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A Comparative Study of ML and DL Classifiers for Land Cover Classifications

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***Abstract*— Multispectral imaging (MSI) has emerged as a powerful tool for detailed land use and land cover classification, leveraging spectral information across multiple wavelength bands. This study presents a comparative analysis of four advanced classifiers: XGBoost, Multi-Layer Perceptron (MLP), DenseNet, and MLP with a global filter (GMLP), applied to multispectral data from the Central State Farm in Hissar, India. The dataset, covering eight land cover classes includes four spectral bands: Red, Green, Blue, and Infrared. Our findings reveal that the MLP with a global filter achieved the highest classification accuracy of 99.77%, demonstrating superior performance in capturing the intricate spectral-spatial relationships in MSI data. DenseNet also performed exceptionally well, with an accuracy of 99.45%. XGBoost, while being the most computationally efficient, achieved an accuracy of 94.59%, highlighting its robustness. This comparative study underscores the importance of selecting appropriate classifiers for MSI applications, with the GMLP showing the greatest promise for accurate land cover classification.**

Keywords— Multispectral imaging (MSI), Multi-Layer Perceptron (MLP), global filter MLP (GMLP), land use and land cover (LULC), Support Vector Machine (SVM), Neural-Network (NN)

I. Introduction

Multispectral imaging (MSI) has revolutionized data acquisition by capturing information beyond the limitations of the human visual system. Unlike traditional RGB cameras, MSI sensors record data across a wider range of wavelengths on the electromagnetic spectrum, encompassing not only visible light but also extending into infrared and ultraviolet regions [1]. This multifaceted approach unlocks a wealth of hidden details within a scene, allowing researchers to analyze subtle variations in material composition, physiological processes, and environmental conditions that would be invisible to the naked eye. The rich spectral information captured by MSI has fueled advancements in numerous fields, including remote sensing for land cover classification with superior accuracy, precision agriculture for crop health monitoring by identifying stress indicators invisible to the human eye, and medical diagnostics for disease detection through unique spectral signatures of tissues [2–4]. MSI is widely used in the food industry to assess quality, detect contaminants, and ensure product authenticity. It enables evaluation of freshness, ripeness, and the detection of defects in food products [5–6].

One of the most significant applications of MSI is in the study of land use and land cover (LULC). Accurate LULC classification is crucial for urban planning, natural resource management, environmental monitoring, and agricultural management. By distinguishing between different types of vegetation, soil, water bodies, and built environments, MSI helps in creating detailed maps that reflect the current state of the land, track changes over time, and support decision-making processes [7–9]. In the context of land use and land cover, MSI provides critical data that can enhance the understanding and management of natural and human-modified landscapes. It aids in monitoring deforestation, urban expansion, crop health, and habitat destruction, providing essential insights for sustainable development and conservation efforts. In [10], Khatami et al. conducted a thorough analysis of the most recent supervised pixel-based image classification techniques for mapping land cover. They discovered overall accuracy of 75% with Support Vector Machine (SVM) and accuracy of 74% using Neural-Network (NN) based classifier. Gislason et al. [11], utilized Random Forest (RF) based classifier for multi-source classification of land cover using geographic data set. In [12], authors have proposed a novel muti-feature model that builds an ensemble of SVM that combines several spatial and spectral characteristics at object and pixel level. Over the past few years, many authors have utilized deep learning (DL) based techniques for classification of multispectral/hyperspectral images obtained using remote sensing to achieve higher accuracy [13–17].

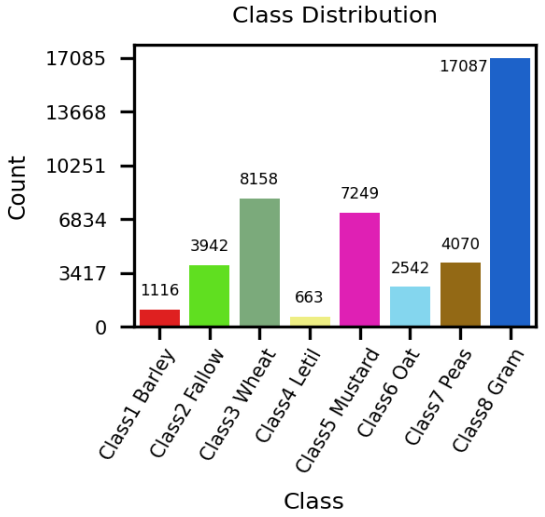


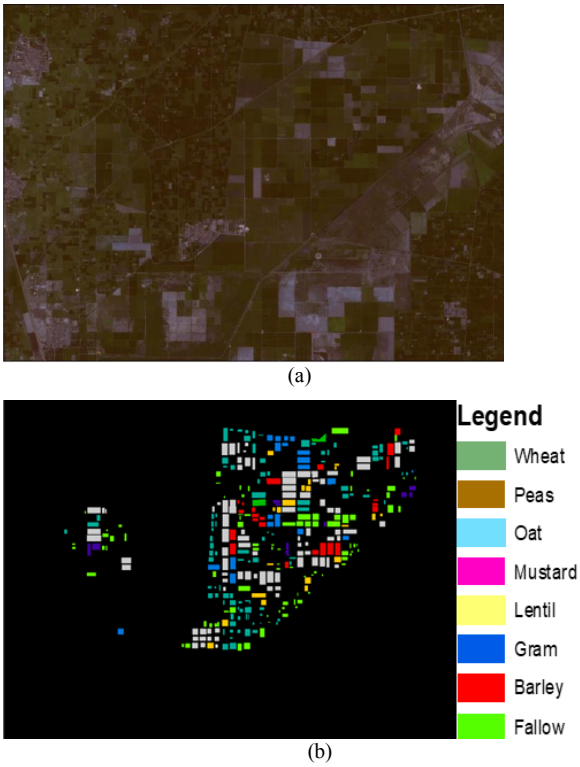
Figure 1. Class-wise data distribution.

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(a)

(b)

Figure 2. (a) Original satellite image (b) Ground truth image

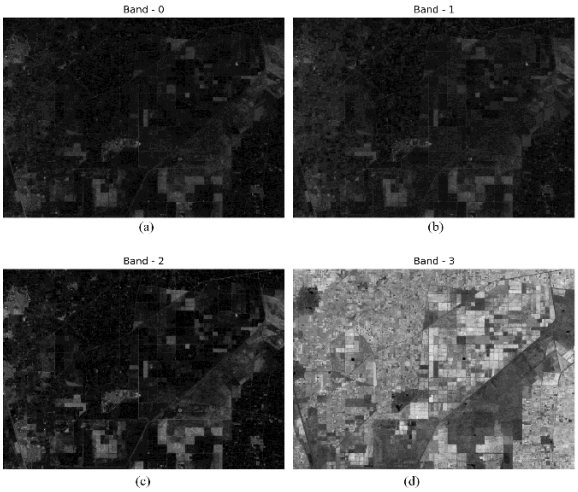


Figure 3. Multispectral images from Band 1 to Band 4.

The processing and classification of multispectral images involve significant challenges due to the high dimensionality and complexity of the data [18]. Each pixel in a multispectral image contains a spectrum of reflectance values across numerous bands, resulting in large datasets that require advanced computational techniques for effective analysis. Traditional classification methods often fall short in handling this complexity, leading to the adoption of sophisticated machine learning and deep learning techniques.

This research paper aims to conduct a comparative study of several prominent classifiers for land cover classification in an agricultural context using MSI data. The focus is on evaluating the performance of these classifiers in handling the unique challenges posed by multispectral LULC data. The classifiers under study include XGBoost, Multi-Layer Perceptron (MLP), DenseNet, MLP with global filter. Through systematic analysis this research seeks to identify the most effective approach for multispectral image classification. By comparing their accuracy, computational efficiency, and robustness, we aim to provide valuable insights that can guide the selection and development of MSI classification technique for LULC applications. This study not only contributes to the theoretical understanding of these classifiers but also has practical implications for improving the accuracy and efficiency of multispectral image analysis across LULC applications.

II. MULTISPECTRAL IMAGE CLASSIFICATION USING DIFFERENT TECHNIQUE

The study area is the Central State Farm in Hissar District, India, covering approximately 72.907 square kilometers. The farm is geographically located with the top left coordinates at 29° 18' 45.65" N, 75° 39' 17.70" E, and the bottom right coordinates at 29° 14' 51.88" N, 75° 45' 26.70" E. The dataset used in this study was obtained from the Sentinel-2 satellite, which provides imagery with a 10-meter spatial resolution. The imagery was acquired on March 8, 2020, and field observations were conducted on March 13, 2020. The data dimensions are 722 x 1014 pixels (width x height). The dataset includes eight classes representing major crops such as wheat, barley, lentil, gram, mustard, oat, peas, and non-agricultural areas. The number of samples corresponding to each class of the dataset are represented in Fig. 1. Further, the original satellite image and the ground truth image are represented in Fig. 2. The MSI images corresponding to all the four bands are respectively represented in Fig. 3 (a), (b), (c), and (d).

A. MSI Classification using XGBoost

The The Extreme Gradient Boosting (XGBoost) algorithm for classification of multispectral images is utilized for our dataset. XGBoost is an efficient and scalable implementation of gradient boosting that builds an ensemble of decision trees in a sequential manner, where each new tree corrects the errors of the previous ones [19]. XGBoost includes regularization techniques to prevent overfitting, handles missing values internally, and leverages parallel processing to speed up the training process. The XGBoost model was trained using the 75% training subset to learn the intricate patterns and relationships within the multispectral data. After training, the model was evaluated on the 25% testing subset to assess its predictive accuracy and generalization capability. The confusion matrix for the XGBoost classifier applied to our MSI dataset with eight classes is presented in Table I. Each row of the matrix represents the actual class, while each column represents the predicted class. Analyzing this confusion matrix provides insights into the classifier's performance across different land cover classes. The classifier shows excellent precision for certain classes, particularly Class 2 and Class 8, while some classes, such as Class 1 and Class 6, exhibit notable misclassifications, particularly into Class 8. The diagonal values in the confusion matrix are relatively high, indicating good overall accuracy, the off-diagonal values highlight specific areas where the model's performance can be further refined.

TABLE I: Confusion Matrix using XGBoost.

	Predicted Class							
Actual Class	175	0	1	0	5	3	0	95
	0	985	0	0	0	0	0	0
	0	1	1932	6	42	1	21	37
	0	0	35	128	1	0	2	0
	13	0	50	0	1731	5	12	1
	0	0	8	0	12	503	7	105
	0	0	53	4	0	0	959	2
	0	0	44	0	30	9	1	4188

B. MSI Classification using MLP

Multi-Layer Perceptron is a type of feedforward artificial neural network, consisting of multiple layers of neurons where each layer is fully connected to the next one [20]. This structure enables the MLP to capture complex, non-linear relationships within the data, making it a suitable choice for MSI classification. While using MLP again the 75% of the data was used for training the model and the remaining 25% reserved for testing the model's performance. The confusion matrix using MLP is presented in Table II. The confusion matrix for the MLP classifier indicates strong performance, with high precision for classes such as Class 2 and Class 4, where almost all instances are correctly classified. Some misclassifications are observed, particularly with Class 3 being confused with Class 5 and Class 8, suggesting areas of spectral overlap.

TABLE II: Confusion Matrix using MLP.

	Predicted Class							
Actual Class	244	0	9	0	3	3	1	19
	0	985	0	0	0	0	0	0
	5	0	1929	6	41	7	21	31
	0	0	4	155	5	0	2	0
	2	0	26	8	1763	4	7	2
	2	0	11	0	7	591	4	20
	1	0	11	4	15	7	974	2
	6	0	32	0	7	5	2	4220

C. HSI Classification using DenseNet

Dense Convolutional Network (DenseNet) architecture is applied to the classification of MSI dataset. DenseNet is chosen due to its innovative approach of connecting each layer to every other layer in a feed-forward fashion, which enhances feature propagation and encourages the reuse of features throughout the network [21]. This densely connected pattern helps in mitigating the vanishing gradient problem, improves model efficiency, and reduces the number of parameters compared to traditional convolutional networks. Fig. 4 presents the architecture of the DenseNet architecture.

The DenseNet model for MSI classification is designed with a filter size of 24 and a growth rate of 12. The model features a dense block size of 3, with each block containing 4 layers. The input shape for the model is a 7x7x4 MSI patch. The architecture includes initial convolution layers followed by four dense blocks (DB-4), each interspersed with batch normalization and ReLU activation functions. Dropout layers are used for regularization, and the network concludes with a fully connected (FC) layer, ultimately producing the classified output. This design leverages the DenseNet's characteristic of dense connections to enhance feature propagation and reduce the vanishing gradient problem, which is crucial for the effective classification of MSI data.

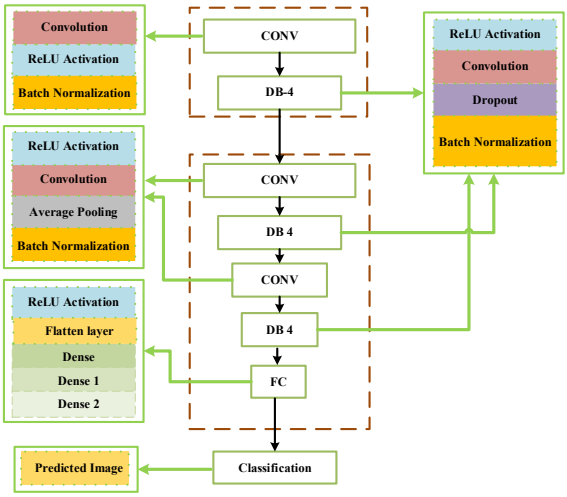


Figure 4. Architecture of DenseNet model

The confusion matrix using DenseNet is presented in Table III. From the confusion it is quite clear that the DenseNet model outperforms compared to XGBoost and MLP. The DenseNet model shows 100% accurate classification for classes 1, 2, 4 and 7. Some misclassifications are observed for classes 2, 5, 6 and 8.

TABLE III: Confusion Matrix using DenseNet.

	Predicted Class							
Actual Class	279	0	0	0	0	0	0	0
	0	985	0	0	0	0	0	0
	0	0	2031	0	4	0	5	0
	0	0	0	166	0	0	0	0
	1	0	13	0	1796	0	2	0
	0	0	0	0	0	619	4	12
	0	0	0	0	0	0	1018	0
	0	0	12	0	1	7	0	4252

D. MSI Classification using MLP with global filter

The global filter is incorporated to preprocess the multispectral data by aggregating spectral information across all bands, thus reducing dimensionality and capturing global spectral features. This preprocessing step enhances the ability of the MLP to learn and classify different land cover types effectively. The global filter extracts significant spectral features from the high-dimensional MSI data, which are then fed into the MLP. This combination leverages the global spectral information and the pattern recognition capability of MLPs, aiming to achieve high classification accuracy. By employing an MLP with a global filter, we seek to improve the classifier's performance in distinguishing between different land cover types. This approach highlights the potential of combining neural networks with advanced filtering techniques to handle the complexities of multispectral data.

TABLE IV: Confusion Matrix using GMLP.

	Predicted Class							
Actual Class	277	0	0	0	0	1	0	1
	0	985	0	0	0	0	0	0
	0	0	2028	0	2	0	5	5
	0	0	0	166	0	0	2	0
	0	0	1	0	1811	0	0	0
	0	0	0	0	0	632	0	3
	0	0	2	0	1	0	1015	0
	1	0	0	0	0	4	0	4267

The confusion matrix for the XGBoost classifier with a global filter (GMLP) shows exceptionally high performance, with most classes achieving near-perfect classification. For instance, Class 1, Class 2, and Class 5, exhibit almost no misclassifications, indicating the model's robust ability to distinguish these classes. However, minor misclassifications are observed in Class 3, Class 4, Class 6, Class 7 and Class 8, where a few instances are incorrectly classified into other categories. Overall, the global filter significantly enhances the model's accuracy, particularly in distinguishing between complex multispectral data.

III. Comparative Analysis of Different Technique

Fig. 5 shows the predicted color map images when all the classifiers applied to the same dataset. In the predicted images for XGBoost and MLP, a few pixels are misclassified, and minor classes are less distinct. However, the DenseNet and MLP with a global filter classifier produce clearer and more detailed color maps. The images generated by these models exhibit well-defined classes with minimal misclassified pixels, demonstrating their superior ability to handle the complex spectral-spatial characteristics of multispectral images.

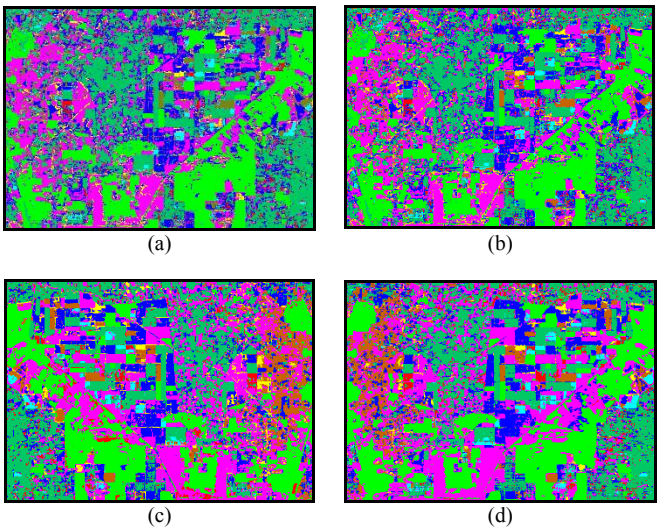


Figure 5. Predicted color map output images (a) XGBoost (b) MLP (c) DenseNet (d) GMLP

The MLP with a global filter, in particular, achieves the highest clarity and accuracy, effectively capturing all classes, including the minor ones, with remarkable precision. Table V highlights the performance metrics of various classifiers applied to MSI classification. The MLP with global filter (GMLP) classifier achieved the highest accuracy of 99.77%, a perfect macro average of 1.00, and a Cohen Kappa score of 0.9970, indicating exceptional performance and reliability in classifying MSI data. DenseNet also demonstrated strong performance with an accuracy of 99.45% and a Cohen Kappa score of 0.9929, albeit with a longer training time of 3327.81 seconds. XGBoost, while being the most computationally efficient with a training time of 1162.28 seconds, achieved accuracy of 94.59% and a Cohen Kappa score of 0.9297. The MLP model showed a balanced performance with an accuracy of 96.91% and a Cohen Kappa score of 0.9601, although it required the longest training time. Overall, the MLP with a global filter (GMLP) stands out as the most accurate and reliable model, while XGBoost offers a robust and efficient solution with shorter training times.

Table V: Performance metrics of different classifiers

Name of the Classifier	**Accuracy**	**Macro Avg**	**Cohen Kappa**	**Train time (Seconds)**
XGBoost	0.9459	0.88	0.9297	1162.28
MLP	0.9691	0.95	0.9601	5432.86
Dense Net	0.9945	0.99	0.9929	3327.81
GMLP	0.9977	1.00	0.9970	1673.41

IV. Conclusion

This research has provided a comprehensive comparison of four advanced classifiers for multispectral image classification, focusing on land use and land cover mapping. The study area, an agricultural farm in Hissar, India, served as an excellent testbed for evaluating the performance of XGBoost, MLP, DenseNet, and MLP with a global filter. Our results demonstrated that the MLP with a global filter significantly outperformed the other classifiers, achieving the highest accuracy and reliability in classification tasks. DenseNet also showed robust performance, though it required a longer training time. XGBoost, despite its lower accuracy compared to the neural network-based models, proved to be highly efficient in terms of computational time. These findings highlight the effectiveness of using sophisticated neural network architectures, particularly those incorporating global filters, for detailed and accurate multispectral image classification. Future work can explore the integration of these classifiers with other advanced preprocessing techniques and the application of these models to different geographical regions and datasets to further validate their generalizability and robustness.

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