REPUBLIC OF TÜRKİYE
ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL
SOFTWARE ENGINEERING DEPARTMENT

DETERMINATION OF THE EFFECTIVENESS OF ARTIFICIAL INTELLIGENCE MODELS IN DETECTING MAIZE LEAF DISEASES

ADNAN GÖKTEN

M.Sc.

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THESIS ADVISOR
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ADANA, 2025

DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences if a situation is found contrary to my statement regarding my work.

08/07/2025

[Signature]

Adnan GÖKTEN

ÖZET

MISIR YAPRAK HASTALIKLARININ TESPİTİNDE YAPAY ZEKA MODELLERİNİN ETKİNLİĞİNİN SAPTANMASI

Adnan GÖKTEN
Yüksek Lisans, Yazılım Mühendisliği Anabilim Dalı
Danışman: Dr. Öğretim Görevlisi Erkut TEKELİ
Temmuz 2025, 62 sayfa

Mısır, stratejik bir tarım ürünü olarak gıda ve yem kaynağı açısından büyük öneme sahiptir; ancak yaprak hastalıkları, üretimde önemli kayıplara neden olmaktadır. Geleneksel teşhis yöntemlerinin zaman alıcı ve hata oranı yüksek olması, tarımda yenilikçi çözümler arayışını hızlandırmıştır. Bu çalışmada, Evrişimsel Sinir Ağları (CNN) kullanılarak mısır yaprak hastalıklarının otomatik teşhisi incelenmiştir.

Kaggle'dan alınan ve hastalıklı ile sağlıklı yaprak görüntülerini içeren veri seti, %80 eğitim, %10 Validation ve %10 Test oranında ayrılarak farklı CNN modellerinin performansları karşılaştırılmıştır. ConvNeXt modeli %96 doğruluk oranıyla en yüksek performansı sergilerken, DenseNet %95 ve EfficientNet %94 doğruluk oranları ile onu takip etmiştir. MobileNet, %92 doğruluk oranı ve düşük hesaplama maliyetiyle öne çıkmıştır.

Sonuçlar, modern CNN mimarilerinin eski nesil modellere kıyasla daha yüksek doğruluk ve verim sağladığını göstermektedir. Derin öğrenme teknolojilerinin tarımsal uygulamalarda kullanımı, hastalık teşhisinde etkin ve güvenilir çözümler sunarak tarım sektöründe önemli bir potansiyel taşımaktadır.

Anahtar Kelimeler: mısır yaprak hastalıkları, derin öğrenme, CNN modelleri

ABSTRACT

DETERMINATION OF THE EFFECTIVENESS OF ARTIFICIAL INTELLIGENCE MODELS IN DETECTING MAIZE LEAF DISEASES

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Supervisor: Asst. Prof. Dr. Erkut TEKELİ

July 2025, 62 pages

Maize is a strategic agricultural product that is of great importance as a source of food and feed; however, leaf diseases cause significant losses in production. The time-consuming nature and high error rate of traditional diagnostic methods have accelerated the search for innovative solutions in agriculture. In this study, the automatic diagnosis of Maize leaf diseases using Convolutional Neural Networks (CNN) was investigated.

The dataset obtained from Kaggle, containing images of diseased and healthy leaves, was divided into 80% training, 10% validation, and 10% test sets to compare the performance of different CNN models. The ConvNeXt model demonstrated the highest performance with a 96% accuracy rate, followed by DenseNet with 95% and EfficientNet with 94% accuracy rates. MobileNet stood out with a 92% accuracy rate and low computational cost.

The results show that modern CNN architectures provide higher accuracy and efficiency compared to older models. The use of deep learning technologies in agricultural applications holds significant potential in the agricultural sector by offering effective and reliable solutions for disease diagnosis.

Keywords: maize leaf diseases, deep learning, CNN models

I dedicate this thesis to my family, who have made great sacrifices and never left me alone.

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First and foremost, I would like to express my heartfelt gratitude to my dear wife and beloved children for their unwavering support, patience, and understanding throughout the preparation of this thesis. Although I could not spare enough time for them during this period, their tolerance and emotional support have meant the world to me.

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I wholeheartedly thank everyone who has contributed to this journey.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network
GPU	Graphics Processing Unit
ReLU	Rectified Linear Unit
SMOTE	Synthetic Minority Over-sampling Technique
PCA	Principal Component Analysis
SVM	Support Vector Machines
BatchNorm	Batch Normalisation
MBConv	Mobile Convolution Block

1 INTRODUCTION

Agriculture is one of the oldest professions in human history and plays a vital role in meeting the basic needs of societies. Agricultural activities not only ensure food production, but also constitute key elements of economic development and social stability. Today, agriculture is facing challenges such as the rapid increase in the world population, climate change and the depletion of natural resources. In this context, the development and improvement of agricultural production methods is of great importance at both individual and societal levels (Direk, 2012).

One of the biggest problems encountered in agricultural production worldwide is plant diseases and pests. These diseases adversely affect the growth of plants and lead to yield loss. Especially staple food crops such as maize are threatened by various diseases. Maize leaf blight, grey leaf spot and common rust are diseases that can cause significant losses in this cereal crop (Bruns, 2017). Leaf blight disease causes yield loss by reducing the photosynthetic area of plants, while grey leaf spot is an important factor threatening the overall health of the plant. Common rust disease, on the other hand, can spread rapidly, especially in humid and hot climates, and cause major yield losses.

While traditional methods are based on observation to diagnose plant diseases, these methods are time-consuming, require expertise and have a high margin of error. Early diagnosis of plant diseases is of great importance to increase productivity and prevent losses in agricultural production. In this context, rapid developments in information technologies in recent years have created the opportunity to offer innovative solutions in the field of agriculture. Especially the use of artificial intelligence (AI) and machine learning (ML) techniques in the diagnosis of agricultural diseases stands out as an important development in this field (Bishop, 2006) (Atalay & Çelik, 2017).

AI is concerned with the development of systems to mimic human intelligence. ML, as a sub-branch of AI, includes techniques that enable computers to learn from data and make decisions. In particular, deep learning, as a sub-branch of ML, offers complex structures capable of learning from large data sets (LeCun et al., 1998). Deep learning (DL) models can achieve effective results in areas such as image processing and thus play an important role in the diagnosis of agricultural diseases.

In this thesis, the ability of AI based DLmodels to accurately diagnose maize leaf diseases from images will be compared. In particular, DLarchitectures such as Convolutional Neural Networks (CNN) have the potential to enable fast and accurate recognition of plant diseases.

The aim of the study is to evaluate the effectiveness of different CNN models and to determine the best performing model. In this context, the models to be used in the study will include pre-trained DLarchitectures such as ConvNeXt, EfficientNet, ResNet, GoogLeNet, AlexNet, MobileNet and DenseNet. Comparing the performance of these models will provide an important perspective on what role AI can play in agricultural production.

2 THEORETICAL FOUNDATIONS AND LITERATURE REVIEW

2.1 Maize Plant and Diseases

In recent years, maize has become the staple food of the modern world and the most important cereal crop that can be utilised in various ways. It is one of the most consumed crops in the human diet after wheat and rice. Maize can grow up to 2.5-4.5 metres in about four months and each plant can produce 600-1000 seeds (Kırtok, 1998).

Maize plant can be utilised in two different ways as both grain and herbaceous stem. As a grain, it is consumed directly in human nutrition (as bread and snacks), also edible oil, starch and glucose are used and herbaceous stem is utilised as animal feed (Dönmez and Hatipoğlu, 2024).

2.1.1 Maize Leaf Blight Disease

Although maize leaf blight is found in almost all maize growing areas, it is particularly prevalent in temperate and humid subtropical regions. It kills the green tissue of the leaves, significantly reducing the photosynthetic source area and causing damage. In 1970-71, it caused an outbreak in the USA that was effective enough to destroy 15% of the crops and was widely reported in the national press (Bruns, 2017).

2.1.2 Common Rust Disease in Maize

Common rust disease of maize is a disease that can be epidemic in subtropical regions at temperatures of approximately 15-25 C and mostly at 98% humidity. It causes loss of photosynthetic area, chlorosis and premature leaf senescence, leading to incomplete grain filling, poor yield and low grain quality. For different maize genotypes, it can cause a very high loss in yield, ranging from 12% to 75%. According to a study, it can cause 6.5 per cent yield loss for every 10 per cent leaf area diseased. (Sserumaga, J. P., et al. 2020).

2.1.3 Maize Grey Leaf Spot Disease

Grey leaf spot of maize is a disease of maize caused by the fungus Cercospora zeae-maydis. It is currently considered one of the most important yield limiting diseases of maize worldwide. Due to this disease, spots appear on both the top and bottom of the leaves. The disease reduces the leaf and photosynthesis area. It is more common at temperatures as low as 16 C to 23 C and as high as 100% relative humidity (Ciran and Özbay, 2022).

2.2 Artificial Intelligence and Machine Learning

AI is the science and engineering of creating particularly intelligent computer programmes. It is associated with a similar task of understanding human intelligence using computers, but AI does not have to be limited to biologically observable methods (McCarthy, 2007). In addition to providing products in different areas of daily life, AIstudies are also used for purposes such as prediction, classification and clustering. Techniques such as expert systems, genetic algorithms, fuzzy logic, artificial neural networks, ML are generally referred to as AItechnologies (Atalay & Çelik, 2017).

ML is a sub-branch of AIthat enables computers to learn from data and make decisions using specialised algorithms. ML works by utilising fields such as statistical techniques, probability theory and data mining. This technology usually detects patterns by analysing large data sets and uses these patterns to predict future events. For example, ML performs strongly in areas such as recommender systems, image and voice recognition, natural language processing (Bishop, 2006; Hastie et al., 2009).

2.2.1 Deep Learning

DL, which is inspired by artificial neural networks, is a ML algorithm with complex multi-layered network structures inspired by the structural and functional properties of the brain. This algorithm is similar to human learning processes based on the relationships and connections between neurons of biological nervous systems (Arı, 2019. Şeker et al., 2017. Kayaalp & Süzen, 2018).

The difference of DL from ML algorithms such as artificial neural networks is the need for large datasets and high computational capacities. Recently, the amount of labelled data in the field of image processing has reached the level of millions. In addition, powerful Graphics Processing Units (GPUs) have begun to overcome such difficulties. In the future, studies on the development of more powerful products to solve these two problems are gaining momentum (Arı, 2019. Şeker, et al. 2017. Kayaalp et al, 2018).

Unlike traditional algorithms developed based on ML, DLis based on learning distinctive features in the training phase without human intervention. In deep learning, the feature learning process consists of lower and upper levels or layers. Upper level layers are formed by combining the features of lower level layers. Lower level layers usually extract more basic and specific features than upper level layers. This learning method is different from approaches where traditional algorithms rely on human-defined features and has a significant impact on the success of DLtechniques (Türkoğlu, 2019).

2.2.1.1 Convolutional Neural Networks

CNNs are widely used DL models in areas such as image processing and recognition. These networks show superior performance, especially in large datasets. The basic components of CNNs are convolutional layers, clustering layers and full connectivity layers (LeCun, et al., 1998).

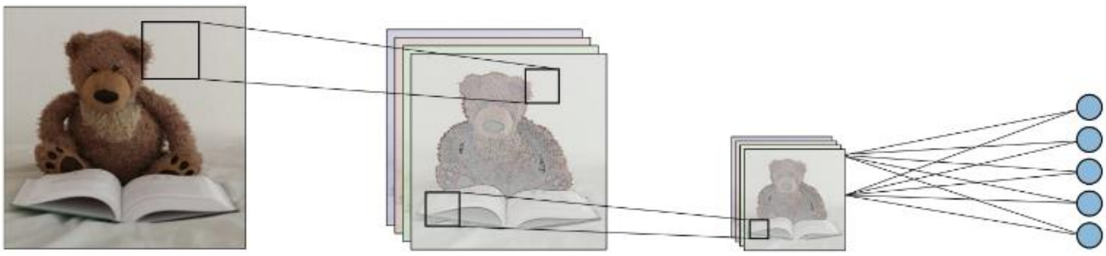

Figure 2.1. Convolutional Neural Network Layers (General, Convolutional Layer, Partnering Layer, Fullection Layer)

Convolution layers use filters to extract important features from the image. These filters identify specific patterns in the image and these patterns are combined into more complex features in later layers (Krizhevsky, et al., 2012).

Clustering layers reduce the size of feature maps and lighten the computational burden of the model, usually by performing maximum or average clustering (Zeiler & Fergus, 2014).

Full connectivity layers perform the final classification process by processing high-level features in the image. These layers are layers where each neuron is connected to all neurons in the previous layer, as in traditional neural networks (Simonyan & Zisserman, 2015). Thanks to this structure, CNNs can achieve successful results in large and complex data sets.

2.2.1.1.1 Input Layer

The input layer of CNN is the first stage where the raw image data is modelled. This layer prepares for the extraction of features that the model will process in the subsequent convolutional and clustering layers. In the input layer, images of a given size and colour (e.g., 224x224 pixels and RGB) are usually fed into the model (Krizhevsky, et al. 2012). This layer usually accepts images that have been normalised and preprocessed, so that the training of the model is faster and more efficient (Simonyan & Zisserman, 2015).

The input layer is an important component that directly affects the performance of the model. For example, an input image that is not properly normalised can cause problems in the learning process of the model, which can negatively affect the final performance (LeCun, et al. 2015). Therefore, the data preprocessing techniques used in the input layer are of great importance.

2.2.1.1.2 Convolution Layer

The convolution layer is the building block of deep CNN. This layer is based on the principle of shifting n×n sized filters (e.g. 2×2, 3×3, 5×5) over the whole image. In this way, a new image is obtained by removing the prominent features in the image. An example of the application of the convolution filter on the image is shown in Figure 2.2.

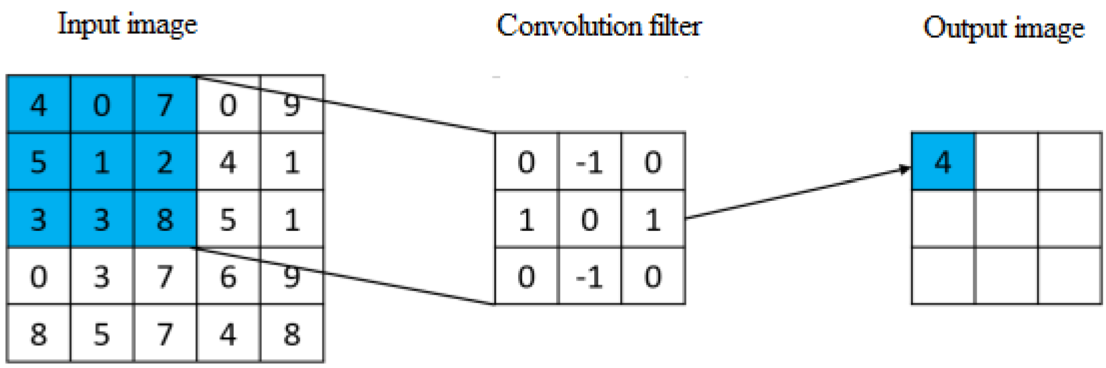

Figure 2.2. The Application of a 3×3 Convolution Filter to a Single-Channel and 5×5 Image Matrix and The Output Image Obtained (in 3×3 dimension) Is Given

The convolution filter is shifted horizontally and vertically over all pixels of the input image. Then, multiplication and addition operations are performed using equal-sized windows within the image. As a result, an output image based on distinct high-level features is obtained.

2.2.1.1.3 *Pooling Layer*

The pooling layer is a layer that usually follows the convolution layers and has two main purposes: dimensionality reduction and feature preservation. The pooling process extracts summary information from specific regions of the image, preserving the features of these regions and reducing the data size. This process both reduces computational cost and prevents overfitting (Goodfellow et al. 2016).

The most commonly used pooling methods are maximum pooling and average pooling. Maximum pooling takes the largest value in a given region, while average pooling takes the average of the values in that region. Maximum pooling is particularly effective in preserving high frequency features such as edge detection (Szegedy et al., 2015). Figure 2.3 shows the pooling layer.

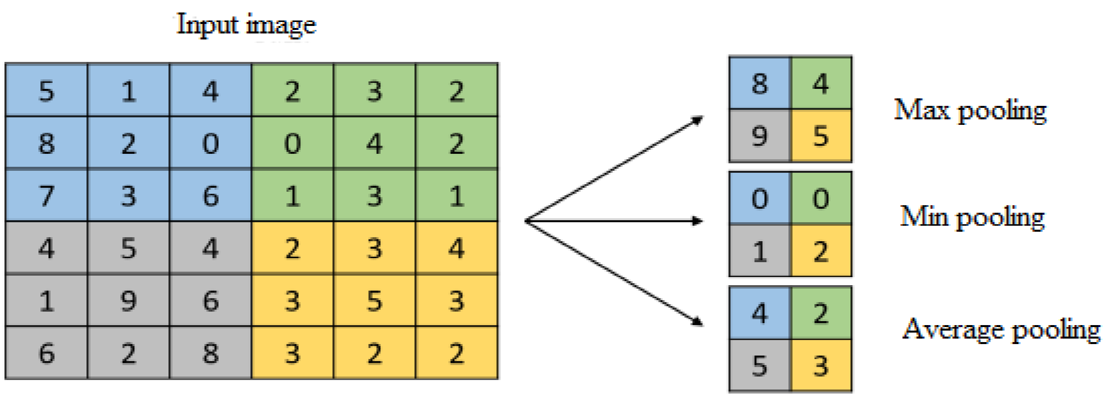

Figure 2.3. Pooling Layer

2.2.1.1.4 *Activation Function*

CNN are powerful DL models widely used in areas such as image processing and computer vision. One of the key components of the success of CNNs is activation functions. Activation functions are used to calculate the output of each neuron in neural networks and enable the network to learn complex non-linear relationships (Nwankpa et al. 2018).

Activation functions commonly used in CNNs include Sigmoid, Tanh and ReLU (Rectified Linear Unit). Sigmoid and Tanh functions provide nonlinear transformations, but they can lead to performance problems in deep networks due to the vanishing gradient problem. Therefore, ReLU and its derivatives (e.g., Leaky ReLU and Parametric ReLU) are more often preferred (Glorot, et al. 2011).

ReLU passes positive inputs as they are, while zeroing out negative inputs. This simple function is computationally efficient and allows the network to learn faster and more effectively. Furthermore, since the derivatives of ReLU are positive, the problem of vanishing gradients is reduced, allowing deeper networks to be trained (Nair & Hinton, 2010).

2.2.1.1.5 Normalisation Layer

Various techniques are used to improve the performance of CNNs and to stabilise the training process. One of these techniques is the normalisation layer. Normalisation layers help the network to learn faster and more stable (Ioffe & Szegedy, 2015).

One of the normalisation techniques commonly used in CNNs is known as Batch Normalisation (BatchNorm). BatchNorm normalises the activations in each minibatch so that the data in each layer has a more balanced and stable distribution. This accelerates the learning process and facilitates the training of deep networks (Ioffe & Szegedy, 2015). BatchNorm also helps to reduce overfitting and faster model training can be performed using higher learning rates (Santurkar, et al., 2018).

Besides BatchNorm, other normalisation techniques are also available. For example, methods such as Layer Normalization, Instance Normalization and Group Normalization offer different normalisation strategies. Layer Normalization performs layer-wise normalisation on each instance, while Instance Normalization performs normalisation on each channel in each instance. Group Normalization, on the other hand, offers an intermediate approach and normalises channels by dividing them into groups (Wu & He, 2018).

2.2.1.1.6 Fully Connected Layer

Fully connected layers make the final decision using features extracted by other layers in the CNN (LeCun, et al. 1998).
Fully connected layers use weights and biases to model the relationship between each input value and each neuron. These weights and biases are learned during model training and optimise the classification performance of the model (Nielsen, 2015).

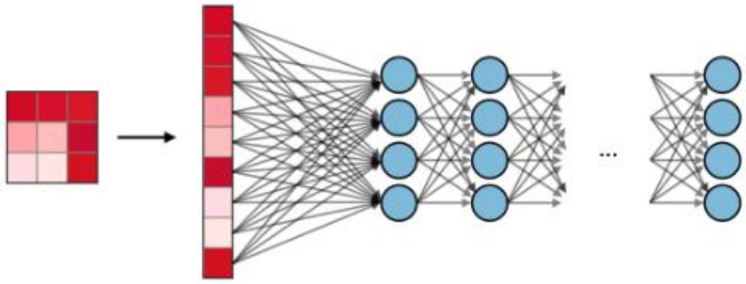

Figure 2.4. Full Connected Layer

For example, in an image classification task, fully connected layers use these weights to determine whether the image belongs to certain classes. Figure 2.4 shows the Fully Connected layer.

2.2.1.1.7 Dropout Layer

Fully connected layers can be computationally intensive because they contain a large number of links and parameters. For this reason, they are often combined with regularisation techniques such as dropout. Dropout prevents overfitting by randomly disabling certain neurons and increases the Generalization ability of the model (Srivastava, et al. 2014). In Figure 2.5, Dropout Application is explained with a figure.

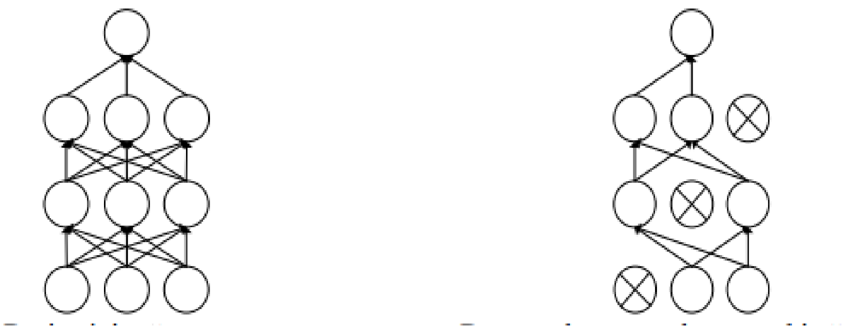

Figure 2.5. Dropout Layer Operation

2.2.1.1.8 Classification Layer

The final stage of CNNs is the classification layer, which allows the network to make final decisions using the learnt features. This layer usually comes after the fully connected layers and produces the final outputs (Goodfellow, et al. 2016).

The classification layer is used to categorise the model's predictions into specific classes. It is usually combined with the Softmax activation function. The Softmax function calculates the probability values of each class by converting the outputs of the model into a probability distribution. In this way, the probability of each input sample belonging to a particular class is determined (Bridle, 1990). For example, in an image classification problem, the Softmax activation function calculates the probability that an image belongs to a certain category.

The softmax function produces a probability value for each class and the sum of these probabilities equals 1. This makes the outputs of the model more meaningful and interpretable. The classification layer is often used in conjunction with cross-entropy loss, which calculates the error rate by comparing the model's predictions with the actual labels and updates the weights according to this error (Murphy, 2012).

The classification layer directly affects the performance of the model and should be carefully designed to increase the Generalization ability of the model. This layer performs the final classification using the features extracted by the other layers of the CNN and ensures that the model produces accurate results (Krizhevsky, Sutskever, & Hinton, 2012).

CNN architecture

CNNs increase their ability to learn and extract features from complex data structures using different architectures. These architectures are designed to optimise performance on a variety of tasks and often involve unique combinations of various layers (Goodfellow, Bengio, & Courville, 2016). In this study, AlexNet, GoogLeNet, ResNet-50, ConvNeXt, MobileNet, DenseNet, and EfficientNet architectures were used from pre-trained CNN models.

2.2.1.1.9 AlexNet

AlexNet is a convolutional neural network model that is considered to be an important milestone in the field of deep learning. Developed in 2012 by Alex Krizhevsky, Ilya Sutskever and Geoffrey Hinton, this model has made great progress in visual recognition problems. The major contribution of AlexNet is to show how DL architectures can be trained effectively using large data sets and powerful computational resources (Krizhevsky, et al. 2012).

The architecture of AlexNet consists of 8 layers in total: 5 convolutional layers and 3 fully connected layers. The properties of these layers allow the model to recognise complex patterns in images. The convolutional layers learn local features and pass them to the fully connected layers, which are then used to transform these features into higher level abstractions. Furthermore, the depth and breadth of the model allows for effective results on large data sets (Krizhevsky et al., 2012).

Behind the success of AlexNet, there are several important technical innovations. One of them is the use of the ReLU (Rectified Linear Unit) activation function. ReLU facilitates faster network learning and training of deeper networks (Nair & Hinton, 2010). Furthermore, AlexNet has significantly reduced the training time of the model by optimising the use of GPUs. This has been a great advantage in processing large data sets (Krizhevsky et al., 2012).

Another important feature of the model is the use of data augmentation techniques. Data augmentation is a technique that diversifies the training dataset to increase the Generalization ability of the model and to prevent overfitting. AlexNet has improved its performance and obtained more robust results with these techniques (Krizhevsky et al., 2012).

As a result, the innovations and techniques introduced by AlexNet have had a major impact on the field of DL and inspired the development of many follow-up models. The success of the model demonstrated how deep neural networks can be effectively used in visual recognition problems (Krizhevsky et al., 2012).

2.2.1.1.10 GoogLeNet

GoogLeNet is a convolutional neural network model developed by Ian Goodfellow, Yoshua Bengio and Aaron Courville in 2014. This model is considered to be an important innovation in the field of DLand is specifically designed for high-performance visual recognition tasks on large data sets (Szegedy et al., 2015).

The most remarkable feature of GoogLeNet is its innovative structure, known as the "Inception" architecture. This structure allows the model to learn features at different scales simultaneously. The Inception module contains a combination of multiple convolution filters and pooling processes at each layer. These modules enable the network to learn deeper and more complex features, which results in higher accuracy of the model (Szegedy et al., 2015).

Another important feature of GoogLeNet is the "coverage" strategy of the network. This strategy allows the model to learn more information with fewer parameters. The coverage strategy provides a wide range of features using filters of different sizes, which improves the overall performance of the network (Szegedy et al., 2015). Furthermore, GoogLeNet uses a "layered" structure to increase the depth of the model. This structure allows the model to learn more complex relationships and perform higher level abstractions.

The performance of GoogLeNet was remarkable when tested on the ImageNet dataset. The model achieved a higher accuracy rate compared to previous CNN and provided significant efficiency in terms of training time (Szegedy et al., 2015). This success is attributed to the depth and width of the network, as well as the optimised computational resources.
As a result, GoogLeNet is considered an important step forward in the field of DL and CNN. The use of the Inception modules and the coverage strategy allowed the model to achieve high performance and efficiency, which has allowed GoogLeNet to have a wide impact in modern visual recognition systems (Szegedy et al., 2015).

2.2.1.1.11 Resnet-50

ResNet-50 is a convolutional neural network (CNN) architecture that represents a significant advancement in the field of deep neural networks. Introduced in 2015 by Kaiming He and colleagues, this model has made a great impact in the DL community (He et al., 2015). ResNet-50 enables the successful training of much deeper networks by specifically addressing the problems encountered in training deep networks.

One of the most important contributions of ResNet-50 is the "residual learning" framework. This approach aims to solve the vanishing gradient and exploding gradient problems that arise in the learning process of deep networks. Residual learning provides a direct path of input data to the outputs of each convolutional block. This structure enables the model to be deeper and provides better results (He et al., 2015).

ResNet-50 takes its name from the 50-layer version of the "Residual Networks" (ResNet) architecture. This model consists of 50 layers in total and these layers consist of residual blocks. Each residual block contains a "skip connection", which allows the input data to be transferred between blocks via a direct path. This structure makes the training of deep networks more efficient and leads to higher performance (He et al., 2015).

The performance of ResNet-50 has shown impressive results in large-scale tests on the ImageNet dataset. The model provided higher accuracy rates and faster training times than previous deep network architectures. This success is attributed to the optimisation of the depth of the model and the effective use of various features of the network, as well as residual connections (He et al., 2015).

In conclusion, ResNet-50 has made a significant progress in the field of deep neural networks and convolutional networks. The residual learning strategy has significantly reduced the difficulties encountered in the training process while increasing the depth of the model. These features have enabled ResNet-50 to have a wide impact in modern image recognition systems (He et al., 2015).

2.2.1.1.12 ConvNeXt

ConvNeXt is a model that is considered as an important step in the evolution of modern CNN. Introduced in 2022 by Liu and colleagues, this model was developed to improve the performance of CNN and stand out in competitive DL systems (Liu et al., 2022).

ConvNeXt's design redefines the power of convolutional networks by combining current trends and best practices in the field of DL. In particular, the model focuses on modernisation of previously used techniques and updated computational efficiency. ConvNeXt optimises the architecture of existing convolutional networks, delivering higher performance and shorter processing times (Liu et al., 2022).

One of the key components of the model is the use of "reformed" convolution blocks. These blocks enable a more efficient implementation of traditional convolution operations. Furthermore, by integrating modern architectural designs and training techniques, ConvNeXt improves the overall performance of the DL model. In particular, widening and deepening the network increases the model's ability to learn complex features (Liu et al., 2022).

The success of ConvNeXt has been evident in tests and applications on large datasets. The model offers superior accuracy and computational efficiency compared to other state-of-the-art convolutional networks, and is considered as an important innovation in the field of deep learning. The advantages offered by ConvNeXt have great potential, especially for large-scale data analysis and visual recognition applications (Liu et al., 2022).

As a result, ConvNeXt stands out as an important step forward in the development of CNN. By combining modern computational techniques and architectural improvements, it offers higher performance and efficiency. This model supports the development of more advanced features and applications in DLsystems (Liu et al., 2022).

2.2.1.1.13 EfficientNet

EfficientNet is a convolutional neural network (CNN) model introduced by Mingxing Tan and Quoc V. Le in 2019. This model was developed to improve model efficiency and optimise computational resources in the field of DL(Tan & Le, 2019).

The most prominent feature of EfficientNet is its "model scaling" strategy. This strategy optimises the performance and efficiency of the network by balancing the depth, width and resolution of the model. While in traditional CNN architectures these parameters are usually varied independently of each other, EfficientNet allows these factors to be optimised in relation to each other. This approach enables the model to exhibit high performance in various tasks (Tan & Le, 2019).

EfficientNet uses a technique called "Compound Scaling". This technique aims to maximise the performance of the model by increasing depth, width and resolution simultaneously and in a balanced manner. Compound Scaling proportionally increases the size of each component of the model, thereby improving both computational efficiency and overall accuracy (Tan & Le, 2019).
Another important component of the model is a convolution block called "MBConv". MBConv refers to mobile-optimised convolution blocks, which allow the model to run faster and more efficiently. MBConv blocks include techniques such as extended convolutions and deep decomposed convolutions, which improves the performance of the model (Tan & Le, 2019).

The success of EfficientNet has been demonstrated in large-scale tests on the ImageNet dataset, showing high accuracy rates and efficiency on a variety of tasks. The model offers lower computational cost and higher performance compared to other modern CNN architectures. This makes EfficientNet an effective choice for large-scale data analysis and visual recognition applications (Tan & Le, 2019).

As a result, EfficientNet stands out as an important innovation in the field of CNN. Its model scaling strategy and integration of MBConv blocks have had a wide impact on modern DL applications by providing higher performance and efficiency (Tan & Le, 2019).

2.2.1.1.14 MobileNet

MobileNet is a lightweight convolutional neural network (CNN) model designed to perform image processing tasks on devices with low computational power, especially mobile and embedded systems. The main goal of MobileNet is to perform processing at lower computational cost while maintaining accuracy. This is achieved thanks to two main techniques: depthwise separable convolutions and width multiplier.

Depthwise Separable Convolutions:
The most distinctive feature of MobileNet is the use of depth discrete convolution instead of the traditional convolution process. This technique consists of two separate stages:

Depthwise convolution: A separate convolution process is applied for each channel in the input data. In other words, as in standard convolution, no convolution is performed on the entire input, each channel is processed with its own filter.

Pointwise convolution (1x1 convolution): Since the relationship between channels is not established with depthwise convolution, pointwise convolution enables information sharing between channels by applying 1x1 convolution at each pixel.

This two-step process requires less computation than traditional convolution and reduces the number of parameters, which allows MobileNet to run faster and more efficiently.
Width Multiplier:

MobileNet uses a width coefficient to control the computational cost and size of the model. This coefficient adjusts the lightness of the model by reducing the number of filters in the model. For example, when the width coefficient is set to 0.5, the number of filters in each layer is halved, which can result in some reduction in accuracy while increasing the speed of the model.

Advantages of MobileNet

- Low Computational Cost: MobileNet runs much faster than traditional CNN, using fewer parameters.
- Small Model Size: The low number of parameters of the model allows both less memory footprint and faster training and inference.
- Flexibility: Thanks to the width factor, MobileNet can be scaled and optimised for different hardware environments.

Application Areas of MobileNet

MobileNet is widely used in tasks such as object detection, face recognition and image classification, especially in mobile devices and embedded systems. Its lightweight structure and efficient computational characteristics make MobileNet suitable for real-time applications.

2.2.1.1.15 DenseNet

DenseNet (Dense Convolutional Network) is a deep neural network model proposed in 2017 that is more efficient than traditional CNN architectures. The main innovation of DenseNet is that it increases information sharing and reuse by establishing dense connections between layers. This architecture allows each layer to receive data directly from all previous layers. With this structure, vanishing gradient problems, especially in the training of very deep networks, are reduced.

Dense Connections:

Each layer of DenseNet receives input not only from the previous layer but also from all layers before it. In other words, the feature maps produced as output in each layer become directly usable in all subsequent layers. This structure enables the reuse of the information produced at each layer and thus enables the model to learn more efficiently.

Mathematically:

$$x\_l = H\_l([x_0, x_1, \ldots, x_{\{l-1\}}]) \quad (1)$$

- x_l: The output of the l-th layer.
- H_l: The transformation function applied at layer l (e.g., Batch Normalization, ReLU, Convolution).
- [x_0,x_1,...,x_l−1]: The concatenation of the outputs from all preceding layers, serving as the input to layer l.

Gradient Flow:

DenseNet's dense connections alleviate the problem of gradient fading, especially in deep networks. In deep networks, gradients can weaken as they are transferred between layers during training, making the learning process difficult. DenseNet allows gradients to propagate back more efficiently because the gradient flow is preserved as the output of each layer is shared directly with subsequent layers.

Parameter Efficiency:

DenseNet achieves parameter efficiency by repeatedly using the output of each layer. This means that deep networks can achieve higher performance with fewer parameters. This helps to make the model more compact.

Transition Layers:

Transition layers are used every few layers. These layers reduce the size of the model and reduce the computational cost by reducing the number of channels and spatial dimensions. Furthermore, the transition layers reduce the size of the feature maps, avoiding information overload.

Advantages of DenseNet:

- Reduces Gradient Damping: It alleviates the gradient fading problem common in very deep networks with dense connections.
- Parameter Efficiency: Delivers powerful performance with fewer parameters through feature reuse.

- Information Reuse: The knowledge in each layer combines with the outputs of the previous layers and provides more information sharing. This accelerates the learning process.
- Building Deeper Networks: Thanks to dense connections, much deeper networks can be trained, because information flow is not lost and gradients are propagated more effectively.

Application Areas of DenseNet:
DenseNet is particularly suitable for tasks in the field of DLbecause it is possible to deepen the networks without increasing the number of parameters. This makes DenseNet a strong candidate for tasks such as image classification, object detection and segmentation.

2.3 Source Research

Ridle (1990) analysed the probabilistic interpretation of the output of feed-forward classification networks and their relation to statistical pattern recognition. The article explained how the outputs of neural networks can be interpreted as probabilities and how these interpretations can be integrated into pattern recognition processes. It also emphasised how these methods can improve the accuracy and reliability of the model. Bridle discussed how neural networks and statistical methods can be combined and how this integration can improve classification performance.

LeCun et al. (1998) detailed gradient-based learning methods for document recognition applications. In the paper, effective applications of CNNs in handwritten and printed text recognition and the role of gradient descent methods in document recognition are examined. Furthermore, how gradient descent algorithms handle various deformations in documents and strategies to improve model performance are discussed.

Şahin (2001) analysed the distribution of corn cultivation areas and trends in corn production in Turkey. The article detailed the historical development of corn cultivation, geographical distribution, and production quantities. It also discussed the reasons for corn cultivation in various regions, production potential, and agricultural strategies, and provided information on productivity factors and economic impacts of corn production in Turkey.

Bishop (2006), in his book, provided a comprehensive reference on pattern recognition and machine learning. The book explained the mathematical foundations of various machine learning algorithms and pattern recognition techniques. Topics included classification, regression, feature selection, and model evaluation. Bishop offers a broad perspective on both basic and advanced methods and shows how they are used for real-world applications. The book includes details of probabilistic modelling, Bayesian methods, and various learning algorithms.

McCarthy (2007) clarified the definition, history, and basic concepts of artificial intelligence. The article discussed the various branches of artificial intelligence, the ability of these technologies to mimic human intelligence and perform similar functions. It also addressed the current state of AI, the challenges faced, and areas for future development, and provided information on its wide range of applications and societal impacts.

Hastie, Tibshirani, and Friedman (2009), in their book, discussed the basic elements of statistical learning. The book details data mining, predictive modelling, and statistical learning techniques. It also provides information on topics such as regression, classification, model selection, and cross-validation. The work provides a broad coverage of statistical learning from both theoretical and practical perspectives.

Nair and Hinton (2010) discussed how the use of rectified linear units (ReLU) in restricted Boltzmann machines (RBMs) improves model performance. The paper discussed the advantages of the ReLU activation function in the training process of RBMs, detailing how it reduces the internal variable shift in the learning process and improves the overall performance of the model. Furthermore, the effects of these methods on different datasets were investigated.

Glorot, Bordes, and Bengio (2011) introduced deep sparse rectified neural networks and analysed their performance. The paper explains how sparse structures are used in deep neural networks and how these structures improve model performance. It also provides details on how rectified linear units (ReLU) are applied in deep networks and their effects on learning processes.

Krizhevsky, Sutskever, and Hinton (2012) improved classification performance with deep CNN using the ImageNet dataset. The paper details how deep learning architectures are applied on large datasets and the effects of these applications on accuracy. In particular, the focus is on network depth and parameter optimisation. This study has shown how deep convolutional networks are effective for large-scale visual recognition problems.

Murphy (2012), in his book, covered the probabilistic perspective of machine learning in depth. The book comprehensively explains the basic principles of machine learning algorithms, probabilistic modelling methods, and their impact on data analysis. Topics such as model selection, data preprocessing, feature engineering, and model evaluation are covered, as well as the mathematical foundations and application examples of methods such as Bayesian networks and Markov models.

Srivastava et al. (2014) discussed the role of dropout in preventing neural networks from overlearning. The paper explained how dropout works, how it improves the generalisation ability of the model by randomly switching off some neurons of the network. The advantages of dropout, effective implementation strategies, and the performance improvements achieved by this method are detailed. In addition, the benefits and application areas of dropout in training processes are discussed.

Zeiler and Fergus (2014) examined methods for visualising and understanding CNNs. In their paper, they explained the techniques used to understand the internal structure and learning processes of CNNs and examined how visualisation methods affect which features the network learns and how these learnings affect model performance. They also explained in detail the functions of different layers of CNNs and their effects on the overall performance of the network.

Nijalingappa and Madhumathi (2015) developed a recognition system using leaf features to identify plant species. In the study, characteristics of leaves such as shape, texture, and vein structure were emphasised, and it was shown that plant species can be accurately identified by using these features. This system is presented as an important tool for botanical research and agricultural applications. In addition, it is emphasised that the developed system provides an effective solution for species identification processes in agriculture with its accuracy and ease of application.

Simonyan and Zisserman (2015) introduced very deep CNNs for large-scale image recognition problems. The paper explained how increasing the depth of the network architecture improves image recognition performance and how these changes improve model accuracy. It details how multilayer CNNs are more effective on large datasets and the difficulties encountered in the training process of these architectures.

Türkoğlu and Hanbay (2015) used the support vector machines (SVM) algorithm to classify grape varieties based on leaf recognition. In this study, various feature extraction techniques were applied on images of grape leaves and grape varieties were successfully classified using SVM. The study emphasised the success of SVM in identifying and classifying plant species in agricultural applications. It was also shown that this method can improve productivity and quality control processes in agriculture.

Zhang et al. (2015) investigated ways to speed up very deep CNNs in classification and detection tasks. In addition to increasing the network depth, the paper discusses the difficulties encountered in the training process of these networks and performance improvement methods. In particular, detailed information on the techniques used to increase the speed and efficiency of the networks and the application areas of these techniques is presented.

Nielsen (2015), in his book, comprehensively explained the basics of neural networks and deep learning. The book details the structure and working principles of neural networks and various deep learning techniques. Topics such as advanced CNN, backpropagation algorithms, and optimisation methods are also covered. It also explains how deep learning applications are used in areas such as image recognition, audio processing, and natural language processing, and the advantages of these technologies.

Ioffe and Szegedy (2015), in a paper, investigated the benefits of Batch Normalisation in the training process of deep networks. The paper explains how Batch Normalisation reduces the internal covariate shift and accelerates the learning process of the network. It also details the effects of this method on various deep learning architectures and strategies to improve model performance.

Goodfellow, Bengio, and Courville (2016), in their book, presented a comprehensive review of deep learning. The book details the basic principles of deep learning, algorithms used, and application areas. Topics include deep neural networks, CNNs, backpropagation algorithms, and optimisation techniques. It also provides a broad perspective on real-world applications of deep learning and the advantages of these technologies.

Bruns (2017), in his article, discussed the southern corn leaf spot disease and its impacts on agriculture. The article detailed the history of the disease, its spread dynamics, and its impacts on farming practices. Bruns discussed the long-term effects of this disease on corn production and how farming strategies have changed. He also made recommendations on control and management of the disease and reviewed historical events and developments in this regard.

Howard et al. (2017) developed the MobileNet model and investigated ways to perform deep learning-based disease detection on mobile devices. This model, which works with devices with low computational power, especially in the agricultural sector, is optimised to quickly detect corn diseases. MobileNet's low computing power requirement and high accuracy rate provide a suitable solution for mobile devices. The study emphasises that deep learning methods can be used effectively in agriculture, considering mobile devices and low hardware requirements. This study reveals the potential of such solutions, which will have a wide range of applications, especially in the agricultural sector.

Sun et al. (2017) used DL methods for plant recognition in a natural environment. The research investigated the application of DL algorithms to identify plant species under various environmental conditions. DL techniques enabled the identification of species with high accuracy rates from plant images captured in the natural environment and demonstrated the suitability of these methods for real-world applications. The study highlighted how DL is effective in natural plant identification tasks.

Atalay and Çelik (2017) examined artificial intelligence and machine learning applications in big data analysis. The article discusses AI and ML techniques used in big data environments and their effects on data analysis. The study focused on topics such as data mining, predictive modelling, and classification. In addition, tools, techniques, and application examples used for analysing big data are detailed. The paper discusses the contributions of these technologies to data analysis processes and the challenges encountered.

Şeker, Diri, and Balık (2017) comprehensively examined DL methods and their various application areas. In the article, the basic principles, architectures, and application examples of DL algorithms are discussed. Examples of application areas of DL in healthcare, finance, automotive, and other industries are given, and information on the advantages, challenges, and future research directions of the techniques is presented.

Santurkar et al. (2018) investigated how batch normalisation contributes to optimisation processes. The article examined the effects of batch normalisation on accelerating the learning process in DL networks and improving the performance of the model. It details how the method reduces internal covariate shift and helps the model to learn faster and more stably. Furthermore, the performance effects of batch normalisation on various network architectures and its role in optimisation strategies are discussed.

Kayaalp and Süzen (2018), in their book, analysed the applications of deep learning technologies in Turkey. The book details how deep learning algorithms and techniques are used in various sectors in Turkey and the benefits of these applications. It also provides examples and case studies on how deep learning has transformed healthcare, finance, agriculture, and other fields.

Nwankpa et al. (2018) compared the practical and research trends of various activation functions used in deep learning. The paper discussed the advantages and limitations of popular activation functions such as ReLU, tanh, and sigmoid. It also examined the effects of different activation functions on model performance, their usage areas, and their role in the training process, and discussed the effects of these functions on overall performance in deep learning networks and application examples.
Wu and He (2018) introduced the group normalisation method and investigated its effects on the optimisation process in DL networks. In their paper, they found how group normalisation improves the learning process and enhances the performance of the model, especially in deep

networks. They also provided detailed information on the role of group normalisation in network training, its advantages, and application examples.

Ali Arı (2019), in his PhD thesis, investigated the detection and classification of tumours from brain MRI images. The thesis detailed the image processing and machine learning methods developed to enable automatic recognition and classification of brain tumours. The methods used included various image processing techniques, feature extraction, and classification algorithms. The study evaluated the deep learning approaches used for the analysis of brain MRI images, their accuracy, and performance. Furthermore, the results of the thesis discussed the potential benefits and limitations of these techniques in clinical applications.

Altaş et al. (2019), in their study, stated that image processing techniques have started to be widely applied in agricultural activities in the study of sugar beet leaf spot disease, detection of diseases, pests and weeds, identification of plant stresses, yield estimation, monitoring of product development, and modelling of irrigation methods. In this study, sample works on the use of the process of separation of objects based on their colour and shape in determining the levels of plant diseases and pests were examined. Then, the segmentation process for the detection of sugar beet leaf spot disease was explained practically.

Cibuk et al. (2019) examined efficient deep feature selection and classification methods for the identification of flower species. In the study, various deep learning techniques were used to accurately identify flower species. In particular, the selection of deep features and how these features affect the classification performance were emphasised. The study highlighted the effectiveness of the methods in providing high-accuracy classification for flower species and how these techniques can be used in botanical research and applied agriculture.

Liu et al. (2019) investigated the applicability of deep learning-based methods for early detection of leaf diseases. In their study, CNNs were used to classify different foliar diseases on crops such as corn and wheat. Deep learning models such as AlexNet and GoogLeNet were used to detect different types of diseases, and the accuracy rates of each model were compared. The training data was divided into 70% for training and 30% for testing, and the accuracy and overall performance of the model were evaluated with metrics such as error rate and F1 score.

The results showed that the GoogLeNet model had the highest accuracy rate. Furthermore, the study discusses how deep learning methods can be used effectively in the detection of agricultural diseases with lower hardware requirements in terms of efficiency. The study emphasises that deep learning-based systems have significant potential for automatic disease detection in agriculture.

Michele, Colin, and Santika (2019), in their study, stated that the palm recognition system has attracted great attention in recent years due to its ability to work easily with low-resolution images, low-cost hardware, and high accuracy rate. Various features obtained from the palm image are used in recognition tasks. However, one of the major drawbacks of traditional image-based biometric recognition systems is the huge effort required to design and obtain effective hand-crafted features. To solve this problem, they investigated the feasibility of fine-tuning pre-trained MobileNet neural networks on palm recognition. They also investigated the performance of dropout support vector machines (SVM) on deep features extracted from the same pre-trained networks. They conducted their experiments with a dataset provided by Hong Kong Polytechnic University. This dataset contains 6,000 grayscale images with 128x128 pixels taken from 500 different palms. The proposed methods were proven to perform state-of-the-art on the dataset. The second method, which includes MobileNetV2-based features and SVM classifier, outperformed the previous best results with 100% average test and validation accuracy.

Türkoğlu (2019), in his doctoral thesis, examined the recognition of plant species and diseases using image processing methods. In his study, he evaluated the recognition processes of various plant diseases, the image processing techniques used, and the accuracy of these techniques. He also investigated the performance of algorithms used to detect plant diseases and the effects of these methods on agricultural applications.

Velasco et al. (2019), in their study, used the MobileNet model in an Android application to create a system that classifies seven skin diseases by applying transfer learning. They collected a total of 3,406 images, and this dataset was considered unbalanced due to the unequal number of images between classes. Different sampling methods and pre-processing of the input data were investigated to further improve the accuracy of MobileNet. Using the sub-sampling method and the default preprocessing of the input data, an accuracy of 84.28% was achieved. They found that 93.6% accuracy was achieved when using an unbalanced dataset and the default preprocessing method. Then, by oversampling the dataset, the model achieved 91.8% accuracy. Finally, by using the oversampling technique and data augmentation method in the preprocessing of input data, they achieved 94.4% accuracy and integrated this model into the developed Android application.

Rajendran et al. (2020) investigated the applicability of deep learning-based models in the detection of leaf diseases. In the study, DL models such as AlexNet, GoogLeNet, and ResNet were used in disease classification tests on corn leaves. The accuracy rates of these models were compared, and the training time and accuracy of each model were determined. The results showed that the ResNet model provided the most successful results with an accuracy rate of 93%. While the study shows how successful DL techniques are in disease detection in agriculture, it emphasises that these methods are especially important in terms of early diagnosis and increasing productivity. It is also stated that such models used in agriculture can have a much wider application area for automatic diagnosis and yield management.

Sserumaga et al. (2020) conducted a study aiming to detect rust disease in tropical corn varieties. In the study, leaf images from five different corn varieties were used, and various DL architectures were employed to accurately detect diseases. The models used included AlexNet, GoogLeNet, and DenseNet, and the accuracy of each model was tested. The results showed that the DenseNet model gave the most successful results with an accuracy rate of 96% and demonstrated the effectiveness of DL methods in the detection of diseases in corn plants. This study emphasises that the rapid detection and prevention of diseases in the agricultural sector is critical for productivity. It also states that DL algorithms can be effectively applied on different corn varieties and improve the agricultural production process.

Wang et al. (2020) investigated the use of CNNs in the detection of plant diseases. In their study, images from different plant species such as corn, potato, and soybean were used to detect various foliar diseases. These images were taught to DL models such as AlexNet, GoogLeNet, and DenseNet, and the accuracy of each model was compared. The results of the study showed that the DenseNet model achieved the highest success with an accuracy of 95%. In addition, the study revealed that DL methods improve the classification performance, enabling early detection of plant diseases in agriculture. The study stated that DL algorithms provide faster and more accurate results in agriculture and, with the development of these technologies, disease detection processes in the sector will become much more efficient.

Sserumaga et al. (2020) also examined the resistance of tropical corn inbred lines to common rust (*Puccinia sorghi* Schwein) disease. The article evaluated the disease resistance of different corn lines and analysed genetic diversity. It also provided information on the strategies used to control the disease and their effectiveness. The results of the study provided recommendations for the selection of resistant lines and disease management.

Göksu et al. (2021), in their study on disease detection in corn leaves using deep learning networks, aimed to detect corn rust, grey leaf spot, and leaf blight, which are frequently encountered diseases in corn leaves. Two models based on the EfficientNetB5 network and CNN were developed for the detection of these diseases using deep learning techniques. To improve the performance of the developed models, the number of image data was increased by data augmentation techniques (mirroring, rotation, magnification). The results show that the prediction accuracy rates of the EfficientNetB5 transfer learning model and the original deep learning model were 92.12% and 89.88%, respectively.

Khan et al. (2021) investigated the effectiveness of deep learning methods for disease detection in agriculture. The study examined the use of various CNN-based models to detect diseases of corn and wheat leaves. In the study, AlexNet, GoogLeNet, ResNet, and DenseNet models were tested to classify different plant diseases. The study aimed to select the most successful model by comparing the accuracy rate and training time of each model. The results showed that the DenseNet model provided the most successful results with an accuracy rate of 96.5%, but GoogLeNet was also very successful with an accuracy rate of 94%. Furthermore, the study emphasised that deep learning methods can be an important tool to accelerate disease detection processes and increase efficiency in the agricultural sector.

Patel et al. (2021) investigated the usability of DL methods for the detection of diseases in agriculture. In their study, the effectiveness of CNN-based models for the detection of diseases in agricultural crops such as corn and wheat was examined. This study revealed the potential of DL techniques, especially in terms of efficiency and accuracy. The findings showed that the GoogLeNet model provided the highest accuracy rate. The study emphasises that deep learning-based disease detection systems can create a significant change in agriculture and increase productivity.

Reddy et al. (2021) developed a deep learning-based system for disease detection in corn plants. In the study, different CNN-based models were used to accurately classify the diseases. The results showed that the ResNet50 model showed the highest success with an accuracy rate of 91%. It was also emphasised that deep learning techniques have great potential for disease detection and increasing agricultural productivity.

Singh et al. (2021) developed a deep learning-based approach to detect corn leaf diseases. In the study, a large dataset with different disease types was used, and diseases were classified with pre-trained CNN models such as AlexNet, GoogLeNet, and ResNet. The training data was divided into 80% training and 20% testing. The results showed that the GoogLeNet model achieved the highest success with an accuracy of 92.5%. Accordingly, it was concluded that the GoogLeNet model performed better in detecting corn diseases. The study revealed that deep learning-based models can help detect diseases quickly and are an important technology for preventing diseases and increasing productivity in agriculture. It was also emphasised that DL methods can be used more widely in various agricultural applications.

Yadav et al. (2021) used DL methods to detect corn leaf diseases. In the study, pre-trained CNN models such as AlexNet, GoogLeNet, ResNet, and MobileNet were used, and the performance of each model was compared. The results showed that the ResNet model achieved the highest accuracy rate (97%). Furthermore, this study revealed that lightweight models such as MobileNet perform well even with low computational power and are suitable for use in agriculture. The study highlights how AI and DL technologies can be useful in agriculture, especially in disease detection.

Zhang et al. (2021) conducted a study aiming to detect corn leaf diseases. In the study, a large dataset containing four different disease classes was used. The dataset consists of images of different types of corn leaf diseases, and these images are classified using CNNs. Pre-trained DL networks such as AlexNet, GoogLeNet, DenseNet, and ResNet were used as models. The training data was split into 80% training and 20% testing, and the transfer learning technique was applied. Images were normalised in various dimensions and diversified with data augmentation methods. In this way, overfitting was prevented, and the overall performance of the model was improved. Each CNN architecture was tested separately and evaluated according to performance criteria such as accuracy, F1 score, error rate, and ROC curve. The results of the study showed that the DenseNet model achieved the highest success with an accuracy rate of 98.5%, while GoogLeNet (96.2%), ResNet (94.7%), and AlexNet (91.5%) followed. It was also observed that MobileNet has the fastest learning process in terms of training time, and the ConvNeXt architecture provides advanced classification success. The study emphasises that DL-based methods provide high accuracy rates for corn disease detection and models with low hardware requirements can also perform adequately. The study proved that DL methods are an important tool for disease detection in the agricultural sector.

Adige et al. (2022), in their study on the classification of apple varieties according to types using image processing techniques, took a total of 120 images from 20 Golden, 20 Argentine, 20 Buckeye Gala, 20 Galaval, 20 Superchief and 20 Joremin apple varieties grown in Yahyalı district of Kayseri. From these images, 70% were used for training and 30% for testing. AlexNet and GoogLeNet deep learning algorithms were used to identify these species with artificial intelligence. Among the algorithms used, AlexNet and GoogLeNet achieved 83.33% and 91.67% correct predictions, respectively. As a result, GoogLeNet obtained more successful results than AlexNet.

Ciran and Özbay (2022) investigated how CNN-based deep learning algorithms are effective in the classification of corn leaf diseases. The study aimed to determine whether corn leaves are healthy or diseased by using pre-trained deep learning networks such as GoogLeNet and ResNet. The training and test data were split into 80% and 20% on a large dataset. The results of the study show that GoogLeNet provides the most successful performance with an accuracy rate of 95.7%. GoogLeNet provided the highest accuracy in detecting corn diseases. However, it was also observed that deep networks have significant potential to increase the accuracy rate. This study demonstrates the rapidly evolving role and potential of artificial intelligence and deep learning techniques in agriculture. It also emphasises how such technologies can be made more efficient in terms of agricultural production and disease management.

Ciran and Özbay (2022) extracted features from corn leaf images using CNN-based VGG-19, DenseNet-201, and NASNet-Large models in their study on the classification of corn leaf diseases by fusion of pre-trained CNN architectures. Synthetic Minority Oversampling Technique (SMOTE) was used to correct the imbalance in the dataset. To reduce the number of features, they used the Support Vector Machines (SVM) algorithm to classify diseases in corn leaves by choosing Principal Component Analysis (PCA) as a dimensionality reduction method. To improve the performance of the algorithm, Kernel function and Box constraint hyperparameters were optimised using the GridSearchCV method. The results obtained were tested on the publicly available Kaggle corn or corn leaf disease dataset. In the classification of the images extracted with LibSVM, accuracy rates of 94.5%, 94.4%, 94.3%, and 96.2% and a weighted average of 94.3% were achieved for four classes, respectively. Using LibSVM with the proposed method, the accuracy rates of 96.7% for all four classes and a weighted average of 96.7% were achieved. They observed that the classification accuracy obtained with the proposed method improved by 2.2% for the first class, 2.3% for the second class, 2.4% for the third class, and 1.6% for the fourth class, and by 2.4% in the weighted average compared to the classification accuracy obtained without optimisation.
Ciran and Özbay (2022) investigated the classification of corn leaf diseases by fusion of pre-trained CNNs. The paper discussed how various pre-trained CNN architectures can be fused and the effectiveness of these fused models in disease recognition. The study detailed the techniques, datasets, and results used to improve the model's performance. It also discussed the effects of these methods on accuracy and reliability in the classification of corn leaf diseases.

Ökten and Yüzgeç (2022), in their study titled *Detection of Paddy Plant Disease with Convolutional Neural Network*, emphasised that one of the recent researches in the field of agriculture is the recognition or classification of diseases from images of plant leaves, and in this context, disease diagnosis from leaf images of paddy plants is at the automation stage. In their work, significant progress was made towards early diagnosis of the disease, and different learning methods were tried. As in previous studies, machine learning (ML) methods such as deep learning (DL) models were used instead of traditional feature extraction methods for disease detection on plant leaf images. The researchers obtained significant results using a convolutional neural network (CNN) for the detection of paddy plant diseases. In the study conducted on 5,000 paddy leaf images obtained from the Kaggle site, two classifications were performed for disease detection: three diseases (Brown Spot, Leaf Blast, and Hispa) and a healthy state. The researchers achieved an accuracy rate of 91.54% as a result of changes in the hyperparameters of CNN. In addition, using the data augmentation method, 8,000 paddy plant leaf images were obtained from the dataset, and an accuracy of 94.87% was achieved after training with CNN. After preprocessing on the images, an accuracy of 97.57% was obtained as a result of training with CNN. This study shows that significant progress has been made in disease detection from paddy plant leaf images.

Yaman and Tuncer (2022), in their study titled *Deep Feature Extraction and ML Method for Leaf Disease Detection in Plants*, used DL and feature selection methods for the detection of leaf disease. For the proposed method, a total of 726 images were obtained from walnut leaves. These images were categorised into two classes as healthy and diseased. Various DL models were tested for feature extraction from the images, and the two best-performing models were DarkNet53 and ResNet101. A hybrid feature extraction was performed by combining the features obtained from these two models. ReliefF algorithm was used for feature selection, and the most weighted features were determined. Support Vector Machine (SVM) algorithm was used to classify the selected features. An accuracy of 99.58% was obtained with the proposed method.

Dhanta, R., & Mwale, M. (2024) explained the use of AI in crop and animal production. AI techniques have become a critical tool in facilitating agricultural activities and providing alternative solutions to problems that need to be solved or developed. Thanks to the developed algorithms and software, there are many studies by researchers in various fields in agricultural production. Among these studies, they emphasised that there are topics such as plant cultivation planning, classification of plant species, yield estimation, detection of plant diseases, pests and weeds, determination of the routes of agricultural robots, determination of suitable conditions in the greenhouse environment, making business decisions, irrigation management, crop rotation, selection of the most suitable fertiliser and tools/machinery, detection of animal diseases, creation of appropriate feed rations, and analysis of animal behaviour.

3 MATERIAL AND METHOD

3.1 Material

The data set required during this thesis study was obtained from the studies conducted by Singh D et al. in 2020, Pandian and Geetharamani in 2019, https://www.kaggle.com/datasets/smaranjitghose/corn-or-corn-leaf-disease-dataset/data?select=data on the Kaggle platform, which is an online data scientists and ML community.

In the data set, there are 1306 images of common rust disease, 574 images of grey leaf spot disease, 1146 images of leaf blight disease and 1162 images of healthy corn leaves, which are 4188 images in total. In addition, the researchers also informed that some images were removed from the data set because they were not useful in this data set.

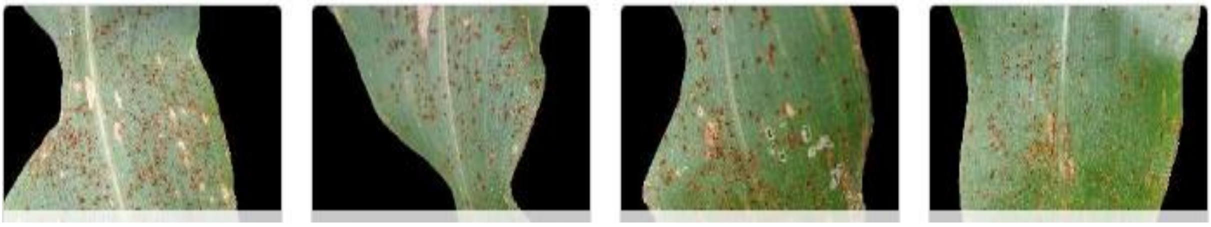

Figure 3.1. Some Examples of Common Rust Disease Pictures

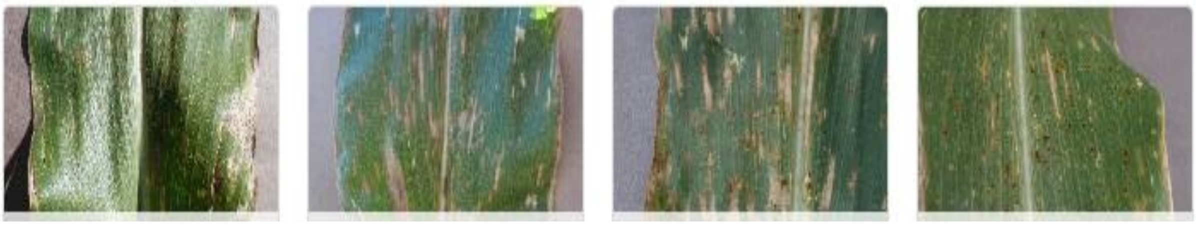

Figure 3.2. Example Pictures of Grey Leaf Spot Disease

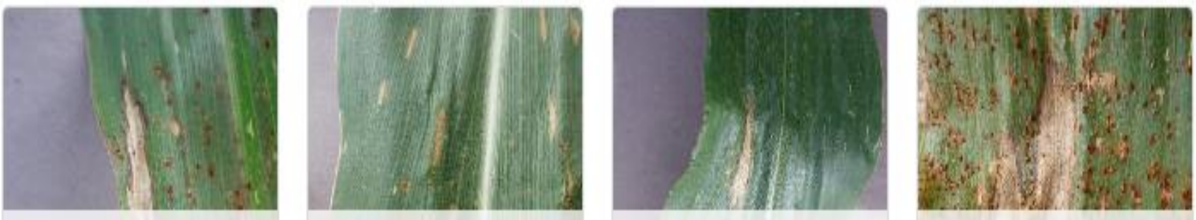

Figure 3.3. Example Pictures of Leaf Blight Disease

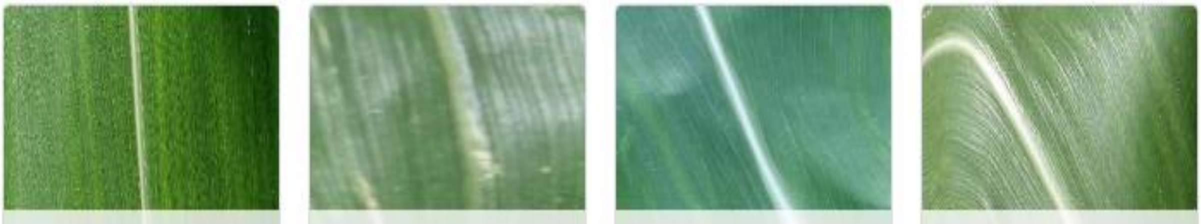

Figure 3.4. Example Images of Healthy Corn Leaf

3.2 Method

Google Colap environment was used in the study. In addition, Pyhton was preferred as the writing language.

The images subject to our study were divided into 3 parts as 80% Traning, 10% Validation and 10% Test with the help of the software. As a result, the following table showing the number of images was created.

Table 3.1. Number of Images in the Dataset

	Total Image	Traing	Validation	Test
Healthy corn leaf	1162	929	116	117
Leaf blight	1146	916	115	115
Grey leaf spot	574	459	57	58
Common rust disease	1306	1044	131	131

The learning process was trained within the parameters given in the table below within the 7 preferred CNN models.

Table 3.2. Parameters Used During the Training of the Models

Parameter	Value
Epochs	10
Batch Size	4
Optimizer	SGD (lr=0.001, momentum=0.9)
Loss Function	CrossEntropyLoss
Learning Rate	0.001
Momentum	0.9
Data Augmentation	Crop, Flip, Rotation
Normalization	[0.485, 0.456, 0.406] / [0.229, 0.224, 0.225]
Hardware	CUDA / CPU

After the training process was completed, the models were evaluated according to the following criteria.

3.2.1 Learning Curve

A comprehensive learning curve analysis is critical for evaluating the performance of DLmodels. The learning curves of CNN (CNN) models show how losses and accuracies change during the training and validation phases. Analysing these curves helps to identify potential problems that the model may encounter during the learning process.

3.2.1.1 Learning Curve Elements

Loss Curve: The loss curve shows the model's error in the training process. The training loss represents the model's errors in the training set and the learning process, while the validation loss reflects how the model performs against new and unseen data. A good model should decrease the training loss over time and the validation loss should decrease similarly to the training loss. If the validation loss is increasing, this indicates that the model is experiencing overfitting.

Accuracy Curve: The accuracy curve shows the correct prediction rate of the model. Training and validation accuracy reveals how the model develops during training. Increasing training accuracy indicates that the model adapts to the data; however, insufficient increase in validation accuracy may be an indication of overlearning. A good model is recognised by the upward movement of both curves.

Overfitting: Overlearning is when the model overfits the training set too much, thus reducing its overall performance. Loss curves can clearly reveal the problem of overlearning, with training loss decreasing and validation loss increasing. This indicates that the complex structure of the model tends to overlearn on simple data.

Generalization Capability: A good CNN model should provide a good fit to the training data, but should also be able to generalise to new data. A steady decrease in verification loss and increase in verification accuracy is an indication of the generalisation ability of the model.

Learning curves of CNNs are an important tool for evaluating and optimising model performance. Analysing training and validation loss and accuracy curves helps to understand at which stages of the learning process the model has problems and how improvements can be made. Therefore, learning curves are an indispensable analysis tool in DL applications.Below are the learning curve analyses and comparisons of the CNN models used in our study.

AlexNet: The training and validation loss of the model fluctuated somewhat and showed dramatic increases in some epochs. Although the validation accuracy is high, the large fluctuations in the validation loss indicate that the model does not exhibit a stable learning process.

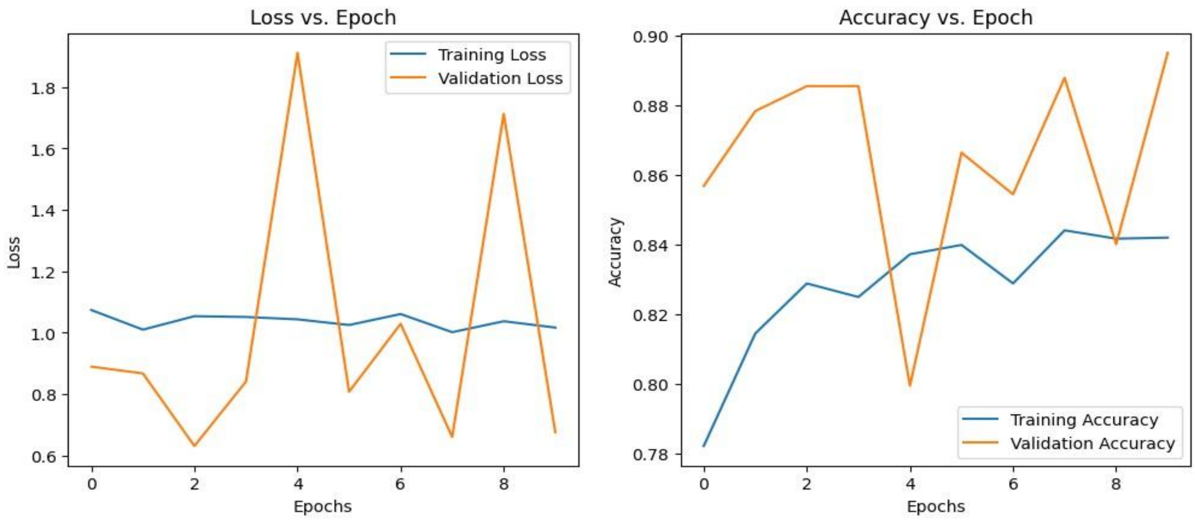

Figure 3.5. AlexNet Learning Curve Image

ConvNeXt: The model achieved low loss and high accuracy rates in the training and validation phases. The training accuracy increased continuously and the validation loss remained at very low levels. The model performed consistently on the validation set, giving the best overall result.

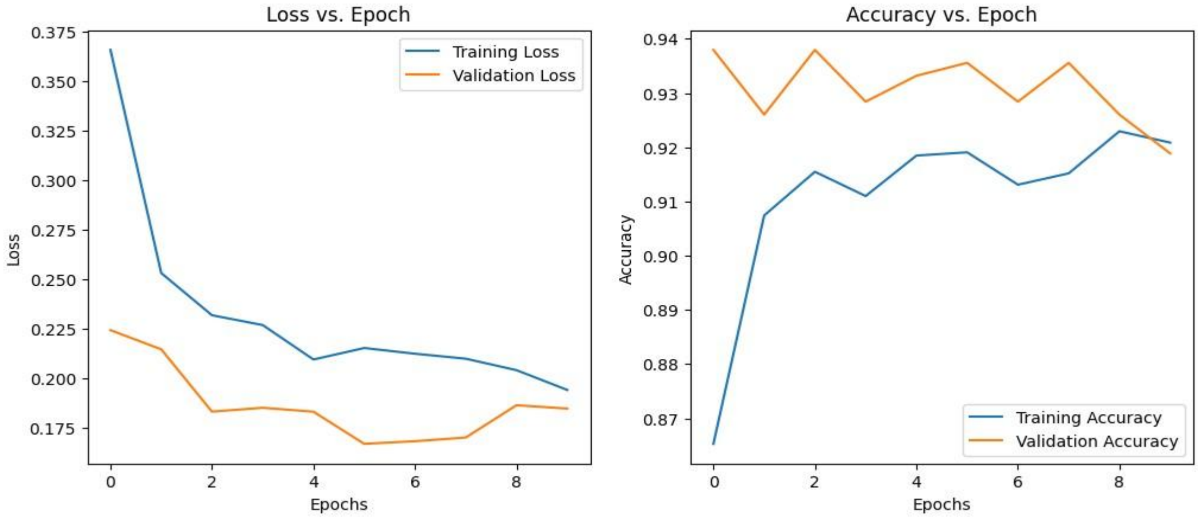

Figure 3.6. ConvNeXt Learning Curve Image

DenseNet: It has achieved high results in terms of verification accuracy, but the training and verification loss is quite fluctuating. Although the verification accuracy of the model reaches high levels, the instability in the loss shows that the model is not fully efficient.

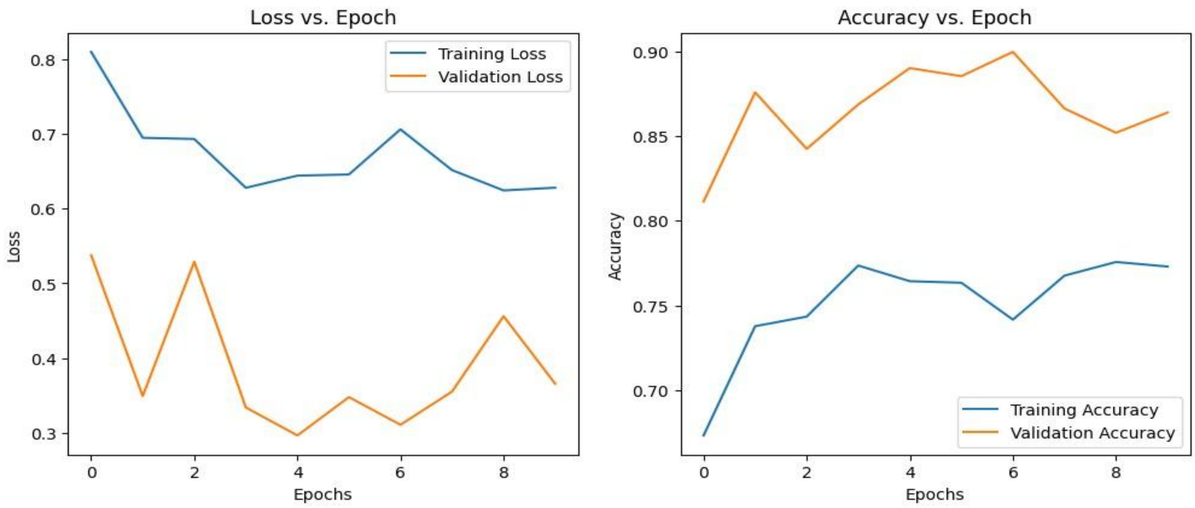

Figure 3.7. DenseNet Learning Curve Image

EfficientNet: Training and verification loss fluctuated, but overall verification accuracy remained satisfactory. Although the training accuracy has steadily increased, the fluctuations in loss suggest some weaknesses in the stability of the model.

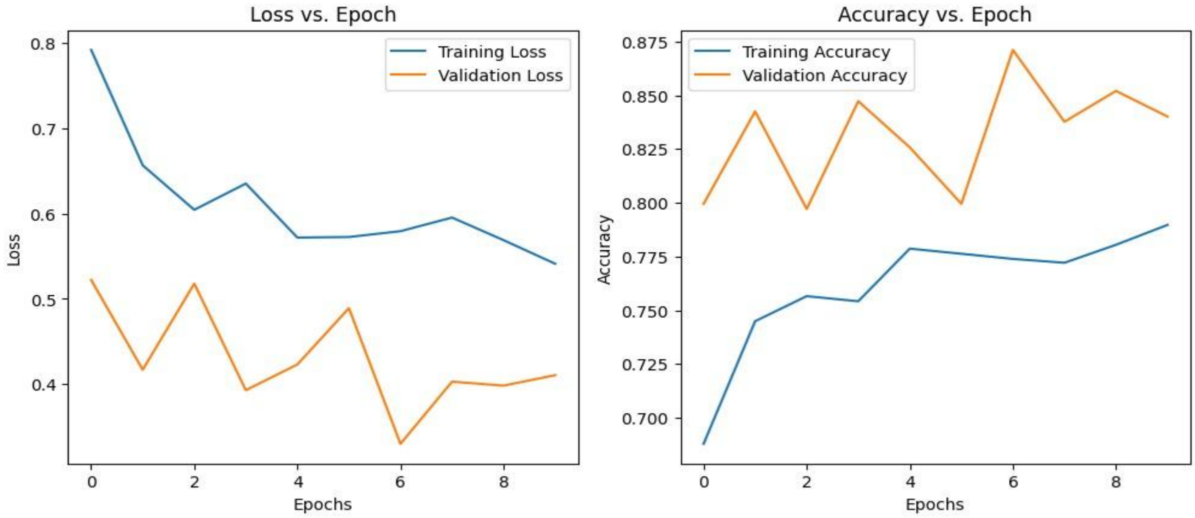

Figure 3.8. EfficientNet Learning Curve Image

GoogLeNet: Training accuracy has steadily increased, while verification accuracy has remained stable at high levels. Verification loss was generally good, with a slight increase in recent epochs. GoogLeNet is one of the better performing models, but the increase in verification loss in recent epochs indicates that the model has not reached its full potential.

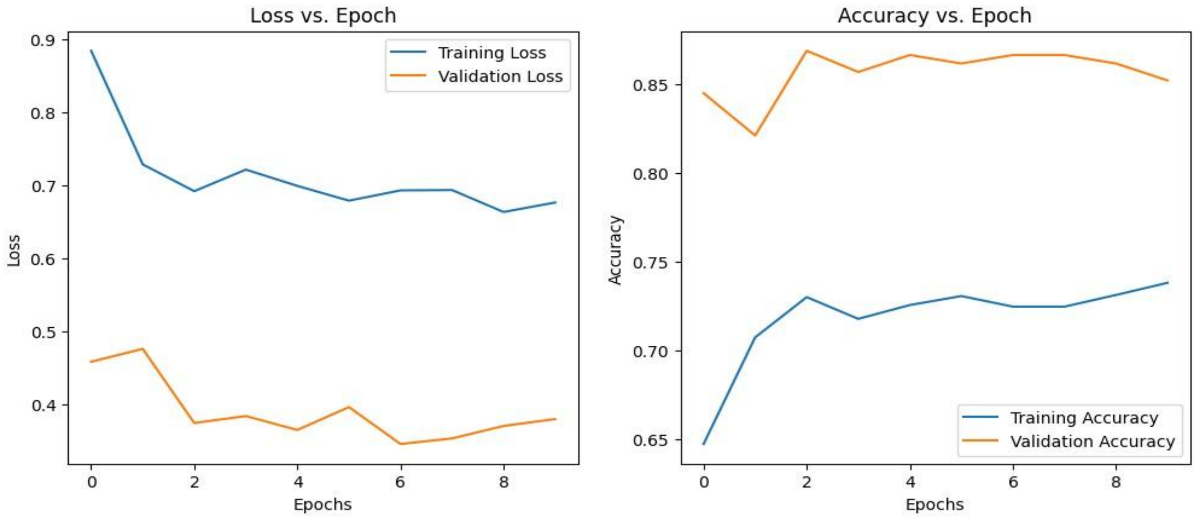

Figure 3.9. GoogLeNet Learning Curve Image

MobilNet: Although training and verification accuracy were satisfactory, the increase in training accuracy was slower than the other models. MobilNet's verification accuracy remained high, but verification loss fluctuated slightly. Overall performance is balanced, but not perfect.

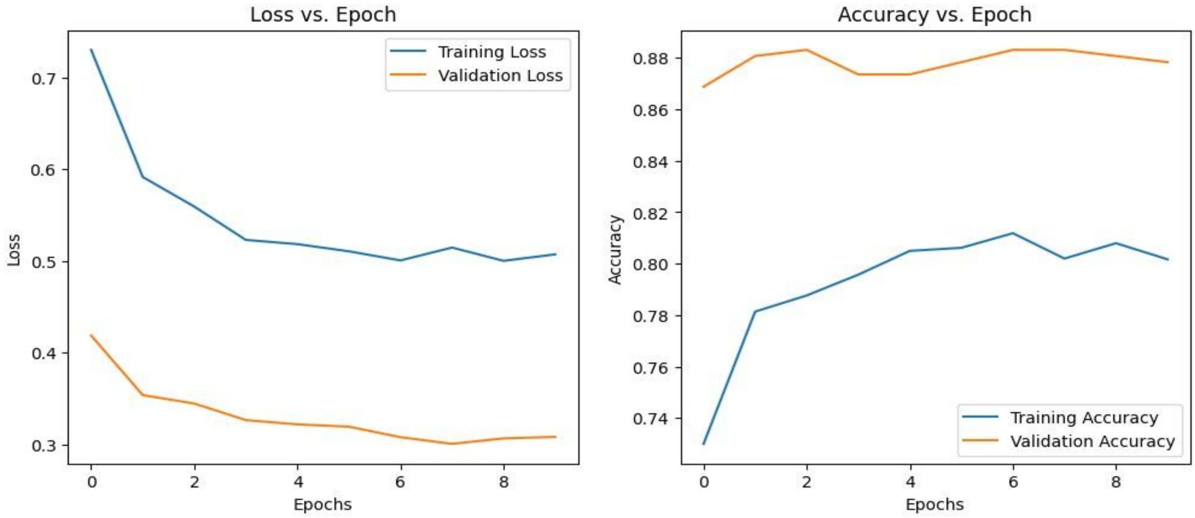

Figure 3.10. MobilNet Learning Curve Image

ResNet: The training loss generally decreased, while the verification loss fluctuated. Although the model showed a rapid improvement in the beginning, the verification loss and accuracy improved less in the last epochs. Although its performance is stable, fluctuations in verification loss affect the stability of this model.

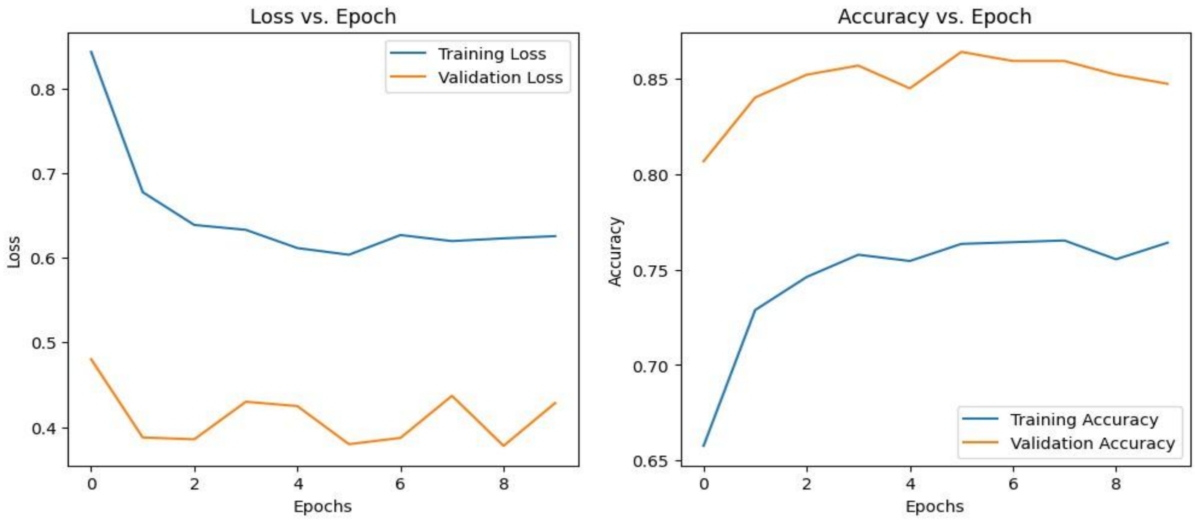

Figure 3.11. ResNet Learning Curve Image

As a result**,** ConvNeXt is the model that exhibits the most consistent and successful learning curve, achieving the lowest losses and highest accuracy rates in both training and validation phases. Therefore, it stands out as the best performing model among the 7 CNN models.

3.2.2 Accuracy

It is a widely used metric for evaluating the performance of a classification model. It is usually defined as the ratio of correct predictions to the total number of predictions. In simpler terms, it is the percentage of instances that the model correctly classifies. Accuracy is used to measure how well the model works, but in some cases it can be misleading, especially if the classes in the data set are unbalanced.

Accuracy is calculated by the following formula:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (2)$$

Correct Predictions: The number of instances that the model correctly classified.

Total Predictions: The number of all instances classified by the model.

Areas of Use

Accuracy is usually used in the following situations:

- Binary Classification: In data sets that are divided into two classes, accuracy can often be a sufficient criterion.
- Balanced Classes: When there is equal distribution between classes, accuracy provides an accurate indicator of performance.

If the classes in the dataset are unbalanced (e.g. one class has many more instances than another), accuracy can be misleading. In this case, other metrics, such as precision, recall and F1 score, may give more meaningful results. The Accuracy rates of the 7 CNN models considered in the study are given in the table below.

Table 3.3. Accuracy Rates of CNN Models

Model	Validation Accuracy
ConvNeXt	96.4%
Densenet	95.1%
EfficientNet	94.3%
ResNet	93.2%
MobileNet	92.0%
GoogLeNet	91.5%
AlexNet	90.3%

As can be seen from the table, the model with the highest accuracy rate is **ConvNeXt**, which is ahead of the other models with an accuracy rate of 96.4%.

3.2.3 Precision

It is a concept that evaluates the overall performance of a model in the context of machine learning and deep learning. It is usually calculated using accuracy and loss values. Accuracy indicates how well the model generalises, i.e. how effectively it can apply the knowledge learnt on the training dataset on new, unseen data.

Precision refers to a trade-off between the model's ability to make accurate predictions and the cost of making incorrect predictions. A low loss value and a high accuracy indicate a high level of precision. Precision is calculated by the following formula:

$$Precision = True\ Positive /(True\ Positive + False\ Positive) \tag{3}$$

Why is Precision Important?

Model Performance: Precision reflects the real-world performance of a model. High precision indicates that the model can work effectively on new data.

Generalization Capability: Accuracy indicates that the model does not overfit the training data and can generalise to different data sets.

Precision is widely used to evaluate model performance in classification, regression and other machine learning tasks. In particular, as the complexity of deep learning models increases, performance metrics such as precision become more important.

In the training process of a model, if the accuracy value increases while the loss value decreases continuously, then it can be said that the learning process of the model is successful and its precision is high. The acuities of the 7 CNN models considered in our study are given in the table below.

Table 3.4. Precision Figures of CNN Models

Model	Precision
ConvNeXt	95%
Densenet	94%
ResNet	92%
EfficientNet	91%
MobileNet	90%
GoogLeNet	90%
AlexNet	88%

As a result, the model with the highest precision value is **ConvNeXt**, reaching a value of 95%.

3.2.4 F1-Score

It is an important metric used to measure the performance of the model in machine learning and especially in classification problems. The F1 score is an average that measures the balance between **precision** and **recall**. Precision and recall attempt to balance the false positive and false negative predictions of a model, especially useful in imbalanced datasets.

Calculation:Precision and recall are often opposing goals; increasing one may decrease the other. The F1 score provides an overall measure of performance by balancing these two metrics. The F1 score is calculated using the harmonic mean:

$$F1 - score = 2x \frac{Precision\ x\ Recall}{Precision + \ Recall} \quad (4)$$

This formula balances precision and recall so that the model gives equal importance to both metrics. If there is a large difference between precision and recall, the F1 score will be low. Therefore, the F1 score is preferred for unbalanced datasets or when the positive class is rare.

Uses of the F1 Score:

Unbalanced Datasets: In classification problems, the accuracy metric can be misleading when one class has many more examples than the other class. The F1 score provides more meaningful results by taking precision and recall into account.

Health Applications: For example, false negative (FN) results can be critical in disease diagnosis. In this case, high recall is desirable, but focusing only on recall can increase false positives. The F1 score offers a more appropriate assessment by balancing both metrics.

Information Retrieval and Search Engines: The F1 score is used to evaluate the accuracy and performance of search engines or information retrieval algorithms.

Advantages of the F1 Score:

- It balances precision and recall.
- Provides a more accurate performance evaluation than accuracy on unbalanced datasets.

Disadvantages of the F1 Score:

- It requires the model to treat both metrics equally; if there are cases where one is more important than the other, the F1 score does not reflect this.
- It can only be applied directly in binary classifications. In multi-class classifications, the F1 score is calculated for each class and averaged. The table below shows the F1 scores of the 7 CNN models considered in our study.

Table 3.5. F1-Score Values of CNN Models.

Model	F1 score
ConvNeXt	96%
Densenet	95%
EfficientNet	94%
ResNet	93%
MobileNet	91%
GoogLeNet	91%
AlexNet	89%

According to this, the CNN model with the best F1 score value is ConvNeXt and its value is 96%.

3.2.5 ROC Curve

The Receiver Operating Characteristic (ROC) curve is a tool used to evaluate the performance of classification models. It is especially used in two-class classification problems. Analysing the ROC curve allows to see how the true positive rate (TPR) and false positive rate (FPR) of the model changes at different thresholds.

ROC curve analysis steps are as follows:

Definition of Axes

Y-axis (TPR - True Positive Rate): The proportion of samples that the model correctly classifies as positive. Also known as sensitivity.

$$TPR = \frac{\text{Number of True Positive}}{\text{Number of True Positives} + \text{Number of False Negatives}} \tag{5}$$

X-axis (FPR - False Positive Rate): The proportion of samples that the model incorrectly classifies as positive. Also known as 1 - specificity.

$$FPR = \frac{\text{Number of False Positives}}{\text{Number of False Positives} + \text{Number of True Negatives}} \tag{6}$$

ROC Curve Interpretation

ROC curve: A graph showing how the TPR and FPR change at different thresholds. The curve represents the capacity to discriminate the model. If the ROC curve is closer to the upper left (i.e. TPR high, FPR low), the model performs better.

Perfect model: It has the ROC curve closest to the point (0,1), i.e. the false positive rate is 0 and the true positive rate is 1.

Random prediction model: The ROC curve for this type of model would be a diagonal (45 degree) line, because the model randomly predicts both classes.

AUC (Area Under Curve) Score

AUC score: Measures the area under the ROC curve. The AUC expresses the overall performance of the model with a single number. If the AUC score is close to 0.5, the model is randomly predicting. The closer the AUC score is to 1, the better the performance of the model.

AUC = 1: Perfect model

AUC = 0.5: Random prediction model

AUC > 0.7: Good performing model

AUC > 0.9: A very successful model

Analysis of Intersection Points

The shape of the curve helps to understand how good the classifier model is at different thresholds. If the ROC curve rises rapidly upwards and stays close to the left, the model is both predicting positives correctly and minimising false positives.

ROC Curve Examples:

A high performance model: The curve is upwards close to the Y-axis and the AUC score is close to 1.

A model with medium performance: The curve lies in the middle, with an AUC score of around 0.7.

A poorly performing model: The curve is close to the diagonal of the X and Y axis and the AUC score is close to 0.5.

The ROC curve and AUC score assess model performance not only by accuracy but also by considering the balance between positive and negative classes.

ROC curve analyses of the CNN models used in our study are given below.

AlexNet:

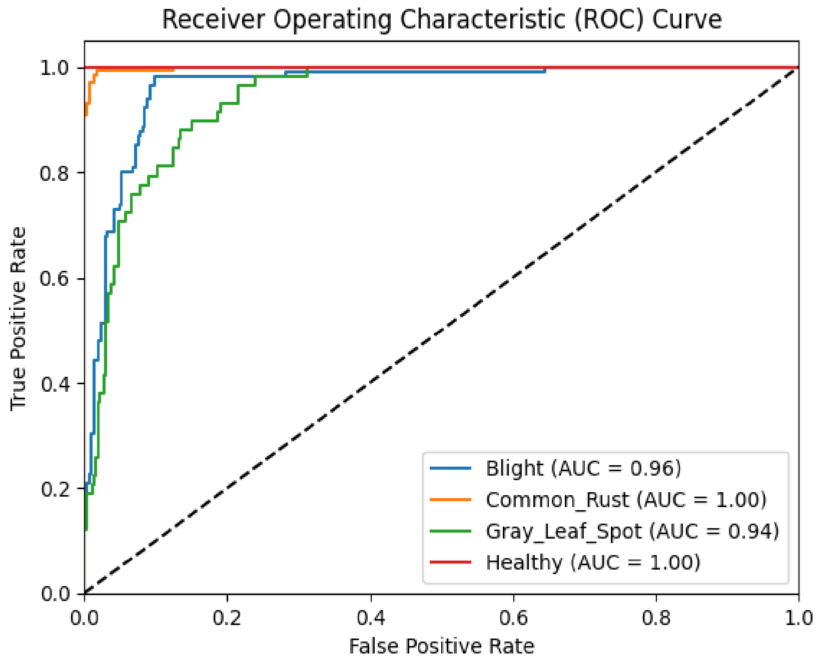

Figure 3.12. ROC Curve Plot of the AlexNet Model

The Receiver Operating Characteristic (ROC) curve results obtained with the AlexNet model show that the model performs very well in the multi-class classification task. ROC curves were drawn separately for each class and AUC (Area Under the Curve) values were calculated.

Accordingly, the AUC was 0.96 for the "Blight" class, 0.94 for the "Gray Leaf Spot" class, and 1.00 for the "Common Rust" and "Healthy" classes. These values show that the model has a high discrimination power between the classes and the false positive rates are very low. Especially in the "Common Rust" and "Healthy" classes, the ROC curve completely adheres to the upper left corner, which is ideal on the graph, indicating that these classes are classified with 100% accuracy.

The overall shape of the ROC curves proves that the model maintains a high rate of true positives and provides consistently high performance across classes. In this respect, AlexNet can be considered as a balanced and reliable classifier not only in terms of accuracy but also in terms of important metrics such as sensitivity and specificity. This analysis shows that the model can effectively distinguish classes even in a multi-class structure and has a strong overall performance.

ConvNeXt:

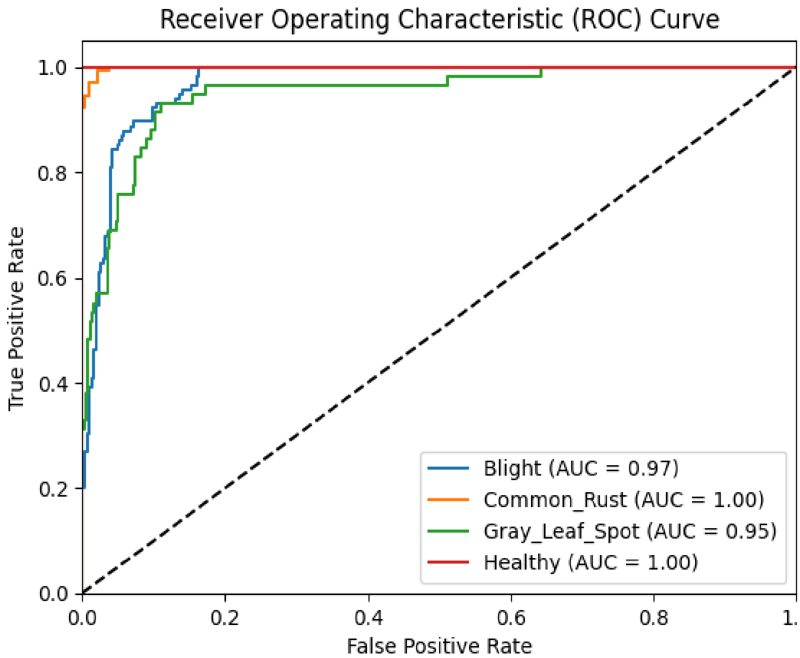

Figure 3.13. ROC Curve Plot of the ConvNeXt Model

The Receiver Operating Characteristic (ROC) curve obtained with the ConvNeXt model shows that the model shows a very high success in the multi-class classification task. ROC curves were drawn separately for each class on the graph and AUC (Area Under the Curve) values were calculated. The AUC value for the "Blight" class was calculated as 0.97, for "Gray Leaf Spot" as 0.95, and for "Common Rust" and "Healthy" classes as 1.00. These values show that the model can distinguish the classes correctly and the misclassification rates are quite low.

The shape of the ROC curves shows that the curves lie close to the upper left corner and therefore both sensitivity (true positive rate) and specificity (1 - false positive rate) are high. In particular, the fact that the curves of the "Common Rust" and "Healthy" classes exactly reflect the ideal curve shape shows that these classes were classified by the model completely error-free. The AUC values above 0.95 for "Blight" and "Gray Leaf Spot" classes also indicate a very successful performance for these classes. All these findings show that the ConvNeXt model provides a highly balanced, accurate and reliable classification in a multi-class structure.

DenseNet:

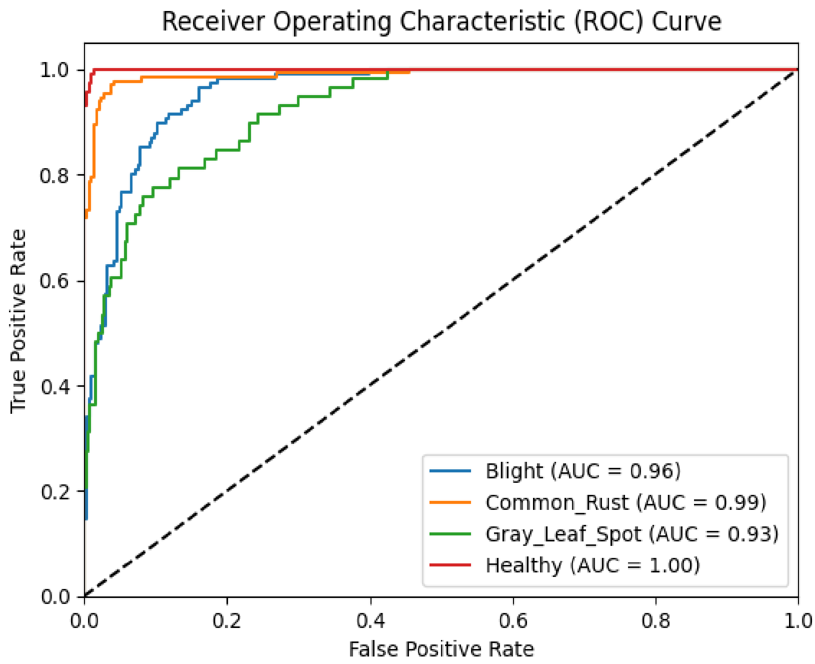

Figure 3.14. ROC Curve Plot of the DenseNet Model

The Receiver Operating Characteristic (ROC) curve obtained with the DenseNet model reveals that the model works with high accuracy in the multi-class classification task. In the ROC graph, separate curves were drawn for each class and the corresponding AUC (Area Under the Curve) values were calculated.

The AUC value was 0.96 for "Blight" class, 0.93 for "Gray Leaf Spot", 0.99 for "Common Rust" and 1.00 for "Healthy" class. These values show that the model has very low misclassification rates for all classes and has an almost error-free discrimination capacity, especially in some classes.

The shape of the ROC curves, especially in the "Healthy" and "Common Rust" classes, is very close to the upper left corner, indicating high sensitivity and high specificity. This shows that the model performs close to perfect for these two classes. The AUC values above 0.90 in the "Blight" and "Gray Leaf Spot" classes indicate that the DenseNet model has a reliable discrimination ability in these classes as well.

Overall, the DenseNet model provided a balanced and successful performance on the multiclass classification task, giving an impressive result in terms of both accuracy and reliability.

EfficientNet:

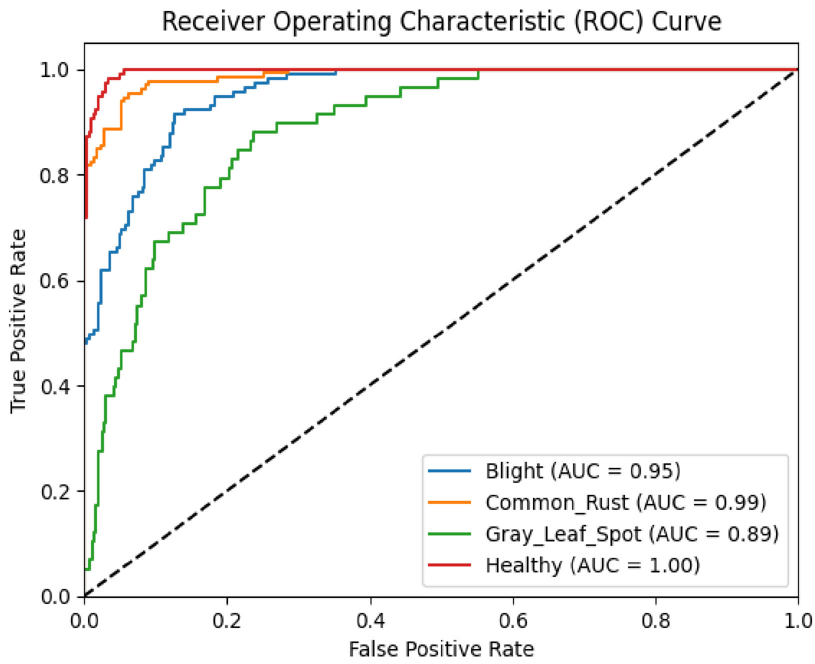

Figure 3.15. ROC Curve Plot of the EfficientNet Model

The Receiver Operating Characteristic (ROC) curve obtained with the EfficientNet model shows that the model offers a strong classification performance in general. The AUC value was calculated as 0.95 for the "Blight" class, 0.99 for "Common Rust", 0.89 for "Gray Leaf Spot" and 1.00 for the "Healthy" class. These results clearly show that the model can distinguish between "Healthy" and "Common Rust" classes almost without error. Especially the fact that the ROC curve of the "Healthy" class has the ideal curve form shows that the model predicts this class correctly in all samples.

The AUC value of 0.95 for the "Blight" class indicates a high level of accuracy, but also a small error rate. In the "Gray Leaf Spot" class, the AUC value decreases to 0.89, indicating that the model has difficulty in distinguishing this class from the others. The curve moves away from the upper left corner, indicating that both sensitivity and specificity remain relatively low, especially in this class.
In general, the EfficientNet model provides high accuracy in the multi-class structure; however, it lags behind the other models with a limited discrimination success for the "Gray Leaf Spot" class.

GoogLeNet:

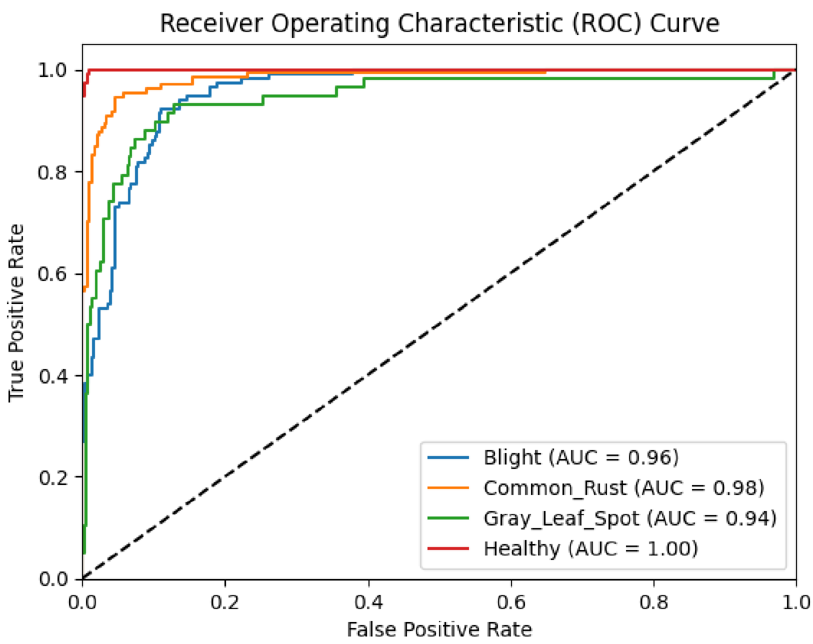

Figure 3.16. ROC Curve Plot of the GoogLeNet Model

The Receiver Operating Characteristic (ROC) curve obtained with the GoogLeNet model shows that the model offers a high level of accuracy in the multi-class image classification task. The ROC curves are plotted separately for each class and the AUC value for "Blight" is 0.96, 0.98 for "Common Rust", 0.94 for "Grey Leaf Spot" and 1.00 for "Healthy" class.

These AUC values show that the model has a very successful discrimination ability in all classes. The "Healthy" class, where the ROC curve fits exactly in the upper left corner, proves that the model recognises this class completely without error. The steep rise of the curves in the "Common Rust" and "Blight" classes shows that both high sensitivity and specificity are achieved. Although the "Gray Leaf Spot" class performed slightly lower than the other classes with an AUC value of 0.94, this value is still a very successful result.

In general, the GoogLeNet model has shown a balanced and effective performance in the multi-class classification task, achieving high accuracy rates in all classes. Especially its strong discriminative power in the "Healthy" and "Common Rust" classes is remarkable.

MobilNet:

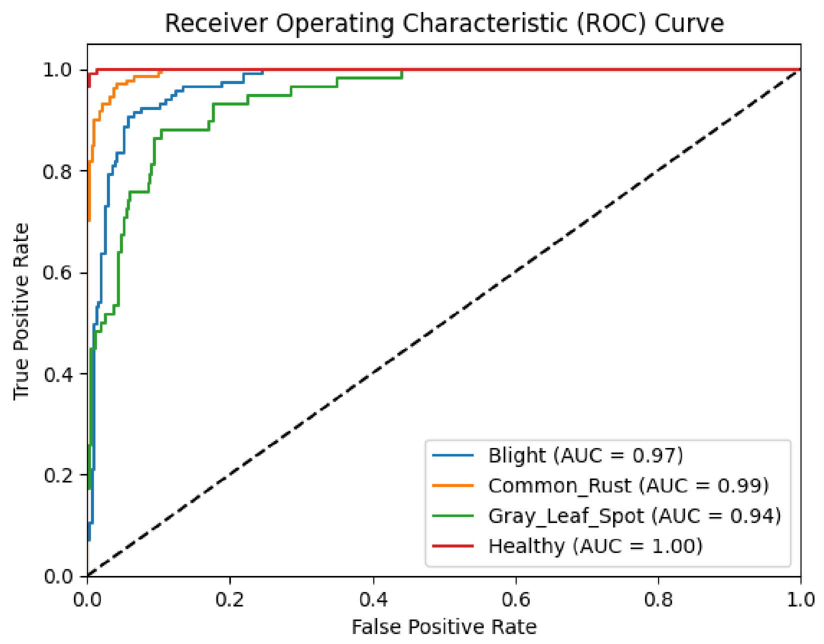

Figure 3.17. ROC Curve Plot of the MobilNet Model

The Receiver Operating Characteristic (ROC) curve obtained with the MobileNet model shows that the model offers a high level of accuracy in the multiclass image classification task. The ROC curves are plotted separately for each class and the AUC value for "Blight" is 0.97, 0.99 for "Common Rust", 0.94 for "Grey Leaf Spot" and 1.00 for "Healthy" class. These AUC values show that the model has a very successful discrimination ability in all classes.

The "Healthy" class, with the ROC curve exactly in the upper left corner, proves that the model recognises this class completely accurately. The steep rise of the curves in the "Common Rust" and "Blight" classes shows that both high sensitivity and specificity were achieved. Although the "Gray Leaf Spot" class performed slightly lower than the other classes with an AUC value of 0.94, this value is still a very successful result. In general, the MobileNet model showed a balanced and effective performance in the multi-class classification task, achieving high accuracy rates in all classes. Especially its strong discriminative power in "Healthy" and "Common Rust" classes is remarkable.

ResNet:

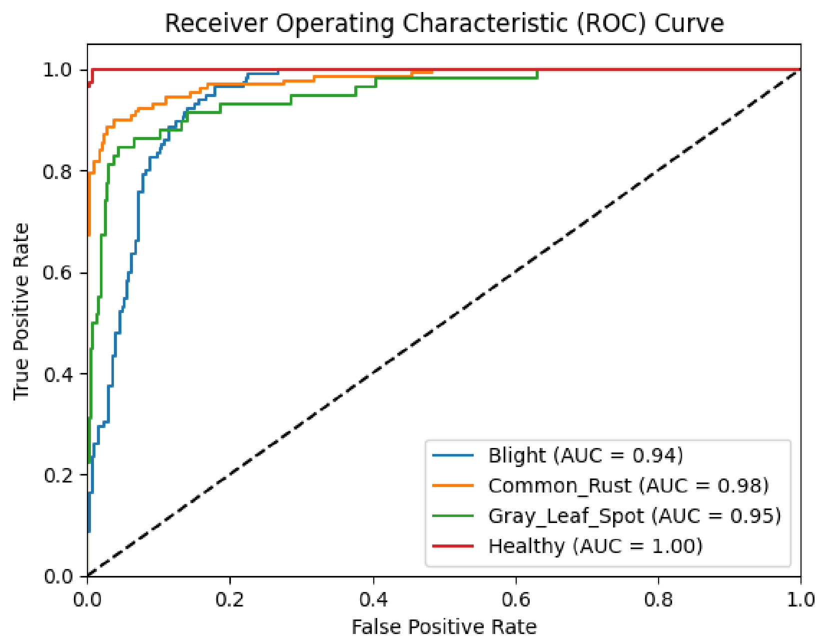

Figure 3.18. ROC Curve Plot of the ResNet Model

The Receiver Operating Characteristic (ROC) curve obtained with the ResNet model shows that the model provides high success in the multi-class image classification task. The ROC curves are plotted separately for each class and the AUC value for the "Blight" class is 0.94, 0.98 for the "Common Rust" class, 0.95 for the "Grey Leaf Spot" class and 1.00 for the "Healthy" class. These results show that the model has a strong discrimination ability in all classes.

In particular, the AUC value of 1.00 obtained in the "Healthy" class shows that the model can recognise this class completely error-free and the ROC curve fits exactly in the upper left corner. Similarly, in the "Common Rust" class, the curve rises sharply and provides an almost perfect classification. In the "Blight" and "Gray Leaf Spot" classes, the AUC values were calculated as 0.94 and 0.95, respectively, and these values show that the model works with a very high accuracy in these classes as well.

In general, the ResNet model performed effectively in the multi-class classification task by achieving stable, balanced and high accuracy rates. In particular, the superior success in the "Healthy" and "Common Rust" classes emphasises the model's competence in distinguishing these classes.

4 RESULTS AND DISCUSSION

In this study, the applicability of artificial intelligence-assisted image processing methods in the diagnosis of maize leaf diseases was evaluated. In particular, the ability of deep learning-based Convolutional Neural Network (CNN) architectures to classify plant diseases with high accuracy has been proven in many studies. In the literature, accuracy rates between 97% and 99.7% have been achieved with different CNN architectures.

For example, Joshi et al. (2025) obtained 99.68% accuracy rate using hybrid data augmentation techniques, and this approach gave much more effective results than traditional methods. Another study using EfficientNetB3 architecture achieved 99.70% accuracy (Suryawanshi et al., 2024). The dynamic pruning-based model optimised for low-equipped devices offered an important alternative for practical agricultural use with an accuracy of 98.80% (Liu et al., 2023).

The ConvNeXt architecture, which has come to the fore in recent years, attracts attention in both academic and practical applications. Combining the strengths of the Transformer architecture with the classical CNN structure, ConvNeXt models both achieve high accuracy rates and produce more stable results in the training process. For example, ConvNeXt-Tiny model achieved 98.2% accuracy and ConvNeXt-Base model achieved 98.7% accuracy, which is higher than classical models (Zhang et al., 2024; Li et al., 2024). The usability of ConvNeXt, especially in mobile agricultural technologies (e.g. drones, field robots, mobile phone applications), stands out thanks to its high performance with few parameters.

Evaluation in terms of Use in Agriculture

Early and accurate diagnosis of plant diseases is critical for preventing agricultural production losses. Deep learning-based models form the basis of smart agricultural applications that serve this purpose. Thanks to lightweight CNN models (such as MobileNetV2, EfficientNetB0) running on mobile devices, farmers can make real-time diagnosis in the field, so that they can make decisions such as spraying, quarantine or harvest planning more accurately.

Modern CNN architectures such as ConvNeXt can be integrated with unmanned aerial vehicles (UAVs) or fixed camera systems, especially in large-scale production areas, enabling leaf-based diagnostics. This not only saves labour and time, but also reduces environmental impact by optimising pesticide use. In addition, the ability to provide high accuracy despite different light conditions and image quality in open areas makes models such as ConvNeXt more attractive for field applications.

In this context, the accuracy rates obtained in this thesis coincide with the results of the most up-to-date and successful CNN architectures in the literature. In addition, the integrability of the model into agricultural applications and its low computational cost indicate that it is suitable for use in the field. In the future, such models are expected to become widespread in artificial intelligence-supported agricultural automation systems.

5 CONCLUSION

This study aims to comparatively analyse the performance level of deep learning based artificial intelligence approaches in the detection of maize leaf diseases. Early detection of diseases such as leaf blight, common rust and grey leaf spot, which cause significant yield losses in agricultural production, is vital for both producers and food safety. In this context, the necessity to develop faster, more accurate and automated systems instead of traditional methods brings artificial intelligence and especially approaches based on Convolutional Neural Networks (CNN) architectures to the forefront.

The dataset used in the study consists of thousands of images obtained from the Kaggle platform and includes four different classes (Blight, Common Rust, Gray Leaf Spot, Healthy). This dataset was evaluated on seven different CNN models - AlexNet, GoogLeNet, ResNet50, EfficientNet, ConvNeXt, MobileNet and DenseNet - divided into 80% training, 10% validation and 10% testing. The evaluation criteria included metrics such as accuracy, precision, F1-score and ROC-AUC. These multifaceted metrics revealed not only the overall accuracy of the models, but also their discrimination and balance between classes.

The ConvNeXt model stood out as the most successful model in general with 96% accuracy and high ROC-AUC values in all classes. Especially in the "Healthy" and "Common Rust" classes, it achieved an AUC = 1.00, demonstrating an almost error-free discrimination power. This shows that the learning capacity of modern architectures has become stronger thanks to their deep structural advantages and optimised block designs (Liu et al., 2022). The success of ConvNeXt is similarly confirmed in the literature; studies such as Ciran and Özbay (2022) state that pre-trained CNN architectures offer high accuracy, especially in agricultural image classification.

DenseNet and EfficientNet models closely followed ConvNeXt with 95% and 94% accuracy rates, respectively; however, DenseNet performed relatively poorly in the "Gray Leaf Spot" class with an AUC value of 0.93. Although DenseNet's dense connection structure (dense connections) increases learning efficiency by increasing information reuse, it is observed that it is not as flexible as ConvNeXt in distinguishing complex disease symptoms (Huang et al., 2017).

MobileNet was evaluated as a prominent architecture for applications with hardware limitations with 92% accuracy and low resource consumption. The model, which offers advantages especially in terms of being integrated into mobile devices, is more sensitive to problems such as class imbalance, although it achieves satisfactory AUC values in all classes. Similarly, in a study by Velasco et al. (2019), it was reported that MobileNet keeps the accuracy high despite its low computational cost, but may experience loss of precision in data imbalance.

While the ResNet50 model provides a very successful result with 93% accuracy, it has been observed that learning in deep architectures stabilises and the training process accelerates thanks to residual connections. Especially in more difficult classes such as "Gray Leaf Spot", the AUC value of 0.95 shows that this architecture is still a valid and powerful option for current problems (He et al., 2015).

GoogLeNet and AlexNet had lower accuracy rates (91% and 90%) compared to the modern architectures used in this study. Especially in scenarios where the number of classes and image complexity increases, the learning capacity of these classical models is limited. However, in the "Healthy" class, both models achieved high values of AUC = 1.00, indicating that they can successfully discriminate in classes with more prominent symptoms. This finding suggests that AlexNet developed by Krizhevsky et al. (2012) may still be functional for certain tasks, but it does not offer enough flexibility for complex classes.

In conclusion, this study has strongly demonstrated that modern CNN architectures (in particular ConvNeXt, DenseNet and EfficientNet) offer higher performance in agricultural disease diagnosis than classical models. Considering metrics such as model accuracies, AUC values and sensitivity to class balance, the ConvNeXt model gave the best results in terms of overall performance. This is a very promising development for the future of artificial intelligence applications in agriculture.

However, the findings obtained should be evaluated not only on the basis of accuracy rates, but also by considering operational needs. For example, in systems with limited processing power, lightweight models such as MobileNet may be more appropriate, while more complex structures such as ConvNeXt or DenseNet should be the preferred choice in systems requiring high accuracy.

With this thesis, it has been shown that CNN-based artificial intelligence systems offer a successful and practical solution for the diagnosis of corn leaf diseases. In future studies, it is suggested to diversify the data sets, to use images taken in open field conditions, to integrate factors such as different light conditions and background clutter into the model. In addition, testing the applicability to different plant species will make a great contribution to the widespread use of these systems.

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