Identification of Foliar Disease in Apple Trees using Deep Learning Techniques

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Identification of Foliar Disease in Apple Trees using Deep Learning Techniques

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Abstract

The earlier apple foliar disease is identified, the more productive and profitable the crop will be. It is a challenge to correctly label a disease in a foliar plant at the right moment in order to prevent significant losses without the help of technology. Recently, a number of deep learning and machine learning methods, including CNN, VGG-16, ResNet50, and SVM, have been developed to identify apple diseases. In this study, multiple transfer learning algorithms such as LittleVGG, MobileNet, and EfficientNet with a Generative Adversarial Network (GAN) are proposed to identify foliar diseases such as apple scab, apple rust, or multiple diseases on a given leaf image. This method avoids the need for time-consuming and expensive manual scouting activities by humans and enables farmers to take appropriate action in response to the results. According to our research, the EfficientNet model outperformed LittleVGG and MobileNet at detecting apple foliar diseases.

1 Introduction

Every year, millions of tons of apples are produced around the world, with China being the leading producer with around 42 million tonnes per year, followed by the United States and Turkey, making it one of the most important fruit industries in the world. The advent of apple leaf diseases, on the other hand, may severely limit the apple industry's ability to grow healthily and stably. During the growing season, the Apple trees' leaves are susceptible to several bacterial and fungal diseases, including apple scab, rust, black rot, and non-infectious disorder such as nutritional and environmental disorders, resulting in low marketability and poor fruit grade, loss of the entire fruit or tree, and large economic losses. Farmers cannot resist the damage since their fruit must look good in order to be sold.

1.1 Motivation and Project Background

The main motivation behind this study is how deep learning networks performs to identify the apple leaf diseases concerning the previous standard machine learning and deep learning techniques used in the research.
Now humans are scouting for leaves manually, an operation that is complex, error-prone, and time-consuming. This process requires training with a variety of foliar disease images, disease pest cycle phases, and knowledge of environmental factors. The farmer or expert may misdiagnose or fail to recognize the disease, resulting in unsuitable pesticides

and reduced fruit quality. If the disease is misdiagnosed manually and based on determination, overuse or underuse of pesticides can lead to the development of resistant strains of bacteria, increased production costs, environmental and health impacts, and even a major outbreak.

Therefore, to avoid human error, it is necessary to implement an accurate automated leaf disease detection and management process for apple leaves. This helps farmers detect disease early and improve fruit quality. In recent years, several machine learning and deep learning techniques have been used to identify various leaf and plant diseases, such as KNNs, random forests, artificial neural networks (ANNs), convolutional neural networks (CNNs), and so on.

Various comparative analyses of standard Machine Learning classifiers such as Knn, SVM, Naive Bayes, and Decision Tree has been performed for disease identification of apple leaf but to learn high-level features from data in an incremental manner is not possible with the above algorithms and thus required Deep Learning algorithms (Singh et al. 2021).

With the help of a genetic algorithm and correlation-based feature selection technique, an SVM classifier was used on the apple image leaf dataset. The data used to identify leaf disease is limited, so the accuracy of the detection may be poor. The diseased leaves were captured in a controlled environment, and image segmentation and feature extraction methods could have been explored in the research (Chuanlei et al. 2017).

Multiple pre-trained image classification networks have been used to train a CNN with a 99% accuracy. The biggest problems with pre-trained networks can be negative transfer and overfitting (ÇETİNER 2021)

Other pre-trained classification networks with the GAN model with the fine-tuning that have not yet been studied have been analysed and compared in this study such as Little VGG, MobileNet, and EfficentNet. Also, the issues of negative transfer learning and overfitting have been taken into consideration while developing the solution.

1.2 Research Question and Objective

Apple foliar disease detection can help farmers not only identify apple leaf diseases at an early stage but also improve food quality, lower production costs, and have the ability to make timely decisions about increasing the yield of crops. This research has identified a reliable way to detect foliar diseases based on their type. This methodology can be used to improve the speed of diagnosis and prevention of other diseases.

*RQ**:** How well transfer learning techniques helps in identification of the different types of leaf diseases in apple leaves to reduce human mistake?*

Sub-RQ1: "Can transfer learning with image augmentation techniques classify leaf disease without negative transfer and overfitting?"
Sub-RQ2: "Can the GAN model helps the transfer learning algorithms to resolve the data imbalance problem for plant leaf disease classification?"

To answer the main research question and its sub-research question, the following objectives have been implemented and achieved.

Objective 1: Investigate and critically review literature from the last six years of leaf disease identification research.

Objective 2: Design and develop a technical framework that can be used to support the implementation of research into disease classification.

Objective 3: Perform Data Cleaning operations i.e. resolve the data imbalance problem.

Objective 4: Implement, Evaluate and interpret the different algorithm implementations to get a better understanding of how they work.

Sub-Obj 4.1: Implementation, Evaluation and Result of LittleVGG.

Sub-Obj 4.2: Implementation, Evaluation and Result of MobileNet.

Sub-Obj 4.3: Implementation, Evaluation and Result of EfficientNet.

Sub-Obj 4.4: Comparison of developed models i.e. Sub-Obj 4.1, 4.2, 4.3, and implemented classification techniques. The result of Sub-Obj 4.1, 4.2, and 4.3 will help to compare the algorithms.

Sub-Obj 4.5: Comparison of developed models (Sub-Obj 4.4) versus Existing models.

Objective 5: What could be the best transfer learning algorithms to solve the disease-related problem? Which ones work best and why?.

The below report is structured in a way that will help achieve the above objectives. Section 2 provides an overview of various related work in the field of plant leaf diseases that have been studied. In Section 4, a technical framework has been designed to support the implementation of disease classification discussed in Section 5 as well as the results are critically analysed and the outputs are evaluated. The feasibility of marketing the project's outcome is discussed in the Discussion part of this project report.

2 Literature Review on Foliar Apple Disease 2015-2021

Detecting apple leaf disease is a severe problem, and numerous researchers are working on various solutions to address it. Their work is an inspiration to others who are trying to solve the same problem using a distinct technique. This section looks at the work that has been done in leaf disease classification and highlights recent, important discoveries. Ultimately, it was determined that all the methods were accurate in identifying the disease in apple leaves.

2.1 A Critique of Techniques used to Identify Foliar Disease using Standard Deep Learning and Machine Learning Algorithms

In 2021, (Ahmed and Reddy 2021) solve the multi-class classification problem and created a 3-layered mobile-based architecture with an imagery dataset containing 96,206 images of the most common 38 plant disease categories in 14 crop species of healthy and infected plants using the CNN model. Layer 1 includes the Intermediate Representation Model, Layer 2 includes the Application layer, and Layer 3 includes the User Layer. The authors could have used better activation functions in Layer 1, such as Tanh or ReLu, instead of the log sigmoid function, which can cause a neural network to get stuck when training the model and another problem is Sigmoid saturates (i.e., the curve becomes parallel to the x-axis) and kill gradients[1]. However, for some classes of diseases, such as tomato leaf diseases, due to the presence of background noise in an image, sometimes the system fails to achieve high confidence levels for detecting the tomato target spot disease. With the help of CNN, (Hasan et al. 2020) have classified the grape leaf disease on the 1000 images dataset. Using the dropout function authors have tried to solve the overfitting problem however for the overfitting problem CNN may perform better on a large dataset. The authors have vaguely described the CNN model process such as which activation function has been used, and whether any optimization technique like SGD or Adam optimizer has been used or not. It seems that the model architecture has not been followed completely in a controlled manner. The two-step classification process with respect to pepper, potato, and tomato leaves have been followed by (Karnik and Suthar 2021) in the research. The first classifier, YOLOv3, is based on the feature extraction of darknet-53, which serves as its backbone architecture. Then the output of this layer is passed to the second classifier Resnet50, which provides the final output. The introduction of two classifier authors has made the process quite complex, which was not required, and due to two more classification models, the computation time has increased, making the process redundant and time-consuming.

A novel mathematical model of plant disease detection and recognition based on deep learning has been implemented by the (Guo et al. 2020). For this, along with transfer learning(VGG-16), Chan-Vese segmentation algorithm is designed to segment the objects without clearly defined boundaries[2] and needs repetitive iterative calculation and runs for a long time, which is not good for the rapid identification results of this method. To speed up the training speed, and end the iteration ahead of time, the authors may have used the neural network to generate a zero initial set corresponding to different leaves with the Chan-Vese algorithm. A 9-layer deep convolutional neural network has been discussed by (G. and Pandian J 2019). The study covers six different types of image enhancement techniques, making it one of a kind in its class. Performance and accuracy were checked with and without augmentation technology. To overcome the overfitting problem, a dropout technique is used and a batch gradient descent optimization method is applied, which can be improved to Adam or SGD optimizers . Using ConvNets, 15 different classes of tomatoes, peppers, and potatoes have been detected and classified. (Lakshmanarao, Babu, and Kiran 2021) says that there is no overfitting, but they did not provide a convincing explanation as to why it is not there and did not provide any evidence about steps to avoid it if it does. Both adam and SGD optimizers have been used and found that using adam optimizer gave good results

A Random Forest algorithm has been implemented by (Ramesh et al. 2018) to detect plant leaf disease, for extracting features of an image Histogram of an Oriented Gradient technique has been used by the team and can achieve 70% of accuracy. However, when training with a large number of images and using other local features as well as global features such as SIFT(Scale Invariant Feature Transform), and SURF (Accelerated Robust Features), the accuracy could have been improved. An SVM technique for classification and k-means clustering for image segmentation was used by (Wahab, Pg Hj Zahari, and Lim

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[1] https://kharshit.github.io/blog/2018/04/20/don%27t-use-sigmoid-neural-nets
[2] https://scikit-image.org/docs/stable/auto_examples/segmentation/plot_chan_vese.html

2019) to identify diseases of Chilli plant leaves. The system can determine healthy sections of a chili plant with accuracy. However, when categorizing images of cucumber mosaic disease, only 57.1 % accuracy was attained. More images of affected plants can be trained to improve this. A fusion classifier has been built by the (Padol and Sawant 2016) consisting of SVM and ANN to detect downy and Powdery Mildew grape leaf diseases and achieved 100% accuracy. The reason author was able to achieve 100% accuracy is the lack of training and test data. Total of 137 images were used for training and testing purposes. By using more images for training, actual accuracy could have been observed, and there will be less chance that the model is overfitted. For the detection and classification of banana leaf diseases, a new feature extraction method Local Binary Patterns (LBP) has been used with cubic SVM and refined KNN classifiers and successfully achieved 89-90% accuracy. To im- prove performance, (Aruraj et al. 2019) can use to extract different texture features and colour features from images, such as grayscale pixel values, mean pixel values of channels, or extracting edges. For the detection and identification of rice leaf diseases, (Sethy, Rath, and Barpanda 2019) have tried to implement a novel approach using multiclass SVM and detection accuracy is improved by using Particle Swarm Optimization(PSO) Technique. For feature extraction, Gray Level Co-occurrence Matrix (GLCM). Other machine learning algorithms, such as KNN and Feed Forward neural network, have also been implemented, but the SVM performs better than other algorithms in terms of accuracy, with an accuracy rate of 90.56%.

To detect tomato plant disease, (Govardhan and M B 2019) multiple machine learning algorithms were developed and evaluated using k-fold Cross-validation. The results of this research are different from those of other researchers, who have identified diseases in leaf plants using machine learning.This study found that SVM performed poorly (22.3%), while Random Forest outperformed other algorithms, but other experts study such as (Sethy, Rath, and Barpanda 2019), (Padol and Sawant 2016), (Wahab, Pg Hj Zahari, and Lim 2019) believe that SVM is better at identifying leaf diseases.

2.2 A Critique of Techniques used to Identify Foliar Disease using Transfer Learning Algorithms

In 2019, (Picon et al. 2019) and the team developed a crop protection app to overcome the limitations of (Johannes et al. 2017). However, Johannes' research was conducted using a limited dataset i.e., a total of 179 images of wheat disease that failed to capture some aspects of the disease which was later corrected by (Picon et al. 2019) and increased the dataset to 3637 images that help train the Deep Learning model more effectively than the prior method. Instead of the standard Machine learning algorithm, which was used by (Johannes et al. 2017), (Picon et al. 2019) used DCNN(ResNet50) for early-stage detection of wheat leaf diseases that can help the user to react in time and plan for some preventive actions. The research by (Ramcharan et al. 2017) shows that transfer-learning only is not the best-accurate algorithm for the identification of cassava disease but for cassava mosaic disease and red mite damage using the original dataset and leaflet dataset, SVM outperforms Inception v3. And for cassava brown streak disease and green mite damage Inception v3 performed better than support vector machines using the leaflet dataset. And for some disease classification, there are discrepancies when leaflets are used instead of whole leaves. In 2020, for the detection of citrus leaf diseases, (Luaibi, Salman, and Miry 2021) have used and compared CNN transfer learning architecture named AlexNet and ResNet. In terms of accuracy with or without data augmentation, AlexNet performs better. In AlexNet no optimization technique has been used but in ResNet, the SGD optimization technique has been used. Nevertheless, AlexNet still outperforms ResNet without any optimization techniques. A DCT image compression technique was used as an input to the ResNet50 algorithm to recognize plant leaf disease on 9 species of crops. The same results were achieved as if using the original image dataset. Working with images that are small in size has the advantage of reducing the cost of storage and computation (Sharma, Rajesh, and Javed 2021).

A hybrid DCNN methodology is used by (Tunio et al. 2021) for rice leaf disease detection. A new data pre-processing technique that is not used in the current literature review by other authors is the geometric transformation technique. Because of less data, the authors faced an overfitting and underfitting problem, which affects the accuracy of the model.

2.3 Comparison of plant leaf disease detection methods with their accuracy

Table 1: Comparison review

Topic Name	Author	Methods with Accuracy
A Mobile-Based System for Detecting Plant Leaf Diseases Using Deep Learning	Ahmed Abdelmoamen and Gopireddy Harshavardhan Reddy (2021)	CNN with 94% accuracy
Identification of plant leaf diseases using a nine-layer deep convolutional neural network	Geetharamani and Arun Pandian J (2019)	9-layer DCNN with 6 different image augmentation technique, 96.46% accuracy
Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming	Yan Guo et al. (2020)	Chan-Vese segmentation algorithm with VGG-16, 83.57% accuracy
Identification of Grape Leaf Diseases Using Convolutional Neural Network	Moh. Arie et al. (2020)	CNN with 91.3% accuracy
Agricultural Plant Leaf Disease Detection Using Deep Learning Techniques	Jashraj Karnik and Anil Suthar (2021)	Two stage classifier YOLOv3 and ResNet50 with 94% accuracy
Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case	Alexander Johannes et al. (2017)	Image processing techniques with Naïve Bayesian segmentation model, AUC of 0.80
Deep Learning for Image-Based Cassava Disease Detection	Amanda Ramcharan et al. (2017)	Inception v3 including SVM and knn with 73% to 91% accuracy
Detection of citrus leaf diseases using a deep learning technique	Ahmed Luaibi, Tariq Salman, and Abbas Miry (2021)	AlexNet with 97.92% and ResNet with 95.83% accuracy
Detection of Plant Leaf Disease Directly in the JPEG Compressed Domain using Transfer Learning Technique	Atul Sharma, Bulla Rajesh, and Mohammed Javed (2021)	DCT image compression technique with RestNet50, 98.94% accuracy

2.4 Identified Gaps and Conclusion

From the reviewed literature, most researchers rely on standard machine learning algorithms and CNNs with transfer learning to identify leaf diseases. But after reviewing the techniques, it was observed that there is still room to implement other transfer learning algorithms with GAN to improve the identification of plant leaf diseases by considering negative transfer learning and overfitting, which led to the research question and answer to Objective 4.

3 Research Methodology used to Identify Apple foliar disease and Design Specification

This section will provide information about the methodology used and any design issues which were encountered and addressed during the development that answer our Objective 2. Then the project design on the basis of implementation steps is discussed.

3.1 Methodology used to Identify Apple foliar disease

For the identification of Apple leaf diseases, the modified CRoss Industry Standard Process for Data Mining (CRISP-DM) process model has been followed and implemented, which provides a blueprint to develop a data mining project. In addition, it offers a roadmap, best practices, and structure for better and more rapid results from data mining. One of the benefits of using the CRISP-DM method is that it is a widely accepted standard that can be implemented in any data science project. The CRISP-DM lifecycle model has six stages, as shown in Figure 1, which include Business understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. For this project development, the deployment section was not followed, but the rest of them were implemented.

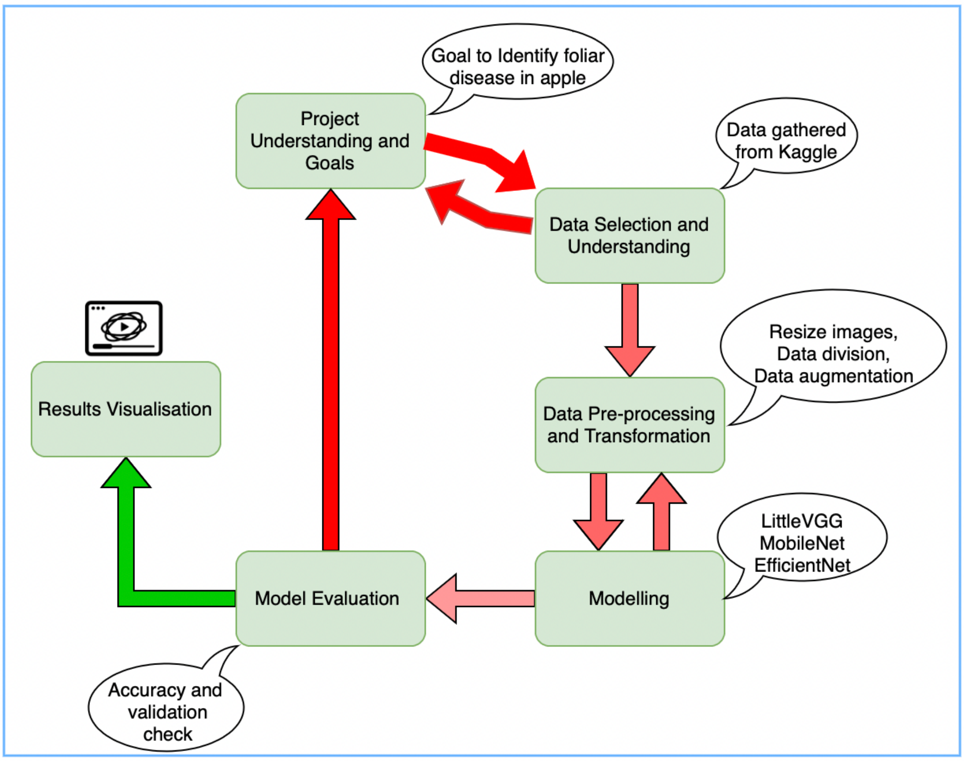

Figure 1: Methodology used for apple foliar disease identification[3]

3.1.1 Project Understanding

When it comes to understanding a business's objectives, there are four main tasks that must be focused on business understanding, the first is to identify the business goals where we focus and understand what the real goals of the project are, and in our case, the goal is to identify the apple foliar diseases. The second is to list out all of the assumptions we need to make to carry out our research. The third step is to determine the data mining goals, and the fourth is to provide a project plan, and all the tools and techniques needed to achieve those goals.

3.1.2 Data selection and understanding

There are 3642 high-quality photographs of RGB symptoms taken in real life. To add more complexity to the images, the photographs are captured at irregular intervals, with a variety of image backgrounds, different maturity stages, multiple diseases on a single leaf, and varying environmental conditions. In this study, 4 different types of images (as shown in Figure 2) have been identified: 1200 images are of apple scabs, 1399 images are of cedar apple rust, 187 images are of mixed diseases, and the remaining 865 images are of healthy leaves.

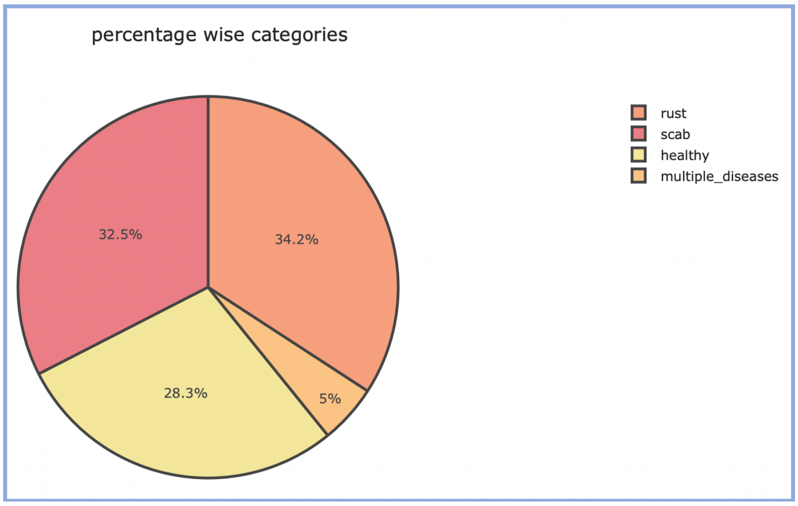

Figure 2: Dataset Categories

The images are manually annotated and verified by a plant pathologist expert using the distinctive and identifiable symptoms of apple scab, cedar-apple rust, mixed diseases, and healthy leaves as shown in Figure 3. It is also observed that there is a data imbalance problem in Figure 2. For the multiple diseases category, there are only 187(5%) images. To resolve this issue, synthetic images have been created, which will be discussed in the upcoming section.

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[3] https://www.datascience-pm.com/crisp-dm-2/

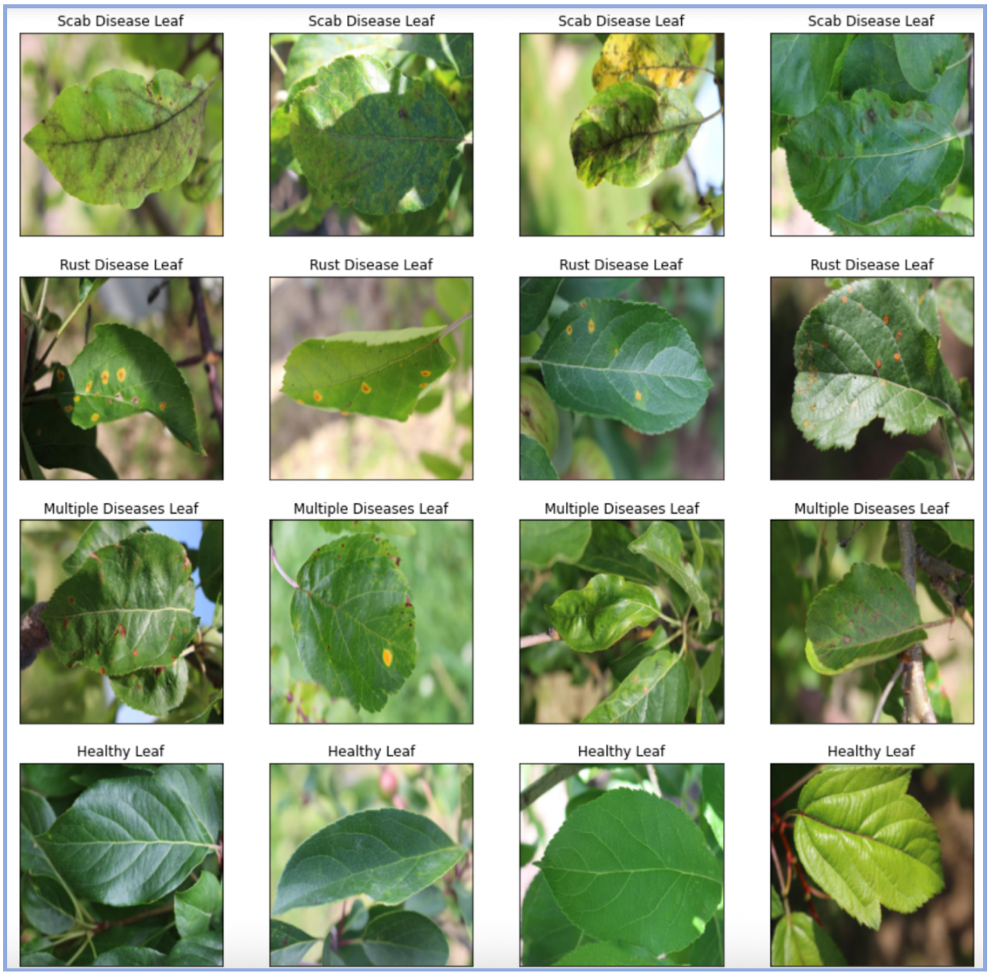

Figure 3: Healthy Leaf and Types of Diseases

3.1.3 Data Preparation or Data Pre-processing and Transformation

In this step, we have finalized the data set and will use it for modeling in the next step, transformed raw data into a structure or format that is better suited for model construction. This step has taken a lot of time while developing the project. Before developing the models, certain preparations with the dataset were made.

a.) All of the images have been reduced in size to the resolution of 224x224 because a larger input image lengthens the training period for the architecture (Saponara and Elhanashi 2022).

b.) The dataset has been divided into training samples and validation samples with a batch size of 16.

c.) To increase the range of training data, a data augmentation technique was used with the ImageDataGenerator class. Images are enhanced by flipping them horizontally, shifting them vertically and horizontally, and rotating them.

d.) Canny Edge Detector which uses a multi-stage algorithm has been used to detect a range of edges in images and remove the unnecessary background noise of the images which we don't require.

e.) Figure 2 shows that there is an imbalance in the multiple diseases category in the dataset, so to resolve this issue, a Generative Adversarial Networks (GAN) was used to generate synthetic images of multiple diseases.

3.1.4 Modeling and Evaluation

In modeling, we have proposed, selected, and applied different modeling techniques, such as LittleVGG, MobileNet, and EfficentNet, and decided if we can use them and see what options we have, there are four main tasks involved in this. First, we selected the model to build and then performed test quality checks to see if there is empirical evidence to support our model (to prove this, previously designed models have been studied such as CNN). The model is developed in the third step, and the fourth is where the model is accessed. And the rest is described in more detail in implementation section 4. After applying the models, the overall result of the developed models is presented, assessed, interpreted, visualized, and represented via various visualizations. The rest is described in more detail in implementation section 4.

3.2 Design Specification

This study has adopted a two-tier architecture approach, with a business layer and a presentation layer as shown in Figure 4. All programming logic, including models for data selection, data preparation, and classification, is performed in the business layer. The client layer or presentation layer is where all of the final predicted results are shown.

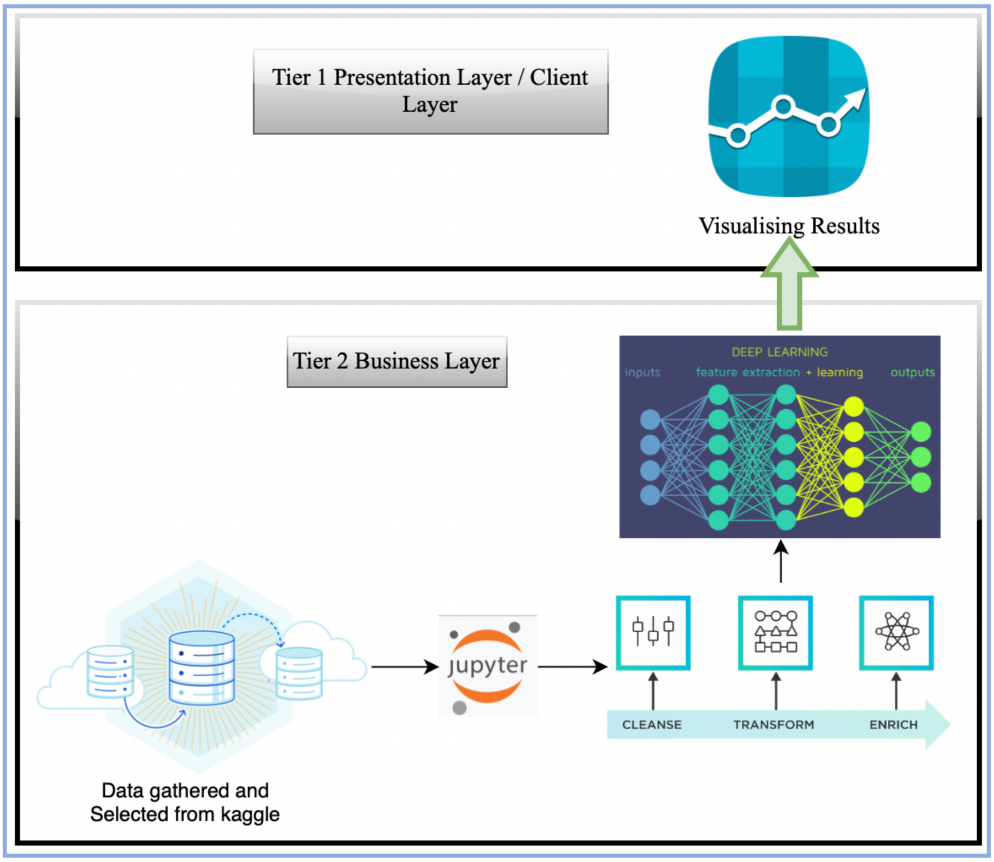

Figure 4: Design Specification

3.3 Conclusion

The above-discussed methodology approach to identify foliar diseases in apple leaves was developed to meet the requirements of the project. It may be said that the project followed the general CRISP-DM methodology standards with a few adjustments. To keep the procedure consistent, each step was carefully followed in each and every model that was used. The data is available on an open-source platform named Kaggle.

4 Implementation, Evaluation and Results of Foliar Disease Identification and Deep Learning Models

To prove objective 4, discussed in section 1.3. This section presents the implementation, evaluation, and results of a particular algorithm, such as LittleVGG, MobileNet, and EfficentNet. The accuracy of the model was determined by looking at how closely the model's predictions matched the actual values in the data. Before doing this, exploratory data analysis was done on the images in section 3 to see images insights such as what kind of differences there were between them. In the final section of this article, a comparison of different algorithms has been presented.

4.1 Implementation of Generative Adversarial Networks

To answer the *Sub-RQ2* and to prove objective 3, the data imbalance issue of the multiple diseases category has been resolved with GAN that has been used to create realistic artificial images that could be almost indistinguishable from real ones. It comprises two types of networks, The generator and discriminator networks. In our research, the Generator network helps us to take a random image initialization and decode it into a synthetic image and then the Discriminator network takes the synthetic image as input and predicts whether this image came from our real dataset, or the image is synthetic as shown in Figure 5.

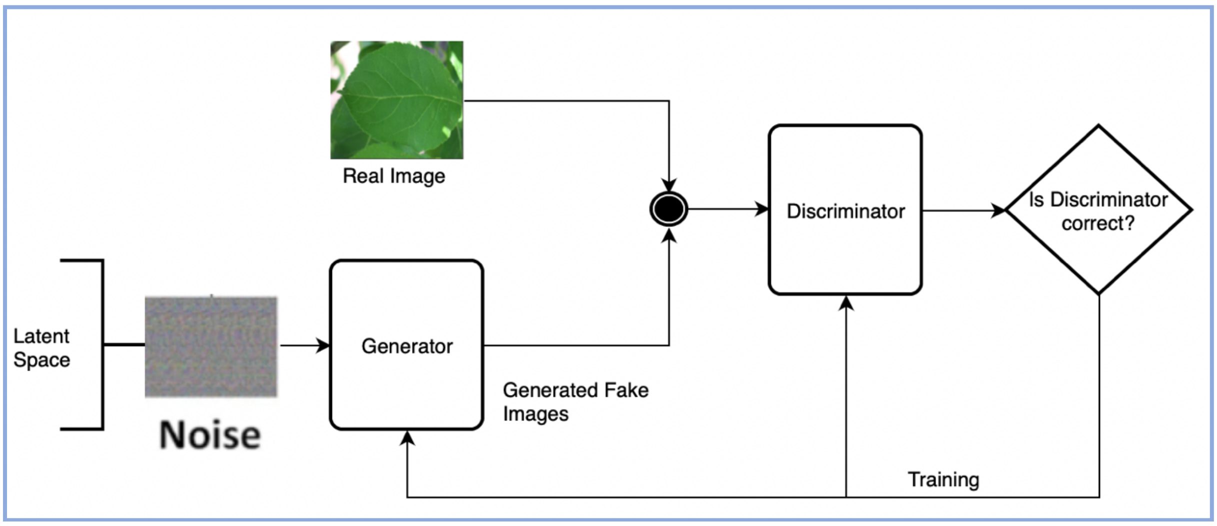

Figure 5: GAN Architecture

After implementing GAN on our data, generated synthetic images of multiple diseases category are merged with the original dataset, and below transfer learning models are then applied to the same for disease classification of the apple plant leaf.

4.2 Implementation, Evaluation and Result of Visual Geometry Group (LittleVGG)

One of the deep learning models used in this study for the classification of apple leaf disease is LittleVGG. LittleVGG is the downsized version of VGG16 or VGG19. VGG inspiring network uses a series of 3X3 convolution layers but in this case 4X4 convolution layers have been used, Convolution to ELU blocks where the number of these filters increases the deeper we go. In the LittleVGG, 9 weight layers have been used with an input of 224X224 RGB images, the first two convolution layers with 64 filters, the next two convolution layers with 128 filters, the next two convolutions with 256 filters, then the next two Fully-Connected layers with 256 filters and finally at the end Fully-Connected layer with the number of classes i.e, 4, with an activation function softmax as shown in Figure 6. The SGD optimizer with learning rate of 0.0005 and categorical_crossentropy for multi-class classification have been used to reduce the overall loss and improve the accuracy of the predictions. The LittleVGG produces only 3.1 million parameters which is quite a very small amount compared to VGG16. While training the neural network, the vanishing gradient problem occurred, which means as the number of hidden layers grows, the gradient becomes very small, and weights will hardly change. This will hamper the learning process and to solve the vanishing gradient problem multiple activation functions have been tried such as Tanh, Leaky ReLu, and ReLu. And after comparing output ReLu has been selected as the activation function.

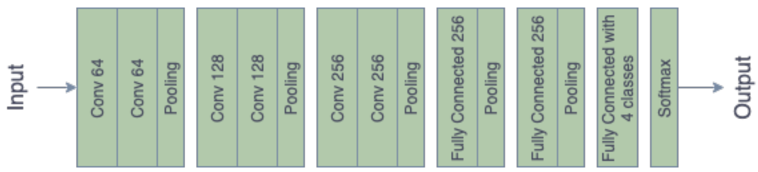

Figure 6: LittleVGG

The LittleVGG deep learning model achieved an accuracy of 41.39% with a validation accuracy of 37.33%. Despite making adjustments to the training process, the accuracy loss has not improved much from 1.31984 to 1.27059. The results of the study suggest that LittleVGG is not effective for apple foliar disease diagnosis and is not recommended to use. Only once during training did LittleVGG accomplish 41%, and even after repeated training, the model was only able to produce outcomes of 35%.

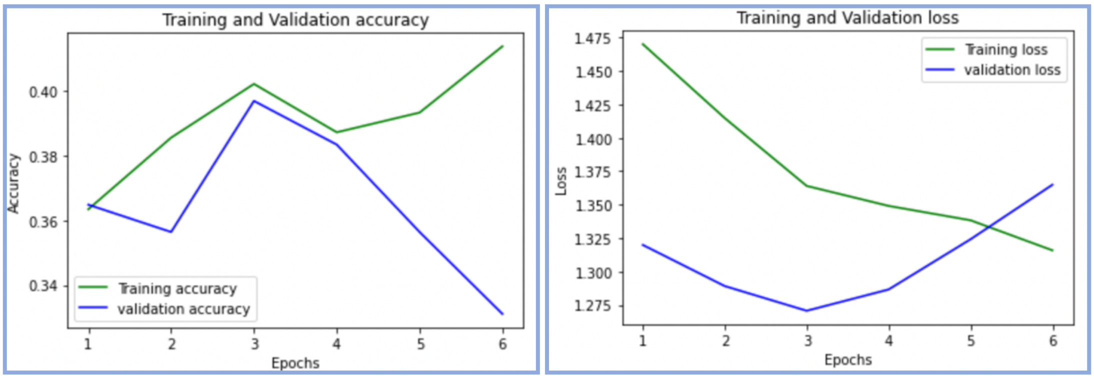

Figure 7: Training and Validation accuracy and loss

4.3 Implementation, Evaluation and Result of MobileNet

The other deep learning model which is used to classify the foliar diseases in apple is MobileNet. One of the reasons why MobileNet was chosen is it trains quite quickly on CPU. Uniform squared pictures measuring 224X224 were created for the input. The weights from the model's final six layers are not included in the top Fully-Connected head layer. The additional six layers, including GlobalAveragePooling2D, 4 Dense layers with various nodes, 4 classes, and a softmax activation function, are added to the Fully-Connected head in place of those six. The model was fine-tuned by freezing layers before training the MobileNet; when a layer is frozen, it signifies that the weights cannot be changed anymore as shown in Figure 9. Even though it may seem obvious, this strategy reduces the computational time for training while only slightly decreasing accuracy. The final four MobileNet layers are set to be non-trainable or frozen and as an activation function, the tanh function has been used. Six million parameters total—2.8 million trainable and 3.2 million non-trainable—are produced as a result of all these steps.

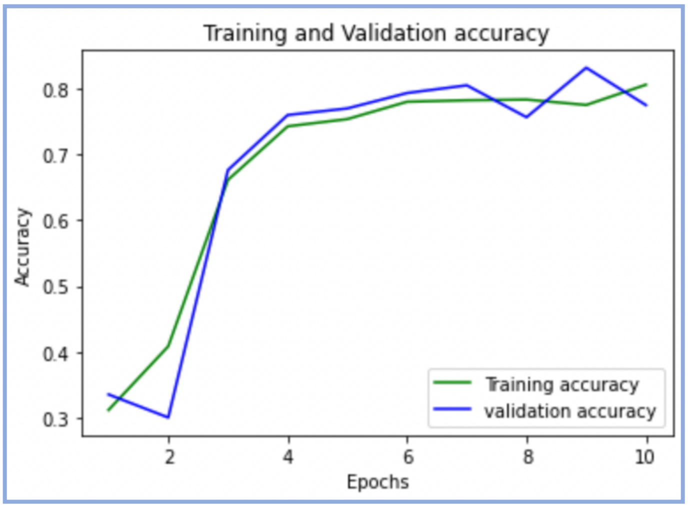

Figure 8: Training and Validation accuracy of MobileNet

The MobileNet deep learning, model has achieved an accuracy of 80.56% with a validation accuracy of 77.46% as shown in the figure 8. Throughout the training process, the loss accuracy has dropped from 1.62090 to 0.49313. Because the EfficientNet model has not yet been implemented, which is done in the following section 4.3, and the results are compared in section 4.4 below, we are unable to say at this time whether this model is good or bad for classifying apple foliar disease. Consequently, this section marks the completion of research objective 4.2.

Figure 9: Fine Tuning

4.4 Implementation, Evaluation and Result of EfficientNet

The third and final deep learning transfer model that has been trained to classify apple leaf diseases is EfficientNetB7. The reason for choosing EfficientNet is that the standard Convolutional Neural Network focused on depth scaling by increasing the number of layers, but EfficientNet does depth scaling, width scaling (increasing the number of feature maps/channels), and resolution scaling (to capture complex features and fine-grained patterns). The input image size was resized to 256X256 pixels, and before training the EfficientNet, the model was tuned by freezing the top layers, and then other layers were added to the head of fully connected layers, such as the GlobalAveragePooling2D and Dense layers with softmax activation function as shown in Figure 9. And while compiling the model Adam optimizer and categorical_crossentropy (for multi-class classification) loss function have been used to reduce the overall loss and improve the accuracy of the predictions.

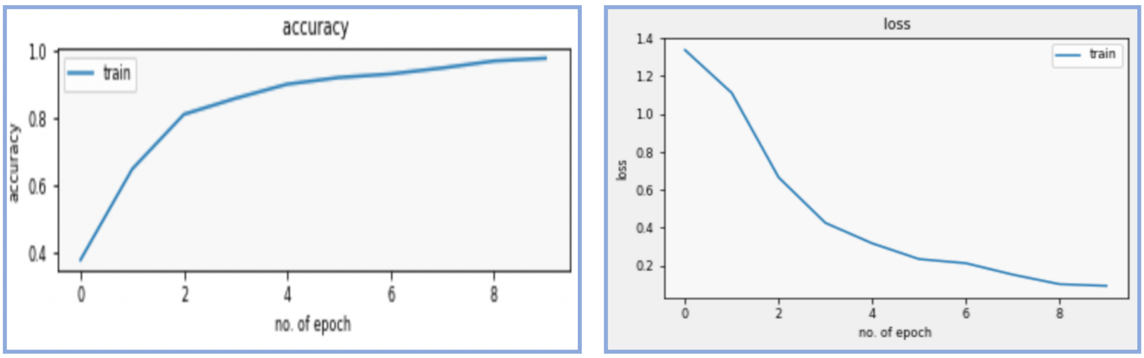

Figure 10: Accuracy and Loss of EfficientNet

The EfficientNet model has achieved a high accuracy of 97.72% with a learning rate of 1.32E-04. As can be seen in the figure 10, the model loss has decreased consistently throughout the training process. The rest of the comparison is done in section 4.4 below. At first glance, it appears that the EfficientNet model has fared better than other models that have been reviewed, such as LittleVGG and MobileNet. As a result, research objective 4.3(Implementation, Evaluation, and Result of EfficientNet) is now complete with this section.

4.5 Comparison of Developed Models

Figure 11 shows the different models that have been developed for training deep learning networks. These models are LittleVGG, MobileNet, and EffiecientNet. It can be seen that EffiecientNet performed better than MobileNet and LittleVGG. In terms of how accurately the developed model identified the type of disease, EfficientNet scored 97.72%, followed by MobileNet and LittleVGG with 80.56 and 41.39, respectively. In this research, it can be observed that LittleVGG performed drastically poorly and is not recommended at all to use. The results of this research help to achieve the research objective 4.4.

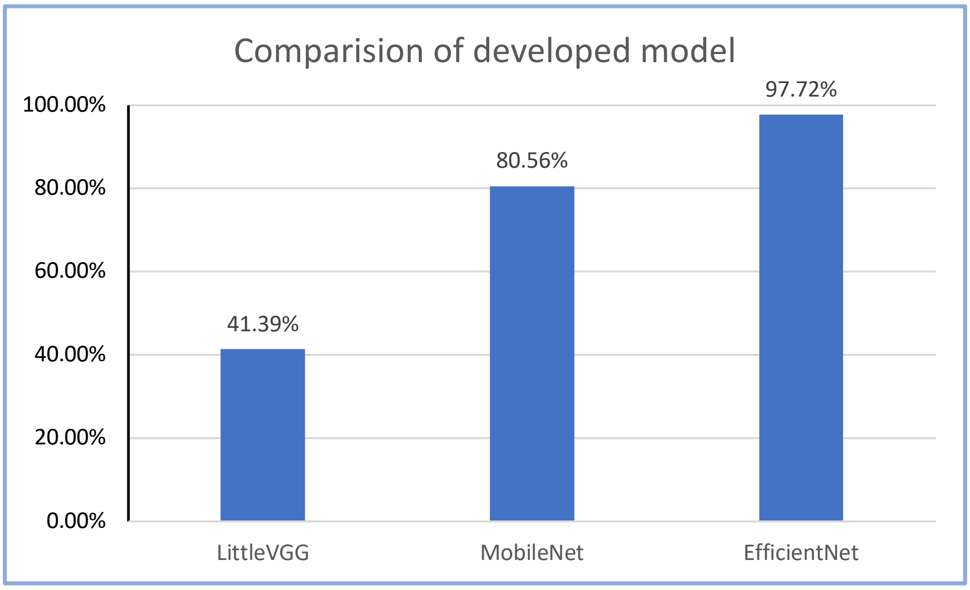

Figure 11: Result Comparison of Developed Models

5 Discussion

5.1 Learning Outcomes and Skills gained

As shown in Table 2, in terms of identifying foliar diseases, EfficientNet outperformed other networks that are commonly used for research, such as CNN, and AlexNet but failed to outperform the ResNet by 0.2%. This research study has provided additional insight into the preparation of image data, data pre-processing, data transformation, and different deep learning models implementation such as LittleVGG, MobileNet, and EfficientNet.

5.2 Comparison of Developed Models Versus State of art Models

In this research, multiple models have been used and compared in Figure 11, and the best performing model i.e., EfficientNet has been chosen to compare with the existing research conducted by other researchers, as shown in Table 2.

According to comparison table 1 of the literature review, Yan Guo et al. (2020) used the VGG-16 model to detect plant leaf disease with an accuracy of 83.57%, while Moh. Arie et al. (2020), Ahmed Abdelmoamen, and Gopireddy Harshavardhan Reddy (2021) used the CNN model with an accuracy of 91.3% and 94%. AlexNet and ResNet have been applied by Ahmed Luaibi, Tariq Salman, and Abbas Miry (2021) with 97.92% and 95.83% accuracy for the identification of citrus leaf diseases using a deep learning technique. And in this current study, EfficientNet reported an accuracy of 97.72%. Table 2 below compares the result of current research and previously developed models by other researchers, and this helps to achieve the research objective 4.5.

Table 2: Result Comparison of EfficientNet with Previous Research

Author Name	**Model Name**	**Accuracy**
Yan Guo et al. (2020)	VGG-16	83.57%
Moh. Arie et al. (2020)	CNN	91.3%
Ahmed Abdelmoamen and Gopireddy Harshavardhan Reddy (2021)	CNN	94%
Ahmed Luaibi, Tariq Salman, and Abbas Miry (2021)	AlexNet and ResNet	97.92% and 95.83%
Rajat (2022)	EfficientNet	97.72%

The research question and sub-research questions have both been answered by the results presented, and all of the objectives of chapter 1, section 1.2, have been accomplished. The implementation, evaluation, and outcomes of all three deep learning models are concluded in this section. In terms of project marketing to the wider audience, suggested future work needs to be included in the existing solution, discussed in the next section.

6 Conclusion and Future Work

Transfer learning algorithms such as LittleVGG, MobileNet, and EffiecientNet have been implemented for the diagnosis of foliar disease in apple trees, and it has been discussed which method may aid better in the identification of foliar disease more precisely. The research question and sub-research questions 1 and 2 in Chapter 1, subsection 1.2, have been answered by the outcomes of these implementations. The questions of "Can transfer learning with image augmentation techniques classify leaf disease without negative transfer and overfitting" and "Can the GAN model help the transfer learning algorithms to resolve the data imbalance problem for plant leaf disease classification" have been satisfactorily addressed, and all of the research's objectives discussed in Chapter 1, subsection 1.2 have been met. Negative transfer learning and overfitting were seen when the LittleVGG model was implemented, however in the other two models, the dataset functioned just fine and produced successful results.

The future work of this research is to not just include the apple leaf disease but to use the other plants with a large dataset as much as possible so that a single algorithm can be developed to identify plant diseases with the help of Capsule Networks.

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