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"HYPERSPECTRAL IMAGE CLASSIFICATION USING DEEP LEARNING"

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Abstract: Hyperspectral Images have hundreds of spectral bands, which makes them rich in information but challenging to classify. Deep learning has been proved to be useful for hyperspectral image classification, but it is important to choose the right architecture and to train the model on a big and diverse dataset. This project offers a deep learning method for classifying hyperspectral images. The proposed method applies preprocessing techniques including noise reduction and feature extraction to extract spectral-spatial characteristics from hyperspectral images using a convolutional neural network (CNN) architecture. Using supervised learning, a sizable dataset of hyperspectral images is used to train the CNN. Then, new hyperspectral images are classified into various land cover classes using the learned model. Additionally, a Support Vector Machine (SVM) is employed alongside the CNN to enhance the classification accuracy. The SVM acts as a complementary classifier, taking the features extracted by the CNN to improve the decision boundaries between different classes. The integration of SVM with CNN helps in achieving better generalization and robustness in classification results. The results of the proposed system show that the suggested technique performs more accurately for hyperspectral image classification using the combined approach of convolutional neural network and support vector machine.

Keywords: Convolutional Neural Network, Hyperspectral, Neural Network, Deep Learning, Spectral, Support Vector Machine.

I. INTRODUCTION

Hyperspectral imaging, a complex technology in remote sensing, captures detailed spectral signatures for every pixel in an image. With applications in fields like environmental science, medicine, defense, and mining, HSI utilizes imaging spectrometers to collect data across numerous contiguous spectral bands, spanning from visible light (400-700 nm) to near-infrared and shortwave infrared areas (700-2500 nm).

In this paper, we use a deep learning model for plant and land cover categorization using HSI. A diverse dataset of HSIs trains the deep learning model, and a held-out test set evaluates its performance. When the model performs well, it is deployed. Common deep learning models for HSI classification include convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs are effective for image classification due to their ability to learn spatial properties, while RNNs can extract temporal characteristics from the spectral bands in HSIs.

The proposed CNN framework for HSI classification balances the number of training samples with network complexity, extracting features through repeated convolution, pooling, and full-connection processes.

The architecture includes three convolutional layers and six fully connected layers, with the convolutional layers teaching the spatial features and the fully connected layers refining higher-level features. The model is evaluated on the Indian Pines dataset, and once performance standards are met, it is put into production.

Additionally, we incorporate a Support Vector Machine (SVM) alongside the CNN. The SVM uses the features extracted by the CNN to enhance classification accuracy by improving the decision boundaries between different classes. This hybrid approach leverages the strengths of both CNNs and SVMs for better generalization and robustness in classification results.

The remainder of this paper is organized as follows: Section 2 provides background information, Section 3 presents the CNN and SVM framework, Section 4 discusses experiments on the Indian Pines dataset, and Section 5 offers conclusions.

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II. LITERATURE REVIEW

The authors of this paper[1] have proposed a way to get over the pre-treatment hassle, making feature extraction easier and requiring less complex data processing. Deep learn-ing is the basis of the approach. It lowers the high spectral dimensionality of the data by combining a multilayer autoencoder with the maximum noise fraction (MNF). High-level feature extraction is accomplished using the SoftMax logistic regression method. A comparison is made between the suggested approach and conventional linear SVM. It is noticed that the proposed technique yields a 90.54% classification accuracy, while linear SVM yields a 79.22% classification accuracy. The suggested approach processes data in 4.3 seconds, while SVM processes data in 32.5 secondsYanan Luo et al.[3] proposed HSI-CNN, a CNN framework for HSI data, which extracts spectral-spatial features and stacks them into a two-dimensional matrix treated as an image for CNN processing. They compared this framework with HSI-CNN+XGBoost and HSI-CapsNet, finding that HSI-CNN achieved the highest accuracy on the Salinas scene, Pavia University scene, and Indian Pines datasets, with accuracies of 99.09%, 99.42%, and 98.95%, respectively.

David Ruiz Hidalgo, Bladimir Bacca Cortes, and Eduardo Caicedo Bravo[2] introduced an unsupervised dimensionality reduction approach using Kohonen self-organized maps, achieving superior classification performance compared to PCA and wavelet decomposition. Their method, coupled with an RBF classifier, achieved an 88.5% classification accuracy and a 64% average dimensionality reduction.

Erting Pan et al.[6] proposed a new paradigm for HSI classification involving separate training and evaluation across different hyperspectral datasets. This method includes label reasoning, feature mapping, and feature embedding, demonstrating the efficacy of zero-shot learning for HSI classification through tests on datasets collected by the same hyperspectral sensor.

III. METHODOLOGY

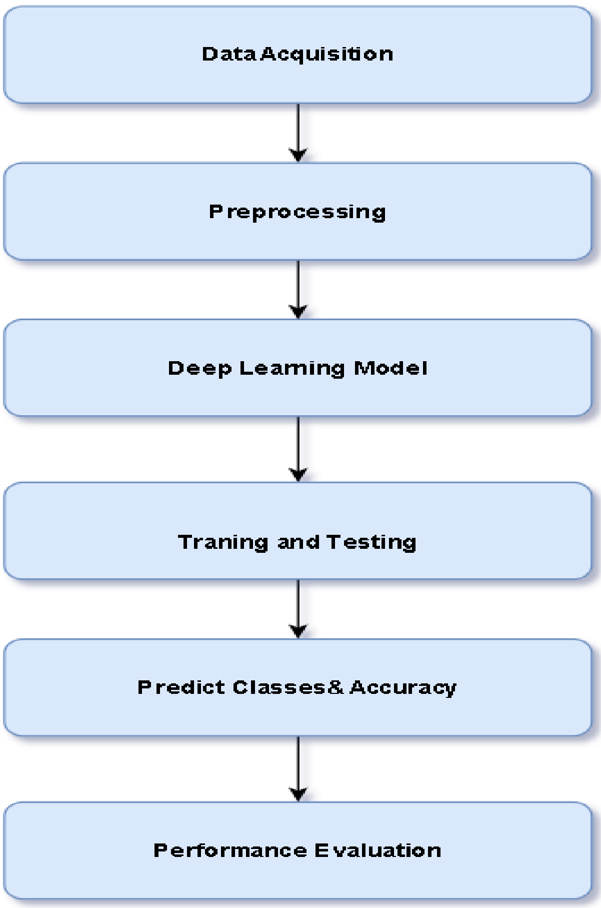

Figure: Work Flow

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Acquisition:
Hyperspectral sensors mounted on satellites, drones, or other platforms capture the data. The data can be in the form of hyperspectral image cubes where each pixel has a full spectrum

PreprocessingPreprocessing:
prepares the raw hyperspectral data for analysis. This step is crucial to ensure the data quality and accuracy of subsequent classification tasks.

CNN:
This step involves selecting and designing a deep learning model to classify the hyperspectral data. Commonly used for spatial-spectral feature extraction.

Training:
The model is trained using labeled data, adjusting weights based on loss functions to minimize classification error

Training and Testing:
This step involves splitting the data into training and testing sets, training the model on the training set, and validating it on the testing set.

Evaluation:
The final step is evaluating the model's performance using metrics such as the confusion matrix, accuracy, precision, recall, and F1-score.

Confusion Matrix:
A table that describes the performance of the classification model by showing the actual versus predicted classifications. Each row represents the actual class, and each column represents the predicted class.

Accuracy: The overall correctness of the model, calculated as the sum of the diagonal elements (true positives) divided by the total number of samples.

Other Metrics: Precision, recall, and F1-score provide more detailed performance analysis, especially in cases of imbalanced data

IV. MODELING AND ANALYSIS

	precision	recall	f1-score	support
Alfalfa	1.00	0.89	0.94	9
Corn-notill	0.82	0.80	0.81	286
Corn-mintill	0.88	0.82	0.85	166
Corn	0.77	0.79	0.78	47
Grass-pasture	0.92	0.96	0.94	97
Grass-trees	0.97	0.98	0.97	146
Grass-pasture-mowed	1.00	0.80	0.89	5
Hay-windrowed	0.99	1.00	0.99	96
Oats	0.60	0.75	0.67	4
Soybean-notill	0.88	0.80	0.84	194
Soybean-mintill	0.85	0.91	0.88	491
Soybean-clean	0.85	0.89	0.87	119
Wheat	0.95	1.00	0.98	41
Woods	0.96	0.98	0.97	253
Buildings Grass Trees Drives	0.92	0.71	0.80	77
Stone Steel Towers	1.00	1.00	1.00	19
accuracy			0.89	2050
macro avg	0.90	0.88	0.89	2050
weighted avg	0.89	0.89	0.89	2050

Figure 1: Classes of SVM

241/241 [==============================] - 1s 4ms/step

	precision	recall	f1-score	support
Alfalfa	0.70	0.26	0.38	27
Corn-notill	0.74	0.76	0.75	1095
Corn-mintill	0.85	0.77	0.81	648
Corn	0.93	0.91	0.92	185
Grass-pasture	0.82	0.97	0.89	343
Grass-trees	0.97	0.97	0.97	569
Grass-pasture-mowed	0.00	0.00	0.00	14
Hay-windrowed	0.92	0.99	0.95	352
Oats	0.00	0.00	0.00	0
Soybean-notill	0.84	0.80	0.82	726
Soybean-mintill	0.80	0.88	0.84	1857
Soybean-clean	0.80	0.56	0.66	434
Wheat	0.97	0.99	0.98	149
Woods	0.95	0.91	0.93	936
Buildings Grass Trees Drives	0.90	0.79	0.85	276
Stone Steel Towers	0.93	0.99	0.96	70
micro avg	0.85	0.85	0.85	7681
macro avg	0.76	0.72	0.73	7681
weighted avg	0.85	0.85	0.84	7681

Figure 2: Classes of CNN

Precision and recall are two metrics used to evaluate the performance of a classification model. Precision is a measure of how many of the positive predictions were actually correct. Recall is a measure of how many of the actual positive cases were identified by the model. The precision, recall, and F1-score are also shown for each class.

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The F1-score is a harmonic mean of precision and recall, which takes both metrics into account. However, there is some variation in performance between different classes

V. RESULTS AND DISCUSSION

Figure 3: Indian pines Remote Image

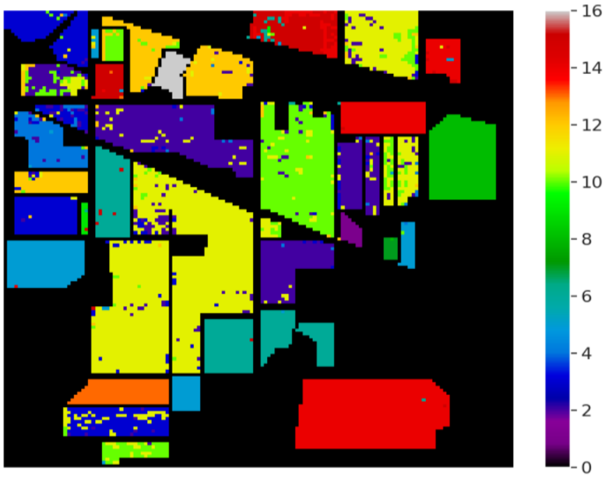

Figure 4: Classified image

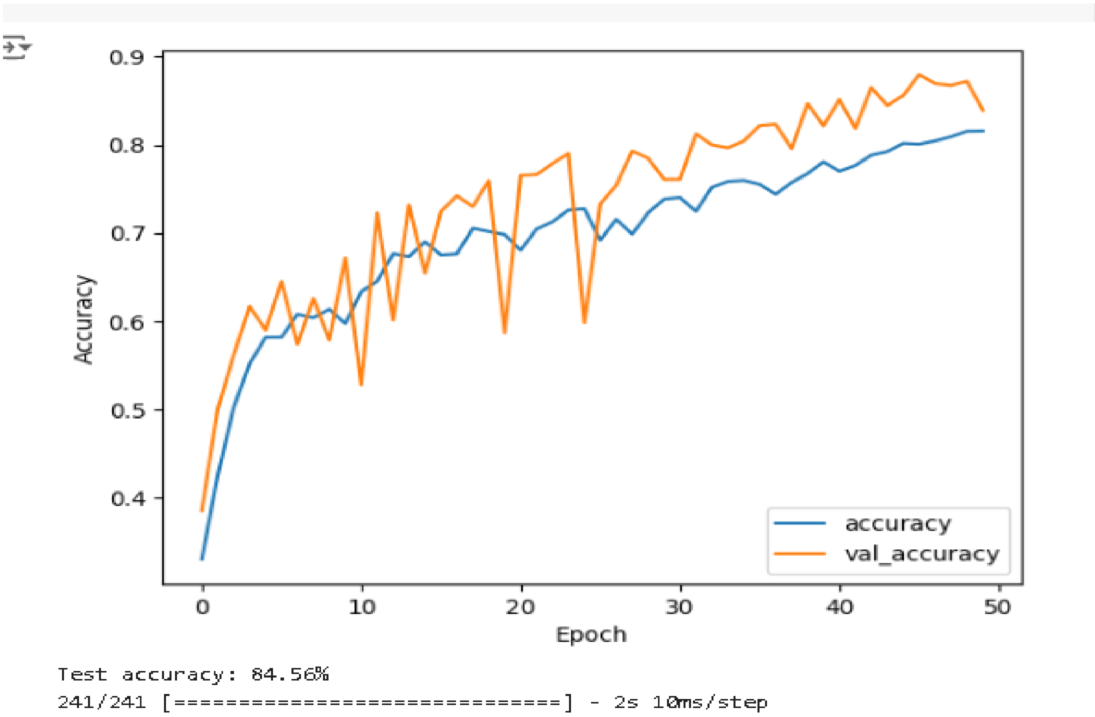

Figure 5: Accuracy Graph

VI. CONCLUSION

In this project, we first implemented the traditional machine learning SVM model. A multiclass SVM classifier is trained for classification using the training data. It predicts the labeled classes of the test data using a trained SVM model. It gives a classification accuracy of 89\%. To prove that the CNN model is better than the traditional SVM classifier, we provide a framework consisting of the CNN model. The constructed network is deep but effective because of the design, and it is able to concurrently utilize the interplay of several spectral and spatial contextual information. When several features are used, the classification results are much better than using a CNN method.

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CNN-based framework can extract deep features automatically and more effectively than SVM classifiers. The deep learning model can achieve high classification accuracy on HSIs, even with limited training data. We suggest that the proposed model can be used for various global applicability. A held-out test set was employed to assess the model. On the held-out test set, the model's total classification accuracy was 84.63\%. In this study, a deep learning model for classifying plant and land cover from hyperspectral images (HSI) was constructed.

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