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Satellite Image Classification Using Extended Local Binary Patterns, SVM AND CNN

CH Sai Yasaswini[1] and Dr. S. Narayana Reddy[2]

*[1]M. Tech student, Department of Electronics and Communication Engineering, Sri Venkateswara UniversityCollege of Engineering, Tirupati, Andhra Pradesh, India

[2]Professor, Department of Electronics and Communication Engineering, Sri Venkateswara University College ofEngineering, Tirupati, Andhra Pradesh, India

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ABSTRACT

In many disciplines and applications, image processing has shown to be an effective research tool. Numerous uses, such as disaster response, law enforcement, and environmental monitoring, depend on satellite imaging. Applications demand manual object and device identification from photos. ELBP-SVM technique is used to categorize the satellite images into a set of distinct classes. Although this work is able to classify distinct classes in addition to the class of satellite images, identifying the characteristics of these other classes, such as forest, desert, oceans, etc., is also straightforward because these other classes have some unique characteristics that can be easy to distinguish and therefore easy to classify. This work uses the suggested ELBP approach to first find local binary patterns. The SVM classifies the test picture class after acquiring the extended features. The ELBP-SVM approach is utilized in this study, and the percentage of correctly identified satellite images is 97%. The results discovered and experimentally acquired on MATLAB 2020a are superior to other research currently accessible for the classification of satellite photos.

Keywords — Extended Local Binary Patterns (LBP), Support vector machine, Satellite image classification.

I. INTRODUCTION

"Remote sensing is the science of acquiring information about the Earth's surface without actually being in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information". Sending radiation from a satellite to Earth or to a target item for study is the essence of remote sensing. Energy is reflected by an object when radiation strikes it. Remote sensing satellites then collected this reflected energy and transmitted it to a distant station where it was transformed into photographs.

Data collection in an image from which energy is reflected is the focus of remote sensing. Remote sensing photos differ from traditional images in that they include extensive spectral data as well as spatial data that reflects their structure, shape, and texture. Numerous studies concentrate on enhancing CNN models to better capture the characteristics of remote sensing images.

For the classification and change detection of urban areas, remote sensing photos have recently been used extensively. Satellite image classification finds applications in various fields. The applications of satellite image classification, such as land cover and land use mapping, urban development monitoring, environmental monitoring (e.g., deforestation, natural disasters), agriculture and crop monitoring, and object detection and recognition

In the era of artificial intelligence, the computing world is becoming increasingly interested in remote sensing, and satellite photography in particular, to improve machine's ability to recognize their surroundings by image classification. Images of the Earth are provided by imaging satellites, which are then gathered, examined, and processed for both civilian and military uses.

It depends on a variety of strategies and techniques that can be used in accordance with particular situations and settings. These strategies and techniques can be divided into five groups: supervised classification, unsupervised classification, pixel-based classification, object-oriented classification, and classification using CNN.

Satellite Image Classification refers to the process of categorizing or labeling pixels or regions within satellite imagery into specific classes or categories. It plays a crucial role in various domains, including environmental monitoring, urban planning, agriculture, and disaster management. This report aims to explore the techniques, applications, and challenges associated with satellite image classification.

Satellite image feature extraction and categorization employ convolutional neural networks. CNN is a deep neural network that works best when processing visual data. By using CNN, classification accuracy will be improved. The overall classification accuracy is estimated using the confusion matrix. A family of machine learning models known as "deep learning" uses numerous processing layers to represent data at various levels of abstraction. By fusing sizable neural network models, or CNNs, with a potent GPU, he obtained astounding results in object identification and classification. For object recognition and classification in pictures, CNN-based algorithms have dominated the biennial ImageNet Large Scale Visual Recognition Challenge.

II. IMAGE CLASSIFICATION TECHNIQUES

Satellite images are divided into 3 types:

1. visible
2. infrared
3. water vapor

Figure 1: Low, Medium and High Spatial Resolution satellite image.

For taxonomy of satellite picture, there are numerous methodologies and procedures (see Figure 2). These techniques can generally be divided into three groups.

1. Supervised classification
2. Un-Supervised classification
3. Semi-Supervised classification

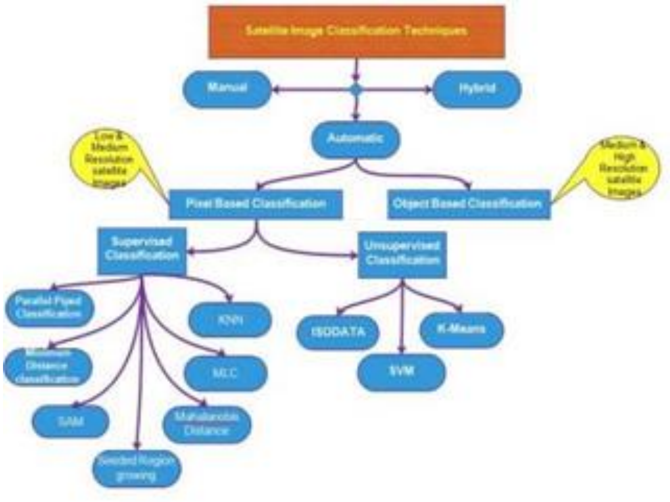


Figure 2: Hierarchy of Satellite image classification techniques.

• Unsupervised image classification: Unsupervised classifiers are used to classify remote sensing images into classes in accordance with the organic grouping of image pixel values. The Iterative Self-Organizing Data Analysis (ISODATA) method and the KNN algorithms are the unsupervised classification algorithms. The primary problems with this unsupervised classification are that it requires a lot of work and is not accurate enough to provide classes that are useful and appealing.

• Supervised classification: Supervised classification classifies satellite images using known inputs, called training data, from analysts. Supervised classification involves training a model using labeled training data and then using this model to classify new satellite images. The popular supervised classification algorithms are Random Forest, Support Vector Machines, and Neural Networks, and introduces evaluation metrics like accuracy, precision, and recall. Types of classes are developed based on the decision rules of classification techniques, and the flow chart of satellite image classification techniques is shown in Figure 2.

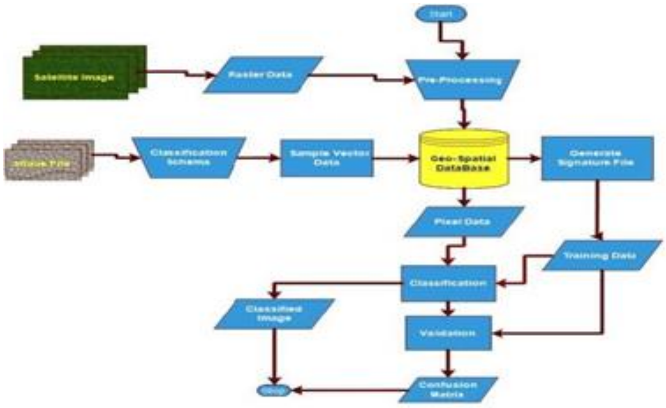


Figure 3 : Flowchart for supervised classification of satellite images.

III. RELATED WORK

Numerous studies have looked into the ideas behind image classification. Some of the more intriguing classification techniques are described in this section.

Anju Asokan et al. (2019) presented a comprehensive approaches of image processing techniques for satellite imagery interpretation. The scale and distance at which satellite images are taken make them vulnerable to noise and other environmental factors. So that researchers can use them for analysis, we process them.

The identification of agricultural land, navigation, and geographic information systems are just a few real-time applications that frequently make use of satellite imagery. Detailed comparisons of several methodologies are also available.

Research work on image processing using deep learning using Deep Neural Networks (DNN) or TensorFlow framework by Mohd Azlan Abu et al (2019).For the TensorFlow Frame work to work python is used as programming language.

Deep Neural Networks (DNN) have been the best option for the training process due to their high accuracy. The results are, with roses we get 90.585% and so with other types of flowers, with results averaging up to 90% or more.

The review of image processing literature by Sohla Losaif et al. (2018) states that the main problems in image processing are extraction of features from the images. He used the bag-of- features method to find image features.

A study on real-time document image processing training and testing is published by Andreas Kolsch et al (2017). Accurate and efficient implementation of training in the production environment is very important. The existing methods do not meet the requirements as they require more time for training. Our two-step method is based on computer vision. So, in the first stage he uses a deep network as a feature extractor and followed by Extreme learning machines (ELMs) for processing.

The accuracy obtained is 24:83% on the Tobacco-3482 dataset, compared to earlier Convolutional Neural Networks (CNN), the suggested strategy exceeds all structural learning and deep learning-based methods so far described. Compared to the baseline strategy, the relative error is reduced by 25%. (DeepDocClassifier).

More significantly, the overall prediction time is 2 seconds, while the ELM training time is only 1:176 seconds. 3 minutes, 066 seconds, 482 pictures.

An anti-spoofing face recognition system using augmented local binary patterns is written by Karuna Grover [6] et al. They created LBPnet by combining modified LBP descriptors with conventional convolutional neural networks. This created an extended local binary pattern.

This approach, which uses texture analysis, has the problem of being useless in low light. NUAA database was used for the experimental part. It has 98% accuracy and a correspondingly lower error rate, but it has trouble capturing features in low light.

Soumya et al. (2017) published a paper on four processing steps: image preprocessing, enhancement, transformation and classification. Preprocessing includes geometric corrections, radiometric corrections, and atmospheric corrections. A tone mapping algorithm is used for improvement. Maximum likelihood methods have been proposed for classification purposes. A method for object- oriented classification is also described in this article.

A study by M. Krishna et al. (2016) involves classifying the pixel values into appropriate classes and calculating the pixels in each class to approximate the area. This effort introduced an efficient and effective automatic classification.

Different methodologies, including minimum distance, SVM, K-means, K-nearest neighbor, and maximum likelihood, are used to test these. Confusion matrices and static kappa were used to assess each method's accuracy, and the best classifier was the maximum likelihood approach.

IV. METHODOLOGY

Figure 4 below shows the block diagram opted for this work. In this work it takes five different classes of images and trains the framework with the highlights of the images. In this work five images are prepared for one class. The next step is the selection of the test satellite image, the test picture can be any other picture, however, it must be unique to prepare the pictures. At that time the highlights of the test picture were extracted as separated from the prepared images. The choice of characterization is based on anyone between ELBP and SVM and CNN.

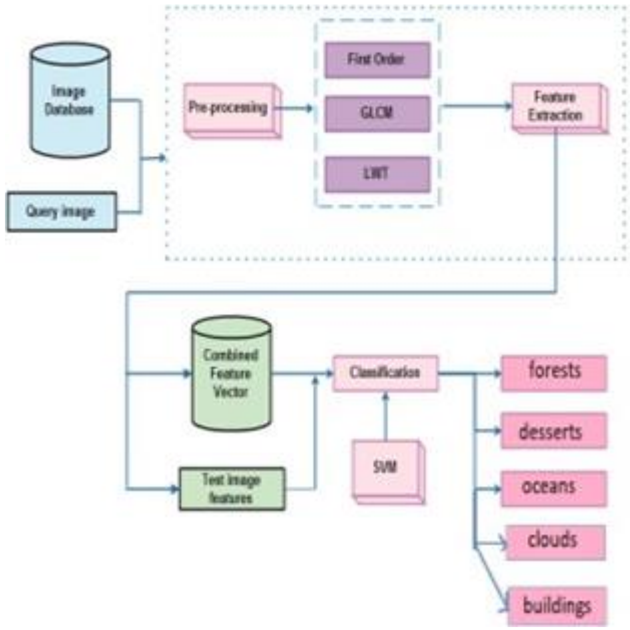


Fig 4: Block Diagram of Proposed Algorithm

A. Satellite image pre-processing

The initial step in any image processing procedure is the pre- processing of the satellite image. Making a picture ready for additional processing is the goal of pre-processing. Utilizing several filters, such as the median filter, this step enhances the image quality. A satellite image's median filter eliminates high frequency elements.

The median filter's key benefit is that it utilizes window-based pixels while maintaining edge information. With a fixed window size of 11 by 11, the median filter is applied to each and every pixel in the image. A front view is shown in Figure 5.

The average value is chosen to alter the image after the pixel values of each window are sorted in ascending order. The CLAHE technique seeks to increase the brightness and contrast of satellite photographs. This makes identifying between several photos easier.

The advantage of CLAHE is its simplicity and ability to protect the image from luminance saturation [18-20]. Figure 5 shows (a) the input image and (b) the pre-processed image. The following subsections describe this process in detail.

Figure 5: Sample pre-processed images

B. Two-Stage Feature Extraction

In this work, features are extracted from both sides using a two-level feature extraction approach. First, GLCM feature extraction techniques and statistics are used to extract texture characteristics. After using DWT, the identical set of characteristics are once more extracted from the image. A feature vector is created by concatenating each of the retrieved features.

The feature extraction procedure is thoroughly explained in the section that follows. The extraction of GLCM features, which is the most widely used statistical technique for obtaining textural information, comes next.

Homogeneity and entropy, two of the most crucial characteristics, are used in this function. When the distribution of grey levels is even and uniform, a measurement called homogeneity is used, and it is indicated by

$$\tau = \frac{\sum_{r=1}^{m-1}\sum_{c=1}^{n-1}(k[r,c])}{1+(r-c)^2}$$

Entropy is also one of the important features of GLCM that shows the information loss in the image. In addition, the amount of data in the image is also calculated.

The measure of the linear dependence of the gray

$$\varphi = \sum_{r=1}^{m}\sum_{c=1}^{n} -k[r,c] * \log k[r,c]$$

levels of neighboring pixels is defined as correlation.

$$\text{Correlation} = \frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i,j)p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$$

The variations in the GLCM(grey level co-occurrence matrix) is measured as contrast.

$$\text{Contrast} \quad \sum_{i=1}^{N}\sum_{j=1}^{N}(i-j)^2 P(i,j)$$

The sum of squared elements in GLCM is known as congruence or angular second moment.

$$Energy = \sum p(i,j)^2$$

A collection of comparable characteristics are again extracted from the image using DWT after these statistical texture features have been extracted. When DWT is used, a further stage of feature extraction is completed.

C. Classification of satellite image using SVM

Using a boundary, the supervised classification technique Support Vector Machine (SVM) classifies images and objects. Because this study uses five separate classes—forest, ocean, overcast, desert, and buildings—multiclass SVM is used.

This approach uses (n-1)/2 classifiers to distinguish between satellite images, and the outcome of all these classifications is taken into account. The maximum-voting policy is used to categorize images. The following equation can be solved to process all the various classes at once.

$$min_{nh,b,sv} \frac{1}{2}\sum_{y=1}^{q} nh_y^p nh_y + c\sum_{i=1}^{r}\sum_{y\neq s_i} sv_{i,y}$$

The critical decision is made by the following equation.

$$decn = max_y(w_y^p \beta(x_i) + b_y)$$

Every categorization is applied to every pair of classes in this technique. Think of an object that needs to be converted into one of three classes, let's say a, b, or c. This is done by applying all the classifiers to the image.

Every time the classifier assigns an object to class a, the value of class an is increased by 1. Based on the greatest number of votes received in the category, the final decision is made. This categorization method concludes with a firm decision in a respectable amount of time.

V. RESULTS AND DISCUSSION

The testing in this proposed method uses satellite pictures taken from the Kaggle website. In this study, the system is evaluated and trained using 25 photos each. Below are the results following classification.

Training: Five different types of images like cloudy, forest, dessert, ocean and buildings are taken and these are trained into different classes (1,2,3,4,5) that is shown below.

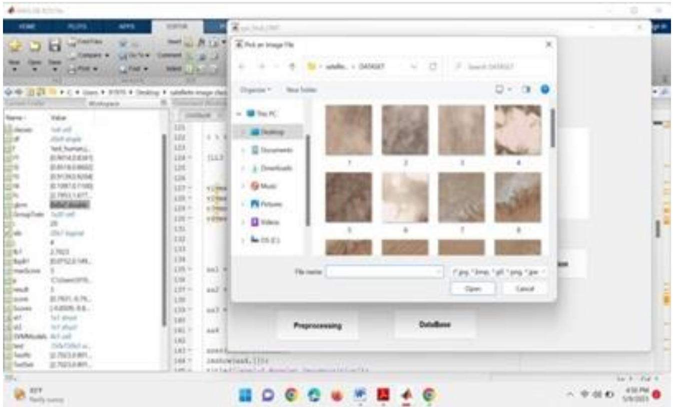


Fig 6: Data set of satellite images

The training of images into class-1 is shown in above figure, the other four images are also trained with the same process.

Test simulation results for ELBP: Read images with different textures using LBP features to distinguish images by texture.

Figure 7: Satellite image to be tested

Figure 8: Training of satellite image in class-3

Figure 9: cloudy image trained as Class-1

The local binary patterns are extracted from the photos in order to obtain the textural information. By comparing the squared errors of the image in Figure 6 with those in Figures 7 and 8, Figure 9 illustrates the differences between the LBP features of the images. When photos share a comparable texture, the squared error is less.

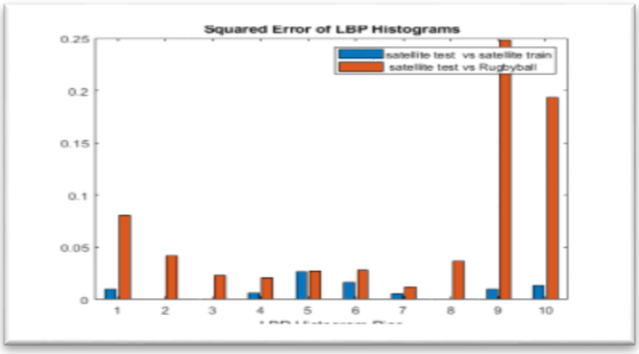


Figure 10: Histogram of LBP features of class 3 VS class 1 and class 3 VS class 3 .

In the figure above the blue bars denote the dissimilarities of features observed between trained satellite images and the test image which is shown in figure 6.The orange bars denote the dissimilarities of features observed between test image and cloudy image which is shown in figure 8.

It is evident that there are very few differences between the test satellite image with class 3 images, whereas there are many differences between cloudy image which is class 1. From this we can classify the test satellite image into class 3 as forest image. The observed rate of accurate classification is 100%.

The table below displays the image features that were extracted and saved from training courses before the code ran.

Command Window

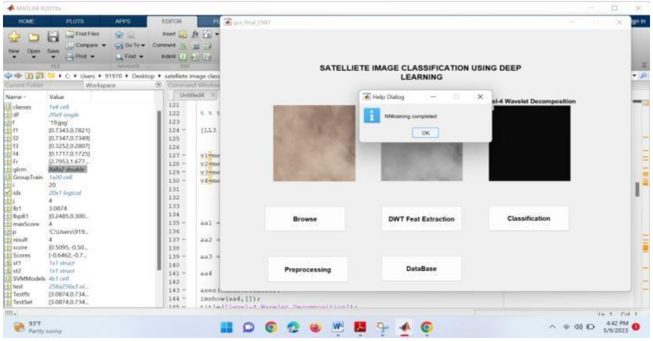
df =

20×9 single matrix

2.3120	0.0283	0.0328	0.9859	0.9836	0.9494	0.9411	0.5011	0.4995
2.2411	0.0749	0.0829	0.9626	0.9586	0.9083	0.8991	0.3796	0.3726
2.2470	0.0239	0.0279	0.9881	0.9861	0.9300	0.9183	0.6801	0.6769
1.9922	0.0761	0.0662	0.9627	0.9670	0.9653	0.9703	0.4769	0.4760
2.3187	0.0518	0.0590	0.9741	0.9705	0.8554	0.8353	0.6226	0.6167
2.0690	0.0337	0.0343	0.9832	0.9829	0.9741	0.9738	0.3280	0.3281
3.0554	0.3134	0.2955	0.8589	0.8660	0.4372	0.4713	0.3518	0.3571
3.0647	0.2536	0.2358	0.8882	0.8933	0.7946	0.8089	0.2490	0.2538
3.0296	0.1717	0.1631	0.9250	0.9275	0.5999	0.6207	0.5641	0.5676
3.0259	0.1171	0.1104	0.9533	0.9554	0.1084	0.1625	0.8167	0.8197
3.0135	0.0619	0.0586	0.9726	0.9739	0.2741	0.3190	0.8812	0.8834
2.9334	0.0186	0.0167	0.9907	0.9916	0.1804	0.2620	0.9594	0.9612
3.0652	0.2016	0.1673	0.8992	0.9163	0.1036	0.2447	0.6150	0.6400
3.0271	0.1620	0.1537	0.9190	0.9235	0.4949	0.5171	0.5449	0.5539
2.9804	0.1779	0.1802	0.9110	0.9116	0.2429	0.2298	0.6291	0.6295
3.0116	0.3327	0.2969	0.8337	0.8516	0.0846	0.1878	0.4146	0.4258
3.0715	0.3944	0.3528	0.8028	0.8236	0.1898	0.2748	0.2744	0.2852
3.0217	0.3982	0.3284	0.8224	0.8425	0.3426	0.4563	0.2718	0.2853
3.0874	0.7343	0.7821	0.7347	0.7349	0.3252	0.2807	0.1717	0.1725
1.6123	0.0111	0.0383	0.9945	0.9808	0.7608	0.1727	0.9428	0.9169

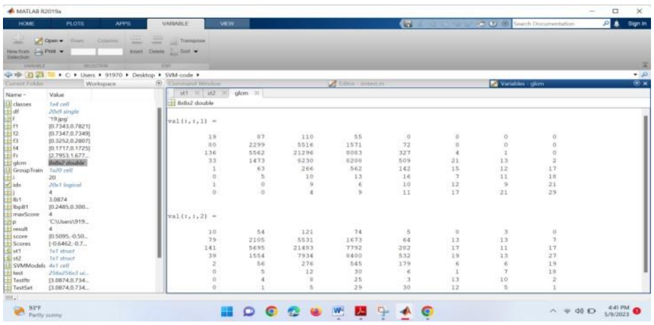
Figure 11: Extracted Features from satellite images

Training of satellite images

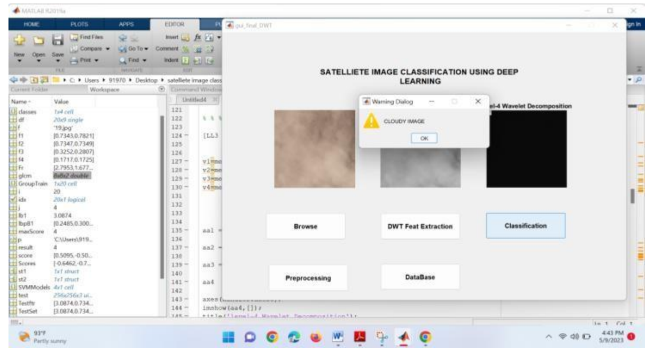


In order to create a GLCM and extract statistical features from it, GLCM functions count how frequently pairs of pixels with specific values and in a particular spatial relationship exist in an image.

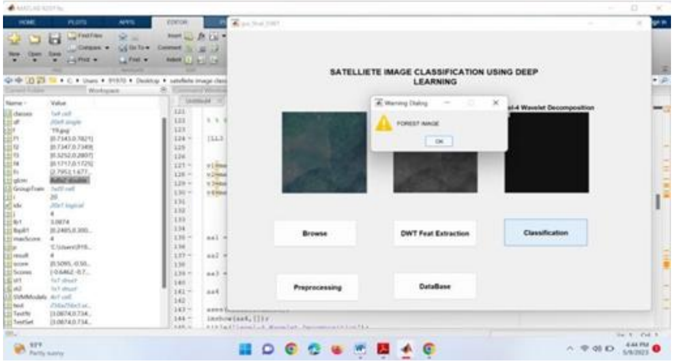
GLCM:



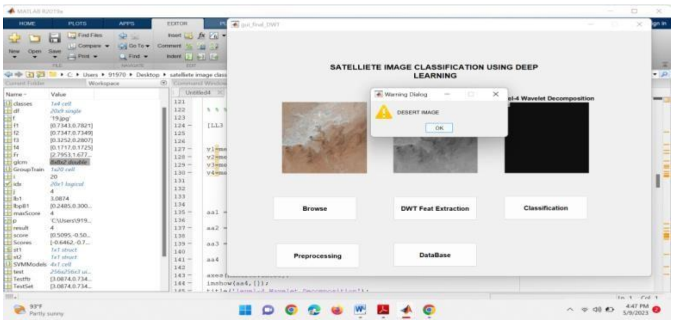
Classification: The classification results are shown in the figure



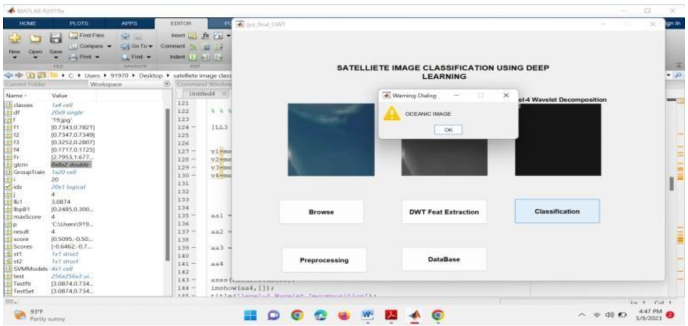
In the above figure the proposed algorithm is showing the image given is classified as a cloudy image and it belongs to class 1.



In the above figure the proposed algorithm is showing the image given is classified as a forest image and it belongs to class 3.



In the above figure the proposed algorithm is showing the image given is classified as a dessert image and it belongs to class 2.



In the above figure the proposed algorithm is showing the image given is classified as a oceanic image and it belongs to class 4.

Table 1 Comparative results

Work	Method	Average Accuracy Observed
Proposed	ELBP-SVM and CNN	97
Anju Asokan [1]	Random Forest with SVM	88
Sehla Loussaief [2]	Speed Up Robust Features and K-mean clustering	89
Mohd Azlan Abul [3]	DNN and Tensorflow	94
Andreas Kolsch [4]	CNN and Extreme Learning Machines	90

The system accurately identifies all five types of image classes using SVM, as seen from the data above. The suggested work's accuracy is evaluated by simulating and classifying 40 test satellite picture classes.

With the suggested image processing method using ELBP, CNN, and SVM classifier machine learning features, a total of 37 satellite photos are accurately identified. Therefore, this function has a 97% accuracy rate.

VI. CONCLUSION AND FUTURE SCOPE

CONCLUSION

This work presents a texture-based classification system for satellite images. This method does feature extraction since the satellite images have rich texture properties. The GLCM features (uniformity, contrast, correlation, and energy) are first extracted by this function. The estimation band is then extracted after applying DWT to the satellite image.

A similar set of features are extracted from the satellite image with DWT applied and a feature vector is formed. CNN is employed to train a set of satellite images. Lastly, SVM classifier is employed to classify the images.

Various techniques and algorithms are used in this work's suggested machine learning framework for processing satellite images. This research shows advanced image processing using machine learning. This study demonstrates by trials that the best prediction average accuracy is achieved when employing the local binary pattern extractor for image vector representation and CNN and SVM classifier. The test scenario focuses on these satellite photos since we plan to employ the taught classifier in a system that is more widely applicable.

FUTURE SCOPE

In order to improve the outcomes, researchers are currently attempting to find some answers by integrating several image processing approaches or by adding hybrid models based on spectral and spatial indices. In future, this combination can be used for improving accuracy.

The number of classes can be improved in the near future as his task has a limit of only 12 classes, the accuracy in this task is 97% which can be improved by using deep learning. In the future, it is planned to analyze the performance of satellite classification by incorporating clustering techniques.

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