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Classification of Apple Diseases and Pests using The Google.com Powered Teachable Machine

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Abstract: Machine learning and deep learning methods are used in the classification of plant diseases. It takes a long time to extract features in machine learning. In deep learning, computers are required to process big data depending on the size of the data set. With Google Teachable Machine, faster results can be obtained without the need for feature extraction or very powerful computers. For this purpose, a model was created with four apple diseases using the data set related to apple diseases. In this model, results of over 95% were obtained in diseases.

Keywords: Plant Disease Detection, Machine learning, Teachable Machine.

Google.com Destekli Öğretilebilir Makine Kullanılarak Elma Hastalıklarının Sınıflandırılması

Öz: Bitki hastalıklarının sınıflandırılmasında makine öğrenimi ve derin öğrenme yöntemleri kullanılmaktadır. Makine öğreniminde özellikleri çıkarmak uzun zaman alıyor. Derin öğrenmede, veri kümesinin boyutuna bağlı olarak bilgisayarların büyük verileri işlemesi gerekir. Google öğretilebilir makina ile özellik çıkarımına veya çok güçlü bilgisayarlara ihtiyaç duymadan daha hızlı sonuçlar alınabilir. Bu amaçla elma hastalıkları ile ilgili veri seti kullanılarak dört elma hastalığı ile model oluşturulmuştur. Bu modelde hastalıklarda %95'in üzerinde sonuçlar elde edilmiştir.

Anahtar Kelimeler: Bitki Hastalığı Tespiti, Makine öğrenimi, Öğretilebilir Makine.

1. Introduction

The fruit sector creates positive value for countries in terms of economy and human nutrition. Since fruits are directly consumable after being harvested, their unprocessed form is also a source of income (Bashimov, 2016). China, the European Union (EU), the United States of America (USA), and Turkey come first in the world ranking of fresh fruit producer countries (Chammem et al., 2018). Plant disease is one of the most important problems encountered in the agricultural sector. This problem negatively affects the industry socially and economically. Plant pests and diseases are responsible for the loss of global food production of up to 40-45% with post-harvest losses. When plant disease is not diagnosed and detected early, it can affect not only one plant but also a large agricultural area (Akbas, 2019).

Farmers struggle to diagnose diseases in apples because the symptoms produced by different diseases can be similar and sometimes appear simultaneously. Machine learning approaches such as deep learning are proposed for the timely and accurate detection of apple diseases from plant leaves (Khan et al. 2021). In addition, this effect can last for many years. Apple, produced within the scope of fruit growing, is one of the fruits traditionally produced in agricultural enterprises (Branco et al. 2020; Chao et al. 2020). Apple adjusts the acid-base balance in the blood with the vitamins and organic acids it contains. It, which is rich in sugars, acids, proteins, fatty substances, vitamins and mineral salts, is also rich in vitamins A and C. It is a fruit that can be consumed in all seasons due to its annual storage possibilities (Kacar, 2019).

Under suitable conditions, apple saplings that have formed the branch infrastructure in nursery conditions begin to produce fruit economically in 2-3 years, while apple seedlings that do not form branches when planted in the garden begin to produce fruit efficiently after 4-5 years (Boyaci, 2009). Losing and replanting existing apple plants and waiting for fruit harvest can cause substantial economic losses. It is both costly and time-consuming to understand whether there is a disease in the plant and to detect this disease type (Turkoglu et al., 2020). When there are any of the known diseases in fruits and vegetables and more plant diseases, the symptoms of diseases such as bacteria, fungi, viruses, molds, and mites are evident in the images and thus can be identified and categorized accordingly (Jasim, 2021).

Machine learning or deep learning methods are used to classify plant diseases (Odabas et al., 2015; Odabas et al., 2016; Caliskan et al., 2017) . Although machine learning methods are low in cost, feature extraction takes time (Senel, 2020; Dammer et al., 2019). Models developed using Deep Learning methods are more successful and eliminate the loss of time in feature extraction (Odabas et al., 2017).

In addition to these advantages, deep neural networks have a significant disadvantage. These powerful hardware resources are required in deep network training and testing because deep network models need high memory and powerful GPU cards to work effectively. Researchers researched disease detection of apple plants using deep convolutional neural networks and achieved an accuracy percentage of 99.54% with the ResNet-34 architecture (Aksoy et al., 2020). In another study, an accuracy rate of 99.30% was performed in the study for the detection of peach diseases (Aslan, 2021).

In the field of agriculture, machine learning and other soft computing methods have been widely employed for the identification and categorization of diseases (Bansal et al. 2021). Teachable Machine (Google 2022) allows us to train our datasets using a web application. Image and sound classification can be made (Google, 2023). There is no need for a high-performance computer and GPU card while training the data. With a mobile application developed, a corn plant recognition application was developed using the data sets of the corn plant, and they achieved an accuracy rate of 80.7% (Aqil et al., 2021). In another study, 97% accuracy rates were obtained in animal classification by the researchers (Agustian et al., 2021). In the research on insect classification, 2646 images were used, and 100% accuracy was achieved (Gupta, 2021).

In this study, real-time apple disease classification was made through a web application designed by training the datasets of the disease of the apples.

2. Material and Method

In this study, the Turkey-Plant Dataset dataset created by Turkoglu et al. was used (Turkoglu et al. 2021). All images in the dataset are 300 x 300 pixels in size (Table 1).

Table 1. Apple diseases examined in the study and the number of images related to them.
Çizelge 1. *Araştırmada incelenen elma hastalık ve zararlılarına ilişkin görsel sayısı.*

Apple diseases	Abbreviation	The number of data
Aphis Spp.	AS	162
Eriosoma lanigerum	EL	366
Monilinia laxa	ML	255
Venturia inaequalis	VI	633

The aphid species (*Aphis* Spp) in apple orchards are the green apple aphid, *Aphis pomi* de Geer, and the spirea aphid, Aphis spiraecola Patch (*Hemiptera: Aphididae*). Green apple aphids reduce tree growth and nonstructural carbohydrate concentration and fruit production in young apple trees. Severe infestation also increases the risk of winter death. The negative impact of green apple aphids is more significant on young trees than on mature trees (Fréchette et al., 2008). Woolly apple aphid (WAA), *Eriosoma lanigerum* is a worldwide pest of apple. It colonizes roots and sites on the trunk and branches previously injured and can also occupy undamaged current-year shoots (Lordan et al., 2015). *Monilinia* spp. is an economically important disease. *Monilinia laxa* is causing mainly blossom and twig blight. Under suitable weather conditions, the disease develops rapidly. That's why, Monilinia spp., before or during storage, is essential for crop losses on pome fruits, especially post-harvest (Spitaler et al., 2022). *Venturia inaequalis* (Cooke Wint) affects the leaves and fruit tissue of trees. The pathogen was placed into the genus Venturia by Winter in 1880. It leads to both a saprophytic and parasitic lifestyle. The pathogen ascospores on the leaves broke the thin surface epithelium of immature leaves when moisture was present. The germ tube differentiates into an appressorium upon coming into contact with a cuticle and releases sticky mucilaginous chemicals that are thought to aid in adhesion to the host surface. Once an infection is established, curative preparations are required to stop further development of the mycelium. In organic apple growing, sulfur, lime, and copper are used for scab disease (Doolotkeldieva and Bobusheva, 2017).

Images of four diseases of the apple plant were trained by a teachable machine. While training the dataset, parameter values are 100 for epoch, 32 for batch size, and 0.001 for learning rate. There are no settings related to training and test datasets. Epoch is a term used to describe an iteration within the scope of training a model in which the model uses the entire training set to update its weights. Updating weights during the training phase usually does not rely on all training sets simultaneously due to computational complexities or a data point due to noise issues. Instead, the update step is done with mini-sets, where the number of data points in a batch is a hyperparameter that we can adjust. Data in mini-clusters is called batch (Amidi, 2022). The learning rate determines the rate at which weights are updated, usually denoted as alpha (α) or sometimes eta (η). It can be fixed or adapted. The most popular method available is called ADAM and it is a method that adjusts the learning rate.

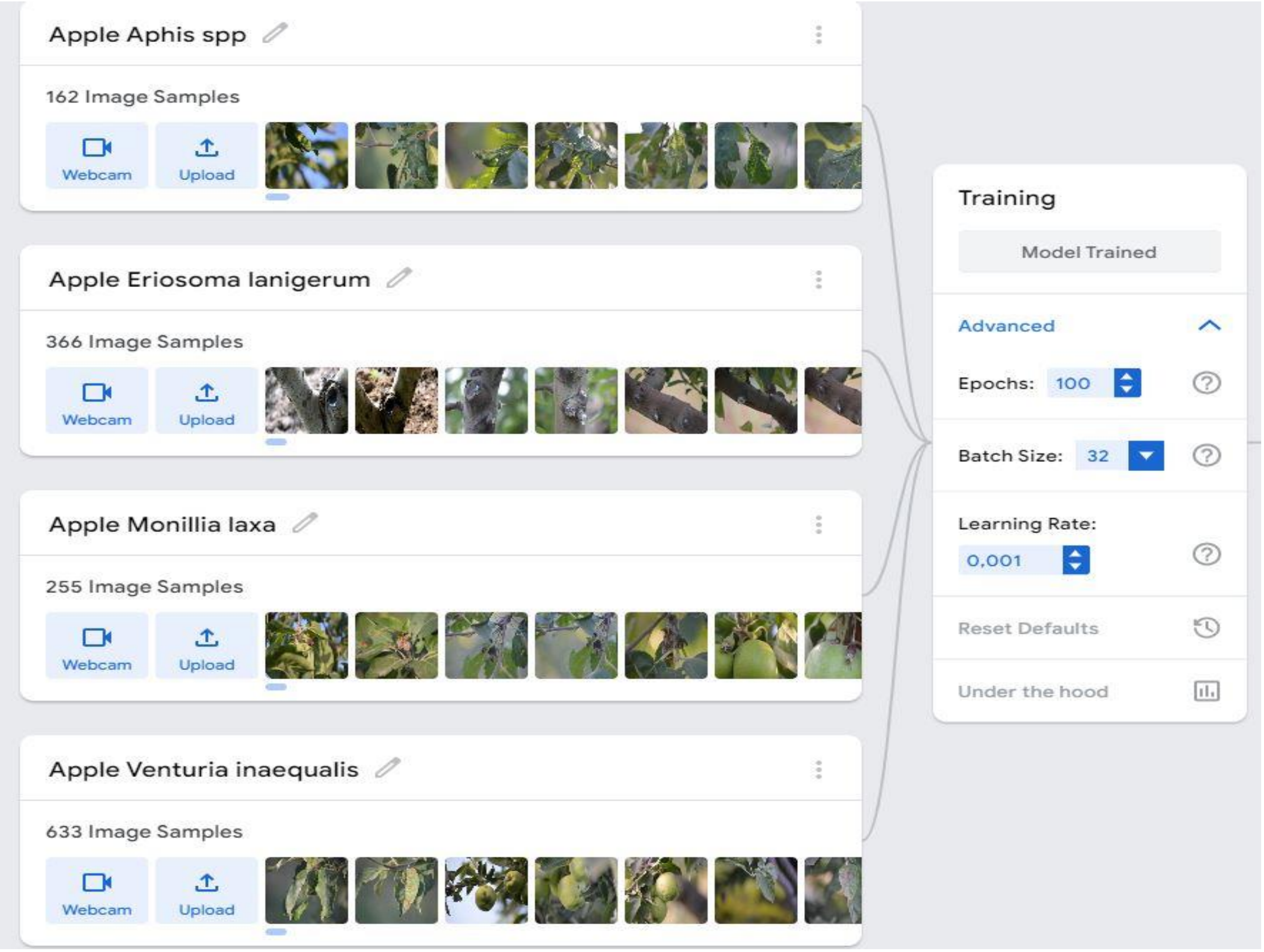


Figure 1. Performing machine learning based classification
Şekil 1. *Makine öğrenimi tabanlı sınıflandırma gerçekleştirme*

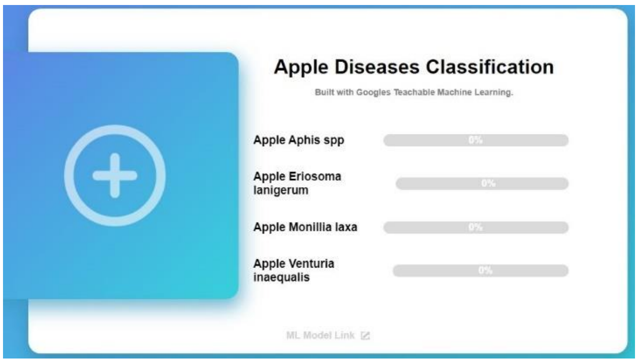


Figure2. Web interface
Şekil 2. *Web arayüzü*

The model formed in the study was designed as a web interface and classified apple disease and transferred to the web interface with the tensorflow.js file (Saka, 2022).

3. Result and Discussion

The appropriate division of a dataset is crucial in leveraging machine learning techniques for the identification and categorization of diseases and pests in apple plants (Thakur et al. 2022). Typically, datasets are segmented into three key sections: the training set, the validation set, and the test set. The training set is utilized to train the model, while the validation set aids in fine-tuning parameters and optimizing the model's performance. Finally, the test set evaluates the model's overall effectiveness. Common ratios for this division include allocating 60-80% for the training set, 10-20% for the validation set, and another 10-20% for the test set. Maintaining randomness in this partitioning process ensures the dataset's diversity and representation. Initially, the dataset is divided into training and temporary subsets, which are further segmented into validation and test sets. Ultimately, this process yields the training set (X_train, y_train), validation set (X_val, y_val), and test set (X_test, y_test). These steps are essential in effectively utilizing machine learning approaches, enabling robust model performance and generalization (Mesías-Ruiz et al. 2023).

After the data set training process was completed, a report on the model consisting of the "Under the hood" menu was received. When this report was examined, it was seen that the data set was divided into 85% training and 15% test set, and the training process was carried out. The results of this training process are given in Table 2.

Table 2. Results obtained at the end of the training
Çizelge 2. *Eğitim sonunda elde edilen sonuçlar*

Class	Accuracy	The number of samples
Aphis Spp.	0.96	25
Eriosoma lanigerum	0.98	55
Monilinia laxa	0.95	39
Venturia inaequalis	0.98	95

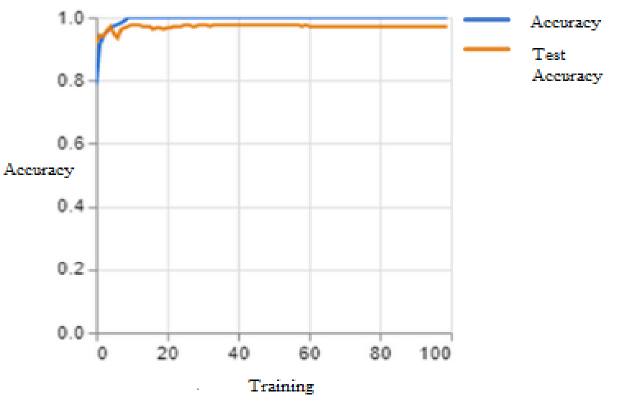
According to the results, the highest accuracy value was seen in Apple Venturia inaequalis disease (AVI) at 98%, and the lowest accuracy value was seen in Apple Monillia laxa (AML) disease at 95%. In the disease prediction table, the accuracy values of the test sets belonging to the classes formed from apple diseases are included. Monillia laxa disease, with the lowest accuracy, was seen to be confused with Venturia inaequalis only (Table 3).

Table 3. Prediction table of apple diseases
Çizelge 3. *Elma hastalıklarının tahmin tablosu*

AAS	24	0	0	1
AEL	0	54	0	1
AML	0	1	37	1
AVI	1	0	1	93
	AAS	AEL	AML	AVI

After the training and test data are divided into two groups, this test set is tested as much as the determined epochs (100) value in the epochs process. Accuracy, and loss values are pivotal indicators in assessing the performance of a machine learning model during training. The accuracy graph tracks the model's precision at each epoch, ideally showing a steady increase and stabilization at high levels across both training and validation sets. Conversely, if accuracy peaks on the training set but declines on the validation set, overfitting may be occurring. Meanwhile, the loss graph demonstrates the model's error rate throughout training, with the expectation that it steadily decreases. A significant gap between training and validation set losses may signal overfitting. Evaluating these metrics together provides valuable insights for model refinement, such as considering model complexity adjustments or the acquisition of additional data to address overfitting issues (Burgkart et al. 2001). Accuracy and loss values are shown in Figure 3.

When the graphs are examined, the epoch value shows that stable results start to be obtained after 30, and it becomes the most stable after 40. After this value, there was a slight decrease in the accuracy value of the test set. In addition, there is a slight increase in the loss amount of the test set after this value.



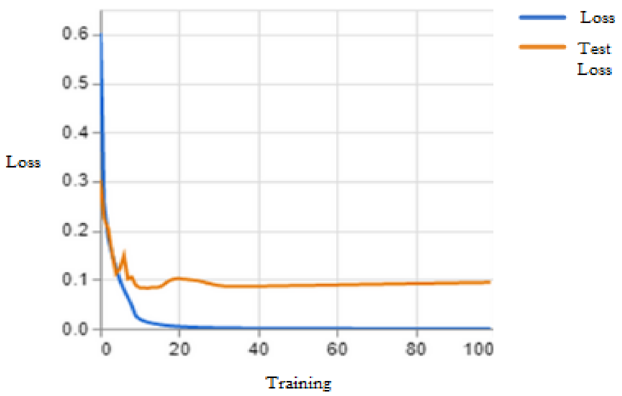


Figure 3. Epochs accuracy and loss values
Şekil 3. *Epoch doğruluğu ve kayıp değerleri*

4. Conclusion

Utilizing a teachable machine to develop a model for detecting four different diseases in apple plants represents a notable advancement in agricultural technology. The achieved accuracy rates, ranging from 95% to 98%, underscore the effectiveness of this approach in disease identification. Furthermore, the study suggests a positive correlation between accuracy rates and the volume of available data, indicating the potential for even greater accuracy with larger datasets.

Support from existing literature in agricultural technology reinforces the importance of accurate disease detection methods. For instance, research conducted by (Kala et al. 2023), emphasizes the crucial role of advanced technology in mitigating the adverse effects of plant diseases on crop yields. Similarly, studies such as (Storey et al. 2022) highlight the significance of employing machine learning techniques for precise disease diagnosis and timely intervention in agricultural contexts. These findings align with the outcomes of the current study, further validating the efficacy of utilizing a teachable machine for disease detection in apple plants.

In the domain of machine learning methodologies, the feature extraction process is acknowledged for its time-consuming nature. However, it is worth noting that accuracy values tend to increase proportionally with the expansion of features. Conversely, deep learning methods, often requiring high-performance computers equipped with GPUs, offer impressive accuracy levels. In contrast, the implementation of a teachable machine proves to be both time-saving and cost-effective, making it a viable solution for disease detection in apple plants.

The findings of this study underscore the feasibility of developing high-accuracy models through the application of appropriate methods and techniques, particularly when employing a teachable machine for processing image datasets. This highlights the potential for widespread adoption of such technologies in the agricultural sector, leading to improved disease management practices and ultimately contributing to enhanced crop yields and agricultural sustainability.

References

Agustian D, Pertama P, Crisnapati PN, & Novayanti PD (2021). Implementation of Machine Learning Using Google's Teachable Machine Based on Android. In 2021 *3rd International Conference on Cybernetics and Intelligent System* (ICORIS), IEEE, 1–7. 10.1109/ICORIS52787.2021.9649528

Akbas B (2019). Plant health's place in sustainable agriculture. *Journal of Agriculture Engineering* (368): 6–13.

Aksoy B, Halis HD, & Salman OKM (2020). Detection of Diseases in Apple Plant with Artificial Intelligence Methods and Comparison of the Performance of Artificial Intelligence Methods. *International Journal of Engineering and Innovative Research* 2(3): 194–210. https://doi.org/10.47933/ijeir.772514

Amidi AA (2022). Deep Learning tricks and tips handbook. https://stanford.edu/~shervine/l/tr/teaching/cs-230/cheatsheet-deep-learning-tips-and-tricks#running-nn 2022.

Aslan M (2021). Detection of Peach Diseases with Deep Learning. *European Journal of Science and Technology* (23): 540–46. https://doi.org/10.31590/ejosat.883787

Aqil M. Tabri1 F, Andayani NN, Panikkai S, Suwardi ER, Bunyamin Z, Azrai M, & Ratuleet T (2021). Integration of Smartphone Technology for Maize Recognition. IOP Conference Series: *Earth and Environmental Science* 911(1): 012037.

Bansal P, Kumar R, & Kumar S. (2021). Disease detection in apple leaves using deep convolutional neural network. Agriculture 11(7): 617. https://doi.org/10.3390/agriculture11070617

Bashimov G (2016). Comparative Advantage of Turkey in Apple Exports. *Journal of Adnan Menderes University Agricultural Faculty* 13(2): 9 – 15. https://doi.org/10.25308/aduziraat.293391

Boyaci S. & Çağlar S. (2009). A Study on The Production of Branched Apple Tree Under Nursery Condition in Turkey. *The Journal of Agricultural Sciences* 2(1): 107–111.

Bracino AA, Concepcion RS, Bedruz RAR, Dadios EP, Vicerra RRP. (2020). Development of a hybrid machine learning model for apple (Malus domestica) health detection and disease classification. *In 2020 IEEE 12th international conference on humanoid, nanotechnology, information technology, communication and control, environment, and management* (HNICEM) (pp. 1-6).

Burgkart R, Glaser C, Hyhlik-Dürr A, Englmeier KH, Reiser M, & Eckstein F. (2001). Magnetic resonance imaging–based assessment of cartilage loss in severe osteoarthritis: accuracy, precision, and diagnostic value. *Arthritis & Rheumatism: Official Journal of the American College of Rheumatology* 44(9): 2072-2077. https://doi.org/10.1002/1529-0131(200109)44:9<2072::AID-ART357>3.0.CO;2-3

Caliskan O, Kurt D, Temizel KE, & Odabas MS (2017). Effect of Salt Stress and Irrigation Water on Growth and Development of Sweet Basil (*Ocimum basilicum* L.). *Open Agriculture* 2(1): 589-594. https://doi.org/10.1515/opag-2017-0062

Chammem N, Issaqui M, De Almedia AID, & Delgado AM (2018). Food Crises and Food Safety Incidents in European Union, United States, and Maghreb Area: Current Risk Communication Strategies and New Approaches. *Journal of AOAC International* 101(4): 923-938. 10.5740/jaoacint.17-0446

Chao X, Sun G, Zhao H, Li M, & He D. (2020). Identification of apple tree leaf diseases based on deep learning models. *Symmetry* 12(7): 1065. https://doi.org/10.3390/sym12071065

Dammer KH, Intreß J, Schirrmann M, & Garz A (2019). Growth Behavior of Ragweed (*Ambrosia artemisiifolia* L.) on Agricultural Land in Brandenburg (Germany) Conclusions for Image Analysis in Camera Based Monitoring Strategies. *Gesunde Pflanzen* 71: 227–235. https://doi.org/10.1007/s10343-019-00488-0

Doolotkeldieva T, & Bobusheva S (2017). Scab Disease Caused by Venturia inaequalis on Apple Trees in Kyrgyzstan and Biological Agents to Control This Disease. *Advances in Microbiology* 7: 450-466. 10.4236/aim.2017.76035

Fréchette B, Cormier D, Chouinard G, Vanoosthuyse F, & Lucas É (2008). Apple aphid, *Aphis* spp. (*Hemiptera: Aphididae*), and predator populations in an apple orchard at the non-bearing stage: The impact of ground cover and cultivar. *European Journal of Entomology* 105: 521–529. 10.14411/eje.2008.069

Google. (2023). Teachable Machine. https://teachablemachine.withgoogle.com

Gupta YM, & Homchan S (2021). Insect Detection Using a Machine Learning Model. *Nusantara Bioscience* 13(1): 68–72. https://doi.org/10.13057/nusbiosci/n130110

Jasim YA (2021). High-Performance Deep Learning to Detection and Tracking Tomato Plant Leaf Predict Disease and Expert Systems. *Advances in Distributed Computing and Artificial Intelligence Journal* 10(2): 97–122. https://doi.org/10.14201/ADCAIJ202110297122

Kacar G (2019). Bioecologies of Pests, Natural Enemies in apple orchards of Seben (Bolu). *International Journal of Agriculture and Wildlife Science* 5(2): 286 – 291. 10.24180/ijaws.605651

Kala KU, Nandhini M, Thangadarshini M, Chakkravarthi MK, & Verma M. (2023). Leveraging Deep Learning for Effective Pest Management in Plantain Tree Cultivation. *In International Conference on Soft Computing and Signal Processing* (pp. 425-434). Singapore: Springer Nature Singapore. 10.1007/978-981-99-8628-6_36

Khan AI, Quadri SMK, & Banday S. (2021). Deep learning for apple diseases: classification and identification. *Int. Journal of Computational Intelligence Studies* 10(1):1-12 https://doi.org/10.1016/j.compag.2022.107093

Lordan J, Alegre S, Gatius F, Sarasúa MJ, & Alins G (2015). Woolly apple aphid Eriosoma lanigerum Hausmann ecology and its relationship with climatic variables and natural enemies in Mediterranean areas. *Bulletin of Entomological Research* 105(1): 60-69. 10.1017/S0007485314000753

Mesías-Ruiz GA, Pérez-Ortiz M, Dorado J, De Castro AI, & Peña JM. (2023). Boosting precision crop protection towards agriculture 5.0 via machine learning and emerging technologies: A contextual review. *Frontiers in Plant Science* 14: 1143326. 10.3389/fpls.2023.1143326

Odabas MS, Radusiene J, Karpaviciene B, & Camas N (2015). Prediction model of the effect of light intensity on phenolic contents in *Hypericum triquetrifolium* turra. *Bulgarian Chemical Communications* 47(2):467-471.

Odabas MS, Kayhan G, Ergun E, & Senyer N (2016). Using Artificial Neural Network and Multiple Linear Regression for Predicting the Chlorophyll Concentration Index of Saint John's Wort Leaves. *Communications in Soil Science and Plant Analysis* 47(2): 237-245. http://dx.doi.org/10.1080/00103624.2015.1104342

Odabas MS, Senyer N, Kayhan G, & Ergun E (2017). Estimation of Chlorophyll Concentration Index at Leaves using Artificial Neural Networks. *Journal of Circuits Systems and Computers* 26(2): 1750026. 10.1142/S0218126617500268

Saka SO (2022). Github. https://github.com: https://sosaka0.github.io/Apple-disease/.

Storey G, Meng Q, & Li B. (2022). Leaf disease segmentation and detection in apple orchards for precise smart spraying in sustainable agriculture. *Sustainability* 14(3):1458. https://doi.org/10.3390/su14031458

Senel FA (2020). Classification of Apricot Kernels by using Machine Learning Algorithms. *Bitlis Eren University Journal of Science* 9(2): 807–15.

Spitaler U, Pfeifer A, Deltedesco E, Hauptkorn S, & Oettl S (2022). Detection of Monilinia spp. by a multiplex real-time PCR assay and first report of *Monilinia fructicola* in South Tyrol (northern Italy). *Journal of Plant Diseases and Protection* 129:1013–1020.https://doi.org/10.1007/s41348-022-00614-7

Thakur PS, Khanna P, Sheorey T, & Ojha A. (2022). Trends in vision-based machine learning techniques for plant disease identification: A systematic review. *Expert Systems with Applications* 208: 118117. https://doi.org/10.1016/j.eswa.2022.118117

Turkoglu M, Yanikoglu B, & Hanbay D (2021). PlantDiseaseNet: Convolutional Neural Network Ensemble for Plant Disease and Pest Detection. *Signal, Image and Video Processing* 16:301-309. https://doi.org/10.1007/s11760-021-01909-2

Turkoglu M, Hanbay K, Sivrikaya IS, & Hanbay D (2020). Classification of Apricot Diseases by Using Deep Convolution Neural Network. *Bitlis Eren University Journal of Science* 9(1): 334–45. https://doi.org/10.17798/bitlisfen.562101