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PRECISE CROP CLASSIFICATION OF HYPERSPECTRAL IMAGES USING NEURAL NETWORK-BASED FEATURE EXTRACTION AND CLASSIFICATION MODEL

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ABSTRACT

Precise crop classification is an essential step towards effective agricultural management. Information about different crop types growing in a region helps in crop monitoring and estimating yield. Advanced remote sensing technologies allow us to map different crops growing in a region more accurately and frequently than traditional field surveys. Hyperspectral data's spectral and spatial richness has made it possible to use this data for more accurate classification of various crops compared to multispectral datasets. The present research focuses on effectively utilizing high-resolution hyperspectral data for agricultural crop classification. Combining hyperspectral data with advanced machine learning techniques, i.e., autoencoder (AE) and artificial Neural Networks (ANN), are used for generating a hybrid crop classification technique based on unsupervised feature extraction and supervised classification. Unsupervised AE techniques are used for feature extraction of high dimensional hyperspectral data and supervised ANN is used for final crop classification with the help of learned features. This research focuses on developing a hybrid AE-ANN-based model to achieve classification with better discrimination. The hyperspectral data acquired by the Airborne Visible Infrared Imaging Spectrometer- Next Generation (AVIRIS- NG) sensor from the Anand region of Gujarat, representing the study area, was used for crop classification. The developed model showed an overall accuracy (OA) of 97% using 20 extracted features. The proposed neural network model outperformed the popular SVM classifier, providing better classification accuracies and demonstrating the excellent discrimination of extracted features.

Key words**:** ANN, AVIRIS-NG, autoencoder, crop classification, feature extraction, hyperspectral

Introduction

The advent of remote sensing technology like Hyperspectral Imaging has increased its utilization for monitoring various objects on Earth Xue *et al.*, (2017). Hyperspectral images are three-dimensional data cubes with spatial information in x and y coordinates and spectral information in z coordinates Wang *et al.*, (2018). The detail and continuous spectral information in hyperspectral data have increased its scope in various application areas like crop classification, mineral mapping, and agricultural application Liang H. and Li Q. (2016). Hyperspectral data's spectral and spatial richness improves crop classification accuracy compared to multispectral datasets Bhattacharya *et al.*, (2018). Feature extraction is crucial in improving classification performance since it is challenging to classify hyperspectral data due to many features. Implementation of linear feature extraction methods like Local Linear Embedding (LLE) and Principal Component Analysis (PCA) and are unable to model nonlinear properties present in hyperspectral data Chen *et al.*, (2014). Various techniques, such as manifold learning, are proposed to extract nonlinear features, but they have limitations due to increased computational complexity Zhang *et al.*, (2012). The related work done in hyperspectral data classification utilizes conventional linear feature extraction and pattern recognition based on raw data. Traditional feature extraction method includes PCA (Principal Component Analysis) Uddin *et* *al*., (2017), LLE (Locally Linear Embedding) Huang *et al*., (2012)., ICA (Independent Component Analysis) Du *et al*., (2006), and LDA (Linear Discriminant Analysis) Yuan *et al*., (2013). These feature extraction methods are linear and cannot account for nonlinear features present in hyperspectral data, which is necessary for better discrimination of different crops in classification. Autoencoder-based feature extraction has a good scope for extracting highly informative features by utilizing a nonlinear activation function. In recent years, neural network models, like deep convolutional neural networks (CNN), have been used in the classification process in various fields. Chen has used AE for hyperspectral data classification. Researchers have utilized CNN for feature extraction in hyperspectral data Chen *et al*., (2014). Neural networks can learn the nonlinear features in the data using various nonlinear activation functions. Therefore, we have utilized an unsupervised network for feature extraction followed by a supervised network for the classification of hyperspectral data. The building of the classification model combines two steps:

1. Unsupervised feature extraction using autoencoder (AE) and
2. Supervised Artificial Neural Network (ANN)

Layerwise training of the autoencoder network is done to learn the critical encoded features. These encoded features are used as inputs for supervised classification using different class labels. By utilizing this model, highly useful features can be extracted and used for classification simultaneously. First, we apply an unsupervised autoencoder network for feature extraction, followed by a supervised artificial neural network utilizing these encoded features for classification.

Material and Methods

Model Architecture

AE network is a feed-forward neural network in which the unsupervised training of the network is done Licciardi *et al*., (2011); Priya *et al*., (2019). Since hyperspectral data consists of many continuous spectral bands containing redundant information, resulting in reduced classification accuracy, feature extraction is a vital step for more accurate classification of hyperspectral data. Most feature extraction methods are linear and do not capture the non-linearity in hyperspectral data. However, the autoencoder (AE) neural network considers the non-linearity present in the data. AE consists of the first input layer, which contains the input data; the middle-hidden layer, which contains encoded features; and a decoding layer, which gives the reconstructed output. These encoded features have been used as input for supervised classification using ANN. The features extracted from the autoencoder network contain maximum information with reduced noise, improving classification accuracy. The ANN for classification consists of an input layer of encoded features, a middle layer containing the ReLu activation function, and the last classification layer using softmax to obtain multiclass classification. The complete overview of the combined model is presented in the Fig. 1.

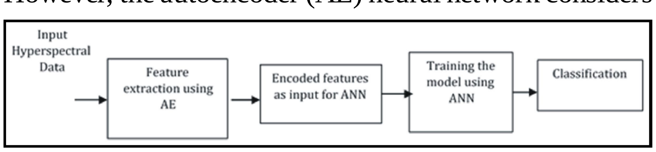

Fig. 1: An Overview of the proposed model.

Autoencoder (AE) for feature extraction

AE is considered an unsupervised feed-forward neural network that contains three layers: input layer, hidden layer or encoding layer, and output or decoding layer. First, the input layer contains the input satellite data *X*; then, the middle hidden layer contains encoded features represented by *G*, and then a decoding layer that gives the reconstructed output represented by $G^{|}$. The number of units in the input layer equals the number of bands present in the input data *X*. Fig. 2 illustrates the architecture of AE, showing the input layer, encoding layer, and reconstruction layer.

The input layer is encoded into the hidden layer using the sigmoid activation function, as illustrated in Equation (1).

$$G = fa\ (wX + b) \quad (1)$$

Where *G* denotes the hidden or encoded feature layer, *w* is the encoded weights, f_a is the activation function,

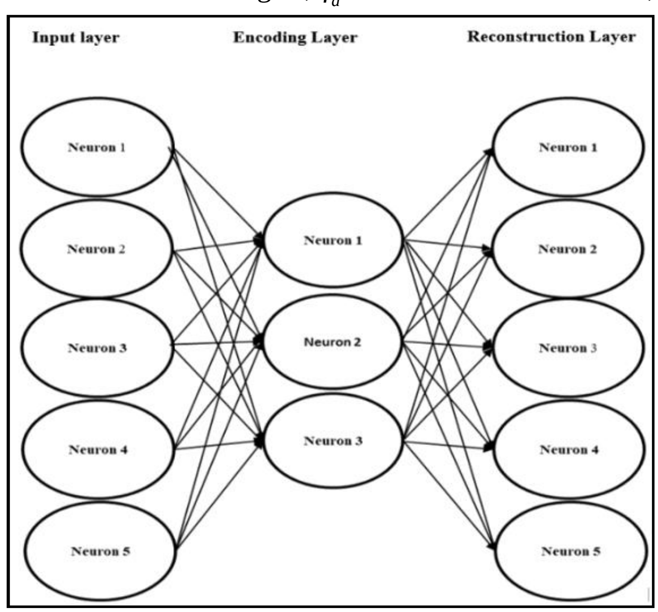

Fig. 2: Architecture of autoencoder.

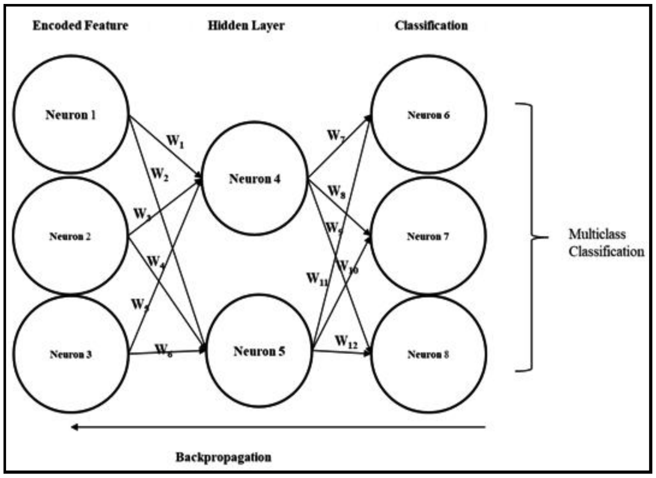

Fig. 3: Neural Network Architecture for classification.

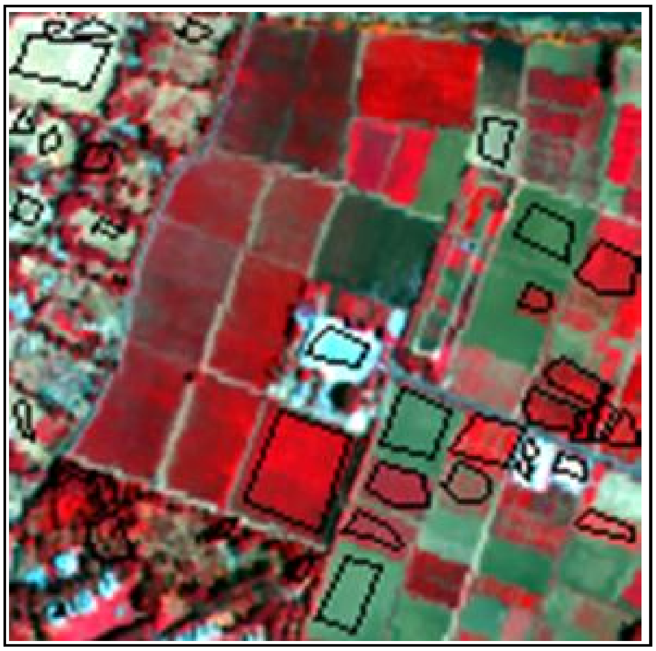

Fig. 4: FCC of AVIRIS-NG showing polygons of labeled classes.

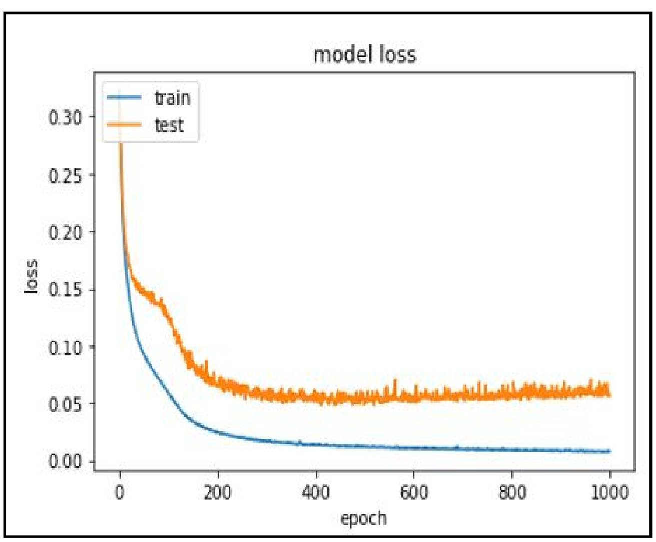

Fig. 5: Model loss in ANN.

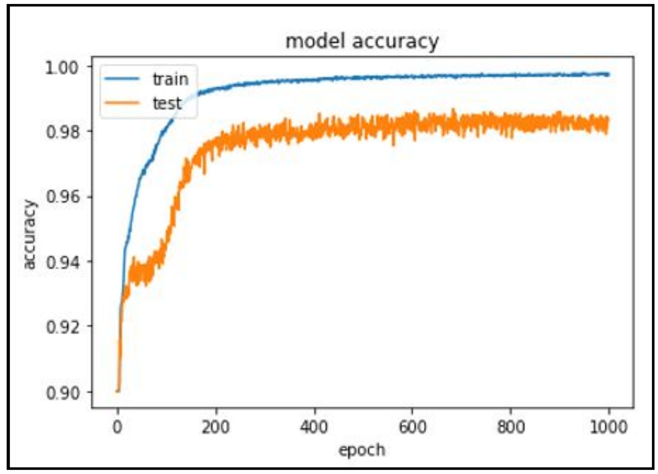

Fig. 6: Classification accuracy of ANN.

and b denotes the bias. The sigmoid activation function accommodates nonlinear features present in the data as represented in Equation (2).

$$f_a = \frac{1}{1+e^{-x}} \tag{2}$$

The sigmoid activation function varies from 0 to 1. These encoded features are then used to reconstruct the original image using a demapping function, as presented in Equation (3).

$$G' = fa\,(w' G + b) \tag{3}$$

where G' is the reconstruction of original data X and W' is considered decoding weights. The output decoding layer has the same number of nodes as the input layer.

ANN for classification

ANN framework consists of the input layer, hidden layer, and output layer, which are linked to each other through weights obtained from using different activation functions depending on the purpose of its application, as

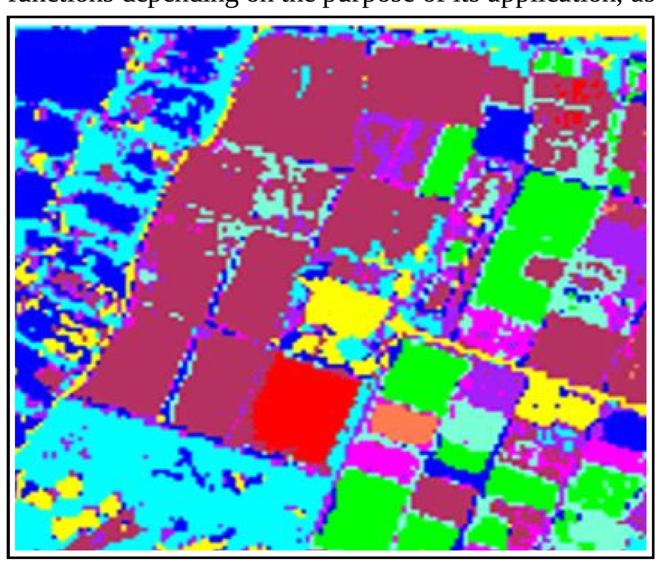

Fig. 7: Classification result of the proposed model with twenty encoded features.

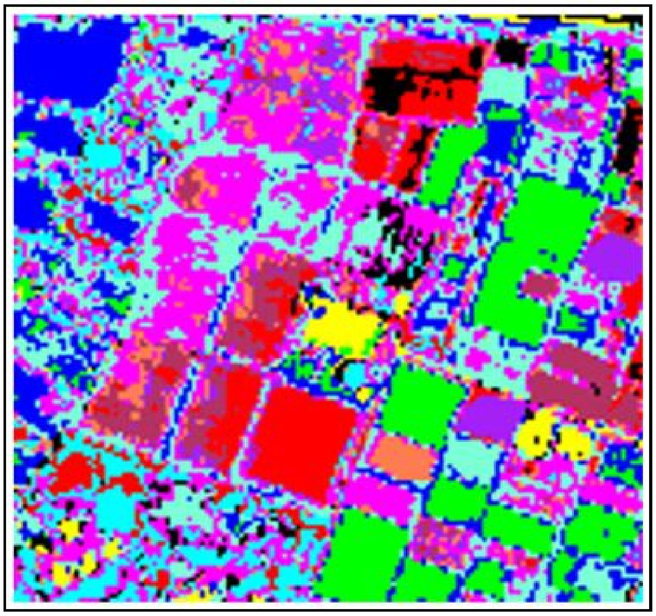

Fig. 8: Classification result of the proposed model with ten encoded features.

depicted in Fig. 3. In this research, we are using the features extracted from AE as the input layer of the ANN model.

Labeled class data is used to fine-tune the model. The ReLu activation function is used in the hidden layer. It is straightforward to implement for classification problems, as illustrated in Equation (4).

$$f(x) = max\ (0, x) \quad (4)$$

In the output layer of the network, classification is done using softmax to obtain a multiclass crop classification. It finds out the maximum probability of the input for being in a particular class represented in Equation (5).

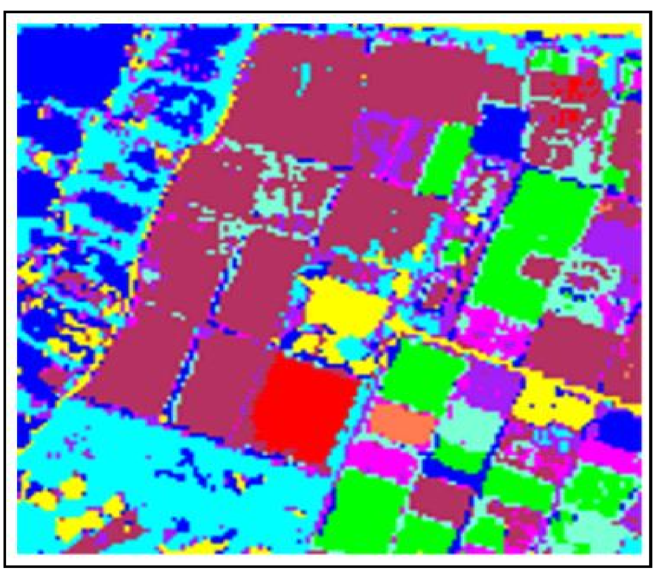

Fig. 9: Classification result of the proposed model with 20 encoded features.

Table 1: Classification accuracy of different classification models.

Classification Model	OA (in %)	Kappa
Proposed model with twenty encoded features	97.74	0.97
Proposed model with ten encoded features	67	0.62
SVM	94.09	0.94

$$\sigma(x)k = \frac{e^{xk}}{\sum_{j=1}^{j} e^{kj}} \ , \ k = 1 \dots , j \quad (5)$$

Here, k is the number of classes. It gives us the probability to determine the classes to which input belongs. It is well suited for multiclass classification problems.

Dataset

For this experiment, we have taken a hyperspectral dataset collected by Airborne Visible Infrared Imaging Spectrometer- Next Generation (AVIRIS- NG) sensor from a test site in the Anand in Gujarat, collected during February 2016 Bhattacharya *et al.*, (2018). The dataset contains 425 spectral bands in the wavelength range of 380-2500 nm with 5 nm spectral resolution.

A small subset of data 145 × 145 pixels is used to evaluate the performance of the proposed model as shown in Fig. 4. The noisy bands and water absorption were removed finally, with a number of bands 368. So, the radiometrically and geometrically corrected L2 data with 368 bands was used for further classification study. Fig. 4 represents the False Colour Composite (FCC) of the hyperspectral dataset by taking the infrared band in the red channel, red band in the green channel, and the

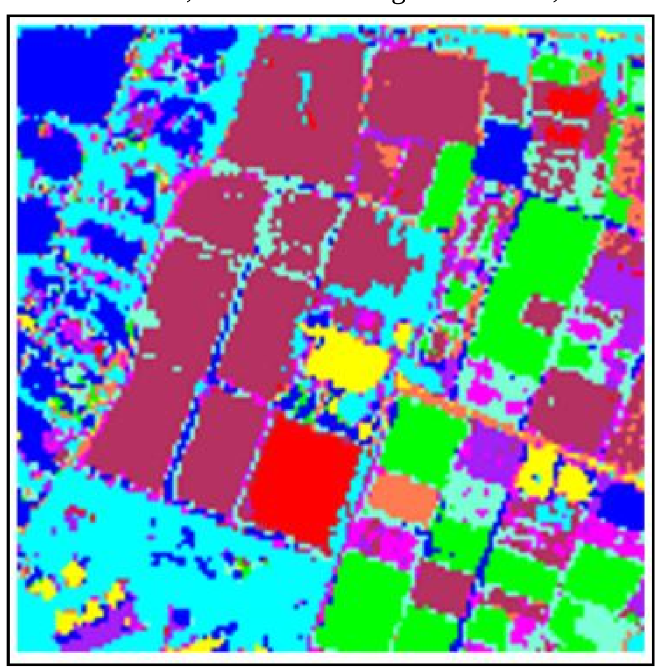

Fig. 10: Classification result of SVM.

green band in the blue channel. Different classes of labeled data are depicted by various polygons indicated in Fig. 4.

Results and Discussion

Steps performed while testing the model over the given hyperspectral dataset are:

- **a.** The hyperspectral dataset is selected, normalized, and randomly split into training and testing sets for the autoencoder network
- **b.** Training of the autoencoder is done by using the sigmoid activation function
- **c.** The features are encoded in encoding layers
- **d.** These encoded features are used as input for classification using ANN
- **e.** The labeled dataset is used for fine-tuning the model
- **f.** The output classified image after applying ReLu and softmax function

The loss function used in ANN is binary cross entropy. Fig. 5 indicates the training and validation loss while training the model for classification in 1000 epochs, while Fig. 6 indicates the training and testing accuracy of the proposed model. The proposed model is compared in terms of classification performance by taking different numbers of encoded features as input and compared in terms of accuracy. The model gave the best performance when 20 encoded features were used for classification, and after that, increasing the encoded features did not improve its accuracy, as represented in Fig. 7 and Fig. 8. The overall accuracy and kappa for different classification models are represented in Table 1. The accuracy was only 67% when ten encoded features were used for classification. The overall accuracy using twenty encoded features increased to 97.74%. The proposed model of a combination of AE and ANN provides good crop

discrimination in classification. The proposed model was also compared with traditional SVM, which gave an overall accuracy of 94%, as in Table 1. The classification results of the proposed model with twenty encoded features and SVM, respectively, are depicted in Fig. 9 and Fig. 10. Table 1 denotes that the model outperformed the SVM classifier.

Conclusion

A cascading neural network model with a combination of unsupervised and supervised algorithms is proposed for hyperspectral feature extraction and classification. AE trains the network in an unsupervised manner, followed by classification in a supervised manner. The features learned by AE are used for further supervised classification using the ReLu activation function to achieve better discriminations of classes by achieving sparsity in features. The proposed model performed best in the experiment when only 20 encoded features were used for classification. So, only 20 spectral features are sufficient for classifying hyperspectral data instead of all 368 spectral bands. Also, the proposed neural network model out performed the popular SVM classifier, providing better classification accuracies and demonstrating the excellent discrimination of extracted features. In this model, we are using only spectral features of data, but spatial information also plays an important role due to the relationship between neighboring pixels. So, further work can be carried out utilizing spatial information for better classification performance.

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