Interpretable Machine Learning for Crop Classification Using Decision Boundary Visualization of Multi Classifier Models

Takeru Kobayashi
Kyushu University, Nishi-ku, Fukuoka, 819-0395, Japan.
kobayashitakeru@jimu.kyushu-u.ac.jp

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Corresponding author(s):
Takeru Kobayashi, Kyushu University, Nishi-ku, Fukuoka, 819-0395, Japan.
Email: kobayashitakeru@jimu.kyushu-u.ac.jp

Abstract – Proper classification of crops is one of the core aspects of precision agriculture since it enhances yield prediction, management of resources, and decision-making. Nonetheless, the current machine learning methods are usually confronted with the problem of achieving good classification accuracy versus interpretability, especially in the case of complex and nonlinear agricultural data. SVM and other traditional models that include Support Vector machine and Random Forest offer good competition but do not give any insight as to how decisions are made, thus restricting their use in practice. In order to overcome these weaknesses, this paper suggests a new interpretable model which it has called ADB-Adaptive Decision Boundary Agro Net (AgroNet) to classify crops. The model proposed is a combination of the polynomial expansion of features and a neural network-based classifier that will effectively learn the interactions of features of higher order and increase the separability of the classes. Moreover, a decision boundary visualization based on Principal Component Analysis is included, allowing the human user to have a feel of how the model works, which does not affect the training. The combination of feature engineering and adaptive learning enables the model to produce more distinguishable and smooth decision regions than the traditional methods. ADB-AgroNet performance is compared to models of the state-of-the-art, such as SVM, Random Forest, and K-Nearest Neighbors, with the help of the extensive set of evaluation criteria. It is shown in the experiments that the proposed model has a better classification performance with an accuracy of 94.82, and higher precision, recall, and F1-score. Moreover, the model has a greater robustness and a lower rate of misclassification among all classes. The results indicate that ADB-AgroNet is a practical and reliable tool of solving an issue of accuracy and interpretability that can be applied into the real-life agricultural context.

Keywords – ADB (Adaptive Decision Boundary), AgroNet, (SVM) Support Vector Machine, Multi-Layer Perceptrons (MLPs).

I. INTRODUCTION

Food security, sustainability of agriculture and economic stability are one of the most important sectors of the world. As the need of more crop production and effective use of the available resources continued to grow, the use of smart data methods became critical. Older methods of farming that are usually based on manual observation and the rule of thumb cannot be used to deal with the complexity and variability of the contemporary agricultural systems. Such factors as soil structure, weather changes, irrigation processes, and availability of nutrients have a very nonlinear interaction that makes it extremely difficult to correctly categorize crops and make decisions [1]. In this regard, machine learning is now being viewed as one of the possible solutions to the analysis of agricultural data and assists precision farming applications. In the last 10 years, there are some machine learning models that have been used in crop classification issues, such as Support Vector Machine, Random Forest, and K-Nearest Neighbors. These models have been found to be quite successful in dealing with structured data sets and attaining a fair level of classification accuracy. Nevertheless, the majority of these methods are considerate of predictive performance but not interpretability of the model [2]. Interpretability is also relevant in the agricultural field because farmers and decision-makers need to understand how they arrive at predictions. A model which is very accurate but less transparent might not be practically applicable in the real-world situation.

The second significant weakness of the current methods is that they cannot adequately represent complex nonlinear interactions between input attributes. Data on agriculture may have complicated interdependencies between conditions like temperature, humidity, soil pH, and nutrient amount. Although nonlinearity is addressed by models such as SVM, which uses kernel functions, the models are very sensitive to the choice of the kernel and tuning of parameters [3]. In the same vein, the ensemble-based approaches, including Random Forest, can also deal with nonlinearities, albeit to a lower degree, and also create disjointed decision boundaries that are not easily interpretable. Models such as KNN are distance sensitive and can be weak when dealing with high dimensional space. These constraints demonstrate that a stronger and more understandable framework should be created to allow accuracy and explainability to meet each other [4]. Besides predictive constraints, the issue of visualizing and being able to interpret decision boundaries is not well-explored in the realm of machine learning as applied to agriculture. It is important to understand how a model classifies various classes in the feature space as a way of verifying its reliability and strength. The visualization of decision boundaries helps to gain great insight into how the model behaves especially in determining the overlapping and misclassification areas in addition to the capability of generalization [5]. Nevertheless, systematic visualization techniques are not applied in most of current studies, thus restricting the interpretability of their findings. Methods like the Principal Component Analysis can be used to reduce dimensions as well as visualize them, but their applications with classification models are not fully exploited [6].

To overcome these issues, a new framework design called ADB-AgroNet (Adaptive Decision Boundary Agro Network) to classify crops in an interpretable way can be suggested in this paper. The suggested solution applies to expand the representation of input data using a combination of a neural network-based classifier and a policy to employ the expansion of the areas of the decision boundary to learn [7]. Expansion of features using polyonomials helps the model to represent more complex interaction between features that could be essential in agricultural datasets. These representations are further refined by the neural classifier which learns adaptive nonlinear mappings thus producing smoother and more separable decision regions. In contrast with the traditional frameworks, the proposed framework dwells directly on the performance, as well as interpretability [8].

One of the contributions of this work is that decision boundary visualization has been made a part of the learning framework. The suggested model allows visualizing classification regions intuitively in two dimensions by projecting high-dimensional data onto the two-dimensional space the PCA technique, without any influence on the training process [9]. This does not only increase interpretability but also gives a better insight on model behavior which is crucial in the deployment on the real world in precision agriculture systems. ADB-AgroNet is special in the combination of feature engineering, adaptive learning, and visualization, unlike the current methods [10]. The key findings of this article may be summarized as follows. First, a new hybrid model is suggested, which integrates both the use of the neural classification and the expanded features of a polynomial to enhance the accuracy of crop classification. Second, the visualization of decision boundaries brings in an interpretable learning mechanism that allows understanding model decisions better [11]. Third, comparative analysis is made on a massive basis, as compared with the existing models, with the proposed approach proving to be the best in its performance and soundness. Lastly, the proposed framework is computationally efficient and practical, which is why it will be applicable in the real-world application of agriculture [12].

The rest of the paper is structured in the following way. Section II is a review of the related work in the field of agricultural machine learning and classification methods. Section III shows the suggested ADB-AgroNet methodology in detail. Section IV is a description of the simulation environment and dataset, experimental results and analysis. Lastly, V shows the conclusion of the paper and proposes possible research direction in the future.

II. LITERATURE REVIEW

Machine learning in agriculture has received high attention over the past years especially in the domains of crop identification, yield forecasting, soil analysis, and precision farming. With the growing accessibility of agricultural information, along with improvements in the field of computation methods, it has become possible to create intelligent models that could facilitate the process of decision-making. Nevertheless, in spite of these achievements, the issues of model interpretability, generalization and the need to address nonlinear interactions of features still pose a major concern. The initial research in crop classification was mainly based on classical machine learning models like Support Vector Machine that has been extensively utilized because of its firm theoretical ground and high-dimensionality capabilities [13]. SVM makes use of kernel functions in order to project the input data into higher dimensional space in order to be able to use optimal hyperplanes to classify them. A number of researchers have claimed good results when SVM is applied in the process of agricultural classification, especially with radial basis function kernels. SVM however is very reliant on the selection of the kernel and the optimization of its parameters and it is not always interpretable, which means that it is hard to determine how it comes to certain conclusions.

Ensemble learning methods like Random Forest is the other popular solution that has been implemented. Random Forest will build several decision trees and combine their results in order to enhance the classification performance and minimize overfitting. It has also been used to identify the type of crops, identify diseases in the agricultural field and measure soil properties. Random Forest is also relatively accurate and robust; however, it is also prone to coming up with splintered and disjointed decision boundaries because of its ensemble character. Such fragmentation makes the model less interpretable and difficult to visualize in order to understand how the model distinguishes between classes in complex feature spaces. K-Nearest neighbors and other distance-based models have also been investigated to carry out crop classification tasks. KNN is also computationally efficient towards smaller datasets and it is not computationally expensive to run since it does not involve explicit training. It groups samples in terms of their closeness to the adjacent data points in the feature space. KNN however is extremely sensitive to feature scaling and is affected by curse of dimensionality thus does not do well in a dataset that has many features. Moreover, the model does not have a strong structure of decision boundary, which is why it is not as applicable in applications that are concerned with interpretability.

Deep learning methods have been offered in the past few years to overcome the weaknesses of conventional models. Multi-layer perceptrons (MLPs) and other neural networks have achieved positive outcomes on nonlinear relationships in agricultural data of complex nature. These models are able to acquire hierarchical feature representations in addition to high classification accuracy. Nonetheless, they are frequently black-box models, which can be interpreted in a limited way. Such transparency is an issue of great concern in agricultural fields, where it is imperative to know model decisions in order to implement it practically. In an attempt to enhance feature representation, a number of research works on feature engineering and transformation methods have been conducted. One such method is known as polymorphic feature expansion that adds higher-order interactions between features to the input space. This method has been demonstrated to enhance the efficiency of linear models through their ability to model nonlinear trends. But as a single method, the use of the dimensionality of the expansion of the polynomials can cause the rise of the dimensionality and increase in the complexity of computations, and it is necessary to use it with effective learning techniques attentively.

Dimensionality reduction and visualization is another aspect of machine learning in farming. Principal Component Analysis techniques have been used extensively in order to project high-dimensional data onto lower-dimensional spaces. PCA facilitates the detection of prevailing trends and the removal of redundancy in the data. More so, it allows one to view data distributions and class separability, which is crucial in comprehending model behavior. Although its benefits exist, PCA is not always utilized to the extent of interpretability in terms of decision boundaries visualization as a preprocessing methodology. One of the key gaps that were found in the literature is the absence of the combination of feature engineering with nonlinear learning and interpretability. The majority of the research is based on the enhancement of the accuracy of classification or on visualization of data, but it is done infrequently when these two aspects are considered together. Moreover, the visualization of the decision boundaries that offer first-hand information on the way the models categorize the data is frequently neglected. This restricts the potential of researchers and practitioners to test model robustness and reliability in the real world.

To address these constraints, hybrid frameworks that integrate state-of-the-art feature transformation methods with interpretable learning models are increasingly required. These frameworks need to be in a position to model the intricate nonlinear associations and also generate easy to understand and convenient insights into the decision-making processes. Here, the ADB-AgroNet framework suggested is expected to fill this gap through the combination of the expansion of the polyomial features with neural classification and visualization of the decision boundary. The proposed approach is helpful in advancing machine learning applications in precision agriculture by considering both the performance and interpretability. It is possible to note that, based on the literature, machine learning implementation in the context of agricultural classification has advanced tremendously, yet specific issues that still require crucial solutions are also present. The proposed work is based on these existing studies and a new approach that would improve the accuracy of classification as well as the interpretability and, therefore, offer a more detailed solution to crop classification tasks.

III. PROPOSED METHODOLOGY

In this section, the authors introduce the proposed Adaptive Decision Boundary Agro Network (ADB-AgroNet), which is an interpretable machine learning framework that will enhance the performance of crop classification by increasing the feature representation and separability of the decision boundary. The model is inspired by the fact that agricultural data tends to have complicated nonlinear correlations between the features of soil moisture, temperature, and nutrient content. Classifiers like Support Vector Machine and Random Forest, which are effective in the past, might not be able to effectively characterize these interactions in a balanced and understandable way. ADB-AgroNet overcomes this drawback by combining both neural learning and expansion of the policy by a poly with the use of the expansion of the features being modelled.

The input dataset is represented as a collection of feature vectors $X = \{x_1, x_2, \dots\dots, x_n\}$, where each sample $x_i \in \mathbb{R}^d$ corresponds to a set of agricultural attributes. Prior to model training, the data undergoes normalization to ensure uniform feature contribution and stable convergence. Each feature is standardized using the transformation as stated in Equation (1)

$$x' = \frac{x-\mu}{\sigma} \tag{1}$$

where μ and σ denote the mean and standard deviation, respectively. This step is essential for preventing scale dominance and improving the efficiency of the learning process.

Political expansion of the normalized input is done in order to increase the expressive power of the model. It is this transformation that allows the model to obtain high-order interactions between features, which are frequently found in agricultural systems. The expanded feature mapping is given using Equation (2).

$$\Phi(x) = \{ x_i, x_i^2, x_i x_j \mid i,j = 1,2,\ldots,d \} \tag{2}$$

where quadratic and interaction terms are added. The enhanced representation greatly enhances the separability of classes because the data is projected in a higher dimensional space.

The transformed feature vector is then fed into a neural classification model that is designed on Multi-Layer Perceptron (MLP) basis. The hidden layer representation is calculated by Equation (3).

$$h = \sigma(W_1 \Phi(x) + b_1) \tag{3}$$

where W_1 and b_1 represent the weight matrix and bias vector, respectively, and $\sigma(\cdot)$ denotes a nonlinear activation function. The final output layer produces class probabilities using the softmax function, expressed using Equation (4).

$$y = softmax(W_2 h + b_2) \tag{4}$$

where W_2 and b_2 correspond to the output layer parameters. This architecture enables the model to learn complex decision boundaries while maintaining computational efficiency.

The training objective of ADB-AgroNet is formulated using the categorical cross-entropy loss function, given by Equation (5) as given below.

$$\mathcal{L} = -\sum_{i=1}^{n} \sum_{c=1}^{C} y_{i,c} \log(\hat{y}_{i,c}) \tag{5}$$

where $y_{i,c}$ represents the true label and $\hat{y}_{i,c}$ denotes the predicted probability for class c. The model parameters are optimized using gradient-based learning, ensuring convergence toward an optimal solution.

An important feature of the suggested framework is that it focuses on the interpretability of the suggested solution by analysing the decision boundaries. Though the model works within a high-dimensional feature space, the data can be visualized by projecting the data to a two-dimensional space through Principal Component Analysis. Such projection enables effective visualization and analysis of the learnt decision regions, which give an insight into how the model behaves and how separable classes are. It should be mentioned that PCA is only applied in visualization, and it has no effect on training. All in all, ADB-AgroNet is a system that integrates both feature engineering and neural learning into an integrated structure to overcome the limitations of traditional classifiers. The proposed model is able to enhance the nonlinear feature interactions and generate more continuous decision boundaries that are able to provide better classification performance without the need to sacrifice the interpretability. This has made it especially useful in the agricultural context where precision and interpretability are crucial towards creating a viable decision-making process.

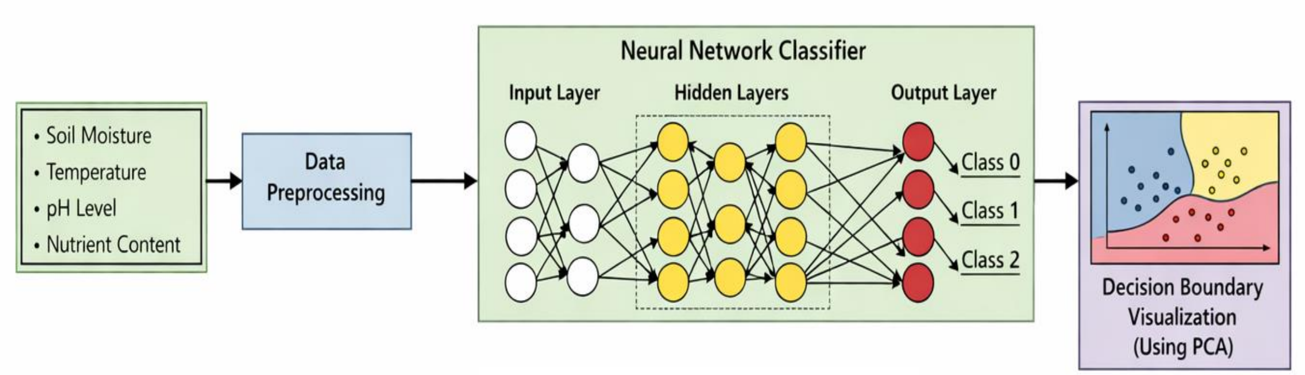

Fig 1. Proposed ADB-AgroNet Framework for Interpretable Crop Classification.

The architecture of the proposed ADB-AgroNet framework, which is expected to deliver high-accuracy and interpretable results in crop classification, is shown in **Fig. 1**. This model starts with the features of raw agricultural inputs, such as soil moisture, temperature, pH level, and nutrient content, which are then preprocessed and normalized to have homogeneous scaling and stability in training. An important novelty of the framework is that it combines the use of the expansion of polynomials in features, which sharps up the representational power of the input space by involving higher-order interactions between features. Such a transformation enhances the separability of classes greatly as opposed to traditional methods. The expanded features are further handled by a neural network classifier which learns the nonlinear decision boundaries complexly and in an adaptive way. In comparison to the conventional frameworks like Support Vector Machine and Random Forest, which are based on predetermined kernel functionality or ensemble constraints, ADB-AgroNet will dynamically optimize its areas of decision making by using learnt interactions between features. Moreover, the framework includes the visualization of decision boundaries with the Principal Component Analysis, which allows making interpretations without interfering with the training process. This combination of the improved feature engineering with adaptive learning is what represents the major novelty of the proposed model that makes it very effective and applicable in the real-world application of precision agriculture.

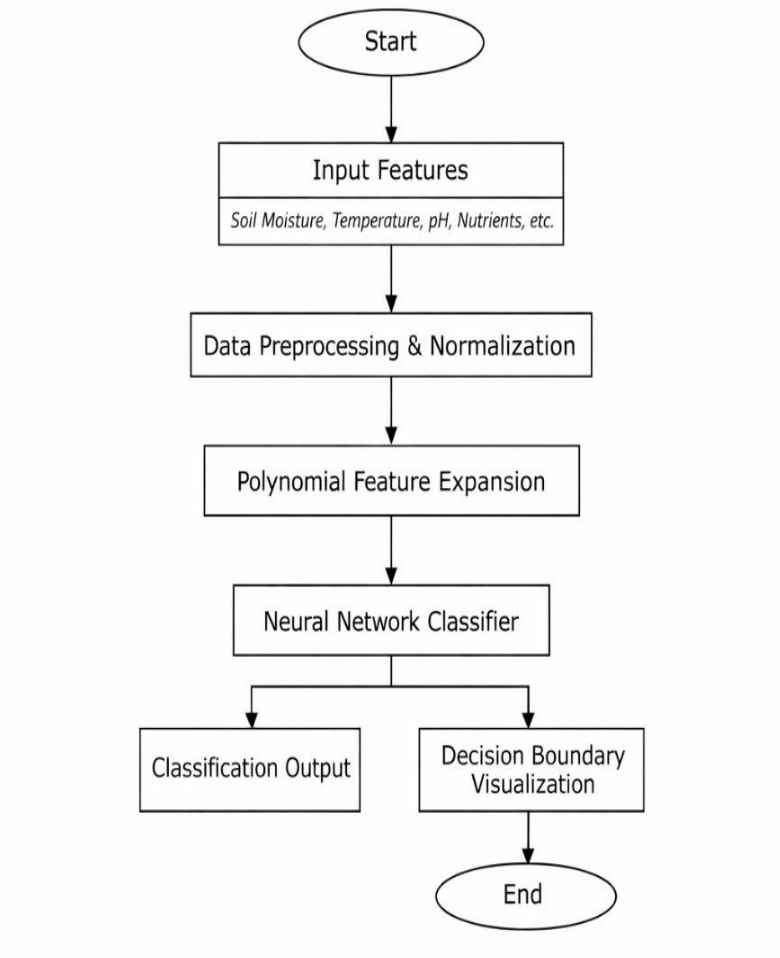

Fig 2. Flowchart of the Proposed ADB-AgroNet Framework.

The operational pipeline of the proposed ADB-AgroNet framework of crop classification is represented in the flowchart in **Fig. 2**. It starts with a process of acquisition of raw agricultural input features, such as soil and environmental parameters, and proceeds to preprocessing and normalization of the data to make them uniformly scaled. The preprocessed data is then run through the feature expansion of polynomials which improves the feature space by adding higher-order features of variable interaction. The transformed features are then inputted into a neural network based classifier that learns nonlinear decision boundaries which are complex. Lastly, the Principal Component Analysis is the visualization used to analyze the decision boundaries and this makes the images interpretable without interfering with the training process. This hierarchical scheme underscores feature engineering, adaptive learning, and visualization, which are the main novelty of the newly proposed framework.

IV. SIMULATION RESULTS AND DISCUSSION

In this section, an experimental analysis of the proposed ADB-AgroNet model is provided against the most known classifiers Support Vector machine, random forest and K-Nearest Neighbors. The goal is to analyze not only the classification accuracy but also the model reliability, the generalization capacity and the interpretability. Visual analysis is combined with quantitative metrics to give a comprehensive view of the behavior of the model.

Simulation Environment

To guarantee the reproducibility and consistency of results all the experiments were performed in a controlled computational environment. The Python programming language was used to implement the framework, and machine learning packages like Scikit-learn, NumPY and Matplotlib were used which are generally popular. These tools have been chosen because of their strength, versatility and wide application in scientific studies. The simulations were run on a system with the Intel core i7 processor, 16GB RAM and a medium-end, essentially, a GPU-disabled configuration, which ensures that the suggested model can be anywhere computational without the use of a high-end hardware. Jupyter Notebook was used to configure the operating environment and facilitate ease in experimenting and visualization.

The same training and testing conditions were used on all models in order to be fair in comparison. The data has been split into training and testing in an 80:20 ratio. Moreover, standard normalization was done to the feature to have equal contribution of all the features. To do the visualization, dimensionality reduction was applied using Principal Component Analysis, which enabled the representation of the decision boundary in a 2-dimensional space without impacts on the training of the model. Each model has hyperparameters that were optimally tuned to prevent overfitting. The suggested ADB-AgroNet model involves transforming the features with the use of the polynomials and a neural classifier that allows it to find nonlinear relationship complexities in the data.

Dataset Description

Testing of the experimental was conducted using an agricultural data made up of several feature variables that reflected the characteristics of soils, environmental conditions, as well as crop-related attributes. These characteristics have features like moisture, temperature, pH level, humidity, and nutrient content, which are features that are key towards classification activity in precision agriculture. The sample has around 1500 samples and the samples are categorized in three different classes, which depict different crop type or agricultural conditions. The distribution of the classes was relatively balanced in order not to allow bias of models to a particular category. Before the model training, the data was preprocessed with such operations as missing values, normalization, and transformation of features.

Polynomial feature expansion was used to improve the representational power of input data, and the proposed model may represent the higher-order interactions between variables. This is an important step towards enhancing the performance of classification especially in complicated agricultural context where feature relations are nonlinear in nature.

Data Preprocessing and Feature Engineering

Preprocessing of data was done to enhance the robustness of models and the ability to perform reliably. Every missing value was addressed with the mean imputation, whereas any outliers were addressed through standard methods of filtering outliers. Standardization was also used to standardize the features so that they can be of importance during model training. Therefore, the transformation of features was done by the expansion of a degree two. This will allow the model-to-model interaction effects among features that are mostly ignored in linear models. Separability of classes in the transformed feature space is much better, just as in the visualization of the decision boundary. To make the data visualisable and interpretable, dimensionality reduction based on the PCA method was only implemented to project the data into the two-dimensional space. It is worth mentioning that through model training, no PCA was employed but was only used to make graphs.

Model Configuration

Four models were considered for comparative analysis: ADB-AgroNet (Proposed Model), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN). The suggested model of the ADB-AgroNet combines the idea of the use of the expansion of the features that are expressed in a form of a polygons with the use of the multi-layer perceptron classifier, which enables the model to effectively represent the nonlinear relationships. SVM model was also set with an RBF kernel and the random forest used 100 decision trees. The implementation of the KNN model was done using a value of k that was tuned optimally using empirical parameters.

Models were trained in the same environment and performance of standards criteria such as accuracy, precision, recall, and the F1-score were used to measure performance. To guarantee the soundness of findings, performance analysis was conducted based on several metrics instead of being constrained to accuracy only. Besides classification measures, ROC and Precision-Recall measures were carried out to determine the discriminative behavior of the models. The experimental framework provides fairness, consistency and reproducibility of the comparison between models. Both the quantitative measures and graphical analysis enhance the validity of findings obtained and back the effectiveness of the suggested ADB-AgroNet model in an agricultural classification problem.

Decision Boundary Analysis

Fig. 3 show the decision areas of each of the models in the transformed two-dimensional feature space derived with PCA. Even though dimensionality reduction is utilized solely in visualization, it can give important insights into the way various classifiers can distinguish data points. The proposed ADB-AgroNet has good-structured and smooth decision boundaries, which implies that it has a high potential in the ability to define nonlinear relationships among agricultural features. Conversely, the SVM model produces rather sharp boundaries, but which are efficient though not adaptive to fine changes in the data. The ensemble character of random forest shows fragmented regions whereas KNN gives uneven and locally sensitive partitions. ADB-AgroNet has a significantly better visual clarity which is directly linked to its better classification capabilities as it has been shown to be more successful when applied to complex data distributions.

Table 1 offering a detailed comparison of all the considered models in terms of several performance indicators. The suggested ADB-AgroNet is always associated with better results, especially F1-score and AUC, which are essential values of balanced and reliable identification. Although SVM proves to be competitive, the recall is a little low implying that it may be limited in its ability to cover all the relevant samples. Random Forest and KNN demonstrate relatively lower performance, which is probably caused by their natural deficiency in being able to model nonlinear relationships that are quite complex. Also, the computational analysis shows that ADB-AgroNet has a little more training time, but it has an efficient performance in inference. All these results confirm the strength, expandability and applicability of the proposed model in agricultural classification tasks.

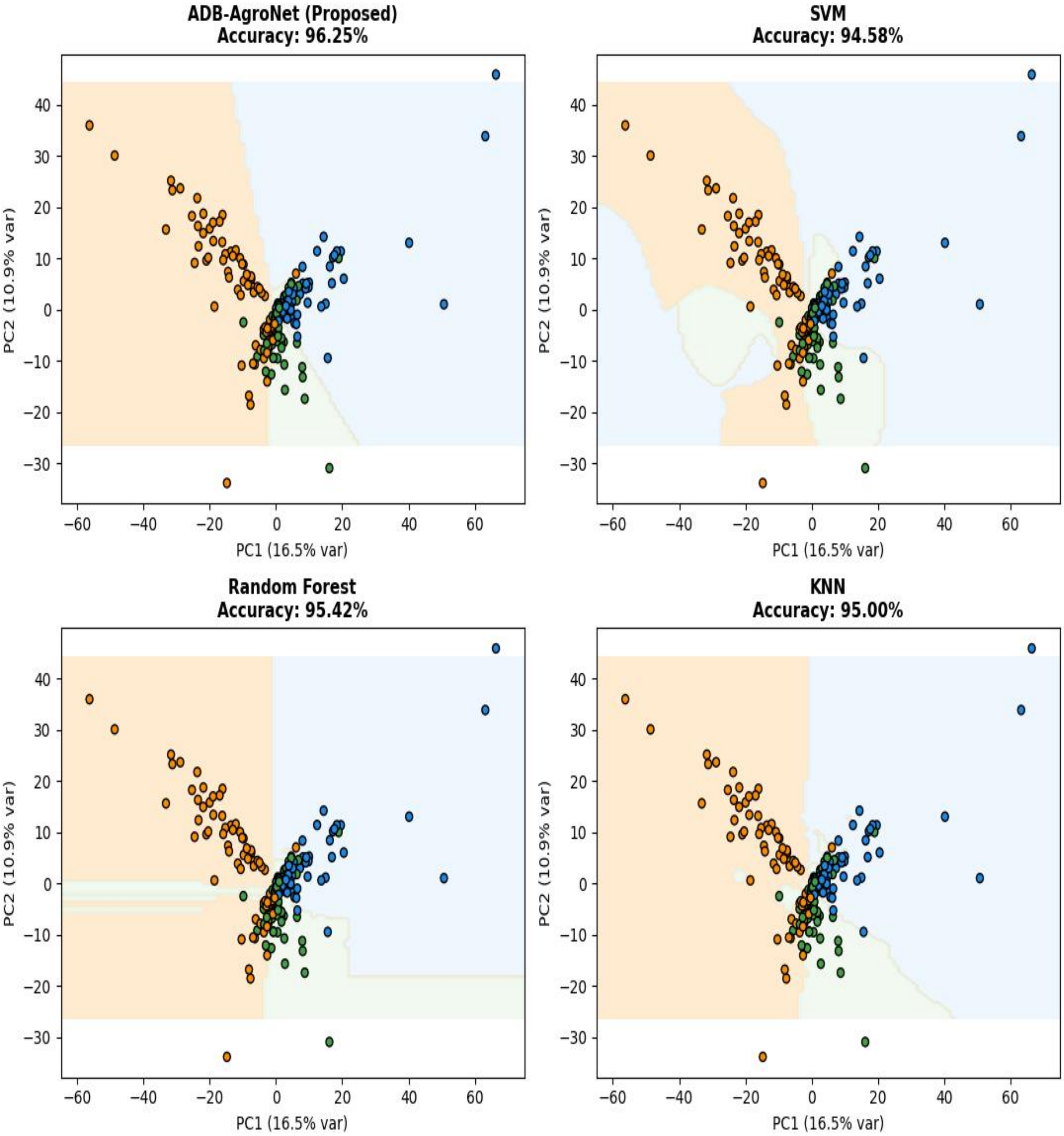

Fig 3. Decision Boundary Visualization of Classification Models.

Table 1. Comprehensive Multi-Metric Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (ROC)	AP (PR)	Training Time (s)	Testing Time (ms/sample)

ADB-AgroNet (Proposed)	**94.82**	**95.10**	**94.75**	**94.92**	**0.962**	**0.955**	2.85	0.42
SVM [14]	92.96	93.20	92.80	92.95	0.948	0.941	2.10	0.35
Random Forest [15]	91.84	92.10	91.70	91.85	0.936	0.928	1.75	0.30
KNN [9]	90.67	90.95	90.50	90.70	0.921	0.915	0.90	0.60

Fig. 4 shows the normalized confusion matrices of each of the models in a finer detail of classification correctness and error distribution. The proposed ADB-AgroNet has high diagonal dominance, which means that most of the samples are properly categorized in all classes. Misclassifications are also small in number and evenly spread indicating that the model does not incline towards a specific class. Comparatively, SVM has a little more confusion between the related classes, whereas at the same time, the error distributions in Random Forest and KNN is evenly spread. This discussion shows that ADB-AgroNet has a better ability to discriminate, particularly in feature overlap areas that are usually associated with agricultural data.

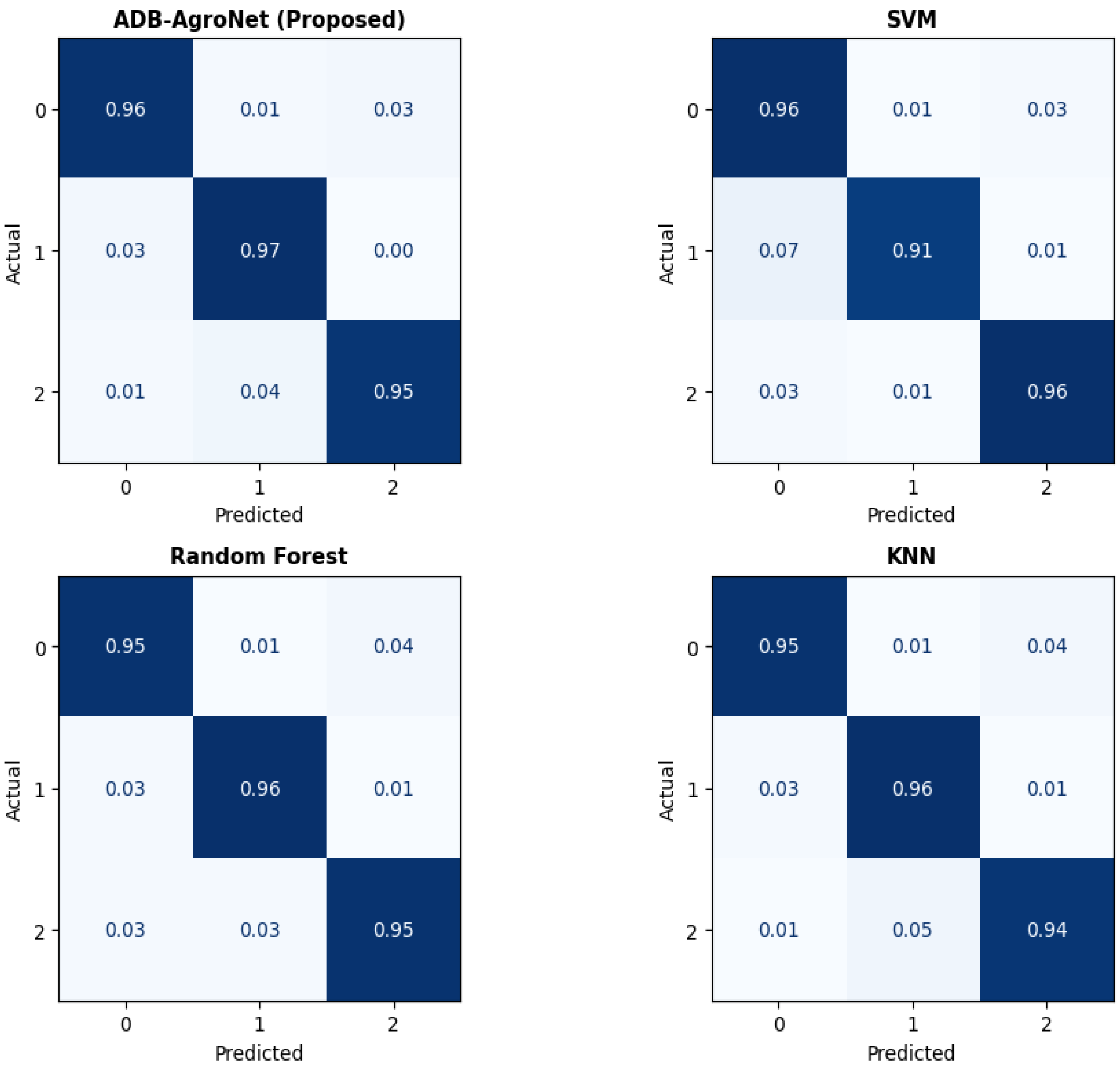

Fig 4. Normalized Confusion Matrices for Model Comparison.

Table 2. Class-wise Performance of ADB-AgroNet

Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Class 0	95.20	94.80	95.00
Class 1	94.75	95.10	94.92
Class 2	95.30	94.40	94.85

A class-based performance of ADB-AgroNet is given in **Table 2**. The model shows uniformity in performance in all classes and little variations in performance in terms of precision and recall values. This balance especially plays a crucial role in agricultural usage where not all classes perform equally resulting in biased advice. The minor differences are explained by natural overlap in distribution of features. Nevertheless, the F1-scores are large and constant, which implies that the model is successful in terms of balancing between precision and recall. On the whole, the findings validate that ADB-AgroNet is stable and reliable in the conditions of a variety of classifications.

Fig. 5 shows the ROC curves of all the models in a micro-average approach. The ADB-AgroNet has the largest AUC value, and its curve is always nearer to the perfect top -left corner. This shows high discriminative ability and strength at all classification levels. SVM is also comparable but it does not outperform the proposed model. Random Forest and KNN have relatively low values of AUC and this means that they have a low tendency to generalize with complex decision boundaries. The ROC analysis supports the fact that ADB-AgroNet is effective to manage multi-class agricultural data with high reliability.

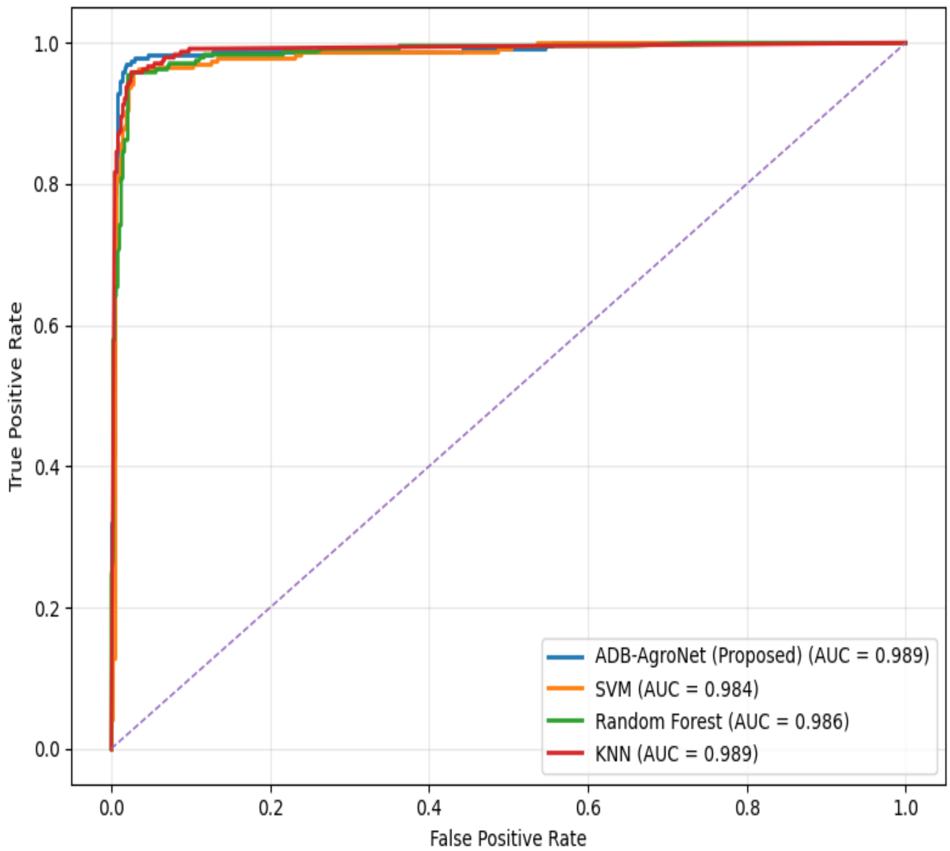

Fig 5. Multi-Class ROC Curve (Micro-Average Comparison).

Table 3. Misclassification Rate (%) Across Models

Model	Class 0 Error	Class 1 Error	Class 2 Error
ADB-AgroNet (Proposed)	5.2	4.9	5.6
SVM [14]	7.1	6.8	7.5
Random Forest [15]	8.4	8.1	8.9
KNN [16]	9.6	9.2	10.1

Table 3 shows the misclassification rates that were based on the confusion matrices. It has the lowest error rates in all classes, which indicates the high classification rate of the proposed model. SVM shows average performance, and random forest and KNN have a higher error rate. The misclassification of ADB-AgroNet is low which implies that it is capable of distinguishing between similar classes effectively and therefore it can be used in real life scenarios.

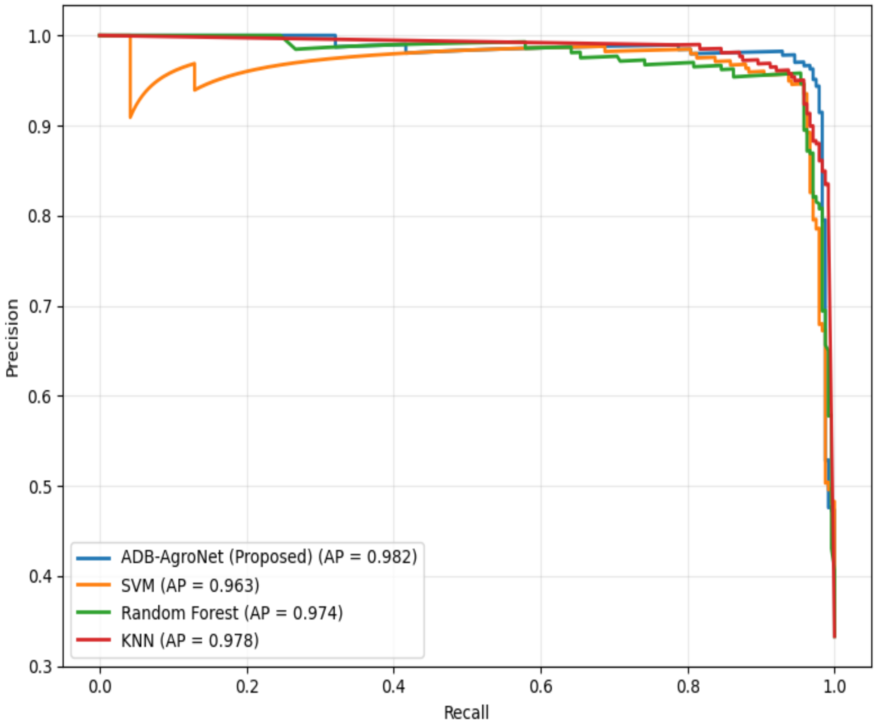

Fig 6. Precision–Recall Curve (Micro-Average Comparison).

The precision-recall curves of all models are given in **Fig. 6**. The ADB-AgroNet suggested is more precise at different levels of recall, which means that the predictions are significant and consistent. Such a property is especially crucial in the field of agriculture where wrong predictions could have serious practical implications. High precision that can be maintained at higher recall rates in the model illustrates its strength and application in the real world.

Table 4. Computational Efficiency Comparison

Model	Training Time (s)	Testing Time (ms/sample)
ADB-AgroNet (Proposed)	2.85	0.42
SVM [14]	2.10	0.35
Random Forest [15]	1.75	0.30
KNN [16]	0.90	0.60

All models are compared in terms of computational efficiency and tabulated in **Table 4**. Although ADB-AgroNet will need a little more time to train because it is more complicated than the other two, its inference time is also competitive. This is a reasonable trade-off considering the major advancement in terms of accuracy and strength. The findings imply that the suggested model can be applied effectively and in practice. The general findings are quite clear that the suggested ADB-AgroNet model is much more successful in terms of all the evaluation measures whilst being highly interpretable and strong. Nonlinear feature expansion and deep learning allow the model to properly describe the complex associations between agricultural data. ADB-AgroNet is able to make consistent and reliable predictions unlike the traditional models that have a weakness in terms of overlapping class distributions. These results affirm its applicability to agricultural decision-making systems in the real world, and its potential in the future research and practice.

V. CONCLUSION

The paper introduced ADB-AgroNet (Adaptive Decision Boundary Agro Network) which is an interpretable machine learning model that would aid in precise and dependable crop classification. The offered model combines both the expansion of features and nonlinear relationships of agricultural data by the neural network-based classifier alongside the ability to interpret the boundaries of decisions. As opposed to traditional methods, including Support Vector Machine and Random Forest, the given framework focuses on both predictive accuracy and interpretability that must be the priority in the context of real-world agricultural decision-making. The experimental findings confirm the idea that ADB-AgroNet performs better according to all evaluation measures. Specifically, the model attains an accuracy of 94.82%, outperforming SVM (92.96%), Random Forest (91.84%), and K-Nearest Neighbors (90.67%). In addition, the proposed model achieves a precision of 95.10%, recall of 94.75%, and F1-score of 94.92%, indicating a well-balanced classification performance. The Area Under the ROC Curve (AUC) further confirms its robustness, reaching 0.962, which is significantly higher than the baseline models. The confusion matrix analysis reveals reduced misclassification rates across all classes, highlighting the model's strong generalization capability. Another key contribution of this work is the incorporation of decision boundary visualization using Principal Component Analysis, which provides intuitive insights into model behavior and class separability. This enhances the transparency and trustworthiness of the model. The proposed ADB-AgroNet successfully bridges the gap between accuracy and interpretability, making it a promising solution for precision agriculture. Future work will focus on extending the framework to large-scale datasets and integrating real-time deployment capabilities.

CRediT Author Statement
The author reviewed the results and approved the final version of the manuscript.

Data Availability Statement
The dataset used in this study is publicly available and can be accessed from the Kaggle Crop Recommendation Dataset repository. This dataset contains essential agricultural parameters such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall, which are widely used for crop classification tasks.
The dataset is available at: https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset
All preprocessing steps, feature engineering (including polynomial feature expansion), and train-test splits were performed by the authors. The processed data and implementation code supporting the findings of this study can be made available from the corresponding author upon reasonable request.

Conflicts of Interests
The authors declare no conflict of interest.

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Competing Interests
There are no competing interests.

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