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Hypersepectral Image Classification Using Hybrid Ensemble Elm

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Abstract Hyperspectral images (HSIs) are commonly utilized in remote sensing because of the continuity of the bands they contain. An important change in HSI categorization was brought about by the development of deep learning methods. The various Convolutional Neural Network (CNN) models are used in several HSI processing applications. The computational cost of HSIs is increased, and the Hughes effect is caused by, their higher dimensionality. As a result, dimensionality reduction (DR) is an essential preprocessing step for most CNN models. The incorporation of spatial and spectral data into HSI classification is a further obstacle to achieving reliable results. A few 3-D-CNN models are built to tackle this problem; however, they aren't as efficient as other approaches in terms of execution time. In this paper, we proposed a hybrid ensemble Extreme Learning Machine to capture spatial and spectral data from HSI images. Based on experimental results, the suggested ensemble model outperforms other models by 98%.

I. INRODUCTION

The use of hyperspectral remote sensing technology is becoming an increasingly significant tool for observing the surface of the earth. Because it contains hundreds of small spectral bands drawn from a broad range of the electromagnetic spectrum, a hyperspectral image (HSI) is especially sensitive to even the most minute shifts that may occur in the conditions under which the image was acquired. For instance, when two labelled reference samples are gathered in two places that are geographically distinct from one another and have a few distinguishing features, the sample distributions will be distinct from one another. In example, gathering information from the ground is an expensive endeavor that cannot always be accomplished through photointerpretation. In order to cut down on expenses and make better use of available resources, a full hyperspectral image contains labels for only a tiny portion of the ground information.

In contrast to a natural image, which only consists of three-color channels, a hyperspectral image (HSI) is comprised of hundreds of feature bands. This type of image has a wealth of information in both the spatial and spectral dimensions, and it is able to uncover more hidden details. As a result, HSIs have found a variety of applications, including disaster investigation, land planning, and environmental monitoring. The precise characterization of HSI is always required for these applications in general. In order to get a higher level of precision with the HSI classification process, there were multiple suggestions made for different classifiers that are completely supervised. Support vector machines and regression trees are two important examples supervised approaches that could be used to solve the issue of HSI classification. Other prominent supervised methods include neural networks and decision trees. In recent years, there has been a rise in the use of techniques that are founded on deep neural networks. This is due to the fact that these techniques are able to identify HSI in a form that is end-to-end and achieve a greater level of precision. Because HSI requires the samples to be labelled on the pixel level, gathering the training sets for it is a challenging task that also takes a lot of time. On the contrary hand, fully supervised classification methods will almost always necessitate a sizeable amount of training samples in order to achieve satisfactory levels of classification results.

II. RELATED STUDY

Classifying hyperspectral images (HSIs) involves attempting to give each individual pixel a name. As the most active topic in the remote sensing world, HSI categorization is a crucial tool for many uses [1]. The collected spectrum information from an HSI, which typically has hundreds of spectral channels, is a great source for categorization. More than a few spectral classifiers, such as k-nearest neighbors, maximum likelihood, support vector machine (SVM), logistic regression, neural network, and random forest, have been presented in the recent two decades for HSI classification. When compared to other common pattern recognition methods, SVMs tend to produce the highest classification accuracy. In [2], a number of popular spectral classifiers for hyperspectral remote sensing data were put through their paces and evaluated severely to one another.

The HSI incorporates a lot of information spanning a variety of different spectral information domains. On the subject of spectral-spatial HSI identification, there is an abundance of research that is now available. Morphometric statuses are capable of successfully retrieving spatial features, and the combined effect of an MP with such a same classify results in the formation of a precise spectroscopic classifier. Other methods of spatial extracting features, including as generative models and Hidden Markov fields, also made contributions to the spectral-spatial classification of HSI [3], which was conducted. In furthermore, a dense representation was built in order to capture the spectral information properties of HSI [4]. This was done in order to improve the accuracy of the data. In contrast, sparse modeling has been combined with a wide variety of different feature extraction strategies in order to achieve an even higher level of classification accuracy. A detailed review from over 20 well-known spectral-spatial classifying techniques were published not too long ago in [5]. This evaluation was just very recently finished.

Because of how good they are, CNN-based techniques have become increasingly popular in recent years as one of the deep learning algorithms for HSI categorization. CNN-based methods can be divided into two categories: spectral analyzers and spectral-spatial coders. Spectral classifiers are the more common of the two. In the research that was done, referred to as [6], CNN was used to determine the spectral characteristics of HSIs. A correctly architected convolutional neural network (CNN) generated better classification results than a support vector machine (SVM) and a conventional deep neural network. After then, in [7], an innovative CNN architecture was introduced to be utilized as a deep spectral classifier in the process of extracting the pixel-pair characteristics of HSIs. This was done in order to improve the accuracy of the extraction process. The primary focus of the vast majority of CNN-based algorithms was the classification of spectral and spatial HSI data. In addition, CNNs can be combined with other techniques, such as dimension reduction and morphology traits, to further improve the classification performance. This can be done by using a combination of the two. In [8], an attempt was made to improve the learnt characteristics by combining a CNN with a sparse representation. Very shortly, a technique that is founded on the integration of morphology traits and a CNN was presented to identify the characteristics of HSIs; this resulted in an increase in performance [9]. The approach was developed to extract the characteristics of HSIs, that led to that of an increase in performance. This approach was fruitful since it enabled more precise results to be obtained.

Despite the fact that deep learning-based approaches, and particularly deep CNNs, have improved the classification performance of HSI, there are still significant drawbacks. To begin, the training samples that are used are frequently insufficient because there are a huge number of parameters that need to be tweaked. In practical applications of remote sensing, one of the most common problems is that there are insufficient training samples. Because of this, deep learning models are susceptible to a problem known as overfitting. This issue manifests itself when a deep model achieves outstanding performance on the training data but relatively low performance on the test data. The purpose of this work is to investigate the use of ensemble learning in combination with a CNN and an Extreme Learning Machine in order to increase the HSI classification accuracy of deep CNN-based approaches.

III. PROPOSED METHOD

The proposed model is divided into three components. The first module is CNN layers, the second is Extreme Learning Machine (ELM), and the final module is the ensemble module. Figure 1 depicts the proposed model.

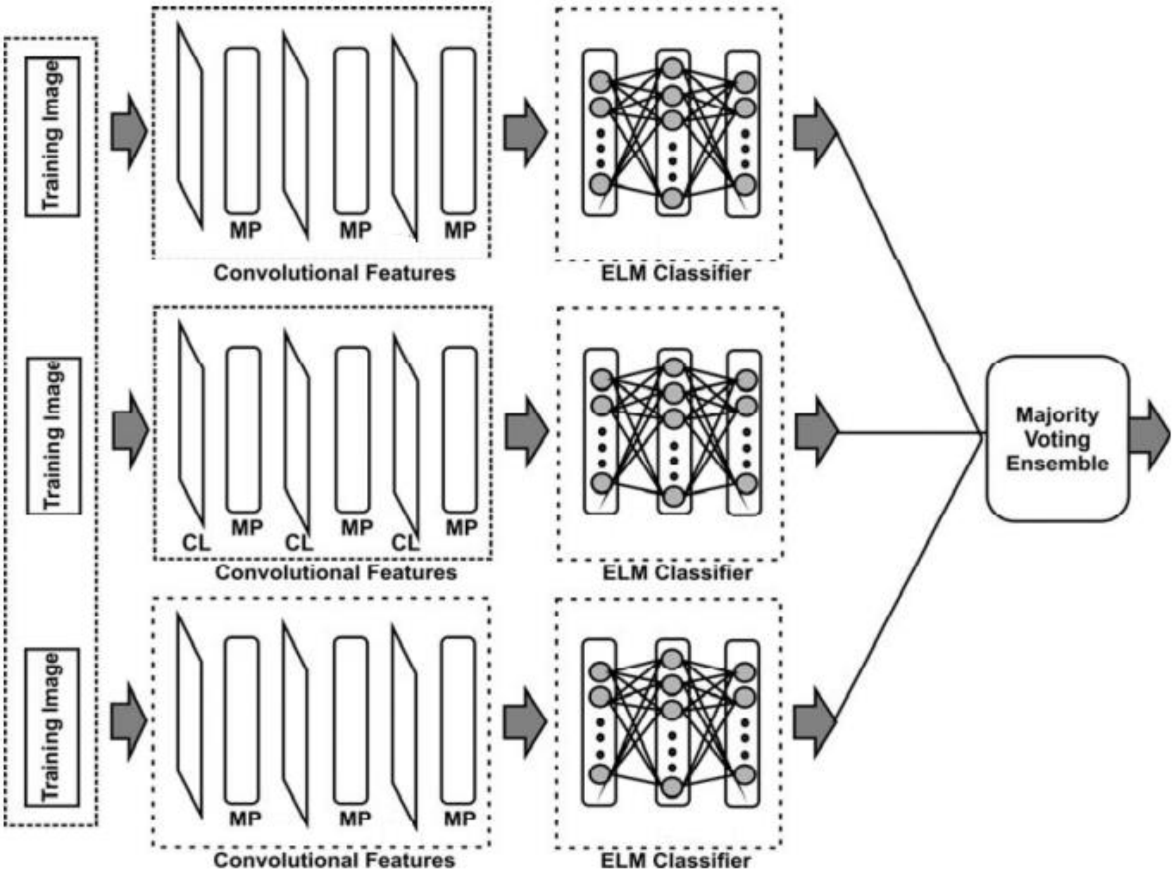

Figure 1: Proposed Model

i. Convolutional Neural Network: In a convolutional neural network, the convolutional layer, the pooling layer, and the softmax layer are the three basic types of layers that make up the network. During the processing of the input image at the convolutional layer, several kernels are convolved with it. When a CNN is first generated, it immediately begins monitoring its immediate environment and producing many feature maps. In order to reduce the overall size of the feature map while maintaining its spatial integrity, the pooling layer applies either an average or maximum operation. The convolutional layer and the pooling layer make up the feature extraction module of a machine learning system. In this study, we extract features with the assistance of a convolutional neural network. The activation function of the SoftMax layer makes use of an input feature map in order to classify data into a value for a certain class. The fundamental benefit of convolutional neural networks (CNNs) is that, in comparison to fully connected networks with the same number of hidden units, they are far easier to train and have a significantly reduced number of parameters.
ii. ELM: An extreme learning machine, also known as an ELM, is a conceptual framework that was developed for the purpose of training a feed-forward neural network that contains only one hidden layer. When using ELM, the nodes of the hidden layer are initially given a random initialization, and subsequently they are fixed without receiving any iterative adjustments. The only information that must

be learned is the weights, or connections, between the hidden layer and the output layer. Training a single-hidden-layer feed-forward neural network using ELM in two discrete phases: the first phase is a random feature mapping, and the second phase involves solving linear parameters. Both phases are independent of one another.

iii. Ensemble Module: The model makes its final decisions using a voting ensemble based on the principle of majority voting. In the first step of the process, a mechanism for majority voting tallies the number of votes received by each of the basic classifiers. The projected class designation is determined based on the majority of the votes. The final forecast is determined by the base classifier that received the most votes overall. Always pick a basic classifier that has an odd number of characteristics to analyse your data. In the event that there is a conflict during voting, the "mode" method will be implemented.

IV. EXPERIMENTAL ANALYSIS

In order to assess the efficacy of the deep CNN ensemble approaches that have been developed, the experiments make use of the benchmark HSI dataset. After deleting 20 water absorption bands, the Salinas dataset consists of 512 by 217 pixels with a spatial resolution of 3.7 metres and 204 bands (bands: [108–112], [154–167], and 224). The resolution of the dataset is measured in metres. There are a total of sixteen distinct land-cover types defined for this location. Regarding the quantity of training samples, a total of three hundred labelled samples from Salinas are chosen at random to serve as training samples. The unlabeled portions of the samples are separated out and utilised as test samples.

Because of this, we only need to use a small number of training samples in order to complete the classification. Dataset sample is shown in Figure: 2. In this paper, the feature extractor that we utilised was a deep CNN, and the classifier that we employed was ELM. The learning rate, the window size, and the number of nodes in hidden layers are all calculated using a method that involves trial and error.

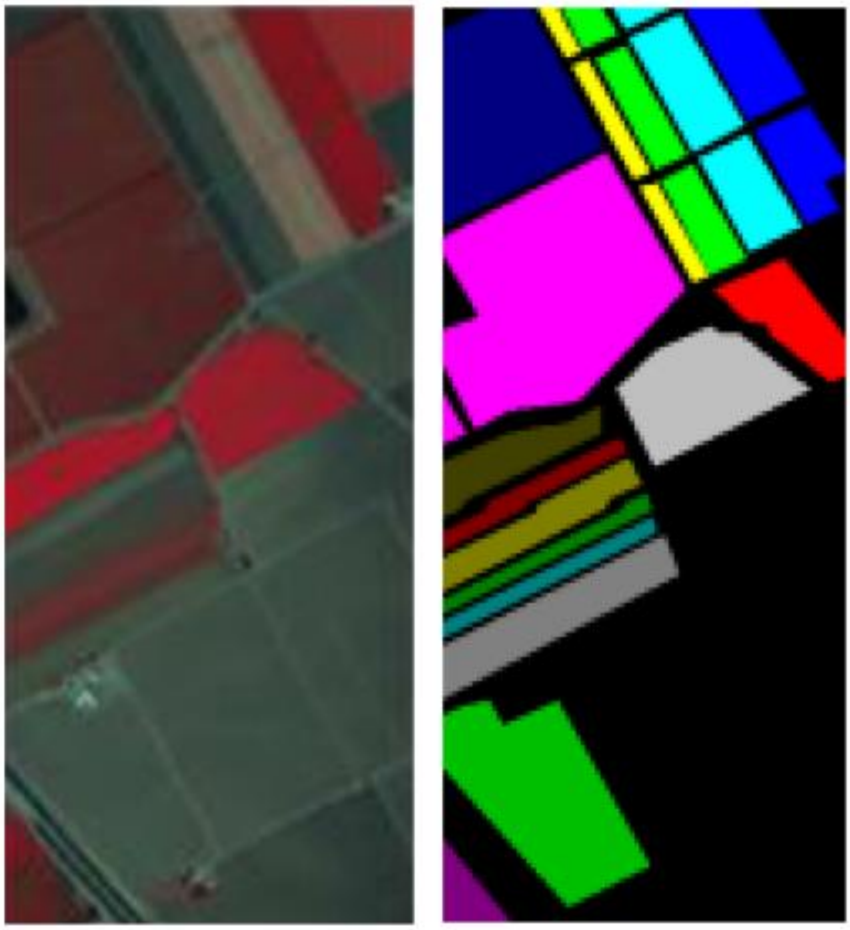

Figure 2: Salinas dataset false color composite with ground truth.

Method	Precision	Recall	F1 Score	Accuracy
SVM	0.9523	0.9545	0.9568	0.9512
Ensemble SVM	0.9689	0.9612	0.9634	0.9699
Deep CNN	0.9712	0.9709	0.9700	0.9711
Ensemble CNN	0.9789	0.9789	0.9768	0.9799
Proposed Model	0.9812	0.9821	0.9845	0.9891

Table 1: Model Comparison

The proposed model is compared to SVM, Ensemble SVM, Deep CNN, and Ensemble CNN using evaluation criteria such as Precision, Recall, F1 Score, and Accuracy. Table 1 shows that our proposed model outperforms the other model with an accuracy of 98%.

V. CONCLUSION

This research proposes a novel ensemble-based CNN-ELM model for hyperspectral image categorization. The model uses a convolutional neural network to learn feature representations, an Extreme learning machine to learn quickly, and a majority voting ensemble to make the ultimate judgement. This model is tested on the MNIST benchmark dataset using industry-standard performance measures to gauge its efficacy. When compared to SVM, Ensemble SVM, Deep CNN, and Ensemble CNN, the experimental results suggest that the ensemble method performs better.

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