Black Sea Journal of Engineering and Science
doi: 10.34248/bsengineering.1322907

Open Access Journal
e-ISSN: 2619 – 8991

Research Article
Volume 6 - Issue 4: 387-393 / October 2023

CORN DISEASE DETECTION USING TRANSFER LEARNING

Cevher OZDEN[1, 2*]

[1]*Akdeniz University, Faculty of Engineering, Department of Computer Science Engineering, 07058, Antalya, Türkiye*
[2]*Cukurova University, Faculty of Agriculture, Department of Agricultural Economics, 01380, Adana, Türkiye*

Abstract: Detecting plant disease is a complicated yet important task to enable sustainable production in agriculture. Especially, early and on-field disease detection provides an opportunity to producers to take necessary precautions before it causes dramatic losses. Corn is one of the most important agricultural products for many countries around the world. It constitutes the main nutrient intake for large populations. This study examines and analyzes the applicability of the pretrained models in corn disease detection. A number of well-known pretrained models including Xception, ResNet50, VGG16, EfficientNetB0, MobileNet and InceptionV3 have been employed for this purpose. SMOTE is employed to solve the imbalanced data and resulting bias problem, which is a common problem in plant disease dataset. The study results indicate that SMOTE provides a good solution to the imbalanced data problem and MobileNet, VGG16 and Xception can be used as base models to develop AI applications to detect corn diseases.

Keywords: Disease detection, Classification, Transfer learning, Imbalanced data

***Corresponding author:** Akdeniz University, Faculty of Engineering, Department of Computer Science Engineering, 07058, Antalya, Türkiye
E mail: efeozden@gmail.com (C. OZDEN)
Cevher OZDEN https://orcid.org/0000-0002-8445-4629

Received: July 05, 2023
Accepted: August 31, 2023
Published: October 15, 2023

Cite as: Ozden C. 2023. Corn disease detection using transfer learning. BSJ Eng Sci, 6(4): 387-393.

1. Introduction

Plant diseases constitute a major problem in agricultural production. Plants exposed to diseases may experience disruptions in their growth processes, decrease in product yield and loss of quality. This leads to economic losses in the agricultural sector. In particular, agriculture is an important economic activity for many countries, and agricultural products are a major source of income for both domestic consumption and exports. Plant diseases can negatively affect this potential in agricultural production.

Plant diseases can also affect product quality, which reduces the marketability of the product and lowers the commercial value. Also, some plant diseases can produce toxins in plant tissues and threaten human health when consumed. Such situations further increase the economic effects of plant diseases.

Economic losses affect not only producer farmers but also other stakeholders along the entire agricultural value chain. Plant diseases can also cause problems in the food processing and packaging industries. Processing poor quality and diseased products can affect the quality of end products and tarnish marketing image. In addition, the storage and transportation of diseased plant material can also lead to economic losses.

Plant diseases also affect trading activities. Trade in diseased plants can lead to the spread of plant diseases between countries. This poses a serious risk for both exporting and importing countries. Diseased plant material can cause new infections or epidemics in other countries. This could accelerate the global spread of plant diseases and create barriers to agribusiness.

Corn production is a key component of the agricultural sector of many countries and plays a critical role in food production, economy and trade. Corn is a product of great importance for Türkiye in terms of agricultural production and economy. Türkiye is an important player in corn production and produces this product for both domestic consumption and export. According to statistics, Türkiye's corn production has increased continuously in recent years. Türkiye's corn production in 2020 was approximately 6.5 million tons (TUIK, 2022). This amount of production helped Türkiye to meet its own corn needs and reduced the need for imports. At the same time, Türkiye shows a significant increase in its corn export. Türkiye's corn export in 2020 was recorded as 1.2 million tons (TUIK, 2022).

However, diseases can reduce the yield in corn production and even cause complete destruction of the product. These diseases are caused by fungi, bacteria, viruses and other microorganisms called plant pathogens. In addition, environmental factors, pests, nutrient deficiencies and other stress conditions can also contribute to the emergence of plant diseases.

Artificial intelligence (AI) technologies play an important role in plant disease diagnosis. AI accelerates the detection of plant diseases and increases its accuracy thanks to its capabilities such as big data analysis, image processing and pattern recognition. These technologies help to minimize losses in agricultural production by enabling early detection of plant diseases. Diagnosis of plant diseases is often visually based. However, it is a difficult task for people to have expert knowledge of thousands of plant species and disease symptoms. AI can automatically diagnose plant diseases using image processing and pattern recognition algorithms. For example, artificial neural networks can determine the type of disease by analyzing spot symptoms on plant leaves. These methods make it possible to obtain fast and accurate results.

Plant disease detection has been a hot research topic among scientists. There have been a number of studies implemented using artificial intelligence methods. The recent studies are summarized in Table 1.

Table 1. Recent studies implemented using transfer learning on plant disease detection

Researchers	Methods	Data	Performance
Paymode et al. 2021	VGG16, ResNet50	Plant Village	98.40% Accuracy
Mukti and Biswas, 2019	ResNet50, VGG16, VGG19, AlexNet	Salathegroup Data	99.8% Accuracy
Khasawneh et al. 2022	DenseNet-201, SqueezeNet, GooglLeNet, Inceptionv3, MobileNetv2, ResNet-101, ResNet-50, ResNet-18, Xception, ShuffleNet, DarkNet-53	Tomato, Mendeley Data	99.2% F1 Score
Bir et al., 2020	EfficientNetB0, MobileNetv2, VGG19	Tomato Plant Village	98.6% Accuracy
Chen et al., 2020	Dens-Incep (DenseNet + Inception)	Rice Plant locally collected	92.22% Accuracy
Feng et al., 2021	Deep CORAL, Deep Domain Confusion, CNN	Rice Plant China Rice Research Institute	88.0% Accuracy
Kathiresan et al., 2021	RiceDenseNet, MobileNet, ResNet50, ResNet101, Xception, Inceptionv3	Rice Plant Combination of three open source datasets	97.71% Accuracy
Shahoveisi et al., 2023	ResNet50, Xception, EFficientNetB4, MobileNet	Rust Disease Detection on various plants	93.52% Accuracy
Abbas et al., 2021	Conditional Generative Adversarial Network + DenseNet121	Tomato PlantVillage	99.51% Accuracy
Hasan et al., 2019	Inception	Tomato PlantVillage	99.0% Accuracy
Vallabhajosyula et al., 2021	Deep Ensemble Neural Network, ResNet50, ResNet101, Inceptionv3, DenseNet121, DenseNet201, MobileNetv3,NasNet	PlantVillage	99.9% Accuracy (NasNet, DenseNet2021, ResNet101)
Reddy and Rekka, 2021	Deep Leaf Disease Prediction Framework (CNN+AlexNet+ GoogLeNet)	Apple PlantVillage	97.62%

The main problem of plant disease detection studies is that datasets contain imbalanced number of classes. In order to eliminate the bias problem that can arise from the dominant class, certain techniques such as under sampling, oversampling, data augmentation and synthetic data creation are employed during data preprocessing phase. Oversampling through duplicating examples in the minority class or under sampling through removing examples in the majority class can make the dataset balanced but both techniques do not provide any additional information, and under sampling even degrades the information further. The solution can be synthesizing new examples using the information in the minority class. The most common approach in literature is Synthetic Minority Oversampling Technique -SMOTE (Chawla et al., 2011). SMOTE is effective as it produces new synthetic examples from the minority class that are relatively close to representing the features of the existing examples. In this study, SMOTE is preferred to eliminate imbalanced data structure and a number of popular pre-trained models are employed to test their applicability and robustness in detecting the diseases of corn products.

2. Materials and Methods

In this study, Plant Village dataset is used. Plant Village is a research unit of Penn State University that aims to alleviate poverty through offering cheap and affordable technologies to farmers. They offer a large collection of databases and resources on plant diseases (Hughes and Salathé, 2015). This platform aims to assist agronomists, farmers, researchers and other interested parties in the diagnosis, identification and management of plant diseases. The database contains thousands of plant disease images, plant damage images, symptoms of plant diseases, and descriptive information. The dataset provides users with information to diagnose plant diseases, recognize disease symptoms, learn appropriate treatment methods and protect their agricultural production. Plant Village dataset consists of 54303 healthy and unhealthy leaf images separated into 38 categories by diseases and species. The dataset contains a total of 3.852 images of corn product which consists of 513 gray leaf spot, 1.192 common rust, 1.162 healthy and 985 northern leaf blight categories. There is imbalance among classes as three classes contains approximately close number of instances; however, the number of instance in gray leaf spot is about half of the other three classes. In order to eliminate the bias problem, Synthetic Minority Sampling Technique (SMOTE) technique has been employed. SMOTE brings balance to the dataset by augmenting the samples in minority classes (Figure 1).

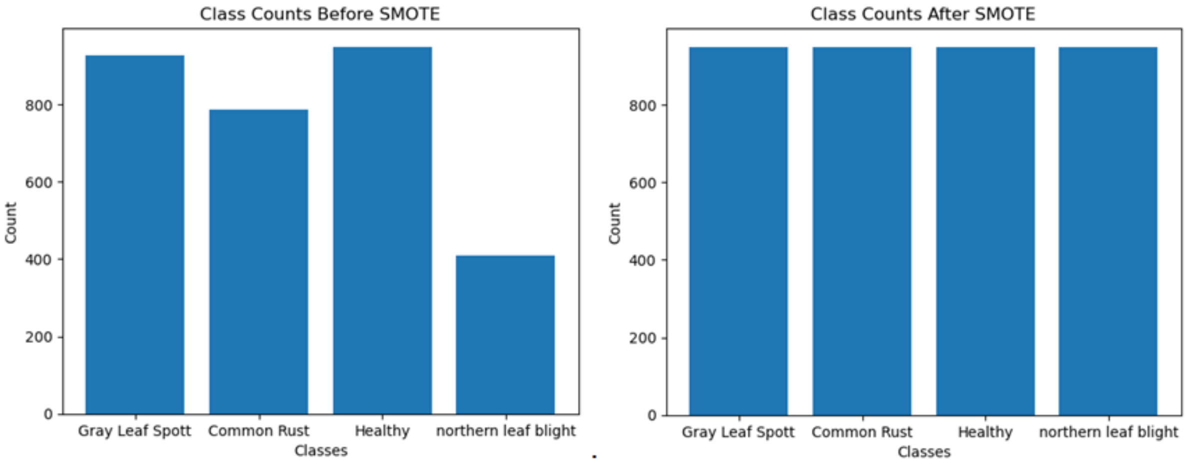


Figure 1. The distribution of classes before and after SMOTE.

SMOTE analyzes the immediate neighbors of the minority class samples and uses the relationships between these samples to generate new synthetic samples. SMOTE method generates synthetic samples through interpolating between the feature values of the base instance and its nearest neighbors given by the user. For each synthetic sample to be generated, (i) it chooses one of the k nearest neighbors randomly, (ii) computes the difference between the feature values of the base instance and the chosen neighbor, (iii) multiplies this difference by a random value between 0 and 1, and (iv) adds the scaled difference to the feature values of the base instance, generating a new synthetic instance. While SMOTE augments samples belonging to the minority class, it also adds random variations to allow for variation and variability between samples. Furthermore, edge-based image segmentation has been applied to separate leaves from their backgrounds (Figure 2).

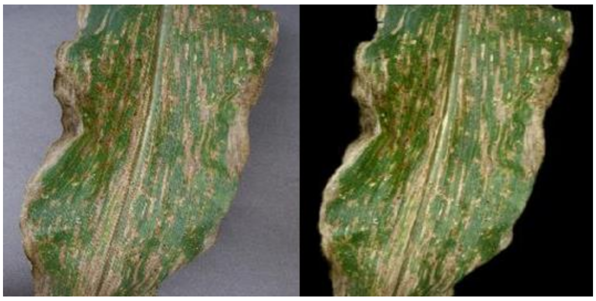


Figure 2. Corn Leaf images before and after segmentation

Transfer learning has been preferred in the study. because it allows to employ information gained from one dataset to another, especially the second dataset is smaller or different such as the case in this study. Leveraging the information gained from large dataset can provide a good head start and potentially better performance. Transfer learning means transferring information learned in one task to another task. It is a method used in the field of machine learning and enables a model to use the information learned by a pre-trained model in a new task. Transfer learning allows using the weights and learned features of this pre-trained model in a new task. The new task is a different dataset or a different problem but may generally contain the same type of data or similar features. That is, the pre-trained model may perform better on the new dataset with less training or less data. The use of a pre-trained model can be used as a starting point for the new task. This can reduce training time because the model does not have to relearn some layers or features.

- This study employs the most-commonly used pretrained models including Xception, EfficientNetV2B0, InceptionV3, MobileNet, VGG16 and ResNet50 (Figure 3). The top layers of the models have been truncated to make them appropriate for the input images. Also, the models have been extended using a Flatten Layer, a Dense Layer (256 neurons), a Dropout Layer (0.3) and an output Dense Layer for 4 classes. Some of the base features of these models are summarized in Table 2. In the table, Time per inference step is reported as the average of 30 batches and 10 repetitions on a computer with CPU: AMD EPYC Processor (with IBPB) (92 core), RAM: 1.7T, GPU: Tesla A100 and batch size: 32.

- Data is separated into 80% training, 10% validation and 10% test sets. All models have been set to train for 50 epochs. Early stopping criteria have been employed to stop training if the validation accuracy does not improve in three successive epochs. RMSprop is used as optimizer with a learning rate of 0.001 and categorical cross entropy is used as loss function. The layers of the pretrained models have been frozen, which means that the weights of these layers are nontrainable because the number of images in the dataset is not sufficient for meaningful update.

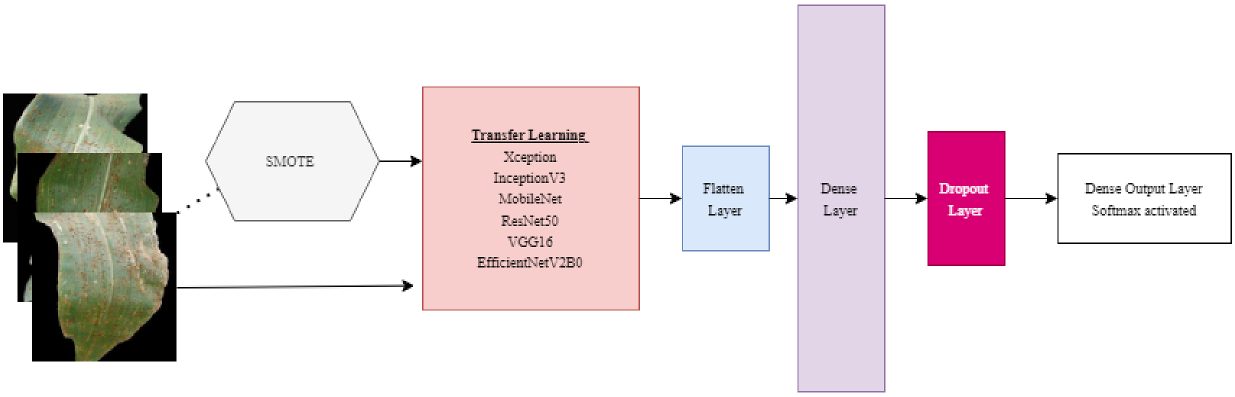


Figure 3. Flowchart of the applied algorithm

Table 2. Model specifications*

Pretrained Networks	Size (MB)[1]	Top-1 Accuracy[2]	Top-5 Accuracy[3]	Parameters	Depth[4]	Time (ms) per inference step (CPU)	Time (ms) per inference step (GPU)
Xception	88	79.00%	94.50%	22.9M	81	109.4	8.1
VGG16	528	71.30%	90.10%	138.4M	16	69.5	4.2
InceptionV3	92	77.90%	93.70%	23.9M	189	42.2	6.9
ResNet50	98	74.90%	92.10%	25.6M	107	58.2	4.6
EfficientNetV2B0	29	78.70%	94.30%	7.2M	132	46	4.9

*Source: https://keras.io/api/applications/
[1]Download size of models, [2]Top-1 accuracy considers the model's most confident prediction. This is the standard accuracy metric where only the single most probable prediction is considered, [3]Top-5 accuracy measures the percentage of images for which the ground truth label is among the model's top five predicted labels, Top-1 and Top-5 accuracy refers to the model’s performance on the ImageNet validation dataset, [4]Number of layers in the model architecture.

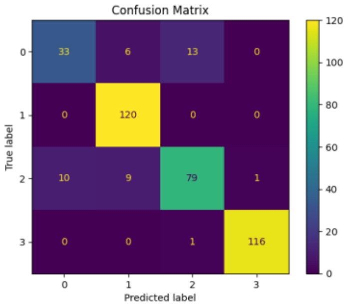
3. Results

The prediction accuracies of the models are given as confusion matrices in Table 3. The results indicate that models have difficulty in separating health corns from gray leaf spot disease class. EfficientNetV2B0 and VGG16 ResNet50 yielded quite poor classification accuracies. On the other hand, the other models achieved reliable accuracies in classification task. The reason behind the poor classification accuracies of EfficientV2B0 and ResNet50 could be attributed to several possible reasons. One is the domain mismatch which arises when ther''s a significant difference between the domain of the pretrained data and the data for your target task. However, all the pre-trained models are reported to be trained on the same ImageNet dataset, which rules out this possibility. Another reason could be architecture suitability that happens when the pre-trained model is designed with specific architectures optimized for particular types of tasks, which is different from the target task.

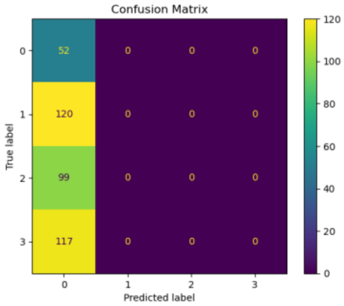
Table 3. Confusion matrices of the models

SMOTE Augmented Data

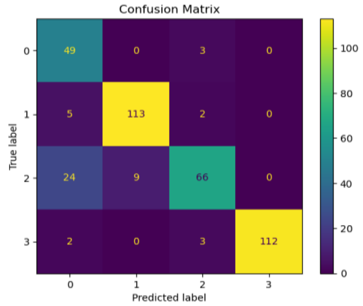
Xception



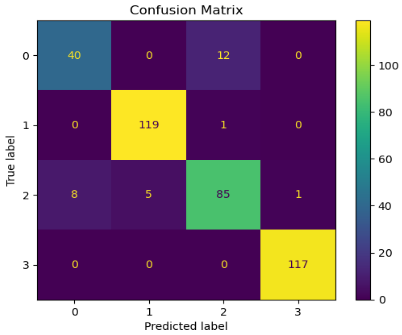
EfficientNetV2B0



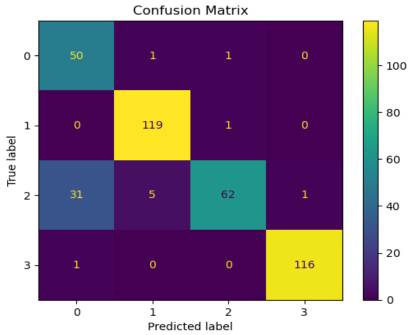
InceptionV3



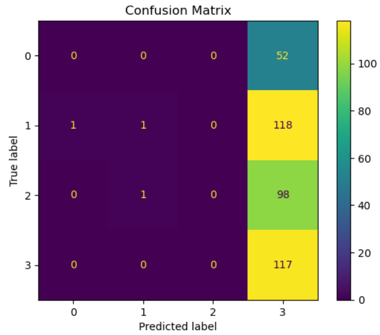
MobileNet



VGG16

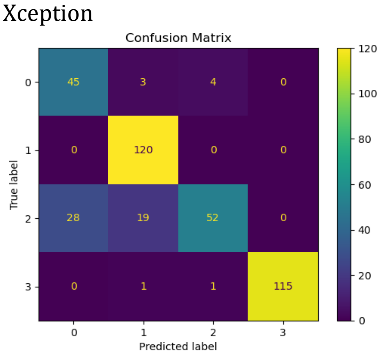


ResNet50

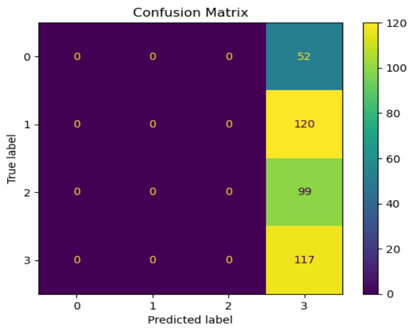


Original imbalanced data

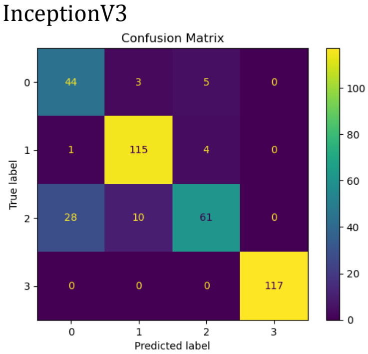
Xception



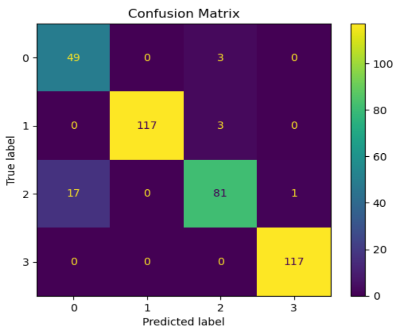
EfficientNetV2B0



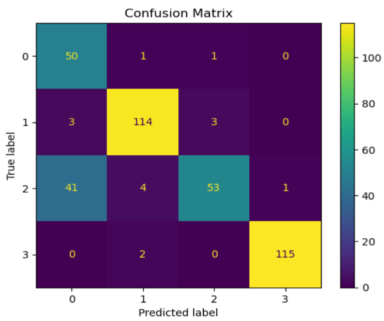
InceptionV3



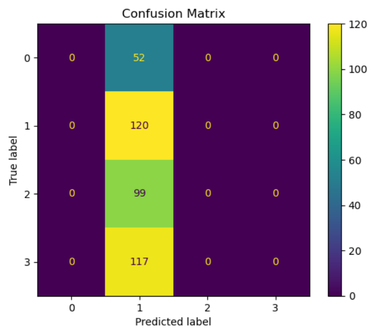
MobileNet



VGG16



ResNet50



Model performances onSMOTE and original imbalanced dataset are given in Table 4. With respect to performance results on Smote augmented data, MobileNet pretrained model achieved the highest accuracy with over 93% on test set. This is closely followed by Xception (90%), VGG16 (89%) and InceptionV3 (88%), while EfficientNet and ResNet50 proved to be quite poor classifier for the study task. InceptionV3 yielded the highest performance by F1 and Recall metrics, which is followed by VGG16, Xception and MobileNet. F1 and Recall metrics provides a better comparison when dealing with imbalanced classes as Accuracy only takes into account the general accuracy, while Recall considers the incorrectly classified instances in the target class, and F1 considers incorrectly classified instances in the target and other classes. When the results on both SMOTE augmented and original imbalanced datasets are compared, model performances are increased by 5-10% on average with the use of SMOTE. The results clearly indicate that SMOTE prevents models to be biased towards the majority class, and has increased the performance on the minority class. This technique can be used to provide a practical and effective solution to mitigate the challenges posed by class imbalance. Paymode and Malode (2022) employed Generative Adversarial Network and Neural Style Transfer along with several other data augmentation techniques like image cropping, flipping, rotation and color transformation on tomato leaf diseases. They used VGG16 as transfer learning base model and reported 98.89% validation accuracy. The downside of their study is that they separated data into training and validation subsets and tested the highest model on field images. However, the study lacks the performance metrics for on-field image testing. Considering the fact that training and validation images are captured in fixed conditions like fixed camera angle, distance and background, it would be quite difficult for such a model to perform well on real field conditions. Mukti and Biswas (2019) used the whole data in salathegroup dataset which contains over 80.000 images in 38 classes. They separated the images into training and validation subsets and used VGG16, VGG19 and AlexNet as transfer learning base models. They employed data augmentation such as flipping, rotation, shifting. They reported that ResNet50 based model yielded highest accuracy on training images with 99.80%. The main drawback of their study is that they did not give any performance result on testing data. The high accuracy in training set could be resulted from the memorization of the data pattern. Khasawneh et al. (2022) employed transfer learning on 9 tomato leaf diseases. They did not use any data preprocessing technique. They used DarkNet-53, DenseNet-201, GoogLeNet, Inceptionv3, MobileNetv2, ResNet-18, ResNet-50, ResNet-101, ShuffleNet, SqueezeNet and Xception. They used 10-fold cross validation using training and validation subsets and reported that DenseNet-201 yielded highest F1 score with 98.5%. The main novelty of the current study is that synthetic data creation method is used with Smote method and the model performances are evaluated on test dataset, which are unseen to models during training phase.

Table 4. Performance metrics of the models

	Model	Train Accuracy	Validation Accuracy	Test Accuracy	F1 on Test Set	Recall on Test Set
SMOTE	Xception	0.9513	0.8923	0.8969	0.8047	0.8168
	EfficientNetV2B0	0.2346	0.3923	0.1340	0.1181	0.2500
	InceptionV3	0.9269	0.8615	0.8763	0.9116	0.9178
	MobileNet	0.9752	0.8692	0.9304	0.7803	0.8292
	VGG16	0.9669	0.9000	0.8943	0.8524	0.8820
	ResNet50	0.2490	0.007	0.3004	0.1147	0.2663
Original Imbalanced Data	Xception	0.8867	0.8000	0.85567	0.8226	0.8434
	EfficientNetV2B0	0.2921	0.0000	0.30154	0.1158	0.2500
	InceptionV3	0.8527	0.8077	0.8685	0.8383	0.8551
	MobileNet	0.9208	0.8462	0.938144	0.9211	0.9339
	VGG16	0.8451	0.7692	0.85567	0.8244	0.8574
	ResNet50	0.3189	0.6077	0.3092	0.1181	0.2500

5. Conclusion

The study aims to analyze the efficiency of the pretrained models in predicting and classifying corn diseases. Popular pretrained models have been used for transfer learning and their accuracies have been compared. The study results indicate that corn diseases can be can be successfully identified using several of the pretrained networks including Xception, VGG16 and InceptionV3 Smote data augmentation clearly improved the prediction results in all models. The model accuracies can be further improved through larger data collected and labeled in the same manner as the Plant Village dataset. In this way, model weights can be set to trainable and updated accordingly. No parameter fine-tuning is made and all parameters are kept the same for each models in order to provide a comparison basis. However, future studies can be implemented to see effects of different parameter fine-tunings on the performance of pretrained models. Further studies can also be carried out to test other pretrained models enabling their layers as trainable. The main limitation of the study is that images in dataset are collected under certain fixed conditions that are remotely related to on-field conditions including many noise and varying backgrounds. Further studies are advice to be implemented with on-field experiments.

Author Contributions

The percentage of the author contributions is presented below. The author reviewed and approved the final version of the manuscript.

	C.O.
C	100
D	100
S	100
DCP	100
DAI	100
L	100
W	100
CR	100
SR	100
PM	100
FA	100

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The author declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans. The authors confirm that the ethical policies of the journal, as noted on the journal's author guidelines page, have been adhered to.

References

Abbas A, Jain S, Gour M, Vankudothu S. 2021. Tomato plant disease detection using transfer learning with C-GAN synthetic images. Comput Electron Agri, 187: 106279. 10.1016/j.compag.2021.106279.

Bir P, Kumar R, Singh G. 2020. Transfer learning based tomato leaf disease detection for mobile applications. Proceedings of 2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON), Oct 2-4, 2020, Galgotias University, Greater Noida, UP, India, pp: 34-39.

Chawla N, Bowyer K, Hall L, Kegelmeyer W. 2002. SMOTE: Synthetic minority over-sampling technique. J Artif Intell Res, 16: 321-357. 10.1613/jair.953.

Chen J, Zhang D, Nanehkaran Y, Li D. 2020. Detection of rice plant diseases based on deep transfer learning. J Sci Food Agri, 2020: 100. 10.1002/jsfa.10365.

Hasan M, Tanawala B, Patel K. 2019. Deep learning precision farming: Tomato leaf disease detection by transfer learning. SSRN Electronic J, 2019: 1-5. 10.2139/ssrn.3349597.

Hughes DP, Salathé M. 2015. An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowdsourcing. URL: https://arxiv.org/abs/1511.08060 (accessed date: March 23, 2022).

Feng L, Wu B, He Y, Zhang C. 2021. Hyperspectral imaging combined with deep transfer learning for rice disease detection. Frontiers Plant Sci, 12: 693521. 10.3389/fpls.2021.693521.

Kathiresan G, Anirudh M, Mathimariappan N, Ramamurthy K. 2021. Disease detection in rice leaves using transfer learning techniques. J Physics, 1911: 012004. 10.1088/1742-6596/1911/1/012004.

Khasawneh N, Faouri E, Fraiwan M. 2022. Automatic detection of tomato diseases using deep transfer learning. Applied Sci, 12: 8467. 10.3390/app12178467.

Mukti I, Biswas D. 2019. Transfer learning based plant diseases detection using ResNet50. Proceedings of International Conference on Electrical Information and Communication Technology (EICT), Oct 2-4, 2020, Greater Noida, UP, India, pp: 1-6. 10.1109/EICT48899.2019.9068805.

Paymode AS, Malode VB. 2022. Transfer learning for multi-crop leaf disease image classification using convolutional neural network VGG. Artificial Intell Agric, 2022: 23-33. 10.1016/j.aiia.2021.12.002.

Reddy T, Rekha K. 2021. Deep leaf disease prediction framework (dldpf) with transfer learning for automatic leaf disease detection. 1408-1415. Proceedings of 5th International Conference on Computing Methodologies and. Communication (ICCMC 2021), 8 – 10 April 2021, Erode, India, pp: 1-6.

Shahoveisi F, Taheri GH, Shahabi S. 2023. Application of image processing and transfer learning for the detection of rust disease. Sci Rep, 13: 5133. https://doi.org/10.1038/s41598-023-31942-9.

TUIK. 2022. Plant Production Statistics. URL: https://data.tuik.gov.tr/Bulten/Index?p=Bitkisel-Uretim-Istatistikleri-2022-45504. (accessed data: August 2, 2023).

Vallabhajosyula S, Sistla V, Kolli V. K. K. 2021. Transfer learning-based deep ensemble neural network for plant leaf disease detection. J Plant Diseases Protect, 129: 1-14. 10.1007/s41348-021-00465-8.