Vision Based Identification of Rural and Urban Surroundings

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Abstract– The study aims to use machine learning (ML)

classifiers to identify whether an image is taken in a rural   
or urban area. The proposed system is built using supervised learning techniques, where a labelled dataset of   
images is used to train the machine learning   
classifiers. The   
system uses a combination of feature extraction and

classification algorithms to accurately classify images as   
rural or urban. The proposed system used BRISK   
feature   
description technique. These descriptive features would   
then be fed into several machine learning (ML)   
classifiers,   
such as Random Forest (RF), K-Nearest Neighbors   
(KNN),   
Decision Tree, Logistics Regression and Support   
Vector   
Machines (SVM) to perform classification. Random Forest   
provides high accuracy as 99.82% when the number of clusters K is 3. The proposed system has practical applications in many fields such as environmental monitoring, land-usage planning, and disaster   
response. By   
accurately identifying rural and urban surroundings, the   
system can provide critical information for policy makers   
and researchers to make informed decisions about land

usage and resource allocation.

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

I.

INTRODUCTION   
 Recent years have seen the quick development of computer   
vision algorithms and it is now possible because of technology   
for remote sensing to automatically differentiate between rural   
and urban areas with high accuracy and efficiency.

This has

wide-ranging practical applications, such as land-usage   
planning, environmental monitoring, disaster   
solution, and   
public health.

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 machine learning 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. Machine learning algorithm’s advancement has brought up new   
prospects for automatic and efficient rural-urban classification.

Machine learning algorithms can learn from large amounts of   
labelled data and extract features automatically, making them   
highly efficient and accurate for identifying rural and urban   
environments. This study gives a summary of the state-of-the-  
art machine learning classifiers for rural-urban categorization   
based on photos from remote sensing.

II.

LITERATURE REVIEW

This paper is a review of the research trends in the field of   
evaluation of an 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 machine learning 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 convolutional neural networks (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 convolutional neural   
networks   
(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 Convolutional Neural   
Networks   
(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   
machine learning 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 machine   
learning 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   
machine learning 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 machine learning method [11].

The paper proposed an overview of the use of machine learning   
in urban spatial analysis. In addition to classifying

trends and   
gaps in the field, the authors hope to provide an overview of the   
many machine learning 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   
machine   
learning   
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 machine learning 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 research focuses on applying machine learning approaches   
to pinpoint mountainous areas with rural residential land that is   
susceptible to desertion. The study makes use of data to develop   
models that forecast the possibility of land   
abandonment   
depending on a number of variables, including   
infrastructure,   
land use, and population density. The findings   
demonstrate that   
machine learning can be a useful technique for   
anticipating land   
abandonment in rural areas, giving decision-makers and land   
managers important information to assist solve the problem   
[18].

The study explains how to define metropolitan zones

using a   
machine learning method. The system precisely locates and   
maps the boundaries of metropolitan regions using satellite   
images and other data sources. The outcomes show how well   
the algorithm defines urban areas precisely, which is important   
for applications like resource management and urban planning.

The study emphasises how machine learning can be used to   
analyse and comprehend the spatial patterns of   
urbanisation   
[19].

The approach for autonomous navigation described in this   
study uses visual data. The system consists of a visual   
positioning system (VPS) that locates the device in an indoor   
or outdoor area using computer vision techniques. The VPS   
functions by identifying elements in the environment and   
comparing them to a previously created map, which enables the   
device to estimate its position in real-time. The system has   
undergone testing in a variety of indoor and outdoor settings,   
and results in terms of precision and effectiveness have been   
encouraging [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 machine learning 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   
machine   
learning   
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 Feature Descriptor): A feature descriptor 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 feature descriptor is used to   
analyze the visual characteristics of the location being   
examined. The brisk feature descriptor 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 feature descriptor 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 feature descriptor 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) Applying K-means Clustering:   
In this clustering algorithm the dataset is grouped into various   
clusters. The value of K should always be odd because if the   
value of K clusters is even then there can be ties in

classification   
so to avoid the tie the value must be odd. In this work the K   
value was kept constant and accuracy of all 5   
classifiers was   
compared, so that the most efficient value of K could be   
obtained. After comparing the accuracy for all the values of K,   
when K value was 5 Random Forest provided the highest of   
99.72%. So, the value of K Means Cluster is 5.

Table.2. shows   
Accuracy of classifiers for value K=5.

Table.2. Accuracy of classifiers for 5 Clusters

Classifier   
Accuracy   
Random Forest   
99.72%   
Decision Tree   
76.70%   
KNN   
77.52%   
SVM   
72.01%   
Logistics Regression   
60%

E) Training & testing classifiers:   
For every classifier, the dataset must be divided into a   
specific proportion (mostly 70% for training and 30% for   
testing). The same thing is done here, the dataset consists of   
2000 images including rural and urban areas. Out of which the   
model has been trained on 1400 images and has been

tested on   
600 images. Proportion for dividing the data into training and   
testing must be proper, if it is not then the   
accuracy can change   
drastically. (Note: - The training and testing data includes both   
rural and urban areas images) Training data is   
usually larger   
than testing data because, by doing so models can learn   
meaningful patterns, hence it is necessary to pass a big portion   
of training data for training the model. Once the model is   
trained, it inherits the patterns from the trained data and makes   
predictions on the basis of testing data. To   
determine the   
accuracy 5 different classifiers are used which provide 5   
different accuracy and later the obtained result is compared.

1) Random Forest Algorithm 2) Decision Tree Classifier 3) KNN   
4) SVM   
5) Logistics Regression

Random Forest Algorithm:   
Random forest is a machine learning classifier which is widely   
used when dealing with the problems related to   
classification.

As shown in Fig. when the K number of clusters were 5

Random Forest provided the highest accuracy of 99.79% Fig.

shows the ROC curve, this curve is a graph which shows the

performance of the classifier. There are 2 parameters plotted on   
the curve.

Fig.5. ROC curve provided by Random Forest Algorithm

Decision Tree Classifier:   
Decision Tree is a classifier which comprises nodes.

It has a   
tree-like structure and on the basis of impurity it determines   
where the next node should go. Further the tree is divided into   
internal nodes and branches. A decision tree is a method used   
for classification and prediction. It is a tree-like structure that   
represents different possible outcomes or decisions based on   
certain input conditions. The tree branches out based on   
specific conditions or rules, and each branch leads to a specific   
outcome or decision. The root node represents the initial input,   
while the leaf nodes represent the final decision.

It’s commonly   
used in machine learning, operations research, and decision   
making. Decision Tree Classifier provided the accuracy of   
82.91%.

K Nearest Neighbour (KNN):   
The simplest machine learning technique. In this algorithm K

number of neighbors are selected and then distance of K nearest   
neighbors is calculated. Then the neighbors which are nearest   
are taken according to their particular Euclidean distance. Then   
the classifier is ready. The main advantage of KNN is its   
simplicity and flexibility, however, it can be   
computationally   
expensive for large datasets. KNN Classifier provided the   
accuracy of 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 machine learning. 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.

Logistics Regression:   
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%.

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 Random Forest   
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   
Random Forest   
99.79%   
Decision Tree   
82.91%   
KNN   
98.92%   
SVM   
73.20%   
Logistics Regression   
59.01%

IV.

CLASSIFIER MODELS RESULT   
Table.4. Performance evaluation

Classifier   
Name   
Accuracy   
Recall   
Precision   
F1-Score   
Random   
Forest   
99.79   
96.33   
92.92   
94.59   
Decision   
Tree   
82.9   
76.34   
74.92   
75.39   
KNN   
98.92   
97.61   
98.82   
99.59   
SVM   
73.20   
71.55   
70.08   
73.78   
Logistics   
Regression   
59.01   
58.23   
53.31   
60.17

After the value of K and k fold is 5, calculated all the   
parameters, because when the value of K Cluster is kept 3 the   
classifier provides efficient results.

V.

RESULT

Fig.6. Detection of Rural area

As shown in Fig.6 the model is able to identify the rural area   
easily. And the message received is “This is a Rural image”.

Now let’s input an urban image to see if the model can detect   
the urban or rural.

Fig.7. Detection of Urban area

As shown in Fig.7 the model is able to identify the area easily.

And the message received is “This is an Urban image”.

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 machine   
learning   
classifiers, including SVM, RF, Logistics regression, Decision   
Tree, KNN, etc. The results indicates that BRISK is a better   
feature extraction approach for feature vectors to be extracted   
for this specific research, with Random Forest 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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