Section A-Research paper
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A DETAILED ANALYSIS ON CLASSIFICATION AND FEATURE EXTRACTION TECHNIQUES FOR HYPER SPECTRAL REMOTE SENSING CROP IMAGES

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ABSTRACT

Crop classification is gaining more attention in the medical and pharmaceutical fields as it benefits in producing medicines for managing life-threatening diseases. Medicinal Crop contributes prevent human and animal health by building medicinal properties on their roots, stem, and leaves. Further different parts of the Crop produces several concentration of distinct molecule compounds as a predominant component of medicinal usage. However manual analysis of the medicinal properties of the Crop is highly complex as it requires taxonomical skills. To alleviate those challenges, a hyperspectral imaging sensor has been employed to extract the biophysical traits of the Crops. Further classification of the biophysical properties is carried out using machine learning and deep learning model. In this article, an extensive study has been carried out on the analysis of the conventional architecture and its formulation to segment and extract the vital features of the Crop and classify it into suitable types for processing the hyperspectral images. Each architecture initializes the process with a dimensionality reduction process to extract only the significant information on transforming the original data into another feature space based on certain evaluation criteria. The reduced feature is analyzed on the classifier to discriminate the feature based on Crop classes on the objective function of the model. Particularly detection and identification of the Crop classes are effectively carried out on the spatial and temporal details of underlying land cover. However, Crop classification concerning spectral characteristics was 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. Extensive analysis of the architectures on results of the classes on various datasets is evaluated using performance measures.

Keywords

Crop Classification, Deep Learning, Segmentation, Hyperspectral Images, Spectral Index, and Feature selection

1. INTRODUCTION

Hyperspectral imaging employs spectroscopy and remote imaging technologies in sensing a large number of narrow spectral bands and a wider range of the electromagnetic spectrum to capture the properties of the object with multiple spectral representations [1]. Hyperspectral Images classification is carried out by discriminating the spectral wavelength of the images. Hyperspectral imaging is exclusively used for mineral identification and vegetation purposes. Nowadays Crop phenotyping is considered an important research topic in various fields especially in the medicinal and pharmaceutical fields as various parts of the Crop parts has various health benefits.

Medicinal Crop has different benefits for human beings of their biophysical properties. Manual quantization of the Crop and its characteristics is highly complex as many medicinal Crops are found in the deep forest and wrong interpretation leads to severe health complications. To alleviate those issues, computer vision analysis using image processing techniques has been widely recognized as a classification and prediction system [2]. Conventional methods of Crop detection and classification using feature extraction, feature selection, and classification processes using machine learning and deep learning architecture. Despite of impressive progress of the deep learning and machine learning model still, several challenges have been exhibited while validating the model.

In this article, extensive analysis has been carried out on the machine learning and deep learning architecture employed for the Crop classification based on its molecular compounds of the biophysical characteristics of the Crop acquired using remote sensing technologies in the form of hyperspectral images. Hyperspectral images have been processed

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concerning region segmentation, end member extraction (feature extraction) of the particular pixel, end member selection (feature selection) on the particular segmented region, and classifier model. Finally, a detailed investigation of those techniques has been validated concerning performance metrics.

The rest of the article is organized as follows, section 2 defines preliminary details of the Crop, sensing technology employed to acquire the Crop information; hyperspectral images datasets representing the Crop information, and processing elements of the hyperspectral images**.** Section 3 details the problem statement. Section 4 details the analysis of the feature selection techniques for hyperspectral images, analysis of spectral indices of the hyperspectral images, and analysis of classification architecture to hyperspectral images on its results on various performance measures to different types of datasets. Finally, the article is concluded in Section 5

2. REVIEW OF REMOTE SENSING DATA

In this section, preliminary details of the Crop, sensing technologies employed to acquire the Crop characteristics information and hyperspectral image dataset, and processing elements of the hyperspectral images have been defined**.**

2.1. Crop

Crop is a source of oxygen and it is a vital part of human being. The crop is more significant to the biodiversity of the earth as provides oxygen to the healthy living of the human and animal being. The crop is used as a source of food and source of medicine for human and animal health. There is a large no of Crops available in the world and it is discriminated based on its biophysical characteristics and biochemical molecule compounds. 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 [27]

2.2. Types of Hyperspectral Imagery

The hyperspectral imager is a sensing technology to acquire the region of interest using it as imaging spectroscopy. It acquires images in the form of spectral bands [3]. A wide variety of hyperspectral imagers has been employed based on the application and its usage. In this work, the hyperspectral imager for acquiring the Crop information is as follows

2.2.1 Proximal HSI system

Ground HSI system used to study Crop properties and conditions for the purpose of monitoring Crop health, detecting diseases, preventing from spreading, and precision control of a herbicide process (i.e., spraying weed species only, hence leading to reduction of herbicide amount, weed species' resistance to herbicide, and pollution effect of herbicide to the environment). Satellite imagery plays a vital role in research and developments for exploration and improvement in agriculture monitoring and catastrophe monitoring and numerous fields [26].

Advantage of the Proximal HSI system

- It captures detailed information, especially in terms of spatial resolution
- It has many spectral indices for Crop properties and conditions
- Reduction in the workforce and the amount of herbicide used
- Improvement in the production process of weed management

2.2.2 Remote HSI systems

Unmanned vehicles and satellites have been utilized to observe large areas as well as can access harsh environments containing various types of Crops. It is highly efficient in the identification of its presence and composition. It is processed based on the absorption features of the Crop for mapping and characterizing the Crop. It is processed on the spectral coverage and spectral resolution based on the abundance of the Crop type. It is observed in visible to the near-infrared region on the spectral features in the ~450, ~530, ~660, 700–720, ~740, and ~760 nm regions. Advantages of the Remote HSI system

- Covering large areas in a single imaging
- Applicability over a wide range of applications- Crop Change detection and Crop Classification

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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 [28]

2.3. Hyperspectral image dataset

Hyperspectral image dataset is obtained using various spectrometers for Crop information from the dense forest regions. The dataset employed for Crop classification is as follows

2.3.1 AVIRIS - Indian Pines

Indian pine dataset is captured using the AVIRIS sensor which is captured in the India regions. The size of the images is 145*145 pixels with spatial resolutions of 20m covering various Crop crops on the inclusion of the ground truth reference data [4].

2.3.2 WHU-OHS dataset

The dataset is captured using Orbita hyperspectral satellite sensor which is captured in the India region ranging from the visible to near-infrared range. The size of images is 512*512 with a spatial resolution of 15m covering various Crops.

2.4. Fundamentals of spectral imaging

Spectral Imaging is the collection of spectral information which is referred to as spectrum at every location in the image. Spectral imaging is used to absorb the area of interest through several criteria including spectral range, spectral resolution, and number of bands.

2.4.1 Reflection of Spectra or Spectral Signature

Reflection of the spectra is termed a Reflectance spectrum as it is independent of the illumination. It identifies the Crop in the monitored region through a library of known reflectance spectra of the objects. Spectral signature is a measure of the variation of reflectance of the material or Crop for wavelength. Image processing is also widely used in agriculture. The technology's main advantage is that it is non-destructive, meaning it can provide vital information on crops without having to touch them [29].

2.4.1 Endmember Spectra

Unique Spectral signature in the particular image pixel or wavelength of the band. It constitutes abundance [5].

3. PROBLEM STATEMENT

Hyperspectral images containing food crops and medicinal crops have been acquired using the Indian spines dataset. Spectral Signature and endmembers of the spectral images have been extracted to classify the species to the spectral indexes. The classification models using the machine learning model and deep learning model will lead to the following issues

- The major challenge of the automated Crop classification system is an overfitting issue on the distributions of HSI data containing noise has been considered a research problem in Crop classification.
- The evolution of spectral intensities in the monitoring region will lead to misclassification. Hence maintaining the quality of the feature for recognition on the fusion is another challenge in enhancing the classification accuracy.
- Redundant information produces greater and more complex feature vectors on the hyperspectral images, which leads to large computation and misinterpretation errors.

4. SPECTRAL INDICES

Spectral indices are used to differentiate between the spectral profile of the Crops on its various conditions over the different regions such as weed and Crop differentiation, healthy and disease Crop differentiation and finally used to determine the severity level of the Crop. The spectral profile of the Crop is measured in terms of the wavelength. Spectral indices are used to calculate the Crop parameters and it is used as a feature.

4.1 Soil-adjusted vegetation index

It is used for analyzing various properties of the Crop and its stress [6]. It has a positive correlation in the visible spectrum was found between leaf pigment contents and seasonal stress levels

- The pigment concentration levels of stressed Crops in seasonal conditions only reached 40–50% of that under the relaxed condition. This means that the variation in the spectral profiles, due to pigment variation, can be used to detect and identify the stressed leaves
- Analysis of green pigment levels (i.e., chlorophyll) as they provide insight into leaf condition on that leaf area and structure plays an important role in estimating green pigment.

4.4.1 Normalized vegetation Difference Index (NVDI)

It is used to measure Crop density and health of the vegetation on remotely sensed images on a value range of -1 to 1. The vegetation region of the monitored region is computed as

- In that non-vegetation area is represented as -1.
- The value ranges between 0.2 to 0.5 is considered sparse vegetation
- A value greater than 0.6 is treated as dense vegetation.

5. REVIEW OF LITERATURE

Image segmentation techniques are employed in hyperspectral images to segment or extract the continuous and similar regions or patterns by dividing the image into disjoint sets as it is complex to exploit the large amount of data in the reflectance spectrum of each pixel in the hyperspectral images. Segmentation facilitates the easier analysis of hyperspectral data. Further in this part, various segmentation techniques are exploited in detail as follows

(Alp Ertürk and Sarp Ertürk) In this segmentation technique, the phase correlation of the images is computed to effectively discriminate similar and dissimilar images based on the peak values of the pixels and threshold. Further, it is capable of detecting the local and global variations of spectral and spatial variability. It is also considered a region-growing technique as it

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deals with a threshold to segment the image. The segmentation model is highly suitable to correct the target spectral signatures under varying conditions. The model is highly capable of discriminating the spectral variability and significantly decreasing the computational load of the classifier [21].

(Pedram Ghamisi, Micael S et al) In this segmentation technique, the high dimensionality of the hyperspectral images uses a multilevel thresholding method through the concept of fractional derivatives on the histograms of the images to achieve the desired characteristics related to food or medicine. Fractional derivatives are used to converge the pixels. It is capable of finding the maximum intensity value on the optimal set of the thresholds to segment end-members of the particular spatial representation on spectral signatures similarity. Further discontinuous and non-differentiable pixels are segmented effectively on processing the parameters of the derivatives. The model is capable of handling the curse of dimensionality issues [22].

(Pedram Ghamisi, Micael S. et al) In this segmentation technique, segmentation of the hyperspectral image is carried as a hierarchical region-based representation in the tree structure. Tree structure explores the pixel at various segmentation scales to obtain the compact representation of the optimal segments Further segmentation process includes various pruning strategies on the spectral Unmixing concepts of the pixel as it contains the spectral signature of the medicinal crop in the particular end member of the images and on their fractional abundances of each pixel. The model is capable of handling the global minimum reconstruction error [23].

(Jun Li, José M. Bioucas-Dias et al) In this segmentation technique, multinomial logistic regression is employed to learn the posterior probability distribution of the spectral information of the hyperspectral image. The subspace projection method is capable of distributing spectral information, especially highly mixed pixels. Further spectral information emphasizes segmentation of the high mixed pixel along the spatial information for high characterization. Model offers the high computation tractability and flexibility [24]

(Mercier, S. Derrode, and M. Lennon) In this segmentation technique, the hidden Markov chain model is considered for the multi-component representation of the hyperspectral image pixel. The parameter of the pixel is computed using the iterative conditional estimation method.

It computes the parameter of the pixel on the transition of the image into the matrix. Matrix operation represents the vector. Vector data process further to combine the similar spectral signature as separate segments [25]. Analysis of the various image segmentation techniques for the hyperspectral image is as follows

Table 1: Analysis of Segmentation techniques for hyperspectral images

Technique	**Objective**	**Advantages**	**Challenges**
Modified Phase Correlation	It is to discriminate similar and dissimilar pixels of the images based on the peak values of the pixels and threshold	The model is highly capable of discriminating the spectral variability with a segmentation accuracy of 98.25%	Lack of robustness
Fractional order particle swarm optimization convolution network	It is estimate the maximum intensity value on the pixel of the image to segment end-members on spectral signatures similarity	It is capable of handling the global minimum reconstruction error and generates a segmentation accuracy of 94.56%	It leads to high computation costs or load
Binary Partition Tree	It processes the image in the Tree structure to explore the pixel at various segmentation scales to obtain the compact representation of the optimal segments	Model is capable of handling the curse of dimensionality issues and it produces a segmentation accuracy of 95.15%	It increases the computation time
Multinomial logistic regression	It is to learn the posterior probability distribution of the spectral information	The model offers high computation tractability and flexibility. It	It produces high generalization errors.

	of the hyperspectral image containing highly mixed pixels	provides a segmentation accuracy of 92.01%	
Hidden Markov chain	It is considered a multi-component representation of the hyperspectral image pixel and it estimates the Parameter of the pixel using iterative conditional estimation method s	It is capable of accurately distinguishing each pixel with a segmentation accuracy of 92.14%	It leads to high computation load and cost

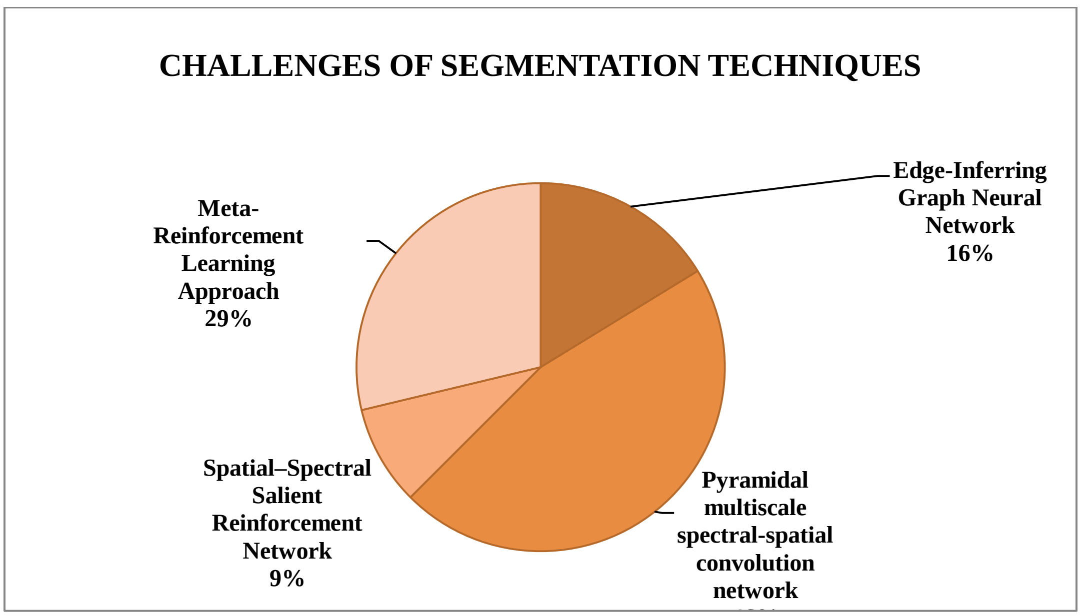

Fig 5.1 Challenges of Segmentation Techniques

Feature extraction is carried the reduced feature space on holding significant information by discarding the redundant and irrelevant features. The spectral and spatial feature is required to increase the classification accuracy. Various techniques are employed for feature extraction to spatial neighborhood relation.

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(Y. Y. Tang, H. Yuan, and L. Li) Principle Component analysis uses the variance of the projection index to extract the spectral features. The principle Spectral feature is extracted on establishing the spectral signature of the image in the form of covariance and correlation matrix. It produces spectral features as none zero Eigen value in the Eigenvector. The transformation matrix of the PCA is composed of weighted learning on the morphological operation of the images [7].

(P. Du, J. Xia, et al) the spectral signature of the image is processed and the feature is extracted using a scatter matrix. The scatter matrix is based on the optimization criteria. It uses the mean vector on the probability and covariance matrix of the spectral signatures on the respective pixel. Further, it uses the conditional probability density function to compute the overlapping wavelength of the hyperspectral images based on information divergence [8].

(J. Xia, P. Ghamisi et al) Discrete wavelet transform extracts the spectral feature based on wavelet decomposition without losing significant information. In this wavelet coefficients were considered as spectral features. Wavelet types extract the spectral features for linear Unmixing of hyperspectral images on the mother wavelet of the kernel functions. Especially Haar Wavelet is represented by the different filter banks on the low pass and high passes filter coefficients. [9].

Table 2 represents the analysis of the feature extraction technique employed for hyperspectral images

Table 2: Analysis of feature extraction techniques for hyperspectral images

Technique	**Objective**	**Advantages**	**Challenges**
Principle Component Analysis	Weighted learning on the fusion of spatial and spectral information	Reduces the Computation cost	Lack of robustness
Linear Discriminant Analysis	Feature Ranking to identify the optimal subset of features	It has a good generalization ability	Relationship between a leaf pigment and its structure

Autoencoder	It is to identify the feature on distance criterion and it identifies the best combination of features.	Each Feature is highly discriminative to the other.	Indices were tested for a limited number of species
Discrete Wavelet Transform	It identifies the spectral features of wavelet decomposition	It abstracts the complex features	It is invariant to changes.

(B. Rivard, J. Feng et al) Autoencoders extract high-level features and progressively learn abstract and complex features from lower ones at higher layers, which are typically invariant to local changes. The image is processed as an input-to-hidden weight matrix. It is capable of minimizing the reconstruction error in producing the reduced set of features. Autoencoder is stacked to generate the deep features. It determines the features of parameters of greedy learning [10].

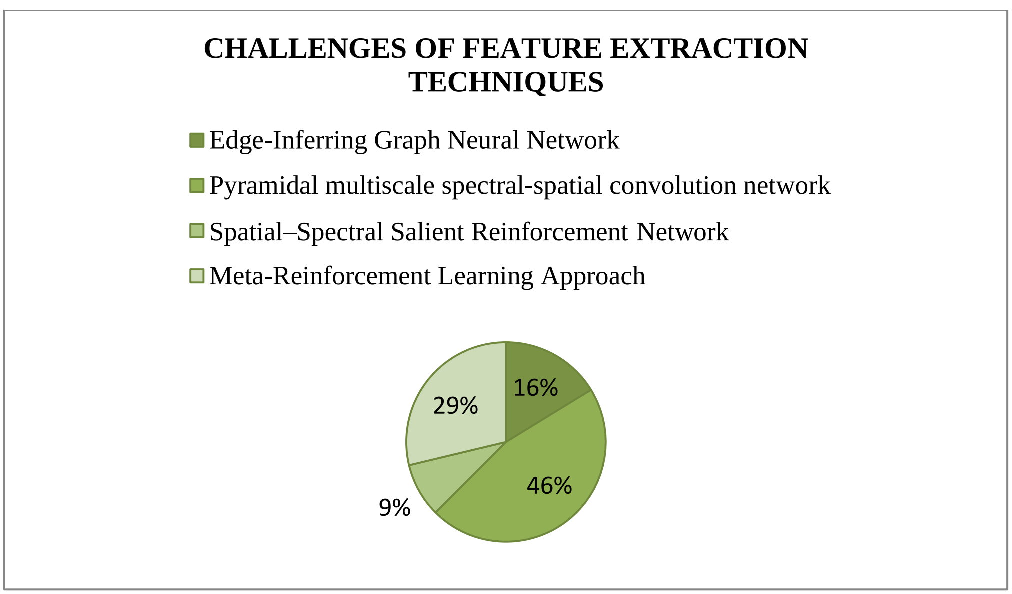

Fig 5.2 Challenges Of Feature Extraction Techniques

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The hyperspectral feature selection technique is to obtain the optimal set of features for classification and it can improve the performance of classification. It consists of criteria along the data characteristic to estimate the optimal subset. Feature selection contains the searching, evaluation, stopping, and validation functions as built-in processes. It is generally categorized based on the evaluation criteria such as wrapper, filter, and embedded. Table 3 provides the analysis of feature selection techniques on features of the hyperspectral images.

Table 3: Analysis of feature selection techniques for hyperspectral images

Technique	**Objective**	**Advantages**	**Challenges**
Genetic Algorithm	It obtains the features of cross-over and mutation operation	Reduces the Computation cost	Lack of robustness
Particle Swarm Optimization	It obtains the spectral and spatial features on the pest and g best operation	It has a good generalization ability	Relationship between a leaf pigment and its structure
Ant Colony Optimization	It obtains the features of correlation constraints	It is capable of extracting the multivariate features.	It is highly uncertain
Grey Wolf Optimization	It identifies spectral features and spatial features of thresholding conditions	It abstracts the complex features	It is not capable low order approximation of the features
Mutual information	It uses effective criteria to select the feature based on nonlinear and non-parametric characteristics	It is capable of measuring the redundancy of the feature	It fails the approximating the features

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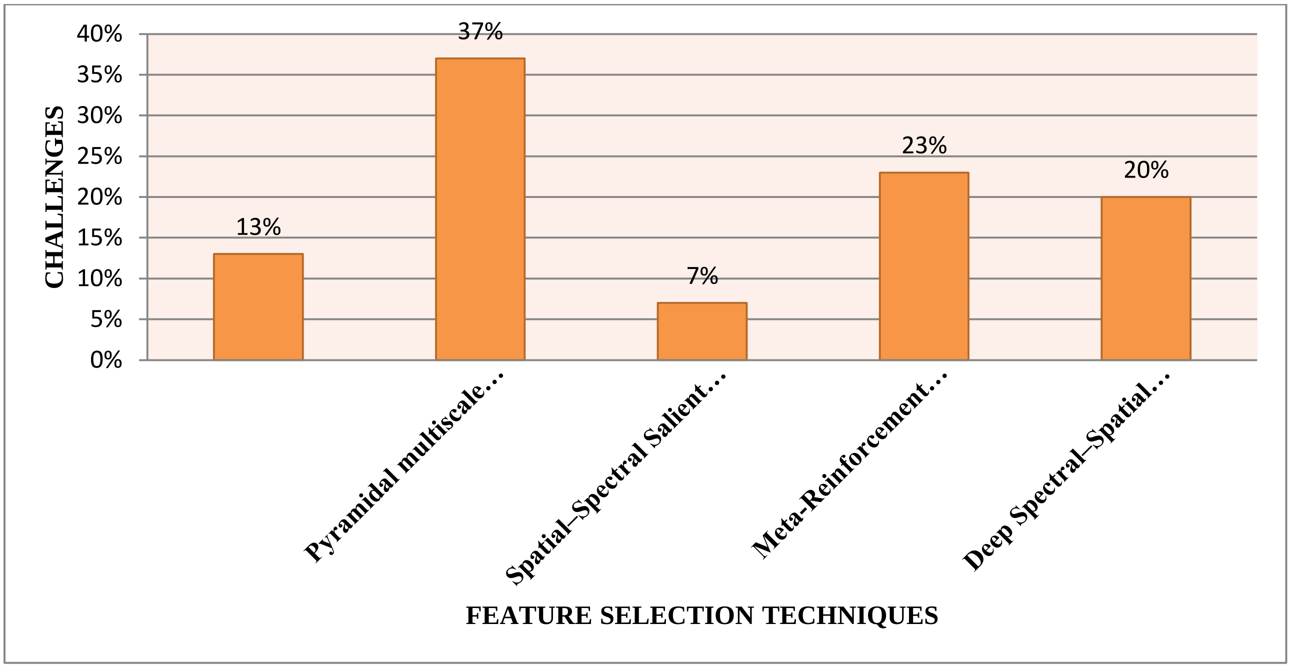

Fig 5.3 Challenges Of Feature Selection Techniques

(Schmalz M.S, Ritter G.X et al) The genetic algorithm computes the optimal features of the spectral endmember and spatial endmembers of various Crop hyperspectral images and is carried out using the crossover and mutation operation of the endmember population. It selects the best spectral and spatial feature for endmember classification. The genetic algorithm considers each end member as a chromosome and selection strategies are carried out concerning crossover [11].

(O. E. Malahlela, M. A. Cho et al) PSO is a population-based search algorithm for optimal spectral and spatial features to Crop classification and the feature vector containing the endmember is initialized as random particles. Each particle has its velocity, and particles with velocities dynamically adjust based on historical behaviors. The particles tend to better search areas in this process and are considered optimal spectral features and spatial features [12].

(Y. Qian, M.Ye, and J. Zhou) ALO mimics the hunting mechanism of ant lions in nature to estimate the optimal features considered as endmembers. It involves five main steps to compute suitable end members for classifications: the random walk of ants, building traps, entrapment of ants in traps, catching prey, and re-building traps [13]

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(Y. Tarabalka, M. Fauvel et al) GWO simulates the leadership hierarchy and hunting mechanism of grey wolves in nature for optimal feature selection containing the spectral signatures of the end members. Four types of grey wolves, namely alpha, beta, delta, and omega, are employed for simulating the leadership hierarchy containing the spectral endmember and spatial endmembers. The three main steps include hunting, searching for prey, encircling prey, and attacking prey [14].

(K. Jia, B. Wu et al) In the Rough set, the artificial bee contains three groups: employed set, onlookers, and scouts which process the extracted feature to select the optimal features for classification. The number of employed bees is equal to the number of food sources, and the employed bee of an abandoned food source becomes a scout. Food sources are considered spectral and spatial endmembers for the classification of the medicinal Crop [15].

The hyperspectral image classification technique to classify the optimal feature is obtained from the feature selection technique. Classifier composed of multiple feature processing elements and layers in machine learning and deep learning model. Further objective function and activation function of the model enables each layer to efficiently discriminate the features into classes based on the functional blocks of the classifier.

Table 4 provides the analysis of the classifier employed for hyperspectral image classification.

Table 4: Analysis of classification techniques for hyperspectral images

Technique	**Objective**	**Advantages**	**Challenges**
Edge-Inferring Graph Neural Network	Graph neural network enables the similarity measurement iteratively infer edge labels with the exploitation of instance-level similarity and the distribution-level similarity	Improve the classification accuracy of the dynamic task-guided self-diagnosis strategy with an accuracy of 98.25%	Lack of robustness

Pyramidal multiscale spectral-spatial convolution network	Self-attention for pixel-wise classification contains three stages: channel-wise feature extraction network, spatial-wise feature extraction network, and classification network, which are used to extract spectral features, extract spatial features, and generate classification results, respectively	It has better converge on the Crop classes in the network with an accuracy of 97.25%	Effectively extract multiscale features of high-resolution HSI in a real-world complex environment
Spatial–Spectral Salient Reinforcement Network	Cross-layer interaction module (CIM) is presented to adaptively alter the significance of features between various layers and integrate these diversified features	It adaptively modifies the center spectrum to reduce intraclass variance and further improve the classification accuracy of the network with an accuracy of 93.15%	It increases the computation time
Meta-Reinforcement Learning Approach	The reward is defined according to an efficient evaluation network for discriminating the feature among the various Crop classes	It ignores the inherent correlation and common knowledge among different features with an accuracy of 92.01%	It is not capable of directly applying to unseen HSI band selection
Deep Spectral–Spatial Feature Fusion-Based Multiscale Adaptable	It uses segments of spectral–spatial features by dual multiscale	It is capable of accurately distinguishing the Crop	It fails to reduce the effect of imbalanced information

Attention Network	adaptable strategies. Spatial wise attention provides an adaptable weight construction strategy for neighboring regions	classes using the attention network with an accuracy of 91.14%	

In this classifier, an optimal feature of the hyperspectral image is projected to the convolution neural network for label prediction The edge-inferring framework with the meta-learning architecture for hyperspectral few-shot classification (HSFSC) along graph neural network enables the similarity measurement iteratively infer edge labels with the exploitation of instance-level similarity and the distribution-level similarity of the Crop classes. Figure 5 provides the performance analysis of the feature classification techniques' accuracy and execution using hyperspectral images.

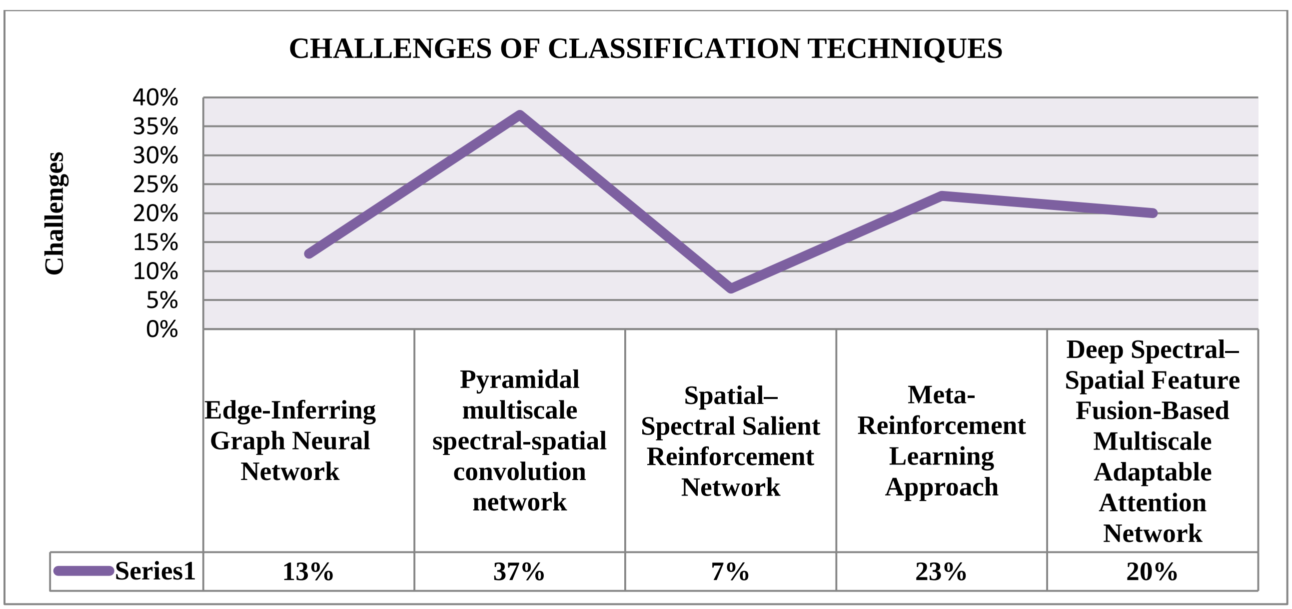

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Fig 5.4 Challenges of Classification Techniques

(J. Lu, L. Tan et al) Besides, in the Meta training stage, the pixel prediction model and the patch prediction model based on edge-inferring architecture are concretized jointly to improve the classification accuracy of the test samples. Expressly, at the met testing phase, the dynamic task-guided self-diagnosis strategy is developed for the first time to diagnose the samples separability of the classification task, which is responsible for dynamically assigning the most reliable Crop class based on the generated reliability grade of the feature [16].

(E. Korot et al) in this classifier, spectral–spatial convolution neural network (CNN) methods with diverse attention mechanisms are employed to classify the optimal features to provide more flexibility over standard convolution blocks. Pyramidal multiscale spectral–spatial convolution network with polarized self-attention for pixel-wise classification contains three stages: channel-wise feature extraction network, spatial-wise feature extraction network, and classification network, which are used to extract spectral features, extract spatial features, and generate classification results, respectively. Pyramidal convolution blocks and polarized attention blocks are combined to extract spectral and spatial features of HSI. Furthermore, residual aggregation and one-shot aggregation are employed to better converge the network [17]

(V. Ayumi, E. Ermatita et al) in this classifier, a deep semantic spectral feature with meaningful constraints has been classified using reinforcement learning. In the spatial dimension, a novel cross-layer interaction module (CIM) is presented to adaptively alter the significance of features between various layers and integrate these diversified features. Moreover, a customized center spectrum correction module (CSCM) integrates neighborhood information and adaptively modifies the center spectrum to reduce intraclass variance and further improve the classification accuracy of the network [18].

(E. Hidayat, Lukman et al) this classifier ignores the inherent correlation and common knowledge among different features. a dynamic structure-aware graph convolution network is constructed to build a common Crop class for the features. Meanwhile, the reward is defined according to an efficient evaluation network for discriminating the feature among the various Crop classes. Further, it uses the state effectively without any fine-tuning to evaluate the classes. Furthermore, a two-stage optimization strategy is incorporated to coordinate optimization directions of shared plat classes for different features. Once the shared Crop classes are optimized, they can be directly applied to unseen HSI band selection tasks without any available samples [19].

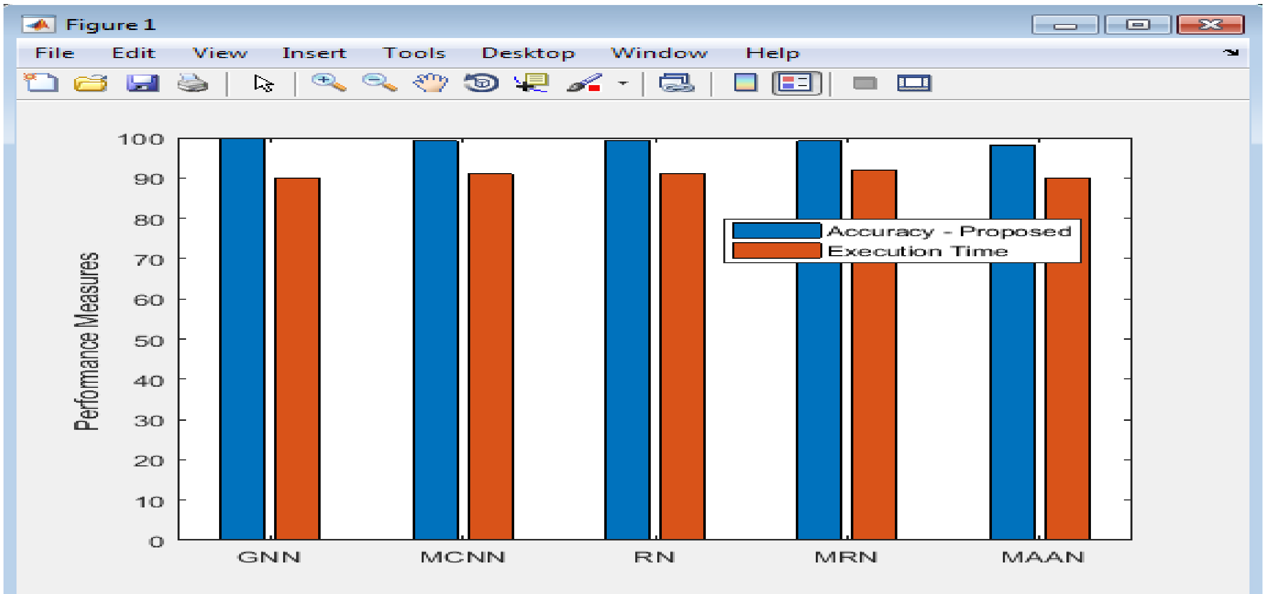

Fig 5.5 Performance Measure of Deep Learning Algorithms

(H. Noprisson, D. I. Sensuse et al)In this classifier, discriminant features captured from the hyperspectral image feature selection technique are used to accurately distinguish the Crop classes using the attention network. It strengthens the local considerable segments of spectral–spatial features by dual multiscale adaptable strategies. Spatial-wise attention provides an adaptable weight construction strategy for neighboring regions. Their adaptive multiscale frameworks reduce the effect of imbalanced information and the spectral-wise attention adaptively strengthens the significant spectral feature for Crop class generation [20].

SUMMARY

In this paper, a detailed analysis on classification, and feature extraction techniques for hyper spectral remote sensing using crop images. Serious issues for crop classification in satellite images using Deep Learning techniques include Random Markov Field, changes in shape and texture properties, and finally spectral signatures. Eventually, crop mapping is conducted in addition to classification on acquired the Indian pines satellite image dataset on several corps.

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The goal of developing new and improved classification models is to improve classification accuracy while keeping computing time within a reasonable range. Urban mapping and planning, agricultural identification and analysis, environmental management, and mineral extraction, to name a few industries, all rely on accurate categorization maps. Two key difficulties have an impact on the categorization results achieved using HSI data: first, the data quality; and second, and the data accuracy. According to the majority of authors, such publications contain several flaws, including a poor accuracy rate and a high maximum classification error rate, as well as high computational values. By increasing the number of optimization components employed and removing the presence of pixel-based classification mistakes, overall performance can be improved. Finally, Review to demonstrate that the proposed method can enhance the severability of crop classes which significantly improved crop classification accuracy. The proposed architecture helps to devise the agriculture decision support for farmers.

6. CONCLUSION

In this article, an extensive study on hyperspectral image classification for Crop classification as different parts of the Crop produces several concentrations of distinct molecule compounds as a predominant component of medicinal usage. Hence deep learning and machine learning classifier for Crop classification using hyperspectral images has been analyzed in detail. The study has been carried out on the analysis of the conventional architecture and its formulation to extract the vital features of the Crop and classify it to suitable type on processing the hyperspectral images using preprocessing, feature extraction feature selection, and feature classification techniques on the spectral and spatial features. Particularly detection and identification of the Crop classes are effectively carried out on the spatial and temporal details of underlying land cover for spectral characteristics obtained on the anatomical features and morphological features.

REFERENCES

[1] M. Fauvel, J. A. Benediktsson, J. Chanussot, and J. R. Sveinsson, “Spectral and spatial classification of hyperspectral data using SVMs and morphological profiles,” IEEE Trans. Geosci. Remote Sens., vol. 46, no. 11, pp. 3804–3814, Nov. 2008

[2] L. He, Y. Li, X. Li, and W. Wu, “Spectral–spatial classification of hyperspectral images via spatial translation-invariant wavelet-based sparse representation,” IEEE Trans. Geosci. Remote Sens., vol. 53, no. 5, pp. 2696– 2712, May 2015

[3] P. Ghamisi et al., "New frontiers in spectral-spatial hyperspectral image classification: the latest advances based on mathematical morphology, Markov random fields, segmentation, sparse representation, and deep learning," IEEE Geosci. Remote Sensing Mag., vol. 6, no. 3, pp. 10–43, Sep. 2018.

[4] B. Waske, S. van der Linden, J. Benediktsson, A. Rabe, and P. Hostert, "Sensitivity of support vector machines to random feature selection in the classification of hyperspectral data," IEEE Trans. Geosci. Remote Sens., vol. 48, no. 7, pp. 2880–2889, Jul. 2010

[5] J. Muñoz-Marí, F. Bovolo, L. Gómez-Chova, L. Bruzzone, and G. Camp-Valls, "Semisupervised one-class support vector machines for the classification of remote sensing data," IEEE Trans. Geosci. Remote Sens., vol. 48, no. 8, pp. 3188–3197, 2010.

[6] J. Xia, M. D. Mura, J. Chanussot, P. Du, and X. He, “Random subspace ensembles for hyperspectral image classification with extended morphological attribute profiles,” IEEE Trans. Geosci. Remote Sens., vol. 53, no. 9, pp. 4768–4786, Sep. 2015.

[7] Y. Y. Tang, H. Yuan, and L. Li, “Manifold-based sparse representation for hyperspectral image classification,” IEEE Trans. Geosci. Remote Sens., vol. 52, no. 12, pp. 7606–7618, Dec. 2014

[8] P. Du, J. Xia, W. Zhang, K. Tan, Y. Liu, and S. Liu, "Multiple classifier systems for remote sensing image classification: A review," Sensors, vol. 12, no. 4, pp. 4764–4792, 2012.

[9] J. Xia, P. Ghamisi, N. Yokoya, and A. Iwasaki, "Random forest ensembles and extended multi-extinction profiles for hyperspectral image classification," IEEE Trans. Geosci. Remote Sens., vol. 56, no. 1, pp. 202–216, Jan. 2018.

[10] B. Rivard, J. Feng, A. Gallie, and A. Sanchez-Azofeifa, “Continuous wavelets for the improved use of spectral libraries and hyperspectral data,” Remote Sens. Environ., vol. 112, pp. 2850–2862, 2008.

[11] Schmalz, M.S., Ritter, G.X., Urcid, G.: Autonomous single-pass endmember approximation using lattice auto-associative memories. In: 10th Joint Conference on Information Sciences. Elsevier, Amsterdam (preprint, 2008) (Special Issue)

[12] O. E. Malahlela, M. A. Cho, and O. Mutanga, “Mapping the occurrence of chromolaena odorata (L.) in subtropical forest gaps using environmental and remote sensing data,” Biol. Invasions, vol. 17, pp. 2027–2042, Jul. 2015.

[13] Y. Qian, M. Ye, and J. Zhou, “Hyperspectral image classification based on structured sparse logistic regression and three-dimensional wavelet texture features,” IEEE Trans. Geosci. Remote Sens., vol. 51, no. 4, pp. 2276–2291, Apr. 2013.

[14] Y. Tarabalka, M. Fauvel, J. Chanussot, and J. A. Benediktsson, “SVMand MRF-based method for accurate classification of hyperspectral images,” IEEE Geosci. Remote Sens. Lett., vol. 7, no. 4, pp. 736–740, Oct. 2010.

[15] K. Jia, B. Wu, Y. Tian, Y. Zeng, and Q. Li, “Vegetation classification method with biochemical composition estimated from remote sensing data,” Int. J. Remote Sens., vol. 32, pp. 9307–9325, 2011.

[16] J. Lu, L. Tan, and H. Jiang, “Review on Convolutional Neural Network (CNN) Applied to Crop Leaf Disease Classification,” Agriculture, vol. 11, no. 8, p. 707, Jul. 2021.

[17] E. Korot et al., “Code-free deep learning for multi-modality medical image classification,” Nat. Mach. Intell., vol. 3, no. 4, pp. 288–298, Apr. 2021.

[18] V. Ayumi, E. Ermatita, A. Abdiansah, H. Noprisson, M. Purba, and M. Utami, “A Study on Medicinal Crop Leaf Recognition Using Artificial Intelligence,” in 2021 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS, 2021, pp. 40–45.

[19] E. Hidayat, Lukman, H. Noprisson, D. I. Sensuse, Y. G. Sucahyo, and E. D. Putra, "Development of a mobile application for documenting traditional knowledge in Indonesia: A Case Study of Traditional Knowledge in Using Medicinal Crop,” in Proceedings - 14th IEEE Student Conference on Research and Development: Advancing Technology for Humanity, SCOReD 2016, 2021.

[20] H. Noprisson, D. I. Sensuse, Y. G. Sucahyo, and Lukman, “Metadata Development for Ethnophytomedicine Resources Using Metadata Analysis Approach,” in The 2016 8th International Conference on Information Technology and Electrical Engineering (ICITEE 2016), 2020.

[21] Alp Ertürk and Sarp Ertürk" Unsupervised Segmentation of Hyperspectral Images Using Modified Phase Correlation" IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. 3, NO. 4, OCTOBER 2006

[22] Pedram Ghamisi, Micael S. Couceiro" Multilevel Image Segmentation Based on Fractional-Order Darwinian Particle Swarm Optimization, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, Volume: 52, Issue: 5, May 2014

[23] Miguel A. Veganzones; Guillaume Tochon; Mauro Dalla-Mura; Antonio J. Plaza; Jocelyn Chanussot"Hyperspectral Image Segmentation Using a New Spectral Unmixing-Based Binary Partition Tree Representation, IEEE Transactions on Image Processing (Volume: 23, Issue: 8, August 2014

[24] Jun Li; José M. Bioucas-Dias; Antonio Plaza "Spectral–Spatial Hyperspectral Image Segmentation Using Subspace Multinomial Logistic Regression and Markov Random Fields"IEEE Transactions on Geoscience and Remote Sensing (Volume: 50, Issue: 3, March 2012)

[25] Mercier, S. Derrode, and M. Lennon, “Hyperspectral image segmentation with Markov chain model,” in Proc. IGARSS, Toulouse, France, Jul. 2003, vol. 6, pp. 3766–3768

[26] N. Thamaraikannan and S. Manju, "Review on Image Classification Techniques in Machine Learning for Satellite Imagery," *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, Coimbatore, India, 2021, pp. 144-149, doi: 10.1109/ICAIS50930.2021.9395808.

[27] N. Thamaraikannan and S. Manju," Classification of Satellite Agriculture Imagery to Identify Crop Type Using Deep Learning Techniques - A Review," 2023 International Conference on Computer Communication and Informatics (*ICCCI)*, Jan. 23 – 25, 2023, Coimbatore, INDIA, 2023, 979-8-3503-4821-7/23/$31.00©2023 IEEE.

[28] S Manju and N Thamaraikannan, "Predictive Analysis on Satellite Imagery Techniques", *Journal of Shanghai Jiaotong University*, vol. 16, no. 9, September 2020.

[29] N. Thamaraikannan and S. Manju," Analysis of Support Vector Machine and Convolutional Neural Network to Improve Satellite Imagery," Indian Journal of Natural Sciences, Vol.12, Issue 70, pg.no38885-38897),0976–0997.