The research focuses on identifying trends combining satellite data and CNNs, in emerging countries, the density of urban homes is increasing. The goal is to create a model that can anticipate events with precision housing density in these areas. The authors used satellite imagery as input and trained a CNN to recognize patterns and structures in the data. As a consequence of the test data, it was evident from the findings that the model could correctly forecast the density of buildings. The study highlights the potential of using CNNs and satellite imagery for analyzing urban density of housing in developing countries [5].

The categorization of land use in remote sensing pictures is done in this article using CNNs. The author aims to develop a system that can accurately identify and classify different types of land usage in satellite images. The system is trained using a large dataset of labelled remote sensing images. The performance shows that the CNN-based approach outperforms traditional land use classification methods in terms of accuracies and computational efficiency. The article emphasises the potential of CNNs for classifying land use and highlights the necessity of having sizable annotated datasets for model training [6].

The paper focuses on using CNNs to classify the degree of deprivation in slums areas with very high-resolution (VHR) images. The authors aim to develop a system that can accurately predict the level of deprivation in slums areas based on the characteristics of the built environment visible in the photos. The model is trained using a dataset of annotated VHR images of slums. The outcomes of the study demonstration that the CNN-based approach is efficient to accurately predict the degree of deprivation in slums based on the features of the built environment visible in the images. The paper highlights the potential of using CNNs and VHR imagery for understanding the characteristics of slums and the level of deprivation experienced by the residents [7].

The research focuses on employing unsupervised deep learning techniques for classification of remote sensing images. To effectively categorise remote sensing photos into several land cover categories, the authors suggest a new technique for unsupervised deep feature extraction. The technique extracts feature from the images using an autoencoder network, which are subsequently utilised to train a classifier. The study's findings demonstrate that the suggested unsupervised deep feature extraction method surpasses more established techniques for classifying remote sensing images in terms of precision and computational efficiency. The promise of unsupervised deep learning algorithms for remotely tracking picture categorisation is highlighted in the paper, as is the significance of feature extraction in this procedure [8].

The study classifies building instances using street view pictures. The authors want to create a model that can recognise and categorise specific buildings in street view pictures. The study's findings demonstrate that the suggested approach can correctly classify buildings in the test data. The proposed approach is trained using a collection of annotated street view photos. The research emphasises the value of large annotated datasets for training such models as well as the potential of employing street view photos for developing instance categorization. The authors then go into how the suggested approach may be used in a variety of industries, such as real estate, disaster response, and urban planning [9].

In this study, ML techniques for planning urban land usage are reviewed. The authors' goal is to give a summary of the many ML approaches that have been used to solve urban land use planning issues while highlighting their advantages and disadvantages. The paper discusses a wide range of subjects, including as urban growth projection, land use change detection, and examination of urban land usage
suitability. The authors provide the findings of recent studies in this area and talk about the various forms of data and techniques employed in these applications. The potential of ML to solve challenging urban land usage planning issues is highlighted in the paper's conclusion, along with the need for additional study to increase the precision and effectiveness of these algorithms[10].

The study focuses on the usage of ANNs and SVMs for picture classification. The authors compare how well these two ML algorithms perform when it comes to picture classification tasks. A dataset of photographs is used in the study to train and test the models. The findings demonstrate that both SVMs and ANNs are effective for picture classification and may attain high levels of accuracy, while ANNs typically beat SVMs in terms of precision and computational effectiveness. The research emphasises the potential of employing both SVMs and ANNs for picture classification tasks and emphasises how crucial it is to take into account the data's properties and the desired outcomes when choosing the best ML method [11].

The paper proposed an overview of the use of ML in urban spatial analysis. In addition to classifying trends and gaps in the field, the authors hope to provide an overview of the many ML techniques that have been used to solve issues in urban settings. The study covers a range of topics, including urban land usage planning, urban growth prediction, urban land usage change identification, and urban heat island analysis. Additionally, the authors suggest areas for future research, including the integration of multiple sources of data and the use of deep learning techniques [12].

In the study , the usage of GIS and RS technologies is investigated for the purpose of identifying and analysing changes in land use patterns between urban and rural areas. In order to track changes in land usage and cover over time, the work probably entails gathering and analysing geospatial data, such as satellite photography. The results of the research may explain the dynamics of urbanisation and its consequences on rural environment, agriculture, and other issues [13].

High-resolution synthetic aperture radar (SAR) images are used in the technique described in this study to identify floods in both urban and rural locations. The suggested technique evaluates SAR data from various sources and aims to offer conclusions very instantly. The findings demonstrate that the suggested strategy may accurately and quickly identify floods in both urban and rural locations. The technique has the potential to be used in numerous flood early warning and monitoring systems [14].

In both rural and urban settings, the study analyses how well different ML algorithms perform when classifying satellite images. According to the findings, depending on the region, the algorithms' performance differs, with some algorithms performing better in rural than in urban settings. Several algorithms were combined to reach the overall optimum performance. The study emphasises how crucial it is to take into account the environment's unique characteristics when choosing a ML algorithm for classifying satellite images [15].

This study suggests a technique for identifying the urban-rural border using data from optical and nocturnal lighting. To gather data on land usage and land cover, the approach uses both optical daytime imaging and night-time light data. The suggested approach has the potential to be used in numerous applications, including land use planning and monitoring urbanisation [16].

The technique described in this research uses Markov Random Fields (MRF)-based super-resolution mapping to detect urban trees in a very high resolution (VHR) photographs. Compared to conventional techniques, the MRF model improves tree detection accuracy by accounting for the spatial interactions between the trees and the structures nearby. The outcomes demonstrate that this technique is successful at mapping urban trees in VHR photos [17].

The authors of this research provide an object-oriented framework technique for mapping urban trees using RF classifiers. They begin by gathering ground truth data on tree locations and high-resolution urban photography. Preprocessing improves the quality of the picture, while feature extraction records the contextual and spectral characteristics of the image objects. This data is used to train RF classifiers to categorize urban trees. After accuracy is ensured by validation, the classifiers are used to map the distribution of urban trees. This method offers precise, scalable mapping of urban trees to support informed decision-making, which benefits urban forestry and land management.[18]

The RF-Cellular Automata (RF-CA) model, a unique method for modeling urban expansion, is presented in this work. The ML algorithm RF is combined with the spatial modeling method Cellular Automata by authors Courage Kamusoko and Jonah Gamba. Obtaining high-resolution spatial data and preparing it for consistency are steps in the technique. Then, using this data, RF classifiers are trained to predict patterns of urban expansion depending on different criteria. The Cellular Automata framework, which models how urban areas change over time depending on local interactions, incorporates these predictions. In order to guarantee the model's accuracy in projecting future urban expansion, it is calibrated and validated using historical data. To evaluate the effects of various policies and actions on patterns of urban development, scenario analysis is carried out.[19].

The main goal is to evaluate DT algorithms' performance as non-parametric techniques for classifying different types of land cover according to particular rule sets. Object-based categorization approaches are utilized to achieve higher accuracy in comparison to pixel-based methods since they take into account contextual and spatial information. Obtaining, preprocessing, and extracting pertinent characteristics from remote sensing data are probably steps in the technique. To make it easier to classify land cover objects, DT algorithms are then used to create rulesets based on these attributes. The study could offer actual data proving that DT algorithms are effective at correctly categorizing items with land cover. Improved resource management, environmental monitoring, and land cover mapping are possible consequences.[20]

Table.1. Comparison of Some Paper

Paper	**Dataset**	**Techniques**
[1] He et al. (2021)	ImageNet, ADE20K, Camvid	CNN(74%), DCNN(81%), SVM(77%)
[4] Guo et al. (2019)	Beijing City	CNN (100%)
[9] Romero et al (2015)	UC-Merced	CNN(84.53%), SVM()

III. Methodology

In this study, a model has been constructed for classifying urban and rural environments using pictures. The images are divided into two groups by the ML model. The proposed work's whole workflow is depicted in Figure 1, starting with data collection, pre-processing of the data, feature definition, and feature selection, followed by testing and training of the model, which provide the final results. The dataset of photos was transformed into feature vectors using a computer vision-based method before being given to the ML algorithms.

The Identification of rural or urban surroundings System

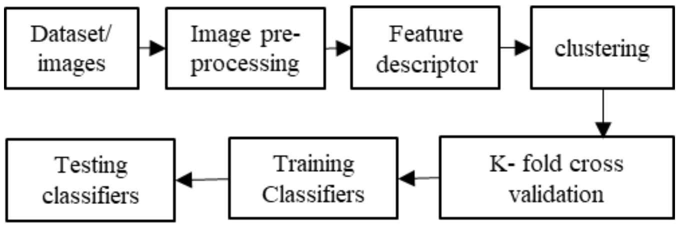

Fig.1: Block diagram of the system

Algorithm 1:

1. Input dataset
2. *for* every image in the dataset:
3. Resize image to 200 x 200 px
4. Convert to Grayscale
5. BRISK features description
6. K- means Clustering
7. K-fold cross validation
8. Training and testing ML classifiers
9. Analysis of performance of classifiers
10. *end* of Algorithm

A) *About the data set:*

Images from both urban and rural surroundings are collected for creating the dataset. Dataset consists total 2000 images, 1000 of which are of urban regions and 1000 are of rural regions.

B) *Image Processing:*

The Identification of rural or urban surroundings system used three image processing techniques:-

Resize the photo:

Resizing is the process of altering an image's size, either making it smaller or larger. This is a typical job in image processing since it may be used to either reduce the size of huge photos or improve the visibility of small ones. Various algorithms, such as nearest neighbour, can be used for resizing.

The aspect ratio must be taken consideration when resizing an image to prevent distortion.

Fig. 2. Images after resizing into 200 x 200

Grayscale to the cropped images:

Images are represented using shades of grey in the colour space known as grayscale. To apply grayscale to an image, its native colour space must be changed to grayscale. This method can be helpful in image processing since it can lessen the amount of information required to represent a picture and facilitate processing. When you crop an image, you choose a certain area and eliminate the rest.

Fig. 3. Gray-Scaled Images

Edge detection (Prewitt):

In image processing, edge detection involves locating the boundaries between objects in an image. One of several edge detection techniques is the Prewitt operator, which determines an image's gradient in both the horizontal and vertical dimensions. The edge map, which indicates the regions of the picture where there are noticeable variations in intensity, may then be made by combining the resultant gradients. For applications like object recognition, picture segmentation, and feature extraction, edge detection is a frequent preprocessing step in image processing.

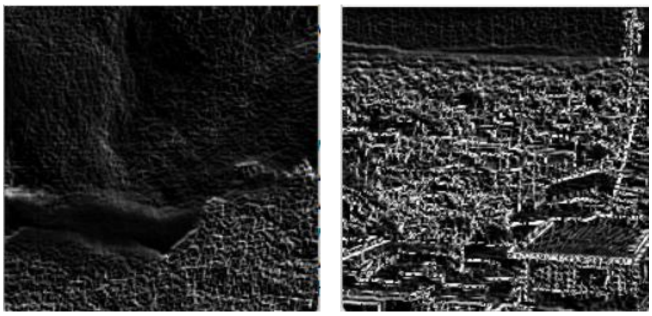

Fig.4.Prewitt Edge detection images

C) Feature Description (BRISK FD):

A FD is a mathematical function or algorithm that is used to extract information from an image or other type of data. In the case of the Identification of rural or urban surroundings system, the brisk FD is used to analyze the visual characteristics of the location being examined. The brisk FD is a popular feature extraction technique that is used in computer vision applications to identify distinctive visual features such as corners, edges, and blobs.

By using the brisk FD in the Identification of rural or urban surroundings system, the system can identify specific visual features that are characteristic of rural or urban areas. For example, the model may detect that a location is rural if it contains more vegetation, fewer buildings, and a lower density of population. Alternatively, the system may identify that an area is urban if it contains more buildings, more roads, and a higher density of population.

Overall, the use of the brisk FD in the Identification of rural or urban surroundings system helps to provide an objective and accurate analysis of a given location based on its visual characteristics.

D) Using K-means Clustering:

The dataset is divided into many clusters using this clustering approach. K should always have an odd value because ties in classification may occur if K cluster values are even. Therefore, the value of K must always be odd to prevent ties. In order to determine the most effective value of K, the accuracy of each of the five classifiers was evaluated while maintaining a constant K value. RF yielded the maximum accuracy of 99.72% when K value was 5, according to a comparison of accuracy for all K values. Thus, K Means Cluster has a value of 5. Table 2.2 displays the classifiers' accuracy for a value of K = 5.

Table.2. Accuracy of classifiers for 5 Clusters

Classifier	Accuracy
RF	99.67%
DT	80.30%
KNN	94.58%
SVM	73.20%
LR	50.52%

E) Training & testing classifiers:

The dataset has to be split into a certain percentage for each classifier (usually 70% for training and 30% for testing). The similar procedure is used here; the dataset comprises 2000 photos, both of urban and rural regions. of which 1400 photos were used to train the model and 600 photographs were used for testing. The ratio used to split the data into training and testing needs to be accurate; else, the accuracy may vary significantly. (Note: - Images from both rural and urban locations are included in the training and testing data.) As a result, a significant amount of training data must pass in order for the model to be trained. This is why training data is typically bigger than testing data. After training, the model uses the testing data to inform its predictions, retaining the patterns from the training set. Five distinct classifiers, each providing five distinct levels of accuracy, are utilized to calculate the accuracy. The resulting results are then compared.

1) RF Algorithm
2) DT Classifier
3) KNN
4) SVM
5) LR

RF Algorithm:
RF is a popular ML classifier for solving classification-related issues. As Fig. illustrates, RF provided the maximum accuracy of 99.79% when the K number of clusters was 5. The ROC curve, a graph that displays the classifier's performance, is displayed in Fig. On the curve, two parameters are displayed.

DT Classifier:
A DT is a node-based classifier. Its structure resembles a tree, and it decides where to put the next node based on impurity. The tree is further split into branches and internal nodes. One technique for prediction and categorization is a DT. It is a structure that resembles a tree that illustrates many outcomes or choices depending on particular input parameters. Each branch of the tree leads to a different choice or result dependent on certain circumstances or regulations. The original input is represented by the root node, while the final decision is represented by the leaf nodes. It is frequently used to decision-making, operations research, and ML. The accuracy given by the DT Classifier was 82.91%.

KNN:
The most basic method of ML. This algorithm selects K neighbors, after which the distance between K closest neighbors is computed. Next, the closest neighbors are selected based on their unique Euclidean distance. The classifier is then prepared. KNN's simplicity and flexibility are its key advantages, although for big datasets, it can be computationally costly. The accuracy of the KNN Classifier was 98.92%.

SVM:
SVM is a well-known technique in supervised learning, which can be used for categorisation and regression problems. However, it is commonly employed for classification problems in ML. The primary objective of the SVM algorithm is to identify the optimal line or decision boundary in n-dimensional space, enabling us to classify new data points into the appropriate category in the future. Here the Linear kernel is used which provides 73.20% accuracy in predicting the classification of new data points.

LR:
It is a data analysis approach that uses mathematics to determine the correlations between two data variables. The connection is then used to forecast the value of one of the parameters depending on the other. Predictions often have a limited number of outcomes, such as yes or no. when liblinear solver is used it gives accuracy 59.01%.

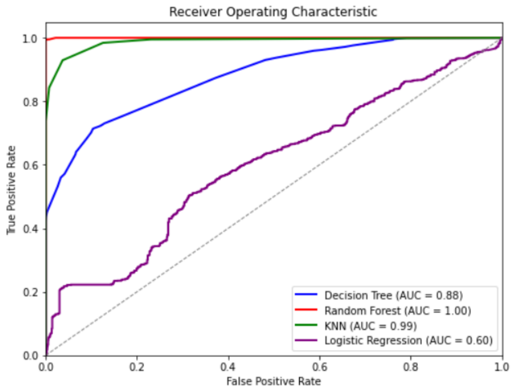

Fig.5. ROC curve for Implemented Algorithms

F) K-Fold Cross Validation:
It divides the dataset into K numbers/samples of groups into the same size. These are known as folds. Here the different prediction function k folds are used for the learning set and the remaining folds are used for the test set. In this work the K value is 3. After comparing the average accuracy for all the values of K, when K value was 5 RF provided the highest of 99.82%. So, the value of K in K-Fold is 3. Table.3. shows average accuracy of different classifiers using k-fold with k value 5.

Table.3. Accuracy of classifiers using k-fold for value K=5

Classifier	Accuracy
RF	99.72%
DT	63.45%
KNN	98.92%
SVM	73.20%
LR	59.01%

IV. CLASSIFIER MODELS RESULT

Table.4. Performance evaluation

Classifier Name	Accuracy	Recall	Precision	F1-Score
RF	99.67	99.83	99.51	99.67
DT	80.30	87.80	71.32	78.71
KNN	94.58	96.33	92.92	94.59
SVM	73.20	71.55	70.08	73.78
LR	50.52	96.13	50.81	66.49

All the parameters were determined once the value of K and the k fold was 5, since the classifier produces effective results when the value of K Cluster is maintained at 3.

V. RESULT

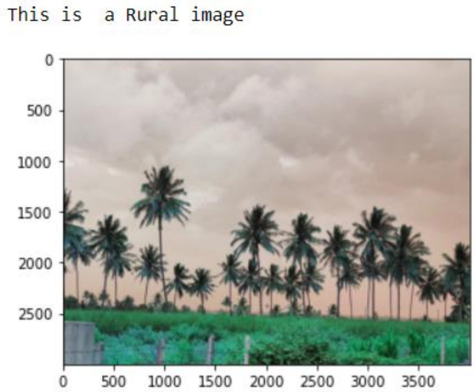

Fig.5. Detection of Rural area

As Fig. 5 illustrates, the model can recognize the rural region with ease. "This is a Rural image," is the message that was sent. To test if the model can distinguish between an urban and rural area, let's input an image of a city.

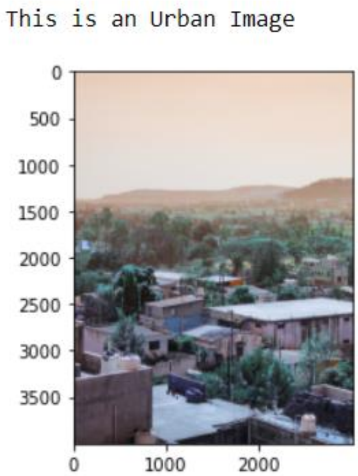

Fig.6. Detection of Urban area

As seen in Fig. 6, the model can recognize the region with ease. "This is an urban image," is the message that was got.

VI. Conclusion and Future Scope

Urban and Rural identification is a challenging problem because there is no clear identification line between two areas. Here, we presented an approach for identifying rural and urban areas, which tended to result in identification maps that were more useful. With this method, it would be possible to classify each building's land use with comparatively high accuracy. The images dataset was provided to various ML classifiers, including SVM, RF, LR, DT, KNN, etc. The results indicates that BRISK is a better feature extraction approach for feature vectors to be extracted for this specific research, with RF giving the highest accuracy of 99.79%. For further work, more data may be included to enhance classification performance, such as text descriptions attached to social media photographs and brand names and other text information that appears in photos.

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