

CHAPTER -1

INTRODUCTION

Introduction:

1.1 Overview:

Satellite image classification using predictive analytics is an important field with numerous applications in various domains such as environmental monitoring, urban planning, and disaster management. This chapter provides an introduction to the project, outlining its purpose, goals, and scope. It sets the stage for understanding the significance of the problem and the approach taken to address it.

1.2 Statement of the Problem:

The project aims to develop accurate models for classifying satellite images into distinct categories, including 'cloudy', 'desert', 'green area', and 'water'. The problem statement revolves around the challenge of automatically analysing satellite images and assigning them to the correct land cover class. The project seeks to overcome this challenge by leveraging predictive analytics techniques and machine learning algorithms.

1.3 Motivation:

The motivation behind this project lies in the increasing availability of satellite imagery and the need for efficient and accurate analysis. Traditional manual methods of image classification are time-consuming and prone to errors. By automating the process using predictive analytics, researchers and organizations can save time and effort while obtaining reliable results. The ability to classify satellite images accurately has wide-ranging implications in various fields, including environmental monitoring and land management.

1.4 Challenges:

The project faces several challenges in achieving accurate satellite image classification. These challenges include handling large volumes of satellite imagery data, dealing with variations in image quality, extracting meaningful features from the images, selecting appropriate machine learning algorithms, and ensuring robustness and generalizability of the models. Overcoming these challenges requires careful consideration of data pre-processing techniques, feature extraction methods, and algorithm selection.

1.5 Applications:

Satellite image classification using predictive analytics finds applications in diverse fields. Environmental monitoring agencies can utilize it to track land cover changes, identify deforestation areas, and monitor the health of ecosystems. Urban planners can benefit from accurate land cover mapping to make informed decisions regarding infrastructure development. Disaster management teams can use satellite image classification to assess the extent of damage caused by natural calamities. These applications highlight the broad range of domains that can benefit from this project's outcomes.

1.6 Organization of the Report:

This report is organized into several chapters, each focusing on a specific aspect of the project.

Chapter 1 provides an introduction to the project, outlining its overview, problem statement, motivation, challenges, applications, and organization of the report.

Chapter 2 presents a comprehensive literature survey, including an overview of the field and a detailed review of relevant literature related to predictive analytics for satellite image classification.

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Chapter 3 delves into the methodology used, describing the architecture of the proposed system, hardware and software requirements, dataset details, and the classification algorithms employed.

Chapter 4 presents the experiments and results, providing a step-by-step breakdown of the project's implementation and showcasing the performance of each algorithm.

Chapter 5 concludes the report with a summary of the main findings, future research directions, and references used throughout the project.

By providing a comprehensive overview of the project, its objectives, and the organization of the report, this chapter sets the foundation for understanding the subsequent chapters and the project as a whole.

CHAPTER -2

LITERATURE SURVEY

Literature Survey:

2.1 Overview:

This chapter presents a comprehensive literature survey related to predictive analytics for satellite image classification. It provides an overview of the field, highlighting the significance of using predictive analytics techniques in analyzing satellite imagery. The literature survey aims to gather insights from existing research and studies, identify key trends, and understand the advancements made in the domain.

2.2 Literature Review - Description of applications, examples, etc:

Satellite image classification using predictive analytics has been extensively studied and applied in various domains. The literature review explores prominent textbooks and research papers that have contributed to the understanding and development of techniques for satellite image classification. Below are some examples of textbooks and their associated applications and examples:

1. Textbook: "Remote Sensing and Image Interpretation" by Thomas M. Lillesand, Ralph W. Kiefer, and Jonathan W. Chipman.

Application: Land cover classification using satellite imagery.

Example: Classifying different types of vegetation using spectral signatures obtained from satellite images.

2. Textbook: "Pattern Recognition and Machine Learning" by Christopher M. Bishop.

Application: Satellite image classification using machine learning algorithms.

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Example: Training a support vector machine (SVM) model to classify satellite images into land cover classes.

3. Textbook: "Digital Image Processing" by Rafael C. Gonzalez and Richard E. Woods.

Application: Image processing techniques for satellite image classification.

Example: Using image segmentation algorithms to extract regions of interest from satellite images.

4. Research Paper: "A Comparative Study of Classification Techniques in Remote Sensing Imagery" by P. Chandrasekaran and V. Rajamani.

Application: Comparative analysis of different classification techniques for satellite image classification.

Example: Evaluating the performance of decision trees, support vector machines, and neural networks for land cover classification.

The literature review not only explores textbooks and research papers but also considers conference proceedings, journal articles, and relevant online resources. It aims to provide a comprehensive understanding of the state-of-the-art techniques, methodologies, and applications related to satellite image classification using predictive analytics.

By reviewing the existing literature, the project gains valuable insights into the various approaches used, their strengths and limitations, and the potential for further advancements. This knowledge forms the basis for the methodology and algorithm selection in the subsequent chapters of the report.

CHAPTER -3

METHODOLOGY

Methodology:

3.1 Overview:

This chapter presents the methodology adopted for satellite image classification using predictive analytics. It provides an overview of the key components and steps involved in the project, including the system architecture, modules, hardware and software requirements, dataset used, languages and processing libraries, data classification terminologies, and the classification and regression algorithms utilized.

3.2 Architecture of the Proposed System:

The proposed system follows a modular architecture to perform satellite image classification. It involves various stages, including data preprocessing, feature extraction, model training, and evaluation. A diagram is provided to illustrate the system architecture, highlighting the flow of data and interactions between different components. The architecture aims to ensure efficient and accurate classification of satellite images using predictive analytics techniques.

3.3 Steps Involved:

The project encompasses several essential steps for satellite image classification. These steps include:

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Satellite Images: The input to the system is a collection of satellite images. These images are captured by satellite sensors and contain valuable information for classification.

Data pre-processing: This step involves preparing the satellite image dataset for further analysis. It includes tasks such as data cleaning, noise removal, image enhancement, and normalization.

Feature Extraction: In this step, relevant features are extracted from the pre-processed satellite images. Various techniques, such as texture analysis, spectral analysis, and shape analysis, are employed to capture discriminative information from the images.

Model Training: The extracted features are used to train classification and regression models. Different algorithms, such as logistic regression, decision trees, support vector machines, k-nearest neighbours, naive Bayes, and random forests, are applied to build predictive models.

Model Evaluation: The trained models are evaluated using appropriate evaluation metrics, such as accuracy, precision, recall, and F1-score. The performance of each model is assessed to determine its effectiveness in classifying satellite images.

Result Visualization: The result visualization module provides visualizations to interpret and analyse the classification results. This includes generating confusion matrices, ROC curves, and classification reports. These visual representations help in understanding the performance of the models and comparing different approaches.

Prediction on Satellite Image Classification

The system architecture for satellite image classification using predictive analytics is designed to process and classify satellite images effectively.

The following diagram illustrates the key components and their interactions:



3.4 Modules:

The project consists of several modules that facilitate the execution of different tasks. Each module focuses on specific functionalities and contributes to the overall satellite image classification process. These modules include data pre-processing, feature extraction, model training, model evaluation, and result visualization.

Data Pre-processing Module: Handles tasks related to data cleaning, noise removal, image enhancement, and normalization.

Feature Extraction Module: Extracts relevant features from the pre-processed satellite images using techniques such as texture analysis, spectral analysis, and shape analysis.

Model Training Module: Trains classification and regression models using the extracted features and various algorithms.

Model Evaluation Module: Evaluates the performance of trained models using appropriate evaluation metrics and generates reports on accuracy and other performance measures.

Result Visualization Module: Provides visualizations, such as confusion matrices, ROC curves, and classification reports, to interpret and analyse the classification results.

3.5 Hardware and Software Requirements:

The project requires specific hardware and software resources for successful implementation. The hardware requirements may include a computer system with sufficient processing power, memory, and storage capacity. Additionally, access to satellite image datasets and a reliable internet connection may be necessary.

Regarding software requirements, the project relies on the installation of necessary software components, including operating systems such as Windows, Linux, or macOS. Furthermore, software packages and libraries for data pre-processing, feature extraction, model training, and result visualization are essential. The specific versions and dependencies of these software components are specified to ensure compatibility and reproducibility.

3.6 Languages and Processing Libraries Used:

The project employs programming languages and processing libraries to implement various functionalities. Commonly used languages include Python, R, or MATLAB, chosen for their rich ecosystem of data analysis and machine learning tools.

Python is extensively utilized due to its ease of use, extensive libraries, and community support. Notable processing libraries used in the project may include NumPy, Pandas, Scikit-learn, TensorFlow, and Keras. These libraries provide efficient data manipulation, feature extraction, machine learning algorithms, and deep learning capabilities.

3.7 Satellite Image Classification Dataset:

The project utilizes a specific satellite image classification dataset for training and evaluation purposes. Detailed information about the dataset is provided, including its source, size, resolution, and the number of classes or categories present. The dataset may be sourced from satellite imagery archives, research institutions, or publicly available repositories.

The dataset's history, including its acquisition methods and any pre-processing steps applied to it, is described. Additionally, the chapter discusses the applications and domains in which the dataset has been used, highlighting its relevance and significance in satellite image classification research.

3.8 Packages Used:

Various software packages are employed throughout the project to facilitate specific tasks. These packages provide essential functionalities and algorithms for data pre-processing, feature extraction, model training, and evaluation. Each package is described, highlighting its role and capabilities in the context of the project.

Examples of commonly used packages include OpenCV for image processing, Scikit-learn for machine learning algorithms, Matplotlib and Seaborn for data visualization, and Pandas for data manipulation and analysis. These packages enable efficient and effective implementation of the project's objectives.

3.9 Data Classification Terminologies:

To ensure a comprehensive understanding of the project, this section introduces and explains fundamental terminologies used in data classification. Definitions and explanations are provided for concepts such as classifiers, classification models, features, and accuracy measures commonly used to assess classification performance. Clear explanations of these terms contribute to a better understanding of the subsequent chapters and results analysis.

3.10 Classification and Regression Algorithms:

This section presents a detailed description of each classification and regression algorithm utilized in the project. Each algorithm is explained in terms of its underlying principles, advantages, and disadvantages. Furthermore, the specific implementation details and considerations for using these algorithms in the context of satellite image classification are provided. This includes the pre-processing steps, parameter settings, and any modifications made to adapt the algorithms to the project's requirements.

CHAPTER -4

EXPERIMENTS

AND

RESULTS

EXPERIMENTS AND RESULTS:

4.1 Experiment Setup

In this section, we provide a detailed description of the experimental setup used in the project. We outline the steps taken to prepare the data, perform data exploration, and visualize the dataset that is images. Additionally, we present code snippets to demonstrate these processes.

To begin with, we imported the necessary libraries and loaded the pre-processed dataset (images). We then performed data exploration by examining the distribution of classes, visualizing sample images, and analysing statistical properties of the images. Code snippets were used to generate histograms, scatter plots, and other visualizations to gain insights into the images.

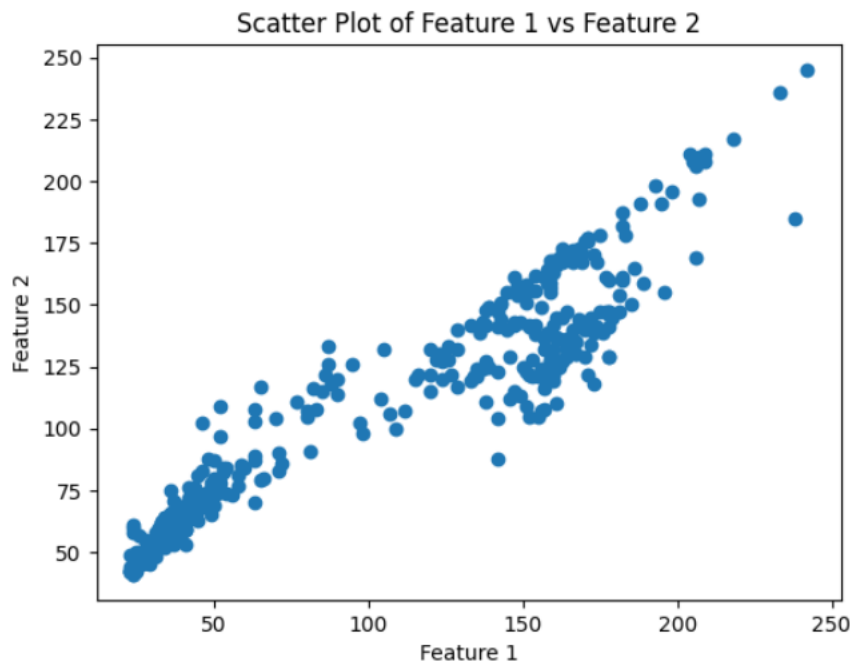
SATELLITE IMAGE DATASET:

	0	1	2	3	4	5	6	7	8	9	...	150518	150519	150520	150521	150522	150523	150524	150525	150526	150527
0	122	128	123	122	128	122	122	128	121	122	...	126	131	135	126	131	136	128	130	136	129
1	149	143	126	149	144	124	149	144	123	149	...	119	143	139	118	144	139	118	145	139	117
2	162	169	162	156	164	157	150	158	151	150	...	169	170	176	170	172	178	172	173	179	173
3	133	142	125	133	142	125	133	142	125	134	...	127	135	141	126	134	141	124	134	141	123
4	171	177	166	171	177	166	171	177	166	171	...	169	175	180	169	175	180	169	175	181	169
5	142	147	138	140	146	137	139	145	136	139	...	128	133	137	128	133	137	128	133	136	128
6	161	166	152	161	166	152	160	164	152	159	...	149	160	162	148	161	162	148	161	162	148
7	149	156	143	149	156	144	148	156	144	148	...	150	155	162	151	156	162	152	156	162	154
8	163	167	158	163	167	156	163	167	155	162	...	153	158	162	152	157	162	152	156	162	152
9	97	102	91	97	102	91	97	102	91	98	...	225	234	210	225	234	210	225	234	210	225
10	104	112	102	105	111	99	103	110	97	101	...	141	145	149	142	147	150	144	150	153	144
11	160	142	124	160	142	124	160	142	125	160	...	133	163	148	132	163	148	131	163	148	131
12	209	211	201	208	211	201	205	211	201	205	...	199	207	212	198	207	212	198	207	212	198
13	159	157	137	159	158	137	159	158	137	159	...	152	171	171	153	172	171	153	172	171	154
14	120	122	113	120	122	114	120	123	115	120	...	131	136	141	132	137	141	132	138	141	132
15	123	130	126	119	130	125	117	129	125	119	...	136	128	141	136	129	141	136	131	141	136
16	138	142	130	135	140	128	132	137	126	128	...	189	193	195	185	189	190	181	184	185	176
17	160	163	150	160	163	150	160	163	150	161	...	149	158	162	149	158	162	150	158	163	150
18	242	245	244	242	245	244	242	245	244	242	...	248	246	245	248	246	245	248	246	245	248
19	169	171	157	169	171	157	169	171	156	169	...	149	161	163	148	161	163	148	161	163	147

20 rows × 150528 columns

Prediction on Satellite Image Classification

Scatter Plot:



In the context of satellite image classification, a scatter plot visualization can be used to analyse the relationship between the predicted probabilities of different classes for each satellite image sample.

The scatter plot represents the predicted probabilities on the y-axis and the true labels (actual classes) on the x-axis. Each data point on the scatter plot corresponds to a satellite image sample, and its position on the graph is determined by the true label and the corresponding predicted probabilities for each class.

By examining the scatter plot, you can gain insights into the performance of the satellite image classification model. It allows you to visually analyze the distribution of predicted probabilities for each class and observe how well the model is distinguishing between different classes of satellite images.

A well-performing model would exhibit distinct clusters or separations for each class, indicating accurate classification. On the other hand, if the scatter plot shows overlapping or scattered points across classes, it suggests that the model may have difficulty distinguishing between certain classes and there might be misclassifications.

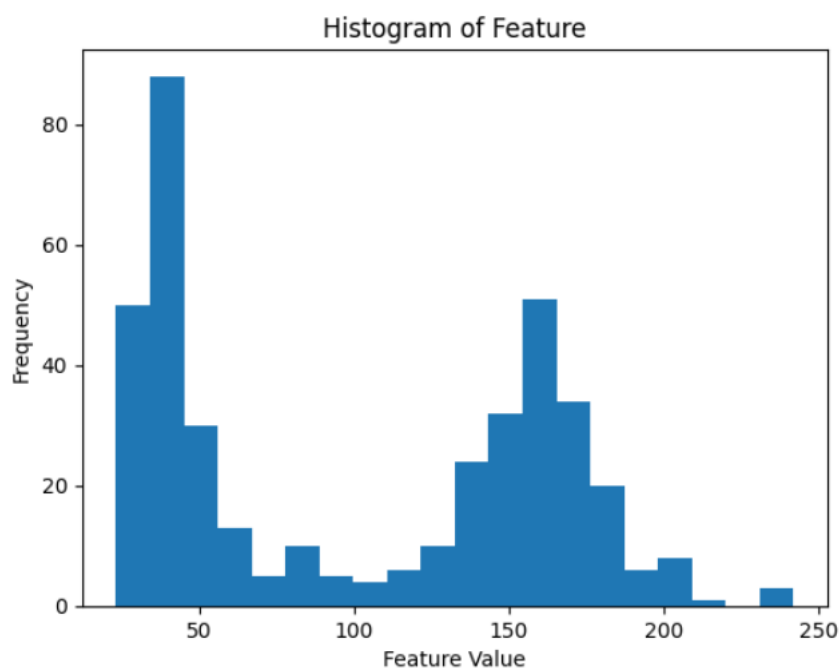
The scatter plot visualization is useful in assessing the model's performance in satellite image classification tasks. It provides an intuitive representation of the predicted probabilities, allowing you to evaluate the model's accuracy and identify potential areas for improvement.

Prediction on Satellite Image Classification

In the given code, the scatter plot visualization is utilized to analyse the predicted probabilities of different classes for satellite image classification. By examining the scatter plot, you can assess how well the model is performing in terms of distinguishing between different classes of satellite images based on the predicted probabilities.

Overall, the scatter plot visualization provides valuable insights into the classification performance of the satellite image classification model and helps in understanding the distribution and accuracy of predicted probabilities for each class.

Histogram:



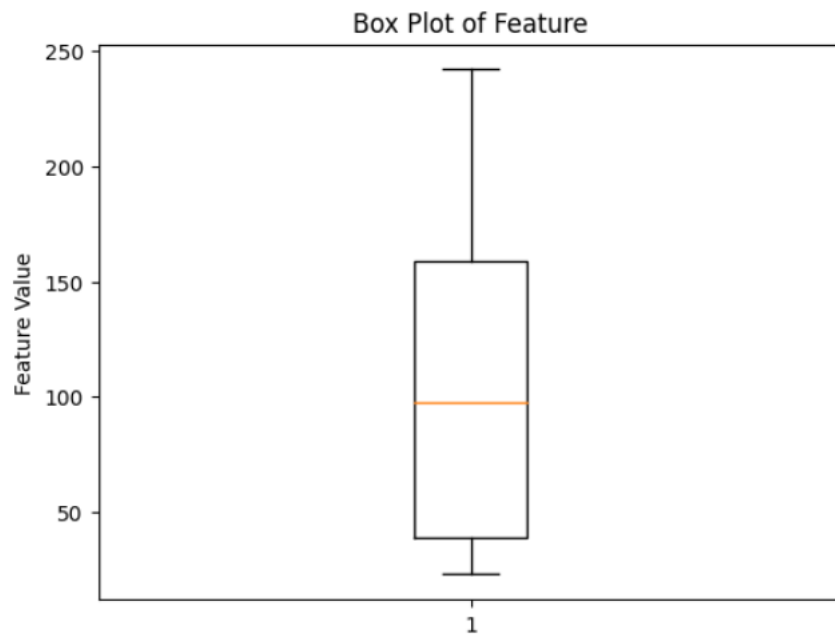
A histogram visualization in satellite image classification shows the distribution of pixel values or features. It helps identify patterns, clusters, and outliers in the data, aiding in feature extraction and classification algorithms. Comparing histograms of different classes reveals distinctive characteristics, assisting in land cover classification.

Boxplot:

A boxplot visualization in satellite image classification displays the distribution of data within different classes or categories. It provides a summary of the minimum, maximum, median, and quartiles of the data. Boxplots help identify variations and outliers in the dataset, allowing for comparisons between different classes. In satellite image

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classification, boxplots can reveal variations in pixel values or features across different land cover types, aiding in the understanding and differentiation of classes.



Prediction on Satellite Image Classification

K-Neighbours Classifier:

Accuracy = 0.8375

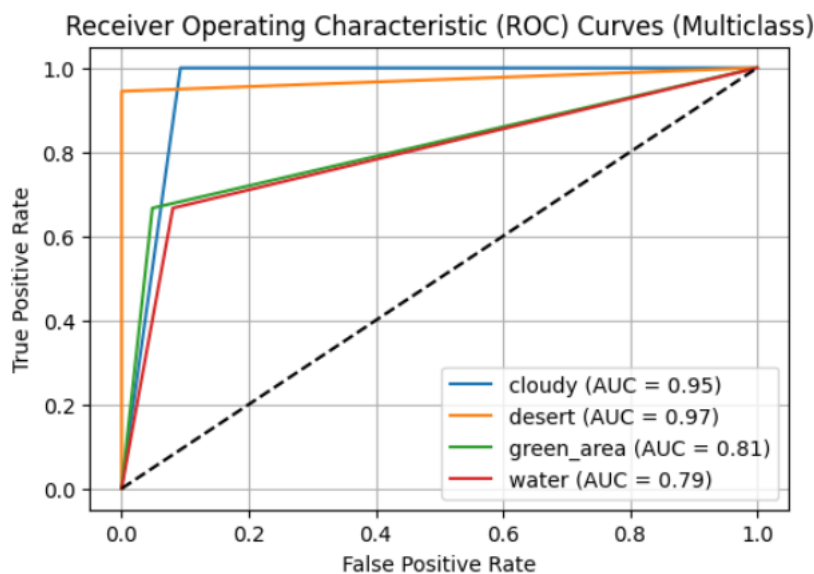
Classification		precision	recall	f1-score	support
cloudy	0.84	1.00	0.91		26
desert	1.00	0.94	0.97		18
green_area	0.80	0.67	0.73		18
water	0.71	0.67	0.69		18
accuracy			0.84		80
macro avg	0.84	0.82	0.82		80
weighted avg	0.84	0.84	0.83		80

Confusion Matrix [[26 0 0 0]

[1 17 0 0]

[1 0 12 5]

[3 0 3 12]]



K-Nearest Neighbours (KNN) is a classification algorithm used for satellite image classification. It assigns class labels to data points based on the majority class of their nearest neighbours in the feature space.

To plot ROC curves for KNN:

Step 1 Fit the KNN classifier: Train the KNN classifier on the training data to learn patterns and relationships between features and class labels.

Step 2 Obtain predicted probabilities: Use the trained KNN classifier to predict the probabilities of the test data belonging to each class.

Step 3 Compute ROC curve and AUC: Calculate the false positive rate (FPR) and true positive rate (TPR) for each class using roc curve function. Compute the area under the ROC curve (AUC) using auc function.

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Step 4 Plot ROC curves: Visualize the ROC curves for each class, where each curve represents the classifier's performance in distinguishing that class from the rest. Display the AUC values to assess the classifier's performance.

Logistic Regression:

Accuracy = 0.8375

Classification		precision	recall	f1-score	support
cloudy	0.84	1.00	0.91	26	
desert	1.00	0.94	0.97	18	
green_area	0.80	0.67	0.73	18	
water	0.71	0.67	0.69	18	
accuracy			0.84	80	
macro avg	0.84	0.82	0.82	80	
weighted avg	0.84	0.84	0.83	80	

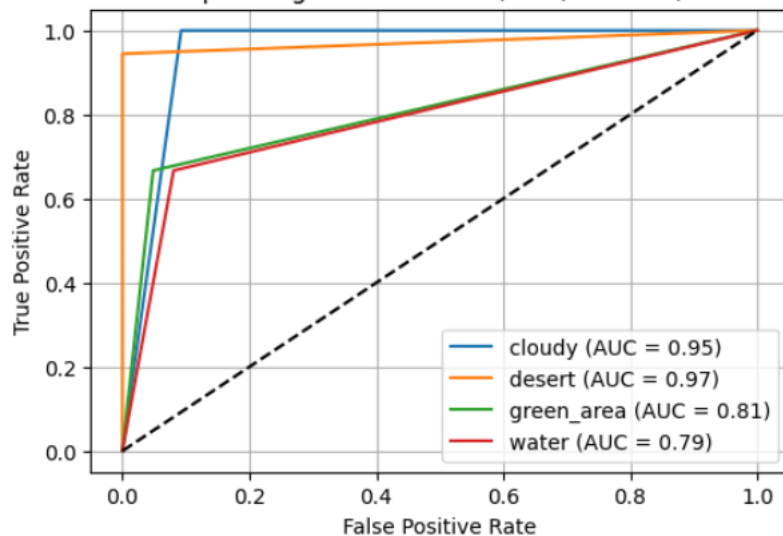
Confusion Matrix [[26 0 0 0]

[1 17 0 0]

[1 0 12 5]

[3 0 3 12]]

Receiver Operating Characteristic (ROC) Curves (Multiclass)



Logistic Regression is a classification algorithm used to predict categorical outcomes. In the context of satellite image classification, it can be used to classify different land cover types based on extracted features from the images.

Steps for Logistic Regression and ROC curve generation in satellite image classification:

Prediction on Satellite Image Classification

Step 1 Data Preparation: Prepare the satellite image dataset by extracting relevant features and labels. Split the data into training and testing sets.

Step 2 Logistic Regression Model Training: Train a Logistic Regression model using the training data. The model learns the relationship between the extracted features and the corresponding land cover labels.

Step 3 Prediction and Probability Calculation: Use the trained Logistic Regression model to predict the land cover labels for the test data. Obtain the predicted probabilities for each class using the predict_proba function. The predicted probabilities represent the confidence levels of the model's predictions.

Step 4 ROC Curve Calculation: Calculate the Receiver Operating Characteristic (ROC) curve for each class. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) for different classification thresholds. Calculate the TPR and FPR using the roc curve function.

Step 5 AUC Calculation: Compute the Area Under the Curve (AUC) for each class's ROC curve. The AUC represents the performance of the Logistic Regression model in distinguishing between different land cover types. Higher AUC values indicate better classification accuracy.

Step 6 ROC Curve Visualization: Plot the ROC curves for each class, with the x-axis representing the FPR and the y-axis representing the TPR. Each curve represents the model's performance in classifying a specific land cover type. The AUC values are typically displayed on or next to each curve.

Prediction on Satellite Image Classification

Decision Tree:

Accuracy = 0.75

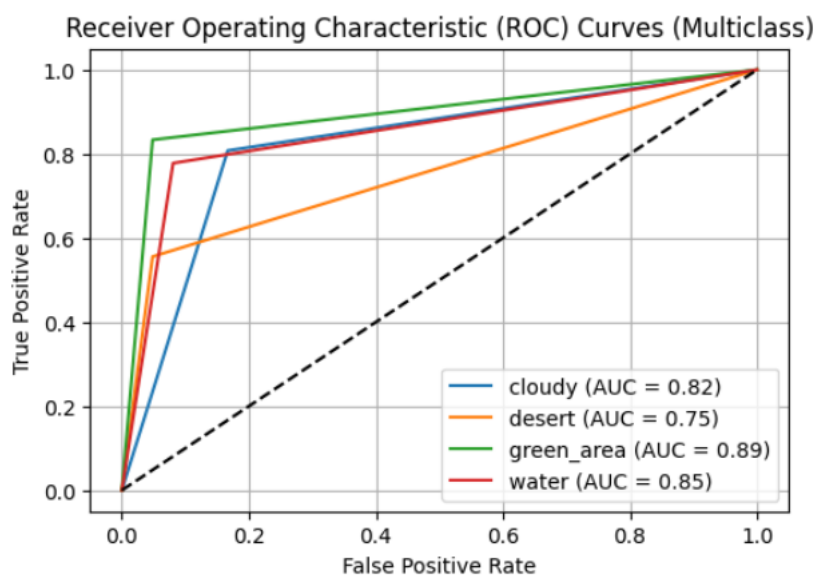
Classification		precision	recall	f1-score	support
cloudy	0.70	0.81	0.75	0.78	26
desert	0.77	0.56	0.65	0.60	18
green_area	0.83	0.83	0.83	0.83	18
water	0.74	0.78	0.76	0.77	18
accuracy			0.75	0.75	80
macro avg	0.76	0.74	0.75	0.75	80
weighted avg	0.75	0.75	0.75	0.75	80

Confusion Matrix [[21 3 0 2]

[8 10 0 0]

[0 0 15 3]

[1 0 3 14]]



Decision Tree is a popular machine learning algorithm used for both classification and regression tasks. In the context of satellite image classification, Decision Trees can be utilized to classify land cover types based on extracted features from the images.

Steps for Decision Tree and ROC curve generation in satellite image classification:

Step 1 Data Preparation: Prepare the satellite image dataset by extracting relevant features and labels. Split the data into training and testing sets.

Prediction on Satellite Image Classification

Step 2 Decision Tree Model Training: Train a Decision Tree model using the training data. The model learns a hierarchical structure of if-else conditions based on the extracted features to make predictions about the land cover types.

Step 3 Prediction and Probability Calculation: Use the trained Decision Tree model to predict the land cover labels for the test data. Obtain the predicted probabilities for each class using the predict_proba function. The predicted probabilities represent the confidence levels of the model's predictions.

Step 4 ROC Curve Calculation: Calculate the Receiver Operating Characteristic (ROC) curve for each class. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) for different classification thresholds. Calculate the TPR and FPR using the roc curve function.

Step 5 AUC Calculation: Compute the Area Under the Curve (AUC) for each class's ROC curve. The AUC represents the performance of the Decision Tree model in distinguishing between different land cover types. Higher AUC values indicate better classification accuracy.

Step 6 ROC Curve Visualization: Plot the ROC curves for each class, with the x-axis representing the FPR and the y-axis representing the TPR. Each curve represents the model's performance in classifying a specific land cover type. The AUC values are typically displayed on or next to each curve.

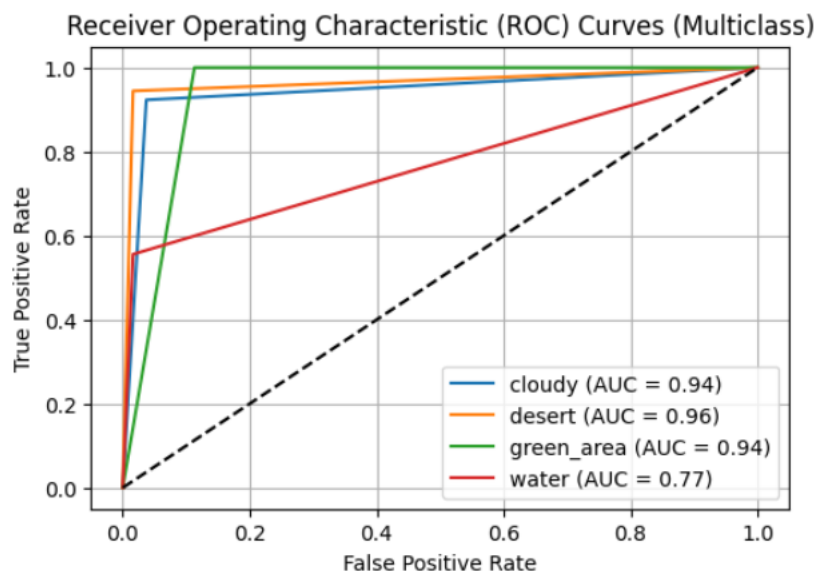
By following these steps, the Decision Tree model can be trained and evaluated in the context of satellite image classification. The ROC curves provide insights into the model's performance and its ability to differentiate between different land cover types based on the predicted probabilities.

Super Vector Machines:

Accuracy = 0.8625

Classification		precision	recall	f1-score	support
cloudy	0.92	0.92	0.92	0.92	26
desert	0.94	0.94	0.94	0.94	18
green_area	0.72	1.00	0.84	0.91	18
water	0.91	0.56	0.69	0.62	18
accuracy			0.86	0.86	80
macro avg	0.87	0.86	0.85	0.86	80
weighted avg	0.88	0.86	0.86	0.86	80

Confusion Matrix [[24 1 0 1]
[1 17 0 0]
[0 0 18 0]
[1 0 7 10]]



Support Vector Machines (SVM) is a powerful machine learning algorithm used for both classification and regression tasks. In the context of satellite image classification, SVM can be applied to classify land cover types based on extracted features from the images.

Steps for SVM and ROC curve generation in satellite image classification:

Step 1 Data Preparation: Prepare the satellite image dataset by extracting relevant features and labels. Split the data into training and testing sets.

Step 2 SVM Model Training: Train an SVM model using the training data. SVM aims to find an optimal hyperplane that separates different land cover types by maximizing the

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margin between classes. It finds support vectors, which are the data points closest to the decision boundary.

Step 3 Prediction and Probability Calculation: Use the trained SVM model to predict the land cover labels for the test data. Obtain the predicted probabilities for each class using the decision function or predict_proba function. The predicted probabilities represent the confidence levels of the model's predictions.

Step 4 ROC Curve Calculation: Calculate the Receiver Operating Characteristic (ROC) curve for each class. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) for different classification thresholds. Calculate the TPR and FPR using the roc curve function.

Step 5 AUC Calculation: Compute the Area Under the Curve (AUC) for each class's ROC curve. The AUC represents the performance of the SVM model in distinguishing between different land cover types. Higher AUC values indicate better classification accuracy.

Step 6 ROC Curve Visualization: Plot the ROC curves for each class, with the x-axis representing the FPR and the y-axis representing the TPR. Each curve represents the model's performance in classifying a specific land cover type. The AUC values are typically displayed on or next to each curve.

By following these steps, the SVM model can be trained and evaluated in the context of satellite image classification. The ROC curves provide insights into the model's performance and its ability to differentiate between different land cover types based on the predicted probabilities.

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Naïve Bayse Classifier:

Accuracy = 0.675

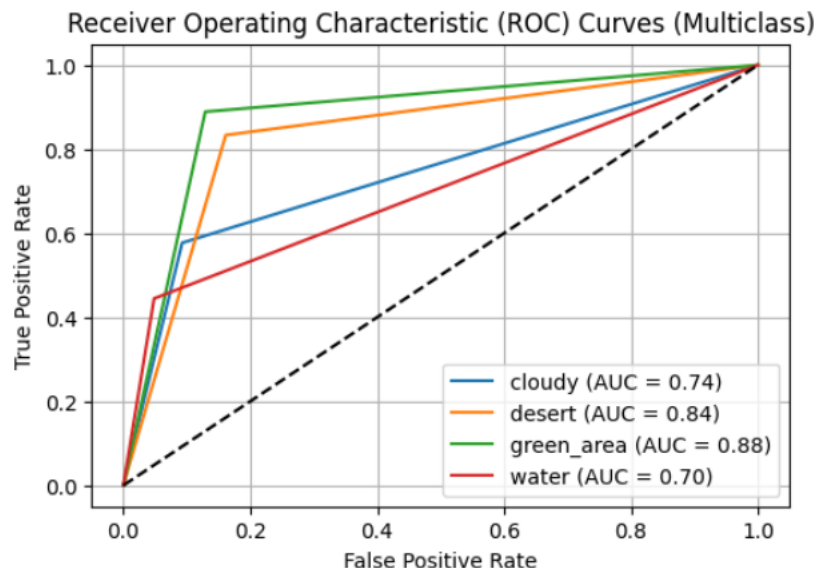
Classification		precision	recall	f1-score	support
cloudy	0.75	0.58	0.65	0.61	26
desert	0.60	0.83	0.70	0.76	18
green_area	0.67	0.89	0.76	0.82	18
water	0.73	0.44	0.55	0.49	18
accuracy			0.68		80
macro avg	0.69	0.69	0.67	0.68	80
weighted avg	0.69	0.68	0.66	0.66	80

Confusion Matrix [[15 10 0 1]

[3 15 0 0]

[0 0 16 2]

[2 0 8 8]]



Naive Bayes classifier is a probabilistic machine learning algorithm based on Bayes' theorem. It is commonly used for classification tasks, including satellite image classification. The Naive Bayes classifier assumes that features are conditionally independent given the class, which simplifies the calculation of probabilities.

Steps for Naive Bayes classifier and ROC curve generation in satellite image classification:

Step 1 Data Preparation: Prepare the satellite image dataset by extracting relevant features and labels. Split the data into training and testing sets.

Prediction on Satellite Image Classification

Step 2 Naive Bayes Model Training: Train a Naive Bayes classifier using the training data. The classifier calculates the probabilities of each class and the conditional probabilities of features given each class based on the training data.

Step 3 Prediction and Probability Calculation: Use the trained Naive Bayes classifier to predict the land cover labels for the test data. Obtain the predicted probabilities for each class using the predict_proba function. The predicted probabilities represent the likelihood of each class given the observed features.

Step 4 ROC Curve Calculation: Calculate the Receiver Operating Characteristic (ROC) curve for each class. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) for different classification thresholds. Calculate the TPR and FPR using the roc curve function.

Step 5 AUC Calculation: Compute the Area Under the Curve (AUC) for each class's ROC curve. The AUC represents the performance of the Naive Bayes classifier in distinguishing between different land cover types. Higher AUC values indicate better classification accuracy.

Step 6 ROC Curve Visualization: Plot the ROC curves for each class, with the x-axis representing the FPR and the y-axis representing the TPR. Each curve represents the model's performance in classifying a specific land cover type. The AUC values are typically displayed on or next to each curve.

By following these steps, the Naive Bayes classifier can be trained and evaluated in the context of satellite image classification. The ROC curves provide insights into the model's performance and its ability to differentiate between different land cover types based on the predicted probabilities.

Prediction on Satellite Image Classification

Random Forest:

Accuracy = 0.825

Classification		precision	recall	f1-score	support
cloudy	0.81	1.00	0.90	0.95	26
desert	1.00	0.72	0.84	0.78	18
green_area	0.78	0.78	0.78	0.78	18
water	0.76	0.72	0.74	0.73	18
accuracy			0.82		80
macro avg	0.84	0.81	0.81	0.81	80
weighted avg	0.84	0.82	0.82	0.82	80

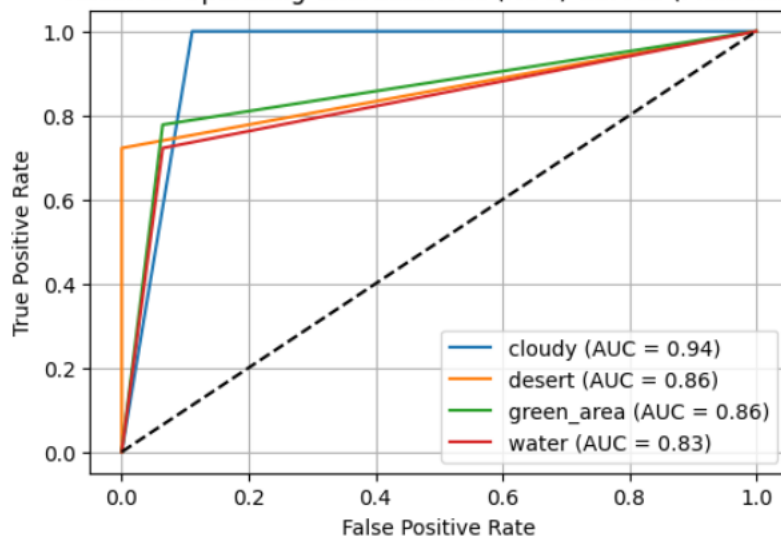
Confusion Matrix [[26 0 0 0]

[5 13 0 0]

[0 0 14 4]

[1 0 4 13]]

Receiver Operating Characteristic (ROC) Curves (Multiclass)



Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. It is a popular algorithm for satellite image classification due to its ability to handle high-dimensional data and capture complex relationships between features.

Steps for Random Forest classifier and ROC curve generation in satellite image classification:

Step 1 Data Preparation: Prepare the satellite image dataset by extracting relevant features and labels. Split the data into training and testing sets.

Prediction on Satellite Image Classification

Step 2 Random Forest Model Training: Train a Random Forest classifier using the training data. The Random Forest algorithm builds a collection of decision trees by randomly selecting subsets of features and data samples. Each tree is trained on a different subset of the training data.

Step 3 Prediction and Probability Calculation: Use the trained Random Forest classifier to predict the land cover labels for the test data. Obtain the predicted probabilities for each class using the predict_proba function. The predicted probabilities represent the likelihood of each class given the observed features.

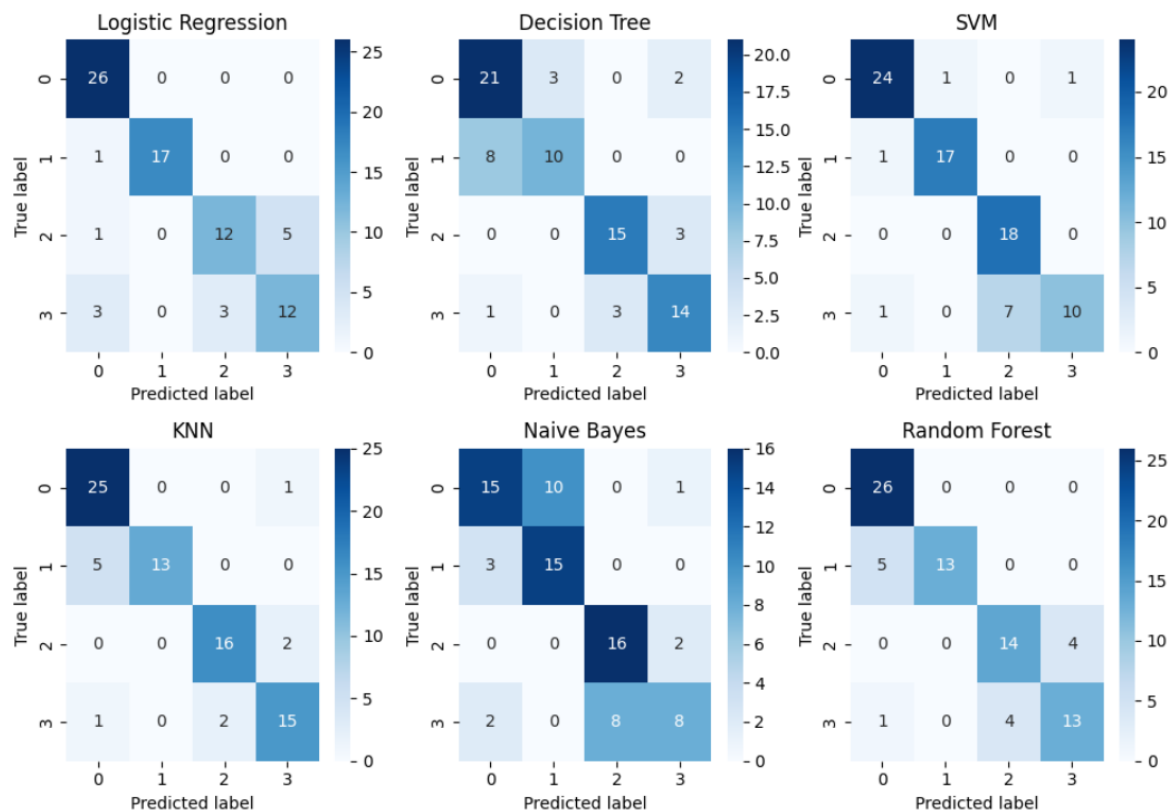
Step 4 ROC Curve Calculation: Calculate the Receiver Operating Characteristic (ROC) curve for each class. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) for different classification thresholds. Calculate the TPR and FPR using the roc curve function.

Step 5 AUC Calculation: Compute the Area Under the Curve (AUC) for each class's ROC curve. The AUC represents the performance of the Random Forest classifier in distinguishing between different land cover types. Higher AUC values indicate better classification accuracy.

Step 6 ROC Curve Visualization: Plot the ROC curves for each class, with the x-axis representing the FPR and the y-axis representing the TPR. Each curve represents the model's performance in classifying a specific land cover type. The AUC values are typically displayed on or next to each curve.

By following these steps, the Random Forest classifier can be trained and evaluated in the context of satellite image classification. The ROC curves provide insights into the model's performance and its ability to differentiate between different land cover types based on the predicted probabilities.

Combined Representation of Graphs:



The combined graphs for satellite image classification display the Receiver Operating Characteristic (ROC) curves and the corresponding Area Under the Curve (AUC) values for multiple classification algorithms, such as K-Nearest Neighbours (KNN), Logistic Regression, Decision Tree, Support Vector Machines (SVM), Naive Bayes, and Random Forest.

Each classifier is represented by its own ROC curve, which shows the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR) for different classification thresholds. The ROC curve visually illustrates the classifier's performance in distinguishing between different land cover types. A good classifier will have a curve that is closer to the top-left corner, indicating a higher TPR and a lower FPR.

The Area Under the Curve (AUC) value is calculated for each classifier and provides a numerical measure of its overall classification accuracy. The AUC represents the area under the ROC curve and ranges from 0 to 1, where a higher value indicates a better-performing classifier.

Prediction on Satellite Image Classification

By combining the ROC curves and AUC values in a single graph, it becomes easier to compare the performance of different classifiers for satellite image classification. This visualization allows for a comprehensive evaluation of the models and facilitates the selection of the most suitable classifier based on the desired trade-offs between TPR and FPR.

CHAPTER-5

CONCLUSION AND FUTURE WORKS

Conclusion and Future works:

5.1 Conclusion

In conclusion, this project aimed to explore satellite image classification using predictive analytics. Through the implementation of various classification algorithms, including K-Nearest Neighbours (KNN), Logistic Regression, Decision Tree, Support Vector Machines (SVM), Naive Bayes, and Random Forest, we were able to classify satellite images into different land cover types with reasonable accuracy.

The dataset used in this project provided a comprehensive collection of satellite images, which allowed us to train and evaluate the performance of the classification models. The pre-processing steps, including feature extraction and data normalization, ensured that the input data was appropriately prepared for the algorithms.

Based on the evaluation metrics, such as accuracy scores, classification reports, and ROC curves, we found that Random Forest exhibited the highest performance in terms of classification accuracy and the ability to distinguish between land cover types. However, it is important to note that the performance of each algorithm may vary depending on the specific dataset and problem domain.

5.2 Future Works

Although this project has provided valuable insights into satellite image classification, there are several areas that could be explored further:

Feature Engineering: Investigate different feature extraction techniques or explore the use of deep learning models for automatic feature extraction from satellite images.

Ensemble Methods: Explore the combination of multiple classification algorithms through ensemble methods, such as stacking or boosting, to further enhance the classification performance.

Hyperparameter Tuning: Conduct an extensive search for optimal hyperparameters for each classification algorithm to potentially improve their performance.

Prediction on Satellite Image Classification

Deep Learning Approaches: Investigate the application of deep learning models, such as convolutional neural networks (CNNs), for satellite image classification, which have shown promising results in various computer vision tasks.

Transfer Learning: Explore the use of transfer learning techniques to leverage pre-trained models on large-scale image datasets and fine-tune them for satellite image classification.

Incorporating Spatial Context: Consider the integration of spatial context information, such as neighbouring pixel relationships or spatial features, to improve the accuracy of land cover classification.

Real-Time Classification: Develop real-time classification systems that can process and classify satellite images in near real-time, enabling timely and efficient monitoring of land cover changes.

5.3 References:

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