# Classification of pest-infested citrus leaf images using MobileNet V2 + LSTM based hybrid model

MSc Research Project
Data Analytics


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# Classification of pest-infested citrus leaf images using MobileNet V2 + LSTM based hybrid model

Aditya Raju Pal
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**Abstract**

One of the most important species of plants in the agricultural domain are citrus plants. They have originated in the tropical and subtropical areas of Southeast Asia. It has been observed that there has been a drop in the production of these plants due to rise in plant diseases. It has always been difficult to get a control over the pests in the field of agriculture as most of them travel and infect through the medium of air. The disease they are infected by are in viral or bacterial form. Therefore, there is a need to have a model for accurate and faster detection of these diseases. The solution should be free from having to connect to internet and should be able to use in remote areas. If the disease are identified at an early stage it will help in quicker application of remedial steps which will decrease the crop loss. In this research, we have applied a deep learning approach and used MobileNet V2 + LSTM based hybrid model for classification pest infected leaves and compared its results with MobileNet model. YOLO V5 is also implemented on a small dataset to perform detection of infected area on the leaf. In the past and present, machine learning is used to detect plant leaf infection but it needs connectivity to internet as models demand for high computing power. MoblieNet V2 is a mobile friendly model open sourced by Google to perform ML applications in light weight systems and the implemented hybrid model showed an accuracy of 93.28%.

# 1 Introduction

## 1.1 Introduction of Citrus Plants and Diseases

Citrus plant species are the natural source of Vitamin C and it is very important for the functioning of human race. It is proven in improving the conditions of patients affected with COVID-19 as Vitamin C increases the free radical movement and antiviral agents in our body (Bae and Kim; 2020). The species of citrus plants has huge range of different types of plants which are lemons, oranges, tangerines, clementine's and more. According to research Zahid Iqbal and Javed (2018), each year approximately 50% crops are damaged due to these plant diseases. Some of the diseases in citrus leaf are found to be melanose, bacterial spots and anthracnose. A brown spot caused due to the presence of Diaprothecitri on the plant or fruit of the plant is called as Melanose. Brown lesion like spots caused on the leaves of the plants are called as bacterial spots and they are often confused with Citrus Crancker. Anthracnose is the most common disease for the citrus plants. Branches, fruits, leaves and flowers are the most impacted in the case of this disease. These highly infectious viral disease can spread at an extreme rate by natural reasons like extreme winds. To lower and reduce the spread, the farmers make use of pesticides such as Iprodione, Tuzet, Procymidone and Prochloraz [1]. If these chemicals are used continuously, it is a threat to human and environmental health (i.e., ground water, human and soil fertility).

## 1.2 China's Contribution

The leading country in the production of citrus plants in the world is China and the production comprised of 37 million metric tons in china (FAO; 2021). The maximum production came from the Guangxi province of China [2].

The graphs below in Figure 1 represents the contribution of China's Agriculture, Forestry and Fishing to its GDP.

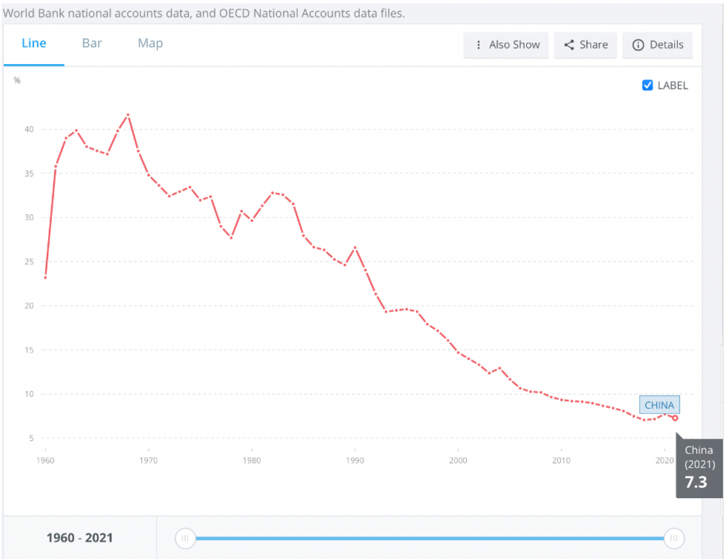


Figure 1: Contribution of China in Agriculture, Forestry and Fishing

We have observed a decline in production in China's agriculture sector from the past two decades when it is compared to the Gross Domestic Product (GDP) of China. The line graph showcases the percentage share of Agriculture, Forestry and Fishing to China's GDP and it is taken from World Bank database [3]. The percentage of contribution in 2021 was 7.3% which was reported to be 7.7% in 2020, it was even higher in 2010 which was 9.3% and 14.6% in 2000. This was a very significant decline in the production as it had a 50% decline in two decades. Plant disease are the main reason behind the deteriorating crop yield as published in the latest study by Zahid Iqbal and Javed (2018). Due to less understanding by farmers and late application of remedial measures there is a significant decrease in the production of crops.

[1] https://www.awiner.com/pesticide-for-citrus-trees/

[2] http://www.statista.com/statistics/242939/citrus-fruit-production-in-china-by-region/

[3] https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?end=2020&locations=CN&start=1960&view=chart/

## 1.3 Motivation

The productivity of the crops is directly impacted with the amount of pest infestation on plants and it also creates an impact on the quality of the yield (Pramod; 2021). Theere is a huge amount of contribution by researchers in the field of plant disease detection by using convolution neural networks (CNN). With the past research we have clearly observed that there is significant and noticeable difference in the accuracy in detection when deep learning models are used when they are equated with machine learning models as stated by (Radha Suja and Sarfraz; 2021). Hence, techniques of deep learning are extremely important in detecting plant disease. As deep neural network has the capability to self-locate essential features with training there is no need to use feature engineering. In case of end user applications, it is always good to use models which have larger run-time for training and shorter run-time for testing. By using auto feature extraction with deep learning we are able to get much more accurate results when compared to conventional methods as stated by (Pramod; 2021). After successful implementation of a mobile based, low resource consuming, mobile application which is workable without internet connection it will be very helpful for farmers. They will have more freedom to detect diseases in remote areas of the farm and the issues of network connectivity will be resolved. The farmers can benefit financially by not using expensive high computational devices for performing the same task.

## 1.4 Research Question

*Can Deep Neural Network with MobileNet V2 + LSTM based hybrid model perform classification of pest-infested citrus leaf images and be used in light weight mobile applications? Can YOLO V5 be used in detecting infected regions of the infected plants*

In this research work, YOLO V5 is designed to perform detection of pest disease regions in the plant leaf. The YOLO models need heavy computational power and resource to run itself and consume a lot of time. But, MobileNet V2 is a lightweight application and it does not require heavy computing or resources. If MobileNet V2 + LSTM based model reaches the accuracy along with other performance metrics to a significant level it will help in development of light-weight and mobile-friendly machine learning models. The datasets used in this research are taken from Kaggle website, the Conghua Citrus Leaf 2020 (CCL'20) dataset containing approximately 4682 images of citrus leaf images and images were also taken from the PlantifyDr Dataset from the Citurs folder. To meet the above research question, following objectives are defined:

- Reviewing the research already done in the domain of plant leaf disease detection.
- Finding dataset related to citrus leaves with infected plant leaves.
- Performing data augmentation to increase the size of relevant images.
- Implementing MobileNet V2 classification model on the dataset.
- Implementing MobileNet V2 + LSTM hybrid classification model on the dataset.
- Implementing YOLO V5 for detecting the infected area on the leaf.
- Comparing the performance of the models that are designed and the one that were observed to be the best performing algorithm models.

In this research, the work has been done on MobileNet V2 + LSTM based hybrid model which is extremely light weight and has demonstrated an accuracy of 93.28% for classifying the pest infected diseases which is significantly higher. The Scaled YOLO implemented earlier had the mAP 0.89 where as the YOLO V5 implemented in this research has demonstrated mAP of 0.92 for detection of pest infection. This hybrid model will help in detecting the plant disease at an early stage and at a faster speed this will be done by building light-weight mobile applications for plant leaf disease detection. This will be significantly helpful for the developers and lastly the farmers significantly and will bring down the need of having a high computing resource device to perform classifications. This will be extremely beneficial for the farmers that are in the remote locations as their economic conditions are not strong in most cases and farmers struggle with financial losses in case of extreme weather conditions along with lack of information and knowledge of diseases in plants in most areas of the world.

## 1.5 Structure of the Paper

Further, this research work is structured in the given manner, section 2 sheds light on the work done in the past few years on the topic of plant leaf disease detection and classification. Section 3 gives us the idea about the methodology that was used in implementing the two ML models i.e. Scaled YOLO V5 and MobileNet V2 + LSTM hybrid model. Section 4 gives us the details about the system used and design metrics of the models. Section 5 gives details about the evaluation parameters which were considered to check the model performance. Lastly Section 7 concludes the research work by giving a summary of the findings of the research and the scope of future work.

# 2 Related Work

## 2.1 Introduction

This part encompasses a detailed summarized information of the work done in the field of classifying and detecting infected plant leaves. It starts from traditional image processing techniques, computer vision techniques, and then leads to machine learning and deep learning models and lastly sheds light on the discovery in transfer learning from the last 3-5 year. A step-by-step review is carried out based on the progress achieved in the model and introduction of new techniques in the domain.

## 2.2 Computer Vision (CV)

According to WHO, approximately 80% of the globe's population still trusts and uses the natural plant-based medicinal drugs, therapy and medications, according to the author of this study. (Gittaly Dhingra and Joshi; 2019) The study employed computer vision (CV) to determine healthy or unhealthy leaves of basil. The study was accomplished in 2 phases. In phase one, an innovative technique of segmentation was devised based on Neutrosophic logic. The dialetheist set, fuzzy set, tautological set, intuitionistic set, paradoxist set and paraconsistent set were already included to the Neutrosophic set. (Gittaly Dhingra and Joshi; 2019) study was divided into three distinct forms, which were (I), (T) and (F). T represents the truth scale, F represents the false scale, and I represents the intermediate scale. In the second stage, a new approach for feature extraction was used, which included the creation of a new feature pool composed of Bin Binary Pattern (BBP), Disease Sequence Region (DSR), Damage Index (DI) and Histogram Information Content (HIC) was used. The researcher employed 9 classifiers to check the percentage of accuracy for newly suggested features and the model gained an accuracy of 98.4%. The research paper indicated that it was implemented on a restricted dataset of 400 photos and highlighted disease categorization as a future topic. This contribution resulted in a slower process in detection but an improved detection in accuracy.

The author Vijay Kakani and Pasupuleti (2020) concentrated on the application of Artificial Intelligence (AI) and Computer Vision (CV) to obtain effective models with good predictable accuracy and smart devices from the standpoint of sustainable agriculture. The United Nations Food and Agricultural Organization (FAO) forecasts that the world's population will touch 9.1 billion by 2050. This will lead in a demand for a 70% increase in worldwide food supply. Finally, the author examined the potential of Fourth Industrial Revolution [4.0 IR] technology like computer vision, robots, and deep learning for sustainable food production. The author also shared his views on the future by directing his attention to the Agri-Tech business, where the application of AI in conjunction with computer vision methods will steer a route to sustainable food production. This study found that using Multi-sensor Imaging Systems (MIS) with Infrared Sensors (IR) linked to drones can assist farmers in locating diseased areas. This imaging approach will help to reduce the risk of disease spread.

## 2.3 Machine Learning (ML)

The author conducts a comparative evaluation on different types of machine-learning classification approaches for plant diseases recognition. According to the author, one of the major reasons for low crop yields is infection which are because of bacteria, viruses, and fungi. The stages of a plant disease detection system have been highlighted in the article, encompassing image acquisition, annotated dataset, image processing, feature extraction, and ultimately classification. When compared to certain other classifiers, the SVM classifier is used by many researchers for illness categorization, according to U. Shruthi and Raghavendra (2019). The author's research demonstrated that CNN classifier identifies a larger number of plant diseases with a 96.4 percent accuracy for all four distinct types of plants studied. With an accuracy of 82.5 percent, KNN was the worst performing algorithm. The author proposed using naive bayes and decision trees in the long term to identify plant disease with machine learning models.

Precision agriculture could be used to inform policy decisions and boost productivity while cutting expenses. Nidhi Goyal and Saraswat (2022) Invasive plant diseases can harm agricultural profits and product quality. Use of image processing techniques for diagnosis and classification of plant diseases has increased dramatically in recent decades. What this means is that heat and humidity are essential for the growth of citrus trees and their fruit. In this work, several methods are employed to selectively remove the toxic molecules from the citrus leaves while retaining the healthy ones. After the image is segmented using done threshold, the features can be retrieved. After that, several meta-heuristics methods are used to settle on a good feature set (e.g., WOA, LOA, CSO, and DE). During the classification phase, the author used the support vector machine (SVM) and the multi-layer perceptron (MLP). The quality of performance is evaluated based on a number of criteria, including as recall and precision. How well and quickly your system recognizes and responds to stimuli is measured by the F1 score. With an accuracy 61.6 percentage points lower than SVM, WOA determined that MLP performed 74.8 percentage points better. The results of the experiments indicate that MLP is the more reliable method.

The author Vinay Kukreja and Solanki (2022) represents, output of wheat in India to be the second highest in the world. Damage caused by aphids results in lower wheat harvests. It is essential to recognize each and every aphid that lives on wheat plants. The process of hand recognition is rather laborious. The Mask RCNN algorithm can precisely pinpoint the geographical location of each aphid on a wheat leaf. A total of 6,500 photographs were taken of wheat in Punjab, each from one of 21 possible angles. Wheat leaves and aphids were need to be tagged. The training dataset has 2300 photographs, while the testing dataset only contains 1000 images. Both datasets were quite substantial. Using the processing capability of a network, mask scoring RCNN makes predictions about the precision of projected instances. Aphids were obtained from 1221 wheat leaves in total. When a manually annotated, ROI is compared to a mask ROI, it is possible to detect wheat aphids. The F1 score utilizing the Mask scoring RCNN model for aphid identification in a single wheat leaf showed great potential (96.66%).

## 2.4 Convolutional Neural Networks (CNN)

The author Mohit Agarwal and Gupta (2020) states that it is worth noting that both white potatoes and sweet potatoes are grown commercially in many different nations. Growing demand has also helped India's tomato farming business expand to the point where it now ranks as the world's second-largest supplier of the fruit. However, the many diseases that can affect tomato plants have a major impact on both the quality as well as the quantity of the yield. In the temperate parts of the world, this is generally the case. This research suggested a method based on deep learning that can be used in disease detection in plant leaves. The paper uses a convolutional neural network-based approach. Two completely linked layers result from stacking the model's three convolution layers on top of its three max-pooling layers. With the papers experimental results, it was demonstrated that the proposed model outperformed the three commonly used pre-trained models (VGG16, InceptionV3, and MobileNet). The suggested model had an overall accuracy of 91.2% (10 disease classes and 1 healthy class), with an accuracy range of 76.2% to 100% for its sub-classes.

According to the researcher Asad Khattak and Gumaei (2021) diseases affecting citrus trees are to blame for the severe drop in citrus fruit production. This highlights the need for an automated disease detection system for citrus trees. Since deep learning techniques were recently effectively applied to a wide range of artificial intelligence challenges, the author chose to employ these methods to solve the difficult problem of disease identification in citrus plants for fruits and leaves. In this research work, he developed a unified methodology for modelling CNNs. The purpose of the CNN model was to distinguish disease-free citrus fruits and leaves from those affected by most frequent citrus diseases like black spot, canker, scab, greening, and Melanosis. The newly proposed CNN model incorporated numerous layers to extract supplementary properties that help discriminate between objects. The CNN model was compared against numerous other cutting-edge deep learning approaches on the Citrus leaves PlantVillage dataset. The CNN model was proved to outperform its competitors in a variety of experimental circumstances. With a detection accuracy of 94.55 percent, the CNN Model was proven to be a useful decision-support tool for citrus growers in the detection of diseases that impair citrus fruit and leaf.

According to the research S. Ashwinkumar and Jegajothi (2022), In India plant diseases account for a total loss of 35 percent of agricultural output per year. There may not be enough time or manpower in laboratories to detect plant disease early on. Therefore, the use of automatic plant disease detection systems will facilitate the monitoring of large crop fields and the identification of leaf symptoms as early warning signs of plant disease. Recent developments in computer vision and deep learning (DL) models made it possible to build autonomous models for diagnosing plant diseases based on external symptoms, such as problems with the leaves. Since the author aimed to create a model for automatic detection and categorization of leaf diseases using mobile convolutional neural networks (OMNCNN). Classification was just one part of this implementation; feature extraction, data segmentation, and preprocessing were also a part. Photos were sent through a pre-processing phase called "bilateral filtering," or "BF," before Kapur's thresholding was done. The EPO technique was used to fine-tune the MobileNet model's hyperparameters for better disease detection in plants. Finally, deep learning algorithms were accurate enough to be used for categorizing images of plant leaves (ELMs). Through simulations, the efficacy of OMNCNN was established. The results of experimentation showed that the OMNCNN algorithmic model was superior to the state-of-the-art methods, with a maximum accuracy of 0.987, precision of 0.985, recall of 0.9892, F-score of 0.985, and kappa of 0.985.

## 2.5 Contribution of Deep Learning (DL)

One of the most sought-after solutions in agricultural research is the automatic identification and diagnosis of diseases that causes damage to the leaves of maize plants. The authors of this study Xihai Zhang and Zhang (2018) had revised the GoogLeNet and Cifar10 models previously used to diagnose disease in maize leaves. Deep learning models allowed to accomplish this outcome. The goal of this study was to improve diagnosis accuracy while decreasing the amount of network parameters required for disease identification in maize leaf samples. To obtain two improved models that can be used for training and testing nine distinct types of maize leaf diseases, it was necessary to modify a large number of parameters, alter the pooling combinations used, add dropout operations and rectified linear unit functions, reduce the number of classifiers, etc. Since the improved models required fewer parameters, they were more precise and efficient than the baseline models like VGG and AlexNet. GoogLeNet showed a 99.1% recognition accuracy compared to Cifar10's 98.1% for identifying eight different maize leaf diseases. When compared to Cifar10's 98.1 percent success rate, there is a huge gap. These developments had the potential to streamline the model training and identification procedures necessary to provide an accurate diagnosis of maize leaf disease in fewer iterations.

The researcher informs about red tomatoes being a type of fruit which are consumed by humans on a daily basis and were initially seen in the Americans people and then spread over the world Siti Zulaikha Muhammad Zaki and Mohamed (2020). Tomatoes are susceptible to a wide variety of diseases, but the most common ones are leaf mould, late blight, and mosaic virus. Tomato plants are vulnerable to a wide range of unusual viruses and fungus. Diseases can easily spread from plant to plant on tomato plants. The author states tomatoes to be a globally important vegetable crop due to their high market value. No matter how diligently plants are cared for, infectious viral diseases cannot be eliminated. Successfully combating plant diseases requires early detection that is both precise and quick. One way to utilize computer vision to find the infection would be to take pictures of diseased leaves and analyze them. A deep learning classifier was used to sort among the many possible leaf appearances. As a result, valid conclusions were able to be drawn. This research of Siti Zulaikha Muhammad Zaki and Mohamed (2020) demonstrated how three common tomato diseases were trained to be recognized by the compact deep learning architecture MobileNet V2. In total, more than 4,671 pictures from PlantVillage were used for quality assurance. The results showed that MobileNet V2 has an accuracy in diagnosis of greater than 90%.

R. Sujatha and Brohi (2021) emphasized significance of flora in the function of the human pyramid food chain for sustenance or therapeutic purposes. The researcher performed plant disease identification on the dataset of citrus leaves using two distinct approaches in order to determine which methodology works good. These 2 strategies were chosen because they were the best in the domain. The initial method involved employing a Machine Learning model in conjunction with Support Vector Machine (SVM), Random Forest (RF), and Stochastic Gradient Descent (SGD). The second method was the application of Deep Learning methods with VGG-16, VGG-19, and Inception-v3. R. Sujatha and Brohi (2021) used 10-fold cross validation for classification, selecting folds so that each fold had nearly equal ratios of the target class. In terms of Deep Learning Models, the author discovered that VGG-16 had the highest classification accuracy (89.5%), while VGG-19 had the lowest. SVM had the highest accuracy of 87.8% among the ML models, while RF had the lowest of all model accuracy of 76.82%. The researcher has also examined several measures such as accuracy, F1-score, area under the curve (AUC), and precision.

Table 1: Summary of Literature Review

| Sr. No. | Name | Year | Authors | Concept | Pros | Cons |
|---|---|---|---|---|---|---|
| 1 | CV | 2019 | G. Dhingra et al. | The study divided into 3 forms T represented the truth scale, F represented the false scale, and I represented the intermediate scale. | An innovative segmentation technique based on Neutrosophic logic was devised. | Performed on a restricted dataset of 400 images. |
| 2 | CV | 2020 | V. Kakani et al. | Application of Artificial Intelligence (AI) and Computer Vision (CV) to obtain effective predictable models. | Multi-sensor Imaging Systems (MIS) & IR sensors linked to drones can help farmers in locating diseased areas. | Slow and not accurate |
| 3 | SVM | 2019 | U. Shruthi et al. | A comparative evaluation on different types of machine-learning classification approaches for recognizing plant diseases | CNN classifier with a 96.4 percent accuracy. | KNN was the worst performing model |
| 4 | SVM-MLP | 2022 | N. Goyal et al. | the classification phase, we employ the support vector machine (SVM) and the multi-layer perceptron (MLP) | MLP performed 74.8 percentage points better | An accuracy 61.6 percentage points lower than SVM, WOA |
| 5 | RCNN | 2022 | V. Kukreja et al. | The Mask RCNN algorithm precisely pinpointing the location of each aphid on a wheat leaf. | Mask scoring RCNN model showed great potential 96.66%. | Small dataset of 1221 wheat leaves. |
| 6 | CNN | 2020 | M. Agarwal et al. | Two completely linked layers resulted from stacking the model's three convolution layers on top of its three max-pooling layers. | An overall accuracy of 91.2%. | Lowest accuracy range of 76.2%. |
| 7 | CNN | 2021 | A. Khattak et al. | The newly proposed CNN model incorporated numerous layers to extract supplementary properties. | A accuracy of 94.55 % | Slow in training |
| 8 | OMNCNN | 2022 | S. Ashwinkumar et al. | A model for automatic detection and categorization of leaf diseases using mobile convolutional neural networks (OMNCNN) | A accuracy of 98.7 % | Requires a preprocessing phase "BR" |
| 9 | GoogLeNet | 2018 | X. Zhang et al. | Revised the GoogLeNet and Cifar10 models previously used to diagnose disease in maize leaf. | GoogLeNet having 99.1% recognition accuracy | Reduced speed |
| 10 | MobileNet V2 | 2020 | S. Zaki et al. | A compact deep learning architecture MobileNet V2 | A accuracy of more than 90 % | Slow rate of detection |
| 11 | VGG-16 | 2021 | R. Sujatha et al. | The initial method involved employing a Machine Learning model in conjunction with SVM, RF, and SGD. The second method was the application of Deep Learning methods with VGG-16, VGG-19, and Inception-v3. | VGG-16 had the highest classification accuracy 89.5% | RF had the lowest accuracy of 76.82% |
| 12 | CenterNet2 with Res2Net101 DCN-BiFPN | 2022 | S. Dhananjayan et al. | Implemented Models like YOLOv4, Faster-RCNN, DetectoRS, Cascade-RCNN, Foveabox, and Deformable Detr are CNN-based detectors. | CenterNet2 with Res2Net 101 DCN-BiFPN achieved greater accuracy | Slow |
| 13 | G-ResNet50 | 2022 | Wenchao et al. | G-ResNet50 model used dropout and batch regularization. The convolutional and pooling layers employed ResNet50's weights. | The model accuracy of 98.67% in recognition. | Requires high computing resources. |
| 14 | C-GAN/ DenseNet 121 | 2021 | A. Abbas et al. | Author used DenseNet121 model, which was trained on real and synthetic images using transfer learning. | 98.51% accuracy when diseases were classified into 5 different types | Reduced accuracy with increase in classification types |

## 2.6 Transfer Learning in Plant Diseases

The author states Sathian Dananjayan and Luo (2022), diseases can infect citrus (Citrus reticulata) plants and inflict major economic losses if left unchecked. Deep learning and computer vision have made it easier to detect and diagnose diseases in plants. Existing citrus leaf datasets lack appropriate annotations for disease diagnosis algorithms. Therefore the author decided to create and use CCL'20 to store diseased citrus leaf photos and correct annotations. Because there exist only a few deep learning models in agriculture, machine learning models are commonly used to identify plant diseases. Models like YOLOv4, Faster-RCNN, DetectoRS, Cascade-RCNN, Foveabox, and Deformable Detr are CNN-based detectors were optimized for the use in the area of agricultural engineering. Through performance and computational analysis, these models' ability to identify citrus leaf disease stages was evaluated. This study presented state-of-the-art CNN disease detectors for citrus leaf samples. It grades them on how well they perform during training and inference. CenterNet2 with Res2Net 101 DCN-BiFPN achieved greater accuracy than other recent and effective detecting models, while Scaled YOLOv4 P7 gave accurate and speedy forecasts of citrus leaf diseases.

The author (Wenchao and Zhi; 2022) implemented G-ResNet50 automated disease identification and classification in strawberries, saving time, money, and human labour. G-ResNet50 used focus loss to zero in on difficult disease photos. Evaluation method used ResNet50. During training, the G-ResNet50 model made use of dropout and batch regularization. The convolutional and pooling layers employed ResNet50's weights. PlantVillage's data improved the model's performance. This approach made an exact network representation. Strawberry leaf has three of diseases which were represented in the images in paper. Powdery mildew, strawberry anthracnose, and leaf spot are present on local plants. Enhancing and expanding the e dataset involved tilting the data, changing brightness and contrast, and adding Gaussian noise. G-ResNet50 had a faster convergence time and higher classification impact on 7,525 datasets, comprising four types of leaf data. The model's 98.67% recognition accuracy ranks first. Based on its precision rate, recall rate, and confusion matrix, G-ResNet50 was proved to be a suitable choice for diagnosing strawberry diseases, with high identification accuracy and dependability.

Despite the fact that advanced deep learning algorithms are always evolving, they have shown to be quite useful in plant disease detection. The author Amreen Abbas and Vankudothu (2021) had stated that perhaps the success of any deep learning model is calculated on the quality and volume of available data for training which is labeled. This study used the PlantVillage dataset to forecast diseases on tomato leaves in ten distinct categories. He presented a deep learning-based technique for detecting tomato diseases using the Conditional Generative Adversarial Network (C-GAN) to produce synthetic imagery of tomato leaves in this research. This data augmentation approach mitigated overfitting in the model and enhanced network generalizability. To categorize the diseases, the author have used DenseNet121 model, which used real and synthetic images and the method of transfer learning to train. The study's findings revealed a 97.11% accuracy when diseases were classified into 10 different categories and an amazing 98.51% accuracy when diseases were classified into 5 different types using the PlantVillage and Synthetic pictures datasets combined. In his future work, the author plans to identify the many stages of plant disease.

# 3 Methodology - CRISP-DM

To have the implementation of the research work set on the correct path it is extremely essential to choose the correct methodology. Before selecting a particular methodology for this research project, it was analyzed for being the best fit and all other implementation methodologies were taken into consideration. The two methodologies analyzed were KDD and CRISP-DM. The main difference between the two methodologies is that CRISP-DM is leaner towards looking at the available data from a business perspective and it is widely used in the projects which are associated with huge datasets. On the other hand, KDD is mainly focused on the part where it will search for the data pattern or information in the given dataset. Due to these reasons, we have decided to use Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology for this research project. CRISP-DM has several different types of steps in implementation and they have been descried in detail in the sections below. The CRISP-DM methodology steps start with understanding of the business, then understanding the data and preparing the data for model, evaluation of the model and lastly deployment of the implemented model. The implemented models will be utilized for development of mobile applications and deployment on smart mobiles phones.

The 6 stages of CRISP-DM technique is represented in Figure 3:

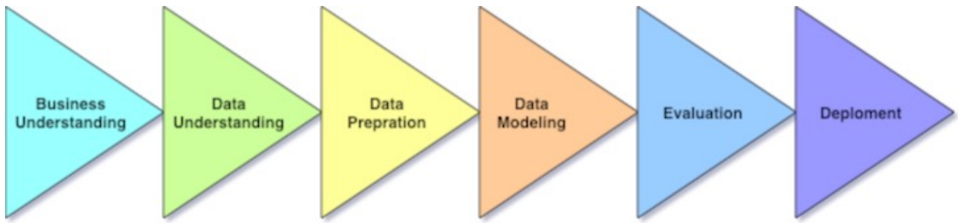


Figure 2: CRISP-DM Process

## 3.1 Business Understanding

Researcher S. Ashwinkumar and Jegajothi (2022) found out that is very difficult to for the farmers to correctly identify if a plant is infected with a pest disease as the growth of infection is a slow activity and takes about a 14 for the plant to show significant signs of infestation. Often when the farmer identifies the infection at a later stage than before which results in use damage to the crops and also financial loss to the farmer. Also there no application in the Apple “App Store” or Android “Play Store” which is able to perform plant disease identification without the use of (cloud) internet connectivity. This is due to the best models for detection require high computing resources and it is not available in the mobile devices. The challenges farmers face is that in rural/ remote areas there is limited connectivity and network connection and it is not possible to upload images with high resolutions to check if a plant is getting succumbed to a disease. With the implementation of MobileNet V2 which is a light weight machine learning model. Farmers will be able to perform this activity without the use of internet connection.

## 3.2 Data Understanding

The problem in conducting research in the domain of agriculture and food industry is challenging as it is a challenge to find huge datasets with a specific problem. As researched by the author by Nidhi Goyal and Saraswat (2022), a huge dataset in case of a machine learning or deep learning application can help in giving better results as it helps the model to be trained efficiently. The dataset utilized in this research activity is taken for the Kaggle free dataset library called the CCL'20 dataset. The name Conghua Citrus Leaf 2020 is the abbreviation for CCL'20. The images are annotated in COCO format and contain 4682 .jpg images. The dataset contains both unhealthy and healthy images of citrus leaf diseases.

## 3.3 Data Preparation

To ensure that there is not any over-fitting in the using the training dataset the research work has made use of various kinds of data transformation techniques. This has also resulted in higher accuracy in the test data. The images that are captured in the have one or more diseases in the images. The possibility of capturing all the diseases in one image and have a dataset comprising of such images in not possible in reality and hence there exists a factor of randomness in the kinds of diseases the dataset can have. The dataset was sourced from Kaggle website from 2 distinct sources and the total number of images used in this research work are 10,375. The validation split was set to 0.2 to ensure k fold cross validation was carried out. The target size of the images were set to 120 x 120.

## 3.4 Data Modeling

- In the first stages, the annotated dataset is downloaded from the Kaggle website.
- Then the dataset was loaded into Jupiter notebook as it is highly recommended for machine learning projects as it make it easy to run models. The downloaded dataset contained 2 different folders which are test and train. The test dataset contained 1206 images in the .jpg format and 9169 images in the train folder in the same format. Augmentation of the images was done while the model was running with the help of tensor flow package.
- The dataset was observed to be split in the test and train format. The dataset was run through the models to identify pest infected leaves.
- To implement the Scaled YOLO V5 the annotated dataset was taken from the dataset but as the COCO format which are not compatible for YOLO model. Therefore, the images were annotated in the YOLO format.
- To implement the MobileNet V2 and LSTM hybrid model the dataset was used and the validation of the model was done by using the K-fold cross validation technique.
- The evaluation of the implemented models was done by using the evaluation metrics for machine learning research which included precision, recall, accuracy, F1 score, Cohen Kappa Score and ROC curve.

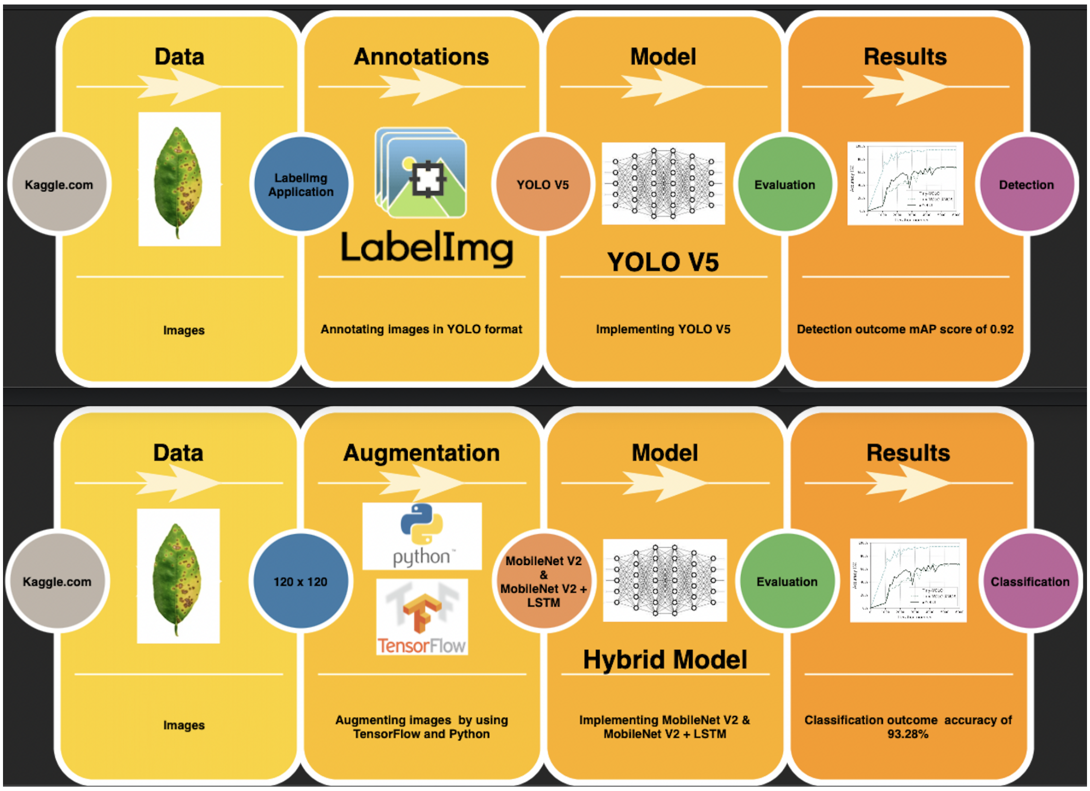


Figure 3: Step by Step model flow

- In the last, we observed the best performing model and it is recommended to be used in mobile applications as it will help end users in performing disease detection without the use of internet.

# 4 Implementation

This implementation part of this research work is discussed in this section. Starting with data preparation this section also sheds light on techniques such as feature extraction and modelling for both of the classification models.

### 4.0.1 YOLO V5

YOLO V5 are known to be one of the most powerful object detection models with highly efficient detection accuracy. Like other YOLO models are divided into three different parts but the YOLO V5 is divided by size. The main criteria to divide this is the idea of depth of the model and the width of the layers being multiple. The first is known to be the 'head' which is mainly constituted of YOLO V3. The next is called as the neck of the model which mainly constitutes of Spatial Pyramid Pooling (SPP)/ Path Aggregation Network (PAN) and in the last the model comprises of backbone which is usually CSPDarkNet. The YOLO V5 is designed to be compatible with different types of GPU's which makes it more versatile in the usability of model. Like other YOLO models, the YOLO V5 also has different types of model within and they need different results as they are known to have different input parameters. Accuracy is incompatible with speed and it is one of the reasons why it is difficult to have both at the same time. The fastest model is known to be YOLO V5 but it has a decreased accuracy. The opposite is the case when we look at YOLO V5x model. The YOLO V5 usually sets in the anchor box and uses it to create the bounding box. The weights of a pretrained dataset in COCO format were used by the author Sathian Dananjayan and Luo (2022) to achieve model performance. The CSP model was given an input in two parts. One part performed convolution and the other part did not perform any convolutions. And as per the information stated CSPNet was able to effectively decrease the load of computation by 50%

### 4.0.2 LSTM

Algorithmic models which are capable of learning order dependence are Long Short-Term Memory (LSTM) networks. These are very complex deep learning models in the domain of machine learning. They are most commonly used in the problems like machine translation or speech recognition which are majorly difficult areas of machine learning. The LSTM models are divided into 3 different parts. In the very first part of the model there is a stream of information that is coming from the last timestamp and the model has to take a decision that the given information is relevant or it not relevant to the current use. If it is then the information should be remembered and if it is not relevant then the information can be discarded. In the second part, new information coming from the first part is captured/ learnt. In the last and the final stage the information is passed on the next timestamp from the current one by the cell. The timestamps in LSTM are very similar to that of RNN's as the current state of the timestamp is represented by the mathematical representation of Ht and the previous hidden state is represented by H(t-1). Alongside this there is also a representation of cell state for current timestamp as C(t) and previous timestamp as C(t-1) [4]. In the LSTM model, the STM stands for short term memory and the LTM stands for long term memory.

### 4.0.3 MobileNet v2

MobileNet is known to be the first model developed on TensorFlow's along with computer vison designed to be used in mobile applications. This model is derived from the CNN class of models which was open sourced by google. Depth wise separable convolutions are used in the MobileNet model and is based on a lightweight deep neural network. When the model which has a network with regular convolutions and has the same amount of depth in the nets is compared with a network having depth wise separable convolutions the number of parameters are reduced by a huge amount. It is very much possible to train in an extremely fast way the classifiers which are extremely small networks. Two operations make up the depth wise separable convolution which are known to be depth-wise convolutions and point-wise convolutions. With the use of recurrent neural network architectures this model is used at a large scale. Within the area of pattern estimation architectures this model is extremely capable of learning the learning sequence. The input shape from the generator was (120, 120, 3). Then we added a custom top for the classification. The custom top had 2 dense layers. The first layer had 1056 neurons. The last layer had 2 neurons (as there were 2 classes). In the first layer the activation function

[4] https://www.analyticsvidhya.com/blog/2021/03/introduction-to-long-short-term-memory-lstm/

used was ‘relu’ to have some non linearity’s. Since it was a binary classification problem, ‘sigmoid’ activation function was there at the final layer.

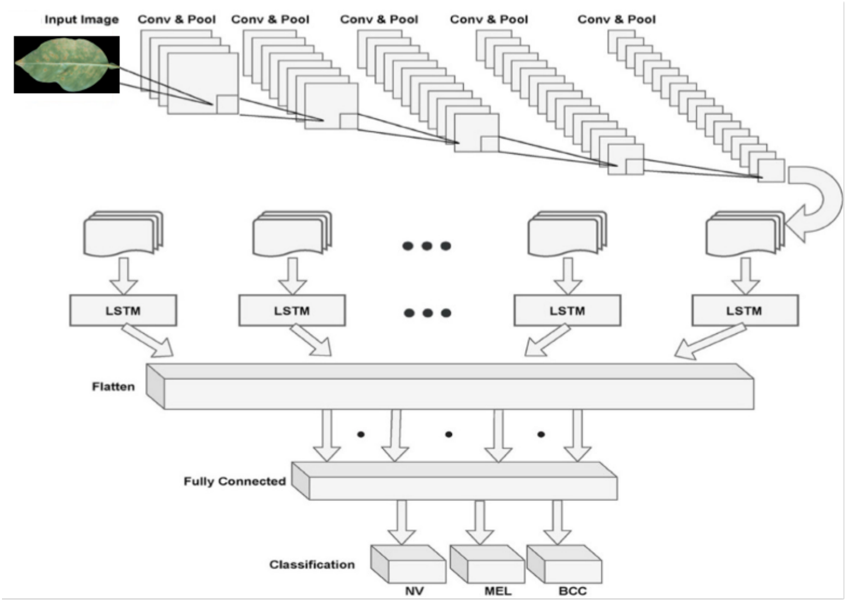


Figure 4: MobileNet + LSTM Hybrid Model

#### 4.0.4 MobileNet v2 + LSTM Hybrid Model

This research work was implemented on Jupiter Notebook which had all the processes like data augmentation, feature extraction, developing machine learning models, and model assessment. The Jupiter notebook was given access to the dataset which was sourced from Kaggle.com. The dataset constituted of 2 classes. The first one was the training dataset which had 9169 images whereas the second dataset was the test data which comprised of 1206 images. Further the augmentation of data was done by TersorFlow package in python. The data was also considered for augmentation which was done using the K fold cross validation technique. The value set for K fold validation was ‘5’. And the batch size was set to ‘500’. In the MobileNet V2 model implementation a function was written to save the best weights in the model. “Softmax” activation function was used for classification. A function was also written to take care of early stopping of the model and then the MobileNet V2 model was applied. The convolutional output was flattened and the dense layers were then added. The model was then compiled by adding a layer of 1056 neurons and 5 neurons were used in the output layer to classify output. Here ‘relu’ and ‘sigmiod’ activation functions were applied respectively. Lastly the best weights were loaded and the prediction of the model was done accordingly. In addition to this in the LSTM model, the layers used were ‘5’ and in the dense layer the activation function used was ‘Sigmiod’.

The figure above Figure 4 is a representation of the complete architecture of the MobileNet V2 with the LSTM model. The LSTM component there is a flattening layer present which is attached to the model. It is with the combination of convolutions and max pooling layers. It is with the help of training that the totally connected layers carryout the correlation of the similar features with the data that is pre-existing. In the end, it is the softmax layer which gives an idea of the possibilities of if the leaf is disease or not. (Parvathaneni Naga Srinivasu and Kang; 2021).

# 5 Evaluation

The MobileNet V2 and MobileNet + LSTM model was evaluated on the bases of accuracy, precision, recall, F1 score, Cohen Kappa Score, and Matthews Correlation Coefficient. The results concluded in the experimentation and implementation have been explained in detail in this section. To evaluate the performance of YOLO V5 we have used tensorboard.

## 5.1 Scaled YOLO V5

The evaluation of the detection model was done by looking the following metrics:

1. mAP
2. Recall
3. Precision

The graph represented below Figure 5 is a output graph representing the performance of the model. The nature of the graph is gradually increasing (exponential growth) which represents the excellent performance of the model.

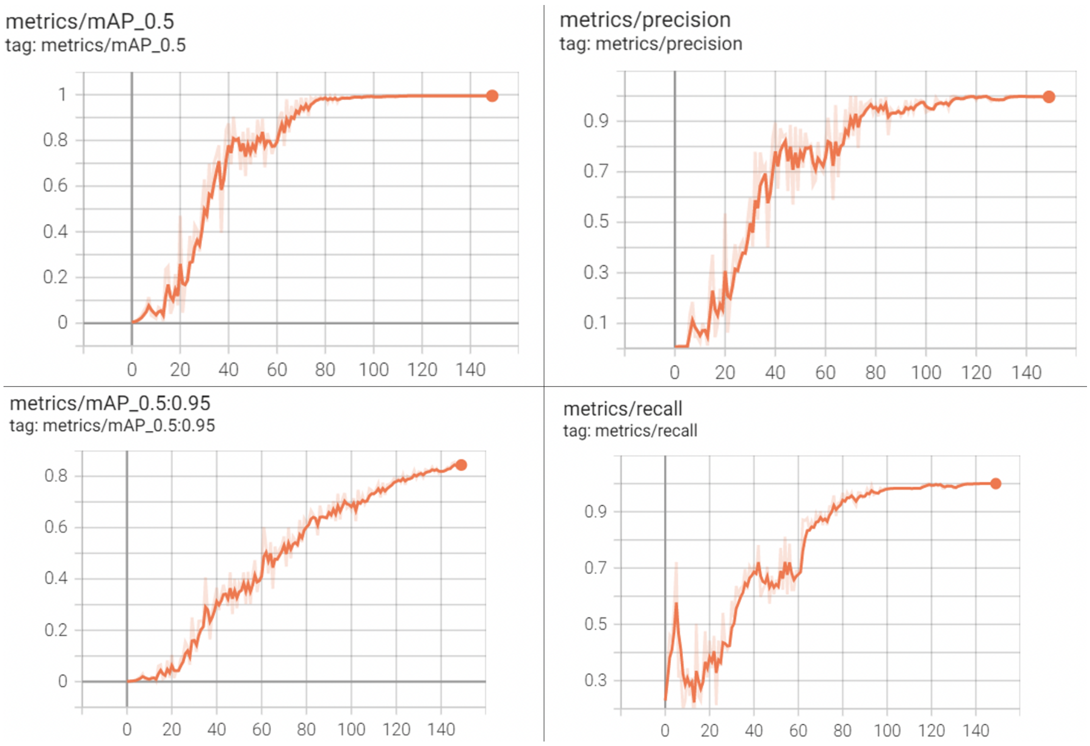


Figure 5: mAP output graph for detection

Below are the results of implementation of YOLO V5 to detect the infected part of the leaf. The Figure 6 is a representation of the output to the end user after successful detection of the infected region.

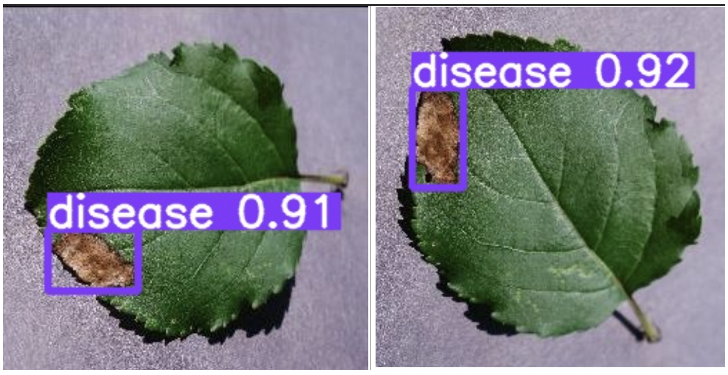


Figure 6: Detection of area of disease in leaf

## 5.2 MobileNet V2

The MobileNet V2 model was implemented and the results of the model implementation are represented in Table 2. The matrix below Figure 7 is of the MobileNet V2 model and the numerical values for the matrix are [[603 0] [ 75 528]].

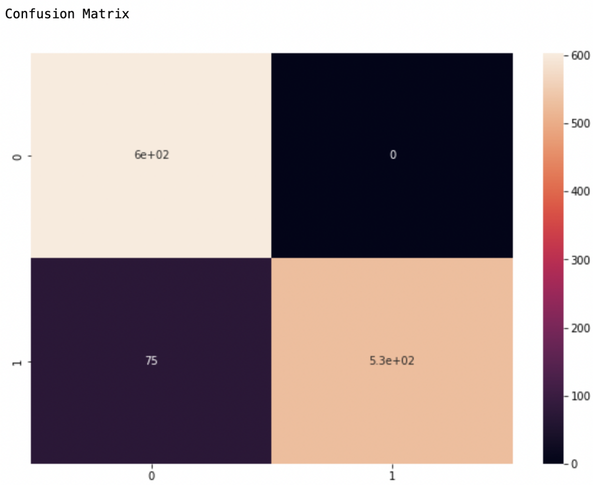


Figure 7: Confusion matrix for MobileNet V2 model

## 5.3 MobileNet V2 + LSTM hybrid model

The MobileNet V2 + LSTM hybrid model was implemented and the results of the model implementation are represented in Table 2. The graph below Figure 8 is of the MobileNet V2 + LSTM hybrid model depicting the ROC curve. The confusion matrix of the model was also generated and the values if it are [[603 0] [ 81 522]].

The result Table 2 below is a comparison of the results of MobileNet V2 and MobileNet V2 + LSTM. The MobileNet V2 model has performed slightly better than the hybrid model. The proposed hybrid model is fast and robust and is been trained on more than 8,ooo images.

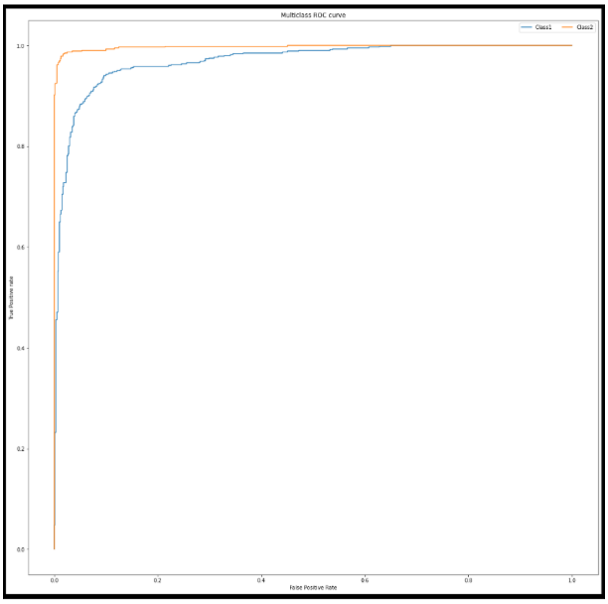


Figure 8: ROC curve plot for Hybrid model

Table 2: Results of both MobileNet V2 models

| **Evaluation Parameters** | **MobileNet V2** | **MobileNet V2 + LSTM Hybrid Model** |
|---|---|---|
| Accuracy | 0.937810945 | 0.932835821 |
| Precision | 0.944690265 | 0.940789474 |
| Recall | 0.937810945 | 0.932835821 |
| F1 Score | 0.937569497 | 0.932531469 |
| Cohen Kappa Score | 0.875621891 | 0.865671642 |

## 5.4 Discussions

This implementation was done to check accuracy and performance of MobileNet V2 + LSTM hybrid model which is know to be a light weight and less resource consuming model when compared to YOLO. Three models were individually implemented and their results have been recorded in this report. The main difficulties encountered in this project are as follows:

1. Support for Scaled YOLO V4: Due less community support on YOLO V4 the bugs faced were unresolved hence the detection model was implemented with a step newer version known as YOLO V5.

2. Annotated data: The available dataset is in COCO format which is not compatible in YOLO implementation hence the annotations had to be done manually in YOLO format with the help of Labelimg tool. A total of 53 images were annotated to perform the experiment on YOLO V5 model.

3. YOLO V4: The research was initially planned to be conducted in the YOLO V4 model as it had proven accuracy in plant leaf and the results were then to be compared with the hybrid model. But due to limited support over YOLO V4 due to introduction of newer YOLO models and increased amount of errors the model was changed to YOLO V5.

4. Disease detection: The research also wanted to detect the disease name after detecting the infected area which would help the farmers in using the appropriate medicine. But due to limited time and the longer training time and tuning times this objective can be taken as future work. Detection of disease names required annotated data in YOLO format in huge number and the annotations were carried out manually with LabelImg tool.

Various different experiments and functions were conducted to try and boost the performance of the implemented models. All the three models were implemented and the results have been described in the section above. The goal to develop a robust model capable of classifying pest disease was achieved by testing and training the algorithm with huge dataset of approximately 10,000 images. All of the previously implemented research works had used half the size of dataset as this one. The YOLO V5 performed better that the last best performing model in YOLO which was Scaled YOLO V4 as mentioned in Sathian Dananjayan and Luo (2022). The MobileNet V2 + LSTM hybrid model was implemented by (Parvathaneni Naga Srinivasu and Kang; 2021) and showcased an accuracy of 85.34% which has now been increased in this implementation to 93.28%.

# 6 Conclusion

In conclusion, the research work which is implemented will be a helpful for the farmers in timely detecting the diseases occurring to citrus plants without the use of network connection and to mobile app developers in building light-weight scalable mobile applications. As in recent years mobile phones have been released with high resolution cameras at relatively low cost this will help in building highly efficient and accurate mobile applications. Although, the detection accuracy of Scaled YOLO V4 was lower the newly implement YOLO V5 model had signs of improvement as mAP was increased from 0.89 to 0.92. In implementing classification of pest infected leaves, the MobileNet V2 model showcased an accuracy of 93.78% and the proposed hybrid MobileNet V2 + LSTM model provided a accuracy of 93.28%. The images of citurs leaves used in this research project are specifically taken from the Goungxi province in China. This research also worked on taking forward the research work cited by Asad Khattak and Gumaei (2021).

From a future work perspective, the models and algorithms implemented in this paper can be to develop a mobile application which can detect and classify infected leaf images without the need to connect to the internet. In addition, the research can also be used in trying to implement real-time applications and predicting the detection task without having the need to connect to the internet.

# 7 Acknowledgement

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