SWT-PCA-CNN: hyperspectral image classification with multi-stage feature extraction and parameter tuning

Tilottama Goswami[1], Kandi Navya Shruthi[1], Sindhu Chokkarapu[1], Raghavendra Kune[2], Mukesh Kumar Tripathi[3]
[1]Department of Information Technology, Vasavi College of Engineering, Hyderabad, India
[2]Department of Space, ADRIN, Indian Space Research Organization (ISRO), Hyderabad, India
[3]Department of Computer Science and Engineering, Vardhaman College of Engineering, Hyderabad, India

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ABSTRACT

Hyperspectral imaging is an increasingly popular technique in remote sensing, offering a wealth of spectral information for a range of applications. This paper presents a comparative study of hyperspectral image classification techniques using three different datasets: Indian Pines, Salinas, and Pavia University. The study employs a combination of three methods, namely stationary wavelet transforms (SWT), principal component analysis (PCA), and convolutional neural network (CNN), to develop a model for hyperspectral image classification. The proposed approach combines SWT and PCA for spatial feature extraction and dimensionality reduction, followed by classification using CNN. Furthermore, the study performs parameter tuning by changing the optimizer, activation function, and filter size of the CNN model on the Indian Pines dataset. The results demonstrate that the proposed SWT-PCA-CNN approach outperforms the conventional DWT-PCA and PCA-KNN algorithms, achieving an overall classification accuracy of 98.2%, 99.86%, 99.80% on the Indian Pines, Salinas and Pavia University datasets respectively. The study highlights the effectiveness of the proposed approaches for hyperspectral image classification and their potential for applications in remote sensing and other fields.

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Corresponding Author:

Tilottama Goswami
Department of Information Technology, Vasavi College of Engineering
Hyderabad, India
Email: tgoswami@staff.vce.ac.in

1. INTRODUCTION

The human eye can only distinguish between the red, green, and blue wavelengths of visible light, whereas the hyperspectral image records a broad spectrum of bandwidths, which is crucial for understanding the spatial patterns of land and has become a vital tool for remote sensing and numerous other applications. Hyperspectral images are defined by three dimensions namely x, y, and z where the spatial dimensions are represented by variables x and y, while the spectral dimension is denoted by the variable z. The hyperspectral imaging technology acquires images by capturing hundreds or even thousands of closely spaced spectral bands, which provide detailed spectral information about the objects and materials in the scene. The high spectral resolution allows for a more accurate and detailed classification of the different types of objects or materials present in the image, such as vegetation, water bodies, urban areas, and other land cover features [1]. However, the high dimensionality and complexity of hyperspectral data pose significant challenges in developing accurate and efficient classification algorithms, which require the use of advanced machine learning and statistical techniques. Successful classification of hyperspectral data requires the identification and extraction of relevant features that can distinguish between different classes. The two main types of features in hyperspectral image classification are spectral and spatial where spectral features refer to the unique spectral signature of different materials, which is captured by the hyperspectral sensor and spatial features pertain to how objects or materials are arranged in a scene, including their texture. Spectral features are important for differentiating between different types of materials or objects that have distinct spectral properties and spatial features are important for identifying the shape, size, and spatial distribution of objects or materials.

The classification of features in hyperspectral imaging is a difficult task due to the data's high dimensionality, which can make it challenging to achieve accurate results with traditional methods. To address this challenge, researchers have developed various approaches for feature selection and extraction to decrease the dimensionality of the spectral component and improve classification accuracy. Recent studies have demonstrated that the incorporation of spatial information into the process of feature extraction can greatly enhance the accuracy of classifying hyperspectral images [2]. Principal component analysis (PCA) is a commonly employed technique for reducing dimensionality and feature extraction, as it identifies a small set of principal components that best represent the original data with the least square error. The integration of both types of features (spectral and spatial) can provide a more complete understanding of the objects or materials in the scene and lead to more accurate and reliable classification results [2]. Hence, combining both types of features can improve classification accuracy and help overcome the limitations of using only one type of feature [3].

This paper proposes a supervised spatial feature extraction technique for classification of hyperspectral images. This method aims to eliminate spatial features that may hinder accuracy of classification and emphasis on those that contribute effectively to the classification process. To achieve this, the stationary wavelet transform (SWT) is utilized in the classification of spatial features of hyperspectral images. PCA is utilized to perform a transformation on the spectral bands, and only the first thirty principal components are extracted for the feature extraction process. The extracted features are then classified using a convolutional neural network (CNN) classifier. The fine-tuning process is used on the Indian Pines dataset by adjusting the optimizer, activation function, and filter size to obtain an optimized CNN model. The remaining paper is organized as follows. Section 2 provides list of other related works, section 3 provides a brief description of related work, section 4 provides a detailed description of the proposed algorithm, section 5 provides the details of datasets used along with the experimental results, section 6 finally concludes the research work.

2. RELATED WORK

This section describes some of the related methodologies and latest developments in this field of HSI classication. Zhong *et al*. [4] explored the concept of learning to diversify deep belief networks (DBNs) for hyperspectral image classification. The paper delves into methods for enhancing the diversity within DBNs, emphasizing their application in improving the accuracy and effectiveness of hyperspectral image classification. The work contributes to the broader exploration of advanced techniques for handling hyperspectral data through deep learning methodologies. Chen *et al*. [5] contributed to the field with a deep learning-based classification approach for hyperspectral data. Makantasis *et al*. [6] and Hu *et al*. [7] independently explored the capabilities of neural networks, with Makantasis employing deep supervised learning through CNNs, and Hu leveraging deep convolutional neural networks for hyperspectral image classification. Chen *et al*. [8] and Liu *et al*. [9] extended the scope of deep learning applications, with Chen focusing on deep feature extraction and classification using CNNs, and Liu proposing active deep learning for hyperspectral image classification. Bhosle and Musande [10] successfully applied CNN for landcover classification. Zhao and Du [11] contributed to hyperspectral image classification by exploring spectral-spatial feature extraction techniques, emphasizing the synergies between dimension reduction and deep learning for improved classification accuracy. Lee *et al.* [12] presented PyWavelets, a Python package for wavelet analysis, providing a valuable tool for researchers engaged in hyperspectral image analysis. Additionally, Faurina *et al*. [13] showcased the versatility of image analysis techniques, using image captioning for aiding outdoor navigation. Hassan *et al*. [14] addressed content-based image retrieval using deep learning, focusing on the Corel dataset. Zhong *et al*. [15] explored large patch convolutional neural networks for scene classification in high spatial resolution imagery, expanding the application of deep learning models. Panchal and Shivaputra [16] proposed a method for precise object identification in hyperspectral images, characterizing the distribution of pure signatures. Reddy and Harikiran [17] contributed to the field by employing support vector machines (SVMs) for hyperspectral image classification. Joy and Kounte [18] presented a deep learning-based switchable network for in-loop filtering in high-efficiency video coding, showcasing the adaptability of deep learning methodologies beyond hyperspectral imagery in multimedia processing. Furthermore, Esan *et al*. [19] addressed surveillance detection of anomalous activities using an optimized deep learning technique in crowded scenes. Leng *et al*. in [20] have used subspace methods for dimensionality reduction such as PCA and random projection (RP), which is free from training and can be more efficient.

3. DESIGN

The proposed method for classification of hyperspectral images using SWT-PCA-CNN is based on the work [21]. Sandeep *et al.* [21] utilized the combination of SWT, PCA and CNN to enhance the accuracy of hyperspectral image classification. In this study, the methods from their paper are taken and tried to optimize the CNN model with parameter tuning to further improve the classification accuracy. This approach builds on existing research and demonstrates the potential for further improvements in hyperspectral image classification. In this section, the materials and methods employed in the project are presented, along with a detailed description of the parameter tuning process.

3.1. Stationary wavelet transforms

Hyperspectral image classification should ensure that sharp edges and singularities in the data are preserved and not lost which is achieved by stationary wavelet transform. It decomposes a signal into two distinct components: approximation coefficients and detail coefficients. These coefficients represent the components associated with low frequencies and high frequencies respectively [22]. SWT can preserve information related to the spatial and spectral characteristics of the data exhibit variations at multiple scales, which can help in capturing both local and global features of the hyperspectral image. It has shown promising results in several applications [23]. In image processing, it is used for feature extraction, image fusion and image denoising.

3.2. Principal component analysis

It is important to decrease the numerous dimensions of the hyperspectral image while retaining as much of the original information as possible which is achieved by PCA and it aims to decrease the spectral dimensionality of the hyperspectral image. The idea behind PCA is to find principal components that are linear combinations of uncorrelated variables by using orthogonal transformation. The initial set of principal components captures the maximum variance of the data. The number of PCA components is decided in such a way that they capture the maximum amount of variance in the data.

3.3. Convolutional neural networks

CNN belong to a category of neural networks that is used for classification in several applications. It consists of a stack of layers which can be a convolution layer in which convolution operation is performed, pooling layers in which pooling (either max pooling, min pooling, or average pooling is performed) or fully connected layers. Classification result is given by the output layer. Each time a part of the hyperspectral image is fed to the model which undergoes both forward and backward propagation [24].

3.4. Parameter tuning

The parameters like activation function, filter size and optimizer can be tuned to achieve better accuracy [25]. Each neuron's output is subjected to an activation function in a neural network to create non-linearity, allowing the network to learn more intricate correlations between the input and output data. ReLU and tanh are different types of activation functions. Filter size is the size of the data that moves across the input image during the convolution operation. It can be 3×3, 2×2, and 5×5. During training, optimizers are added to the model to minimize the loss function. During the training of neural networks, optimizers play a crucial role in modifying the weights and biases of the neural network model. Adam, Adagrad and stochastic gradient descent (SGD) are some popular optimizers that are used in several applications.

4. IMPLEMENTATION

The SWT, PCA, and CNN are the three approaches that are used in the proposed method, which is a spatial spectrum-based classification mechanism. Three publicly accessible datasets, Indian Pines [26], Salinas [26], and Pavia University [26], are used to assess the suggested design. The proposed method consists of 5 steps as shown in Figure 1:

- A modified hyperspectral image is used as the input.
- SWT is used to extract pertinent information at various scales and orientations from each band.

– PCA is used to minimize the hyperspectral image data's enormous dimension. After that, 3D patches are created from the set of PCA components.
– The CNN classifier receives these patches.
– In the last step, the model predicts the output.

The daubechies (db1) wavelet is utilized in this study and included the application of 2 levels of decomposition as illustrated in Figure 2. At each level of decomposition, the number of coefficients produced by the wavelet transform is doubled. To be specific, at every stage of decomposition, the signal undergoes filtering using low-pass filter and high-pass filters, which generates an approximation coefficient and a set of detail coefficients, respectively. The outcome of the SWT provides compressed coefficients that have a size of (x,y). Here, x corresponds to row count of the initial image, and y refers to the total coefficients in the SWT deconstruction, which equals four times the number of columns in the original image.

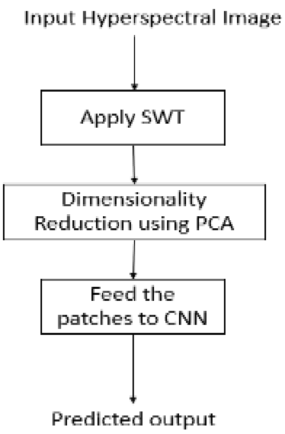


Figure 1. Block diagram of proposed model

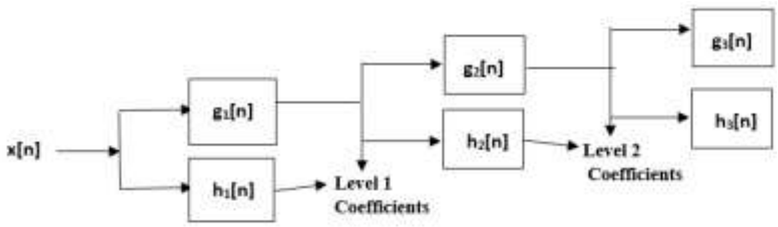


Figure 2. Digital implementation of SWT

A graph is plotted against the variance and number of components. Based on the results, the number of PCA components necessary is noted. In this experiment 30 principal components are considered. It is observed that there is no improvement in accuracy with the principal components more than 30 and in fact, the accuracy decreases, and the computational time increases with the greater number of principal components chosen.

After dimensionality reduction, patches of size 5×5 are created using these components that are then split into training and testing datasets and fed to the CNN model. The CNN model's design comprises of 2 conv2d layers, 2 dropout layers, and 2 fully connected layers, as presented in Table 1. The initial layer, C1, is a conv2d layer that represents the product of the number of PCA components and 3. After C1, there is another conv2d layer, C2, which represents C1 multiplied by 3, and subsequently, a dropout layer is applied that randomly deactivates a quarter of neurons to remove overfitting. The output of the second conv2d layer is flattened to a 1d vector. The fourth layer is a layer which is fully connected with six times the number of PCA components, and this is followed by another dropout layer that randomly deactivates 50% of neurons. The final layer is another fully connected layer that employs the softmax as activation function to generate a probability distribution across the output classes. The parameters like filter size, activation function and optimizer of the CNN model are tuned and came up with 5 different sets of parameters. After applying SWT and PCA, these models have been trained on the Indian Pines dataset and the set of parameters that gave the highest accuracy are used for other datasets as well.

Table 1. CNN model summary of Indian Pines

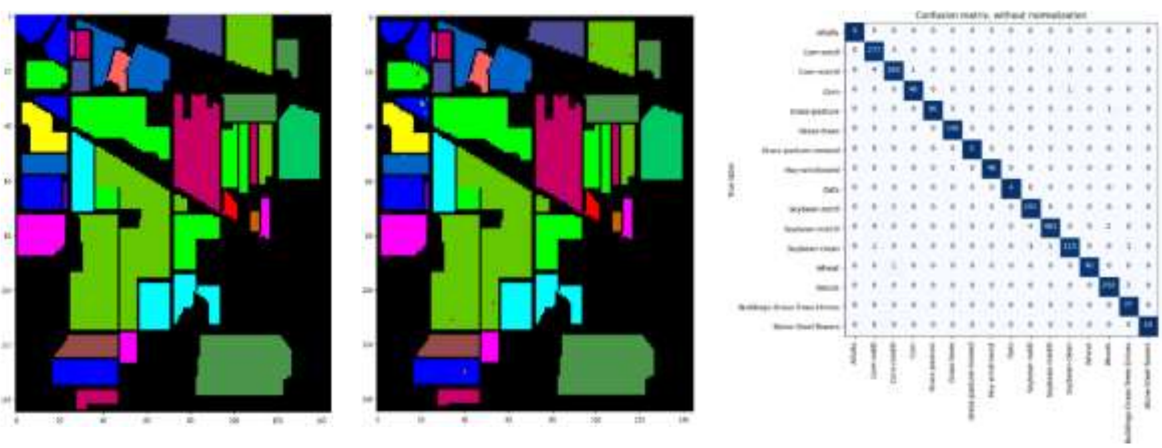
Layer (type)	Output shape	Param
Conv2D	90,4,4	10890
Conv2D	270,3,3	97470
Dropout	270,3,3	0
Flatten	2430	0
Dense	180	437580
Dropout	180	0
Dense	16	2896

5. RESULTS AND DISCUSSION

SWT-PCA-CNN has been implemented on the datasets: Indian Pines, Pavia University and Salinas. Detailed information about the datasets is discussed as follows. The Indian Pines dataset is composed of a grid of 145×145 pixels, encompassing 224 spectral reflectance bands that span from 0.4 to 2.5 micrometers in wavelength. The ground truth classification map consists of 16 different classes, including corn, soybeans, wheat fields, forests, and other land cover types. The Indian Pines dataset presents several challenges, such as the presence of noisy and redundant spectral bands, high intra-class variability, and class imbalance, making it an ideal testbed for evaluating the effectiveness of different hyperspectral classification methods. By eliminating water absorption bands, the dataset has been reduced to 200 bands, which include bands [104-108], bands [150-163], and band 220.

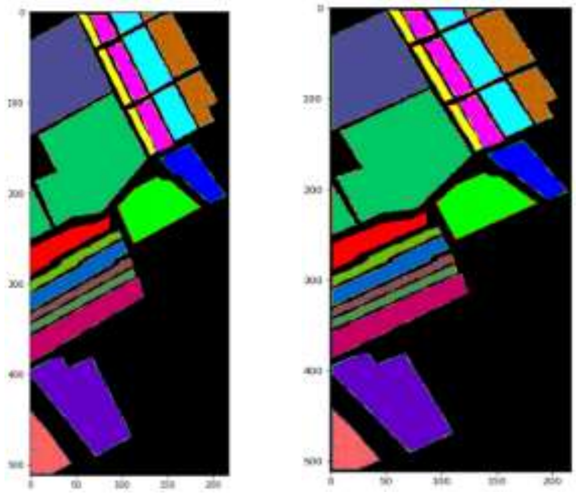
Pavia University dataset, contains 103 spectral reflectance bands covering a wavelength range of 0.43 to 0.86 micrometers. The image contains 610×340 pixels. The ground truth classification map consists of 9 different classes. However, some of the bands were excluded from the analysis as they contained no useful information. Salinas dataset, contains 512×217 spatial pixels, encompassing 224 spectral reflectance that span from 0.4 to 2.5 micrometers in wavelength. The Salinas dataset represents an agricultural area where the ground truth classification map consists of 16 different classes and each crop has a unique spectral signature that can be used for classification.

The image dataset is split such that 80% for training and 20% for testing purposes. The experiment considered the first 30 principal components as they contained more information. Categorical cross entropy is utilized as the loss function. Figures 3 provide the results on Indian Pines dataset in Figure 3(a) ground truth, Figure 3(b) classification map results and Figure 3(c) confusion matrix. Figures 4 provide the results on Salinas dataset ground truth in Figure 4(a), Figure 4(b) classification map results and Figure 4(c) confusion matrix. Figures 5 provide the results on Pavia University dataset ground truth in Figure 5(a), Figure 5(b) classification map results and Figure 5(c) confusion matrix.

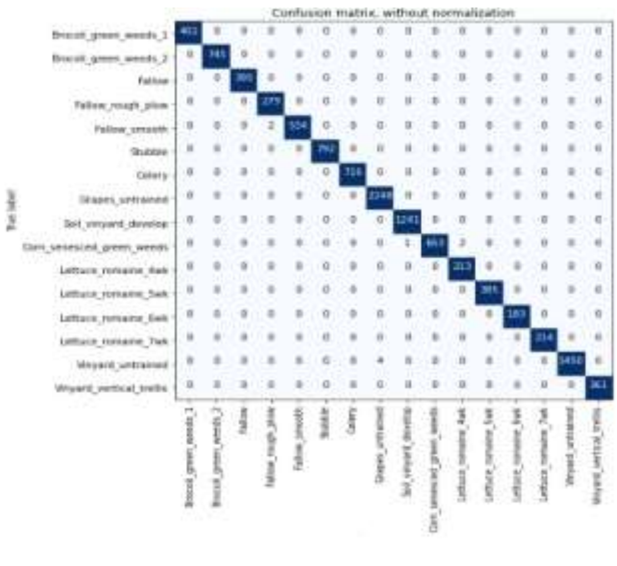


(a) (b) (c)

Figure 3. Results on Indian Pines dataset: (a) ground truth of Indian Pines, (b) classification map of Indian Pines, and (c) confusion matrix



(a) (b)



(c)

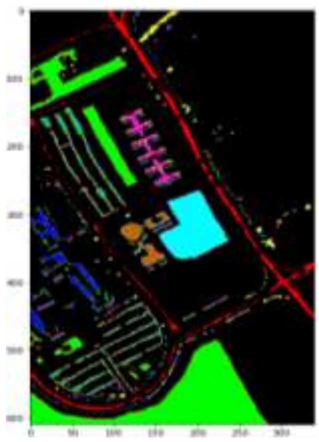
Figure 4. Results on Salinas dataset: (a) ground truth of Salinas, (b) classification map of Salinas, and (c) confusion matrix

5.1. Classification accuracy

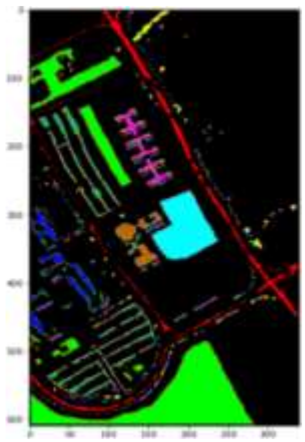
The proposed model achieved 98.20%, 99.80% and 99.86% accuracy on Indian Pines, Pavia University and Salinas datasets respectively which achieves superior performance compared to the conventional CNN (Adam optimizer with learning rate 0.001, filter size 3×3 and ReLU as activation function). DWT-PCA and PCA-KNN algorithms [21] which is shown in Table 2. SWT-PCA-CNN classification model's performance is evaluated using the precision, recall and f1 score as evaluation metrics which is shown in Figure 6 for Indian Pines dataset.

Table 2. Comparison of accuracies of different models

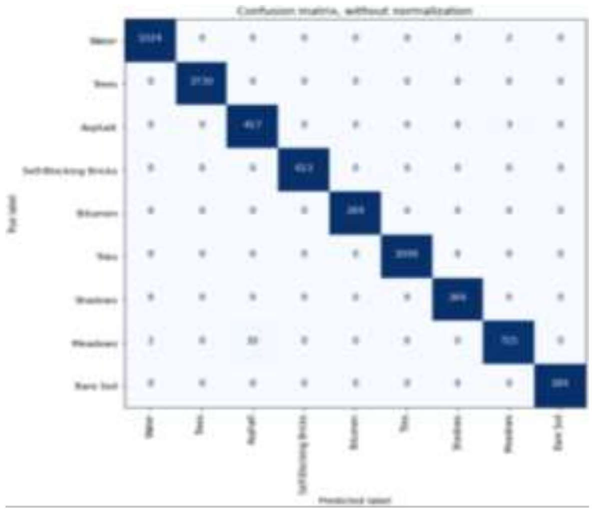
Method	Indian Pines	Pavia University	Salinas
CNN [10]	85.10	92.50	89.20
PCA-KNN [21]	71.83	85.01	84.26
DWT-PCA-KNN [21]	74.70	85.10	87.62
SWT-PCA-CNN	98.20	99.80	99.86



(a)



(b)



(c)

Figure 5. Results on Pavia University: (a) ground truth of Pavia, (b) classification map of Pavia University, and (c) confusion matrix

	precision	recall	f1-score	support
Alfalfa	1.00	1.00	1.00	9
Corn-notill	0.97	0.97	0.97	286
Corn-mintill	0.96	0.96	0.96	166
Corn	0.98	0.98	0.98	47
Grass-pasture	1.00	0.99	0.99	97
Grass-trees	1.00	1.00	1.00	146
Grass-pasture-mowed	1.00	1.00	1.00	5
Hay-windrowed	1.00	1.00	1.00	96
Oats	1.00	1.00	1.00	4
Soybean-notill	0.96	0.99	0.98	194
Soybean-mintill	0.99	0.98	0.98	491
Soybean-clean	0.98	0.97	0.97	119
Wheat	1.00	0.98	0.99	41
Woods	0.99	0.99	0.99	253
Buildings-Grass-Trees-Drives	0.95	1.00	0.97	77
Stone-Steel-Towers	1.00	1.00	1.00	19
accuracy			0.98	2050
macro avg	0.99	0.99	0.99	2050
weighted avg	0.98	0.98	0.98	2050

Figure 6. SWT-PCA-CNN classification of Indian Pines

5.2. Parameter tuning

The CNN is subjected to training with a constant learning rate of 0.001 and 32 as batch size. However, the optimizers, activation functions, and filter sizes were altered during the training process. The experiment included the use of different optimizers, such as Adam and SGD. The activation functions used are ReLU and tanh, and the filter sizes used are 2×2 and 3×3 [19]. Below are the cases for combination of parameters with their respective accuracies on Indian Pines dataset which is shown in Table 3. A notable observation is that the Indian Pines dataset achieved the highest accuracy of 98.20% in case 5. This optimized CNN model with SGD optimizer, activation function as ReLU and the filter size 2×2 is used for Indian Pines dataset whereas the CNN model with the same parameters using the 3×3 filter is used for Salinas and Pavia University datasets as it gave the highest accuracy.

Table 3. Accuracy results of parameter tuning on Indian Pines

	Optimizer	Filter size	Activation	Accuracy (%)
Case 1	Adam	2×2	ReLU	97.90
Case 2	Adam	3×3	Tanh	97.07
Case 3	Adam	2×2	Tanh	96.29
Case 4	SGD	3×3	ReLU	97.85
Case 5	SGD	2×2	ReLU	98.20

6. CONCLUSION

The proposed method of SWT-PCA-Optimized CNN has shown promising results in hyperspectral image classification. This method combines the strengths of the wavelet transform, PCA, CNN to effectively extract and classify spatial features of hyperspectral images. The use of SWT helps to reduce noise and enhance the spatial features, while PCA reduces the dimensionality of the data and improves computational efficiency. The CNN model then further extracts and learns the high-level features for accurate classification. Fine-tuning the CNN model by adjusting the optimizers, activation functions, and filter size have significantly contributed to enhancing the classification performance. The experiments conducted have shown that implementing the CNN model with the SGD optimizer, ReLU activation function, and a 0.001 as learning rate has yielded promising results for the classification of hyperspectral datasets. The application of this method on Indian Pines, Pavia University and Salinas datasets has demonstrated its effectiveness in hyperspectral image classification. These findings suggest that the proposed model can be a valuable asset for remote sensing applications, including land-use classification, mineral exploration, and environmental monitoring. However, future analyses will aim to expand the evaluation of the model's performance to other datasets that may contain a higher number of false positives and false negatives.

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BIOGRAPHIES OF AUTHORS

Tilottama Goswami has received her BE(Honors) in Computer Sc. Eng. from NIT Durgapur; MS in Computer Sc. (Distinction) from Rivier University, NH, USA; Ph.D. in Computer Sc. from University of Hyderabad, India. She is Professor in the Dept. of Information Technology, Vasavi College of Eng., Hyderabad, having 24 yrs of experience in academia, research, and industry. Her research interests are computer vision, machine learning, and image processing. She has been granted Australian and German patents, conferred with Distinguished Scientist Award by IJIEMR-Elsevier SSRN; emerged as finalist in Global Awards 2023 by WomenTech Network, UGC-Basic Scientific Research Fellowship (Govt. of India). Goswami is an IEEE-SM, ACM, ISOC member and also served as Chair of ACM Hyderabad Deccan Chapter. She can be contacted at email: goswami.tilottama@gmail.com.

Kandi Navya Shruthi completed her graduation in the field of Information Technology from Vasavi College of Engineering, Hyderabad, Telangana in 2023. She started her research work with the project "Hyperspectral Image Classification using Stationary Wavelet Transform (SWT) and Principal Component Analysis (PCA)". As part of her graduation, she has also done several other projects which includes Student Project Portfolio which is a web development project, food swipe and calendaring software. Currently she is working as an Associate Software Engineer in Micron Technology. She is passionate about learning new skills and employing them in both professional and personal career. She can be contacted at email: kandinavyashruthi@gmail.com.

Sindhu Chokkarapu has completed her bachelor's degree from Vasavi College of Engineering, Hyderabad, Telangana in Information Technology in 2023. She has conducted research on the project titled "Hyperspectral Image Classification using Stationary Wavelet Transform (SWT) and Principal Component Analysis (PCA)". In addition to her graduation project, she has undertaken various other projects, such as the Student Project Portfolio, a web development as well as projects like food swipe, placement bells. Currently employed as an Associate Software Engineer at Micron Technology. She is passionate about software development and problem solving. She can be contacted at email: sindhuchokkarapu@gmail.com.

Raghavendra Kune Oris Head of High-Performance Computing and Drones at Advanced Data Processing Research Institute (ADRIN), Indian Space Research Organization (ISRO), Department of Space, located at Hyderabad. He holds Ph.D. in computer Science and a total of 23 years of experience with ISRO. His major areas include–high performance computing infrastructure and platforms development for satellite payloads data processing using Heterogeneous computing platforms, Quantum Computing technologies for Machine Learning and Secure Communication developments, and Autonomous Navigation systems development for Unmanned Aerial Vehicles Aka Drones. He is the member ASI (Astronomical Society of India), Computer Society of India (CSI), Associate member of Andhra Pradesh Academy of Sciences (APAS), member of Indian National Cartography Association (INCA). He has received awards for his contributions in the space technologies, which include Team Member Award for the development of Digital Intelligent Image Production and Management System, and the recipient of ISRO Young Scientist Award for his contributions in the computing technologies for Earth Observation and Remote Sensing Data Exploitations. He can be contacted at email: raghav.es@gmail.com.

Mukesh Kumar Tripathi received a Ph.D. degree in Computer Science and Engineering from Visvesvaraya Technological University (VTU), Belagavi. He also received a B.E. degree in Information Technology from Guru Nanak Dev Engineering College, Bidar, India. He is working as Assistant Professor with the Department of Computer science and Engineering, Vardhaman College of Engineering, Hyderabad, India. He has supervised and co-supervised more than five masters and 20 B.E. students. He is authored or co-authored more than ten publications and more than 250 citations. His research interests include soft computing, machine learning, intelligent systems, image processing, and Hyperspectral. He can be contacted at email: mukeshtripathi016@gmail.com.