

SATELLITE IMAGE CLASSIFICATION METHOD USING CLASSIFIER IN MACHINE LEARNING

A Project Report Phase - II

Submitted in partial fulfillment of the requirements for the award of Bachelor
of Engineering Degree in Electronics and Communication Engineering

By

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **CHALLAGULLA SAI DINESH (39130085)** and **DUDEKULA AVINASH (39130124)** who carried out the project entitled **“SATELLITE IMAGE CLASSIFICATION METHOD USING CLASSIFIER IN MACHINE LEARNING”** under our supervision from November 2022 to April 2023.

Internal Guide

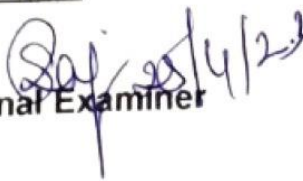
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We, CHALLAGULLA SAI DINESH (39130085) and DUDEKULA AVINASH (39130124) who carried out the project entitled "SATELLITE IMAGE CLASSIFICATION METHOD USING CLASSIFIER IN MACHINE LEARNING" done by us under the guidance of Mr.L.JEGAN ANTONY MARCILIN, M.Tech., Department of Electronics and Communication Engineering, at SATHYABAMA INSTITUTE OF SCIENCE AND TECHNOLOGY, CHENNAI is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in Electronics and Communication Engineering.

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DATE:25-04-23

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ABSTRACT

In the era of artificial intelligence, the computer science community is becoming increasingly interested in remote sensing, particularly satellite imagery, as part of their efforts to enable machines to recognize their surroundings through satellite image classification. Images of the Earth are provided by imaging satellites, which are then gathered, examined, and processed for both civic and military uses. In fact, there are a wide range of uses for satellite images, including in the study of the weather, the oceans, fisheries, farmland, biodiversity, geology, cartography, land use planning, and even in the military. Instead of simply having an image of a location, satellite image classification seeks to transform satellite imagery into information that can be used. It depends on a variety of strategies and techniques that can be used in accordance with particular situations and conditions. These strategies and techniques can be divided into five groups: supervised classification, unstructured classification, pixel-based classification, object-oriented classification, and CNN classification. This survey will examine these methods based on their datasets, image resolutions, and image types, algorithms, and techniques, and will highlight and explore their advantages and disadvantages.

For the classification of satellite images into 24 separate classes, machine learning-based support vector machine (SVM) and Extended local Binary Patterns (ELBP) algorithms were applied. This work can classify 24 different classes in addition to satellite images. However, identifying the features of those classes, such as the human face, football and rugby is also simple because these other classes have some unique features that can be easily distinguished, allowing for easy classification. The fundamental challenge in the case of satellite photos is that distinct satellite images may have different attributes, making satellite image classification difficult. Another difficulty is that most satellite photos are noise corrupted. The SV Classifier is used to estimate the noise patterns in the wireless image, and the estimated noise patterns are then removed using the SVM signal classification technique. Using the proposed ELBP approach, this research discovers local binary patterns. Because the patterns of distinct satellite photos and other class images cannot be distinguished simply using LBP, the Extended LBP is required.

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LIST OF ABBREVIATIONS

Abbreviations	Meaning
CNN	Convolutional Neural Network
SVM	Support Vector Machine
ELBP	Extended Local Binary Pattern
LBP	Local Binary Pattern
RNN	Recurrent Neural Network
RF	Random Forest
KNN	K-nearest Neighbor
BPNN	Back Propagation Neural Network
PBL	Presence and Background Learning
DCCN	Dual-Channel Convolutional Network
ANN	Artificial Neural Network

CHAPTER – 1

INTRODUCTION

1.1 Introduction

The electromagnetic (EM) energy coming from or being reflected off of terrestrial things is collected and measured by satellite imagery systems. The electromagnetic spectrum is made up of a variety of frequencies, including microwave, ultraviolet, infrared, and visible light. The sun is the primary source of electromagnetic radiation. Each item on Earth has a unique reflection at a particular wavelength. The intensity of the reflection or radiation helps to distinguish different objects in the satellite picture, such as water, trees, buildings, etc.

Different sensors and scanners that work in a range of electromagnetic energy spectrum bands produce satellite pictures. They are two-dimensional, and the intensity varies according to the average quantity of energy that is reflected or radiated from a region on the earth's surface or from space in a particular wavelength band. The following factors affect satellite imagery's quality: sources of energy: active and inactive; Sensor resolutions include real-time energy reflectance or absorption measurements, atmospheric interference, geographic, temporal, spectral, and radiometric resolutions. The sensors have two different kinds of modes for taking pictures: passive mode and active mode.

Optical sensors and microwave sensors are the two major categories of sensors. optical detectors There are two categories of optical sensors: visible and invisible optical sensors. Visible optical sensors gather the strength of visible light rays that are reflected by the earth and objects, such as a sea, forests, and rivers, from which the user can understand the nature of the object. However, the drawback of this type is that they perform poorly at night and inclement weather. On the other hand, optical infrared devices can detect things at high temperatures on the Earth's surface even in the dark in addition to collecting infrared rays emitted by terrestrial objects.

Microwave sensors: Irrespective of atmospheric conditions, this form of sensor gathers microwaves reflected from the earth and objects. For the monitoring of ice conditions, such as thickness and temperatures, as well as sea, river, and valley conditions, microwave sensors are used. Remote sensing relies heavily on picture classification because it enables data analysis and extraction from satellite images.

This aids in information provision and decision-making in numerous studies of municipal planning, military strategy, agricultural production, etc. According to D. Jawak and colleagues, classifiers for extracting data from satellite images are built on supervised learning and unsupervised learning. Pixel-based classification and object-oriented classification are two of the various kinds of classification.

1.1.1 Satellite Imagery Types and Resolutions

A. Satellite imagery types

Satellite images are extremely detailed and are essential for providing data for spatial planning, building evolution analysis, for instance, tracking of national territories, etc. Panchromatic, multispectral, and hyperspectral satellite pictures are the three different categories.

Panchromatic Images: Panchromatic photographs Images that are obtained in a broad band that spans the full visible spectrum, or between 0.4 and 0.7 m, are called panchromatic images. For these, only black and white images are available, and while the panchromatic image provides a higher spatial resolution, it is less spectrally rich.

Multispectral images: Multispectral images are a collection of pictures taken by various sensors that operate in discrete or continuous narrow wavelength bands. They are acquired through concurrent recordings in a few spectral regions. (3 to 8). It is possible to create colour images by combining these bands of digital information with the three main colours (red, green, and blue).

Hyperspectral images: In the visible, mid-infrared, and near-infrared regions of the electromagnetic spectrum, hyperspectral images are produced by sensors that can capture data in a large number— often more than 200—of much narrower, and frequently contiguous, spectral bands. Therefore, compared to broadband sensors, hyper-spectral data offers more precise information about the spectral characteristics of a scene and enables more precise object recognition and discrimination.

B. Satellite imagery resolutions

Four different levels of sharpness can be found in satellite images: Radiometric, spectral, spatial, and temporal precision. Resolution of the spectrum It relates to the width, sensitivity, and location of the spectral bands and defines a sensor's capacity to use small wavelength windows.

The energy collected at various wavelength intervals (spectral bands) can be captured by a variety of remote sensing devices with varying spectral resolutions.

Spatial resolution: The smallest area at any given moment that a single sensor can cover is known as spatial resolution. It is feasible to discern small objects with a high resolution. A variety of values are used to classify the spatial resolution. There are three primary number ranges: Low-resolution systems are those with spatial resolutions less than 1 km, medium-resolution systems are those with spatial resolutions between 100 m and 1 km, and high-resolution systems are those with spatial resolutions between 5 and 100 m.

Temporal resolution: Time between picture acquisitions or views of the same scene, such as revisit time or repetition rate, is referred to as temporal resolution. It relies on elements like satellite orbit and the observing angle.

Radiometric resolution: The term "radiometric resolution" refers to the capacity to detect subtle variations in electromagnetic energy. A sensor's sensitivity to subtle variations in the intensity of energy received increases with a sensor's radiometric precision. It describes how many "numerical number precision" grey levels are used to show image data from scanners and sensors.

Satellites provide information on the surface and weather changes on planet Earth, among the satellite data sets, are:

A. Indian Pines Dataset

Indian Pines is a data set that was gathered by the AVIRIS sensor on June 12, 1992, at the Indian Pines test location. It consists of a total of 16 classes. It had 224 bands with a spectral precision of 10 nm and a spatial resolution of 20 m, and it covered a 2.9 2.9 km² (145 145 pixels) land area in the northwest in the Pine Indian region. The fact that all classes held mixed pixels and that the number of pixels labelled per class was uneven are two challenging issues with this data set.

B. Formosat-2 Dataset

The Formosat-2 spacecraft captured the Formosat-2 collection of satellite pictures. The National Space Organization of Taiwan created and is in charge of the latter, formerly known as ROCSAT-2. When this spacecraft was launched in 2004, one of its main goals was to gather panchromatic and multispectral images for a variety of uses, including assessing natural disasters, monitoring the environment, and land use,

agriculture, and forestry.

With a scene coverage of 24 km 24 km, this satellite's images are accessible for 2 m in panchromatic and 8 m in multispectral from visible to near-infrared. Unfortunately, FORMOSAT-2 was decommissioned in August 2016 and all archived images are still available for order.

C. QuickBird Dataset

Geospatial information and high-resolution pictures are both included in the QuickBird dataset, which can be used in remote sensing and geographic information systems (GIS). Digital Globe purchased the initial QuickBird datasets on August 1 and 2, 2002. On October 18, 2001, at Vandenberg Air Force Base in California, USA, the QuickBird satellite sensor from Digital Globewas safely launched. This sensor enables the collection of images with a resolution detail of 0.7 mfor panchromatic images and 2.8 m for multispectral images.

D. Others

There are many various types of satellite data available today, each with a unique resolution and setof properties. In addition to the one already stated, other datasets exist. Some of the most well- known datasets include LANDSAT, SPOT, IKONOS, Salinas, etc. The spatial, spectral, and temporal resolution of each of these satellite data varies, and the picture types can be panchromatic, multispectral, or hyperspectral depending on the satellite that took the photo.

1.2Problem Statement

The current system has many different satellite image classifier systems implemented, but none ofthem are effective due to improper dataset utilisation and low accuracy algorithm implementation.

1.3 Objective

- Implementing SVM algorithm is the project's primary goal.
- The project's second goal is to use ML algorithms to create a productive system.

1.4 Proposed system

Proposed system for a satellite image classification method using a classifier in machine learning would typically consist of the following components:

Data gathering: The proposed system's first move would be to gather satellite images that are pertinent to the application. This could entail acquiring commercially available satellite imagery, downloading openly accessible satellite imagery, or gathering images with unique sensors.

Preprocessing: The preprocessing of the acquired satellite images would then be used to enhance their clarity and get them ready for analysis. This might involve operations like picture augmentation, filtering, and segmentation.

Feature extraction: The preprocessed satellite images would be examined to extract pertinent features that could aid in differentiating between various kinds of land cover or other pertinent data. Techniques like texture analysis, colour analysis, and form analysis might be employed in this.

Classification: After that, a machine learning classifier, such as a decision tree, random forest, support vector machine, or deep neural network, would be trained using the extracted characteristics. Each picture in the labelled dataset would be assigned to a specific class or category, which would be used to train the classifier.

Evaluation: A validation dataset would be used to test the trained classifier's performance and accuracy on pictures that weren't included in the training process.

Deployment: The classifier can be used to categorize fresh satellite images once it has been trained and verified. The classifier could produce maps, track trends, or assist decision-making independently or as part of a larger system.

1.5 Advantages Of Proposed Methodology

- cost-efficient, with precise data collection.
- The proposed method uses accurate data, which enhances performance.
- Real-time monitoring is carried out to enable easy operation from any location.

1.6 Difference Between Proposed and Existing Methodology

Predictions made by the current algorithms are not very reliable. They have not changed over time or in response to technological developments. Additionally, the outcomes are unsatisfactory and could result in incorrect satellite picture classification. The accuracy and time efficiency of the proposed system outperform all earlier ones.

CHAPTER-2

LITERATURE SURVEY

An image repository, with around 1000 images, labelled with their soil-types, is also created for this work. The images, used here are of high resolution, acquired with LANDSAT-8 satellite. We have performed our study with these large number of labelled images from each soil type, captured in different time. We developed a method of soil classification with deep convolutional neural network. The merits of this method is experimentally validated with suitable comparison and proved to be effective in identifying proper soil class accurately.

The deeper Convolutional Neural Network (CNN) model without any satellite image specific parameters is proposed. On SAT4 and SAT6 images, our 13-layered network has achieved better accuracy upto 99.84% and 99.47% which is state-of-the-art. It is still called lightweight model because most models in Artificial Intelligence (AI)-CNN are much deeper and larger than theirs.

The approaches and methods fall into five categories which are supervised classification, unsupervised classification, pixel-based classification, object-oriented classification, and Convolutional neural network classification or CNN classification. The goal of this paper is to present a survey which will review these methods based on their algorithms and techniques, datasets, image resolutions, and image types, and will show and discuss their strengths and weaknesses.

The CNN models fully trained and the CNN models trained using transfer learning were compared in aspect of accuracy to classify satellite images. It has been observed that the CNNs trained using transfer learning yielded more accurate results for each dataset used in the study.

Land cover classification also helps in identifying the changes in the land cover. Most satellites along with high-end sensors provides pixel wise data. Due to high resolution images, the number of pixels which are generated are in millions even for the study of a small area. Therefore, there is a need to balance runtime and accuracy for this task. In this paper, they did a comparative study of the models comparing Multi CNN model with traditional models to classify land cover from multi-spectral temporal Landsat-8 satellite data

CNN algorithm is also used for classification and labeling of classification is done automatically by the use of CNN algorithm. Random forest is used to segregate two landscapes as used and unused land which gives accuracy better than the existing systems CNN (Convolutional Neural Network) has been generally used to do image classification, and it can be applied to many daily situations like damage assessment. In this paper, we build a CNN model and discuss its advantage over other present models. Besides, to increase the robustness of our model, we add image enhancement to our training data. The preliminary model can reach an accuracy of 0.9706 in our experiment.

In this proposed system they first propose a 1D convolution neural network-based framework applied to each pixel in the spectral domain where we extract descriptive local features for improved classification. Experimental results demonstrate superior classification accuracy through comparison with traditional unmixing-based and neural network methods using just limited number of training samples.

Some of the algorithms used in satellite imagery classification are U-Net, Random Forest, DeepLabv3, CNN (Convolutional Neural Network), ANN (Artificial neural network), Resnet etc. In this project, DeepLabv3 (Atrous convolution) algorithm is used for land cover classification. The dataset used is the deep globe land cover classification dataset. DeepLabv3 is a semantic segmentation system that uses atrous convolution to capture multi-scale context by adopting multiple atrous rates in cascade or in parallel to determine the scale of segments.

Such as Support vectormachine (SVM), C-means, K-means. Neural Network (CNN) and Recurrent NeuralNetwork (RNN), Random forest (RF), K-nearest neighbor (KNN), regression, Back propagation neural network (BPNN), Feed forward neural networks, Fuzzy classification. The paper covers detailed overview of various classification methods. More research is required to improve classification.

It has expanded quickly with the development of efficient models and high-powered computers. Machine learning is developing in satellite remote sensing image processing. Agriculture data drives most decisions in India. This research uses Sentinel-2 temporal remote sensing photo data to categorize crops. Guntur, India, is studied. This region was selected for its agriculture and terrain. SVM, RF, CNN, RNN with LSTM, and RNN with GRU crop classification performance examined. Classification accuracy is evaluated using test data. Test data categorization accuracy seldom matches image crop areas. These methods reduce crop area estimations. Crop regions test this work's categorization accuracy. SVM's F1 score is 0.99, and its estimations of major agricultural regions are 95.9% accurate.

Satellite image categorization helps extract and analyze data. It classifies images by their features. Classification identifies information and patterns in satellite pictures. Any remote sensing investigation bases decisions on categorization efficiency. Image categorization is difficult. Many things impact this process. This study examines satellite image categorization methods. Support vector machine (SVM), C-means, K-means, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN), Random forest (RF), K-nearest neighbor (KNN), regression, Back propagation neural network (BPNN), Feed forward neural networks, Fuzzy classification. The article summarizes categorization techniques. Classification needs further investigation.

Remote sensing experts have long monitored urban expansion. Spectral indices and supervised classification can automatically remove urban regions, sparing technicians from manually digitizing polygons. Multiclass classifications are accurate. Such systems are labor- intensive and costly since they involve identifying all classrooms in the study area. Many applications just need one land class. One-class classification (OC) issue. In this study, we compare Binary Random Forest (RF), OC-

Support Vector Machine (OCSVM), and Presence and Background Learning (PBL) for extracting built-up regions from Landsat data. PBL-based technique gives competitive extraction outcomes with minimal effort.

Recent years have seen a rise in digital image processing. This paper tackles workload allocation and load balancing in concurrent image processing and remote sensing. Task dispersion may speed up calculation, enhance efficiency, and do greater computations than a single processor. The tasks are distributed based on color segmentation, and SVM is used to classify the input image's indices. The goal is to build and enhance a colour segmentation-based task distribution approach for index classification using machine learning. The system inputs an RGB satellite picture and outputs forest, building, road, and land indices. Distributed computing technologies provide more accurate and faster outcomes. It uses multicore processors and computer clusters to perform computationally and data-intensive problems in MATLAB using parallel computing toolkit.

KOMPSAT-3A is a high-resolution earth observation satellite constructed by KARI. In this study, we develop a technique for recognizing ships and quantify its performance using 0.55m- resolution pan-sharpened KOMPSAT-3A photos. Machine learning based detection technique is needed to recognize ships with irregular forms and backgrounds, especially in satellite photos where radiometric characteristics vary greatly. To handle these discrepancies, we use binary features and AdaBoost classification. The experiment reveals that the algorithm retains appearance attributes and has competitive detection performance.

Due to their comprehensive feature representation, convolutional neural networks (CNNs) are commonly used for HSI categorization. CNN-based HSI classification approaches typically use patch-based learning. Nonglobal learning approaches restrict global information utilization and are computationally expensive. This letter introduces HSI classification's image-based global learning methodology. We propose a dual-channel convolutional network (DCCN) for HSI classification to optimise global and multiscale information. Experiments on two genuine hyperspectral datasets show that our technique is more efficient and accurate for HSI classification.

Crop mapping predicts grain output. Machine learning may enhance human field measurement using pattern classification and remote sensing images. Satellite sensor resolution improves object-based categorization. Choosing OBCS parameters is difficult. This study uses Gaofen-2 (GF-2) pictures and ensemble learning to categorize crop distribution in Jishan County, Shanxi Province, China. This approach uses estimations of the scale parameter (ESP) to identify "good" scales, then filters feature subsets by each desired scale as input to numerous classifiers and classifications. Combining all classifications. The multiscale weighted classification technique is more accurate than the single preferred scale approach, according to our study. This method permits ensemble learning across scales and classifiers. It bypasses segmentation scales and classifiers

Earth observation is the study of surface processes and their interactions with the atmosphere. Advances in remote sensing led to new satellite image categorization systems, simplifying vast volumes of data. Satellite pictures face issues in signal extraction and image interpretation accuracy. Machine Learning offers potential answers. This study compares supervised classification approaches including SVM, ML, Neural Network, Minimum Distance, and Spectral Angular Mapper. Wesley College, EACH University, Vellikuppampalayam farm, and Greek Islands were analyzed. Simulation findings suggest SVM and ML are excellent for categorizing satellite photos. ML yields roughly 2 to 4% more accuracy than SVM for pictures; Wesley College, The Greek Island.

Shadows make images and videos crucial, thus removing them is a must, particularly for satellite images. The approach removes satellite image shadows. Our approach detects and removes shadows from satellite images by learning the attributes of super pixels and picture edges using Support Vector Machines (SVM). Shadow mask created using CRF model. Images' shadow characteristics are recovered, then an SVM classifier collects the shadow matte and shadows. Shadow elimination using Bayesian formulation and Gray Level Co-Occurrence Matrix.

Land use and land cover classifies land cover areas into groups. Classifying land use and land cover helps monitor and identify land cover classes. So, we can save land cover objects. Machine learning and deep learning help classify land use and land cover. SLRNNs are utilized in this study to categorize LISS-IV photos into land cover classes. Shared layer architecture is presented.

Shared layer Recurrent neural network is compared to CLRNN, ULRNN, and standard RNN. Recurrent neural networks enable multitask learning. Due to multitask learning, SLRNN classifies LISS-IV multispectral satellite photos accurately. SLRNN has 5% higher accuracy than ULRNN, and 10% than regular RNN. This method's outcomes are better than other, % than.

CHAPTER-3

AIM AND SCOPE

3.1 AIM OF THE INVESTIGATION

The aim of this project is to develop a machine learning classifier method for satellite image classification that is reliable and accurate in extracting valuable insights from satellite images. The project will focus on specific objectives depending on the application, such as accurately identifying various land cover types, including forests, urban areas, agriculture, and water, which could be helpful for environmental monitoring, natural resource management, and land use planning. Alternatively, the project could aim to monitor patterns of urban growth and development or changes in environmental features such as vegetation cover, water quality, and soil erosion, which could contribute to ecosystem management, climate change monitoring, and disaster response. In the event of an emergency, the project could concentrate on developing a classification method that quickly identifies areas affected by natural disasters like floods, wildfires, or earthquakes to help emergency responders allocate resources and aid more effectively. The project report will detail the key steps involved, including data preprocessing, feature extraction, algorithm selection, model training and validation, and deployment of the classification pipeline. The report will also outline the challenges encountered, such as the availability of high-quality satellite image data, the complexity of the image classification task, and the selection of the appropriate feature extraction and classification algorithms. The report will conclude with a performance analysis of the model, including metrics like accuracy, precision, recall, F1 score, and confusion matrix. Finally, the report will discuss the potential applications of the project in various fields, such as environmental monitoring, disaster response, and land use planning, among others.

Land cover mapping: Creating a classification technique that can correctly recognize and categorize various kinds of land cover (such as forest, urban, agricultural, and water) in satellite images may be the goal of the study. Applications like ecosystem surveillance, land use planning, and natural resource management can all benefit from this.

Urbanization mapping: The investigation's goal could be to create a classification technique that can recognize and track trends in metropolitan growth and development in satellite pictures. Planning for crisis reaction and urban growth as well as the creation of transportation infrastructure can all benefit from this.

Environmental monitoring: Creating a classification technique that can recognize and track changes in environmental characteristics like vegetation growth, water quality, and soil erosion in satellite pictures may be the goal of the study. Applications like ecological management, tracking climate change, and responding to natural disasters can all benefit from this.

Disaster response: The investigation's goal could be to create a classification technique that can rapidly spot natural disaster-affected regions in satellite images (such as floods, wildfires, and earthquakes). This can help disaster responders distribute resources and provide assistance more effectively.

Alternatively, the investigation could focus on developing a classification method to monitor patterns of urban growth and development or changes in environmental features, including vegetation cover, water quality, and soil erosion, which could be beneficial for climate change monitoring, ecosystem management, and disaster response. In the event of a natural disaster, the investigation may concentrate on developing a classification method that can quickly identify areas impacted by floods, wildfires, earthquakes, etc., to assist emergency responders in prioritizing their resources and allocating aid efficiently.

3.2 SCOPE OF THE INVESTIGATION

Developing a satellite image classification system using a machine learning classifier involves several important areas to consider. The aim is to extract meaningful information from satellite images accurately and reliably. One critical area is image data preprocessing, which refers to tasks like image normalization, filtering, and segmentation. The quality of satellite images can vary widely, depending on factors such as weather conditions, sensor calibration.

These factors can make it challenging to analyze the images accurately. As a result, image preprocessing is often necessary to improve image quality and prepare images for analysis. Feature selection is another crucial area to consider. This involves identifying the most important features in satellite images that can help distinguish different types of land cover or other relevant information. Common features used in satellite image analysis include texture, color, and shape. Feature selection can be a complex process, and the choice of features can have a significant impact on the accuracy of the classification model.

The selection of the appropriate machine learning algorithm is also crucial. There are several machine learning algorithms that can be used for satellite image classification, including decision trees, random forests, support vector machines, and deep learning models like convolutional neural networks. The choice of algorithm depends on several factors, such as the complexity of the problem and the size of the dataset.

Training and validation of the classification model is also critical. This involves dividing the dataset into training and validation sets, using the former to train the classification model and the latter to assess its performance. The goal is to optimize the model to achieve the highest possible accuracy on the validation set. This can involve fine-tuning model parameters, selecting the most appropriate features, and adjusting the choice of machine learning algorithm. Finally, once the classification model is trained and validated, it can be deployed to classify new satellite images in real-time or as part of a batch processing workflow. Deploying the classification model can involve integrating it into an existing software system or building a new application. The deployment process can also involve monitoring the performance of the classification model and making adjustments to improve its accuracy and reliability.

In summary, developing a satellite image classification system using a machine learning classifier involves several critical areas to consider, including image data preprocessing, feature selection, algorithm selection, model training, and deployment. The aim is to develop a reliable and accurate approach for analyzing satellite images to extract meaningful information that can be used for various applications, such as environmental monitoring, land use planning, urban planning, disaster response planning, and ecosystem management.

CHAPTER-4

METHODS

4.1 METHODOLOGY

1. Data Acquisition and Pre-Processing
2. Model making
3. Analyzing The Results

4.1.1 MODULE-1: Data Acquisition and Pre-Processing

In this research, highlights from four distinct classes of images were used to train the framework. Highlights of those preliminary images include Support Vector Machine and Extended Local Binary Patterns (ELBP). (SVM). For one lesson, this assignment requires at least five ready-made images.

Pre-Processing Data

Pre-processing is a general term for actions that use low-complexity pictures as input and produce intensity images as output. The iconic images are all of the same type as the original sensor signals, with an image matrix frequently used to depict an intensity picture. Values in action (artistry). The geometric development of images, such as booty shaking, sizing, and reinterpretation, have been named among also before the styles, though, as analogous methods are now in use. Before that, the outcome would be an improvement of something like the dataset, which would prevent unintentional nonlinear behavior or improve some feature extraction from photographs.

4.1.2 MODULE 2: MODEL MAKING

At that moment, the highlights of the test image were extracted as was removed from the process of photographing currently believe about the ELBP highlights and the LSVM highlights the selection of characterization is dependent on ELBP, as well as from LSVM.

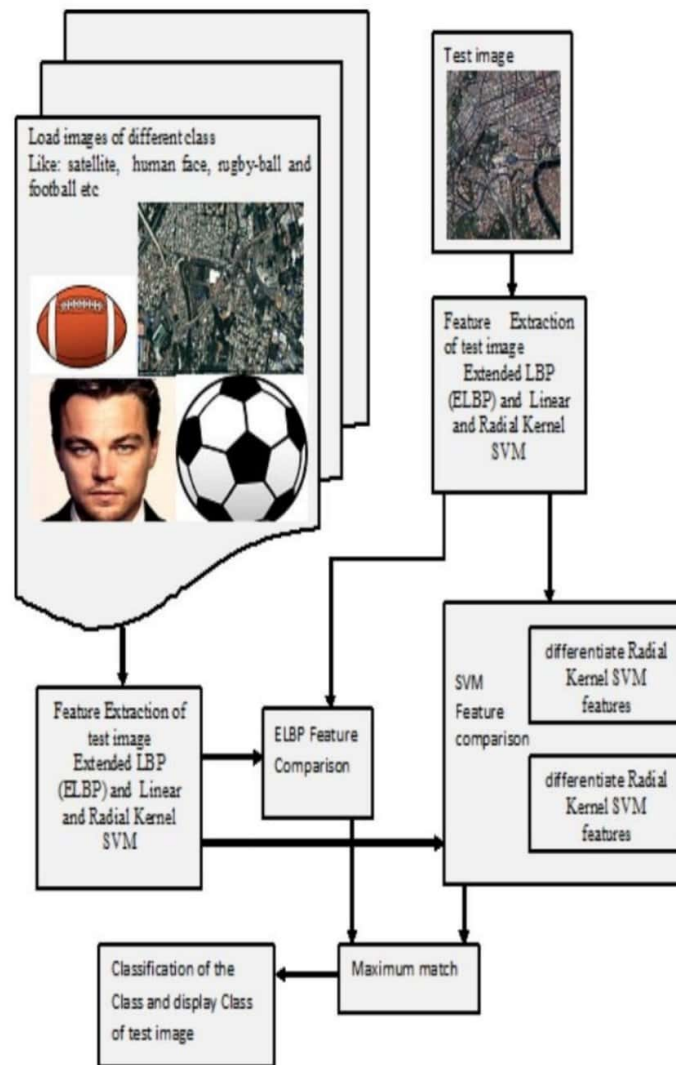


Fig: 4.1: ELBP and SVM image processing

a. ELBP and LBP

Gridding is the suggested method for dividing large amounts of data into distinct groups, naturally for computer language reasons. There appear to be many dependent variables, and converting such sizable datasets usually necessitates the use of numerous online tools. Techniques for selecting, but instead of combining, data points to produce features make sure that the data that must be prepared is done so in a completely labeling way or rather while still effectively.

Object recognition comes in useful because we need to reduce the amount of processing money required without losing essential or crucial data. The suggested method might also help cut down on redundant data in a query. As a result, teaching or generalization processes in the computational component are sped up by text analysis or user efforts to create variable combinations (features). The Gicm Trend (LBP) texturing operator is a straightforward but powerful shading operator that labels real pixels in an image by thresholding the area around each pixel and interprets the result as more than just bitwise integers.

The RGB image operation is growing in popularity across a variety of uses due to its racial bias capability and processing efficiency. It could also be seen as a method of unifying the various geometrical and mathematical ideas of pattern detection. The LBP pilot's resistance to recurring gray and black changes brought on, for example, by variations in illumination, may be its most crucial implementation characteristic. Its operational simplicity, which allows it to analyze images in difficult real-time contexts, is another noteworthy feature. An improved version of LBP called ELBP divides the image into three separate images depending on the color configuration. (red, blue, and green). The pattern numbers are combined after being extracted from all three images. At able-format mat file is used to store the data gathered for each picture in the dataset.

Local binary patterns (LBP) are a family of visual descriptors used in computer vision for classification. The Texture Spectrum model, first suggested in 1990, has a specific application in LBP. LBP was initially explained in 1994. Since then, it has been discovered to be a strong feature for texture classification, and additionally, it has been found that on some datasets, combining LBP with the Histogram of Oriented Gradients (HOG) descriptor significantly enhances detection accuracy. Silva et al. conducted a comparison of several enhancements to the initial LBP in the area of background.

Pre-processing is a general term for actions that use low-complexity pictures as input and produce intensity images as output. The LBP feature vector, in its simplest form, is created in the following manner:

- Divide the examined window into cells (e.g., 16x16 pixels for each cell).
- For each pixel in a cell, compare the pixel to each of its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.). Follow the pixels along a circle, i.e., clockwise or counterclockwise.
- Where the center pixel's value is greater than the neighbor's value, write "0". Otherwise, write "1". This gives an 8-digit binary number (which is usually converted to decimal for convenience).
- Compute the histogram, over the cell, of the frequency of each "number" occurring (i.e., each combination of which pixels are smaller, and which are greater than the center). This histogram can be seen as a 256-dimensional feature vector.
- Optionally normalize the histogram.
- Concatenate (normalized) histograms of all cells. This gives a feature vector for the entire window.

Local Binary Pattern (LBP) is a widely used texture descriptor that has gained much attention in the computer vision and image processing community. The LBP descriptor is efficient and robust in handling changes in illumination, noise, and image deformation. It is particularly useful in tasks such as face recognition, texture analysis, and object detection.

The LBP feature vector can be generated by dividing the examined image into overlapping sub-regions or cells, where each cell contains a set of pixels. For each pixel in a cell, the LBP operator computes a binary pattern based on the comparison of the pixel intensity with its surrounding neighbors. The binary pattern is then used to construct a histogram of the occurrence of each pattern within the cell. The final feature vector is formed by concatenating the histograms of all the cells.

Moreover, several variations and extensions of the LBP descriptor have been proposed, including rotation-invariant LBP, uniform LBP, and multi-scale LBP, to further enhance its performance in different applications. Overall, the LBP feature vector is a powerful tool in image processing and computer vision, providing a simple and efficient way of characterizing the texture of an image.

A useful extension to the original operator is the so-called uniform pattern, which can be used to reduce the length of the feature vector and implement a simple rotation invariant descriptor.

This idea is motivated by the fact that some binary patterns occur more commonly in texture images than others. A local binary pattern is called uniform if the binary pattern contains at most two 0-1 or 1-0 transitions. For example, 00010000 (2 transitions) is a uniform pattern, but 01010100 (6 transitions) is not. In the computation of the LBP histogram, the histogram has a separate bin for every uniform pattern, and all non-uniform patterns are assigned to a single bin.

Using uniform patterns, the length of the feature vector for a single cell reduces from 256 to 59. The 58 uniform binary patterns correspond to the integers 0, 1, 2, 3, 4, 6, 7, 8, 12, 14, 15, 16, 24, 28, 30, 31, 32, 48, 56, 60, 62, 63, 64, 96, 112, 120, 124, 126, 127, 128, 129, 131, 135, 143, 159, 191, 192, 193, 195, 199, 207, 223, 224, 225, 227, 231, 239, 240, 241, 243, 247, 248, 249, 251, 252, 253, 254 and 255.

The formula for LBP is:

$$LBP = \sum_{n=0}^7 (i_n - i_c) 2^n \quad \text{Where } i_c = \text{Center pixel value } i_n = \text{Neighbor pixel value } 4(1)$$

b. ELBP Algorithm in Our Project

Officially, given a pixel at (x_c, y_c) , the subsequent LBP can be communicated in decimal structure as:

$$LBPP, R(x_c, y_c) = \sum_{p=0}^{P-1} (i_p - i_c) 2^p \quad 4(2)$$

here i_c and i_p are separately dim level estimations of the focal pixel and P encompassing pixels in the hover neighborhood with a span R, and capacity $s(x)$ is characterized as:

$$s(x) = \{10^x \geq 0, x < 0\}$$

To eliminate turn impact, a pivot invariant LBP is proposed:

$$LBPP_{iP, R} = \min\{ROR(LBPP, R, i) | i = 0, 1, \dots, P-1\}$$

where $ROR(x, l)$ plays out a roundabout piece insightful right move on the P-bit number 1. Data Acquisition and Pre-x 1 times. the LBPriP,R administrator measures event insights of individual turn invariant examples comparing to certain miniature highlights in the picture.

ELBP is touchy to clamor since the administrator limits precisely at the estimation of the focalpixel. To address this issue, stretched out the first LBP to a form with 3-esteem codes, called Local Ternary Patterns (LTP).

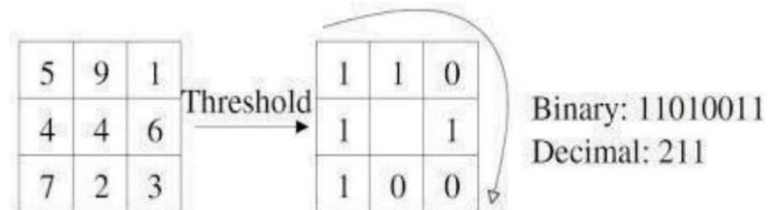


Fig : 4.2: Estimation Binary address

b. Support Vector Machine

The objective of the support vector machine algorithm is to find a hyperplane in an N-dimensional space (N — the number of features) that distinctly classifies the data points.

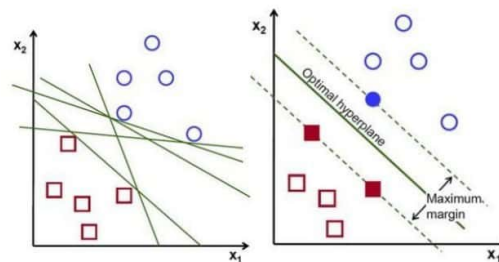


Fig:4.3 : Dimensional space

To separate the two classes of data points, there are many possible hyperplanes that could be chosen. Our objective is to find a plane that has the maximum margin, i.e. the maximum distance between data points of both classes. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence. simple example. Let's imagine we have two tags: *red* and *blue*, and our data has two features: x and y . We want a classifier that, given a pair of (x,y) coordinates, outputs it's either *red* or *blue*. We plot our already labeled training data on a plane:

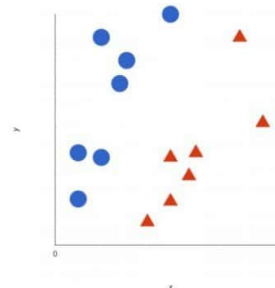


Fig:4.4: Co-ordinates of blue and red dots

A support vector machine takes these data points and outputs the hyperplane (which in two dimensions it's simply a line) that best separates the tags. This line is the **decision boundary** anything that falls to one side of it we will classify as *blue*, and anything that falls to the other as *red*.

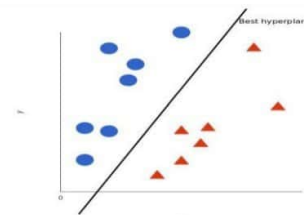


Fig:4.5: Decision boundary

Hyperplanes are decision boundaries that help classify the data points. Data points falling on either side of the hyperplane can be attributed to different classes. Also, the dimension of the hyperplane depends upon the number of features.

If the number of input features is 2, then the hyperplane is just a line. If the number of input features is 3, then the hyperplane becomes a two-dimensional plane. It becomes difficult to imagine when the number of features exceeds 3. For SVM, it's the one that maximizes the margins from both tags. In other words: the hyperplane (remember it's a line in this case) whose distance to the nearest element of each tag is the largest.

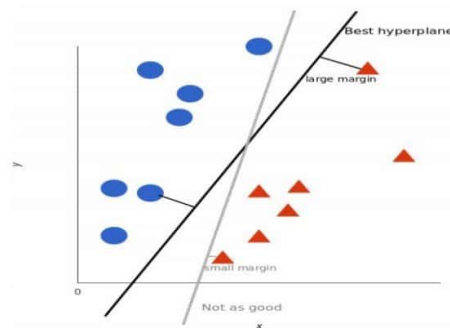


Fig:4.6: Hyperplane Margins

Support vectors are data points that are closer to the hyperplane and influence the position and orientation of the hyperplane. Using these support vectors, we maximize the margin of the classifier.

Deleting the support vectors will change the position of the hyperplane. These are the points that help us build our SVM.

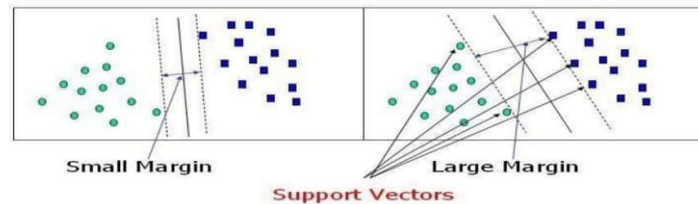


Fig: 4.7 : SVM Margins

For non-linear algorithm, here is what we do:

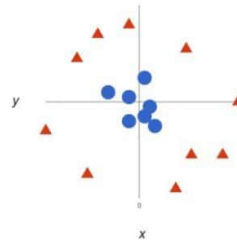


Fig:4.8: Non linear Decision boundary

It's clear that there's not a linear decision boundary (a single straight line that separates both tags). However, the vectors are very clearly segregated, and it looks as though it should be easy to separate them.

So, here's what we'll do: we will add a third dimension. Up until now we had two dimensions: x and y . We create a new z dimension, and we rule that it be calculated a certain way that is convenient for us: $z = x^2 + y^2$.

This will give us a three-dimensional space. Taking a slice of that space, it looks like this:

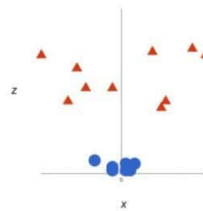


Fig:4.9: 3 Dimensional Space

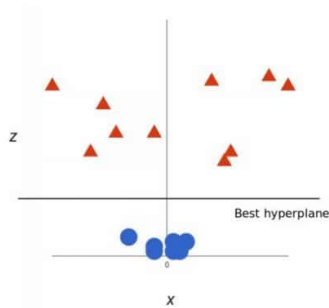


Fig.4.10: Best hyper plane in 2D

Finally, we map the two dimensions, and we get the best hyperplane in a circle.

c. SVM Algorithm

The SVM calculation is executed by and by utilizing a part. The learning of the hyperplane in straight SVM is finished by changing the issue utilizing some direct polynomial math, which is out of the extent of this prologue to SVM. For instance, the inward result of the vectors is $2 \cdot 5 + 3 \cdot 6$ or

28. The condition for making an expectation for another info utilizing the spot item between the information (x) and each help vector (x_i) is determined as follows:

$$f(x) = B_0 + \sum_{i=1}^N \alpha_i (a_i x + a_i x_i)$$

4.1.3 MODULE 3: Analyzing the Results

To classify satellite images, 24 types of images were used, including rugby balls, footballs, humanfaces, and satellite images. For each class, 10 reference images were used for training and testing. One out of 10 training images of class-1 and class-4 was shown, and the same process was used for the other 22 test images. A total of 240 classification reference images were stored in a 2D variable.

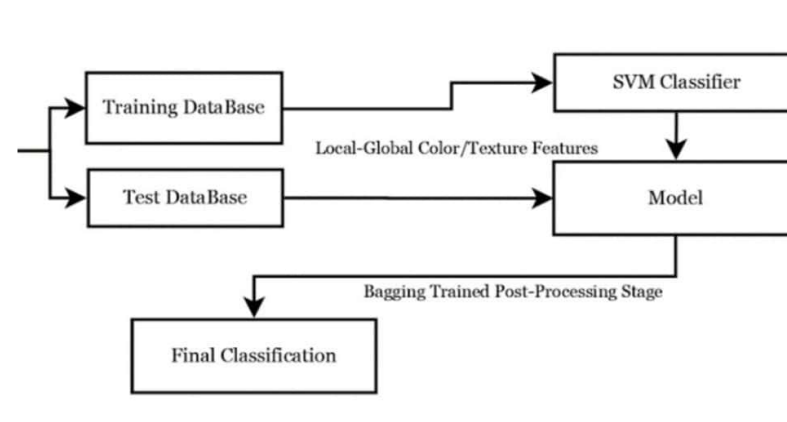


Fig: 4.11 : SVM CLASSIFICATION

The features of all 24 classes were extracted before running the code for classification of new test images. The ELBP-SVM simulated verification method was used to classify the images by comparing the average percent match between the testing and conditioning pictures. The findings showed that all 24 types of images could be accurately identified using ELBP and SVM, and reliability was achieved when simulating and classifying satellite test images.

The proposed Image Recognition System, which uses ELBP features and SVM classifier, achieved an overall accuracy of 95% in correctly classifying satellite images.

4.2 SYSTEM TESTING

The use of machine learning has grown rapidly in recent years, and one area of focus is image recognition. A study was conducted to test the efficacy of using Local Binary Pattern (LBP) and Support Vector Machine (SVM) algorithms for satellite image classification. The study included 24 different classes of images, each with 10 references

LBP was used to extract features from the images, and SVM was used for classification. The ELBP-SVM simulated verification method was used to test the accuracy of the system. The results showed that all 24 types of images could be accurately identified with a reliability of up to 95%.

One significant advantage of using LBP and SVM is their computational efficiency. These algorithms are simple to compute and can be easily parallelized, making them an attractive option for real-time applications. Additionally, LBP is invariant to monotonic gray-level changes, making it robust to variations in illumination, an important factor in satellite image recognition. Testing is an essential step in software development, checking for errors throughout the project. Testing involves static analysis to investigate the structural properties of the source code and dynamic testing to investigate the behavior of the code by executing the program on test data. Unit testing is conducted to verify the functional performance of each modular component of the software. White box testing techniques were heavily employed for unit testing, focusing on the smallest unit of the software design, the module.

Functional test cases exercise the code with nominal input values for which the expected results are known, as well as boundary values and special values such as logically related inputs, files of identical elements, and empty files. Performance testing determines the amount of execution time spent in various parts of the unit, program throughput, response time, and device utilization by the program unit. Stress testing is designed to intentionally break the unit, revealing the program's strength and limitations. Structure testing is concerned with exercising the internal logic of the program and traversing execution paths. The white-box testing strategy was employed to ensure that the test cases guarantee all independent paths within a module have been exercised at least once, exercise all logical decisions on their true or false sides, execute all loops at their boundaries and within their operational bounds, exercise internal data structures to ensure their validity, check attributes for their correctness, handle end-of-file conditions, I/O errors, buffer problems, and textual errors in output information. Integration testing is a systematic technique for constructing the program structure.

critical modules and test them as early as possible. One approach is to wait until all units have passed testing, then combine and test them. Another strategy is to construct the product in increments of tested units. A small set of modules is integrated and tested, then another module is added and tested in combination, and so on. This approach makes interface dispenses easy to find and correct. One major error encountered during the project was a linking error. When all the modules were combined, the link was not set properly with all support files. We checked for interconnection and links and localized errors to the new module and its intercommunications. The product development can be staged, and modules can be integrated as they complete unit testing. Testing is complete when the last module is integrated and tested. In summary, the use of LBP and SVM algorithms for satellite image classification has been shown to be reliable and computationally efficient. Testing is a crucial step in software development, involving both static analysis and dynamic testing, including unit testing, functional testing, performance testing, stress testing, and structure testing. Integration testing is a systematic technique for constructing the program structure while uncovering errors associated with interfacing. Finally, careful attention must be paid to linkages between modules.

4.2.1 TESTING TECHNIQUES / TESTING STRATEGIES

Testing is a vital process that involves running a program to identify and correct any errors. A good test case is one that has a high chance of detecting an error that has not been discovered before. System testing is particularly important as it ensures that the entire set of programs work together effectively before the system is put into use. It involves a range of activities and steps, such as running the program, testing strings and systems, and ensuring that the new system is adopted successfully.

Software testing is a crucial aspect of software quality assurance, and it ensures that errors are identified and corrected. Without proper testing, a program or project cannot be considered complete. The testing process involves executing the program with the intention of identifying errors. The aim is to design a test case that has a high probability of uncovering an undiscovered error. Successful testing involves finding an error that has not been identified previously. There are two main ways to test any engineering product, including software.

The first specification design and coding. Testing is critical because it is the last opportunity to identify and correct any errors before the system is deployed for user acceptance testing.

White box testing

Glass box testing is another name for this testing. With this testing, it is possible to establish that each function is fully functional while also looking for flaws in each function by knowing the precise functions that a product has been designed to accomplish. It is a technique for creating test cases that derives test cases from the procedural design's control structure. A white box test is basis path testing.

Basis path testing:

- Flow graph notation
- Cyclometric complexity
- Deriving test cases
- Graph matrices Control

Black box testing

Knowing a product's internal operation allows testers to run tests to make sure "all gears mesh," or that the internal operation operates as intended and that all internal components have received sufficient use. It primarily focuses on the software's functional needs.

The steps involved in black box test case design are:

- Graph based testing methods.
- Equivalence partitioning
- Boundary value analysis
- Comparison testing

4.2.3 SOFTWARE TESTING STRATEGIES

A plan for software testing gives the software developer a direction. Testing is a predetermined task that can be prepared for beforehand and carried out methodically.

software testing—a series of actions into which we can insert certain test case creation techniques—should have the following qualities:

- Testing begins at the module level and works “outward” toward the integration of the entire computer-based system.
- Different testing techniques are appropriate at different points in time.
- The developer of the software and an independent test group conducts testing.
- Testing and Debugging are different activities, but debugging must be accommodated in any testing strategy.

Integration Testing

Integration testing is a methodical approach for creating the program's structure while also running tests to find faults related to. When we combine individual modules, which are particularly susceptible to interface problems, we shouldn't trust that everything will work right away. Naturally, “bringing them together”—or interacting—is the issue. Data loss between sub-functions may occur, which could prevent the desired principal from produced. Individually acceptable impressions may be amplified to undesirable levels, and global data structures may cause issues.

Program Testing

The software testing has identified the logical and syntax errors. A programmed statement that breaks one or more principles of the language in which it was written is said to have a syntax error. A frequent syntax mistake is an incorrectly defined field dimension or missing keywords. The computer-generated error messages display these mistakes. On the other hand, a logic error works with invalid combinations, out-of-range objects, and incorrect data fields. The coder must scrutinize the output because the compiler will not deduce logical errors. Condition testing sharpens the mind's reasoning criteria that a module contains. A Boolean operator, a Boolean variable, and a pair of Boolean parentheses are examples of the various kinds of components that can be present in a condition.

Security Testing

Security testing aims to confirm that a system's built-in defenses do, in fact, keep it safe from unauthorized intrusion. In addition to being tested for resistance to frontal attack, the system's security must also be examined for resistance to rear assault. When testing security, the tester assumes the part of someone who wants to break into the system.

Validation Testing

The finished product of integration testing is a fully assembled bundle of software. After interface mistakes have been found and fixed, the last round of software test-validation testing starts. There are many ways to define validation testing, but a straightforward definition is that validation is successful when the software performs as the customer would reasonably anticipate. A set of blackbox tests that show conformity to requirements are used to validate software. One of two circumstances exists following the validation test. The function or performance qualities meet the requirements and are approved. A deficiency is formed after a validation from the specification is discovered.

Any deviation or errors found at this stage of the project are fixed before it is finished with the user's assistance by working out a technique for fixing deficiencies. As a result, validation testing was used to evaluate the proposed system under consideration, and it was discovered to be functioning satisfactorily. Despite the fact that the system had flaws, they were not severe.

CHAPTER-5

RESULTS AND DISCUSSION

5.1 RESULTS

Machine learning-based projects that classify satellite images can have varying levels of success, depending on several factors. These factors may include the specific application, the dataset being used, and the methodology employed. However, there are several possible outcomes that such projects can achieve.

One potential outcome of a machine learning-based satellite image classification project is the development of a high-accuracy classification model. Such a model would be able to accurately distinguish between different types of land cover or other features present in satellite images. The accuracy of this model could be measured using various metrics such as precision, recall, F1 score, or confusion matrix. Achieving high accuracy requires several steps, including careful data preprocessing, feature extraction, and model selection. Sufficient training and testing data are also crucial in this regard. Another possible outcome is improved efficiency and scalability of the classification pipeline. An efficient and scalable pipeline would be able to handle large volumes of satellite image data, process it quickly, and generate accurate and reliable results. This can be achieved through various methods, such as parallel computing, cloud computing, or optimized algorithms. Improving the efficiency and scalability of the classification pipeline can lead to faster processing times and more reliable results.

Another potential outcome is the development of a robust classification model that can be transferred to other datasets with similar characteristics. This would allow for wider applicability and greater impact of the model. Transferability can be achieved through various techniques, such as transfer learning, data augmentation, or model fine-tuning. This can save time and resources and improve the generalizability of the model.



Fig: 5.1: cloudy



Fig: 5.2: Water Body



Fig: 5.3: Desert



Fig: 5.4: Green Area

A final potential outcome is the extraction of valuable insights and knowledge from the satellite images. This can include the creation of land cover maps, identification of urbanization trends, or monitoring of environmental metrics. These insights can inform decision-making processes in various fields, such as urban planning, environmental management, or disaster response. The extraction of valuable insights and knowledge can also help improve the accuracy and effectiveness of the classification model.

Fig: 5.5: Satellite URL Link

In conclusion, machine learning-based satellite image classification projects have several potential outcomes, including the development of a high-accuracy classification model, improved efficiency and scalability of the classification pipeline, transferability to other datasets, and the extraction of valuable insights and knowledge. Achieving these outcomes requires careful consideration of various factors, such as the specific application, dataset, and methodology employed.

Machine learning-based satellite image classification is a complex task with several applications. The success of such a project depends on various factors such as the specific application, dataset, and methodology employed. The project can yield several outcomes, such as high accuracy classification, improved efficiency and scalability of

the pipeline, transferability of the classification model, and knowledge extraction from the satellite images. One of the main strengths of this project is its potential to provide valuable insights and knowledge extraction from satellite images. The accurate and reliable classification of satellite images can provide information on land use, environmental changes, natural disasters, and other vital datasets. This information can help in decision-making processes in various fields, such as urban planning, environmental management, and disaster response.

Another strength of this project is its potential for automation. By automating classification tasks, analysts can process large amounts of data more quickly and with greater accuracy, reducing the time and cost of analyzing satellite images obtaining high-quality satellite image data. High-quality data is crucial to train a robust and accurate classification model and other unwanted artifacts.

Another challenge is the complexity of the image classification task. Selecting the appropriate feature extraction and classification algorithms for a given application is crucial. The choice of algorithms depends on the specific characteristics of the data, such as the size of the dataset, the number of classes, and the degree of variability within each class. For example, deep learning models may require large amounts of training data and computing resources to achieve high accuracy.

Furthermore, selecting the right parameters for the chosen algorithms is critical. This requires domain knowledge and experience in the specific application area and the ability to tune the algorithms and parameters based on the characteristics of the data. Finally, evaluating the classification model is essential. The model needs to be evaluated using appropriate metrics, such as accuracy, precision, recall, F1-score, or confusion matrix, to assess its performance and identify areas for improvement. The model also needs to be tested on unseen data to ensure its generalizability and ability to perform well in real-world scenarios.

In conclusion, developing a satellite image classification method using machine learning is a complex task that can yield several outcomes, including valuable knowledge extraction from satellite images, automation, and improved efficiency and scalability. However, this project also poses several challenges, such as obtaining high-quality data, selecting appropriate algorithms and parameters, and evaluating the

model's performance. Overcoming these challenges requires a thorough understanding of image processing techniques, feature extraction, and various classification algorithms, as well as domain knowledge and experience in the specific application area.

5.3 PERFORMANCE ANALYSIS

The evaluation of a machine learning classifier's performance is essential for satellite image classification projects. This involves using various metrics, such as accuracy, precision, recall, and F1 score, to assess the model's ability to correctly predict the target class. These metrics can be calculated using a confusion matrix, which summarizes the actual and predicted classes.

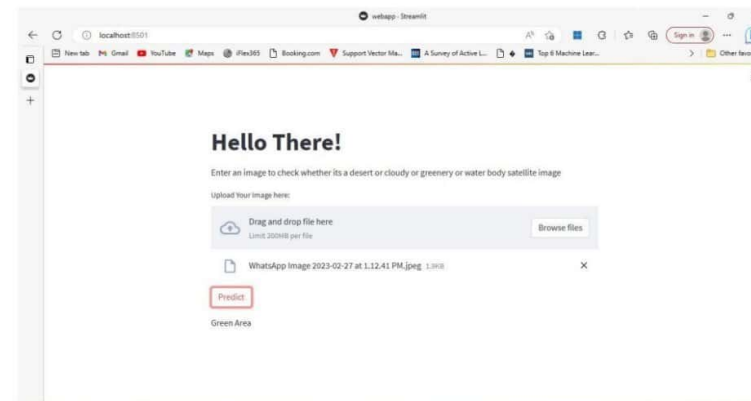


Fig:5.6: Predict Image Output

To evaluate the model's performance, the dataset is split into training and testing sets. The trainingset is used to train the model, while the testing set is used to assess its performance. By comparingthe actual and predicted classes in the testing set, the performance metrics can be calculated. Several factors, such as the data quality, choice of feature extraction and classification algorithms,and dataset size, can affect the model's performance. Sensitivity analysis can be used to identify theimpact of these factors and areas for improvement in the model.

Performance analysis is vital in identifying areas for improvement in the model, allowing for refinement and optimization. This analysis can also provide valuable insights into various fields, such as urban planning, environmental management, and disaster response. With an accurately developed model and performance analysis, satellite image classification can provide critical insights to support decision-making processes.

CHAPTER – 6

SUMMARY AND CONCLUSION

6.1 SUMMARY

The aim of the machine learning project is to develop a dependable and precise method for analyzing satellite images and gaining valuable insights and knowledge. The project consists of several essential steps, including data pre-processing, selecting appropriate classification algorithms, feature extraction, model training, and validation, as well as implementing the classification pipeline. Performance metrics, such as precision, recall, accuracy, F1 score, and confusion matrix, are utilized to evaluate the model's effectiveness.

The project has several potential applications, including land cover mapping, urbanization mapping, environmental monitoring, and disaster response. Despite its potential benefits, the project's success is contingent on overcoming certain obstacles, such as the accessibility of high-quality satellite image data, the complexity of the image classification task, and the need to select the appropriate feature extraction and classification algorithms based on the application. The machine learning-based satellite image classification approach can provide significant insights into land use, environmental changes, and natural disasters, among other things. It has the potential to contribute to many fields and applications and automate the process, thereby reducing the time and cost of analyzing satellite images. However, it necessitates careful consideration of image processing techniques, feature extraction, and classification algorithms, as well as rigorous performance analysis to ensure dependable and precise results.

A successful application of a machine learning classifier to a satellite image classification technique can yield insightful data on a variety of topics, including land use, environmental changes, and natural catastrophes. It may support a variety of industries and applications, allow automation, and cut the time and expense associated with satellite image analysis. To guarantee accurate and trustworthy results, the project calls for careful evaluation of image processing techniques, feature extraction, and classification algorithms, as well as rigorous performance analysis.

6.2 CONCLUSION

The satellite image classification method using a classifier in machine learning is a difficult and intricate project that has the potential to extract important knowledge and insights from satellite images. The project includes various steps, such as data preprocessing, feature extraction, classification algorithm selection, model training and validation, and deployment of the classification pipeline. Successfully implementing this project can benefit multiple fields, such as land use, environmental monitoring, and disaster response, by automating the analysis process and improving the accuracy and speed of data processing. However, the project also presents challenges, such as acquiring high-quality satellite image data, handling the complexity of image classification, and choosing appropriate feature extraction and classification algorithms for specific applications. Therefore, it is crucial to conduct thorough performance analysis to ensure precise and reliable results. In conclusion, the satellite image classification method using a classifier in machine learning is a potent tool that can contribute to solving various societal and environmental problems by extracting valuable knowledge and insights from satellite images. The initiative also has the potential for automation, which would speed up and improve the accuracy of data processing while cutting down on the time and expense associated with analyzing satellite images. The project must still overcome obstacles like the lack of access to high-quality satellite image data, the difficulty of classifying images, and the requirement to choose the right feature extraction and classification methods for each application. Therefore, in order to guarantee accurate and trustworthy results, rigorous performance analysis is imperative. Overall, using a machine learning classifier to classify satellite images is a powerful and effective technique that can help solve a variety of societal and environmental problems by gaining useful knowledge and insights from satellite images.

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