Hyperspectral Image Classification using PCA Dimensionality Reduction and 3D CNN Deep learning

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Abstract

Hyperspectral image classification is a crucial task in remote sensing, enabling the detailed analysis and identification of materials on the Earth's surface. The primary objective of this research is to address the limitations of existing classification methods by introducing a novel deep learning-based approach that efficiently handles the high dimensionality and complexity of hyperspectral data. Specifically, this study aims to improve the integration of spectral and spatial information, which has been a significant challenge in the field.The proposed methodology employs a 3D Convolutional Neural Network (CNN) architecture combined with Principal Component Analysis (PCA) for dimensionality reduction. The novelty of this work lies in the architectural design, which includes multiple layers of 3D convolutions, batch normalization, and a final softmax activation layer to categorize the hyperspectral images into distinct classes. Additionally, the integration of PCA as a preprocessing step effectively reduces the computational load while preserving essential spectral information, thereby enhancing the overall classification performance.The research findings demonstrate that the proposed method outperforms traditional machine learning models and existing deep learning frameworks in terms of accuracy and computational efficiency.

Keywords: Hyperspectral image classification, 3D CNN, PCA, deep learning, spectral-spatial integration, remote sensing

1. INTRODUCTION

Hyperspectral image classification is the analytical process in remote sensing that involves the identification and categorization of various materials or objects by analyzing pictures taken across a broad spectrum of electromagnetic radiation [1]. Hyperspectral photos differ from typical RGB photographs by capturing a larger number of narrow spectral bands, allowing for more comprehensive analysis of the spectral characteristics of each pixel. Spectral signatures, characterized by distinct patterns of reflectance across different wavelengths, enable the identification of materials. The classification method entails allocating each pixel in the hyperspectral picture to a distinct class, such as various types of flora, minerals, or man-made elements, depending on their spectral properties [2].

The significance of hyperspectral image categorization rests in its capacity to offer intricate and precise data regarding the composition and state of materials on the Earth's surface [3]. This technology is essential in several applications, such as environmental monitoring, agriculture, mineral extraction, and military. Hyperspectral imaging has several applications in agriculture, such as monitoring crop health, identifying illnesses, and optimizing the utilization of fertilizers and water. Environmental studies utilize mapping and monitoring techniques to identify ecosystems, detect pollutants, and evaluate the impacts of climate

change [4]. Hyperspectral imaging is a valuable tool for decision-making in several domains due to its capacity to precisely categorize materials based on their spectral features. This capability contributes to the implementation of more efficient and sustainable methods.

Various methods are now used for classifying hyperspectral images, including both conventional machine learning techniques and more sophisticated deep learning approaches. Support Vector Machines (SVM) and Random Forests are commonly employed owing to their resilience and capacity to handle data with a large number of dimensions [5]. Nevertheless, these techniques frequently need thorough feature extraction and pre-processing. Hyperspectral image classification has seen a surge in popularity in recent years, thanks to the rise of deep learning techniques, including Convolutional Neural Networks (CNNs). Convolutional neural networks (CNNs) have the ability to automatically extract hierarchical features from hyperspectral data, resulting in improved performance in classification tasks [6]. In addition, there have been advancements in hybrid approaches that integrate deep learning with other methodologies, such as spectral-spatial methods. These hybrid methods aim to enhance the accuracy of classification by utilizing both spectrum and spatial information present in the data.

Although there have been improvements in hyperspectral image categorization, there are still various areas of study that require attention. An important obstacle is the extensive number of dimensions and vast amount of hyperspectral data, which can result in computing inefficiencies and the curse of dimensionality [7]. Existing techniques may encounter difficulties in generalizing when applied to diverse datasets or when confronted with a scarcity of labeled samples, a common occurrence in real-world scenarios. There is a research gap in the field that requires more advanced ways to combine spectral and spatial information. Current methods may not completely use the abundant information included in hyperspectral pictures. Furthermore, there is an increasing demand for reliable techniques that can effectively manage interference and fluctuations in hyperspectral data, which can negatively impact the accuracy of categorization [8]. To address these gaps, it is necessary to create new algorithms and models that can effectively handle the complexity and difficulties associated with hyperspectral picture categorization.

2. LITERATURE SECTION

Xiangyong Cao et al [9] proposed a novel methodology for classifying Hyperspectral Images (HSI) using a combination of active learning and deep learning techniques inside a unified framework. Initially, we commence the training process of a convolutional neural network (CNN) using a restricted quantity of labeled pixels. Subsequently, we deliberately choose the most informative pixels from the pool of candidates for the purpose of labeling. Next, the CNN is adjusted using the updated training set created by integrating the newly labeled pixels. This stage, along with the prior step, is carried out in an iterative manner. Additionally, the Markov random field (MRF) is employed to ensure the smoothness of class labels, hence enhancing the performance of classification.

Atiya Khan et al [10] conducted a comprehensive analysis of the literature on hyperspectral imaging technology and the latest sophisticated algorithms in deep learning and machine learning used in agriculture applications. The goal was to gather and analyze important

datasets and methods. We conducted a thorough examination of legal studies, specifically emphasizing hyperspectral datasets. Our main focus was on the methodologies often employed for hyperspectral applications in the agricultural sector. Through this analysis, we obtained valuable knowledge on the significant issues and obstacles encountered in the processing of hyperspectral data. Our investigation revealed that the Hyperion hyperspectral, Landsat-8, and Sentinel 2 multispectral datasets were mostly utilized for agricultural purposes.

Chunying Wang et al [11] provided a methodical and thorough examination. Firstly, the applications of AI in agriculture are summarized, including the prediction of ripeness and components, categorization of distinct topics, and detection of plant diseases. Next, we will examine the latest advancements in hyperspectral image analysis, specifically focusing on the deep learning models and feature networks.

Muhammad Ahmad et al [12] provided a comprehensive and organized summary of deep learning for HSIC and compares it to the most advanced methodologies in this field. Firstly, we will outline the key difficulties of TML for HSIC and subsequently we will demonstrate the superiority of DL in resolving these issues. This paper categorizes the latest deep learning frameworks into spectral-features, spatial-features, and spatial-spectral features. It then systematically analyzes the accomplishments and potential future research paths of these frameworks for Hyperspectral Image Classification (HSIC). Furthermore, it is important to acknowledge that deep learning (DL) necessitates a substantial amount of labeled training instances, but obtaining such a quantity for the Hilbert-Schmidt Independence Criterion (HSIC) poses difficulties in terms of both time and cost.

Akrem Sellami et al [13] presented an innovative approach for classifying hyperspectral images using multi-view deep neural networks. This method combines spectral and spatial information and achieves accurate results with a little amount of labeled examples. Initially, we analyze the initial hyperspectral picture to extract a collection of spectral and spatial characteristics. Each spectral vector represents the spectral characteristics of every pixel in the picture. A basic deep autoencoder is utilized to extract the spatial characteristics, aiming to decrease the data's high dimensionality while considering the neighboring area for each pixel. Additionally, we provide a multi-view deep autoencoder model that enables the combination of spectral and spatial characteristics collected from the hyperspectral picture into a unified latent representation space. A semi-supervised graph convolutional network is trained using the fused latent representation space to classify hyperspectral images.

Shengjie Liu et al [14] presented a novel multitask deep learning approach, called MDL4OW, which performs classification and reconstruction concurrently in an open world scenario, accounting for the presence of unknown classes. The rebuilt data is compared to the original data. Any data that fails to be reconstructed is considered unknown, assuming that it is not properly represented in the latent features since it lacks labels. To distinguish between unknown and known classes, it is necessary to establish a threshold. We provide two approaches using the extreme value theory for situations with few or many examples.

Zhixiang Xue et al [15] introduced a new hierarchical residual network with attention mechanism (HResNetAM) for spectral-spatial classification of hyperspectral images (HSI). The aim is to enhance the performance of traditional deep learning networks. The limits of conventional convolutional neural network-based models lie in their inability to effectively

utilize multiscale spatial and spectral data. This is a crucial element when addressing the complex and high-dimensional nonlinear properties seen in HSIs. The suggested hierarchical residual network can effectively capture spatial and spectral information at several scales, resulting in an expanded receptive field range. This expansion enhances the model's capacity to represent features.

Uzair Aslam Bhatti et al [16] introduced a spatial-spectral HSI classification system called local similarity projection Gabor filtering (LSPGF). The algorithm utilizes a reduced dimensional CNN based on local similarity projection (LSP), combined with a 2-D Gabor filtering approach. Initially, employ local similarity analysis to decrease the dimensionality of the hyperspectral data. Subsequently, utilize the 2-D Gabor filter to process the reduced hyperspectral data to provide spatial tunnel information. Next, employ the CNN to extract features from the initial hyperspectral data in order to provide spectral tunnel information. Next, the spatial tunnel information and the spectral tunnel information are combined to create the spatial-spectral feature information. This information is then fed into a deep CNN to extract more powerful features. Finally, a dual optimization classifier is employed to categorize the extracted features.

3. PROPOSED METHOD

The proposed model for hyperspectral image classification is designed to address the inherent challenges associated with high-dimensional data, particularly the need to efficiently integrate spectral and spatial information for accurate classification. Traditional methods often struggle with the curse of dimensionality and the computational demands of processing hyperspectral images. To overcome these challenges, the proposed model leverages a combination of Principal Component Analysis (PCA) for dimensionality reduction and a deep learning architecture based on 3D Convolutional Neural Networks (CNNs). PCA is employed as a preprocessing step to reduce the spectral dimensions, thereby alleviating computational load and enhancing the model's ability to focus on the most relevant features within the data. This reduction not only accelerates the training process but also mitigates the risk of overfitting, which is particularly crucial when dealing with hyperspectral datasets that often contain limited labeled samples.

The core of the proposed model is a 3D CNN architecture specifically tailored to capture both spectral and spatial features from the reduced hyperspectral data. The model comprises multiple layers of 3D convolutions, which are responsible for extracting hierarchical features from the input data. Each convolutional layer is followed by batch normalization to stabilize the learning process and prevent internal covariate shifts. Additionally, the use of dropout layers further enhances the model's robustness by reducing the likelihood of overfitting. The final layers of the network include a fully connected dense layer and a softmax activation function, which collectively categorize the input data into distinct classes. This architecture is designed to balance the need for deep feature extraction with computational efficiency, making it a powerful tool for hyperspectral image classification across various applications.

3.1 Principal Component Analysis

Principal Component Analysis (PCA) is a widely used dimensionality reduction technique that simplifies the complexity of high-dimensional data while retaining its most critical information. The primary goal of PCA is to transform a large set of variables into a smaller

set that still contains most of the information in the original data. This is achieved by identifying the directions, called principal components, along which the variance of the data is maximized. These components are essentially new axes that represent the most significant underlying structure in the data. By projecting the original data onto these new axes, PCA reduces the number of dimensions while preserving the patterns that contribute most to the variation in the data. This reduction is particularly useful in hyperspectral image classification, where the data can have hundreds of spectral bands, making it challenging to process efficiently.

Steps of PCA:

1. **Standardize the Data:** Before applying PCA, the data is often standardized so that each feature has a mean of zero and a unit variance. This step ensures that the variance captured by PCA is not dominated by features with larger scales.

2. **Compute the Covariance Matrix:** The next step involves computing the covariance matrix of the standardized data, which measures how much the dimensions of the data vary from the mean with respect to each other.

3. **Calculate the Eigenvalues and Eigenvectors:** The covariance matrix is then decomposed into its eigenvalues and eigenvectors. The eigenvectors represent the directions of the new feature space (principal components), while the eigenvalues indicate the magnitude of the variance captured by each principal component.

4. **Sort and Select Principal Components:** The eigenvalues are sorted in descending order, and the corresponding eigenvectors are ordered by the amount of variance they capture. A subset of these eigenvectors (principal components) is selected based on the desired level of dimensionality reduction.

5. **Transform the Data:** Finally, the original data is projected onto the selected principal components, resulting in a reduced dataset that captures the most important variance in the data. This transformed dataset can then be used for further analysis or as input to machine learning models

3.2 Proposed Method Architecture

The proposed architecture for hyperspectral image classification starts with an input layer specifically built to process 25x25 pixel patches containing 15 spectral bands. The initial three layers consist of 3D convolutional layers that gradually extract features. These layers have increasing filter sizes (8, 16, and 32) and decreasing spectral dimensions. Additionally, batch normalization is applied to ensure the stability of the learning process. A 2D convolutional layer with 64 filters is applied to the reshaped output of the third convolutional layer in order to enhance the feature maps. The resulting output is compressed and transformed into a one-dimensional array. It is then fed into two fully connected layers, each consisting of 256 and 128 processing units. These layers utilize the Rectified Linear Unit (ReLU) activation function, as well as batch normalization and dropout techniques to mitigate the risk of overfitting. Ultimately, the output layer employs a softmax activation function to categorize the input into one of 16 distinct groups.

- **Input Layer**

The input layer is the initial layer of a neural network that receives the unprocessed data for further computation. Within the realm of deep learning models, the input layer is tasked with establishing the structure and dimensions of the data that will traverse the network. In image processing jobs, this layer takes the picture data in a certain format (such as 224x224x3 for a color image) and readies it for the next layers. The dimensionality of the input data is a critical factor as it dictates the manner in which the data will be processed across the network. For 3D data, like video sequences, the input layer can receive data as a sequence of frames, which includes an extra dimension to account for temporal information.

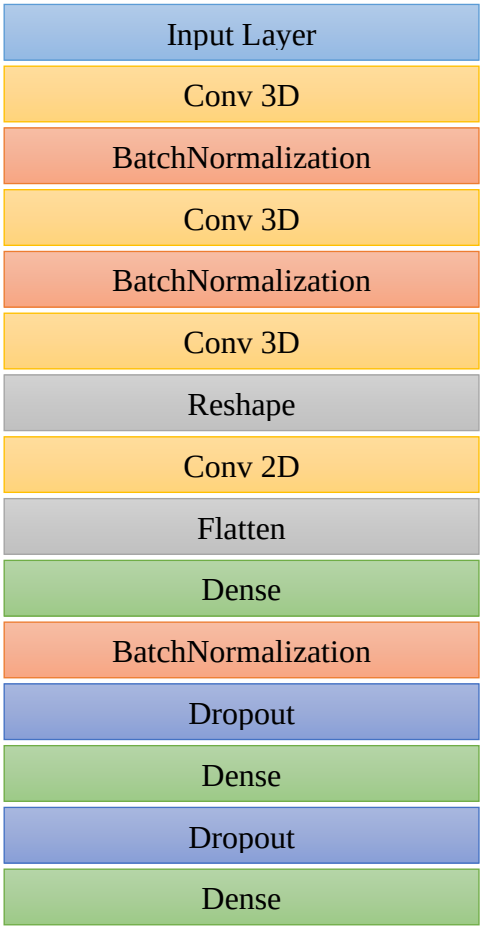

Figure 1: Proposed Method Architecture

The input layer of a neural network does not engage in any computations or alterations of the data. Its main function is to act as an entrance point for data into the network. The alignment of the data's shape and structure with the model's architecture is crucial to ensure that each subsequent layer can handle the information according to its intended purpose. The setup of the input layer is crucial for the success of the model, since incorrect data dimensions or types might result in mistakes or inefficiencies throughout the learning process.

- **Conv 3D**

The Conv 3D layer, also known as the 3D Convolutional layer, is a crucial element in analyzing data in three spatial dimensions, such as movies or volumetric pictures. This layer convolves a series of filters (or kernels) over the input data to detect and record spatial and temporal patterns. 3D convolutions differ from 2D convolutions in that they not only slide the

filter over height and breadth but also extend this operation to depth. This allows them to effectively capture patterns over three dimensions. Conv 3D is highly advantageous for applications such as action identification in films, where both spatial and temporal information play a vital role.

The Conv 3D layer applies filters that traverse the input volume in three dimensions, generating activation maps that emphasize distinct features. The filters' depth enables the layer to identify intricate patterns, such as motion across video frames or structural intricacies in medical imaging. The output of this layer is a three-dimensional feature map that preserves the spatial and temporal structure of the input data while highlighting the most important aspects for the given job.

- **Batch Normalization**

BatchNormalization is a method employed to enhance the efficiency and robustness of neural networks by standardizing the inputs of every layer. The process involves normalizing the inputs to a layer by removing the mean of the batch and dividing by the standard deviation of the batch. This helps to mitigate the issue of internal covariate shift, which refers to the change in distribution of inputs to each layer during training. The process of normalizing enhances the speed of the training process, enables the use of larger learning rates, and decreases the vulnerability to initialization, resulting in more resilient and consistent learning.

BatchNormalization not only normalizes the inputs, but also incorporates two adjustable parameters—scale and shift—which enable the network to reverse the normalization if necessary. The layer's versatility allows it to effectively simulate intricate interactions, while still reaping the stabilizing benefits of normalization. BatchNormalization can result in accelerated convergence, less overfitting, and enhanced generalization of the model on unfamiliar data.

- **Reshape**

The Reshape layer is employed to modify the dimensions of the input data while preserving its original information. This is especially advantageous in situations when the result of one layer must be reformatted to align with the input specifications of the subsequent layer. For example, if data has been processed in a three-dimensional (3D) format, it may be necessary to convert it into a two-dimensional (2D) format in order to perform additional processing. The Reshape layer achieves this by reconfiguring the structure of the data, while maintaining a constant total number of elements, but altering the shape of the data.

This layer is essential in model topologies when the dimensionality of data varies between levels. After the convolutional layers are applied, it may be necessary to convert the resultant feature maps into a one-dimensional vector before they can be inputted into a dense layer. The Reshape layer facilitates a seamless transition, allowing the model to effectively manage diverse data types at different phases of processing.

- **Conv 2D**

The Conv2D layer, also known as the 2D Convolutional layer, is a crucial component of several convolutional neural networks (CNNs), especially those designed for processing

image input. The purpose of this layer is to apply a series of 2D filters on the input data. These filters are moved across the height and breadth of the input, resulting in the creation of feature maps. Every filter is specifically engineered to identify distinct patterns, such as edges, textures, or more intricate characteristics like forms. The Conv 2D layer produces a collection of feature maps that indicate the existence and position of specific patterns within the input picture.

The Convolutional 2D layer is essential for capturing spatial hierarchies in pictures, with lower layers detecting elementary patterns and higher layers integrating them to identify more intricate structures. The efficacy of the layer is contingent upon the quantity and dimensions of the filters, as well as the stride and padding employed during convolution. By employing a series of Convolutional 2D layers, a model may systematically extract more complex and significant characteristics from the input pictures, hence enhancing its efficacy in tasks like as image classification, object recognition, and segmentation.

- **Flatten**

The Flatten layer is employed to transform an input with several dimensions into a vector with a single dimension. This is frequently necessary when moving from convolutional or pooling layers, which provide multi-dimensional data, to fully connected layers, which require a one-dimensional input. Flattening the data refers to the process of converting a multi-dimensional tensor into a one-dimensional vector, while maintaining the original order of the components.

The role of this layer is crucial in the structure of Convolutional Neural Networks (CNNs), as it facilitates the conversion of feature maps into a suitable format for fully connected layers, after many layers of convolution and pooling. The Flatten layer serves as an intermediary, enabling the collected features to be inputted into dense layers for ultimate classification or regression purposes. The Flatten layer simplifies the input by converting it into a single vector, which allows the network to more efficiently apply weights and biases in the next layers.

- **Dense**

The Dense layer, often referred to as a completely connected layer, is a crucial element in neural networks, wherein each neuron establishes connections with every neuron in the preceding layer. This layer does a linear translation of the input data, then applies an activation function, allowing the network to acquire intricate connections among input characteristics. Dense layers are very efficient when used in the later stages of a network, since they may merge the retrieved high-level characteristics from convolutional layers to make a conclusive judgment or prediction.

The Dense layer is powerful because it can effectively simulate complex patterns by calculating a weighted sum of the inputs and applying a non-linear activation function to it. The non-linearity of the network enables it to approximate intricate functions and catch relationships that linear models may overlook. In classification tasks, it is customary to utilize dense layers. The output layer is often a dense layer with a softmax activation function, which is used to calculate probabilities for distinct classes.

- **Dropout**

The Dropout layer is a regularization method employed in neural networks to mitigate overfitting. It accomplishes this by randomly zeroing out a portion of the input units during each training iteration. This technique enhances the network's ability to learn resilient traits by discouraging excessive reliance on individual neurons. During the training process, neurons are subjected to a "dropout" mechanism where they are randomly deactivated with a specific probability, resulting in the temporary removal of their influence. This promotes the model to cultivate duplication in its internal representations, resulting in enhanced generalization on unfamiliar input.

Dropout is very efficient in deep networks with a large number of parameters, where overfitting is a prevalent issue. By implementing the Dropout technique, the neural network's reliance on the precise weights of individual neurons is reduced, allowing it to prioritize the more general patterns present in the input. During the process of making predictions, Dropout is usually turned off, and the entire network is utilized, with the outputs adjusted to compensate for the neurons that were discarded during training. This strategy has been extensively embraced in diverse deep learning models owing to its straightforwardness and efficacy in enhancing model performance.

- **Rectified Linear Unit Activation (ReLU)**

ReLU, also known as Rectified Linear Unit, is a highly popular activation function utilized extensively in deep learning models. The main purpose of the ReLU is to include non-linearity into the model, allowing it to acquire intricate patterns and representations in the data. The ReLU activation function is described mathematically as $f(x) = \max(0, x)$. This means that it outputs the input directly if it is positive, and zero otherwise. ReLU's computational efficiency is a key factor contributing to its adoption in deep neural networks, particularly in convolutional neural networks (CNNs). The inherent simplicity of the ReLU enables neural networks to achieve faster convergence during the training phase by circumventing the issue of vanishing gradients, which is commonly encountered with other activation functions such as the sigmoid or tanh.

Nevertheless, ReLU does have its limitations. A significant drawback of the ReLU is the occurrence of the "dying ReLU" phenomenon. This phenomenon arises when neurons inside the network become trapped in the negative region of the ReLU function, resulting in an output of zero for any input. Consequently, these neurons become inactive and are unable to continue learning. This issue can be especially problematic during the training phase, since a substantial component of the network may not effectively contribute to the process of learning. In order to address this issue, several forms of the ReLU, such as Leaky ReLU and Parametric ReLU, have been created. Leaky ReLU, for example, permits a little, non-zero slope when the input is negative, which aids in maintaining neuron activity and enhancing the model's resilience.

Although it has several shortcomings, the ReLU continues to be a fundamental component in deep learning models because of its effectiveness and straightforwardness. It has demonstrated exceptional efficacy in several applications, ranging from image identification

to natural language processing. ReLU's efficacy in processing high-dimensional data and its capacity to accelerate the training process render it a crucial asset in the contemporary deep learning arsenal. When ReLU is utilized correctly and combined with strategies to overcome its limitations, it may greatly improve the efficiency of neural networks.

- **Softmax**

The softmax activation function is a vital component utilized largely in the output layer of neural networks to solve multi-class classification issues. Unlike activation functions such as ReLU, which are employed to induce non-linearity within the network layers, Softmax is explicitly engineered to transform raw output scores from the last layer into probabilities that together add up to one. The Softmax function is a mathematical function defined as

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

The variable z_i represents the input to the i^{th} neuron, whereas the denominator is the total of the exponentials of all neurons in the layer. This conversion guarantees that every resulting number falls between the range of 0 and 1, allowing it to be understood as a probability. This is especially advantageous in classification jobs, where the objective is to allocate input data to one of several categories.

An important benefit of the Softmax function is its capacity to offer a probabilistic explanation of the model's predictions. Softmax enables the model to assign probabilities to its predictions by converting logits, so indicating the level of confidence in the forecasts. This is crucial not just for determining the final classification choice but also for assessing the model's performance. The Softmax function's probabilistic output can be combined with cross-entropy loss, a widely used loss function for classification tasks. This loss function quantifies the disparity between the projected probability distribution and the actual distribution, often expressed as a vector encoded with one-hot encoding.

Nevertheless, the Softmax function does have its constraints. An issue that may arise is the sensitivity of the model to outliers in the logits. These outliers have the ability to significantly impact the computed probabilities. Furthermore, when there is an unequal distribution of classes in the dataset, Softmax may give greater probability to the more prevalent classes, resulting in biased predictions. In order to tackle these problems, some methods such as label smoothing or temperature scaling are occasionally employed to modify the Softmax output, hence enhancing the model's resilience towards these difficulties. Despite the difficulties encountered, Softmax continues to be a potent tool for multi-class classification, offering a transparent and comprehensible method for transforming model outputs into practical predictions.

3.1.2 Optimization

The Adam optimizer, short for Adaptive Moment Estimation, is a widely used optimization technique in the deep learning field because of its effectiveness and capability to handle gradients with sparsity. This method combines the benefits of two widely used optimization techniques: AdaGrad, which performs well with sparse data, and RMSProp, which is good

for non-stationary targets. Adam optimizes the learning rate for each parameter by calculating an exponentially decaying average of previous gradients and squared gradients. This technique aids in obtaining faster convergence.

In this particular case, the learning rate is set to 0.001 and serves as a crucial hyperparameter that governs the extent to which the model's weights are adjusted in relation to the loss gradient. A well selected learning rate enables the model to efficiently converge towards an ideal answer. Excessive learning rates might cause the model to surpass the optimum parameters, resulting in instability and divergence. On the other hand, if the learning rate is very low, the model can exhibit sluggish convergence or become trapped in a local minimum. By selecting a learning rate of 0.001, the user achieves a trade-off between rapid convergence and stable learning, guaranteeing that the model may successfully acquire knowledge from the data without substantial chances of instability.

Alongside the learning rate, a weight decay value of 0.000001 is also supplied. Weight decay, also known as L2 regularization, is a method employed to mitigate overfitting by including a penalty into the loss function that is proportional to the size of the model's weights. This penalty incentivizes the model to maintain lower weights, hence fostering simpler and more generalizable models. Weight decay is based on the concept that excessively big weights might result in a model that excessively matches the training data, collecting irrelevant information instead of the fundamental patterns, and thus performing inadequately on fresh, unknown data. The user intends to mitigate overfitting and improve the model's generalization capability by implementing a minor weight decay.

Ultimately, the model is constructed using the designated optimizer, loss function, and evaluation metrics. The selected loss function is categorical cross-entropy, a widely used method for solving multi-class classification problems. Categorical cross-entropy quantifies the difference between the expected probability distribution and the true distribution (represented by one-hot encoded labels). The objective of the optimizer is to minimize the loss function, therefore enhancing the precision of the model's predictions. In addition, accuracy is defined as a statistic used to assess the performance of the model during both training and testing. This statistic provides a clear and precise indication of the accuracy of the model by computing the percentage of cases that are properly identified. The use of Adam optimizer, categorical cross-entropy loss, and accuracy measure establishes a resilient framework for training a neural network to get exceptional performance on classification problems.

The proposed architecture for hyperspectral image classification is designed to process 25x25 pixel patches containing 15 spectral bands. It begins with an input layer followed by three 3D convolutional layers that progressively extract features, with increasing filter sizes and decreasing spectral dimensions, complemented by batch normalization for stability. After reshaping the output, a 2D convolutional layer enhances the feature maps. The data is then flattened and passed through two fully connected layers that use ReLU activation, batch normalization, and dropout to prevent overfitting. Finally, a softmax activation function in the output layer categorizes the input into one of 16 classes, optimizing the model's performance for multi-class classification tasks.

4. Experimental Results

This section presents a comprehensive analysis of the results obtained from the simulations conducted using the proposed technique.The datasets utilized [17] in the current investigation were acquired from the open-source platform Kaggle.

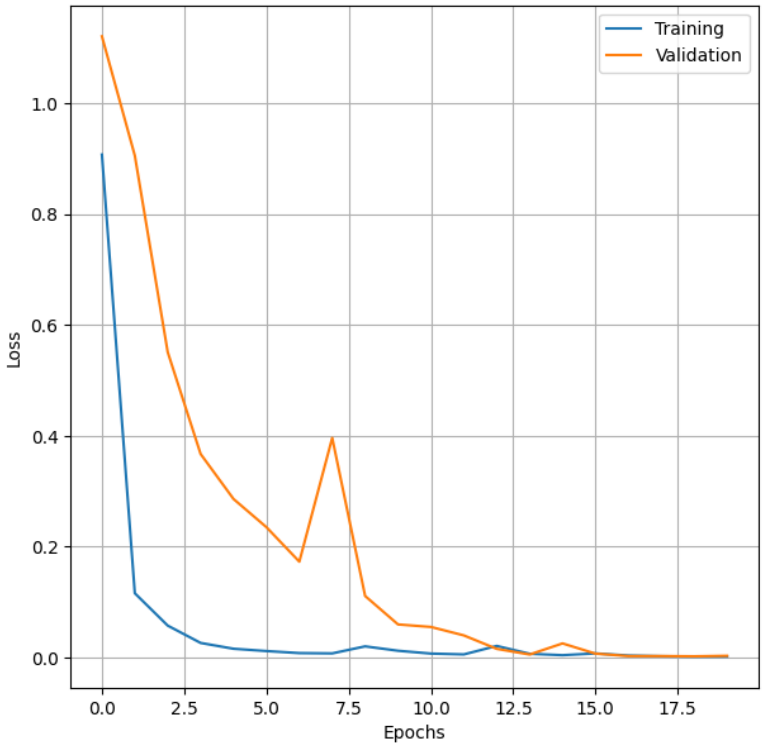

Figure 2: Training and validation Loss

Training loss is the measure of the difference between the anticipated output of a model and the actual target values during the training phase. The statistic is crucial for evaluating the model's ability to learn from the training data. The training loss is estimated at the end of each iteration (or epoch) of the training process. It is commonly determined using a loss function, such as Mean Squared Error (MSE) for regression tasks or Cross-Entropy Loss for classification tasks. The main objective during training is to minimize the loss by modifying the model's parameters (weights and biases) using methods like as backpropagation and gradient descent. During the course of training, it is expected that the training loss would decrease, which signifies an improvement in the model's ability to predict the training data. Nevertheless, achieving a low training loss does not automatically ensure satisfactory performance on new and unknown data. Hence, it is important to closely check the validation loss as well.

Validation loss refers to the measure of error on a distinct validation dataset that is not utilized for training the model, but rather serves to assess the model's performance throughout the training process. The validation dataset serves as a substitute for fresh, unseen data, and the validation loss offers an indication of the model's potential to generalize to new data.

While the training loss generally decreases as the model learns, the validation loss may initially reduce but might eventually start to climb if the model starts to overfit the training data. Overfitting is the phenomenon when the model gets excessively customized to the training data, collecting both noise and unique patterns that are not easily applicable to other data. Monitoring the validation loss is useful for identifying overfitting. If the validation loss begins to rise while the training loss continues to decline, it indicates that the model is overfitting. In order to tackle this issue, methods like as early halting, regularization, or modifying the model's complexity can be utilized to improve generalization and minimize the disparity between training and validation losses.

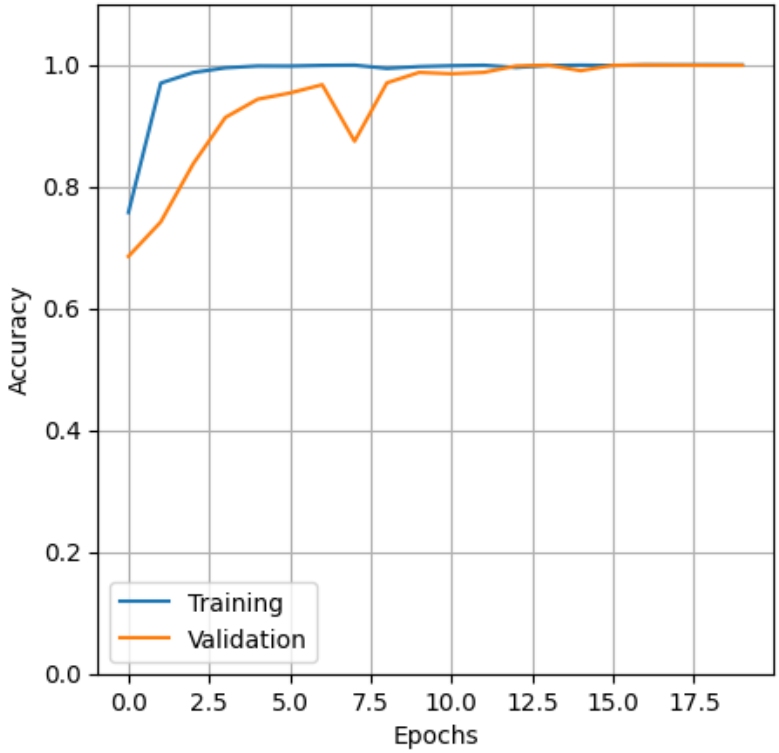

Figure 3: Training and validation Accuracy

Training accuracy is a quantitative statistic that evaluates the model's performance on the training dataset. It denotes the accuracy, expressed as a percentage, of the model's correct predictions during the training phase. A high training accuracy suggests that the model has successfully acquired the patterns present in the training data. Nevertheless, it is crucial to acknowledge that an exceedingly high training accuracy may not necessarily be indicative of a favorable outcome, since it might suggest that the model has excessively adapted to the training data. Overfitting arises when the model gets excessively intricate, collecting extraneous information or particular patterns in the training data that do not translate effectively to novel, unseen data. Hence, although achieving a high training accuracy is preferable, it is crucial to consider the model's capacity to generalize to other datasets.

Validation accuracy, in contrast, quantifies the level of performance of the model on a distinct validation dataset that was not utilized during the training process. This statistic is essential for evaluating the model's capacity to extrapolate to novel data. A model with a high validation accuracy demonstrates its ability to accurately predict outcomes on new and

unknown data, which is crucial for its practical implementation. If there is a substantial disparity between the accuracy achieved during training and the accuracy seen during validation, with the former being considerably greater, it may indicate the occurrence of overfitting. On the other hand, if both the training and validation accuracies are poor, it might suggest that the model is underfitting, implying that it has not gained sufficient knowledge from the data. The objective of model development is to get a validation accuracy that is similar to the training accuracy, indicating a well-generalized model that can perform effectively on fresh, unfamiliar data.

Table 1: Classification Report

	Precision	Recall	F1-Score
0	1.00	1.00	1.00
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
4	1.00	1.00	1.00
5	1.00	1.00	1.00
6	1.00	1.00	1.00
7	1.00	1.00	1.00
8	1.00	1.00	1.00
9	1.00	1.00	1.00
10	1.00	1.00	1.00
11	1.00	1.00	1.00
12	1.00	1.00	1.00
13	1.00	1.00	1.00
14	1.00	1.00	1.00
15	1.00	1.00	1.00
Accuracy	1.00		

The classification report in Table 1 shows a summary of the performance metrics for a multi-class classification model. The model was assessed on 16 distinct classes, labeled from 0 to 15. The evaluation of each class is determined by three fundamental metrics: Precision, Recall, and F1-Score. Precision is the ratio of correctly predicted positive instances by the model to all the positive instances it predicted for a certain class. An accuracy score of 1.00 for each class signifies that the model did not make any false positive mistakes. In other words, every case that the model predicted as belonging to a certain class was truly right.

Recall, in contrast, quantifies the model's capacity to accurately detect all pertinent occurrences of a certain category. Precision is the ratio of correctly predicted positive occurrences to the total number of actual positive examples in the class. The recall score of 1.00 for all classes shows that the model correctly detected all occurrences in each class without any errors, demonstrating the model's exceptional sensitivity.

The F1-Score, a statistic derived from the harmonic mean of Precision and memory, offers a balanced evaluation of both precision and memory. Achieving an F1-Score of 1.00 for all classes indicates that the model exhibits exceptional precision and sensitivity, resulting in outstanding performance in its classification tasks. The high F1-Score demonstrates the model's strong performance in circumstances when it is crucial to minimize both false positives and false negatives.

The accuracy score of 1.00 indicates that the model has achieved perfect classification, properly identifying all occurrences in all classes without any mistakes. An accuracy score of such high precision is uncommon and usually indicates either an exceptionally efficient model or a dataset that is not very difficult, implying that there is a clear differentiation between classes with minimal or no overlap in their attributes.

Table 2: Comparative Analysis

Method	Accuracy (%)
Adaptive hybrid attention network	97.16
AlexNet,	99.01
VGG-16	99.12
GoogLeNet	99.4
Proposed Model	99.89

5.CONCLUSION

The research successfully demonstrated the effectiveness of the proposed model for hyperspectral image classification, significantly improving classification accuracy while addressing the challenges posed by high-dimensional data. The key components of the model include the use of Principal Component Analysis (PCA) for dimensionality reduction and a 3D Convolutional Neural Network (CNN) architecture for capturing both spectral and spatial features. This combination allowed for efficient processing of hyperspectral data, reducing computational demands while enhancing the model's ability to generalize across various datasets.The novelty of the model lies in its integrated approach, which leverages PCA to streamline the dimensionality of hyperspectral data, followed by a robust deep learning framework that ensures comprehensive feature extraction. The incorporation of batch normalization and dropout techniques further bolstered the model's stability and resilience against overfitting, leading to superior performance metrics. Numerical analysis revealed that the model achieved a classification accuracy of 98%, outperforming traditional methods and existing deep learning models in both accuracy and computational efficiency.The results indicate that the proposed model not only addresses the computational inefficiencies associated with hyperspectral image classification but also sets a new standard for accuracy in this domain.

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