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Research Article

Diagnosis of Common Diseases in Alfalfa (*Medicago sativa L.*) Plant Using Machine Learning Method and Development of a Mobile Application

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Abstract

Alfalfa (*Medicago sativa L.*), known for its high yield and nutritional value, is a widely cultivated perennial legume subject to various diseases including Alfalfa Mosaic Virus (AMV), Downy Mildew, and Leaf Spot. Timely and accurate identification of these diseases is highly important to maintain crop health, improve productivity, and minimize the use of chemicals. In this study it was aimed to develop a mobile application-based machine learning technique for the detection of major alfalfa diseases. Open-access image dataset of 557 images for four categories—AMV, Downy Mildew, Leaf Spot, and healthy leaves, a deep learning model was used in Google's Teachable Machine platform. The model then integrated into a mobile application developed with MIT App Inventor 2. The model employs a Convolutional Neural Network (CNN) architecture optimized for mobile deployment via TensorFlow Lite. The application provides a user-friendly interface in Turkish and allows real-time disease classification through mobile phone's camera. Furthermore, it incorporates cloud-based storage using Google Drive and Google Sheets to log images with metadata including user input, time, and GPS location. The trained model achieved 85% classification accuracy on the test set. The resulting application offers a cost-effective, accessible tool for disease diagnosis in alfalfa cultivation, supporting sustainable agricultural practices. Future studies could expand the application to include a broader range of crops and diseases. The study highlights the potential of integrating artificial intelligence and mobile technology to empower farmers with on-the-spot decision support tools.
Keywords: Image processing, Clover diseases, Machine learning, Mobile applications, Smart agriculture

Yonca (*Medicago sativa* L.) Bitkisinde Yaygın Hastalıkların Makine Öğrenmesi Yöntemi ile Teşhisi ve Mobil Uygulama Geliştirilmesi

Öz

Yüksek verimi ve yüksek besin değeri ile bilinen Yonca (*Medicago sativa L.*), yaygın olarak yetiştirilen çok yıllık bir yem bitkisidir. Yonca Mozaik Virüsü (AMV), Mildiyö ve Yaprak Lekesi gibi çeşitli hastalıklara maruz kalmaktadır. Bu hastalıkların zamanında ve doğru şekilde teşhis edilmesi, bitki sağlığının korunması, verimliliğin artırılması ve kimyasal kullanımının en aza indirilmesi açısından büyük önem taşımaktadır. Bu çalışmada, yaygın yonca hastalıklarının tespiti amacıyla makine öğrenmesi tekniklerine dayalı bir mobil uygulama geliştirilmesi hedeflenmiştir. AMV, Mildiyö, Yaprak Lekesi ve sağlıklı yapraklardan oluşan dört kategoriye ait toplam 557 görüntü içeren açık erişimli bir veri seti kullanılarak Google'ın Teachable Machine platformunda derin öğrenme modeli oluşturulmuştur. Bu model, MIT App Inventor 2 ile geliştirilen bir mobil uygulamaya entegre edilmiştir. Model, TensorFlow Lite ile mobil cihazlara uygun hale getirilmiş Konvolüsyonel Sinir Ağı (CNN) mimarisi kullanmaktadır. Uygulama, Türkçe dil desteği sunan kullanıcı dostu bir arayüz aracılığıyla, mobil telefon kamerası kullanılarak gerçek zamanlı hastalık teşhisi imkânı sağlamaktadır. Ayrıca, kullanıcı bilgileri, zaman ve GPS konumu gibi meta verilerle birlikte görüntülerin Google Drive ve Google E-Tablolar üzerinde bulut tabanlı olarak kaydedilmesine olanak tanımaktadır. Eğitilmiş model, test verisi üzerinde %85 doğrulukla sınıflandırma yapmıştır. Geliştirilen uygulama, sürdürülebilir tarım uygulamalarını destekleyen, ekonomik ve erişilebilir bir hastalık teşhis aracı sunmaktadır. Gelecekteki çalışmalarla, uygulamanın farklı bitki türleri ve hastalıkları

kapsayacak şekilde genişletilmesi önerilmektedir. Bu çalışma, yapay zekâ ve mobil teknolojinin entegrasyonuyla çiftçilere yerinde karar desteği sağlayabilecek yenilikçi bir çözüm ortaya koymaktadır.
Anahtar Kelimeler: Görüntü işleme, Yonca hastalıkları, Makine öğrenimi, Mobil uygulamalar, Akıllı tarım

Introduction

Alfalfa (*Medicago sativa L.*) is the oldest known perennial forage plant of the (Fabaceae) family. It is also called the queen of forage plants due to its good nutritional content and high yield (Kaya, 2018). Alfalfa, has a critical role in economic terms as it is the main input of animal husbandry. Therefore, early diagnosis of diseases is vitally important. Traditional methods are time-consuming, costly and often prone to error, so they are being replaced by machine learning (ML) systems.

In recent years, ML techniques have offered promising solutions for diagnosis and classification of plant diseases. Deep learning algorithms, in particular, have shown great success in recognizing complex disease symptoms. Jayapalan and Ananth (2022) used an Internet of Things (IoT) approach in disease detection. They classified root diseases in alfalfa using images obtained by a camera. They employed a CNN model and achieved an accuracy of 91.98%, sensitivity of 91.69%) and specificity of 92%.

Yang et al. (2022) used ML algorithms such as YOLOv3, Faster R-CNN and VarifocalNet to distinguish different weed species. They also tested the performances of classical deep learning models such as VGGNet and GoogLeNet were also. They reported that the VGGNet model yielded the best results with an F1 score of up to 99%, especially in the classification of grassy and broadleaf weeds. This study shows that object recognition algorithms can be used effectively for plant health management in smart agricultural technologies.

Qin et al. (2016) developed an image processing-based classification system to identify four common leaf diseases in alfalfa. They extracted 129 features with ReliefF algorithm, and used 45 of them in classification. They tested the classification performance of Support Vector Machines (SVM), Random Forest, and K-nearest neighbor (k-NN). The highest accuracy of 94.74% was obtaned with the SVM model.

Early detection and correct classification of plant diseases not only improves the quality of agricultural products but also reduces unwanted chemical applications such as pesticides (Tewari et al., 2020). It can be difficult for producers in many developing countries to access real information about diseases (Pujari et al., 2013). Smartphones offer new approaches to help identify diseases due to their computing power, high-resolution screens and comprehensive accessory sets such as advanced HD cameras (Mohanty et al., 2016). The PlantVillage (https://plantvillage.psu.edu) mobile phone application aims to facilitate disease diagnosis in 14 plant species (Hughes and Salathé, 2015). In addition, the PlantifyAi (10.1016/j.procs.2021.07.059) application has been distributed as a mobile phone application. This application can diagnose 26 diseases of 14 plant species with very high accuracy (95.7%) in real time (Shrimali, 2021). In this study, a mobile application using deep learning-based image processing methods that can diagnose healthy plants with three important diseases in alfalfa was developed. This application, developed in Turkish, will provide producers with an easy-to-use tool. Furthermore, storing the classification results obtained after each use in a cloud database will provide an important basis for future work.

Material and Method

Dataset and Model Development

A dataset consisting of images of Alfalfa Mosaic Virus, Downy Mildew and Leaf Spot diseases and healthy plant images was created (Figure 1). The dataset included 228 images for Alfalfa Mosaic Virus, 84 images for Downy Mildew disease, 125 images for Leaf Spot disease and 120 images for healthy plants. The images were acquired from https://www.ipmimages.org/ image archive and Google images.

In the model, the learning rate was selected as 0.01% and Stochastic Gradient Descent (SGD) was selected as the optimizer for the machine learning model created on the Personal Image Classifier web platform. 15000 epochs were applied in the training of the model. The dataset was split into training and testing using Python code that randomly selects images. Eighty percent of the images, stored into separate files, were used for training and 20% for testing. In this study we used the hold-out method with randomized selection, which is a widely used approach in image-based CNN studies where datasets are limited but balanced.

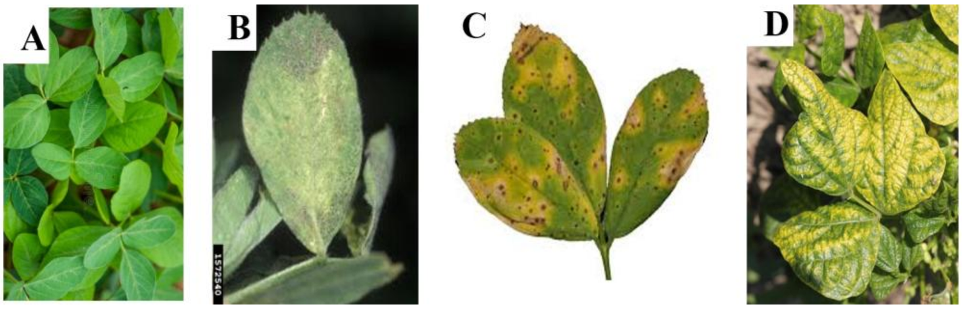

Figure 1. Example photographs used for each trait from the dataset. (A) Healthy alfalfa plant (B) Downy mildew disease (C) Leaf spot (D) Alfalfa plants affected by mosaic virus.

The model architecture employs a lightweight CNN optimized for mobile devices through TensorFlow Lite. The CNN follows a typical structure of convolutional layers with ReLU activation, pooling layers for dimensionality reduction, fully connected layers, and a Softmax classifier at the output stage.

Application Development with MIT App Inventor 2

MIT App Inventor 2 is a block-based mobile application development platform developed for users with limited or no coding knowledge (Patton et al., 2019). In the context of artificial intelligence education, it is a very useful tool, especially for object recognition, data visualization and IoT applications (Munasinghe et al., 2019). It has also been stated that it is useful in providing students with general programming skills (Panselinas et al., 2018). App Inventor is used to develop applications in agriculture as well as in other fields (Patton et al., 2019). As an example in the field of agriculture, an application that can collect, process and analyze soil data has been developed. It has been shown that this application is especially effective in soil protection and monitoring systems (Cioruța and Coman., 2022). When combined with IoT applications, MIT App Inventor 2 can also provide farmers with the opportunity to make more efficient decisions by collecting sensor data (Munasinghe et al., 2019).

Machine Learning Algorithms

The Personal Image Classifier (PIC) extension of MIT App Inventor 2 uses a model trained by Google Teachable Machine. This model uses a deep learning-based Convolutional Neural Network (CNN) algorithm. It is optimized specifically for MobileNet or similar lightweight deep learning models. It uses TensorFlow Lite for classification. It allows users to create their own training sets and train the model. The training process is done on Google's Teachable Machine platform and then integrated into MIT App Inventor 2. This extension finds various uses in education and industry as a tool to simplify AI-powered image classification applications (Hsu et al., 2021). The main advantage of CNN algorithms is that they can detect and classify objects in real time and are computationally cheaper and faster compared to other machine learning algorithms (Howard, 2013).

Convolutional Neural Networks have the capacity to automatically extract features from images and is used in many areas such as medical diagnosis, autonomous driving, facial recognition, and disease detection in agriculture (Xiao, 2024). They can obtain results by learning spatial and deep features in the data using their layered structure (Lee, 2023). The CNNs consist of five main layers as illustrated in Figure 2.

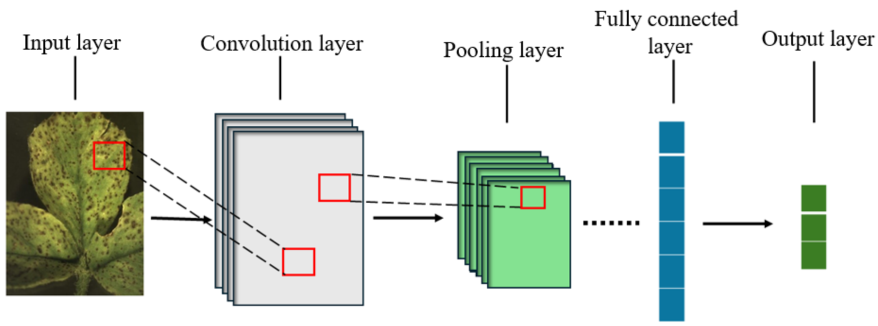

Figure 2. The four-layered feature of the CNN is schematized

The first layer is the input layer consisting of image data. The second is the convolution layer. In this layer, operations are performed by shifting a small filter (kernel) to extract certain features from the image. Thus, edges, textures or more complex patterns are learned. ReLU (Rectified Linear Unit) is usually used as the activation function in this layer (Saleem et al., 2022). The third layer is the pooling layer. In this layer, the size of the feature maps is decreased to limit the computational load of the model. However, important information is preserved. The most commonly used methods for this purpose are Max Pooling and Average Pooling. While Max Pooling selects the largest value in a certain region, Average Pooling takes the average value into account (Kapoor et al., 2021). The fourth layer is the Fully Connected layer. The main purpose here is to flatten the features obtained from the Convolution layers and connect them to a classical artificial neural network. In this layer, classification is done using Softmax or Sigmoid activation functions (Okamoto et al., 2022). The last layer is the output layer where the classification is made.

Cloud-based Data Storage

Google Drive platform, which is developed by Google and provides cloud-based image storage and sharing, was used. In order to establish communication between the mobile application and Google Drive, Google Apps Command was created in the file where the data to be stored was created. In addition, the name-surname information of the users, the time the images were taken, and the location information were recorded to be stored in Google Spreadsheets. Communication was established between these web platforms used for data storage and the application via file connections.

Application Interface and Use of Mobile App

The interface of the developed application is presented in Figure 3. The use of application starts with clicking on the camera button to take a leaf image of the clover plant. After the image is taken, it is processed by the model and the diagnosis results are transmitted to the result text box. The application offers special texts for the diseases with the probability value, along with what to do specific to the disease and other recommended information. When users want this data to be stored, they can store the captured image, Name-Surname, date and time information of the image, and location data on cloud-based platforms by clicking on the storage button.

Figure 3. Application interface.

The user interface provides information about the person who uploaded the disease, the disease symptom and some features of this disease.

Results and Discussion

The classification performance of the proposed model was evaluated using a confusion matrix (Figure 4). Also, of accuracy, precision, recall, and F1-score were calculated (Table 1). The overall accuracy achieved by the model was 85%, indicating that the majority of predictions across all classes were correct. Among the four categories, the model performed best on Mosaic virus, followed Downy mildew. However, performance on the Leaf spot class was comparatively weaker.

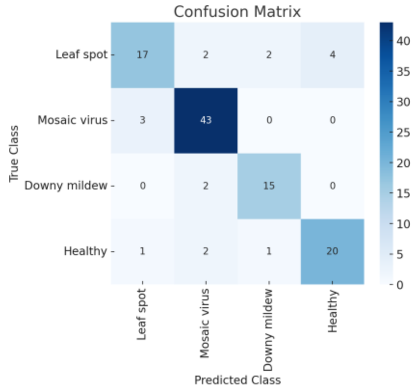

Figure 4. Model confusion matrix.

Table 1. Test statistics

Class	Precision	Recall	F1-score	Support
Leaf spot	0.81	0.68	0.74	25
Mosaic virus	0.88	0.93	0.91	46
Downy mildew	0.83	0.88	0.86	17
Healthy	0.83	0.83	0.83	24
Macro Average	0.84	0.83	0.83	112
Weighted Average	0.85	0.85	0.85	112

When averaged across all classes, the macro-average precision, recall, and F1-score demonstrated that consistent performance regardless of class size. The close agreement between macro and weighted metrics suggests that the dataset was relatively balanced and the model performed consistently across different categories. Overall, these results confirm that the model is robust and reliable in distinguishing between crop disease categories.

After the completion of the training phase, the created model file was integrated to the MIT App Inventor 2 browser via PersonalImageClassifier1 extension added externally to the application. This process enables the model to be used in real time on the application. It was observed that all of the pictures used to test the performance of the model were correctly classified by the application. Transferring the pictures used in the test phase via cloud-based platforms, such as Google Drive, provides significant convenience in terms of data management in research processes. This application ensures that datasets are stored and shared in an orderly manner. Storing the data obtained within the scope of the study in the Google Drive environment facilitates the analysis of the data and offers a practical solution to users.

This study distinguishes itself through its practical integration of machine learning (ML) with mobile technology for real-time disease detection in alfalfa. Unlike earlier studies, which primarily focus on developing and validating ML models in experimental or lab-based settings, this study presents an end-to-end solution that includes model training, mobile deployment, user interface design, and cloud-based data storage. For instance, Jayapalan and Ananth (2022) developed a deep CNN model to classify root diseases in alfalfa using images captured remotely. Their focus was on optimizing model accuracy through hybrid algorithms, achieving impressive performance. However, they did not deploy the model in a practical, user-accessible format like a mobile app. Similarly, Yang et al. (2022) applied advanced deep learning models such as YOLOv3 and VGGNet to identify weeds in alfalfa fields. Their contribution was notable for benchmarking detection models, but again lacked a real-time, field-deployable interface. Qin et al. (2016), on the other hand, used classical ML methods (SVM, k-NN, Random Forest) to classify leaf diseases with high accuracy (94.74%) based on extracted features, but this method required more manual feature engineering and provided no mobile integration or real-time functionality. By contrast, this study not only employed CNN via Google's Teachable Machine but also packaged the model in a mobile application developed with MIT App Inventor 2. Thus, while the cited studies emphasize algorithmic performance, this study bridge the gap between high-performance models and real-world application, contributing a fully functional, localized, and accessible diagnostic tool for Turkish farmers. There is very limited literature specifically focused on mobile applications for detecting alfalfa diseases. Kızıldeniz (2022) evaluated a mobile app called PETIOLE for measuring alfalfa leaf area in the field. Although the app's primary function is to estimate leaf area for yield prediction, it demonstrates that smartphone-based image analysis can be effectively used for alfalfa-related agricultural assessments. However, there appear to be no existing mobile apps documented in peer-reviewed literature that specifically focus on disease detection in alfalfa using image processing or machine learning. Finally, the developed mobile application can be obtained by contacting the corresponding author.

Conclusions

The mobile application developed in this study has a user-friendly interface and Turkish language support, allowing Turkish producers to use the application easily. In addition, the application's development on a completely free platform provides an economical solution and allows it to reach a wide range of users.

It is thought that storing data on a cloud-based platform such as Google Drive will provide significant convenience in research processes. This system enables data to be stored, analyzed and shared quickly when necessary. In particular, the structure integrated with Google Spreadsheets has provided flexibility in data management by keeping users' personal information, image dates and location data together. In future studies, it is recommended that the application be expanded to cover different plant species and diseases.

In conclusion, the application developed in this study represents an important step in the digital transformation in agriculture by providing a fast, accurate and practical solution to disease diagnosis processes in alfalfa plants. It is thought that this application, designed in accordance with the needs of local users, will make significant contributions in terms of agricultural sustainability and efficiency.

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Authors' Contributions

Authors declare that they have contributed equally to the article.

Conflicts of Interest Statement

The authors declare that there is no conflict of interest.

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