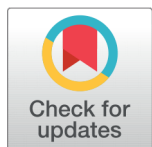


ORIGINAL ARTICLE



Land Cover Classification using Hyperspectral Imagery: A Deep Learning Approach

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Abstract

Objectives: This research aimed to perform proper land cover classification of the Krishnagiri and Dharmapuri districts using hyperspectral imagery. This research also attempted to determine the usefulness of deep learning models in detecting large land cover classes, such as quarry, barren, forest, built-up, and agricultural land, using hyperspectral data. **Method:** The analysis of the land cover patterns in the study area used hyperspectral images (HSI) taken between 2015 and 2022, which had 230 spectral bands. A total of 3000 hyperspectral images were processed, 2000 of which were utilized for training and 1000 for testing. The images were then preprocessed, segmented into superpixels using superpixel segmentation, and classified. Three deep learning models, a Convolutional Neural Network (CNN), Residual Neural Network 18 (ResNet-18), and Visual Geometry Group-16 (VGG-16), were used as classification models. Standard measures of accuracy, precision, recall, and F-score were used to evaluate the performance and effectiveness of the models. **Findings:** The results indicate that ResNet-18 outperformed the other models in determining land cover classes using hyperspectral images. The model has shown high classification levels among various types of land, with built-up land having an accuracy level of approximately 95.09, indicating a better ability to extract and classify features than CNN and VGG-16. **Novelty:** The novelty of this study lies in the combination of hyperspectral image processing with deep learning frameworks to classify regions based on land cover. The relative analysis of CNN, ResNet-18, and VGG-16 demonstrated the usefulness of residual learning networks in enhancing the classification accuracy in hyperspectral remote sensing scenarios.

Keywords: Hyperspectral Image (HSI); Land Cover Classification; Deep Learning; Convolutional Neural Network (CNN); ResNet-18; VGG-16; Remote Sensing; Spectral-Spatial Analysis

1 Introduction

Land cover classification plays a vital role in sustainable resource management, environmental monitoring, and planning. Satellite-based Earth Observation systems have revolutionized large-scale geographical analysis of the Earth, especially in the field of remote sensing^{(1), (2)}. Of these technologies, hyperspectral imaging appears to be a game-changing technology that records spectral information within hundreds of contiguous bands of wavelengths, allowing unprecedented discrimination between land cover types^{(3), (4), (5)}. Multispectral imagery differs from hyperspectral imagery in that hyperspectral imagery has rich spectral signatures that help identify subtle surface features, which is useful for various applications, including vegetation monitoring, mineral exploration, and urban mapping. In recent years, hyperspectral image classification has undergone tremendous changes owing to the development of deep learning technologies. While machine learning methods such as Support Vector Machines, Random Forests, and k-nearest neighbors have proven successful in remote sensing, these methods are based on handcrafted features and are unable to capture the complex spatial-spectral relationships present in high-dimensional hyperspectral data⁽⁶⁾. In contrast, deeper architectures have transformed this scene by allowing automatic hierarchical feature extraction from raw data without any manual feature engineering^{(7), (8)}. CNNs have been a great success in image classification that has been able to capture both spatial and spectral features and novel architectures like Residual Networks (ResNet) and VGG networks that have pushed classification performance to new heights by using deeper network designs and skip connections that reduce the gradient vanishing issues^{(9), (10)}. Recent studies have shown that hybrid architectures that integrate several deep learning paradigms can significantly enhance hyperspectral classification. CNN–transformer fusion networks have been developed as cutting-edge methods that combine the advantages of CNN’s ability to capture local features with those of the CNN’s global contextual modeling ability, resulting in better multi-scale spectral-spatial feature representation. Classification accuracy has also been improved with the inclusion of attention-based mechanisms, such as channel-spatial attention and coordinate attention modules, which selectively emphasize spectral bands and spatial areas, respectively, discriminative to the target object. Newly developed ensemble and neural architecture search methods have enabled the automatic optimization of network architectures for individual hyperspectral datasets. Furthermore, some approaches have been developed to tackle the small-sample problem and enable deep learning to be applied to scenarios where there is a limited amount of label data, a situation that is typical in practical remote sensing applications, such as data augmentation, semi-supervised learning, self-supervised pre-training, and transfer learning.

1.1 Research Gaps and Motivation

Although these advances have been made, there are still areas of the literature that are lacking. First, most recent studies have focused on architectures comprising CNNs or hybrid CNN-transformers, while comparatively few extensive studies have been conducted on classical deep learning models (CNN, ResNet, VGG) for hyperspectral data from specific geographical regions. Second, there is a lack of a systematic comparative analysis of residual learning and conventional convolution-based methods on regional hyperspectral images, particularly in the context of rapid urbanization for land cover classification. Third, the use of multiple deep learning architectures in regional-scale analysis with Indian hyperspectral remote sensing data is still under-explored because most studies have been conducted on benchmark datasets (Indian Pines, Salinas, and Pavia University) rather than region-specific data. Fourth, detailed performance metrics and ablation studies are needed to show the relative effectiveness of feature extraction strategies across a wide variety of land cover categories found in developing regions with rapidly changing land use.

Table 1. Comparison with Existing Literature

Study	Dataset	Method	Limitation	Present Study Contribution
⁽³⁾	Land use imagery	CNN models	Limited hyperspectral focus	230-band hyperspectral classification
⁽⁵⁾	HS-LiDAR review	Review study	No experimental framework	Experimental comparative implementation
⁽⁶⁾	Benchmark HSI datasets	Deep CNN	General overview only	Regional real-time hyperspectral evaluation
⁽¹¹⁾	Multispectral datasets	ResNet-18	Limited regional analysis	Regional hyperspectral land cover comparison
Present Study	Krishnagiri & Dharmapuri HSI	CNN, ResNet-18, VGG-16	—	Comparative regional hyperspectral framework

Table 1 presents a comparative analysis of recent hyperspectral land-cover classification studies with respect to datasets, deep learning methods, limitations, and research contributions. This comparison highlights existing research gaps and demonstrates the novelty and significance of the proposed regional hyperspectral classification framework.

1.2 Research Objectives and Contribution

The novelty of this work lies in the use of a single comparative deep learning framework for hyperspectral land cover classification with the same preprocessing, segmentation, optimization, and validation conditions. In contrast to most previous studies that have studied a single-model implementation or a complex hybrid transformer architecture, the present work systematically evaluates the performance of CNN, ResNet-18, and VGG-16 for feature extraction from 230-band hyperspectral imagery within a uniform experimental setup. Moreover, the combination of superpixel segmentation and residual learning-based classification enhances the efficiency of feature representation in complex mixed land cover environments. Thus, the proposed framework presents a baseline classification in a hyperspectral approach, which is computational and theoretically sound in the context of studying the region and can be confirmed by experiments.

2 Methodology

The proposed methodology for land cover classification using hyperspectral imagery consists of dataset acquisition, preprocessing, segmentation, deep learning-based classification, internal validation and performance evaluation. The overall workflow of the proposed framework is shown in Figure 1. Initially, hyperspectral and multispectral images of the Krishnagiri and Dharmapuri districts were collected from publicly available remote sensing repositories, including the United States Geological Survey (USGS) Earth Explorer and AVIRIS hyperspectral data portals. In this study, hyperspectral images of the Krishnagiri and Dharmapuri districts were gathered, preprocessed, and segmented using a superpixel segmentation method⁽¹²⁾. The segmented images were then classified using CNN, ResNet-18, and VGG-16. The operational, mathematical modeling, and performance measurements of these models were also investigated.

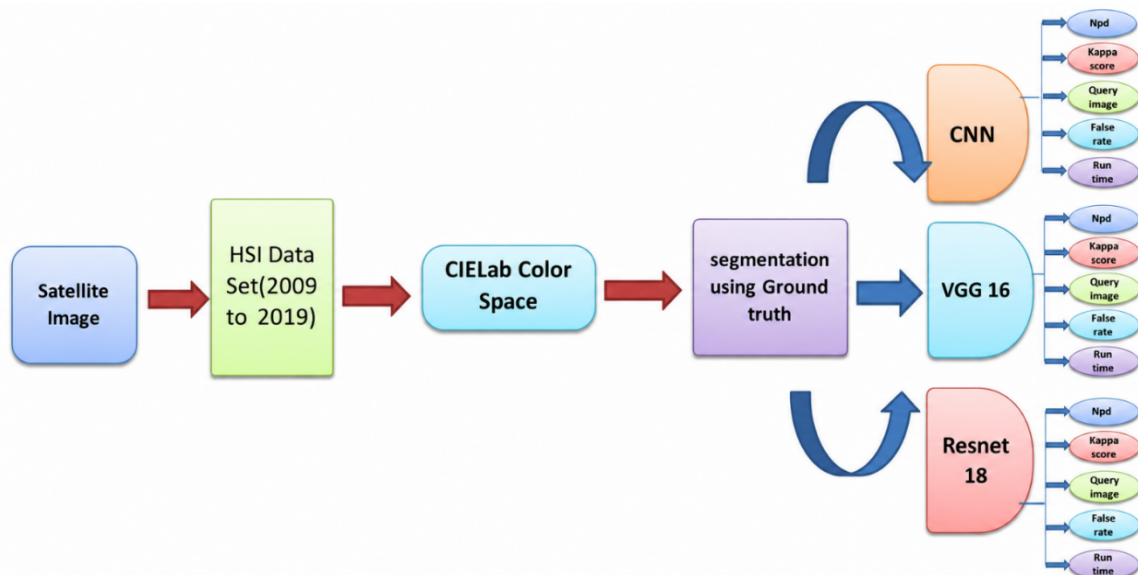


Fig 1. Block Diagram of Hyperspectral Image (HSI) Classification using Deep Learning Models.

2.1 Hyperspectral Dataset

Spectral imaging techniques record a continuous spectrum for each pixel of an image across a given range of wavelengths. Spectral images contain more information than traditional monochromatic or RGB images do. Spectral imaging technology has entered a new research horizon with a wide spectrum of spectral information that can be found in a hyperspectral image

in the analysis of pixel content at the microscopic scale. This colossal expansion in the image processing study division will bring revolutionary advances in all domains of human existence in the future. Spectral images can be classified as multispectral (less than 20 wavelength bands) and hyperspectral (more than 20 wavelength bands). An annual time series of LandsatAT 7 and LandsatAT 8, as well as an AVIRIS satellite, was used to produce Hyperspectral and Multispectral images. This study used images from 2015 to 2022 obtained from USGS. The AVIRIS platform was used to gather hyperspectral images, whereas Landsat 7 and Landsat 8 were used to gather multispectral images. Both hyperspectral and multispectral images were used to classify land cover in this study. Table 2 lists the details of the hyperspectral images used in this research.

Table 2. HSI Dataset Details

S. No.	Parameter Description	Description
1	Satellite Image	Multispectral Image
2	No. of Bands	230
3	Image use Period	2015-2022
4	Total no. of Images	3000
5	Total no. of images for Training and Testing	2000 and 1000
6	Source of an Image link	https://earthexplorer.usgs.gov/ .
7	Distance Coverage	25 Km
8	Place of study	Krishnagiri and Dharmapuri
9	Longitude and Latitude	11 ⁰ 12'N to 12 ⁰ 49'N and, 77 ⁰ 27'E to 78 ⁰ 38'E
10	Target Class	5

2.1.1. Hyperspectral Image

In remote sensing, hyperspectral sensors are generally used to observe the Earth's surface with high-resolution data. In this study, to manipulate the input hyperspectral image, the qualities read from the information document were masterminded into a three-dimensional (3-D) 512×512 and 230 bands considered hypercube in our simulation software tool, Matlab 2019a. The input area covered by the Krishnagiri and Dharmapuri districts had wavelengths ranging from 450–550 nm. These were classified into five classes: quarry, bare land, forest, built-up land, and agricultural land. A total of 3000 samples were processed in the TIF format, and the samples were processed to predict the land cover (LC) classification in the study area.

3 Classification Methods

This study is based on three different classification methods: CNN, ResNet 18, and VGG 16^{(13), (14), (15), (16)}. In all the classification methods, two different datasets, HSI and MSI, were trained, tested, and classified into five classes. However, the following attributes were the same for all the experiments: the hardware configuration of the system was 8 GB of RAM with an Intel(R) Core (TM) i7-5600 AMD X86-64 Processor.

3.1 Convolutional Neural Network (CNN)

A convolutional neural network (CNN) is a powerful tool used in geospatial databases such as remote sensing data. CNNs improve the classification accuracy by learning important features from the training data⁽¹⁷⁾. A CNN has three main parts: a convolutional layer, a nonlinear mapping layer, and a pooling layer. These parts are connected using fully connected layers. CNNs are composed of perceptrons, similar to neurons in the human brain. Each perceptron operates based on the synaptic weights and biases. The output is a nonlinear function of the weights and inputs. perceptron passes its output to the next layer to obtain the desired result. They learn continuously using an incremental-learning approach. The hidden layers in CNNs use convolution and pooling by adjusting the learning weights. Each perceptron is fully connected to the perceptions of the subsequent layer. CNNs operate on small images, such as 28 × 28 RGB images⁽¹⁸⁾. For larger images, such as 256 × 256, the layers become more complex, requiring more computations and causing overfitting. A multilayer perceptron uses three perceptions from the previous layer, called activation units⁽¹⁹⁾. It processes input images by focusing on the feature areas. It uses spatiotemporal data by linking them to receptive fields. The perceptions share the same weights. The roles of each CNN layer are as follows: Input layer: The first layer holds the input images as raw pixel values with a size of 212 × 212 × 3, where three is the number of bands. Convolutional layer: This layer calculates the perceptron using linked activation units. It deals with local spatial data in terms of perceptions. It includes the following: a) desired output count, b) kernel size controlling the

spatial area, c) stride for sliding windows, and d) padding for sizing hidden layers. This is the basic CNN block that performs the convolution operations. The model consists of three blocks. The convolution operation uses a kernel/filter in this layer with kernel sizes of 16, 32, and 64 for blocks 1, 2, and 3. The filter was adjusted vertically and horizontally based on the stride rate until the entire image was scanned.

3.2 ResNet 18 Architecture

The major problem of the vanishing gradient is solved by ResNet-18. This problem occurs when the gradient is calculated in the presence of the loss function, which easily approaches zero after many chain rule applications in deep networks⁽¹¹⁾. Therefore, no learning was performed because the weights never updated their values. In the ResNet-18 architecture, the gradients flow straight through the skip connections rearward to the initial filters from the following layers⁽²⁰⁾. In ResNet-18, the first 16 layers of each block extract the general features of the images based on the relevant model. The last two layers of the four blocks, layers 17 and 18, were classified into the required class for land cover classification. Therefore, the first 16 layers of the four blocks were frozen to achieve better accuracy.

3.3 Visual Geometry Group (VGG 16)

VGG 16 is a well-known deep-learning model. It uses images with a size of 224×224 pixels and three color channels: red, green, and blue. Before processing, the color values of each pixel were adjusted by subtracting the average value⁽²¹⁾. The first two layers are referred to as the convolutional layers. They used small 3×3 filters. The image passes through these layers and then through the ReLU activations. There were 64 filters in these layers. The image size remained the same because of the padding and stride settings. A max-pooling layer with a 2×2 window reduces the output size by half. Therefore, the output size after the first layer was $112 \times 112 \times 64$. Subsequently, the output passed through another set of layers with 128 filters. The size was $56 \times 56 \times 128$. This process continues with a third set of layers, which includes a max pooling layer and three convolutional layers. This set had 256 filters, and the output size was $28 \times 28 \times 256$. Subsequently, the output is passed through two sets of three layers, each with 512 filters⁽²²⁾. The final output size was $7 \times 7 \times 512$. Three fully connected layers were added after these layers. Flattening layers were present between them. The first two layers each had 4,096 neurons. The last layer has 1,000 neurons, which correspond to the 1,000 classes in the ImageNet dataset. The last layer used a softmax activation for classification. Furthermore, although the VGG Net model has 138 million parameters and can be attained through transfer learning, it is challenging to operate it. The fine-tuning methodology was used in the VGG-16 model. General image features were obtained using the initial layers of the network according to the pretrained model. The fifth block (layers 13 and 14) was used as the last layer in the classification of land cover classes. To enhance the classification accuracy and simplify the tasks involved in the computations, the initial layers of the first four blocks were frozen during training, and only the last layers were fine-tuned for the land cover classification task.

4 Results and Discussion

4.1 Performance Analysis of Hyperspectral Images using CNN

The proposed CNN determines the primary head component of the source hyperspectral images of input images. Subsequently, an underlying arrangement map was generated by executing the CNN on the hyperspectral images with a 3D size of $212 \times 212 \times 230$ and the primary head segment. According to the CNN grouping map, M nodes are fed into the CNN. Here, M defines the quantity of classes. To capture the spatial data of the characterized information tests, the input image was obscured by the ground truth comparison of Indian pines and Salinas and Pavia University. These are managed in the last cycle, which assists in generating new 3D images. The confusion matrix of the LC classification using CNN for HSI is presented in Table 3.

Table 3. Confusion Matrix of CNN using HSI

Classes	No. of Predicted Classes				
	Quarry land	Barren Land	Forest land	Build up Land	Agriculture Land
Quarry Land	189	2	3	2	4
Barren Land	3	190	2	3	2
Forest Land	4	3	188	2	3
Build up Land	3	2	1	191	3
Agriculture Land	4	1	2	1	192

The results of the classification by the CNN model, as indicated in the confusion matrix in Table 3, showed that among the 200 quarry-land images, 189 images were correctly classified; the remaining images were misclassified as barren land (2), forest land (3), built-up land (2), and agricultural land (4). In the barren land group, 190 of the 200 images were classified correctly; the other images were incorrectly identified as quarry land (3), forest land (2), built-up land (3), and agricultural land (2). In forest land, the number of correctly classified images was 188, and the number of misclassified images was 132, including quarry land (4), barren land (3), built-up land (2), and agricultural land (3). For built-up land, 191 images were identified correctly, and there were three images misclassified as quarry land, two as barren land, one as forest land, and three as agricultural land. In the agricultural land group, 192 of the 200 images were placed in the correct category, and the other images were placed in the wrong category as quarry land (4), barren land (1), forest land (2), and built-up land (1). Overall, the confusion matrix shows that the CNN model works successfully in the classification of various land cover types, and most images are identified correctly in all classes.

Table 4. Performance Analysis of CNN using HSI

Performance Metrics (%)	Quarry land (%)	Barren Land (%)	Forest Land (%)	Build-up Land (%)	Agriculture Land (%)
Accuracy	78	75	71	67	69
Precision	74	69	68	69	71
Recall	69	71	75	75	68
F Score	69	65	69	72	72

Table 4 shows the performance analysis of the CNN model on hyperspectral image (HSI) classification, and it provides a graphical analysis of the CNN. The classification percentages of quarry, barren, forest, built-up, and agricultural land were 78%, 75%, 71%, 67%, and 69%, respectively. The quarry and built-up lands were classified as having the highest and lowest classification accuracies of 78 and 67, respectively. The accuracy rates of the quarry, barren, forest, built-up, and agricultural lands were 74%, 69%, 68%, 69%, and 71%, respectively. The precision value of 74 for quarry land was the highest, indicating that it was more predictable than the other classes. Similarly, the quarry, barren, forest, built-up, and agricultural lands had recall values of 69, 71, 75, 75, and 68%, respectively. Forest and built-up land had the highest recall values of 75%, indicating that they were well detected in the dataset. The F-scores for quarry, barren, forest, built-up, and agricultural lands were 69, 65, 69, 72, and 72%, respectively. The largest F-score of 72% was obtained for built-up and agricultural land, which implies that both precision and recall were balanced between the two classes. Overall, the findings indicate that the CNN model is effective in the classification of hyperspectral images, particularly for quarry land. Nevertheless, there are classes, such as built-up land, that are comparatively less accurate; therefore, more sophisticated models are required to enhance classification.

The training and testing accuracies of the hyperspectral image classification using the CNN model are shown in Figure 2. As shown in the graph, the training and testing accuracies slowly increased with an increase in the number of epochs. The accuracy values indicated a consistent learning process during the training process, implying that the CNN model successfully learned the spectral and spatial features in the hyperspectral data. The validation and training accuracies were tested at different epochs with variations of 10 to 100.

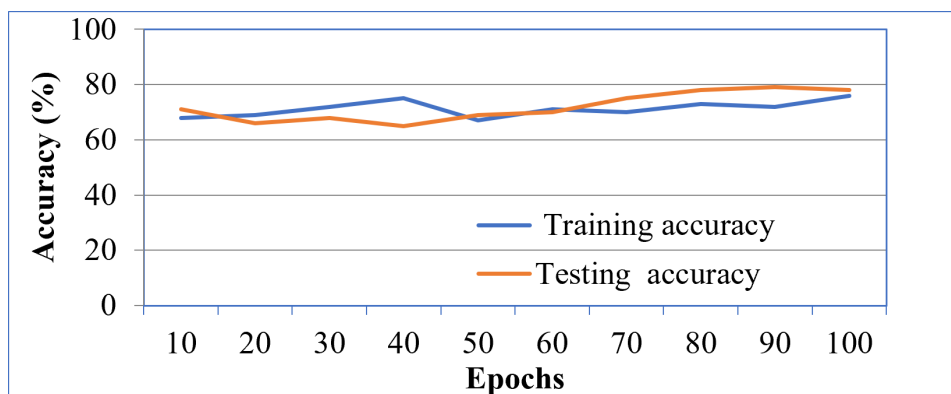


Fig 2. Accuracy Graph for CNN – Training and Testing

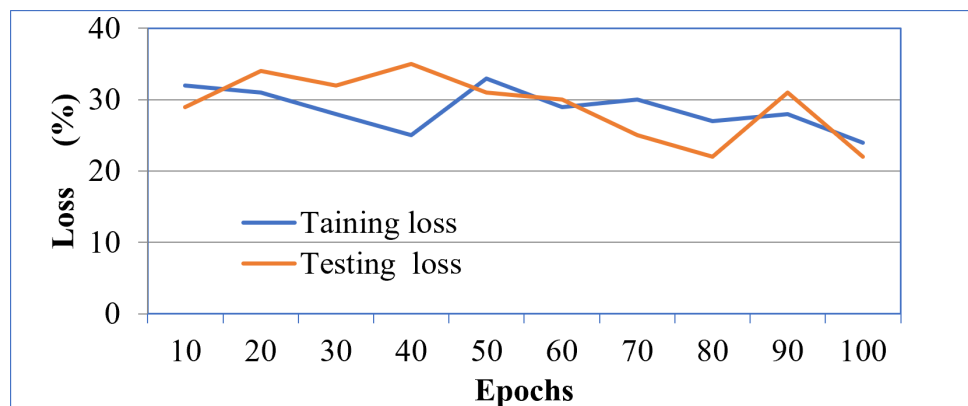


Fig 3. Loss Graph for CNN – Training and Testing

The graphical findings showed that the rate at which the training accuracy incrementally increased attained an optimal point when the number of epochs approached 90–100. The training and testing loss curves of the CNN model are shown in Figure 3, which depicts the learning process. The loss values also decreased steadily as the number of epochs increased, indicating a better model convergence. Although slight deviations were noted between epochs, the general trend showed a decrease in the loss in both the training and testing sets. This action proved that the CNN model reduced the classification errors during learning. In general, the experimental results demonstrated consistent training and testing using the CNN model. The progressive increase in accuracy and reduction in loss signified good learning and model convergence, respectively. Finally, the highest classification accuracy of the proposed CNN model was 78%, with a minimized loss, implying that it can be used for hyperspectral land cover classification.

4.2 Performance Analysis of Hyperspectral Images using ResNet 18

It is a part that was applied with ResNet 18 conducted classification of Hyperspectral images. ResNet 18 comprises a mixture of convolutional and residual blocks. ResNet-18 was separated into four steps, where the residual blocks had three convolutional layers. In this experiment, initial layer tenability was used because it was disabled because the ResNet-18 neural network has batch-normalization layers. The model was trained on a target dataset different from that initially used to train the model. This is because the batch-normalization layer uses the statistics of the training data rather than those utilized in inference. The final layer of the architecture is the fully connected layer, which is substituted with a new layer of dense layers, a softmax activation functional, and an output layer to classify five-class outputs. Land cover (LC) classifications with different performance measures were identified and verified. Table 5 lists the confusion matrix for ResNet-18 with HSI data.

Table 5. Confusion Matrix of ResNet 18 using HSI

No. of Actual classes	No. Predicted Classes				
	Classes	Quarry land	Barren Land	Forest land	Build up Land
Quarry Land	194	2	1	2	1
Barren Land	2	195	1	2	2
Forest Land	3	1	193	1	2
Build up Land	3	1	2	191	3
Agriculture Land	2	2	1	2	193

Based on the confusion matrix, 194 images of quarry land were correctly identified; however, the remaining images were incorrectly identified as barren land (2), forest land (1), built-up land (2), and agricultural land (1). In the barren land class, 195 of the 200 images were correctly identified; the remaining images were incorrectly identified as quarry land (2), forest land (1), built-up land (2), and agricultural land (2). The number of forest land images that were properly classified was 193, and the

remaining images were erroneously classified as quarry land (3), barren land (1), built-up land (1), and agricultural land (2) land. In addition, for the built-up land class, 191 images were correctly identified, and the remaining images were incorrectly identified as quarry land (3), barren land (1), forest land (2), and agricultural land (3). With respect to agricultural land, 193 of the 200 images were correctly identified; the remaining images were incorrectly identified as quarry land (2), barren land (2), forest land (1), and built-up land (2). As the confusion matrix shows, the proposed model has good classification performance, as the count of true positive samples is high for all land cover types. The classification based on HSI using the ResNet-18 model was evaluated for land cover classification (Table 6). The classification scores were 94.34, 90.28, 93.47, 95.09, and 94.67% for quarry, barren, forest, built-up, and agricultural land, respectively. The built-up land class had the highest accuracy of 95.09%, indicating the suitability of the ResNet-18 architecture for deriving the spectral-spatial land features of HSI data. The accuracies for quarry, barren, forest, built-up, and agricultural lands were 92.45, 91.18, 94.39, 96.38, and 95.07%, respectively. The built-up land class had the highest precision of 96.38%, indicating a very high classification performance. Similarly, the recall values for quarry, barren, forest, built-up, and agricultural land were 85.25, 87.23, 88.47, 86.12, and 88.47%, respectively. The maximum recall of 88.47% was obtained for the forest land class, indicating that the model was efficient in recognizing forest areas in HSI data. The F-scores for quarry, barren, forest, built-up, and agricultural lands were 87.34, 86.27, 89.12, 88.37, and 85.65%, respectively. Of these, the forest land class scored the best F-score of 89.12%, indicating a fair performance in the average of both precision and recall. From the Table 6, it is observed that the ResNet 18 model performs effectively for the classification of hyperspectral images, with particularly strong performance in quarry land mapping. However, certain classes such as built-up land achieve comparatively lower accuracy. For this reason, the use of more advanced and sophisticated models is necessary to further improve and strengthen the overall classification performance.

Table 6. Performance Analysis of ResNet 18 using HSI

Performance Metrics (%)	Quarry land (%)	Barren Land (%)	Forest Land (%)	Build-up Land (%)	Agriculture Land (%)
Accuracy	94.34	90.28	93.47	95.09	94.67
Precision	92.45	91.18	94.39	96.38	95.07
Recall	85.25	87.23	88.47	86.12	88.17
F Score	87.34	86.27	89.12	88.37	85.65

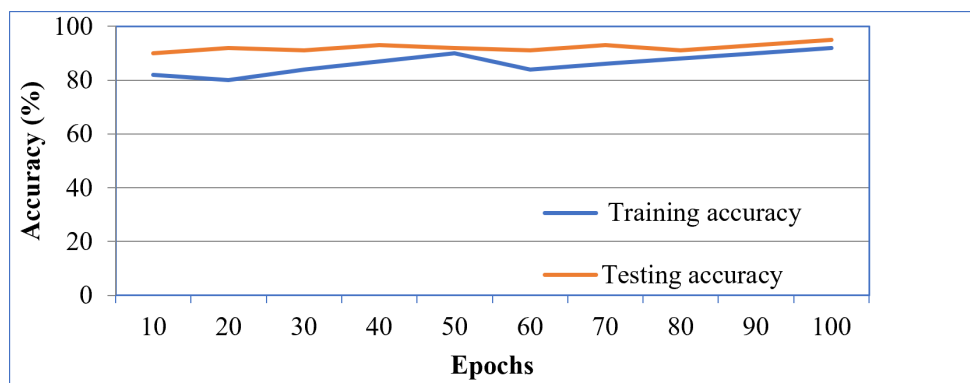


Fig 4. Accuracy Graph for ResNet 18 using HSI – Training and Testing

Figure 4 shows the training and testing accuracy curves of the ResNet-18 model. These findings suggest that the training and testing accuracies developed steadily with an increase in the number of epochs, proving the model learning and solution convergence. The testing accuracy was similar to the training accuracy, indicating weak overfitting and that the model was well-generalized. Overall, the experimental findings indicate that the ResNet-18 model is highly effective in enhancing HLC classification performance with high accuracy and feature representation compared with traditional CNN models. The training and testing loss curves of the CNN model during the learning process are shown in Figure 5. The loss values decreased substantially with an increase in the number of epochs, which is a better indicator of model convergence.

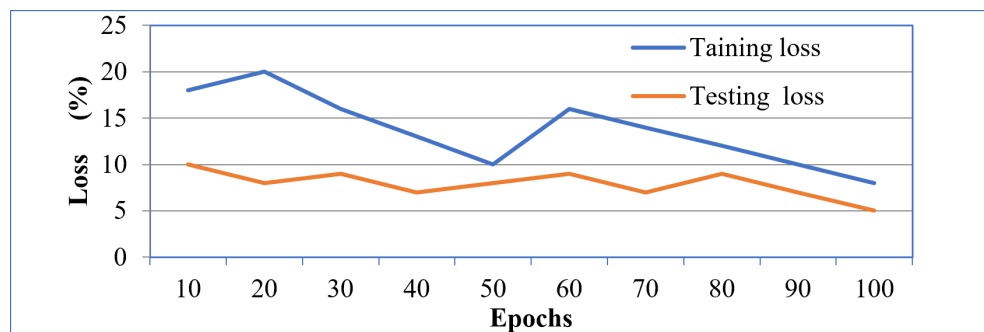


Fig 5. Loss Graph for ResNet 18 – Training and Testing using HSI.

4.3 Performance Analysis of Hyperspectral Images using VGG 16

A diverse set of predefined hyperspectral datasets (2015–2022) was used for land cover classification in the Krishnagiri and Dharmapuri districts using VGG 16. In VGG 16, each layer has a capacity driven by its synaptic load. HL1 is a transitional correspondence layer for information and the HL layers. This helps the hidden layers obtain information from the immediate calculation obtained from the input layer. The calculation among the input and hidden layers with related loads is known as layer load. The confusion matrix for land cover classification using VGG 16 for HSI is shown in Table 7.

Table 7. Confusion Matrix of VGG 16 using HSI

No. of Actual classes	No. of Predicted Classes					
	Classes	Quarry land	Barren Land	Forest land	Build up Land	Agriculture Land
Quarry Land		192	2	1	2	3
Barren Land		4	191	1	2	2
Forest Land		3	1	189	4	3
Build up Land		2	1	2	192	3
Agriculture Land		3	2	3	2	190

Based on the confusion table, of the 200 quarry-land images, 192 were correctly identified, and the remaining images were incorrectly identified as barren land (2), forest land (1), built-up land (2), and agricultural land (3). In terms of barren land, 191 of the 200 images were correctly identified; the remaining images were incorrectly identified as quarry land (4), forest land (1), built-up land (2), and agricultural land (2). For forest land, 189 images were correctly classified, and the misclassified images were identified as quarry land (3), barren land (1), built-up land (4), and agricultural land (3). Similarly, 192 images were correctly identified as built-up land, and the remaining images were misidentified as quarry land (2), barren land (1), forest land (2), and agricultural land (3). For agricultural land, 190 of the 200 images were correctly identified; the remaining images were not identified because they were classified as quarry land (3), barren land (2), forest land (3), and built-up land (2). In general, the results of the confusion matrix indicate that the model was successful in classifying the majority of the land-cover type categories, with many correctly predicted samples in all categories.

Table 8. Performance Analysis of VGG 16 using HSI

Performance Metrics (%)	Quarry land (%)	Barren Land (%)	Forest Land (%)	Build-up Land (%)	Agriculture Land (%)
Accuracy	82	85	86	84	82
Precision	81	79	81	84	88
Recall	82	86	85	84	82
F Score	79	81	75	83	79

Table 8 presents the performance analysis of the land cover classification model using VGG-16 based on hyperspectral images (HSIs). The accuracies of the classification of quarry, barren, forest, built-up, and agricultural land were 82%, 85%, 86%, 84%,

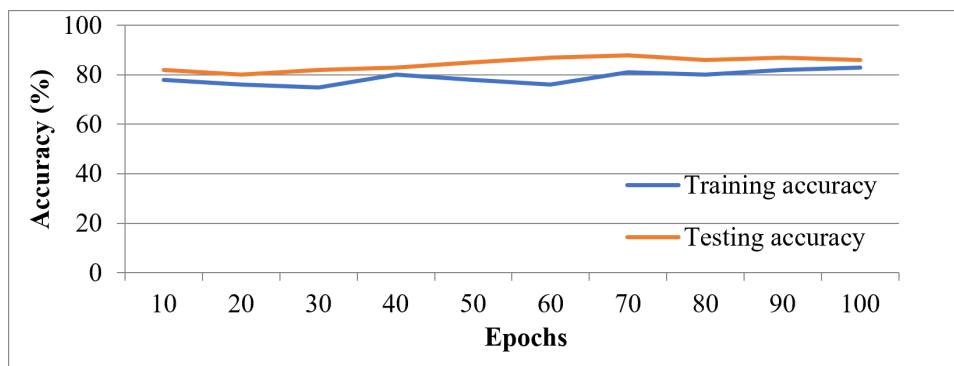


Fig 6. Accuracy Graph for VGG 16 using HSI – Training and Testing

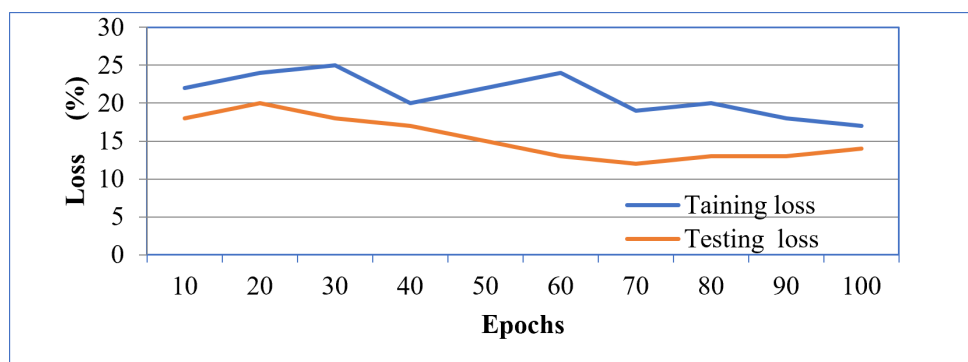


Fig 7. Loss Graph for VGG 16 – Training and Testing

and 82%, respectively. Forest land had the highest classification accuracy of 86%, indicating that the VGG-16 model can be used successfully to capture the spectral and spatial attributes of vegetation-related class. The accuracies of the classification of quarry, barren, forest, built-up, and agricultural land were 81%, 79%, 81%, 84%, and 88%, respectively. The highest precision value of 88% was recorded for agricultural land, implying that the model was dependable when predicting the land. Likewise, the recall values for quarry, barren, forest, built-up, and agricultural lands were 82%, 86%, 85%, 84%, and 82%, respectively. The highest recall percentage of 86% was achieved for barren land, indicating that the model was successful in identifying this class in the hyperspectral data. The F-scores of the quarry, barren, forest, built-up, and agricultural lands were 79%, 81%, 75%, 83%, and 79%, respectively. The best F-score of 83% was obtained for built-up land, with precision and recall being balanced in the case of built-up land. Figure 6 shows the training and testing accuracy curves of the VGG-16 model at various epochs. This graph shows that the training and testing accuracies increased slowly with the number of epochs, indicating that there was no change in the learning behavior, and the model performed better as training proceeded. Likewise, Figure 7 demonstrates the training and testing loss curves of the VGG-16 model. As the number of epochs increased, the loss values decreased progressively, indicating that the model was effective in minimizing classification errors throughout the training process. Although variations were noted between epochs, the overall trend direction supported the successful convergence of the VGG-16 model.

Table 9. The Computational accuracy percentage of SGD

Models	Accuracy without SGD (%)	Accuracy with SGD (%)
ResNet 18 (Proposed)	88	95.09
VGG 16	82.2	86.6
CNN	73	78

Table 9 shows the increase in the accuracy of the computations using the Stochastic Gradient Descent (SGD) optimizer. The findings indicate that the SGD optimizer is effective in enhancing the classification of deep learning models. In particular, the convolutional neural network (CNN) model accuracy was enhanced to 73% and 78%, the ResNet-18 model accuracy was

enhanced to 88% and 95.09%, and the VGG-16 model accuracy was enhanced to 82.2% and 86.6%, respectively. The learning rate was lowered to 0.001, and the active optimization of the model weights helped achieve better optimization and higher recognition accuracy. In general, the findings of this study suggest that hyperspectral image classification can be enhanced using deep learning models and the SGD optimizer. The classification accuracy of the tested models was highest for the ResNet-18 model, followed by VGG-16 and CNN, demonstrating the usefulness of residual learning structures for hyperspectral land cover classification.

The results of the present study clearly show that hyperspectral image classification techniques based on deep learning can be successfully used for the identification and classification of different land cover categories, such as quarry, barren, forest, built-up, and agricultural land. ResNet-18 exhibited the highest classification accuracy and overall performance among the evaluation models compared to CNN and VGG-16. The superior performance of ResNet-18 is attributed to the residual learning structure, which enhances feature extraction in the spectral–spatial domain and reduces the vanishing gradient problem in deep neural networks. The results obtained are consistent with those reported in the hyperspectral remote sensing literature. To overcome the limitation of efficient learning of hierarchical spectral features, it is reported that the residual deep learning frameworks can considerably improve the accuracy of hyperspectral image classification⁽⁶⁾. Similarly, to classify remote sensing images, Zhao et al.⁽¹¹⁾ proved that ResNet outperforms conventional CNN architectures for improved propagation and optimization. The current findings are consistent with these observations, especially for the classification of built-up areas and agricultural land classes with a ResNet-18 accuracy of over 94%. The findings of the present study also align with those of 5. Rehman et al.⁽⁵⁾ who reported that deep learning techniques give superior land cover classification performance with less bands. In this study, 230 spectral bands were added to further improve the spectral discrimination capability, which led to improved land cover identification. Moreover, the results are consistent with those of Chaurasia et al.⁽³⁾, who revealed the excellent performance of deep convolutional models in large-scale land use and land cover classification applications. However, some observations in this study are contrary to previous reports on VGG-based architectures. In previous work, VGG-16 was demonstrated to be a competitive classification model for remote sensing applications with small datasets and low spectral dimensionality. However, the performance level of VGG-16 was relatively low on high-dimensional hyperspectral imagery with 230 spectral bands, as observed in the present study. This degradation in performance can be linked to the increased complexity of the computation of the VGG network and the number of parameters to be calculated for these networks, which could impact the efficiency of generalization in hyperspectral classification problems.

The same is true for the conventional CNN model, which obtained a lower classification accuracy than ResNet-18. CNN can extract fundamental spectral–spatial features; however, its performance is limited in dealing with complicated hyperspectral patterns and mixed pixel information. This observation provides further confirmation of the effectiveness of residual learning strategies for hyperspectral image analysis. This research has important implications for environmental monitoring and land resource management applications. The use of hyperspectral imagery in the accurate classification of land cover can aid in the analysis of urban expansion, monitoring of quarries, agricultural land assessment, forest management, and sustainable environmental planning. The developed framework can be expanded to large-scale remote sensing applications in other geographical regions. Although promising results were obtained, the present study has some limitations. Hyperspectral image processing requires high computational resources owing to the large number of spectral bands and deep learning parameters. Furthermore, it is crucial for the developed models to have labelled training sets to learn effectively. These results could be further influenced by variations in atmospheric conditions, seasonal changes, and mixed pixel effects. Moreover, training deep neural networks becomes significantly more time-consuming as the number of hyperspectral datasets increases.

5 Conclusion

This study developed an effective deep learning-based framework for hyperspectral land cover classification in Krishnagiri and Dharmapuri districts of Tamil Nadu using 2015–2022 hyperspectral imagery. The proposed framework integrated preprocessing, superpixel segmentation, and deep learning models (CNN, ResNet-18, and VGG-16) to classify five land cover classes: quarry, barren, forest, built-up, and agricultural land. Among the evaluated models, ResNet-18 achieved the best performance, with classification accuracies of 94.34%, 90.28%, 93.47%, 95.09%, and 94.67% for quarry, barren, forest, built-up, and agricultural land, respectively. The results demonstrate that residual learning effectively extracts spectral–spatial features from high-dimensional hyperspectral data and provides superior classification accuracy and generalization compared with CNN and VGG-16. Confusion matrices, precision, recall, F-score, and convergence curves further confirmed the robustness of the proposed framework. The methodology has potential applications in environmental monitoring, quarry management, agricultural assessment, urban expansion analysis, and land-use planning. However, computational complexity, limited labeled data, atmospheric and seasonal variations, and mixed pixels remain key limitations. Future studies may improve scalability and efficiency through lightweight networks, attention mechanisms, transformers, hybrid deep learning, real-time processing,

and the integration of LiDAR and SAR data. Overall, the proposed ResNet-based framework demonstrates strong potential for reliable and scalable hyperspectral land cover monitoring.

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