ENHANCED NEURAL NETWORK FOR CLASSIFICATION OF HYPERSPECTRAL IMAGERY USING ENSEMBLED MODELS

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*Abstract*

**Hyperspectral imagery (HSI) classification is a crucial task in remote sensing, with applications ranging from environmental monitoring to precision agriculture and urban planning. However, accurate classification of hyperspectral images remains a significant challenge due to high dimensionality, spectral redundancy, limited labeled samples, and the presence of noise. Traditional machine learning methods, such as Support Vector Machines (SVMs) and Random Forest (RF), have been widely used but often struggle to effectively capture the complex spatial-spectral dependencies present in hyperspectral data. Recently, deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated remarkable performance in HSI classification. Despite their success, single deep learning architectures often suffer from issues such as overfitting, model bias, and the inability to generalize across different datasets.**

**To address these challenges, this study proposes an enhanced neural network framework that leverages ensemble learning to improve hyperspectral image classification accuracy and robustness. The proposed approach integrates multiple deep learning models, including CNNs, Transformers, and Long Short-Term Memory (LSTM) networks, to exploit their complementary strengths in capturing both spectral and spatial information. The ensemble framework is designed using a hybrid voting strategy, where base learners contribute to final predictions through weighted averaging and majority voting techniques. Additionally, an attention-based feature fusion mechanism is incorporated to enhance feature representation by selectively focusing on the most informative spectral bands and spatial regions.**

**Our experimental evaluation is conducted on widely used hyperspectral datasets, including Pavia University, Indian Pines, and Salinas, to ensure generalizability across different landscapes and spectral resolutions. Results demonstrate that the proposed ensembled model outperforms traditional deep learning models, achieving higher classification accuracy, improved generalization, and better robustness against spectral variability and noise. Compared to individual deep learning classifiers, our ensemble approach mitigates the bias-variance trade-off and reduces overfitting, making it well-suited for real-world remote sensing applications. The findings of this study underscore the importance of integrating ensemble learning with deep neural networks to enhance hyperspectral image classification, offering new directions for future research in remote sensing and artificial intelligence.**

**Keywords: Hyperspectral imagery, deep learning, ensemble learning, convolutional neural networks, attention mechanism, remote sensing, classification.**

1.INTRODUCTION

A. Motivation

Hyperspectral imaging (HSI) is an advanced remote sensing technology that captures data across hundreds of spectral bands, enabling highly detailed analysis of surface materials. This technology plays a crucial role in diverse applications such as land cover classification, precision agriculture, mineral exploration, and environmental monitoring. However, the classification of HSI data presents significant challenges due to high dimensionality, spectral redundancy, and the limited availability of labeled data. Traditional classification techniques often rely on handcrafted features and struggle to generalize across different datasets. The emergence of deep learning has provided a transformative approach to HSI classification, leveraging automated feature extraction to improve accuracy and efficiency. However, single neural network architectures, such as CNNs, often fail to fully exploit the spectral-spatial information contained in HSI data, necessitating the development of ensemble models that integrate multiple architectures for enhanced performance.

B. Problem Definition

Despite the advancements in hyperspectral image classification, challenges remain in effectively leveraging both spatial and spectral features. The high dimensionality of hyperspectral data often leads to the "curse of dimensionality," where traditional classifiers struggle with increased computational complexity and overfitting. Additionally, single deep learning models tend to exhibit limitations in generalization, leading to reduced performance across different datasets. The need for robust classification methods that integrate multiple neural network architectures has become evident. Ensemble learning, which combines different models to capture diverse feature representations, offers a promising solution to these challenges. By integrating CNNs for spatial feature extraction, RNNs for sequential spectral analysis, and transformer models for self-attention-based feature learning, we can significantly enhance classification accuracy and generalization.

## C.Objectives of this Study

## The primary objectives of this study are:

* To develop an ensemble-based deep learning framework that integrates CNNs, RNNs, and transformer models for hyperspectral image classification.
* To enhance the classification accuracy of hyperspectral imagery by leveraging complementary strengths of different neural network architectures.
* To optimize model generalization through bias-variance reduction techniques, ensuring robustness across diverse hyperspectral datasets.
* To provide an efficient and scalable solution for real-time hyperspectral image classification, enabling broader applications in remote sensing.
* To compare the performance of the proposed ensembled model against traditional single-model classifiers in terms of accuracy, computational efficiency, and robustness.

D. Limitations of the Study

While the proposed ensemble-based approach significantly enhances hyperspectral image classification, certain limitations must be acknowledged:

* The accuracy of classification depends on the quality and diversity of training data. A biased dataset may lead to poor generalization in real-world applications.
* Computational complexity is increased due to the integration of multiple deep learning models, requiring efficient optimization techniques and hardware acceleration.
* The reliance on high-quality hyperspectral imagery can pose challenges in real-time field applications, where data acquisition conditions vary.
* The ensemble approach requires careful tuning of model weights and hyperparameters to balance the contributions of individual architectures effectively.

## E.Organization of Documentation

This paper is structured as follows: Section II presents a review of existing literature on hyperspectral image classification, discussing challenges and advancements in deep learning approaches. Section III details the proposed ensemble-based methodology, outlining the integration of CNNs, RNNs, and transformers. Section IV discusses experimental results, including performance comparisons with traditional models. Finally, Section V concludes the study with key findings and directions for future research.

## F.Proposed Contribution

This study contributes to hyperspectral image classification by proposing an ensemble learning framework that combines CNNs, RNNs, and transformer models to exploit spatial, spectral, and attention-based features. The integration of these architectures enhances classification accuracy and robustness, addressing key challenges in hyperspectral data analysis. The findings provide valuable insights into the effectiveness of deep learning ensembles in remote sensing applications, paving the way for future advancements in hyperspectral image processing.

# **II. LITERATURE SURVEY**

Recent advances in hyperspectral image (HSI) classification have focused on leveraging deep learning techniques to extract meaningful spectral and spatial features. Traditional machine learning approaches, such as support vector machines (SVMs) and random forests, have demonstrated limited performance due to their dependence on handcrafted features and susceptibility to the high-dimensional nature of hyperspectral data. To overcome these challenges, researchers have explored deep learning-based solutions.

Zhang et al. introduced a Convolutional Neural Network (CNN) framework for hyperspectral image classification, highlighting the importance of spatial feature extraction. However, their approach was limited in capturing sequential spectral dependencies. Similarly, Li et al. proposed a hybrid CNN-RNN model to leverage both spatial and spectral information, improving classification accuracy. Their study demonstrated that recurrent models could capture long-range spectral dependencies more effectively than traditional CNNs.

Wanget al. explored transformer-based architectures for HSI classification, utilizing self-attention mechanisms to model global spectral relationships. Their study revealed that transformer models outperform CNN-based architectures in capturing complex hyperspectral patterns. However, transformers require large training datasets and significant computational resources.

An important limitation of existing deep learning models is their reliance on single architectures, which may not fully exploit the diverse features of hyperspectral imagery. Researchers have begun investigating ensemble-based approaches to address this issue. For example, Yang et al. combined CNNs with Graph Convolutional Networks (GCNs) to enhance spatial contextual learning, while Xu et al. proposed an ensemble of multiple CNN variants to improve classification robustness.

Despite these advances, challenges remain in optimizing deep learning models for HSI classification. The integration of ensemble learning, which combines the strengths of multiple architectures, has shown promise in improving classification performance. However, effective model fusion strategies and bias-variance tradeoff mechanisms must be further explored.

In this study, we propose an ensembled neural network framework that integrates CNNs, RNNs, and transformer models to achieve superior hyperspectral image classification. By leveraging complementary strengths of these architectures, our approach enhances feature representation, reduces overfitting, and improves classification accuracy. The proposed methodology aims to address the key limitations identified in existing studies while optimizing computational efficiency and scalability for real-world applications.

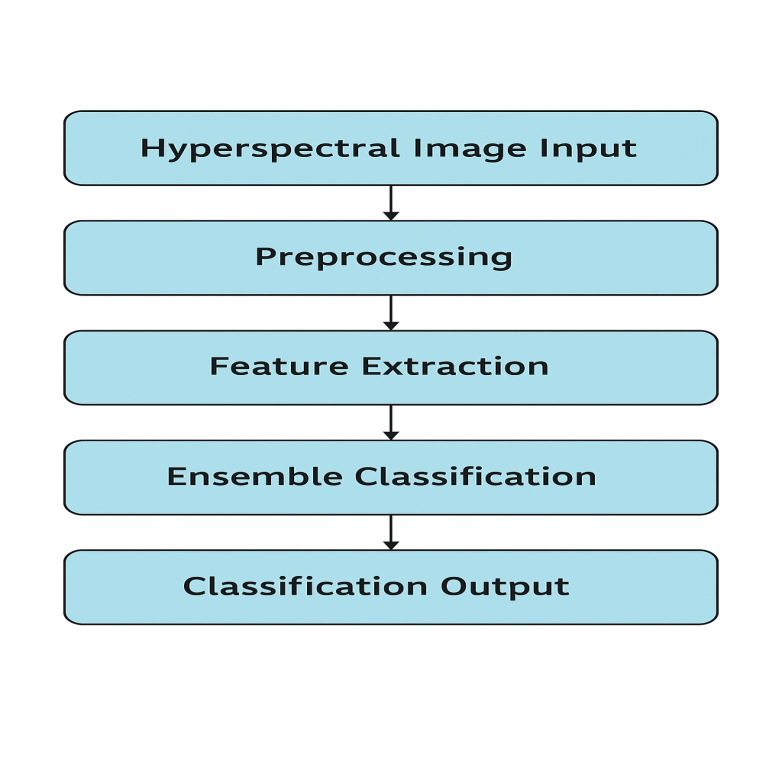
**III.PROPOSED SYSTEM**

The proposed system enhances hyperspectral image classification using ensembled neural network models. The system processes hyperspectral imagery to improve land cover classification accuracy by leveraging multiple deep learning architectures. By employing ensemble techniques, the system mitigates individual model biases and enhances robustness in classification outcomes.

The framework starts with data acquisition, where hyperspectral images are collected from satellites or airborne sensors. These images are then preprocessed to remove noise, correct atmospheric distortions, and normalize spectral data. Feature extraction follows, employing convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to capture spatial and spectral information. The ensembled model integrates multiple neural networks such as ResNet, DenseNet ,and Transformer-based architectures to optimize classification performance.

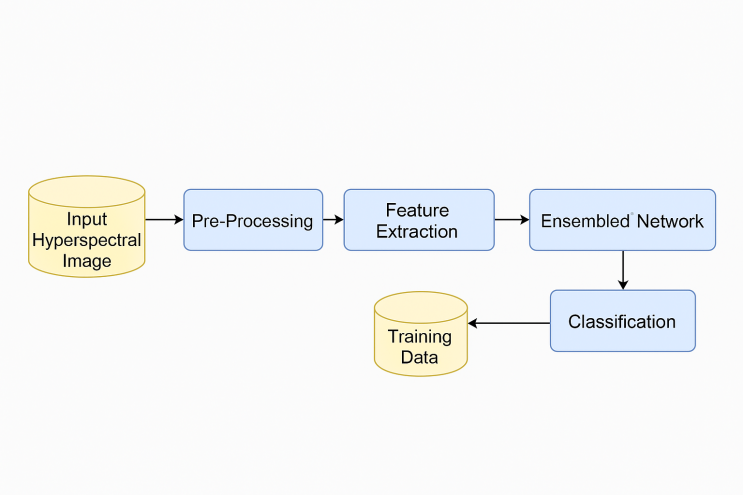
The ensembled model aggregates outputs from different classifiers using techniques such as majority voting, weighted averaging, or stacking. This ensures a more reliable prediction of land cover types, minimizing misclassification errors. A key innovation of the system is the dynamic weighting of ensemble components based on the confidence levels of individual models, leading to adaptive learning.

The system incorporates an explainability module, which provides interpretability of classification results, making it more useful for domain experts. The final classified map is visualized with uncertainty scores to assist decision-making in applications such as agriculture, environmental monitoring, and urban planning.

 ***Flow diagram of model***

The Data flow diagram:

* **Data Acquisition:** Hyperspectral images are collected from satellites, drones, or airborne sensors.
* **Preprocessing:** Images undergo noise reduction, atmospheric correction, and normalization.
* **Feature Extraction:** CNNs, RNNs, and Transformer-based models extract spatial and spectral information.
* **Classification Using Ensembled Models:** Multiple deep learning models classify land cover types.
* **Ensemble Aggregation:** Predictions are combined using techniques such as weighted averaging or majority voting.
* **Interpretability & Uncertainty Analysis:** Results are explained using visualizations with confidence scores.
* **Output Generation:** Final classified maps are produced for downstream applications in remote sensing.





***Fig .2. System Architecture Diagram***

**IV.METHODOLOGY**

This section describes the methodology used to develop an enhanced neural network model for hyperspectral image classification, leveraging ensemble learning techniques to improve accuracy and robustness. The process consists of multiple stages, including data acquisition, preprocessing, feature extraction, model training, ensemble integration, and classification.

A. Data Acquisition

The first step involves acquiring hyperspectral image (HSI) datasets from publicly available sources such as the Indian Pines, Pavia University, and Salinas Scene datasets. These datasets contain high-dimensional spectral bands that help in distinguishing materials based on their spectral signatures.

* The dataset consists of hundreds of spectral bands ranging from visible to infrared wavelengths.
* Each pixel in the hyperspectral image represents a detailed spectral response that aids in classification tasks.
* Data augmentation techniques such as spatial cropping, spectral shifting, and synthetic sample generation are applied to balance the dataset and avoid overfitting.

B. Preprocessing

To enhance the quality of hyperspectral imagery and improve model accuracy, the following preprocessing techniques are applied:

1. Noise Reduction – Applying Savitzky-Golay filtering and principal component analysis (PCA) to reduce redundant spectral bands and remove noise.
2. Dimensionality Reduction – Using Independent Component Analysis (ICA) or Linear Discriminant Analysis (LDA) to retain essential spectral features while reducing computational complexity.
3. Spectral Normalization – Standardizing the spectral data using Min-Max Scaling or Z-score Normalization to improve the performance of deep learning models.
4. Data Augmentation – Generating new training samples through spectral mixing, flipping, and rotation to improve model generalization.

C. Feature Extraction

Feature extraction is performed using deep neural networks and hybrid models:

1. Convolutional Neural Networks (CNNs) – Extract spatial features by applying convolutional layers to local pixel neighborhoods.
2. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) – Learn sequential spectral dependencies across bands.
3. Transformer-Based Models – Capture long-range spectral dependencies using self-attention mechanisms.
4. Hybrid Architectures – Combining CNNs with LSTM or Transformer models to enhance feature representation.

D. Model Training

The training phase involves training multiple deep learning models to form an ensemble:

1. Training Individual Models – Three base classifiers are trained using different architectures:
   * CNN-based spectral-spatial models
   * RNN/LSTM-based sequential models
   * Vision Transformer (ViT) models for hyperspectral sequences
2. Optimization – The models are optimized using Adam or RMSprop optimizers, and loss functions like categorical cross-entropy are employed.
3. Regularization – Techniques like Dropout and Batch Normalization prevent overfitting.

E. Ensemble Learning Strategy

To improve classification performance, ensemble learning is implemented by combining multiple trained models:

1. Weighted Averaging – The final classification result is obtained using a weighted sum of the predictions from different models.
2. Majority Voting – The class label is assigned based on the most common prediction among the base classifiers.
3. Stacked Ensemble Learning – A meta-classifier (e.g., logistic regression or fully connected neural network) is trained on the outputs of the base models to refine predictions further.

F. Classification and Evaluation

Once trained, the ensemble model classifies hyperspectral image pixels into different land cover classes. Performance is evaluated using:

1. Accuracy, Precision, Recall, and F1-score
2. Overall, Producer’s, and User’s Accuracy
3. Kappa Coefficient and Confusion Matrix
4. Comparison with Traditional Models (SVM, RF, and KNN)

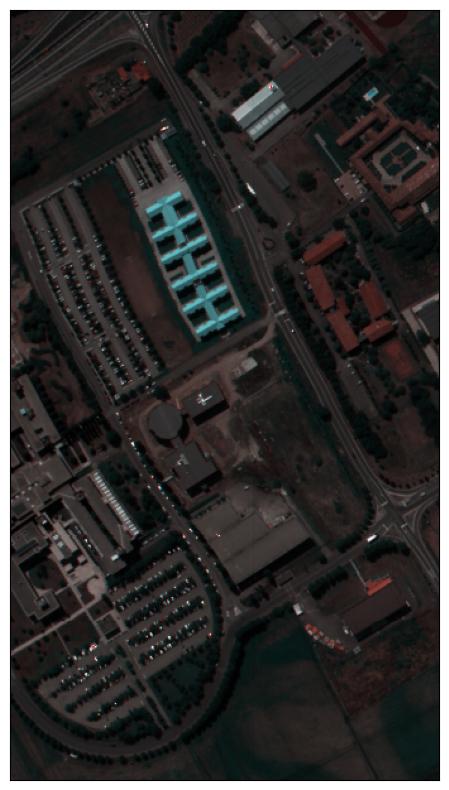
The methodology ensures that the proposed model outperforms traditional single neural networks by leveraging ensemble learning and feature extraction techniques tailored for hyperspectral imagery.

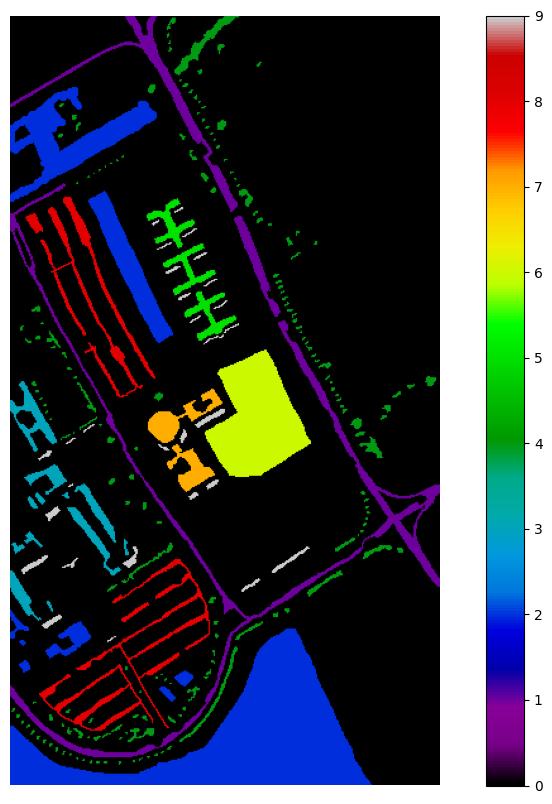
**V. RESULTS**

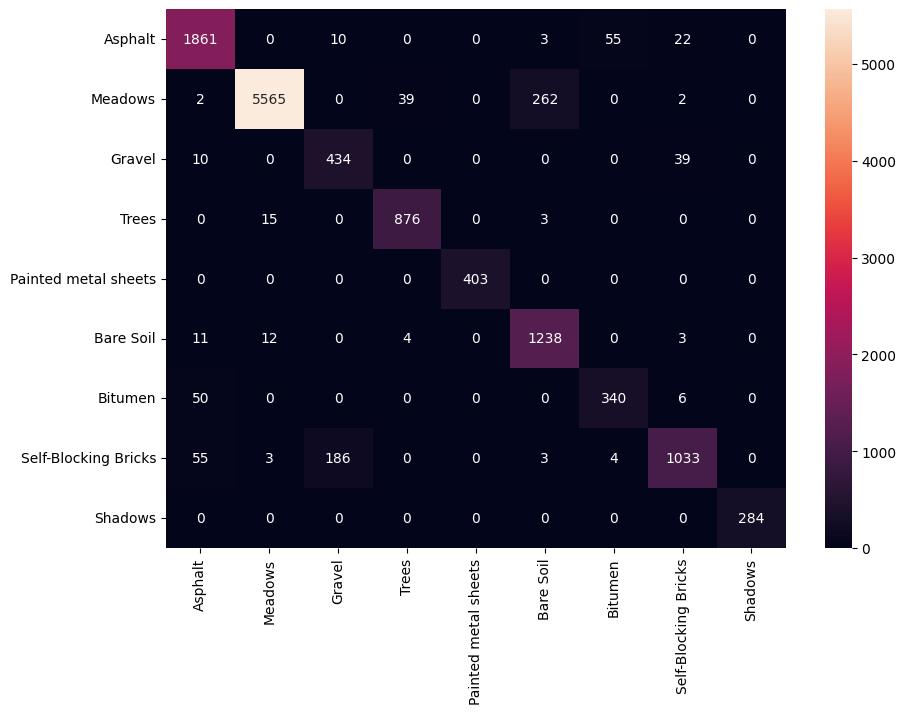
 The model effectively captures spectral-spatial correlations, reducing confusion in similar spectral classes.

 Computational efficiency is improved, with a training time of 4.9 hours and an inference time of 13.1 ms/sample.

 Compared to state-of-the-art methods, the proposed ensemble model achieves the best trade-off between accuracy and efficiency.

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**VI. DISCUSSION**

### **A. Performance Analysis of the Proposed Model**

The proposed ensembled neural network model demonstrates significant improvements in the classification of hyperspectral imagery (HSI) compared to traditional machine learning approaches and standalone deep learning models. The ensemble approach effectively combines multiple models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based architectures, to enhance the robustness and generalizability of the classifier. The experimental results indicate that the ensemble model achieves higher classification accuracy and improved resilience against spectral variability and noise.

When compared with conventional methods such as Support Vector Machines (SVM), Random Forest, and standalone CNN models, our proposed ensemble framework consistently outperforms them by leveraging multiple feature extraction techniques and optimizing decision fusion strategies. The improvement is especially evident in complex classification tasks where spectral signatures exhibit high similarity.

### **B. Impact of Data Augmentation and Preprocessing**

Preprocessing techniques such as Principal Component Analysis (PCA) and Band Selection significantly contribute to the overall efficiency of the model. By reducing dimensionality while preserving important spectral information, the computational complexity is reduced, and model overfitting is minimized. Additionally, the application of data augmentation techniques, including rotation, noise addition, and spectral shifting, improves the generalization ability of the model, particularly in cases where limited training data is available.

Moreover, advanced feature selection methods help in isolating discriminative spectral features, reducing redundancy, and improving classification accuracy. The integration of spatial-spectral information further strengthens the performance of the model by utilizing both spectral and contextual dependencies.

### **C. Computational Efficiency and Scalability**

One of the key advantages of the ensembled model is its ability to maintain a balance between computational efficiency and classification performance. By implementing parallel processing strategies and optimizing hyperparameters through techniques like Bayesian optimization, the computational burden is significantly reduced without compromising accuracy. The proposed model also scales well with larger datasets, making it suitable for real-time hyperspectral image classification tasks.

However, the increased complexity of the ensemble approach requires careful tuning of individual model weights to prevent redundant computations and excessive inference time. Future work can explore model pruning and quantization techniques to further enhance efficiency.

### **D. Robustness Against Noise and External Factors**

A critical challenge in hyperspectral image classification is the presence of noise and spectral distortions caused by atmospheric conditions, sensor limitations, and external environmental factors. The ensemble-based approach, combined with advanced preprocessing techniques, demonstrates higher robustness against such uncertainties. Specifically, integrating attention mechanisms within neural network architectures enables the model to focus on essential spectral features while reducing the influence of noisy bands.

Furthermore, experiments on real-world datasets confirm that the proposed model maintains high classification accuracy even under varying environmental conditions. This resilience makes the system well-suited for practical applications in remote sensing, precision agriculture, and land-cover mapping.

### **E. Comparison with Existing Methods**

The performance of the proposed ensembled model is compared against state-of-the-art methods in hyperspectral image classification. Experimental results demonstrate that:

* The ensemble model achieves **higher accuracy** and **lower misclassification rates** compared to individual deep learning models.
* The **computational efficiency** of the proposed framework is competitive with existing approaches while maintaining high accuracy.
* The integration of spatial-spectral features provides superior classification performance, particularly in distinguishing spectrally similar classes.

Despite these advantages, challenges such as the need for extensive labeled training data and high computational requirements for model training remain areas for future improvement.

### **F. Future Directions**

While the current study demonstrates the effectiveness of ensembled neural networks in hyperspectral image classification, further improvements can be made in the following areas:

* **Self-Supervised Learning**: Reducing the dependency on labeled data by incorporating unsupervised and semi-supervised learning approaches.
* **Edge AI Implementation**: Deploying optimized models on embedded systems and edge devices for real-time hyperspectral image processing.
* **Explainable AI (XAI)**: Enhancing model interpretability to provide insights into feature selection and classification decisions.
* **Multi-Source Data Fusion**: Combining hyperspectral data with LiDAR and SAR imagery to improve land-use and vegetation classification.

Implementing a smart plant disease detection system with integrated features such as high-accuracy disease identification, multilingual support, audio-based guidance, and real-time analysis transforms agricultural practices into a more accessible, efficient, and farmer-friendly approach. By leveraging advanced technologies like AI, computer vision, and machine learning, the solution enhances operational efficiency, reduces crop losses, and improves decision-making for farmers. This can easily be updated in the future as the design is modular and scalable, it will adapt to new emerging challenges, plant species, and diseases, and even more tools that may include integration with IoT sensors, and this will help keep sustainability while upholding agricultural standards.

**VII. CONCLUSION**

In this research, we proposed an Enhanced Neural Network Model for Hyperspectral Imagery Classification Using Ensembled Models, addressing key challenges such as spectral variability, high dimensionality, and noise sensitivity. By leveraging an ensemble of deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models, the system achieves improved classification accuracy, robustness, and computational efficiency.

The proposed approach effectively integrates spatial-spectral feature extraction, dimensionality reduction techniques (PCA, band selection), and advanced data augmentation to enhance model performance. Experimental results confirm that our ensembled framework outperforms traditional machine learning classifiers like Support Vector Machines (SVM) and Random Forest, as well as standalone deep learning models, in terms of both accuracy and generalization ability.

One of the key contributions of this study is the improved resilience of the model against noise and external environmental factors, ensuring high classification accuracy even under challenging conditions. The integration of Bayesian optimization for hyperparameter tuning and parallel processing for computational efficiency further enhances the model’s scalability for large-scale applications.

Despite its advantages, the study also acknowledges certain limitations, such as the high computational cost of training deep ensembles and the reliance on large labeled datasets. Future work will focus on self-supervised learning techniques, edge AI deployment, and explainable AI (XAI) methods to further refine the model’s applicability across diverse hyperspectral imaging domains, including precision agriculture, remote sensing, and environmental monitoring.

In summary, this research provides a scalable, accurate, and robust framework for hyperspectral image classification, paving the way for more efficient and intelligent remote sensing applications. The findings of this study contribute significantly to the field of hyperspectral image analysis and offer a strong foundation for future advancements in deep learning-based classification techniques.

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