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Research Article

Corn and Wheat Plant Identification on Radar and Optical Image Data

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ABSTRACT: In recent years, prediction, detection, and classification applications have been made in many fields such as agriculture, health, stock market, economy, cybersecurity, etc., in Machine Learning and Artificial Intelligence. These applications are user-friendly and provide fast, high-quality, and accurate results. The advancements in these fields have shown that machine learning and deep learning methods are very useful in classifying large and complex data, especially when human brain and physical power are insufficient. Today's findings suggest there have been promising studies using these models, focused on time- and cost-effective and high-quality products. These studies provide efficiency in agricultural areas, thereby guiding both farmers and policymakers. In addition, the development and widespread implementation of unmanned aerial vehicles (UAVs) accelerated the process of obtaining multispectral aerial images. With the combined use of these technologies and high-speed computer software and hardware for precise and high-quality production in agriculture, it was possible to determine plant species and increase product quality. In this study, a dataset consisting of radar and optical image data was used to classify corn and wheat crops cultivated in agricultural areas. Four different machine learning models, namely Decision Tree (DT), K-Nearest Neighbors (K-NN), Naive Bayes (NB), and Support Vector Machines (SVM), were trained and compared on the dataset consisting of 174 features from Winnipeg, Canada. The dataset has been divided into 80% for training and 20% for testing. According to the results, the SVM model performed the best with the highest accuracy (0.9998) and F1-Score (0.9996), while the NB model performed the worst accuracy (0.9895) and F1-Score (0.9835). The detection of wheat and corn crop types by processing radar and optical image data with machine learning models has shown that other crops in cultivated lands in the Southeastern Anatolia Project (GAP) region can be classified using the same method, which shows the importance of this study.

KEYWORDS: Machine learning, classification, multispectral aerial images, plant species.

ÖZET: Makine Öğrenmesi ve Yapay Zeka konularında son yıllarda tarım, sağlık, borsa, ekonomi, siber güvenlik vb. birçok alanda tahmin, tespit ve sınıflandırma uygulamaları yapılmıştır. Bu uygulamalar hızlı, kaliteli ve yüksek doğrulukta sonuç alınabilen kullanıcı dostu uygulamalardır. Bu alanlardaki gelişmeler, makine öğrenimi ve derin öğrenme yöntemlerinin, özellikle insan beyninin ve fiziksel gücün yetersiz kaldığı durumlarda, büyük ve karmaşık verilerin sınıflandırılmasında çok faydalı olduğunu göstermiştir. Günümüzde bu modellerin kullanıldığı, zaman ve maliyet etkin, yüksek kaliteli ürün odaklı umut verici çalışmalar yapılmıştır. Bu çalışmalar tarım alanında verimlilik sağlayarak gerek çiftçi gerek ise politika yapıcıları yönlendirmektedir. Ayrıca, insansız hava araçlarının (İHA) geliştirilmesi ve yaygın kullanımı, çok spektrumlu hava görüntülerinin elde edilme sürecini hızlandırmıştır. Tarımda hassas ve kaliteli üretim için bu teknolojiler ile yüksek hızlı bilgisayar yazılım ve donanımlarının birlikte kullanılmasıyla bitki türlerinin belirlenmesi ve ürün kalitesinin artırılması mümkün olmuştur. Bu çalışmada, tarım alanlarında yetiştirilen mısır ve buğday mahsullerini sınıflandırmak için radar ve optik görüntü verilerinden oluşan bir veri seti kullanılmıştır. Karar Ağacı (KA), K-En Yakın Komşular (K-EYK), Naif Bayes (NB) ve Destek Vektör Makineleri (DVM) olmak üzere dört farklı makine öğrenimi modeli, Kanada'nın Winnipeg kentinden alınan 174 özellikten oluşan veri kümesi üzerinde eğitilmiş ve karşılaştırılmıştır. Veri kümesi, eğitim için %80 ve test için %20 olarak ayrılmıştır. Sonuçlara göre, DVM modeli en yüksek doğruluk (0,9998) ve F1-Skoru (0,9996) ile en iyi performansı gösterirken, NB modeli en düşük doğruluk (0,9895) ve F1-Skoru (0,9835) performansını göstermiştir. Radar ve optik görüntü verilerinin makine öğrenmesi modelleri ile işlenerek buğday ve mısır ürün türlerinin tespit edilmesi, Güneydoğu Anadolu Projesi (GAP) bölgesindeki ekili arazilerde bulunan diğer ürünlerin de aynı yöntem kullanılarak sınıflandırılabileceğini göstermiş ve bu çalışmanın önemini ortaya koymuştur.

ANAHTAR KELİMELER: Makine öğrenmesi, sınıflandırma, multispektral hava görüntüleri, bitki türleri.

1. INTRODUCTION

With the acceleration of artificial intelligence research, machine learning methods have had many positive effects on human life. In recent years, products offered to end-users, such as AI-powered chatbots, smart robot vacuum cleaners, smart assistants, and autonomous cars, reveal today's technology and demonstrate the contemporary technology and importance of artificial intelligence. In particular, with the increased interest in autonomous technologies, many new technologies beneficial to humanity are being introduced in areas such as production, transportation, the defense industry, and agriculture. The backbone of these technologies involves machine learning models, and large datasets are processed.

On human interaction and socio-cultural impact, Altinel conducted a sentiment analysis study on social media using machine learning methods. Since classifying and analyzing the large amount of data generated by the ideas shared on these platforms would require a large workforce when done with human, it was determined that emotion analysis should be done with a number of existing algorithms. In this study, used five various datasets from various platforms and used four distinct algorithms for machine learning (K-NN, NB, RF, SVM) for each dataset, aiming to identify the most accurate model through performance comparison [1].

A dynamic Turkish sign language recognition [2] using machine learning models and a leap motion sensor was studied in order to facilitate the lives of deaf and hearing-impaired people by Demircioglu. The importance of this study was revealed by the communication difficulties experienced by hearing-impaired people in society, particularly in environments where they cannot understand sign language. Within the scope of this thesis, software that can run on a mobile device with a minimal size sensor and processor has been created, and solving this problem has been set as a goal. It is aimed at developing a highly efficient recognition system using machine learning methods [2].

On agricultural applications, Mucherino et al. concentrated on the implementation of data mining techniques in agriculture, noting that neural networks do not rank among the top ten data mining methods and that their applications in agriculture are limited [3]. Tabanlioglu et al. proposed the use of UAVs to monitor the productivity of large agricultural lands, as taking images from the ground is inefficient and time-consuming [4]. In this study, aerial images of agricultural lands in the GAP region were analyzed with image processing techniques, and color analysis was performed to control productivity in a computer environment. In addition, it is aimed to increase productivity and economic growth by suggesting that the most important development factor in this region is agricultural practices [4]. Rumpf et al. pointed out that the use of automated systems for the prompt identification of plant diseases are essential for precision in plant protection, and a study was conducted for prompt identification and differentiation of sugar beet problems with a SVM algorithm generated from hyperspectral plant image data [5]. Gumuscu et al. used K-NN, SVM, and DT classification algorithms to determine the planting date, taking into account the significant impact of planting dates on agricultural production. In the proposed method, meteorological data was used as input, and it was aimed to provide farmers with the correct planting date and to achieve higher yields. In order to reduce the number of features in the high-dimensional dataset, a genetic algorithm was used to eliminate the excessively high processing time and to improve the prediction performance [6]. Karadag et al. suggested that irrigation should be done by considering soil and climatic factors and pointed out that irrigation frequency is one of the most important issues that determine the increase of productivity and soil quality in agriculture. In this study, water stress in pepper plants was tried to be detected by using spectral images, and classification of feature vectors related to the data was performed with K-NN and Artificial Neural Networks methods [7]. Gunes et al. used the VGG16 model, a deep learning technique, for the classification of hazelnut products. In this study, a large dataset consisting of hazelnut images was created. In addition, this dataset was used in different ratios to detect and classify the ratio of hazelnut kernel, damaged hazelnut, and quality hazelnut, and the performance of the model was determined [8]. Boyar et al. proposed the Yolo-v5 model, a machine learning algorithm, to detect healthy and diseased regions in hazelnut tree leaves. In this study, a unique data set was processed, and an object detection model, the Yolo model, was used to detect powdery mildew disease on the leaf image. According to the performance results of the model, a successful detection mechanism was developed, and a scientific contribution was made to increase hazelnut production efficiency [9]. Ngugi et al. conducted a comprehensive literature search and review of the most recent studies in the detection and classification of plant diseases. In this study, performance analysis was performed using state-of-the-art machine learning (ML) and deep learning (DL) models. They stated that traditional ML and convolutional neural network (CNN) models are often preferred in many studies. They suggested that new DL algorithms such as capsule neural networks and image transformers should be focused on. They also emphasized that the datasets used are only for specific crops and a large image dataset with a wider range of crops is needed. Instead of focusing on ML or DL models in plant disease detection, they suggested the development of a combination of ML and DL algorithms for the detection of several plant diseases [10]. Khalid et al. emphasized that traditional detection methods for early and accurate diagnosis of plant diseases are inefficient, laborious, and prone to false results. In their study, they investigated the effective segmentation ability of DL models by focusing on CNN and MobileNet architectures. In addition, they included eXplainable Artificial Intelligence (XAI), which enables the explanation of disease markers in plant images with the GradCAM technique in the decision-making process of these models. According to the performance results, it was revealed that the DL model was more successful in image segmentation in plant disease detection [11].

Artificial intelligence technology, which has become pervasive in almost every area, is increasingly used in agriculture for determining planting areas, classifying planted products, and deriving statistical results from these areas. Studies conducted for determining and classifying planting areas in agricultural lands gain importance in preventing illegal, prohibited, and incorrect cultivation of products. In particular, in order to prevent the abuse of the misuses of government subsidies provided to the producers for agricultural support and to make these expenditures in the right areas, their detection can be done quickly thanks to the use of machine learning methods with aerial images. In this context, a crop classification study conducted with data obtained from UAV and satellite radar images provides great savings in terms of time, cost a high-technological environment. In addition, in studies carried out with deep learning models in order to increase production, grow quality products, and increase precision in agriculture, crop variety and disease classification can also be done with machine learning models.

In this paper, we utilize an existing dataset, created and labeled from aerial images of corn and wheat crops, to compare the performances of machine learning methods commonly used in the literature for the classification of cultivated land. The primary aim of the study is to develop a method for identifying the appropriate machine learning algorithm works better to classify corn and wheat plant species from multispectral aerial images that can be collected by UAV or satellite radar systems over cultivated lands in the GAP region. The reference dataset consists of radar optical image features of corn and wheat plants. Due to the complexity and large size of this dataset, model performance is low, training time is lengthy, and achieving high accuracy is very difficult. However, by mixing the dataset, we can reduce the possibility of memorization and increase the accuracy rate. This process necessitates a significant amount of time and robust computer hardware. In addition, model performance decreases and training time increases as the number of classes and features increases. Although this is a very common problem when applying machine learning techniques, class imbalance correction techniques such as dataset reduction and feature selection can be used to counteract this bias [12]. After the dataset imbalances are removed, the models are trained using machine learning algorithms. Since there are many machine learning models in the literature and it would be time-consuming to evaluate all of them, this study compares the effectiveness of the 4 most widely used machine learning algorithms (DT, K-NN, NB, and SVM) for plant species classification. The studies concluded that data obtained from optical radars can successfully classify the croplands cultivated with corn and wheat on agricultural lands in the GAP region. This study will be a quality reference for statistical information and plant classification for the GAP region.

2. MATERIAL AND METHOD

2.1. Dataset

The dataset used is two-time optical radar data with combined temporal, spectral, textural, and polarimetric features for cropland classification provided by UC Irvine Donald Bren School of Information & Computer Sciences [13]. The imagery was collected by RapidEye satellites (optical) and Unmanned Aerial Vehicle Synthetic Aperture Radar (UAVSAR) on July 5 and 14, 2012, over an agricultural region near Winnipeg, Manitoba, Canada. Only data pertaining to corn and wheat species were retained, while data related to other plant species were removed from the dataset. In addition, the wheat class has been relabeled as ‘2’. It consists of two classes (1-Corn, 2-Wheat), 2x49 radar, and 2x38 optical, totaling 174 features and 124236 rows of data.

In this dataset, two crop type classes, namely Corn and Wheat, were studied for the classification of cultivated lands in the agricultural areas of the Southeastern Anatolia Project (GAP) region. It is anticipated that if high performance is achieved with the machine learning models used with this dataset, this study will serve as a quality reference for the GAP region.

In all models, the first 80% of the dataset was allocated for training, and the remaining 20% for testing. The network was trained with and without normalizing the dataset, and the highest accuracy and performance results were obtained when the network was trained without normalizing the dataset. In addition, all models were trained and compared separately when the dataset was randomized and when it was not. In this case, the randomized dataset provided the best results, and the study continued with it.

2.2. Machine Learning Methods

DT, K-NN, NB, and SVM models, which are the most favored in classification tasks within supervised learning frameworks of machine learning, were used. The flow diagram depicting the stages of dataset organization, including its division for training, and testing, as well as the execution of machine learning models, is shown in Figure 1.

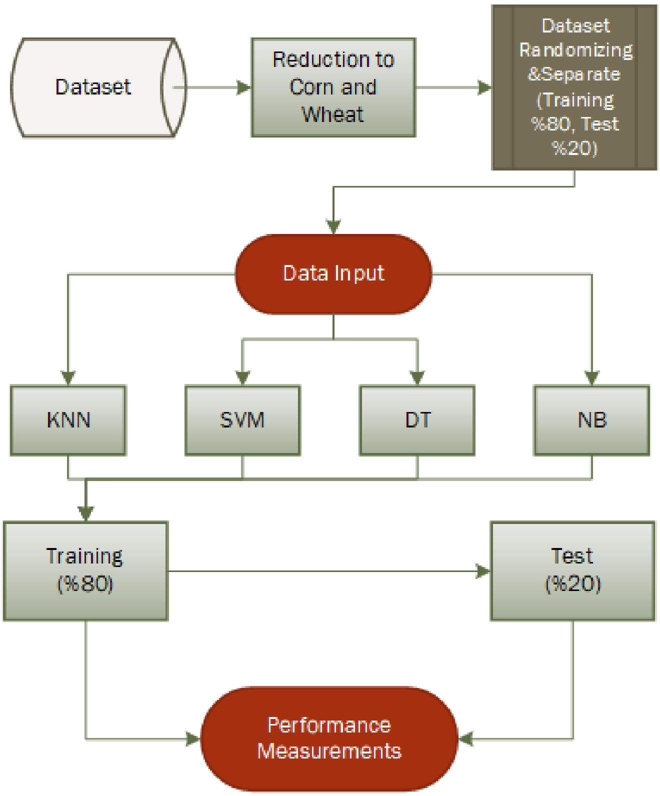

Figure 1. Flow chart

2.2.1. Decision Tree

The DT model can be utilized for both classification and regression purposes. DT is represented by a tree structure that makes decisions based on features in the dataset and is used to model complex relationships in the data using the features and target variables in the dataset [14-16]. Here, the target variables can be labels for classification or target variable values for regression. The two internal nodes that form the branches are the decision-making dataset (decision node), which consists of various branches in the algorithm, and the finalizing leaf node, which is the output of the decision nodes and has no other branches. Its shape resembles a tree. In general, decision trees start from a root node and continue with a series of internal nodes and leaf nodes. Each internal node performs a test from a feature or attribute and selects a branch as a result of this test [17]. Leaf nodes contain the results [14]. DT basically divides the tree into subtrees based on the answer to the question, i.e., whether it is true or false [17].

When constructing a DT, determining which feature to test at each internal node is crucial. Feature selection can be done using measures such as information gain, entropy (amount of homogeneity) or other metrics based on the features and target variable of the dataset [15].

Entropy, a dataset's homogeneity or uncertainty, is a measure of information. Here, $\boldsymbol{S}$ represents the dataset, $\boldsymbol{c}$ represents the number of classes, and $\boldsymbol{p_i}$ represents the probability of each class. The following formula facilitates entropy calculation:

$$E(S) = -\sum_{i=1}^{c} p_i \log_2(p_i) \tag{1}$$

Information gain, measures how much the entropy of the dataset decreases when a feature is used. Here, $\boldsymbol{S}$ represents the original dataset, $\boldsymbol{A}$ represents the selected feature, ***Values(A)*** represents the values that the feature $\boldsymbol{A}$ can take, $\boldsymbol{S_\vartheta}$ represents the examples with the value $\boldsymbol{v}$ for the feature, and $\boldsymbol{|S|}$ represents the size of dataset. The following formula calculates the information gain:

$$IG(S,A) = E(S) - \sum_{\vartheta \in Values(A)} \frac{|S_\vartheta|}{|S|} \times E(S_\vartheta) \tag{2}$$

DT is easy to understand, highly interpretable, and quite resilient to imbalanced and missing data in the dataset. However, they may exhibit a tendency to overfit, so proper parameter tuning and model validation are important [15].

2.2.2. K-Nearest Neighbors

The K-NN algorithm is a fundamental and efficient method for data classification, especially favored in scenarios with high uncertainty. It was created for uniform analysis when decision-making based on probabilistic densities via parametric estimate proves difficult. Calculations indicate that when k=1 and n approaches infinity, the classification error of K-NN is constrained to double the error rate of Bayes [17]. K-NN is a straightforward and efficient machine learning technique, predominantly utilized for classification and regression applications, with a bias towards classification issues. As indicated by its designation, it forecasts outcomes based on the predominant influence of neighboring data points [18].

2.2.3. Naive Bayes

The NB model is a parametric supervised classifier grounded in the Bayesian probability theorem and the principle of strong independence among features [20, 21]. This classifier is referred to as 'naive' due to its assumption that each characteristic is independent of the others in the classification process. The likelihood of a feature being associated with a specific class is determined by training the model using a training dataset. The program employs this data to compute the mean vectors and covariance matrices for each class to facilitate predictions [19, 22]. The Bayesian theorem calculates the probability of an event, while the Naive Bayes classifier identifies the class of a data point using the subsequent formula:

$$P(c_k|x) = \frac{P(x|c_k) \times P(c_k)}{P(x)} \tag{3}$$

$\boldsymbol{P(c_k|x)}$, is the probability that a data point belongs to class $\boldsymbol{c_k}$ given the occurrence of $\boldsymbol{x}$. $\boldsymbol{P(c_k)}$, is the prior probability of the class (the probability of $\boldsymbol{c_k}$). $\boldsymbol{P(x|c_k)}$, is the probability that a data point belongs to class $\boldsymbol{x}$ given that $\boldsymbol{c_k}$ has occurred. $\boldsymbol{P(x)}$, is the prior probability of the predictor (the probability of $\boldsymbol{x}$).

2.2.4. Support Vector Machines

The SVM model used in classification problems is a machine learning technique based on the concept of an optimal separating hyperplane, which usually discriminates between two classes [23]. Basically, SVM draws a decision boundary between classes and classifies data points according to which side of this boundary they fall on. This decision boundary is set in such a way that the data points achieve the maximum margin. SVM uses a set of kernel functions, such as linear, polynomial, and radial basis functions, which can transform the low-dimensional input space into a higher-dimensional space [24]. The SVM model is used in many fields such as driverless cars, chatbots, face recognition, etc. [17]. SVM can be a two-class or a multi-class model (a combination of a chain of two-class SVMs) [23]. To train the algorithm, SVM learns the boundary between training samples belonging to different classes, projects them into a multidimensional space, and finds a hyperplane or a set of hyperplanes that maximizes the discrimination of the training dataset between a predefined number of classes [21, 25, 26]. The SVM distinguishes two classes and finds the optimal hyperplane using the following equation [23]:

$$\min_{w,b,\varepsilon} : \tfrac{1}{2} w^T w + c \textstyle\sum_{i=1}^{1} \varepsilon_i \tag{4}$$

This formula is valid under the following constraints:

$$y_i(w^T \varphi(x_i) + b) \geq 1 - \varepsilon_i \qquad \varepsilon_i \geq 0 \tag{5}$$

Here, $\boldsymbol{w}$ denotes the normal vector to the hyperplane, $\boldsymbol{b}$ (bias) represents the distance of the hyperplane from the origin, $\boldsymbol{\varepsilon_i}$ are positive slack variables, and $\boldsymbol{c}$ (> 0) is the penalty parameter for errors [23].

SVM minimizes the misclassified examples on the decision boundary. However, sometimes datasets are not linearly separable. In such cases, the $\boldsymbol{c}$ parameter can be used to adjust the misclassification errors of the decision boundary. $\boldsymbol{c}$ is a hyperparameter that needs to be tuned during training. Larger values of $\boldsymbol{c}$ impose a higher penalty on misclassification errors, while smaller values of $\boldsymbol{c}$ impose a lower penalty on misclassification errors [23].

In machine learning methods and statistical modeling, several mathematical calculation methods are used to assess categorization performance and evaluate the efficacy of test findings and the methodologies utilized. AUC, F1-Score, specificity, precision, recall, and accuracy are the most common metrics used in classification problems and statistical calculations. Each metric evaluates different aspects of the model and is useful for specific situations. In this study, calculations are made using these metrics in accordance to accurately assess the performance results.

2.3. Performance Metrics

In machine learning methods and statistical modeling, several mathematical calculation methods are used to assess categorization performance and evaluate the efficacy of test findings and the methodologies utilized. AUC, F1-Score, specificity, precision, recall, and accuracy are the most common metrics used in classification problems and statistical calculations. Each metric evaluates different aspects of the model and is useful for specific situations. In this study, calculations are made using these metrics in accordance to accurately assess the performance results.

The complexity matrix is a 2x2 matrix that visually illustrates the efficacy of the used classification model. It is widely used particularly for two-class classification problems, but can also be generalized to multi-class problems. Figure 2 illustrates the correlation between actual classes and predicted classes as represented in this matrix.

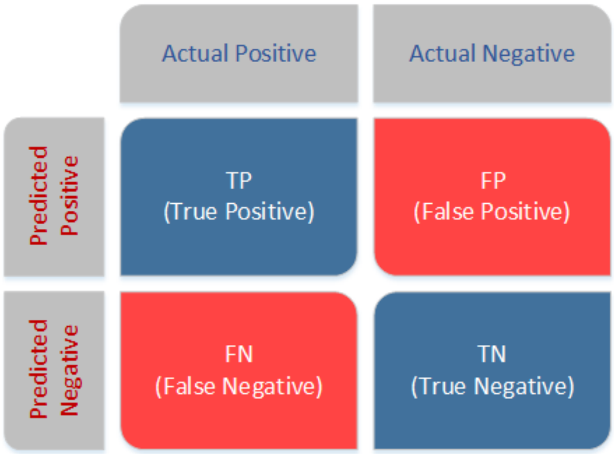

Figure 2. Confusion matrix

True Positive (TP) are accurate instances that the model identifies as positive. **True Negative (TN)** are accurate instances that the model categorizes as negative. **False Positive (FP)** are negative instances that the model by mistake categorizes as positive. **False Negative (FN)** are positive instances that the model by mistake categorizes as negative (missed) [6, 19, 27, 28].

Accuracy, quantifies the proportion of true predictions made by the model. It is the proportion of accurately classified instances to the total number of instances. However, it can be misleading in imbalanced datasets because errors in the minority class may be masked by the accuracy of the majority class [6, 19, 27, 28].

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \tag{6}$$

Precision, quantifies the ratio of true positive predictions to the total positive predictions made. It is particularly important in situations where reducing false positives is crucial, such as ensuring that a non-diseased individual is not incorrectly diagnosed. For instance, when diagnosing a disease in a plant species, the precision calculation is crucial to avoid misdiagnosing the non-diseased plant [6, 19, 27, 28].

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

Recall (Sensitivity), quantifies the ratio of true positive cases accurately detected by the model. It is *important* for situations where false negatives are to be reduced. For instance, it is crucial not to miss a diseased plant [6, 19, 27, 28].

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

Specificity, quantifies the ratio of true negative instances accurately identified as negative. Important for situations where the false positive rate is to be reduced [6, 19, 27, 28].

$$Specificity = \frac{TN}{TN+FP} \tag{9}$$

The **F1-score** is the harmonic mean of precision and recall. It is beneficial in situations requiring a balance between precision and recall, particularly in imbalanced datasets or when balancing precision with recall is desired. The F1-Score is utilized when the model needs to both effectively predict positive classes (recall) and avoid false positives (precision). When calculating the model's performance, an F1-Score closest to 1 (one) is expected [6, 19, 27, 28].

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{10}$$

The AUC quantifies the area beneath the ROC (Receiver Operating Characteristic) curve and serves as a tool for evaluating the efficacy of a classification model. The ROC curve is a graphical representation used to evaluate the performance of a classification model. This metric summarizes the performance of a classification model at all threshold values with a single numerical value. The AUC value typically ranges from 0 (zero) to 1 (one), where a higher AUC value indicates better model performance. The AUC value can be calculated using the formulas for sensitivity and specificity as follows [23].

$$AUC = \sum_{i=1}^{n-1} \frac{1}{2} (Recall_i + Recall_{i+1}) \times (Specificity_{i+1} - Specificity_i) \tag{11}$$

3. RESULTS AND DISCUSSION

We built the models on a workstation computer with an Intel Xeon E-2221G CPU, 16GB of RAM, and an NVIDIA Quadro P620 graphics card. We allocated 80% of the dataset for training, and 20% for testing in all models. The training and testing performance results of the models are as shown in Tables 1, and 2, respectively.

Table 1. Training performance results of the models

	Accuracy	Specificity	Precision	Recall	F1-Score	AUC
DT	0.9998	0.9999	0.9998	0.9996	0.9997	0.9997
KNN	0.9997	0.9998	0.9997	0.9993	0.9995	0.9996
NB	0.9932	0.9929	0.9848	0.9938	0.9893	0.9934
SVM	0.9999	0.9998	0.9999	0.9998	0.9999	0.9999

Table 2. Test performance results of the models

	Accuracy	Specificity	Precision	Recall	F1-Score	AUC
DT	0.9983	0.9992	0.9983	0.9962	0.9973	0.9975
KNN	0.9996	0.9999	0.9997	0.9992	0.9994	0.9996
NB	0.9895	0.9926	0.9840	0.9830	0.9835	0.9862
SVM	0.9998	0.9999	0.9996	0.9994	0.9996	0.9996

Figures 3, 4, 5, and 6 illustrate the graphical comparison of the training and test performance outcomes of the models.

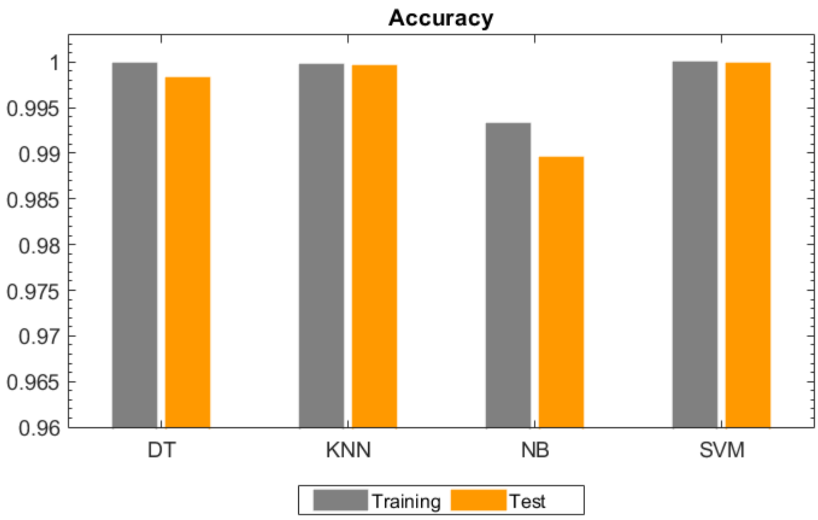

Figure 3. Accuracy performance graph of the models according to training and test data

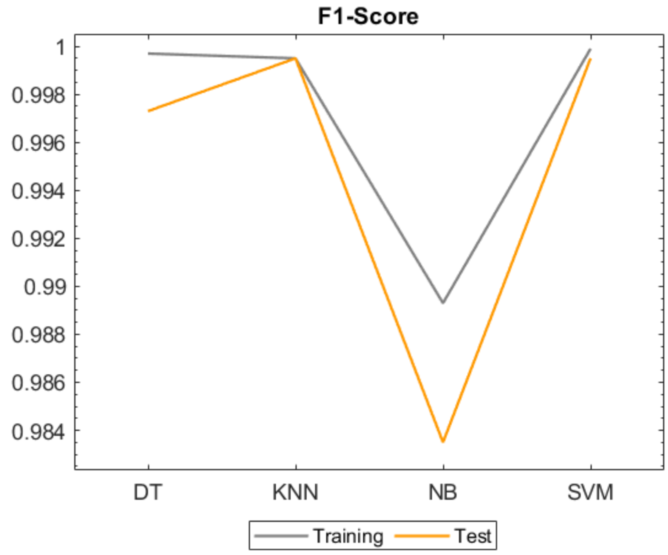

Figure 4. F1-Score performance graph of the models according to training and test data

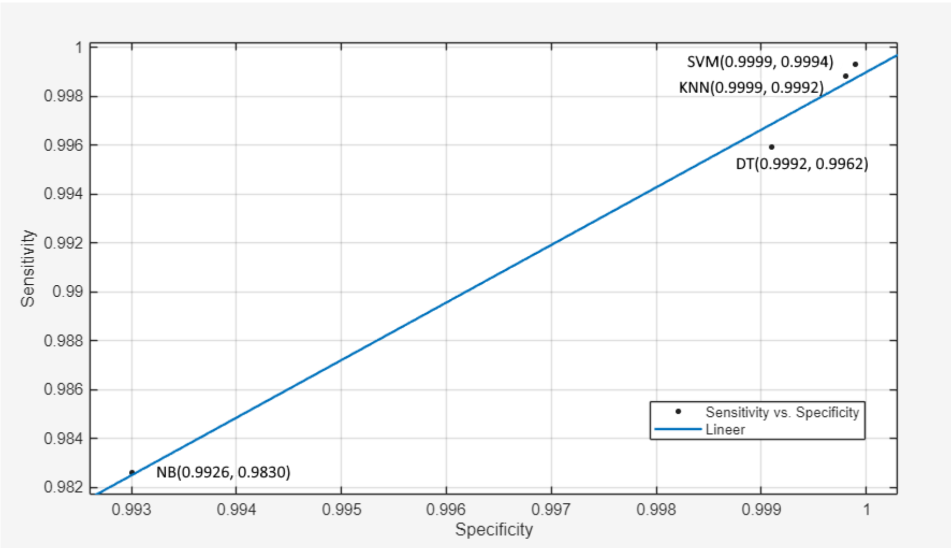

Figure 5. Specificity and sensitivity performance graph of the models according to test data

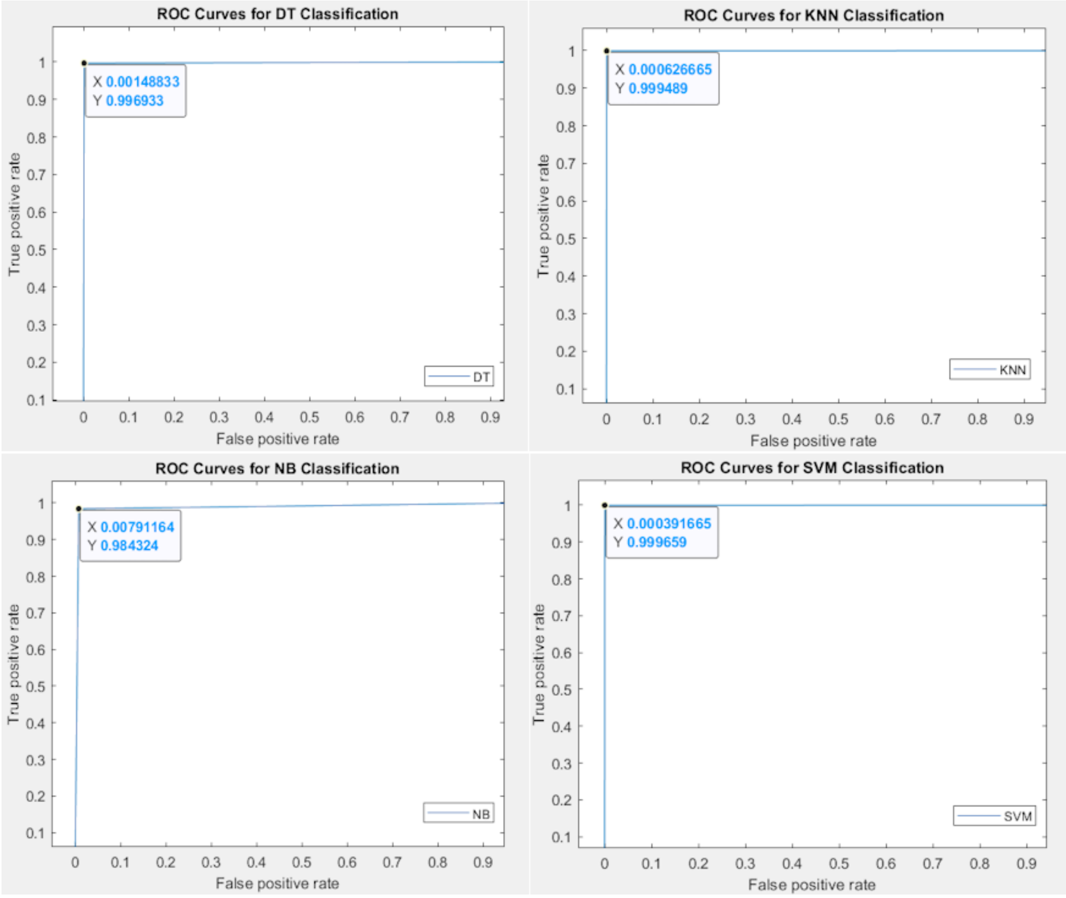

Figure 6. ROC curves graphs of the models according to test data

In addition to these results, the results obtained in this study were compared with the studies conducted. The results obtained in the study were compared with the studies presented in [29] and [30]. The comparison results are given in Table 3.

Table 3. Comparison Results

	Li et al. [29]	**Sankaran et al. [30]**	**This Research**
Accuracy	0.9862	0,9930	0.9998

When the results given in Table 3 are considered, it is understood that the results of the method proposed in the study are acceptable.

4. CONCLUSION

In this paper, we compared machine learning models that can be used for the identification and classification of corn and wheat cultivated agricultural lands in the GAP region by using an aerially captured and combined optical radar dataset from agricultural lands in the Canadian region as a reference and determined the most suitable methods based on performance results. We used supervised learning models such as DT, K-NN, NB, and SVM among the machine learning methods and compared their performances. The dataset contains a total of 174 polarimetric and optical features and 124236 rows of data for two plant species (corn, wheat). We used the dataset in two distinct ways; the first version of the dataset ordered the features as corn and wheat, leading to lower performance and accuracy rates, while the second version randomly processed the data, resulting in higher performance and accuracy rates. In all the models we analyzed, we evaluated the Area Under the Curve, F1-Score, and accuracy measures. According to the accuracy criterion results, SVM = 0.9998 > K-NN = 0.9996 > DT = 0.9983 > NB = 0.9895. According to the F1-Score results, SVM = 0.9996 > K-NN = 0.9994 > DT = 0.9973 > NB = 0.9835. These comparisons are based on the results of the model in the test phase. This study has demonstrated that classification applications for agricultural products can yield high accuracy results in this constantly developing field. In the light of the results obtained in Table 3, it is concluded that especially the wheat and corn species classified in this study can be distinguished effectively with the relevant data collection tool. In future studies, a large data set consisting of more plant species can be trained to increase the variety of crops that can be detected. By providing an infrastructure that includes the pre-trained model, a web or desktop application designed for the end user with an intuitive user interface can be developed. Such an application can expedite the government's crop detection process and timely intervene against corruption. It can also allow farmers to statistically determine the type and quantity of crops they plant.

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DECLARATION OF COMPETING INTEREST

The authors declared that no ethics committee permission was required for the materials and methods used in this article.

CONFLICT OF INTEREST

No conflict of interest has been declared in this study.

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