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Segmentand Classify Satellte Images to Analyze The Environment and Ensure Safety, Using Machine Learning

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Abstract: *Image segmentation is a difficult task in computer vision. The process includes the classification of visual input to segments to simplify image analysis. There are many types of method for the image segmentation some of the common methods are edge detection based method region-based methods, clustering-based method, partial differential equation-based, watershed-based method, and neural network-based method. The proposed project work is mainly focused on image segmentation. Satellite images are given as the input of the proposed system. Machine learning techniques plan an important role in various domains. Here the remotely sensed data can be segmented by using the K-Means clustering method. Compared with other traditional methods this clustering technique yields better results. The system is implemented using the Matlab tool. Machine learning concepts drastically decrease the time needed to arrange an exact map.*
the project will be using K Nearest Neighbor (KNN) as existing and Support Vector Machine (SVM) as proposed system for classification and calculates results in terms of accuracy. From the results obtained its proved that proposed SVM works better than existing KNN.

Keywords: machine learning, K Nearest Neighbor (KNN), Support Vector Machine (SVM)

I. INTRODUCTION

In remote sensing images, lot of predictions can be made without any intervention of the human being. Remotely sensed image is digital representations of the Earth, by using this, places which cannot be accessed is viewed by the remote sensing images, this will encourage the process of those interior parts. In a remotely sensed image data, each pixel represents an area of the Earth at a specific location. If a pixel satisfies a certain set of criteria then that pixel is assigned to the class that corresponds to those criteria. This process is referred as image classification. Presently, image classification method can be grouped into two main categories depending on the image primitive i.e. pixel based and object based method.

Pixel based methods classify individual pixels without taking into account any neighborhood or spatial information of the pixel. Object/ Region based methods are also able to handle high resolution imagery which aggravates the classification process for most pixel based methods. Depending on the type of information extracted from the original data, classes will be identified with the known features on the ground. An example of a classified image is a land cover map, showing vegetation, bare land, pasture, urban, etc. In remote sensing imagery, a pixel might represent a mixture of class covers, within-class variability, or other complex surface cover patterns that cannot be properly described by one class.

Finding about vegetation indices level is very important to know about the used lands and agricultural levels in the particular region. To achieve this, the remote sensing image has to be taken for processing, in this work LANDSAT image is taken and it is processed to identify the used land. In the processing initially LANDSAT image is checked for noise freeness. Using this image the required features are extracted. For this feature extraction the different

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features like vegetation indices, used land, forest and unused land are considered. After extracting the features from the image, classification algorithms are applied to get the different classification groups, in this KNN, SVM, Fuzzy algorithms are applied to get the classified image. These results were compared with the MOKNN and MOSVM. Modified algorithms which gives the better result comparing with the existing algorithms. To predict the overall accuracy of the algorithms, different metrics are used like user's accuracy, producer's accuracy, omission error and commission error.

Satellite remote sensing programs have produced an archive of images of the earth that are becoming an increasingly valuable source of data for the study of land cover and land use change. The foremost example is the Landsat program, which has been in operation since 1972. The entire Landsat archive has become freely available, allowing public access to time-series data for most parts of the world. Interpretation of these images, however, remains a challenge.

Conventional supervised image classification relies on *training data* (sites for which there are direct observations of land cover) that coincide temporally with the images used. Training data and the multi-spectral satellite data for the same sites are used in multivariate statistical algorithms to create a predictive model, referred to as "spectral signatures", that is used to classify the satellite image into land cover classes. Training data, however, are usually not available for the majority of images in a time series, and can, in many cases, no longer be easily obtained for older images.

One approach to overcome this problem of missing training data is using visual interpretation, but this is difficult, time-consuming, and possibly very subjective. An alternative approach is to use a signature derived from training data and a matching image from another period and apply this to the images for which no training data are available. Such *signature extension* (referred to as *signature generalization* has been used to classify images by applying signatures obtained from a different domain, whether location, time period, or sensor. Studies that date back to the 1970s have explored signature extension for Landsat Multi-Spectral Scanner (MSS) images. More recently, this approach has been re-examined in response to advances in atmospheric correction and the need to monitor large areas efficiently.

II. LITERATURE REVIEW

[1] SAR Image Land Cover Datasets for Classification Benchmarking of Temporal Changes Corneliu Octavian Dumitru ; Gottfried Schwarz ; Mihai Datcu IEEE 2023.

The increased availability of high-resolution synthetic aperture radar (SAR) satellite images has led to new civil applications of these data. Among them is the systematic classification of land cover types based on the patterns of settlements or agriculture recorded by SAR imagers, in particular the identification and quantification of temporal changes. A systematic (re)classification shall allow the assignment of continuously updated semantic content labels to local image patches. This necessitates a careful selection of well-defined and discernible categories being contained in the image data that have to be trained and validated[1]. These steps are well-established for optical images, while the peculiar imaging characteristics of SAR sensors often prevent a comparable approach. Especially, the vast range of SAR imaging parameters and the diversity of local targets impact the image product characteristics and need special care. In the following, we present guidelines and practical examples of how to obtain reliable image patch classification results for time series data with a limited number of given training data. We demonstrate that one can avoid the generation of simulated training data if we decompose the classification task into physically meaningful subsets of characteristic target properties and important imaging parameters. Then, the results obtained during training can serve as benchmarking figures for subsequent image classification. This holds for typical remote sensing examples such as coastal monitoring or the characterization of urban areas where we want to understand the transitions between individual land cover categories. For this purpose, a representative dataset can be obtained from the authors. A final proof of our concept is the comparison of classification results of selected target areas obtained by rather different SAR instruments. Despite the instrumental differences, the final results are surprisingly similar.

[2] Deep Self-Paced Residual Network for Multispectral Images Classification Based on Feature-Level Fusion Jiaqi Zhang ; Dan Zhang ; Wenping Ma ; Licheng JiaoIEEE 2023.
The classification methods based on fusion techniques of multisource multispectral (MS) images have been studied for a long time. However, it may be difficult to classify these data based on a feature level while avoiding the inconsistency of data caused by multisource and multiple regions or cities. In this letter, we propose a deep learning structure called 2-branch SPL-ResNet which combines the self-paced learning with deep residual network to classify multisource MS data based on the feature-level fusion. First, a 2-D discrete wavelet is used to obtain the multiscale features and sparse representation of MS data. Then, a 2-branch SPL-ResNet is established to extract respective characteristics of the two satellites[2]. Finally, we implement the feature-level fusion by cascading the two feature vectors and then classify the integrated feature vector. We conduct the experiments on Landsat_8 and Sentinel_2 MS images. Compared with the commonly used classification methods such as support vector machine and convolutional neural networks, our proposed 2-branch SPL-ResNet framework has higher accuracy and more robustness

[3] Supervised and Adaptive Feature Weighting for Object-Based Classification on Satellite Images Ya'nan Zhou ; Yuehong Chen ; Li Feng ; Xin Zhang ; Zhanfeng Shen ; Xiaocheng ZhouIEEE 2023.
Object-based image analysis (OBIA) technique has been representing an evolving paradigm of remote sensing application, along with more high-resolution satellite images available. However, too many derived features from segmented objects also present a new challenge to OBIA applications. In this paper, we present a supervised and adaptive method for ranking and weighting features for object-based classification[3]. The core of this method is the feature weight maps for each land type resulted from prior thematic maps and their corresponding satellite images of study areas. Specifically, first, satellite images to be classified are segmented using an adaptive multiscale algorithm, and the multiple (spectral, shape, and texture) features of segmented objects are calculated. Second, we extract distance maps and feature weight vectors for each land type from the prior thematic maps and corresponding satellite images, to generate feature weight maps. Third, a feature-weighted classifier with the feature weight maps, is applied on the segmented objects to generate classification maps. Finally, the classification result is evaluated. This approach is applied on a Sentinel-2 multispectral satellite image and a Google Map image to produce objected-based classification maps, compared with the traditional feature selection algorithms. The experimental results illustrate that the proposed method is practically efficient to select important features and improve classification performance

[4] Learning Multiscale Deep Features for High-Resolution Satellite Image Scene Classification Qingshan Liu ; Renlong Hang ; Huihui Song ; Zhi LiIEEE 2023.
In this paper, we propose a multiscale deep feature learning method for high-resolution satellite image scene classification. Specifically, we first warp the original satellite image into multiple different scales. The images in each scale are employed to train a deep convolutional neural network (DCNN). However, simultaneously training multiple DCNNs is time-consuming. To address this issue, we explore DCNN with spatial pyramid pooling (SPP-net). Since different SPP-nets have the same number of parameters, which share the identical initial values, and only fine-tuning the parameters in fully connected layers ensures the effectiveness of each network, thereby greatly accelerating the training process[4]. Then, the multiscale satellite images are fed into their corresponding SPP-nets, respectively, to extract multiscale deep features. Finally, a multiple kernel learning method is developed to automatically learn the optimal combination of such features. Experiments on two difficult data sets show that the proposed method achieves favorable performance compared with other state-of-the-art method

III. IMPLEMENTATION

In Image Acquisition, real-time satellite images from the Google map are captured. The captured images are cropped to a specific size. The cropped RGB images are converted to grayscale in Image Preprocessing. Image Segmentation is the third component. It consists of segmenting the converted grayscale images using K means filtering. This helps to get rid of problems like backgrounds, illumination of light, etc. Feature Extraction is extracting or showing the portion of the segmented images so that classification becomes easy. The last module includes the classification in which Tensor Flow and Support vector Machine is used.

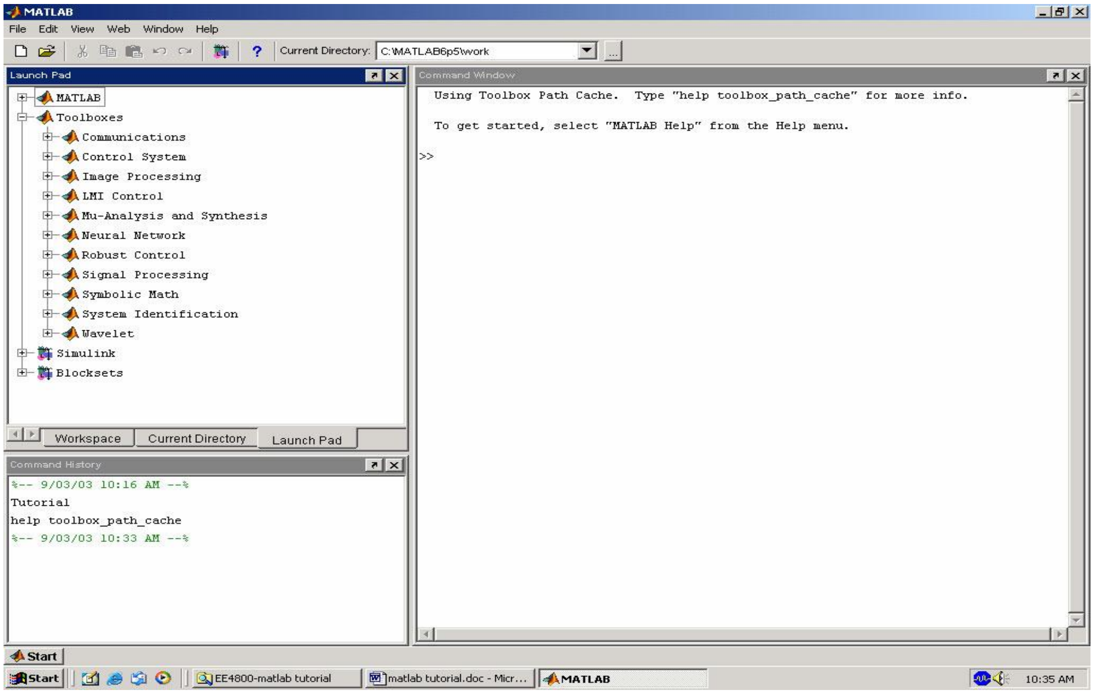

Figure: File Openin

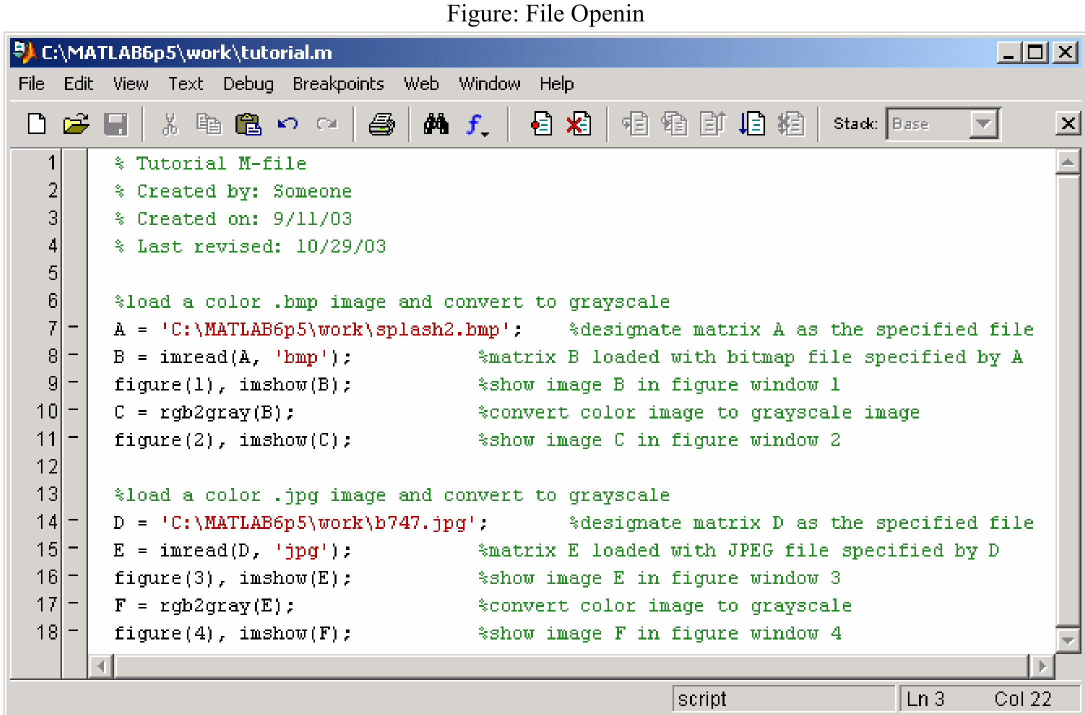

Figure: M-file for Loading Images

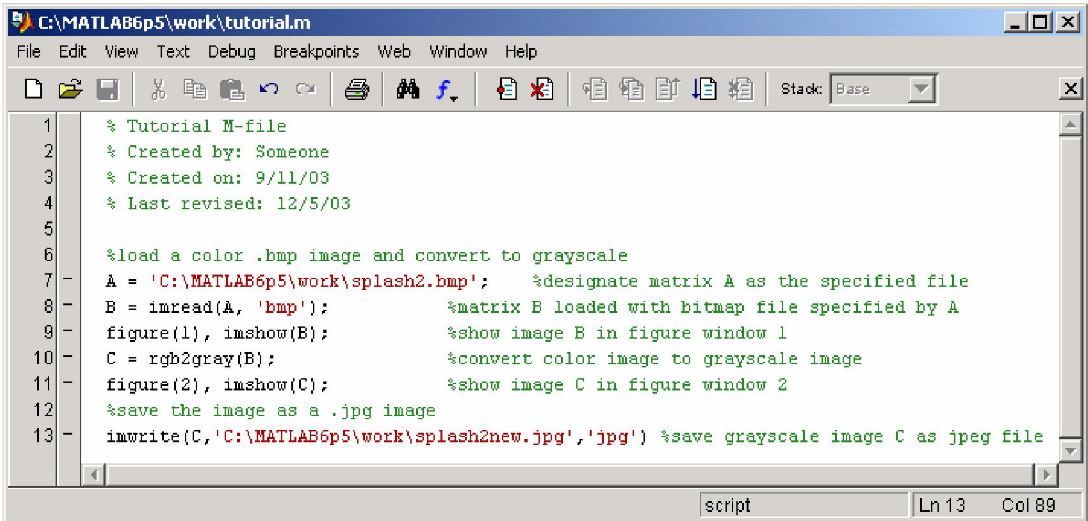

Figure: M-file for Saving an Image

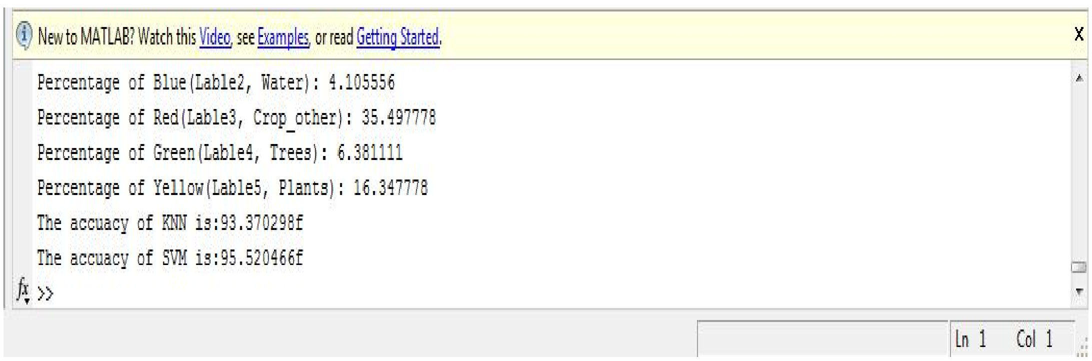

Figure: Final result of Image

IV. CONCULSION

This project gives a summary on automated satellite image classification methods and compares several reviews done by various researchers. Automated satellite image classification methods can be classified into 1) supervised 2) unsupervised. Supervised and unsupervised satellite image classification methods differ in the way of grouping pixels into meaningful categories. In the literature, researchers have presented survey on satellite image classification methods and evaluated the performance against different datasets. This project summarizes the various reviews on satellite image classification methods and techniques. The summary helps researchers to select appropriate satellite image classification method or technique based on the requirements.

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