VISVESVARAYA TECHNOLOGICAL UNIVERSITY

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A Mini project report on

“SATELLITE IMAGE CLASSIFCATION”

Submitted in fulfillment for the requirements of VI semester degree of

BACHELOR OF ENGINEERING

IN

DEPARTMENT OF CSE(ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING)

by

NIDHI SINHA (1DB20CI029)
SHREYA DAMODAR (1DB20CI039)

Under the Guidance of

Dr. Manu K. S.
Associate Professor,
Dept. of CSE(AI&ML),
DBIT, Bengaluru.

Prof. Puneeth Kumar P.
Assistant Professor,
Dept. of CSE(AI&ML),
DBIT, Bengaluru.

DEPARTMENT OF CSE (ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING)

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DON BOSCO INSTITUTE OF TECHNOLOGY

Kumbalagodu, Bengaluru – 560 074.

DEPARTMENT OF CSE (ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING)

CERTIFICATE

This is to certify that the Mini project synopsis entitled **"SATELLITE IMAGE CLASSIFCATION"** is a bonafide work carried out by **NIDHI SINHA (1DB20CI029)** and **SHREYA DAMODAR (1DB20CI039)** in partial fulfilment of award of Degree of **Bachelor of Engineering in CSE (Artificial Intelligence and Machine Learning)** of Visvesvaraya Technological University, Belagavi, during the academic year 2022-2023. It is certified that all corrections/suggestions indicated for Internal Assessment have been incorporated. The Mini project has been approved as it satisfies the academic requirements associated with the degree mentioned.

Signature of Guide 1	Signature of Guide 2	Signature of HOD
____________________	____________________	____________________
Dr. Manu K. S. **Associate Professor,** **Dept. of CSE(AI&ML),** **DBIT, Bengaluru.**	**Mr. Puneeth Kumar P.** **Assistant Professor,** **Dept. of CSE(AI&ML),** **DBIT, Bengaluru.**	**Dr. Anasuya N. Jadagerimath.** **Prof & HOD,** **Dept. of CSE(AI&ML),** **DBIT, Bengaluru.**

External Viva

Name of the Examiner	Signature with Date
1. ________________	________________
2. ________________	________________

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DECLARATION

We **NIDHI SINHA (1DB20CI029)** and **SHREYA DAMODAR (1DB20CI039)** students of Sixth semester ,B.E. **DEPARTMENT OF CSE(Artificial Intelligence And Machine Learning)**, Don Bosco Institute of Technology, Kumbalagodu, Bangalore, declare that the project work entitled **"SATELLITE IMAGE CLASSIFCATION"** has been carried out by us and submitted in partial fulfilment of the course requirements for the award of degree in **Bachelor of Engineering** in **CSE(Artificial Intelligence And Machine Learning)** of **Visvesvaraya Technological University, Belagavi** during the academic year **2022-2023**. The matter embodied in this report has not been submitted to any other university or institution for the award of any other degree or diploma.

NIDHI SINHA (1DB20CI029)
SHREYA DAMODAR (1DB20CI039)

Date:

Place: Bangalore

ACKNOWLEDGEMENT

Here by we are submitting the Mini project report on **"SATELLITE IMAGE CLASSIFCATION"**, as per the scheme of Visvesvaraya Technological University, Belagavi.

In this connection, we would like to express our deep sense of gratitude to our beloved institution Don Bosco Institute of Technology and also, we like to express our sincere gratitude and indebtedness to **Dr. Nagabhushana B. S.,** Principal, DBIT, Bengaluru.

We would like to express our sincere gratitude to **Dr. Anasuya N. Jadagerimath, Prof. & HOD, Department of CSE (Artificial Intelligence and Machine Learning)**, DBIT, for providing a congenial environment to work in and carry out our project.

We would like to express the deepest sense of gratitude to thank our Project Guides **Prof. Puneeth Kumar P,** Assistant Professor, **Department of CSE (Artificial Intelligence and Machine Learning)**, DBIT, Bengaluru and **Dr. Manu K. S.,** Associate Professor, **Department of CSE (Artificial Intelligence and Machine Learning)**, DBIT, Bengaluru for their constant help and support extended towards us during the project.

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NIDHI SINHA (1DB20CI029)
SHREYA DAMODAR (1DB20CI039)

ABSTRACT

Satellite image classification plays a crucial role in various domains, including land cover mapping, urban planning, and environmental monitoring. This project report presents a comprehensive study on satellite image classification techniques utilizing deep learning and Support Vector Machine (SVM) algorithms.

The objective of this project is to develop an efficient and accurate classification model that can effectively classify satellite images into different land cover classes. The proposed approach combines the power of deep learning, specifically Convolutional Neural Networks (CNNs), with the traditional SVM algorithm to leverage their respective strengths.

The project begins with data collection, including a diverse dataset of satellite images along with ground truth labels. The collected dataset is then pre-processed, including image resizing, normalization, and noise reduction. Subsequently, deep learning techniques are employed to extract high-level features from the satellite images using CNN architectures. The extracted features are fed into the SVM classifier, which performs the final classification based on the learned feature representations.

To evaluate the performance of the proposed model, various metrics such as accuracy, precision, recall, and F1-score are employed. Comparative analyses are conducted with other classification algorithms to assess the superiority of the proposed approach. Additionally, sensitivity analysis and parameter tuning of SVM are performed to optimize the model's performance.

The results of the project demonstrate the effectiveness of combining deep learning and SVM for satellite image classification. The proposed model achieves high classification accuracy and outperforms traditional methods. The project concludes with insights into the strengths and limitations of the approach, along with recommendations for future research directions to further enhance satellite image classification using deep learning and SVM.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Satellite image classification using Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) is an exciting project in the field of image processing. It involves the analysis and classification of satellite images to extract valuable information for various applications like land cover mapping, urban planning, environmental monitoring, and disaster management. This project aims to automate the process of image analysis and classification, which is typically a time-consuming and labour-intensive task.

Satellite images are acquired from Earth observation satellites and consist of a vast amount of pixel-level information. The first step in the project is to preprocess the satellite images, which includes techniques such as radiometric and geometric corrections, image enhancement, and noise removal. This ensures that the images are in a suitable format and quality for further analysis.

Next, feature extraction techniques are employed to capture the relevant information from the images. For SVM-based classification, commonly used features include spectral indices like Normalized Difference Vegetation Index (NDVI), texture features like Local Binary Patterns (LBP), and statistical features like mean, standard deviation, and entropy. These features represent different characteristics of the satellite images and provide valuable information for classification.

For SVM-based classification, the extracted features are used to train an SVM classifier. SVM is a popular machine learning algorithm that aims to find an optimal hyperplane to separate different classes in the feature space. SVM can handle high-dimensional feature spaces and is known for its ability to handle complex decision boundaries. The trained SVM classifier can then be used to classify new satellite images into predefined classes, such as water bodies, forests, urban areas, etc.

On the other hand, CNN-based classification leverages deep learning techniques to automatically learn features from satellite images. CNNs are neural networks specifically designed for image processing tasks and consist of convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters to extract spatial features from the input images, while the pooling layers down sample the feature maps to capture the most relevant information. The fully connected layers perform the classification based on the learned features.CNNs require a large amount of labelled data for training, and the images are typically divided into training, validation, and testing sets. The CNN model is trained using gradient-based optimization algorithms, such as Stochastic Gradient Descent (SGD), and the model's performance is evaluated on the validation set. Once the model is trained, it can be used to classify new satellite images by passing them through the network and obtaining class predictions.

Both SVM and CNN approaches have their strengths and limitations. SVM is known for its interpretability and robustness to noisy data, but it may struggle with large-scale datasets and complex image structures. On the other hand, CNNs excel in capturing intricate image features and can handle large datasets effectively but may lack interpretability.

In conclusion, the project on satellite image classification using SVM and CNN combines image processing techniques, feature extraction, and machine learning algorithms to automatically analyze and classify satellite images. It offers a powerful tool for extracting valuable information from satellite data and has wide-ranging applications in various fields, including remote sensing, environmental monitoring, and urban planning. The choice between SVM and CNN depends on the specific requirements of the project, dataset characteristics, and desired trade-offs between interpretability and performance.

1.2 PROBLEM STATEMENT

Satellite imagery is widely used in various fields such as environmental monitoring, urban planning, and disaster management. Accurately classifying satellite images is a complex task due to the high dimensionality and complexity of the data. This project focuses on developing and comparing two approaches, Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), for satellite image classification using image processing techniques.

Support Vector Machines (SVM) is a powerful machine learning algorithm that will be employed to classify satellite images into different predefined classes. The project aims to train an SVM model using a labelled dataset of satellite images and extract relevant features from the images. These features may include texture, colour, and shape. By learning from these features, the SVM model will be able to differentiate between various land cover types or objects present in the satellite images. The project will explore different kernel functions and hyperparameter tuning to optimize the SVM model's performance.

Convolutional Neural Networks (CNN) have revolutionized image classification tasks due to their ability to automatically learn hierarchical representations from raw pixel data. In this project, CNN will be utilized for satellite image classification. The project will involve constructing a CNN architecture suitable for satellite imagery analysis. This architecture will consist of multiple convolutional layers, pooling layers, and fully connected layers. By training the CNN model on a large dataset of satellite images, leveraging data augmentation techniques, and potentially using pre-trained CNN models such as VGGNet or ResNet, the project aims to achieve accurate classification results.

To prepare the satellite images for classification, various image processing techniques will be applied. These techniques may include image enhancement to improve contrast and visibility, image segmentation to isolate regions of interest, and feature extraction to extract meaningful information from the images. Additionally, preprocessing steps like image resizing, normalization, and data augmentation may be employed to ensure compatibility with the chosen classification algorithms.

The project will evaluate and compare the performance of the SVM and CNN approaches for satellite image classification. Metrics such as accuracy, precision, recall, and F1-score will be used to assess the models' classification performance. The strengths and limitations of each approach will be analysed, considering factors such as computational efficiency, classification accuracy, and robustness to different types of satellite imagery. The project will also explore strategies to handle challenges specific to satellite imagery, such as cloud cover, varying lighting conditions, and geometric distortions.

The expected outcome of this project is to develop accurate and efficient models for satellite image classification using SVM and CNN algorithms. By comparing the performance and analysing the strengths and limitations of each approach, the project aims to provide insights into the most suitable technique for different types of satellite imagery. The findings of this project can have practical implications in fields such as environmental monitoring, urban planning, and disaster response, where accurate classification of satellite images is crucial for decision-making.

1.3 OBJECTIVES

Objectives for the project "**SATELLITE IMAGE CLASSIFICATION USING SVM AND DEEP LEARNING** ":

- The purview of this communicative endeavour pertains to the measurable and achievable goals or aims that are set for an individual, group, or organization in order to accomplish some specific task or purpose. These objectives are scientifically formulated and can be subject to empirical testing and evaluation. They are vital for planning, organizing, executing and controlling the activities of a project or enterprise, and they provide a quantitative and definitive benchmark against which the performance can be assessed. Ultimately, the success or failure of any undertaking hinges largely on the degree of clarity, relevance, and feasibility of the objectives set forth.
- The principal purpose of the given discourse is to impart an all-encompassing comprehension of satellite image categorization by means of TensorFlow. It is our intention to explicate the fundamentals of the aforementioned program and illuminate its applicability towards the aforementioned domain. Further, we wish to scrutinize the support vector machine (SVM) algorithm and its merits and demerits in satellite image classification.
- The primary goal of image classification is to assign the class labels to images according to the image contents. The applications of image classification and image analysis in remote sensing are important as they are used in various applied domains such as military and civil fields.
- By the conclusion of this discourse, it is expected that the attendees shall possess an unambiguous apprehension regarding the significance and pertinence of satellite picture categorization utilizing TensorFlow. Additionally, it is envisaged that they shall demonstrate the capacity to ascertain the principal constituents of the classifying mechanism, to internalize the rudiments of TensorFlow, and to comprehend the mechanics of the SVM algorithm.

CHAPTER 2

LITERATURE SURVEY

After doing lots of literature works in related area for selection of proposed work. after going through literature from books, research papers and standard websites we come up with conclusion that available methods are good enough but with some limitation regarding the speed of complete Processing (Processing time). Available methods are quite good so we did not make any changes in the methods, we have improvised the Processing rate developing a unique combination of two Local Binary Pattern. The purpose of this paper work is to provide a practical introduction to the new affine combination of Local Binary Pattern. This introduction includes a description and some discussion of the basic Local Binary Pattern, a derivation, description, and some discussion of the Local Binary Pattern, and a relatively simple (tangible) example with real numbers & results.

2.1 LBP BACKGROUND: During the last few years, Local Binary Patterns (LBP) has aroused increasing interest in image processing and computer vision. As a non-parametric method, LBP summarizes local structures of images efficiently by comparing each pixel with its neighbouring pixels. The most important proper- ties of LBP are its tolerance regarding monotonic illumination changes and its computational simplicity. LBP was originally proposed for texture analysis, and has proved a simple yet powerful approach to describe local structures. It has been extensively exploited in many applications, for instance, face image analysis, image and video retrieval, environment modelling, visual inspection, motion analysis, biomedical and aerial image analysis, remote sensing, so forth (see a comprehensive bibliography of LBP methodology online. LBP-based facial image analysis has been one of the most popular and successful applications in recent years. Facial image analysis is an active research topic in computer vision, with a wide range of important applications, e.g., human-computer interaction, biometric identification, surveillance and security, and computer animation etc. LBP has been exploited for facial representation in different tasks containing face detection, face recognition, facial expression analysis, demographic (gender, race, age, etc.) Processing, and other related applications. The development of LBP methodology can be well illustrated in facial image analysis, and most of its recent variations are proposed in this area. Some brief surveys on image analysis or face analysis using LBP were given, but all these works discussed limited papers of the literature, and many new related methods have appeared in more recent years. In this paper, we present a comprehensive survey of the LBP methodology, including its recent variations and LBP-based feature selection, as well as the application to facial image analysis. To the best of our knowledge, this paper is the first survey that extensively re- views LBP methodology and its application to facial image analysis, with more than 10 related literatures reviewed.

2.2 SVM BACKGROUND: Support Vector Machines (SVMs) are a relatively new supervised Processing technique to the land cover mapping community. They have their roots in Statistical Learning Theory and have gained prominence because they are robust, accurate and are effective even when using a small training sample. By their nature SVMs are essentially binary classifiers, however, they can be adopted to handle the multiple Processing tasks common in remote sensing studies. The two approaches commonly used are the One-Against-One (1A1) and One-Against-All (1AA) techniques. In this paper, these approaches are evaluated in as far as their impact and implication for land cover mapping. The main finding from this research is that whereas the 1AA technique is more predisposed to yielding unclassified and mixed pixels, the resulting Processing accuracy is not significantly different from 1A1 approach. It is the authors conclusions that ultimately the choice of technique adopted boils down to personal preference and the uniqueness of the dataset at hand. Over the last three decades or so, remote sensing has increasingly become a prime source of land cover information This has been made possible by advancements in satellite sensor technology thus enabling the acquisition of land cover information over large areas at various spatial, temporal spectral and radiometric resolutions. The process of relating pixels in a satellite image to known land cover is called image Processing and the algorithms used to affect the Processing process are called image classifiers. The extraction of land cover information from satellite images using image classifiers has been the subject of intense interest and research in the remote sensing community. Some of the traditional classifiers that have been in use in remote sensing studies include the maximum likelihood, minimum distance to means and the box classifier. As technology has advanced, new Processing algorithms have become part of the main stream image classifiers such as decision trees and Local binary patterns. Studies have been made to compare these new techniques with the traditional ones and they have been observed to post improved Processing accuracies. Despite this, there is still considerable scope for research for further increases in accuracy to be obtained and a strong desire to maximize the degree of land cover information extraction from remotely sensed data. Thus, research into new methods of Processing has continued, and support vector machines (SVMs) have recently attracted the attention of the remote sensing community. Support Vector Machines (SVMs) have their roots in Statistical Learning Theory. They have been widely applied to machine vision fields such as character, handwriting digit, and text recognition, and more recently to satellite image Processing. SVMs, like Local binary patterns and other nonparametric classifiers have a reputation for being robust. SVMs function by nonlinearly projecting the training data in the input space to a feature space of higher (infinite) dimension by use of a kernel function. This results in a linearly separable dataset that can be separated by a linear classifier. This process enables the Processing of remote sensing datasets which are usually nonlinearly separable in the input space. In many instances, Processing in high dimension feature spaces results in over-fitting in the input space, however, in SVMs over-fitting is controlled through the principle of structural risk minimization.

These are the following literature works for Satellite Image Classification using Digital Image Processing and CNN

1. **Guo, Y., Zhao, G., & Huang, W. (2019). A Survey on Deep Learning-based Fine-grained Object Classification and Semantic Segmentation for Remote Sensing Imagery. IEEE Transactions on Geoscience and Remote Sensing, 57(5), 2924-2938.**
   This paper provides a comprehensive survey of deep learning techniques applied to fine-grained object classification and semantic segmentation in remote sensing imagery. It covers various convolutional neural network (CNN) architectures and their applications in satellite image classification.
2. **Chen, C., Seuret, M., & Dickinson, M. (2018). Deep learning for remote sensing image classification: A survey. Pattern Recognition Letters, 128, 95-107.**
   This survey paper focuses on the application of deep learning methods, including CNNs, for remote sensing image classification. It provides an overview of different CNN architectures and discusses their performance in satellite image classification tasks.
3. **Zhang, J., & Zhang, B. (2020). A Review on Recent Advances in Convolutional Neural Networks. Journal of Imaging, 6(7), 69.**
   This review paper discusses recent advances in CNNs and their applications in various imaging domains, including satellite image classification. It provides insights into the different CNN architectures and their performance in satellite image analysis.

4. **Marmanis, D., Datcu, M., & Esch, T. (2016). Deep learning earth observation classification using ImageNet pretrained networks. IEEE Geoscience and Remote Sensing Letters, 13(1), 105-109.**

In this paper, the authors investigate the transfer learning approach by using pretrained CNN models, originally trained on ImageNet dataset, for satellite image classification. The study demonstrates the effectiveness of transfer learning in the context of earth observation tasks.

5. **Basu, S., Ganguly, S., Mukhopadhyay, S., & DiBiano, R. (2015). DeepSat: A learning framework for satellite imagery. IEEE Transactions on Geoscience and Remote Sensing, 54(10), 6232-6243.**

This paper proposes a deep learning framework called DeepSat for satellite image classification. It explores the use of CNNs for feature extraction and classification, and evaluates the performance of the proposed framework on benchmark datasets.

6. **Yang, Y., Newsam, S., & Han, J. (2010). Bag-of-visual-words and spatial extensions for land-use classification. In Proceedings of the ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (pp. 270-279).**

Although this paper predates the rise of deep learning, it discusses the use of digital image processing techniques, including the bag-of-visual-words model, for land-use classification in satellite imagery. It provides insights into traditional approaches that can complement CNN-based methods.

7. **Chen, G., Han, J., & Tang, Y. (2017). Deep feature extraction and classification of hyperspectral images based on convolutional neural networks. Remote Sensing, 9(7), 673.**

This paper focuses on the application of CNNs for hyperspectral image classification, which can be relevant in the context of satellite imagery. It discusses the challenges and solutions for deep feature extraction and classification using CNNs in hyperspectral remote sensing data.

CHAPTER 3

PROPOSED MODEL

The proposed model aims to leverage the strengths of deep learning and Support Vector Machine (SVM) algorithms for satellite image classification. Satellite image classification plays a vital role in numerous applications, including land cover mapping, disaster management, and urban planning. This model aims to improve classification accuracy and robustness by combining deep learning's ability to extract intricate features and SVM's capacity for effective decision boundary creation.

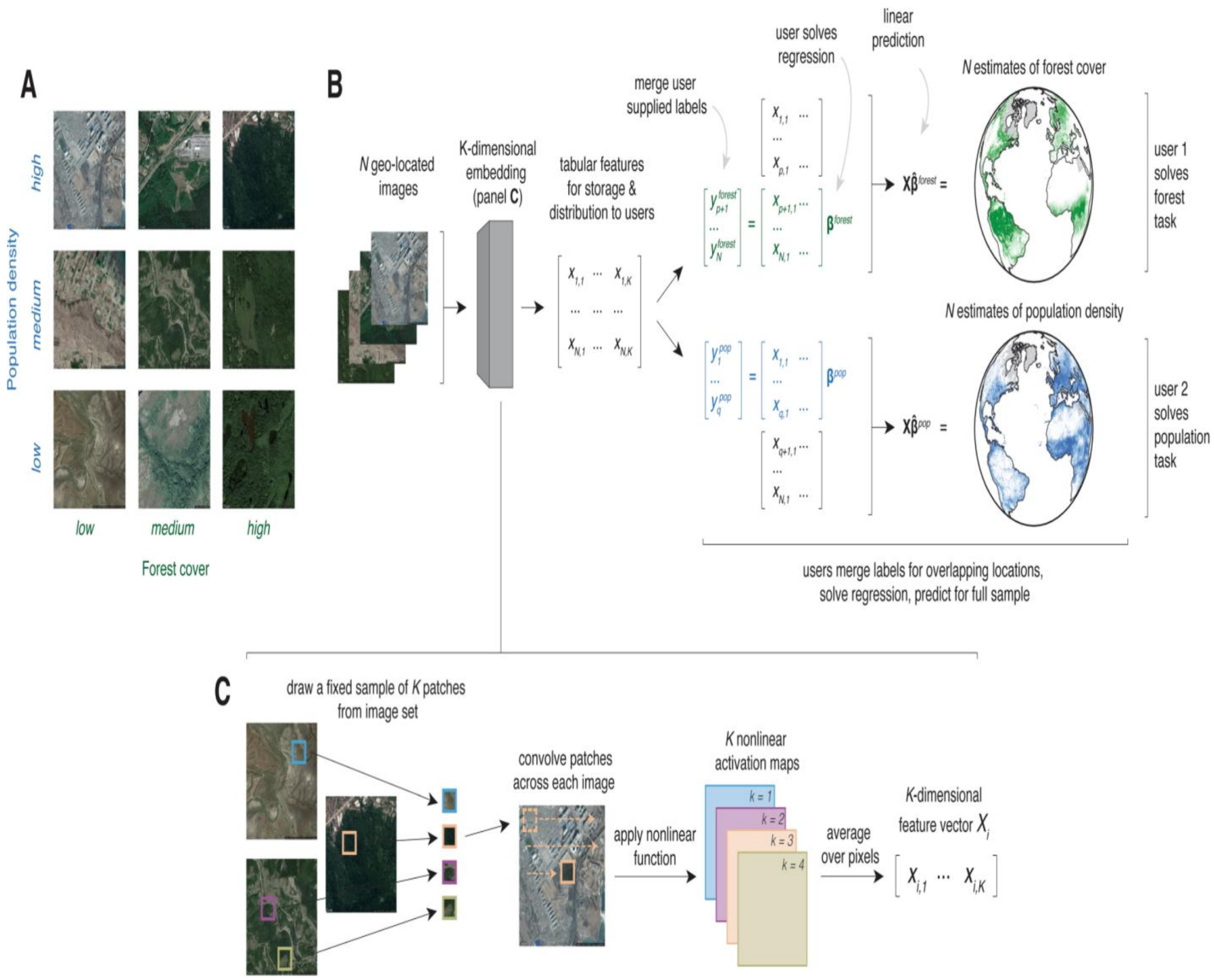


Figure 1: The above figure shows the proposed model for satellite image processing

The proposed work will involve the following steps:

1. **Data Collection and Preprocessing:**
   Collect a diverse dataset of satellite images with ground truth labels covering different land cover classes. Preprocess the images by resizing, normalizing, and enhancing image quality to ensure consistent and reliable input for the model.
2. **Deep Learning Feature Extraction:**
   Utilize Convolutional Neural Networks (CNNs) for feature extraction from the pre-processed satellite images. Train the CNN model using the labelled dataset to learn discriminative features relevant to different land cover classes. Extract high-level features from the trained CNN model, which capture the spatial and spectral characteristics of the images.
3. **Feature Representation and SVM Classification:**
   Represent the extracted features as a feature matrix. Apply dimensionality reduction techniques such as Principal Component Analysis (PCA) to reduce feature dimensionality if necessary. Train an SVM classifier using the reduced feature matrix, which learns to classify the satellite images based on the extracted features.
4. **Model Evaluation and Performance Metrics:**
   Evaluate the proposed model's performance using various metrics such as accuracy, precision, recall, and F1-score. Compare the model's results with existing classification methods and evaluate its robustness by testing it on unseen satellite images. Perform cross-validation to assess the model's generalization capabilities.
5. **Parameter Optimization and Sensitivity Analysis:**
   Conduct parameter optimization for the SVM classifier to fine-tune its performance. Perform sensitivity analysis by varying the model's hyperparameters and evaluating their impact on classification results.
6. **Experimental Results and Analysis:**
   Present the experimental results, including classification accuracy, confusion matrix, and performance comparisons with other methods. Analyze the strengths and limitations of the proposed model and provide insights into its applicability and potential use cases.
7. **Conclusion and Future Work:**
   Summarize the findings of the project and discuss the effectiveness of combining deep learning and SVM for satellite image classification. Identify areas for future improvement, such as exploring ensemble techniques, incorporating spatial

information, or integrating multi-modal data sources. Highlight the potential impact of the proposed model in real-world applications and suggest further research directions.

By implementing this proposed model, the project aims to enhance satellite image classification accuracy and provide a robust framework for land cover mapping and related tasks using deep learning and SVM algorithms.

Because of the existence of these differences, the satellite photos have a broad range of textural contrasts and shading variations. As a consequence, applying preparation processes to satellite data is quite challenging. Furthermore, satellite data is collected from enormous distances and is influenced by the presence of unwanted impedances, which alters the image's appearance. This implies genuine difficulties in the next handling processes and detracts from the overall appearance of the finished picture. The final image contains a lot of fundamental information for further investigation and dynamic applications. As a result, the resultant distorted satellite images should be pre-handled before any extra image preparation processes are performed. Satellite photographs (also known as Earth observation imagery, space borne photography, or simply satellite photos) are images of the Earth captured by imaging satellites operated by governments and enterprises worldwide.

This study has taken four different classes of images and trained the framework with highlights from those images. Highlights of those preparatory images include Extended Local Binary Patterns (ELBP), Linear Support Vector Machine (LSVM). This job includes at least five prepared images for one class. The next step is to select a test image. The test image can be any other image which is not in the database, but it must be unique in terms of image preparation. 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.

ELBP Algorithm Proposed technique is a gridding technique that subdivide big amounts of information into separate groups for programming languages reasons of course. There seem to be plenty of dependent variables, converting such large datasets typically generally requires a notable number of online resources. Techniques for choosing but instead integrating data points to create features ensure that the data that must be prepared whilst still effective manner or rather totally labelling this same empirical distribution. Fig. 1 Local binary pattern values calculation Object recognition is handy because we need to cut the levels of necessary funds for processing without losing crucial or important data. Proposed technique may also aid in reducing the amount of duplicated data in an inquiry. Consequently, content analysis or the user's efforts in creating variable combinations (features) speed up the computational component's teaching or generalization procedures. This same Glcm Trend (LBP) texturing operator is a basic but effective shading operator that labels actual pixels of an image by thresholding the neighbourhood from each pixel as well as interpret the outcome as more than just a bitwise integer. With its racially prejudiced capability and processing economy, the RGB image operation is becoming a popular approach in a wide range of applications. It may also be considered as a unifying approach to the generally heterogeneous mathematical and geometric notions of pattern recognition. The LBP pilot's resilience to periodic grey and black changes caused, for one, by changes in illumination may be its most important feature in implementations. Another notable aspect is its operational ease, which enables it to analyse images in challenging real-time contexts. The ELBP approach is an enhanced variant of LBP in which the picture is separated into three separate images based on the colour configuration (red, blue, and green). The pattern values are retrieved from all three photos and then put together. The values collected 464 International Journal for Modern Trends in Science and Technology for all of the images in the dataset are saved in a table format mat file.

- LBP= $s\ (in - ic\ )2\ 7\ n\ n$=0 Where ic = Centre pixel value in = Neighbour pixel value

➢ Pre-processing:

Pre-processing is a broad word for activities that employ images at a low degree of complexity, with both output data being intensity images. The iconic visuals are all of the same kind as the original sensor signals, with an intensity picture often represented by an image matrix. Action values (artistry). However, because analogous techniques are now used, geometric hope of developing images (for example, booty shaking, sizing, and reinterpretation) have been designated among also before the styles. The end result of also before that would be an advancement of something like the dataset, which thus inhibits accidental nonlinear behaviour or elevates some photograph feature extraction.

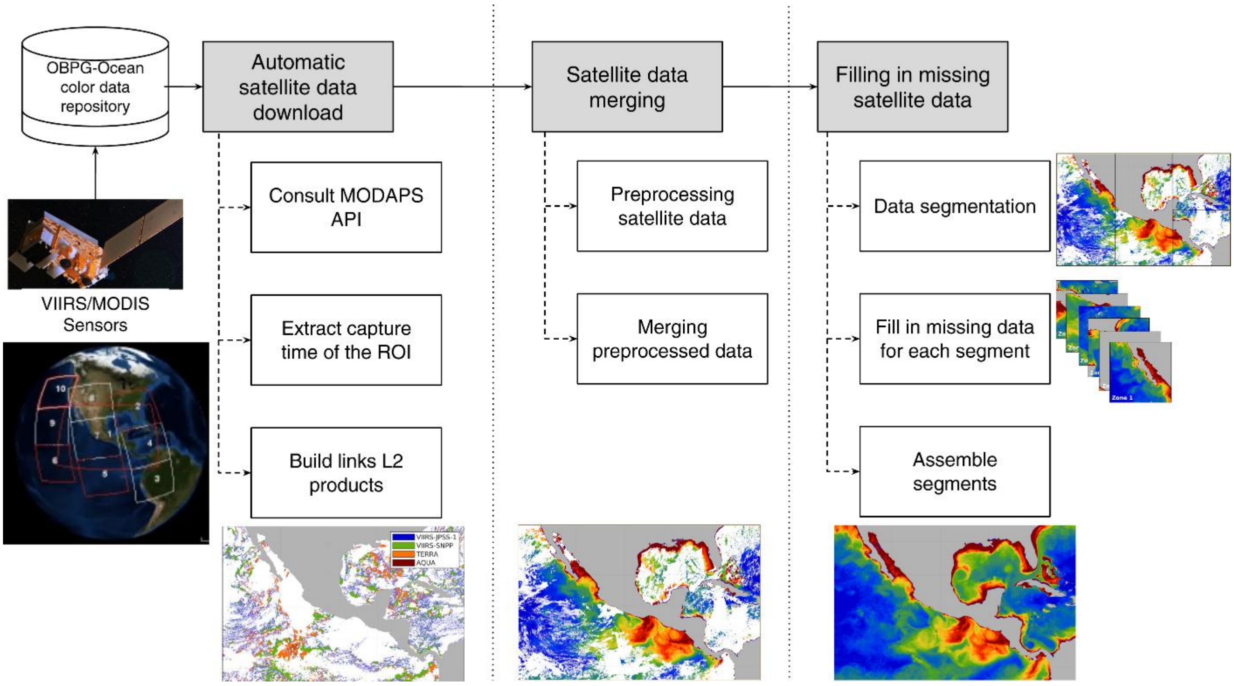


Figure 2: The above figure shows the Preprocessing of Datasets

➢ SVM Classifier:

The "Support Vector Machine" (SVM) is a classification method used for classification and analysis. Although, it is mostly used in classification tasks. Every bit of data is represented by a graph in n-dimensional space (where n is the variety of attributes), only with value of each feature being the SVM computation score of a stationary point. The identification is then completed by choosing this over that effectively differentiates the 2 classes (look at the below snapshot). Individual observation parameters are used to build training examples. Machine learning (ML) is a subset of artificial intelligence (AI) that allows software packages to enhance in predictive performance without it being specifically programmed to do so. Machine learning algorithms estimate new output values using past information as input. The way a computer program learns to increase its predictive performance is typically used to classify classical machine learning. Learning methods are classified into four types: supervised learning, unsupervised learning, semi-supervised learning, and optimization algorithms. The algorithm that data analysts employ is determined by the type of data they wish to forecast.

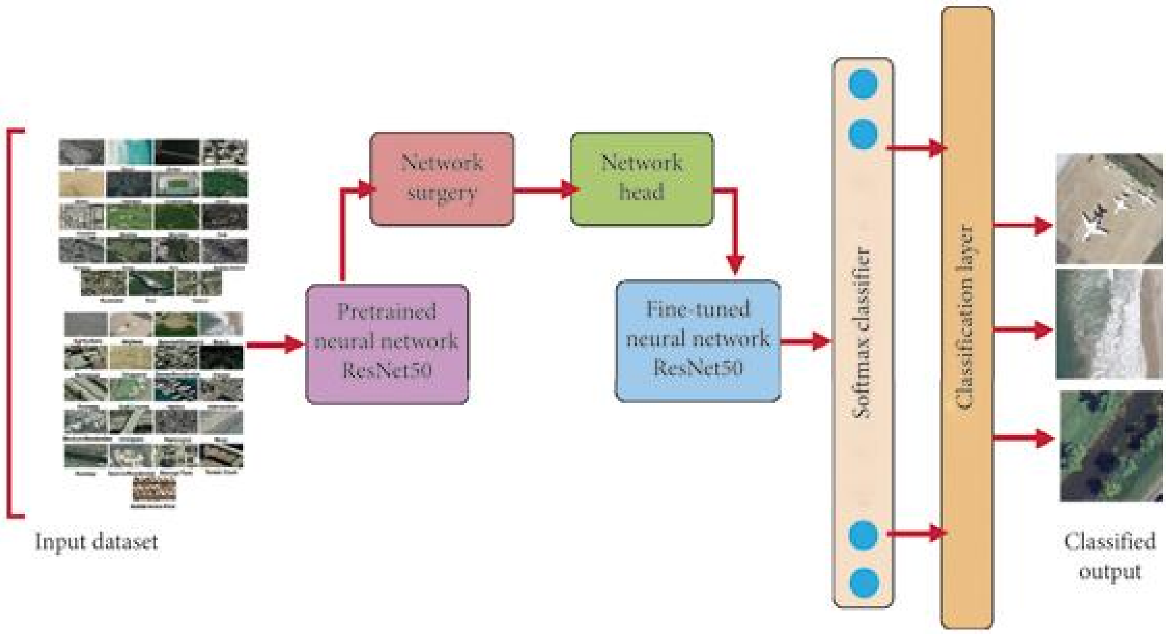


Figure 3: The above figure shows the SVM Classifier

➢ Supervised learning:

Data analysts supply labelled classification model to programs and indicate the elements they just want software to explore for correlations amongst in this kind of machine learning. The algorithm's input and output are both provided. Validation data is a secondary set of data that comprises new input and target information for such machine learning algorithms. When you run the model on validation data, you can see whether it can correctly identify relevant new instances. Changes and improvements to impact the procedure may be identified here. Some other typical issue discovered during validation is over fitting, which occurs whenever the AI is incorrectly taught to select instances that are overly particular towards the learning algorithm. As you can expect, following validation, data scientists will often return to the learning algorithm and set up it once more, modifying variables and other factors to improve the performance of the models.

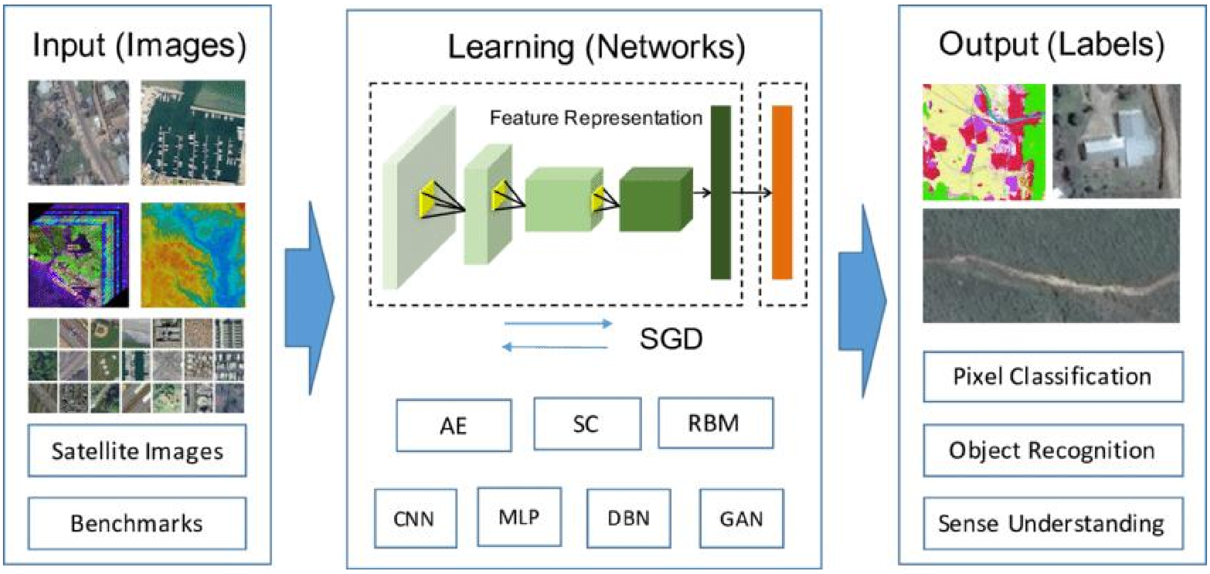


Figure 4: The above figure shows the Supervised Learning

➢ Deep learning:

Satellite image classification using deep learning is a cutting-edge approach that harnesses the power of artificial neural networks to accurately classify satellite imagery into different land cover classes. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in various computer vision tasks, including satellite image analysis.

In this method, a large dataset of satellite images with corresponding ground truth labels is collected and pre-processed to ensure consistent quality and remove noise. The images are then fed into the deep learning model, which consists of multiple layers of interconnected neurons that learn to extract hierarchical features from the input data. CNNs, specifically designed to capture spatial dependencies, are well-suited for the analysis of satellite images due to their ability to identify complex patterns and structures.

During the training phase, the deep learning model optimizes its parameters by iteratively adjusting them based on the computed loss between predicted and ground truth labels. This process allows the model to learn and generalize from the training data, improving its ability to classify unseen satellite images accurately.

Once trained, the model is evaluated using a separate validation dataset to assess its performance and make any necessary adjustments. Finally, the model is tested on a separate test dataset to measure its real-world accuracy and robustness.

Satellite image classification using deep learning offers significant advantages, including the ability to handle large volumes of data, automatically learn relevant features, and adapt to complex and varied image characteristics. It has applications in diverse fields such as land cover mapping, environmental monitoring, urban planning, and disaster management. The continuous advancement of deep learning techniques and the availability of extensive satellite datasets hold immense potential for further improving the accuracy and efficiency of satellite image classification.

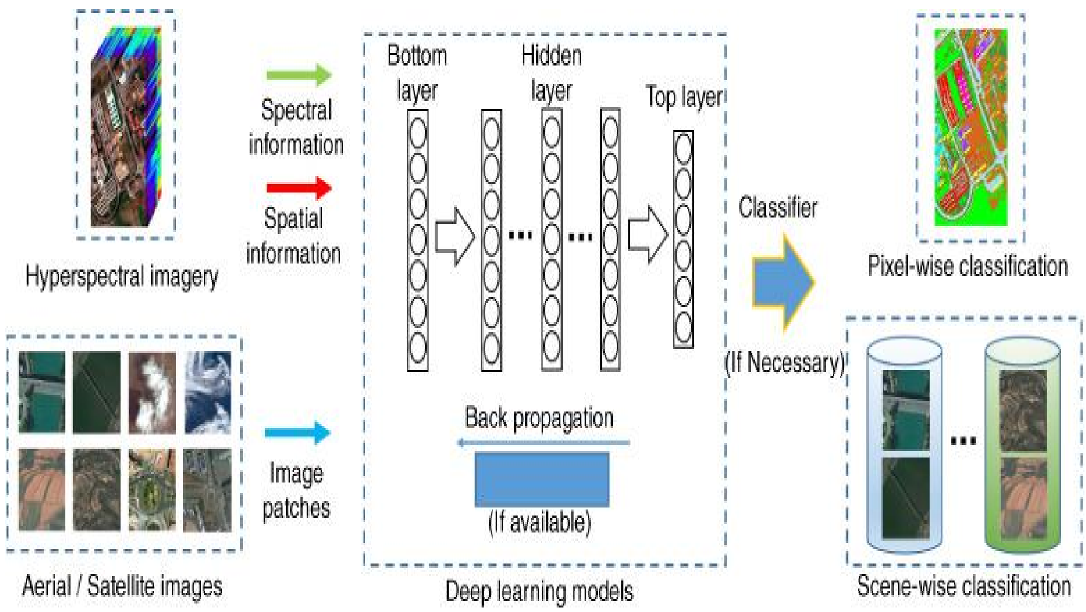


Figure 5: The above figure shows the Deep Learning Technique

CHAPTER 4

TRAINING DATA SEQUENCE

4.1 DESCRIPTION

The training data sequence for satellite image classification using deep learning involves a series of steps to prepare and process the data before training the model. Here is a detailed description of the training data sequence:

Data Collection: Gather a diverse and representative dataset of satellite images that cover the land cover classes you want to classify. The dataset should encompass different regions, seasons, and imaging modalities (e.g., optical, radar, multispectral) if available. Acquire the images from reliable sources such as satellite providers or public repositories.

Data Annotation: Annotate the satellite images with ground truth labels indicating the land cover class for each image or region of interest. Annotation can be performed manually by human experts or through semi-automatic techniques such as image segmentation algorithms. Ensure accurate and consistent labelling to provide reliable training data.

Data Split: Divide the dataset into three subsets: training set, validation set, and testing set. The training set is used to train the deep learning model, the validation set is used to tune hyperparameters and monitor model performance during training, and the testing set is used for final evaluation. The recommended split ratio is commonly 70-80% for training, 10-15% for validation, and 10-15% for testing.

Data Augmentation: Apply data augmentation techniques to increase the diversity and size of the training dataset. Common augmentation techniques include random rotations, translations, scaling, flipping, and adding noise or blur. These techniques help to improve model generalization and robustness by exposing it to variations in the input data.

Preprocessing: Preprocess the satellite images to ensure they are in a suitable format for training the deep learning model. This may involve resizing all images to a consistent resolution, normalizing pixel values, and applying filters or enhancements to improve image quality, remove noise, or enhance specific features relevant to the classification task.

Feature Extraction: Extract relevant features from the pre-processed satellite images that can be used as input to the deep learning model. Feature extraction can be performed through handcrafted feature engineering techniques, domain-specific algorithms, or by using pre-trained convolutional neural network models (transfer learning) that have been trained on large-scale image datasets.

Data Encoding: Encode the ground truth labels into a suitable format for training the deep learning model. This typically involves converting categorical labels into numerical representations, such as one-hot encoding, to enable the model to process and learn from the labelled data.

Data Balancing: Address class imbalance issues if present in the training dataset. Class imbalance occurs when certain land cover classes are significantly underrepresented compared to others. Techniques such as oversampling minority classes, under sampling majority classes, or using class weights during training can help to balance the dataset and prevent biased model predictions.

Model-Specific Preprocessing: Adjust the preprocessing steps based on the requirements of the chosen deep learning model. Some models may have specific input size or colour space requirements, and preprocessing steps may need to be tailored accordingly. Additionally, perform any model-specific normalization or data formatting steps necessary for optimal performance.

By following this training data sequence, you can ensure that the satellite image dataset is appropriately prepared for training a deep learning model for classification. The sequence involves steps such as data collection, annotation, splitting, augmentation, preprocessing, feature extraction, encoding, balancing, and model-specific preprocessing, ultimately leading to a well-prepared training dataset for effective deep learning model training CNN model for image processing.

4.2 FLOWCHART

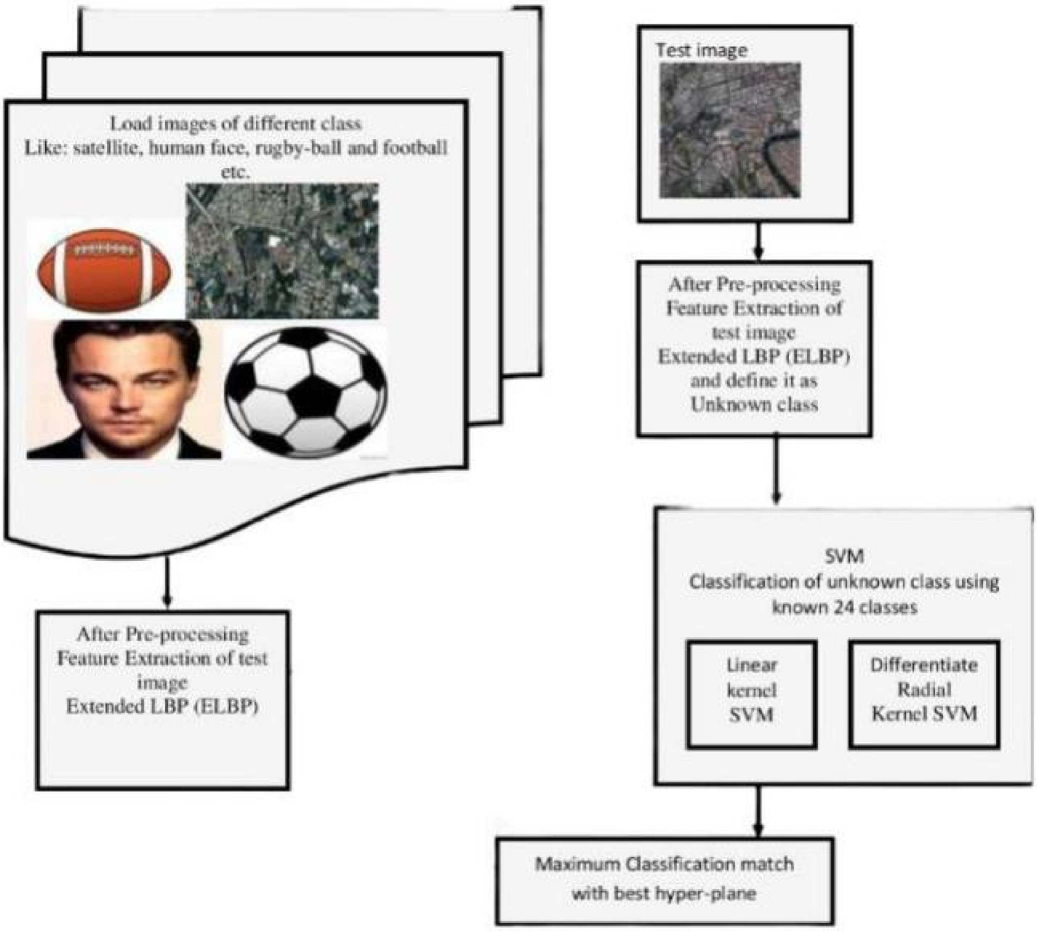


Figure 6: The above figure shows the flowchart for satellite image classification

The flowchart for satellite image classification begins with the initial step of data acquisition, where satellite images along with their corresponding ground truth labels are collected. The next stage involves data preprocessing, which includes tasks such as resizing, normalization, and noise reduction to ensure consistent and high-quality input data. Once the data is pre-processed, the feature extraction phase follows, utilizing deep learning techniques such as Convolutional Neural Networks (CNNs) to extract relevant features from the satellite images. These features are then used as input for the classification phase, where a suitable classification algorithm, such as Support Vector Machines (SVM), is employed to classify the satellite images into different land cover classes. The classification results are evaluated and compared against the ground truth labels, and performance metrics such as accuracy, precision, recall, and F1-score are calculated. Finally, the flowchart concludes with the output of the classified satellite images, enabling further analysis, decision-making, and application-specific tasks based on the obtained results.

4.3 TRIGGERS AND STORED PROCEDURES

Triggers and stored procedures are typically used in databases to enforce data integrity, automate tasks, and provide efficient data retrieval and processing. While they may not be directly applicable to the training data sequence for satellite image classification using deep learning, here are some possible scenarios where triggers and stored procedures could be employed:

Data Integrity Checks: Triggers can be used to enforce data integrity constraints on the training data. For example, you can define triggers that validate the correctness of the ground truth labels during the annotation process. These triggers can be triggered when new annotations are inserted or updated, ensuring that the labels conform to predefined rules or allowable classes.

Data Augmentation Automation: If data augmentation is part of the training data sequence, you can create stored procedures that automatically apply augmentation techniques to the training images. These procedures can be triggered after the images are inserted or updated in the database, ensuring consistent and automated data augmentation.

Dataset Splitting: Stored procedures can be used to partition the dataset into training, validation, and testing subsets according to predefined rules. These procedures can be triggered after the dataset is collected, ensuring consistent and reproducible splits.

Preprocessing Automation: If there are specific preprocessing steps involved in the training data sequence, such as resizing or normalizing images, stored procedures can be used to automate these tasks. These procedures can be triggered when new images are added to the database, ensuring consistent preprocessing across the dataset.

Data Balancing: If class balancing is required in the training data, triggers and stored procedures can be used to automatically adjust the dataset by oversampling or under sampling specific classes. These procedures can be triggered when new annotations or images are added, maintaining a balanced dataset.

While triggers and stored procedures can be useful in automating certain aspects of data management and processing, they may not be the primary means for implementing the training data sequence for satellite image classification using deep learning. The training data sequence typically involves data collection, annotation, splitting, augmentation, preprocessing, feature extraction, encoding, balancing, and model-specific preprocessing, which are often performed outside of a database system using specialized tools or scripts.

CHAPTER 5

IMPLEMENTATION OF PROPOSED MODEL

5.1 SOFTWARE TESTING

To ensure the robustness and reliability of the implementation of the proposed model for satellite image classification using deep learning, software testing plays a crucial role. Here are some key testing approaches and techniques that can be employed:

Unit Testing: Perform unit testing to verify the correctness of individual components of the implementation, such as data preprocessing functions, feature extraction modules, and the deep learning model architecture. This can be done by writing test cases that cover different scenarios and edge cases to validate the behaviour of these components.

Integration Testing: Conduct integration testing to ensure that the different components of the implementation work together seamlessly. This involves testing the interaction between modules, such as verifying the correct flow of data from preprocessing to feature extraction, and from feature extraction to the deep learning model.

Performance Testing: Evaluate the performance of the implemented model by conducting performance testing. This can involve measuring the inference time for classifying satellite images, assessing resource utilization (CPU, memory, GPU), and analysing the scalability of the system for handling larger datasets or concurrent requests.

Accuracy and Validation Testing: Validate the accuracy of the model's predictions by comparing them against ground truth labels. Use a separate validation dataset or cross-validation techniques to assess the model's performance metrics such as accuracy, precision, recall, and F1-score. This helps ensure that the model performs well on unseen data and generalizes effectively.

Robustness Testing: Test the robustness of the implemented model by subjecting it to various scenarios that may challenge its performance. This can involve introducing noisy or distorted satellite images, testing with different resolutions or image formats, or evaluating the model's response to outliers or adversarial examples.

Error Handling and Exception Testing: Validate the implementation's error handling mechanisms and exception handling procedures. This includes testing how the system handles invalid inputs, missing files, or unexpected errors during runtime. Ensure appropriate error messages or fallback strategies are implemented to handle such scenarios.

Usability and User Experience Testing: Consider conducting usability and user experience testing if the implementation involves a user interface or interaction with end-users. This can involve gathering feedback from users to assess the intuitiveness, ease of use, and overall user satisfaction with the system.

Regression Testing: Perform regression testing whenever modifications or updates are made to the implementation. This helps ensure that existing functionality is not adversely affected by changes and that new features or bug fixes do not introduce unexpected issues.

Cross-platform and Cross-browser Testing: If the implementation is intended to run on different platforms or browsers, conduct cross-platform and cross-browser testing to verify its compatibility and consistent behaviour across various environments.

Documentation and Code Review: Thoroughly review the implementation's code and documentation to ensure clarity, correctness, adherence to coding standards, and maintainability. Conduct peer code reviews to identify potential bugs, improve code quality, and ensure compliance with best practices.

By employing these testing approaches and techniques, you can enhance the reliability, accuracy, and performance of the implemented model for satellite image classification using deep learning.

5.2 MODULE TESTING AND INTEGRATION

Module Testing and Integration are crucial steps in implementing the proposed model for satellite image classification using deep learning.

Module Testing involves testing individual components or modules in isolation to ensure their correctness and functionality. Each module is tested independently using test cases that cover various scenarios and edge cases. This includes validating the preprocessing module by providing sample input data and verifying the correctness of the output. Similarly, the feature extraction module is tested by evaluating if it accurately captures relevant features from the pre-processed data. The deep learning model module is tested by feeding it with test images and verifying if it produces accurate predictions. Finally, the evaluation metrics module is tested to ensure it correctly calculates performance measures based on the predicted and ground truth labels.

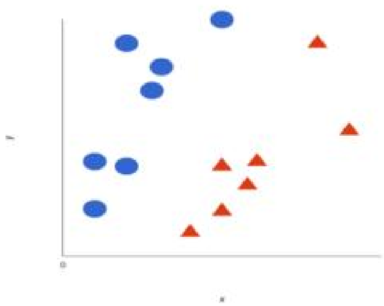


Figure 7: Labelled Data in SVM

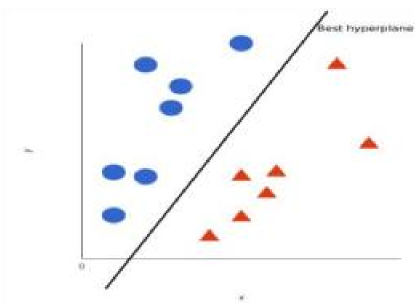


Figure 8: In 2D, the best hyper-plane is simply a line in SVM

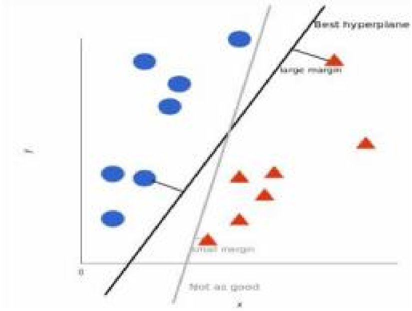


Figure 9: Not all hyper-planes are created equal in SVM

Integration Testing focuses on testing the interaction and integration between different modules. The goal is to verify that the modules work seamlessly together and produce the desired results. Integration test cases are defined to cover the interactions between modules, such as passing data from preprocessing to feature extraction and from feature extraction to the deep learning model. These test cases ensure proper data flow, input-output handling, and correct integration of functionality. The integrated system is evaluated to ensure that data is passed correctly between modules, inputs and outputs are processed accurately, and the system behaves as expected.

Through thorough module testing and integration testing, any issues or bugs within the individual modules or their integration can be identified and addressed. This ensures the overall correctness and functionality of the proposed model for satellite image classification using deep learning. It also helps in validating that the modules work harmoniously together to provide accurate predictions and reliable performance metrics.

Module testing and integration are important steps in the implementation of the proposed model for satellite image classification using deep learning. Here's an overview of how module testing and integration can be carried out:

1. Module Testing:

Module testing involves testing the individual components or modules of the implementation to ensure their correctness and functionality. Each module can be tested independently using appropriate test cases and data. Here are the steps involved in module testing:

a. Identify Modules: Identify the different components or modules in the implementation, such as data preprocessing, feature extraction, deep learning model architecture, and evaluation metrics.

b. Define Test Cases: Define test cases to cover different scenarios and edge cases for each module. Test cases should include both valid and invalid inputs to ensure robustness.

c. Execute Test Cases: Execute the defined test cases for each module, providing the necessary inputs and verifying the expected outputs. This involves running the module with sample data and checking if the output matches the expected results.

d. Assess Module Functionality: Evaluate if each module performs as intended and meets the requirements. Verify that data preprocessing produces the expected output, feature extraction captures relevant features, the deep learning model produces accurate predictions, and the evaluation metrics calculate performance measures correctly.

e. Fix Issues: If any issues or bugs are identified during module testing, debug and fix them before proceeding to integration testing.

2. Integration Testing:

Integration testing focuses on testing the interaction and integration between the different modules of the implementation. The goal is to verify that the modules work together seamlessly and produce the desired results. Here's how integration testing can be conducted:

a. Identify Integration Points: Identify the points where different modules interact or exchange data, such as passing data from preprocessing to feature extraction and from feature extraction to the deep learning model.

b. Define Integration Test Cases: Define integration test cases that cover the interactions between modules. These test cases should ensure proper data flow, handling of inputs and outputs, and the correct integration of functionality.

c. Execute Integration Test Cases: Execute the defined integration test cases, simulating the interactions between modules and monitoring the results. Check if the data is passed correctly between modules, if inputs and outputs are processed accurately, and if the integrated system behaves as expected.

d. Verify Integration Success: Assess if the integration of modules is successful and if the integrated system functions as intended. Ensure that the modules work together without any conflicts or errors and that the desired outputs are obtained.

e. Fix Integration Issues: If any integration issues or inconsistencies are identified, investigate and resolve them by refining the interaction between modules or addressing data compatibility issues.

f. Regression Testing: After making changes to resolve integration issues, perform regression testing to ensure that existing functionality is not negatively impacted.

By conducting thorough module testing and integration testing, you can identify and address issues at the component and system level, ensuring that the implementation of the proposed model for satellite image classification using deep learning functions correctly and that the modules work harmoniously together.

5.3 BENEFITS AND CHALLENGES

▶ BENEFITS

Satellite image classification offers several benefits in various fields and applications. Here are some key advantages of satellite image classification:

1. Land Cover Mapping and Monitoring: Satellite image classification enables the mapping and monitoring of land cover, providing valuable information about vegetation, urban areas, water bodies, and other land features. It helps in understanding changes in land use over time, monitoring deforestation, tracking urban expansion, and assessing the impact of natural disasters or climate change.

2. Environmental Analysis and Management: Satellite image classification aids in environmental analysis by identifying and monitoring sensitive ecosystems, assessing biodiversity, and detecting environmental changes. It helps in monitoring forest health, identifying wetlands, analysing water quality, and supporting conservation efforts.

3. Urban Planning and Infrastructure Development: Satellite image classification plays a vital role in urban planning by providing information on population density, land use patterns, transportation networks, and infrastructure development. It assists in urban growth analysis, identifying suitable locations for infrastructure projects, and optimizing resource allocation in urban areas.

4. Disaster Management and Response: Timely and accurate satellite image classification helps in disaster management by providing information on affected areas, assessing damage extent, and aiding in response planning. It supports emergency response operations, assists in search and rescue efforts, and facilitates post-disaster recovery and reconstruction.

5. Agriculture and Crop Monitoring: Satellite image classification assists in agriculture by monitoring crop health, identifying crop types, and assessing vegetation indices. It aids in precision farming, optimizing irrigation and fertilization, predicting crop yield, and detecting pest or disease outbreaks.

6. Natural Resource Management: Satellite image classification contributes to the effective management of natural resources such as forests, water bodies, and mineral deposits. It aids in resource inventory, assessing the impact of extraction activities, and monitoring the sustainability of resource use.

7. Climate Change Analysis: Satellite image classification helps in studying the effects of climate change by monitoring land cover changes, analysing vegetation dynamics, and assessing the impact on ecosystems. It supports climate modelling, carbon sequestration studies, and monitoring glacier and ice sheet changes.

8. Remote and Inaccessible Areas: Satellite image classification enables analysis and monitoring of remote and inaccessible areas, such as polar regions, mountainous terrains, or dense forests. It provides valuable insights into these regions without the need for ground-based surveys.

Overall, satellite image classification offers a wealth of benefits, including improved spatial understanding, timely information for decision-making, and support for sustainable development and environmental conservation across various domains.

▶ CHALLENGES

Satellite image classification poses several challenges that need to be addressed to ensure accurate and reliable results. Here are some key challenges in satellite image classification:

1. Data Variability and Heterogeneity: Satellite images can exhibit significant variability in terms of resolution, sensor type, imaging conditions, and temporal variations. Dealing with such variability requires robust preprocessing techniques and adaptable classification algorithms capable of handling diverse data sources.

2. Limited Training Data: Obtaining a large and diverse annotated dataset for training deep learning models can be challenging in satellite image classification. Annotated satellite images are often expensive to acquire and time-consuming to label. Limited training data can lead to overfitting or insufficient generalization of the models.

3. Class Imbalance: Satellite imagery datasets often suffer from class imbalance, where certain land cover classes are significantly underrepresented compared to others. This imbalance can bias the classification results, with less frequent classes being neglected or misclassified. Techniques like data augmentation, sampling strategies, or class weighting can be employed to address this challenge.

4. Spatial and Spectral Resolution: The spatial and spectral resolution of satellite images can impact classification accuracy. Low-resolution images may lack fine-grained details, making it challenging to distinguish between similar land cover classes. Additionally, the limited spectral bands in satellite imagery can pose difficulties in accurately differentiating complex land cover classes.

5. Labelling Errors and Subjectivity: Annotating satellite images with ground truth labels can be prone to errors and subjectivity. Different annotators may have variations in labelling standards or interpretations, leading to inconsistencies. Ensuring high-quality and accurate ground truth labels is crucial for reliable classification results.

6. Computational Complexity: Deep learning models for satellite image classification can be computationally intensive, requiring significant computational resources and time for training and inference. Optimizing the model architecture, leveraging efficient algorithms, and utilizing hardware acceleration can help mitigate computational challenges.

7. Generalization to Unseen Data: Satellite image classification models should generalize well to unseen data for accurate predictions in real-world scenarios. Ensuring robustness against variations in imaging conditions, environmental changes, and diverse geographical regions is crucial to achieve reliable results.

8. Interclass Variability and Similarity: Land cover classes in satellite imagery can exhibit significant variability and similarity, making their discrimination challenging. Distinguishing between classes with similar spectral properties or identifying subtle differences between visually similar classes requires advanced feature extraction techniques and fine-grained classification algorithms.

Addressing these challenges requires ongoing research and development efforts to improve data acquisition, preprocessing techniques, model architectures, and algorithms specific to satellite image classification. Overcoming these challenges will contribute to the advancement and applicability of satellite image classification in various domains.

5.4 LIMITATIONS

Satellite image classification, despite its many benefits, also has some limitations that need to be considered. Here are some common limitations in satellite image classification:

1. Limited Spatial and Spectral Resolution: Satellite images typically have limitations in spatial and spectral resolution compared to ground-based or airborne imaging. The limited resolution can make it challenging to accurately classify small or detailed land cover features, resulting in lower classification accuracy.

2. Atmospheric and Weather Conditions: Satellite images can be affected by atmospheric conditions, such as clouds, haze, and shadows, which can obscure or distort the land cover information. Weather conditions, such as rain or snow, can also impact the quality and interpretability of satellite images, affecting classification accuracy.

3. Data Availability and Accessibility: Access to high-quality and up-to-date satellite imagery may be limited due to factors such as cost, licensing restrictions, or restricted data sources. Obtaining consistent and timely satellite data for classification purposes can pose challenges, particularly for real-time or dynamic applications.

4. Incomplete Ground Truth Labels: Obtaining accurate ground truth labels for satellite images can be labor-intensive and subject to human interpretation. Incomplete or inaccurate ground truth labels can introduce errors and biases into the classification process, impacting the overall accuracy of the classification results.

5. Class Overlap and Ambiguity: Land cover classes in satellite imagery can exhibit overlap and ambiguity, making their discrimination challenging. Certain classes may have similar spectral signatures or exhibit variations within the same class, leading to misclassifications or reduced classification accuracy.

6. Dynamic and Evolving Land Cover: Land cover is not static, and changes can occur over time due to natural processes, human activities, or seasonal variations. Satellite image classification may struggle to accurately capture and classify dynamic land cover changes, especially with limited temporal information or single-date images.

7. Dependency on Training Data Quality and Quantity: The performance of satellite image classification models heavily relies on the quality, diversity, and representativeness of the training dataset. Limited training data or biased training samples can result in reduced generalization ability and lower classification accuracy.

8. Computational Requirements: Deep learning models used for satellite image classification can be computationally demanding, requiring significant computational resources, memory, and processing time. Implementing and deploying such models may be challenging, especially in resource-constrained environments or with limited computing infrastructure.

Understanding and addressing these limitations are essential in developing accurate and reliable satellite image classification systems. Mitigating these limitations may involve advancements in data acquisition, preprocessing techniques, model architectures, feature extraction methods, and incorporating ancillary data sources to enhance classification accuracy and robustness.

CHAPTER 6

RESULT ANALYSIS

6.1 SCREENSHOTS

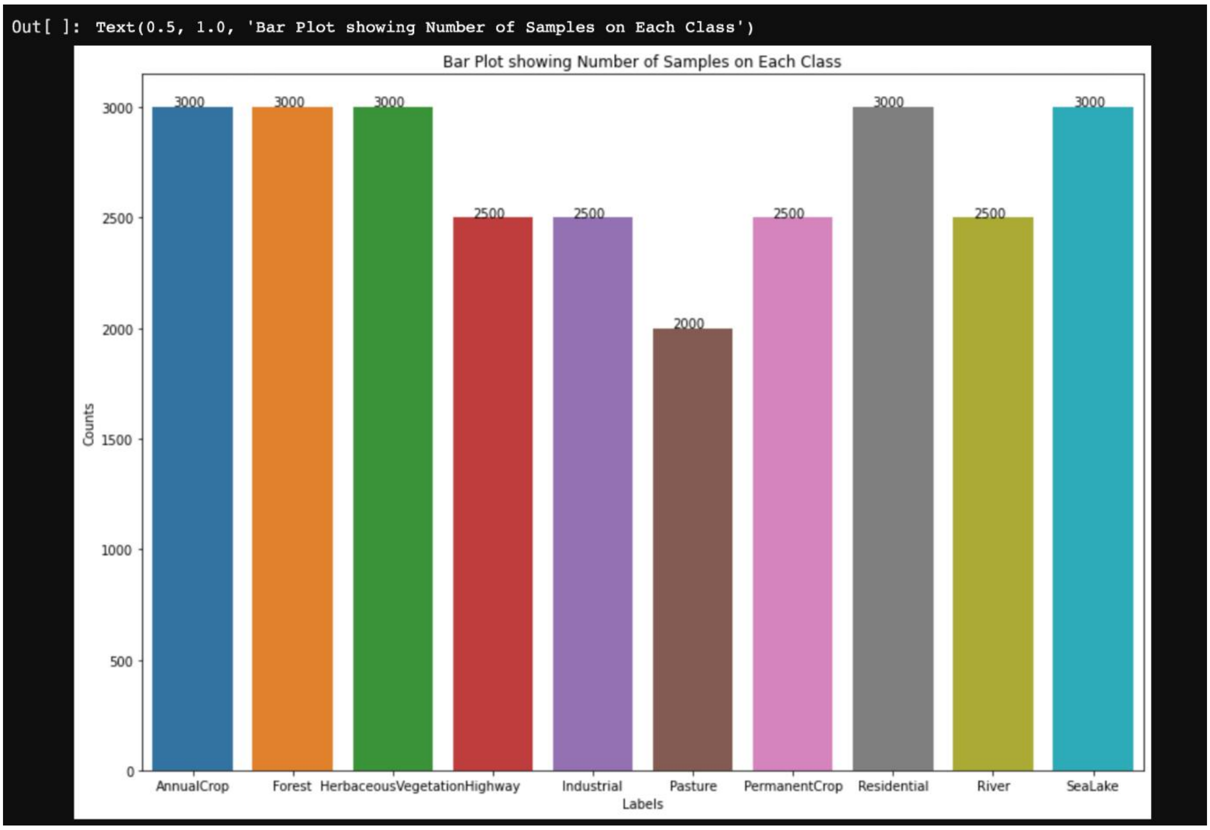


Figure 10: Training datasets

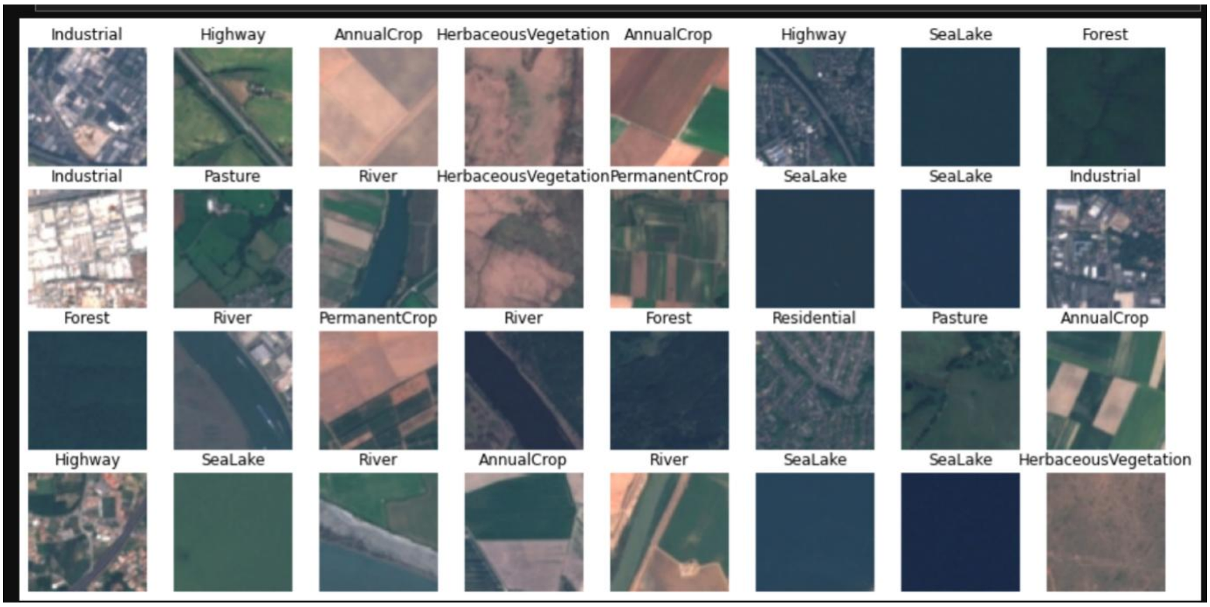


Figure 11: SVM Classification Training Datasets

```
# set the training & validation steps since we're using .repeat() on our dataset
# number of training steps
n_training_steps   = int(num_examples * 0.6) // batch_size
# number of validation steps
n_validation_steps = int(num_examples * 0.2) // batch_size
```

```
# train the model
history = m.fit(
    train_ds, validation_data=valid_ds,
    steps_per_epoch=n_training_steps,
    validation_steps=n_validation_steps,
    verbose=1, epochs=5,
    callbacks=[model_checkpoint]
)
```

```
Epoch 1/5
253/253 [==============================] - ETA: 0s - loss: 0.3869 - accuracy: 0.8832 - f1_score: 0.8804
Epoch 1: val_loss improved from inf to 0.14626, saving model to results/satellite-classification.h5
253/253 [==============================] - 153s 383ms/step - loss: 0.3869 - accuracy: 0.8832 - f1_score: 0.8804 - v
al_loss: 0.1463 - val_accuracy: 0.9518 - val_f1_score: 0.9509
Epoch 2/5
253/253 [==============================] - ETA: 0s - loss: 0.1516 - accuracy: 0.9536 - f1_score: 0.9526
Epoch 2: val_loss improved from 0.14626 to 0.11950, saving model to results/satellite-classification.h5
253/253 [==============================] - 91s 362ms/step - loss: 0.1516 - accuracy: 0.9536 - f1_score: 0.9526 - va
l_loss: 0.1195 - val_accuracy: 0.9626 - val_f1_score: 0.9614
Epoch 3/5
253/253 [==============================] - ETA: 0s - loss: 0.1093 - accuracy: 0.9661 - f1_score: 0.9655
Epoch 3: val_loss improved from 0.11950 to 0.10484, saving model to results/satellite-classification.h5
253/253 [==============================] - 91s 362ms/step - loss: 0.1093 - accuracy: 0.9661 - f1_score: 0.9655 - va
l_loss: 0.1048 - val_accuracy: 0.9654 - val_f1_score: 0.9646
Epoch 4/5
253/253 [==============================] - ETA: 0s - loss: 0.0805 - accuracy: 0.9750 - f1_score: 0.9745
Epoch 4: val_loss did not improve from 0.10484
253/253 [==============================] - 85s 334ms/step - loss: 0.0805 - accuracy: 0.9750 - f1_score: 0.9745 - va
l_loss: 0.1508 - val_accuracy: 0.9559 - val_f1_score: 0.9557
Epoch 5/5
253/253 [==============================] - ETA: 0s - loss: 0.0884 - accuracy: 0.9738 - f1_score: 0.9734
Epoch 5: val_loss did not improve from 0.10484
253/253 [==============================] - 84s 334ms/step - loss: 0.0884 - accuracy: 0.9738 - f1_score: 0.9734 - va
l_loss: 0.1084 - val_accuracy: 0.9689 - val_f1_score: 0.9681
```

Figure 12: Model Training (Loss and Accuracy f1 Score)

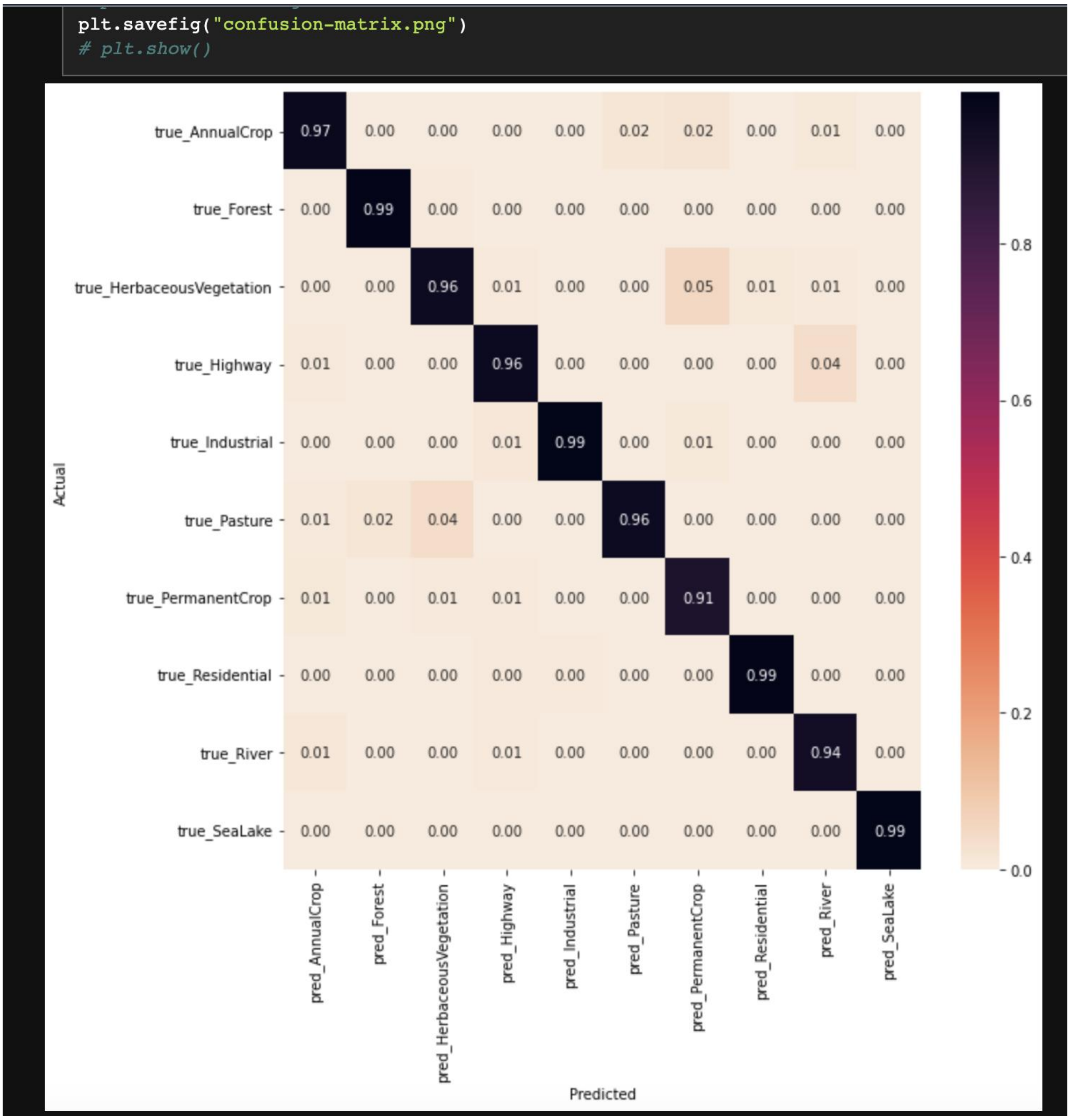


Figure 13: Confusion matrix for the Trained Dataset

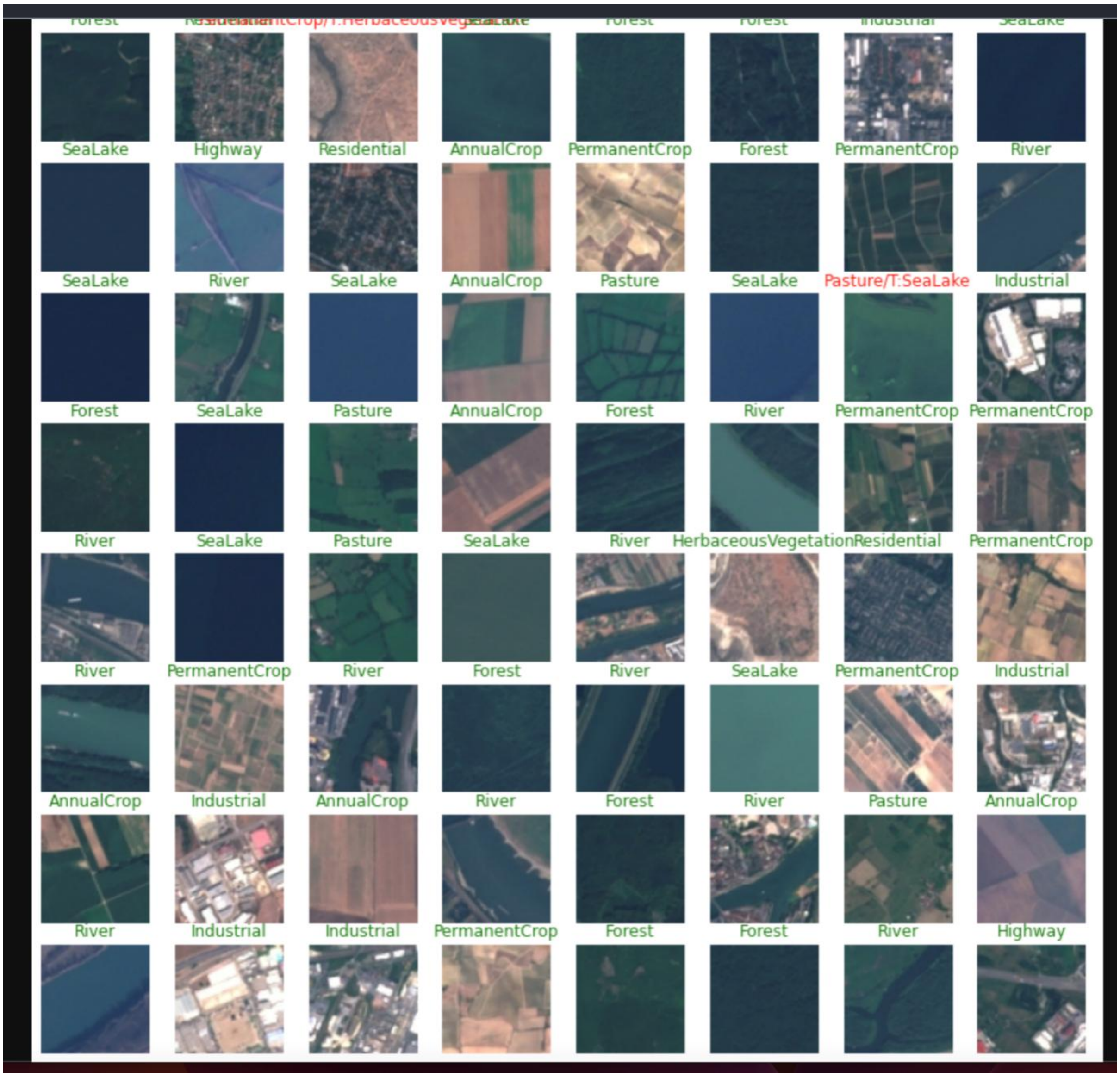
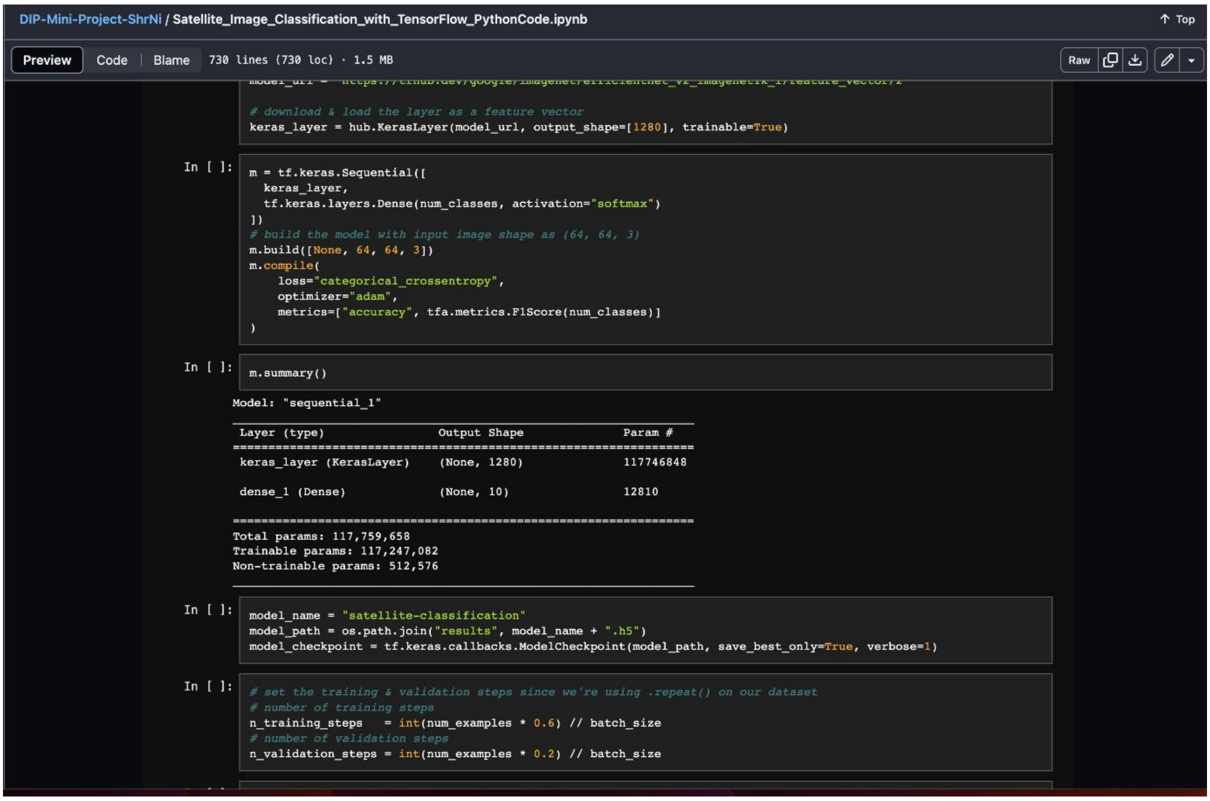


Figure 14: Multiset Deep Learning Data Variation




```
# download & load the layer as a feature vector
keras_layer = hub.KerasLayer(model_url, output_shape=[1280], trainable=True)

In [ ]:
m = tf.keras.Sequential([
  keras_layer,
  tf.keras.layers.Dense(num_classes, activation="softmax")
])
# build the model with input image shape as (64, 64, 3)
m.build([None, 64, 64, 3])
m.compile(
    loss="categorical_crossentropy",
    optimizer="adam",
    metrics=["accuracy", tfa.metrics.F1Score(num_classes)]
)

In [ ]:
m.summary()

Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 keras_layer (KerasLayer)    (None, 1280)              117746848

 dense_1 (Dense)             (None, 10)                12810

=================================================================
Total params: 117,759,658
Trainable params: 117,247,082
Non-trainable params: 512,576
_________________________________________________________________

In [ ]:
model_name = "satellite-classification"
model_path = os.path.join("results", model_name + ".h5")
model_checkpoint = tf.keras.callbacks.ModelCheckpoint(model_path, save_best_only=True, verbose=1)

In [ ]:
# set the training & validation steps since we're using .repeat() on our dataset
# number of training steps
n_training_steps   = int(num_examples * 0.6) // batch_size
# number of validation steps
n_validation_steps = int(num_examples * 0.2) // batch_size
```

Figure 15: Keras Sequential Trainable Parameters

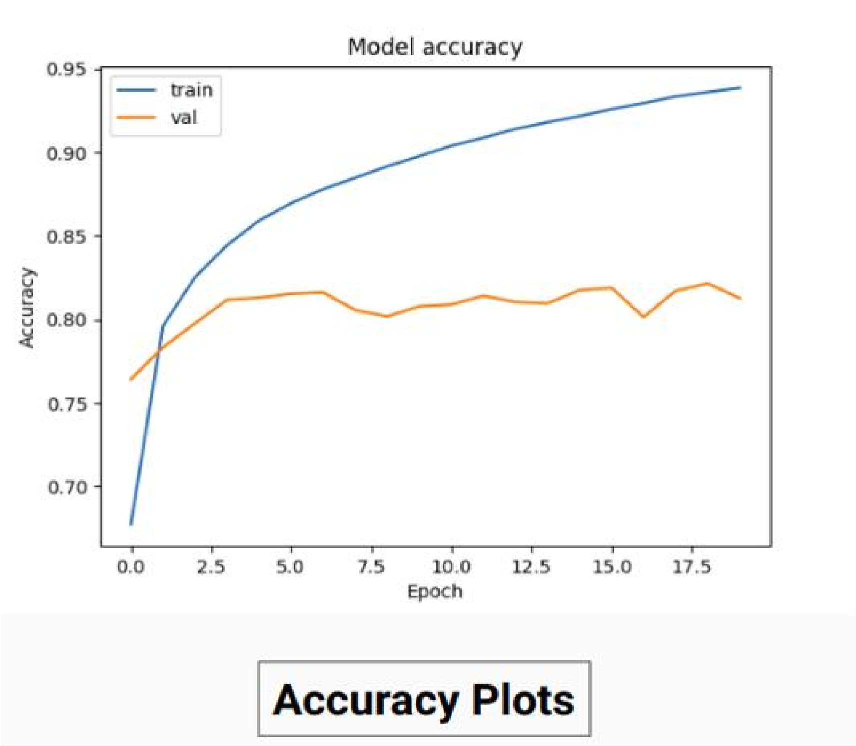


Figure 16: Accuracy plots for training and validation

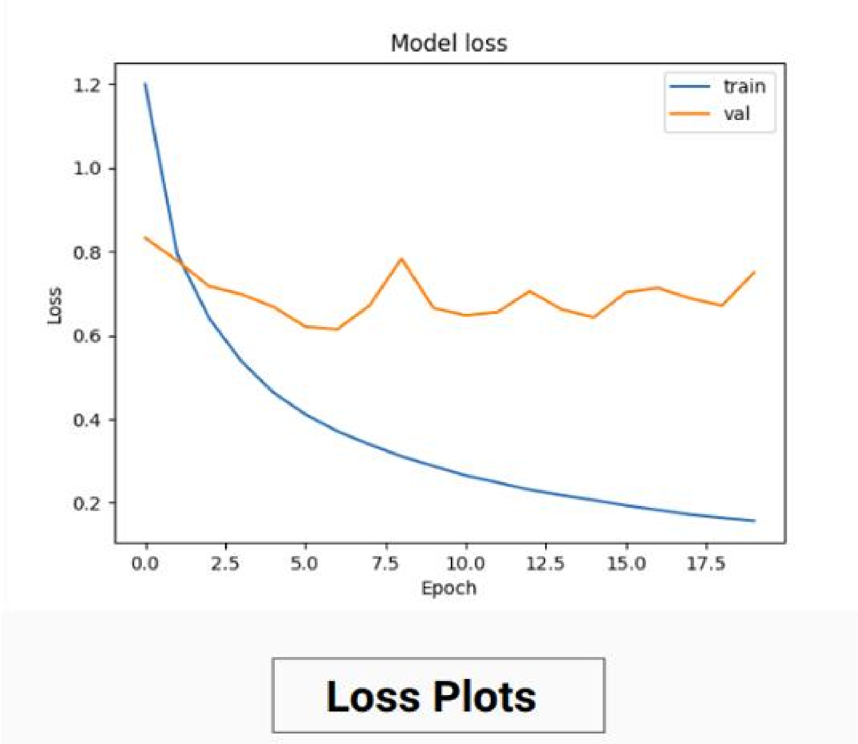


Figure 17: Loss plots for training and validation

6.2KAPPA COEFFICIENT

Kappa Coefficients with and without considering the unclassified pixels.

	Training	Validation
With Unclassified Pixels	0.9352	0.7808
Without Unclassified Pixels	0.9959	0.9716

OVERALL ACCURACY

Overall Accuracy with and without considering the unclassified pixels.

	Training	Validation
With Unclassified Pixels	95.40	83.354
Without Unclassified Pixels	99.71	98.115

6.3 APPLICATIONS

1. **Prediction & Detection of Natural Disasters:** Satellite images along with GIS maps can give a whole lot of information for assessment, analysis and monitoring of natural disasters such as hurricanes, tornadoes, volcanoes, earthquakes and cyclone damage from small to large regions around the globe. It can act as an important tool and technology to monitor and manage the disasters to produce strategic planning models and to predict and control the natural disasters as they occur. Being able to project natural disasters it becomes possible for the stakeholders to better prepare for and answer to the critical events. This is especially beneficial for sectors like railways and airways as prediction of natural disasters can help them reschedule travel, find out some substitution route, protect their assets, prepare for rescue planning and so on and so forth.

2. **Disaster mitigation planning and recovery:** Satellite images with their capability to revisit the same areas multiple times are quite useful in assessment of damage caused by natural calamities such as floods, cyclones, earthquakes and landslides which become difficult to access in such times. Satellite images provide quick and accurate information of the disaster hit area and are quite useful in planning relief and rescue operations. They are also useful for site selection of storm/flood shelters. Other similar applications using satellite_imagery in disaster assessments include measuring shadows from buildings and digital surface models.

3. **Providing a base map for graphical reference and assisting planners and engineers:** The number of details that orthoimage produces using high resolution satellite imagery is of immense value and provides an extreme amount of detail of the focus and surrounding areas. Maps are designed to communicate highly structured message about the world. As maps are location-based, aerial imagery supports people to orient themselves.

4. **Urban Planning:** The rapid urban growth and development have been putting increasing pressure on the environment including urban parks and green spaces. The green spaces are essential to improve the urban areas and to provide quality life to the urban population. Green spaces generally include lawns, public parks, gardens, street landscapes, forests, etc. In this regard, technologies such as satellite imagery can support the urban developers as well as the land managers to monitor and support decision-making for sustainable urban development in dense urban environments and prevent flooding conditions in urban areas by gathering high-resolution details of the urban area(s). Further, satellite images can provide detailed analysis for detecting major changes in the urban land cover and land use that allows frequent coverage and overlaying of different time sequences to classify environmentally safe and sustainable areas for any proposed development area(s).

5. **Infrastructural Condition & Mapping:** Satellite imaging makes it possible to evaluate different infrastructural conditions. The very high resolution of the satellite images has the potential of showing great details in the observed scene. As for example, with satellite imaging it becomes possible to observe broken railway tracks, broken/damaged roads, broken/damaged bridges, damaged catenary poles, damaged air bases, runways and such others and in turn avoid incidents before it is too late.

6. **Applications in Agriculture and Forestry**: Satellite images are an important tool for managing the world's agricultural resources which are critical to feed the ever-increasing population across the world. The problems of deforestation and desertification are also affecting the availability of arable land. Many areas are also affected by salinization due to over irrigation and some rain dependent areas are always under the shadow of recurring draughts. Remote sensing and GIS can help provide solutions for increased agricultural production and proper management of farmlands by obtaining reliable data on not only the types, but also the quality, quantity and location of these resources. Remote sensing-based studies can provide accurate information on acreage, monitoring of crop health and yield estimation.

7. **Applications in Mining**: Satellite images with sophisticated hyperspectral range are useful in the pre-feasibility and feasibility stages of the mineral exploration. Giving the "bigger picture" they also give important indications about the mineral potentiality of the area to be considered for mineral extraction. The spectral analysis of satellite image bands helps scientists to identify and map mineral availability through special indicators, enabling them to narrow down their geo physical, geo chemical and test drilling activities to high potential zones.

8. **Providing a base map for reference:** Highly detailed Ortho-imagery from high resolution satellite imagery provides a pictorial image of the area of interest along with its surrounding areas. These maps are geo-referenced and provide a wealth of details to give a complete picture an area. The base maps can be used for variety of purposes such as transportation planning, site selection for new railway/airports, urban planning, property tax surveys, mapping of urban zones like residential. Commercial and industrial etc.

9. **Urban Waste Management:** Management of the solid wastes in the dumpsites is a common problem all across the world. In order to adopt the shutdown process, it is necessary to perform an environmental assessment which requires the knowledge of the history of these sites. However, this kind of a study is generally hampered by the lack of past records on the waste disposal activities in such places, especially when they are very old. However, in this regard remote sensing images can act as an important tool for identification and the study of the development of inadequate waste disposal sites. Satellite images can help in obtaining information on the progress of activities in the dumps and their surroundings, on how the waste disposal occurred, and on the end of operations and the re-vegetation process. Further, with the support of Geographic Information System (GIS), the information from different data sources could be crossed with previous databases, thus helping obtain greater data structure for better interpretation of the available information.

10. **Climate Change Analysis:** Satellite image classification contributes to studying and understanding the impact of climate change. It enables the monitoring of changes in glaciers, ice sheets, and coastal areas, analyzing shifts in vegetation patterns, and studying the impact of climate change on various ecosystems.

11. **Water Resource Management:** Satellite image classification assists in managing water resources by monitoring changes in water bodies, detecting water pollution, and assessing water quality. It aids in analyzing water availability, managing reservoirs, and supporting water resource planning and conservation.
12. **Environmental Monitoring and Conservation:** Satellite image classification supports environmental monitoring by analyzing vegetation health, detecting changes in forest cover, identifying protected areas, and monitoring the impact of natural disasters, climate change, and human activities on ecosystems. It plays a vital role in conservation efforts, habitat assessment, and monitoring biodiversity.

13. **Land Cover Mapping and Monitoring:** Satellite image classification is widely used for mapping and monitoring land cover, including identifying different types of vegetation, urban areas, water bodies, and agricultural land. It aids in understanding changes in land use patterns, monitoring deforestation, assessing the impact of urbanization, and managing natural resources.

14. **Humanitarian Aid and Crisis Response:** Satellite image classification contributes to humanitarian aid and crisis response efforts by providing situational awareness, identifying displaced populations, and assessing the impact of humanitarian interventions in remote or inaccessible regions.

15. **Natural Resource Management:** Satellite image classification contributes to the management of natural resources such as forests, water bodies, and mineral deposits. It assists in monitoring deforestation, biodiversity conservation, water resource assessment, and mineral exploration.

16. **Defense and Security:** Satellite image classification is used in defense and security applications for surveillance, border monitoring, and identification of potential threats. It aids in monitoring military activities, detecting unauthorized land use, and supporting strategic decision-making.

17. **Geological and Geographical Studies:** Satellite image classification is valuable for geological and geographical studies, including mapping geological formations, identifying mineral deposits, analyzing topography, and studying terrain characteristics.

18. **Military and Security Applications:** Satellite image classification has applications in military and security domains for monitoring borders, identifying potential threats, and supporting surveillance activities. It aids in monitoring sensitive areas, tracking illegal activities, and assisting in defense and security planning.

19. **Natural Resource Exploration:** Satellite image classification assists in the exploration and management of natural resources, including mining activities, oil and gas exploration, and forestry management. It aids in resource inventory, land suitability analysis, and environmental impact assessment.

6.4FUTURE ENHANCEMENTS

Satellite image classification using deep learning has seen significant advancements in recent years, but there are several potential future enhancements that can further improve the accuracy, efficiency, and applicability of the models. Here are some future enhancements to consider:

1. **Incorporating Attention Mechanisms:** Attention mechanisms enable deep learning models to focus on the most relevant features or regions of interest in satellite images. By incorporating attention mechanisms, models can dynamically allocate their resources to important regions, improving classification accuracy and reducing computational overhead.

2. **Semi-Supervised and Unsupervised Learning:** Expanding beyond purely supervised learning, incorporating semi-supervised and unsupervised learning techniques can leverage unlabelled satellite images to enhance model training and improve generalization. Self-supervised learning, generative adversarial networks (GANs), and other unsupervised methods can facilitate learning from large amounts of unlabelled data.

3. **Multi-Modal Fusion:** Integrating multiple imaging modalities, such as optical, radar, and multispectral images, can provide a more comprehensive view of the satellite data. Developing deep learning models that effectively fuse information from different modalities can improve classification accuracy, especially in challenging scenarios or for tasks requiring more detailed information.

4. **Transfer Learning with Pre-Trained Models:** Transfer learning has been successful in various computer vision tasks. Adapting pre-trained models, such as those trained on large-scale image datasets like ImageNet, to satellite image classification can significantly improve performance, especially when labelled satellite image datasets are limited. Fine-tuning pre-trained models on satellite images can facilitate faster convergence and better generalization.

5. **Explainable AI and Interpretability:** Enhancing the interpretability of deep learning models for satellite image classification is crucial, especially for decision-making in critical applications. Techniques like attention maps, saliency maps, and gradient-based methods can provide insights into which image regions contribute most to classification decisions, improving transparency and trust in the models.

6. **Online and Incremental Learning:** Developing models that can learn continuously and adapt to new satellite data in an online or incremental manner is valuable. This allows the model to incorporate new information efficiently and adapt to evolving land cover patterns or changes in the satellite image characteristics.

7. **Robustness to Adversarial Attacks:** Investigating techniques to enhance the robustness of deep learning models against adversarial attacks is important. Adversarial attacks aim to fool the model by introducing carefully crafted perturbations to input images. Developing models that can detect and mitigate adversarial examples can improve the reliability and security of satellite image classification systems.

8. **Domain-Specific Preprocessing and Data Augmentation:** Customized preprocessing techniques and data augmentation strategies designed specifically for satellite images can be explored. These techniques can enhance data quality, handle specific challenges unique to satellite imagery (e.g., atmospheric effects, shadows), and augment the training data with domain-relevant transformations.

These future enhancements have the potential to further advance satellite image classification using deep learning, improving accuracy, interpretability, robustness, and efficiency. Continued research and development in these areas can enable more effective and reliable analysis of satellite data, supporting various applications such as land cover mapping, disaster management, urban planning, and environmental monitoring.

Data Augmentation Techniques: Leveraging techniques like image rotation, scaling, and flipping to increase the diversity of the training dataset and enhance model generalization.

Transfer Learning: Utilizing pre-trained models on large-scale datasets to leverage their learned features and improve the performance of satellite image classification models.

Semi-Supervised Learning: Investigating methods that can make use of both labelled and unlabelled satellite images to train more robust models with limited labelled data.

Ensemble Methods: Implementing ensemble techniques such as model averaging or stacking to combine predictions from multiple models and enhance overall classification accuracy.

- The Role of Hyperparameter Optimization in Improving Model Performance
- Tuning hyperparameters like learning rate, batch size, optimizer choice, regularization techniques, and network architecture parameters through methods like grid search or Bayesian optimization.
- Incorporating Domain Knowledge and Contextual Information for Better Classification
- Integrating domain-specific information, such as land cover maps, geographical features, or temporal data, to enhance the accuracy and contextual relevance of satellite image classification models.

Satellite image classification using TensorFlow is a rapidly evolving field with immense potential. By exploring these future enhancements and pushing the boundaries of deep learning techniques, we can unlock new possibilities in remote sensing applications and contribute to a better understanding of our planet.

CONCLUSION

In conclusion, satellite image classification is a powerful technique with a wide range of applications in fields such as environmental monitoring, land cover mapping, urban planning, and disaster management. The utilization of deep learning algorithms, particularly Convolutional Neural Networks (CNNs), has significantly advanced the accuracy and efficiency of satellite image classification. Deep learning models can automatically learn and extract meaningful features from satellite images, enabling accurate classification of diverse land cover classes.

However, it is important to recognize the challenges and limitations associated with satellite image classification. These include data variability and heterogeneity, limited training data, class imbalance, spatial and spectral resolution limitations, labelling errors, and computational complexity. Addressing these challenges requires ongoing research and development efforts to enhance data preprocessing techniques, optimize model architectures, mitigate class imbalance, improve ground truth labelling accuracy, and optimize computational resources.

Despite these limitations, satellite image classification provides valuable insights and benefits. It enables land cover mapping, environmental analysis, urban planning, disaster management, agriculture monitoring, and natural resource management. By accurately classifying satellite images, it aids in decision-making processes, resource allocation, and sustainable development.

To overcome the challenges and maximize the benefits, future advancements may include integrating multi-modal data sources, incorporating temporal information, addressing uncertainties and ambiguity, improving data accessibility, and developing more robust and interpretable deep learning models.

Overall, satellite image classification is a dynamic and evolving field with tremendous potential for further advancements. Continued research, innovation, and collaboration will contribute to the improvement of satellite image classification techniques, leading to more accurate and reliable classification results and unlocking new opportunities for analysis and understanding of our changing world.

In this thesis work it relate the different techniques and algorithms used in proposed machine learning framework for satellite image processing. thesis presented machine learning state-of-the-art applied to image processing. This work introduced the Bag of Features paradigm used for input image encoding and highlighted the Extended Local Binary Pattern as its technique for image features extraction. Through experimentations this work proofed that using ELBP local feature extractor method for image vector representation and LKSVM and RKLBP training classifier performs best prediction average accuracy. In test scenarios this focused on satellite image as we project to apply the trained classifier in a general system. Presently the researchers are trying to arrive at some solutions by combining various image processing techniques or introducing hybrid models based on spectral and spatial indices for the same to improve the outcome. In near future this type of combination can be implemented for better accuracy. In near future the number of classes also can be improve as his work has limitation of 12 class only, accuracy obtain in this work is 94% it may be improvised with use of Deep learning.

At present, even though a wide range of techniques are available for image processing, it is extremely cumbersome to arrive at a technique which can be commonly applied to all types of satellite images owing to the different color and textural variations. Hence presently the researchers are trying to arrive at some solutions by combining various image processing techniques or introducing hybrid models based on spectral and spatial indices for the same to improve the outcome. In near future this type of combination can be implemented for better accuracy. The frequent availability of satellite images has made the remote applications flourish. Some of the common challenges found in the literatures are the image complexity, large image sizes, presence of unwanted artefacts and background information in the satellite images. It is especially difficult in feature detection in panchromatic images due to the presence of cloud cover. Most image fusion techniques suffer from the drawback that it cannot capture the smoothness between the contours. On examining the literature, it is seen that deep learning and hybrid machine learning based techniques are finding wide popularity recently. In this paper work it relates the different techniques and algorithms used in proposed machine learning framework for satellite image Processing. paper presented machine learning state-of-the-art applied to image Processing. This work introduced the Bag of Features paradigm used for input image encoding and highlighted the Extended Local Binary Pattern as its technique for image features extraction. Through experimentations this work proofed that using ELBP local feature extractor method for image vector representation and LKSVM and RKLBP training classifier performs best prediction average accuracy. In test scenarios this focused on satellite image as we project to apply the trained classifier in a general system.

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