International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8s
DOI: https://doi.org/10.17762/ijritcc.v11i8s.7249
Article Received: 26 April 2023 Revised: 22 June 2023 Accepted: 04 July 2023

A Novel Densenet-324 Densely Connected Convolution Neural Network for Medical Crop Classification using Remote Sensing Hyperspectral Satellite Images

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Abstract— In the past few decades, importance of the medicinal Crops is extending to a large extent due to its benefits in treating life-threatening diseases. Medicinal Crop has excellent medicinal properties on its roots, stem, and leaves to prevent human and animal health. Particularly detection and identification of the Crop classes are effectively carried out using hyperspectral images as discrimination of the target feature or objects is simple and it contains rich information containing the spatial and temporal details of underlying the land cover. However, Crop classification using machine learning architectures concerning spectral characteristics obtained on the anatomical features and morphological features. Extracted features towards classification lead to several challenges such as large spatial and temporal variability and spectral signatures similarity between different objects. A further hyperspectral image poses several difficulties with changes in illumination, environment, and atmospheric aspects. To tackle those non-trivial challenges, DenseNet-324 Densely Connected convolution neural network architecture has been designed in this work to discriminate the crop and medical Crop effectively in the interested areas. Initially, the Hyperspectral image is pre-processed against a large number of noises through the employment of the noise removal technique and bad line replacement techniques. Pre-processed image is explored to image segmentation using the global thresholding method to segment it into various regions based on spatial pieces of information on grouping the neighboring similar pixels intensity or textures. Further regions of the image are processed using principle component analysis to extract spectral features of the image. That extracted feature is employed to ant colony optimization technique to obtain the optimal features. Computed optimal features are classified using Convolution Neural Network with a hyper parameter setup. The convolution Layer of the CNN architecture process spatial, temporal, and spectral feature and generates the feature map in various context, generated feature map is max pooled in the pooling layer and classified into crops and medicinal Crop in the SoftMax layer. Experimental analysis of the proposed architecture is carried out on the Indiana Pines dataset using cross-fold validation to analyze the representation ability to discriminate the features with large variance between the different classes. From the results, it is confirmed that the proposed architecture exhibits higher performance in classification accuracy of 98.43% in classifying the Crop species compared with conventional approaches.

Keywords- Remote Sensing, Hyperspectral Images, Medical Crops, Deep learning, Global Threshold Segmentation, Principle Component Analysis, Ant colony Optimization, Convolution Neural Network.

I. INTRODUCTION

Crops are very essential part of human and animal life as it provides food, medicine, and oxygen. Specifically, Crop is classified into food crop Crops and medicinal Crop based on their purposes. Nowadays farmers are employing technologies that provide accurate and timely information about the Crop's nutrients. Moreover, accurate detection and classification of the Crop species among a wide variety of species around the wide ranges of land regions are highly complex and time-consuming. The complexity of the detection and classification task on a wide range of land regions could be reduced by employing remote sensing technologies. Satellite imagery is widely used to plan the infrastructure to monitor the environmental conditions to detect upcoming disasters. Satellite image processing is a kind of remote sensing is works on pixel resolutions to collect meaningful information about the Earth's surfaces [18]

Precise Crop classification from satellite-based remote sensing imagery using machine learning algorithms including support vector machine, Random forest, and decision tree algorithms has achieved remarkable results. However, it exhibits many challenges in illumination, environment, and atmosphere aspects such as low spatial and temporal resolutions and large spatial and temporal variability, spectral signatures similarity between different Crop regions. These limitations produce high classification errors and are time-consuming. To mitigate those non-trivial challenges, deep learning architecture has emerged as an advanced solution. Satellite imagery plays a vital role in research and developments for exploration and improvement in agriculture monitoring and catastrophe monitoring and numerous fields [16]

In this article, novel architecture has been designed and implemented to discriminate the cop Crops and medical Crops effectively in processing hyperspectral satellite images. Hyperspectral satellite images are pre-processed against a large number of noises through the employment of the noise removal technique and bad line replacement techniques. The proposed model is highlighted with the main contributions of the articles as

- Image segmentation uses a global thresholding method to segment it into various regions based on spatial information on grouping the neighbouring similar pixels' intensity or textures.
- Feature extraction using principle component analysis to extract spatial and spectral features of the image.
- Feature selection using the ant colony optimization technique is to obtain the optimal features. The embedding layer establishes the association on the semantic representation of the known classes through ground truth data and unknown classes using label prediction to the extracted features. Label prediction is considered label reasoning
- Finally, a hyper-parameter optimized convolution neural network is employed to classify the crop and medicinal Crop by utilizing the various layers such as the convolution layer, pooling layer, activation layer, embedding layer, SoftMax layer, and loss layers.

Medicinal Crop contributes prevent human and animal health by building medicinal properties on their roots, stem, and leaves. [20]

The remainder of the article is organized as follows; section 2 represents different deep learning architectures that have been widely employed for Crop classification has been analyzed. The section deals with the methodology of the proposed hyper parameter-optimized convolution neural network. Experimental and performance analysis of the proposed model against conventional approaches is detailed in section 4. Finally, the article is concluded with future suggestions in section 5.

II. RELATED WORK

In this section, various conventional approaches behind proposed research work towards a large number of Crop classifications using deep learning and machine learning model to hyperspectral image dataset has been discussed in detail on various aspects as follows

2.1. *Crop classification using Convolution Neural Network*

Convolution Neural Network employed to Crop classification composed of multiple layers along its weights to extract the informative features. The feature represents the spectral signatures and it is extracted in the convolution layer and max pooling layer. The activation layer uses the ReLu function effectively discriminate the feature into effective classes. SoftMax layer and loss layer processes the class feature to eliminate the classification error. It computes the variance among each feature in the classes on application of cross entropy function. Crop prediction in agriculture is a complicated process one of the main challenges that researchers in this field face are the lack of culturally labeled data that is synchronized throughout spatial and temporal [17]

2.2. *Crop classification using Support Vector Machine*

In this literature, multiclass classification of the hyperspectral images is carried out using a Support vector machine. Support vector machine locates the optimal hyper plane between classes of the interest and rest of the classes to the high dimensional feature space. The edge of the class distribution to the feature space is represented as support vectors. The support vector contains the spectral and spatial features of the remote-sensed images. The generated support vector containing the features is classified using the kernel function.

III. PROPOSED METHODOLOGY

In this section, a hyper parameter-optimized classifier for Crop classification using hyperspectral images has been designed extensively with pre-processing and feature extraction steps to exploit the spectral, spatial, and temporal features to increase the classification of the model

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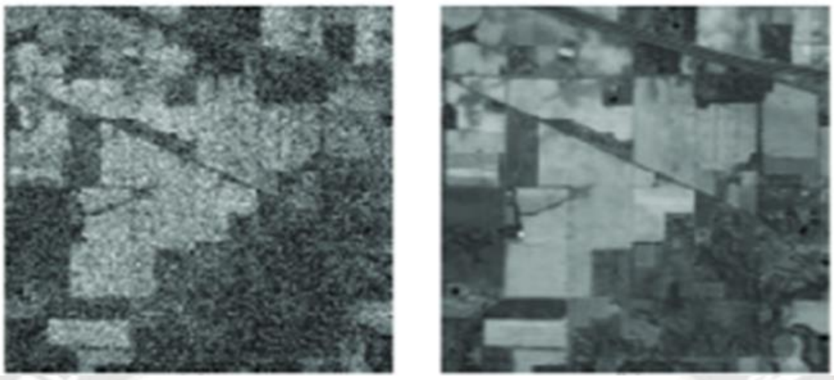
3.1 Image Pre-processing

In this work, Hyperspectral images are represented as a combination of spectral pixel vectors and spectral bands as a cube. Mostly Spectral bands contain noisy spectral bands. It can be removed using the denoising technique. The denoising technique using the 3D wavelet technique employed for the hyperspectral image is capable of de-correlating the pixel dependencies with 10 coefficients to produce the denoised hyperspectral images without bad lines. Figure 1 represents the image pre-processing using the denoising technique.



(a) (b)

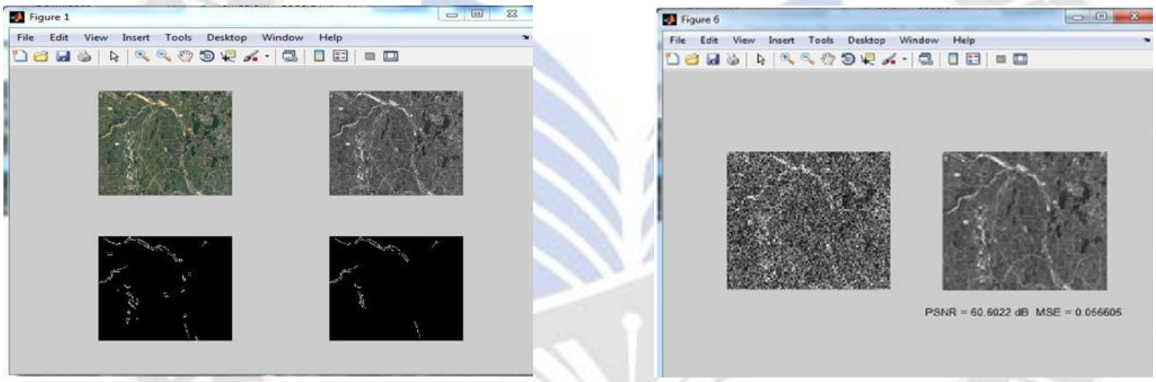


Figure 1: Image Pre-processing (a) Input Image (b) Pre-processed Image

3.2 Image Segmentation

Image segmentation using global thresholding uses the single threshold value for image region segmentation with similar spectral signatures. It segments the image into various homogenous regions with the criteria. A segment of the image spectral signatures uses the single threshold spectral signature to select the most distinctive and informative bands which describe the objects. Figure 2 represents the image segmentation of the Crop regions. The threshold is computed as

- Select an initial estimate for T
- Segment the image using T to produce two groups of spectral signatures: G_1 consisting of signature with spectral signature >T and G_2 consisting of pixels with grey spectral signature ≤ T
- Compute the average spectral signature of the image in G_1 to give μ_1 and G_2 to give μ_2

Computing the new threshold

$$T = \frac{\mu_1 + \mu_2}{2}$$

Repeat steps until the difference in T in successive iterations is less than a predefined limit T_{limit}

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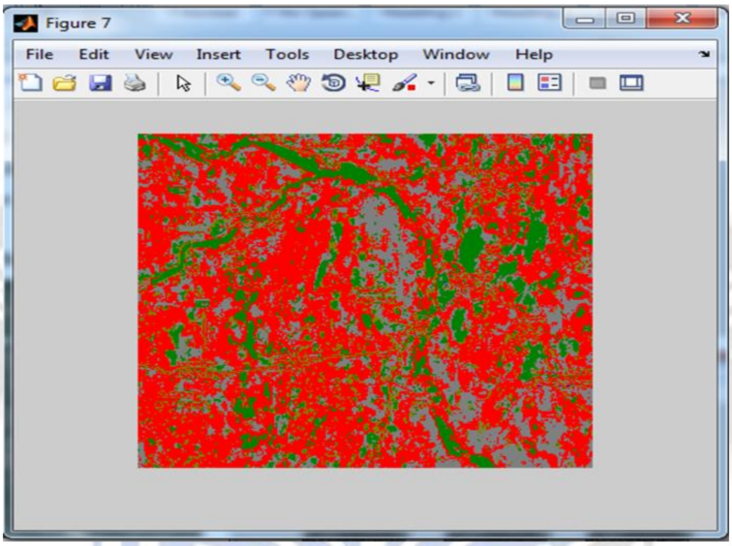
(a) (b) (c)

Figure 1: Image segmentation (a) Input Image (b) Segmented Image (c) Ground truth Image



3.3. Feature extraction –Principle Component Analysis

Principle component analysis is employed to compute the spectral feature of the hyperspectral data. The original dimensionality of the segmented region of the images is projected as D dimensional subspace. Segmented regions of the image are represented in the orthogonal matrix for linear transformation. Orthogonal matrix attempts to maximize the data variances projected spectral space of eigenvectors and minimizes the mean square distance between the spectral signature and projection.Spectral Signatures are given as

$$\mathbf{w}_1 = \arg\max_{\|\mathbf{w}\|=1} \frac{1}{m}\sum_{i=1}^{m}\{(\mathbf{w}^T\mathbf{x}_{\text{i}})^2$$

To maximize the variance of the spectral signature in the vector is given by

$$\mathbf{w}_k = \arg\max_{\|\mathbf{w}\|=1} \frac{1}{m}\sum_{i=1}^{m}\{[\mathbf{w}^T(\mathbf{x}_i - \sum_{j=1}^{k-1}\mathbf{w}_j\mathbf{w}_j^T\mathbf{x}_i)]^2\}$$

Where $\sum_{j=1}^{k-1}\mathbf{w}_j\mathbf{w}_j^T\mathbf{x}_i)^2$ is the PCA reconstruction

The covariance of the spatial vector is $\Sigma = \frac{1}{m}\sum_{i=1}^{m}(\mathbf{x}_i - \overline{\mathbf{x}})(\mathbf{x} - \overline{\mathbf{x}})^T$

On processing of the covariance matrix, the spectral features of the image are generated with high variance to the particular spatial feature or vector. Figure 3 represents the proposed architecture of the model.

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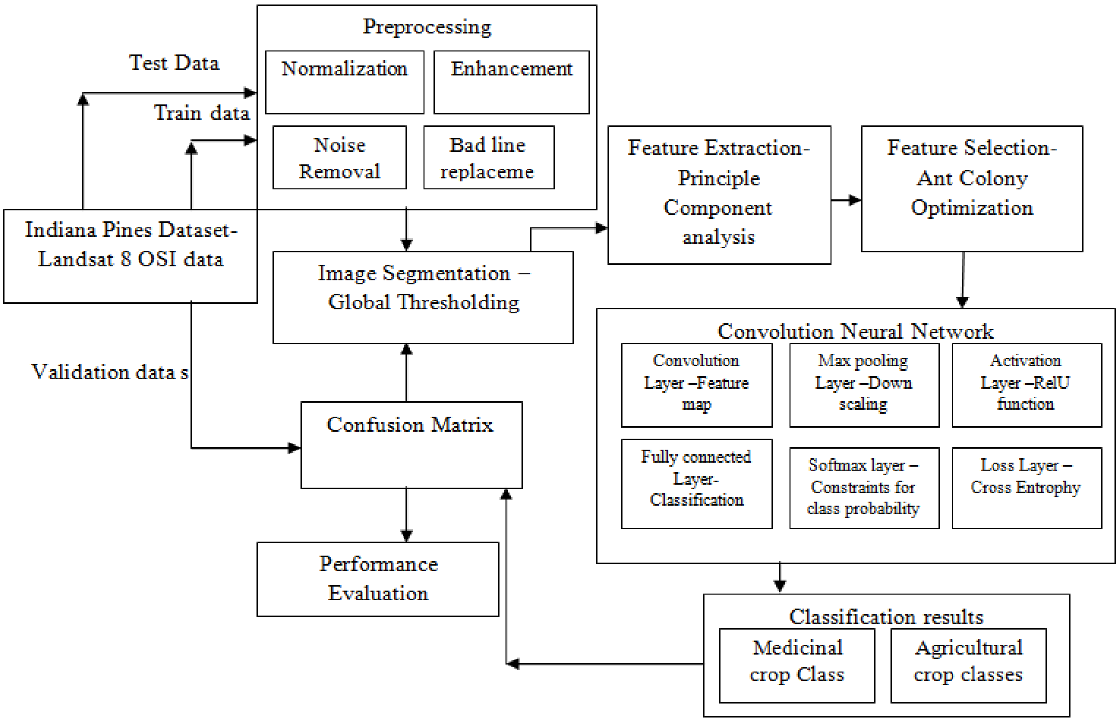

Figure 3: Proposed Architecture

3.4. Feature Selection –Ant Colony Optimization

Ant colony optimization is employed to the set of the spectral feature vector and spatial feature vector as it is to select the important feature bands. It is considered as Meta heuristic approach. The optimal feature band for the classification of the Crop is obtained effectively on the fitness criteria. It eliminates irrelevant features from the feature vector. Figure 4 represents the principles or optimal features selected for Crop classification

Pheromone of feature (local importance) P=

$$\hat{\underline{x}} = B^T M_B \{B\underline{y}\} = \sum_k B_k^T M_k \{B_k \underline{y}\}$$

Feature band selected for region is represented as F_r= {b1, b2, b3...bn}

In this b1, b2 represents the feature bands selected for the set of feature band vectors of similar spectral signatures. The irrelevant feature is computed using the pheromone local importance. Pheromone local importance is represented as the weight of the feature in the vector or region. It also represents the feature band. In Figure 4, PC-1, PC-2 ,...PC-8 represents the principle feature bands of the segmented region.

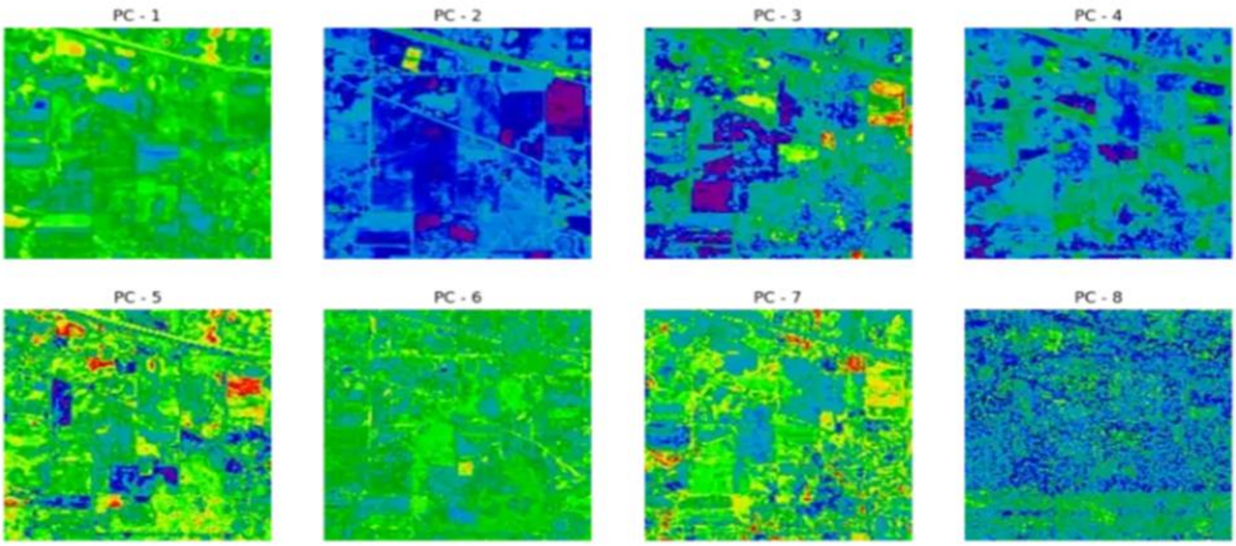

Figure 4: Optimal features (Feature Band) Selected for Crop Classification on particular Region of Interest

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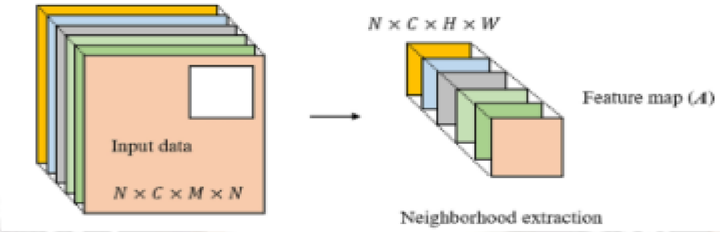
3.5. Feature Classification

Feature classification of the Crop class is carried out using the DenseNet 169 which is considered a densely connected convolution neural network. A densely connected Convolution Neural Network is composed of several layers such as the Convolution layer, Max Pooling layers, Activation Layer, Dense Layers, Fully connected layer, SoftMax layer, and loss layer.

- **Convolution Layer**

The convolution layer is composed of multiple filters or kernels to convolve with optimal features to derive the feature map which is termed as activation map. Convolution is a mathematical operation represented as the multiplication of the image matrix and multiple filters. The feature matrix of hyperspectral image 5*5 is multiplied with kernel 3*3 matrix to provide a convolution matrix or feature map. Convoluted the spectral feature is represented as



1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Spectral Feature Matrix

1	0	1
0	1	0
1	0	1

Kernel Matrix

4	3	4
2	4	3
2	3	4

Feature Map

The convolution layer provides the feature map of the convolution operations. Convergence of the feature map is carried out using epoch and it increases the feature generation on normalization of the activation function represented as ReLu to obtain the linear feature map. The distance among the feature is computed using a cosine distance measure

The cosine distance of the features in the feature map is evaluated as

$C_f = y(m^t f^t + c)$

- Pooling layer

The pooling layer further reduces the spatial dimension of the image or region segmented. Hence it is considered spatial pooling for the hyperspectral images. It is also termed as downsampling of spatial features by decreasing the dimension of the spatial feature on retaining only selected weighted features. The selected weighted feature has the greatest spectral reflectance value. The Max Pooling layer connects the spectral features into small patches on account of the spectral signatures. Max pooling is used to estimate the greatest no of the features for each subset. It further enhances the model generalization [13]. Feature pooling of the convoluted matrix is presented as

4	3	4
2	4	3
2	3	4

Convoluted feature

4	3
3	4

Max pool Features

- Dense Layer –Fully Connected Layer

The dense layer of the CNN is organized as the fully connected layer with multiple constraints to process the feature map. Feature map composed of the spatial and spectral features of the specified regions segmented. A discriminative feature map is composed of temporal features along with spatial and spectral information. A fully connected layer uses the activation function to process feature normalization or feature flattening as a layer to eliminate the non-linearity and overfitting issues in the feature bands. A fully connected representation of the feature bands is represented below

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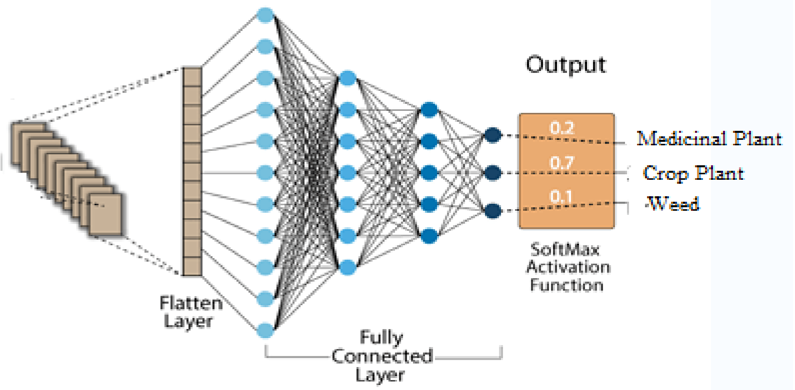

The softmax layer is employed in the fully connected layer to generate the Crop classes by deducing the feature vector into the Crop class vector. It is to verify the reliability of the model. Further loss layer is incorporated in a fully connected layer to minimize the spatial variance on the classes of the features. The closest approximation of the testing sample may be from various classes, which represents that the minimal residual may be derived from numerous classes. The final classification result is generated by integrating the results based on the voting rule.

The class coefficients for the spectral and spatial feature interpretation are given by class objective function as

$$Y = \beta_0 + \beta_1 X$$

Where the class coefficients are represented as

$$\beta_1 = \frac{n\sum xy - \sum x \sum y}{n\sum x^2 - (\sum x)^2}$$

The integral derivates of the class objective function concerning the class coefficients have been extracted on the estimation of Error Sum of Square (SSE). The Softmax layer which follows the delta rule is given by the loss function of the hyperparameters. It is to determine multiple linear weights of spatial features. In addition, feature weight can be computed through iterations.

$\Delta W_i = C(t\text{-}net)x_i$

where **'c'** is the learning rate

'x' is the input for that weight

On the objective of minimizing the SSE and solving the loss of the classifier, the Delta rule will be updated. Algorithm 1 explains the working of the proposed Crop classification model

Algorithm 1: Crop Classification

Input: Indiana Pines Hyperspectral Image Dataset

Output: Crop Classes

Process

Preprocess

Denoising ()

D= 2Dwavelet(matrix(Input Images))

Normalized Image N = BadlineFilter(D)

Segmentation

Segment S= Global Thresholding(N)

Compute the Spectral Signature of each band)

For (Spectral length [i]!=0) &(Spectral length >0) & (Spectral length ++)

If (spectral Signature of Spectra 1= Spectral signature of Spectra 2)

Merge Both Spectra 1 and Spectra to mark the boundary

Else If (spectral Signature of Spectra 1= Spectral signature of Spectra 3)

Merge Both Spectra 1 and Spectra to mark a boundary

Segment S= (Region 1, Region 2… Region n)

Feature Extraction

Extract principle feature of segmented Region

Generate the matrix for Segmented Regions

Compute Covariance Matrix and Correlation Matrix

Obtain Eigen Vector = V with eigenvalue

Eigen Vector V is a spatial Vector containing Spectral features represented as eigenvalues

Feature Selection

Define Fitness Criteria F

Compute Fitness for the Eigen Vectors

Obtain Optimal Features

Feature Classification ()

Densenet324()

Convolution Layer() reduces the spectral feature and generates the feature map

The pooling layer () reduces the spatial features and generates the feature map

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Fully connected Layer ()

The dense layer() deepens the connection between the spatial and spectral features

Flatten layer () normalizes the features

Softmax layer classifiers the features into Crop classes

The loss layer minimizes the spatial and spectral variance in class generated

Output layer () generates the Crop classes

Output = { Medicinal Crop, Crop Crop, weed }

Algorithm explains the processing of the hyperspectral images towards the classification of the Crop into multiple classes based on the spectral, spatial, and temporal feature processing in the unique dense convolution neural network.

IV. EXPERIMENTAL RESULTS

In this section, performance analysis of the experimental outcomes has been computed and evaluated on cross-fold validation of the Indian Pines dataset obtained from Landsat 8 OSI [14]. Performance analysis of the model is exhibited on the optimal parameters for the proposed densenet324 architecture for Crop classification. The architecture is simulated in the Matlab tool. The dataset containing hyperspectral images was classified into a training set, testing set, and validation set. The spectral reflectance value of the dataset is illustrated in Figure 4.1

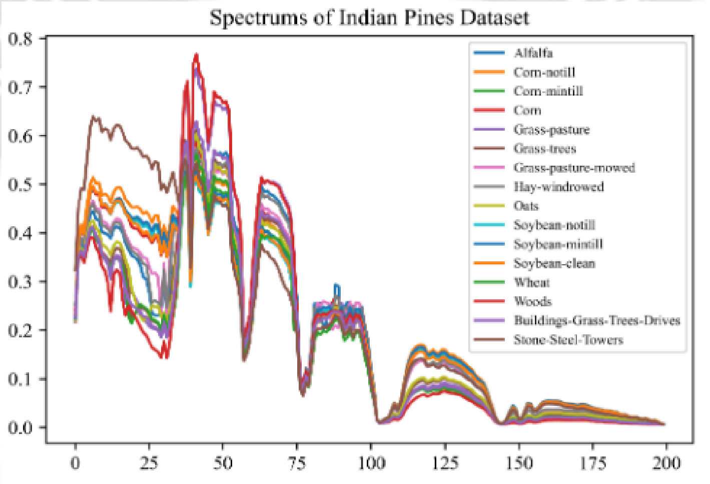

Figure 4.1 Spectral of Indiana pines Dataset

In this 80% of images were used to train the architecture and 20% were used to test the architecture. On 80% of training images, it was further classified into 60% for training the architecture and 20% to validate the trained model. 5-fold cross-validation has been used to enhance the accuracy of the proposed architecture in Crop classification [10]. DCNN training parameter has been illustrated in Table 1

Table 1: DCNN training parameters

PARAMETER	VALUE
Activation Function	ReLu
Spatial Size	28*28
Learning rate	10^{-6}
Loss Function	Cross Entropy
Spectral Feature dimension	128
No grouping band	10
Batch size	10
Drop Out	0.4
Max epoch	100

The hyperspectral images taken for processing of the Crop classes will measure the variation in the Crop spectral values in terms of ground truth value. Spectral evolution is measured effectively using the spectral reflectance value of the Crop region. Figure 6 represents the outcome of the Crop classification using the proposed architecture.

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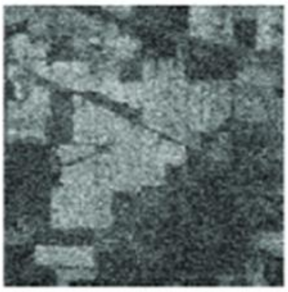

(a) Input Image

(b) Ground truth

(c) Output image

Figure 4.2 represents the performance of the proposed architecture against the conventional approach concerning precision [15]. In this model, spectral and spatial features produce high accuracy.

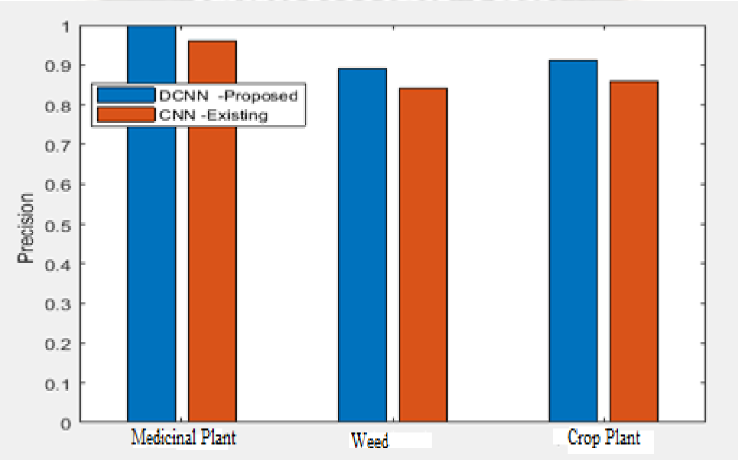

Figure 4.2 Performance Evaluation of the proposed model on precision

The precision, recall, and F measure has been calculated using a confusion matrix with parameters like true positive, false positive, false negative, and true negative. Performance values have been extracted from different instances of classes to determine the performance accuracy on the spectral indices at different wavelengths of the pixel of the proposed model and it is compared with classified pixels of the spectral images. Further, it has been modeled to compute the classes on an aspect of covariance and correlation of the spectral signatures

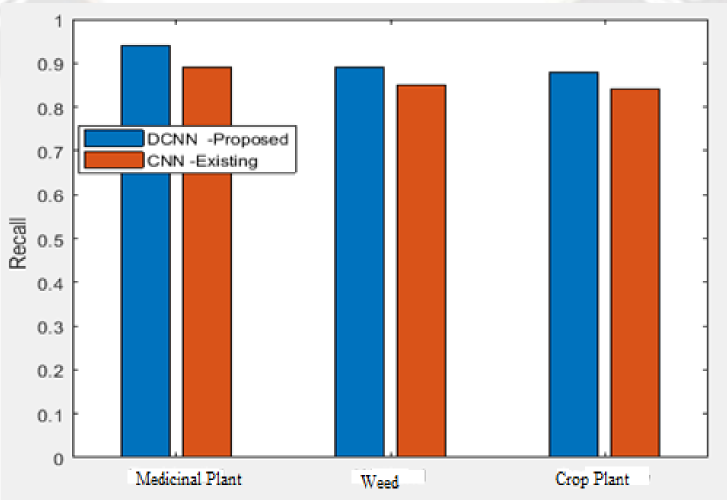

Figure 4.3 Performance Evaluation of Proposed Architecture against Conventional Model on Recall

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Figure 4.3 illustrates the performance of the proposed architecture towards the classification of the hyperspectral images in terms of recall on the Crop class's results with reduced spatial and spectral feature variances. On analysis, it produces effective results on true positive values computation. Figure 4.4 provides the performance results of the f measure on outcomes of classes containing Crop classes

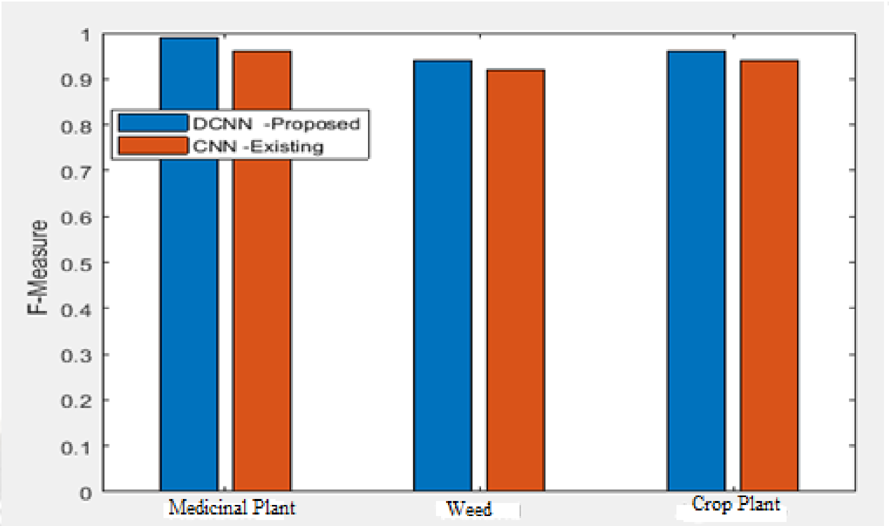

Figure 4.4 Performance Evaluation of Proposed Architecture against Conventional Model on F measure

Interestingly, the accuracy values of the proposed model are high in the classification of hyperspectral images on Multiobjective activation functions of the DenseNet324 classifiers. It classifies the discrete spectral values. This paradigm can be applied to any type of dataset of hyperspectral images. Table 2 represents the performance of the classification accuracy on the proposed classifier against the conventional approach.

Table 2: Performance computation of proposed architecture on Crop Classification

Techniques	**Classes**	**Precision**	**Recall**	**F measure**
Proposed Technique –Dense Convolution Neural Network	Medicinal	0.99	0.94	0.99
	Weed	0.89	0.96	0.99
	Crop	0.94	0.88	0.99
Existing Technique- Graph Convolution Neural Network	Medicinal	0.96	0.89	0.96
	Weed	0.84	0.94	0.94
	Crop	0.89	0.84	0.98

The performance of the proposed approach produces classification maps with high classification accuracy [10]. The proposed model can highly minimize data redundancy and enhances classification efficiency based on the dataset. Finally, the proposed model is highly capable of producing high accuracy in capturing the distinctive features and information between various Crop classes across various hyperspectral imaging datasets. The technology's main advantage is that it is non-destructive, meaning it can provide vital information on crops without having to touch them [19].

V. CONCLUSION

In this work, a densely connected Convolution Neural Network for Crop classification of hyperspectral images has been designed and implemented. The proposed model computes the effective activation function based on spectral indices as it increases the computation time in class informative feature classification with large feature weight on the spectral, spatial, and temporal features. Initially pre-processing is carried out using denoising techniques and feature extraction using principle component analysis and feature selection using the ant colony optimization. Optimal features have been employed in convolution neural networks to generate the Crop classes with high accuracy. It achieves classification accuracy in processing the features on the convolution layer, pooling layers, and fully connected layer. The fully connected layer is composed of a dense layer to flatten the features, a softmax layer to classify the Crop features, and a loss layer to minimize the classification error by reducing the spectral and spatial variances of the features in the class. To further enhance the performance of HSI classification, multiple strategies have been incorporated via convolution and softmax layer to minimize the classification error Finally Dense Convolution Neural Network calculates the diversity of the features effectively. The experiment analysis was evaluated and tested on the Landsat 8 OLI dataset to compute its effectiveness and efficiency in terms of accuracy.

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