Development of AI-based Detection and Classification Model for Apple Crop Diseases

Amit Kumar
Senior Software Engineer
India

Abstract — In India, the valley of Kashmir holds the maximum share of Apple production with more than 75% of total apple production. Currently, around 160000 hectares of land in the Valley is under apple cultivation with an annual productivity of around 180000 MTs [source: Directorate of Horticulture, 2021], in which most part is exported to various regions of the world. Apple orchards are under constant threat from various types of viral pathogens, fungus, bacteria, and insects. They continuously damage the apple fruits and leaves, this is primary cause of low apple yield and results in a huge economic loss to the apple industry every year. Diseases like apple Scab, Apple Cedar Rust, Powdery Mildew, apple Blotch and apple Rot remain a major threat for the apple growers. Early diagnosis of apple diseases can help in controlling of infection spread and ensure higher yield, thus preventing substantial economic losses. Therefore, timely detection of diseases is crucial for enhancing both quality and quantity of apples. Traditional manual disease identification and inspection is laborious, time-consuming, error prone and requires a thorough knowledge of apple plant pathogens. Instead, automated approaches save both time and effort. In this research, , developed an AI based detection and classification model for apple crop diseases using deep learning architecture based on transfer learning convolutional neural network called YOLOv5. The model is improved to optimize for both detection speed and accuracy and applied to multi class apple plant disease detection in the real environment. The dataset corpus is formed which consists of 7909 images belonging to 6 classes namely apple scab, apple cedar rust, powdery mildew, healthy, apple blotch and apple rot. Then, the data annotation process is performed on all the images as per their target classes and saves the labels in a text file. During annotation of images in the training dataset, each text file contains information about the target class and the corresponding bounding coordinate. Several data augmentation techniques are performed to enrich and diversify the dataset which improves the model generalizability and eliminates the problem of overfitting. The non-maximum suppression (NMS) algorithm is used with darknet 53 framework. The mean average precision (mAP) and F1-score of the trained detection model is 90.22% and 92.5%, respectively. The developed model can be employed as an effective and efficient method to detect different apple plant diseases under complex orchard scenarios and can be extended to different fruit crops and automated agricultural detection processes.

Keywords: Convolutional Neural Network, Apple Scab, Apple Black Rot, Apple Cedar Rust, Apple Leaves Disease, Deep Learning, CNN, YOLO

I. INTRODUCTION

Apples are one of the most extensively produced fruits in the world and are farmed all over the world. Because of its high remedial and nutritional properties, apple fruit is one of the most fruitful fruits. With more than 75% of total apple production in India, the valley of Kashmir has the highest proportion of Apple production. Currently, approximately 160000 hectares of land in the Valley are under apple cultivation, with an annual productivity of approximately 180000 MTs [1], of which a large proportion is exported to various parts of the world. Agriculture is the main driver of economic growth in the country. The Himalayan ecosystem is famous for its specialty of apples all over India. Fruits are exposed to diseases caused by insects, fungi, and bacteria. Fruit diseases reduce the quality of the apples and the quantity as well.Diseases such as Scab, Apple cedar rust, rot, blotch, Alternaria and Powdery Mildew continue to pose a significant danger to apple farmers. Alternaria emerged in apple orchards in July 2013 and spread like wildfire, infecting more than 70% of cultivars in various Valley areas. As a result of the disease, there was a significant amount of fruit fall, which resulted in a decline in fruit productivity [2]. The same disease attack was recorded again in 2018 [3]. One of the key causes for the emergence of this devastating disease, according to domain experts and scientists, was a lack of an effective disease forecasting and detection system [2]. In 2020, a serious scab infection broke out, and viruses harmed more than 30% of the crop despite the application of fungicides. Crop wastage was high as a result of the infection [4].

Apple Scab is a fungus that attacks the leaves, fruit and stems of the plant. It causes small spots on the lower surface of the leaves and the buds. The condition causes a pale yellow or brown colour on the upper surface of leaves. As the lesions develop, they become more definite and become darker grey. Leaves become distorted, damaged, and shriveled, and they fall early if the condition is extreme. In case of scab fruit disease, the lesions begins as water-soaked regions and spread to velvety green to olive brown lesions. Lesions have a blistered or “scabby” look with a distinctive border as they grow. This will cause cracking and may result in deformity and uneven development as shown in Figure 1.

Gymnosporangium juniperivirginianae causes the fungal disease apple cedar rust. This disease may infect a broad variety of hosts, including cedar, apple, pear, and quince. The presence of cedar apple rust can degrade the quality and look of the fruit, making it unsuitable for fresh market sale. With a severe high infection, the foliage of the leaves will be badly impacted, ultimately resulting in canopy defoliation.

Fig. 1: Apple Scab disease in fruit and leaves

On infected branches, large light brown/tan galls can be detected. These galls need two years to mature to the point of spore release and spread, thus the galls will expand into orange horn-like formations in the second year. The fungal structures appear orange and gelatinous during sporulation and dissemination of fungal inoculum. Once the infection has taken hold in the apple, cedar apple rust lesions show on the upper side of the leaf as brilliant yellow-orange dots with a red ring around the edges. The spore-producing structure looks as a brown patch with elevated black spots on the underside of the leaf. When immature fruit becomes infected, orange spots appear in a circular pattern as shown in Figure 2.

Fig. 2: Apple cedar rust disease in leaves

Powdery mildew is caused by Podosphaera leucotricha, an ascomycete fungus. Powdery mildew grows on buds, blooms, leaves, twigs, and fruit. It is an obligatory biotroph, meaning it cannot thrive without its host. It can cause defoliation and lower apple output and quality due to stunted development or die back of twigs and leaves, as well as diminished fruit set. The best conditions for infection are high relative humidity and temperatures ranging from 66 to 72 degrees Fahrenheit. The first signs are usually isolated colonies of white-silver grey fungal mycelium growing on the lower leaf surface as shown in Figure 3. Dormant branches infected heavily the previous growing season are coated with thick white mycelium, and the terminal bud is pinched and shrivelled. Infections on the blooming receptacle or on early fruit generate net-like russet and discolouration as the fruit grows. Fruit that has been infected may become deformed and/or dwarfed.

Fig. 3: Powdery Mildew disease in leaves

Rot can be brown, white and bitter. Botryosphaeria doth- idea, often known as Botryosphaeria rot or bot rot, is a fungal disease that affects apples. Black rot is caused by Diplodia seriata fungal and Bitter rot is caused by Colletotrichum gloeosporioides fungi externally, all three infections exhibit identical symptoms, beginning with little light brown to red lesions with a blood red halo as shown in Figure 4. White rot forms a cylindrical lesion in the fruit core and finally consumes the entire fruit, whereas bitter pit stays a cone- shaped lesion that does not penetrate the core. White rot, like black rot, causes circular brown lesions; however, black rot lesions remain solid and flat, but white rot lesions sink and seem watery.

Fig. 4: Apple Rot Disease

The fungus marssonina coronaria and Alternaria Mali cause the apple blotch disease, which results in mid-season defoliation. Its occurrence has been detected on all commercial cultivars cultivated in India. Disease develops on both the foliage and the fruit. Dark brown spots appear on the upper surface of the leaves and range in size from 5 to 10 mm in diameter, indicating the presence of the blotch symptoms. Depending on the environmental circumstances, various tiny and big blotches combine to produce enormous dark brown blotches, and the surrounding regions turn yellow. The yellowing progresses towards the petiole end, causing midseason defoliation. It reduces the size of the fruit and causes it to bloom later as shown in Figure 5. The fruits are discoloured and flavourless. The disease is distinguished by irregular necrotic spots on mature leaves. During June and July, the blotches appear suddenly and swiftly, causing yellowing and defoliation. Mid- season defoliation may be responsible for poor growth of fruiting buds, resulting in reduced yield.

Fig. 5: Apple Blotch Disease

Early disease diagnosis is critical for improving both the quality and quantity of apples. An on-time detection system would identify the disease and prevent it from spreading to other plants, saving significant economic losses. Pests and infections not only lower yield but also have a negative impact on fruit quality. Correctly identifying a disease allows the farmer to take appropriate preventative measures or apply just the right amounts of pesticides resulting in both economic and environmental advantages.

Traditionally, plant disease diagnosis was done by domain specialists by visually studying the leaves. However, this was a time-consuming and labor-intensive practice. Furthermore, the professionals must be competent and have significant understanding of numerous diseases, their symptoms, and possible treatments. An autonomous detection system capable of detecting plant diseases in their early stages would be a viable alternative to such labor-intensive tasks. Machine learning has been widely used in agriculture to diagnose diseases in various plants. Through their ability to learn and improve, they can detect different diseases in different plants and produce accurate and rapid results .Various computer vision and image processing algorithms have been investigated and developed over the years in this area to detect and diagnose plant diseases.

Deep Learning is sub field of machine learning. Deep learning algorithms are a special type of Artificial Neural Networks which extract high-level representations of data while training without any human intervention. They can solve real life complex problems and have shown excellent performance in many computer vision and machine learn- ing tasks like image classification, object detection, speech recognition, voice recognition, natural language processing, medical imaging etc [5]. It is now being widely used in plant disease identification and diagnosis. Due to their ability to learn features directly from images, deep learning algorithms like Convolutional Neural Networks (CNN) have found their application in Agriculture as well.

Plant disease identification entails numerous problems owing to a variety of factors, and we are attempting to solve these challenges in this research by proposing a real-time and accurate End-to-End apple disease detection system [6]. Plant disease patterns differ depending on the season as well as other conditions such as CO_2 concentration, humidity, temperature, and water availability. Because each disease responds differently to these variations, these factors can have a significant impact on disease progress. Furthermore, disease patterns vary significantly due to factors such as leaf morphology, non- homogeneous background, age of infected cells, differences in leaf colour and light illumination, exposure during imaging. The visual symptoms of different diseases may appear similar (low inter-class variation) due to varying lighting conditions, light exposure and other factors. The identification of tiny spots in the early stages is the next difficulty. Detecting small objects is a difficult task and most of the object detection algorithms have tough time in dealing with small objects [7]. Disease spots arise in a broad range of forms, sizes, and colours, and they appear at random on the leaf surface. These spots are generally small or even tiny when they first appear, and they change colour, size, and shape over time, making standard detection methods difficult to use. Another issue is the scarcity of datasets on apple crop diseases. Deep learning algorithms are data-hungry algorithms that demand massive amounts of data for training. There are a few apple leaf disease classification datasets available online, but they only cover a few diseases and are not suitable for this research because they are not annotated. As a result, we created a large enough quality dataset that included all of the major apple diseases.

Variables like shade, light, and soil might make it difficult to identify apple leaf disease. Deep convolutional networks are end-to-end systems that can automatically detect discriminative features of an image and provide direct input to the model. Deep learning techniques are commonly used for processing large amounts of data and can be applied to different formats of images. To address these issues, this article uses the most recent deep learning object detection and classification algorithm , which is based on enhanced deep convolutional neural networks, to identify apple leaf disease in real-time. In this study, we have used deep learning approach YOLO v5 which gives best results in precision and recall without any traditional segmentation or preprocessing for detection and classification of apple crop diseases.

The following are the key contributions of this paper.

- For real-time detection of apple crop diseases, a deep learning based CNN model YOLO v5 is used for the disease detection and classification.
- The rich collection of apple crop disease dataset
- This paper concentrated on discovering diseases in apple crops and leaves using images as weel from videos.
- The proposed deep-learning-based YOLO model can detect the five major forms of apple crop disease, namely Apple scab, Apple cedar Rust, Apple Rot,Powdery Mildew,apple blotch a with high accuracy by automatically identifying the discriminative characteristics of infected apple images and from videos .
- The model is able to classify the apple crop diseases into six classifiers namely- scab, rust, powdery mildew, blotch, rot and healthy.

The following research document is structured as: section 2 has the literature review and related works. Section 3 the proposed work which consist of dataset collection, data augmentation, data normalization, modelling, Implementation and training. Section 4 discussing the results and evaluating the model, and section 5 is conclusion and section 6 tells about the future scope.

II. LITERATURE REVIEW

Gilandeh et al. [1] have used digital image processing to identify various apple pests and diseases. Sparse coding was applied to boost processing speed by analysing only a section of the image instead of analysing the entire image. Examining a portion of the apple fruit that exhibits pest or disease can help in minimising the processing time. The diseased apples were gathered from various plots in Naghadeh, West Azerbaijan province, Iran. The total apples were divided into 18 groups, with 16 groups containing diseased apples and two groups containing healthy apples. A total of 819 images were captured from three points of view of 273 apple samples.

Jimcoe [8] proposed a method for detecting and classifying three prevalent apple fruit diseases named apple rot, apple scab, apple blotch. The image processing-based approach consists of three major steps: image segmentation using the K-Means clustering segmentation algorithm in the first step, extraction of state-of-the-art features from the segmented image in the second step, and classification of images into one of the classes using the Learning Vector Quantization Neural Network in the third step. The experimental findings demonstrated that the proposed method may considerably aid in the accurate identification and categorization of apple fruit diseases. They get greater than 95% classification accuracy using the proposed solution.

S.Xing et al. [9] on their image dataset collection, proposed a basic yet effective CNN model. The proposed network was created with parameters efficiency in mind. To accomplish this, the complexity of cross-channel operation was increased, and the frequency of feature reuse was adjusted to account for network depth. Experiment findings revealed that Weakly DenseNet-16 achieved the maximum classification accuracy with fewer parameters, owing to its lightweight nature, which allows it to be utilised on mobile devices. The dataset used in the experiment contained 17 citrus pest species and seven citrus disease categories. The majority of the pest images were obtained from the Internet. Images containing diseases were captured using a high-resolution camera at a tangerine orchard on Jeju Island.

A. Fuentes et al. [10] proposed three detector families, which they termed “deep learning meta-architectures”: Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD). Each of these meta- architectures is combined with “deep feature extractors” such as VGG net and Residual Network (ResNet). They also propose an approach for local and global class annotation, as well as data augmentation, to improve accuracy and minimise false positives during training. Experiment results indicate that the proposed system can efficiently distinguish nine distinct types of diseases and pests, as well as handle complicated scenarios from the surrounding environment of a plant.

Bin Liu et al. [11] proposed a deep convolutional neural network for apple leaf diseases. It consists of creating a sufficient number of diseased images and developing a unique architecture for a deep convolutional neural network based on AlexNet to identify apple leaf diseases. The algorithm has been trained to recognise four prevalent apple leaf diseases. The experimental results shows an overall accuracy of 97.62 percent, the model parameters are reduced by 51,206,928 compared to those in the standard AlexNet model, and the accuracy of the proposed model with generated pathological images improves by 10.83 percent.

J Liu et al. [12] proposed a VGG16-based better model for identifying apple leaf diseases in which the global average poling layer replaces the fully connected layer to minimise parameters and a batch normalisation layer is added to increase convergence time. To circumvent a lengthy training period, a transfer learning approach is applied. The experimental find- ings demonstrate that the proposed model’s overall accuracy for apple leaf classification can reach 99.01 percent. When compared to the traditional VGG16, the model parameters are reduced by 89 percent, recognition accuracy is enhanced by 6.3 percent, and training time is cut to 0.56 percent of the original model.

M. Turkoglu et al. [13] generate a dataset of tomato plant diseases and pests in their natural environment, optimise the feature layer of the Yolo V3 model by using an image pyramid to achieve multi-scale feature detection, increase the detection accuracy and speed of the Yolo V3 model. The model was able to detect the location and category of tomato diseases and pests.

Muammer et al. [14] introduced Multi-model LSTM-based Pre-trained Convolutional Neural Network CNN model (MLP- CNNs) as an ensemble majority vote classifier for plant disease and pest detection. The presented hybrid model is built using an LSTM network and pre-trained CNN models. For feature extraction, the AlexNet, GoogleNet, and DenseNet201 models are used. The collected deep features are then put into the LSTM layer to build a strong hybrid model for detecting apple disease and pests. The class labels of the input images were afterwards chosen by a majority vote classifier based on the output predictions of three LSTM layers.

C.B Murthy et al. [15] provides a comprehensive survey of recent advances and milestones in object detection utilising various deep learning approaches. Viola–Jones (VJ), histogram of oriented gradient (HOG), one-shot and two-shot detectors, benchmark datasets, assessment metrics, speed-up approaches, and current state-of-the-art object detectors are few of the subjects covered. There have been detailed talks on certain major applications in the object detection fields, such as pedestrian detection, crowd detection, and real-time object detection on GPU-based embedded systems.

H.Zhu et al. [16] presented a literature review on video object detection. First, an overview of known datasets for video object detection is provided, together with widely used evaluation metrics. The methods for detecting video objects are then classified and described in detail. Two comparison tables are presented to show the differences in accuracy and computational efficiency. Finally, several future directions in video object detection are discussed in order to address the challenges involved.

Gokulnath B.V et al. [17] proposed an efficient loss-fused convolutional neural network model. In this paper ,method combines the benefits of two separate loss functions, resulting in better prediction. In the last layer of the model, the diseases were identified based on features retrieved from plant leaves. The dataset included in this experiment was obtained from the Plant Village Dataset. Their approach achieved 98.93 percent accuracy in distinguishing impacted samples from unaffected samples. The outcome of the model demonstrates its advantage in the categorization of disease-affected leaf samples over other current approaches.

S.Kumar et al. [18] focuses on identifying plant diseases and minimising economic losses. For image recognition, they presented a deep learning-based technique. They studied three major Neural Network Architectures: Faster Region-based Convolution Neural Network (Faster R-CNN), Region-based Fully CNN (R-CNN), and Single Shot Multibook Detector (SSD). The system proposed in their study can detect several forms of disease effectively and deal with complex situations. The validation results shows an accuracy of 94.6 percent, demonstrating the practicality of the Convolution Neural Net- work and presenting the way for an AI-based Deep Learning Solution to complex problems.

F.R.Albogamy et al. [19] provides a study on, an au- tonomous diagnostic aid system for leaf diseases developed us- ing a convolutional neural network with a batch normalization- based deep learning technique for identifying plant diseases. The use of deep learning technology has potential to create the system end-to-end, autonomous, accurate, less expensive, and more convenient for detecting plant diseases from their leaves. An experiment is carried out using a public dataset including 20654 images of 15 plant diseases in order to evaluate the proposed model. The experimental validation findings on 20% of the dataset demonstrated that the model can classify the 15 plant disease labels with 96.4 percent testing accuracy and 0.168 percent testing loss. These findings validated the suggested model's applicability and efficacy for the plant disease detection job.

Prakhar Bansal et al. [20] introduced an ensemble model using pre-trained DenseNet121, EfficientNetB7, and Efficient- Net NoisyStudent that uses images to classify apple tree leaves into one of four categories: healthy, apple scab, apple cedar rust, and many diseases. Various Image Augmentation approaches are used in their study to improve the dataset size and, as a result, the model's accuracy improves. On the validation dataset, the proposed model obtains an accuracy of 96.25 percent. The proposed model has a 90% accuracy rate in identifying leaves with multiple diseases. The proposed model performed well on several criteria and may be used in the agricultural area to correctly and quickly determine plant health.

H.Al-Hiary et al. [21] takes RGB images in order to execute colour space transformation. After these images have been segmented using k-means clustering, the value of the green pixels is masked using the threshold produced using Otsu's approach. Furthermore, the hue saturation value was applied to the affected clusters. The SGDM matrix is used to create each image for texture analysis. Finally, the ANN classifier performs the disease detection and classification.

A.Abbas et al. [5] presents a DL-based approach to deter- mine tomato disease that use the C-GAN to produce synthetic photos of tomato leaves for data augmentation. Then, using generated and actual data, a pre-trained DenseNet121 model is fine-tuned to categorise tomato leaf images into ten disease categories. In classifying tomato leaf photos to the categories of 5, 7, and 10, the proposed method achieved an accuracy of up to 99.51 percent, 98.65 percent, and 97.11 percent, respectively. It is demonstrated that this method outperforms conventional methodologies. The C-GAN reduces overfitting and improves network generalisation.

H.Sun et al. [22] introduces MEAN-SSD, a lightweight CNN detection model appropriate for mobile device deploy- ment, for detecting apple leaf diseases in real time. Data anno- tation and augmentation approaches were utilised to produce 26,767 disease spot images for training by gathering 2230 original photos from the laboratory with simple backgrounds and complicated backgrounds images from the orchard. The algorithm can automatically extract the characteristics of five typical disease spots from apple leaves. The findings demon- strated that the MEAN-SSD model is capable of properly detecting apple diseases, with a mAP of 83.12 and a speed of 12.53 FPS. The MEAN block is used as a basic module to speed up detection and reduce model size.

J.S.H Albayati et al. [23] utilised a DNN to identify apple leaf diseases such as black rot, apple scab, and cedar rust using the GOA and Robust Accelerated Feature SURF, where GOA was used for feature optimization and SURF was used for feature extraction. Many processes were completed before to the introduction of DNN, such as images enhancement in the pre-processing phase and ROI segmentation. The features were then retrieved using the SURF descriptor, followed by optimization using the GOA method, and ultimately, disease classification was performed using DNN.The experiments re- vealed that the approach based on DNN optimised by SURF delivers a higher mean value of 98.28 percent when compared to the other methods, increasing the model's accuracy by 18.03 percent. As a result, the fundamental model is more transferable than the metric model.

G.Storey et al. [24] combines instance segmentation for the purpose of detecting leaf and rust disease in apple orchards by utilising Mask R-CNN. For the objectives of object identifica- tion, segmentation, and disease detection, three distinct Mask R-CNN network backbones (ResNet-50, MobileNetV3-Large, and MobileNetV3-Large-Mobile) are trained and assessed. The authors annotate segmentation masks on a sample of the Plant Pathology Challenge 2020 database, and these are utilised for training and evaluating the proposed Mask R-CNN- based models. According to the study, a Mask R-CNN model with a ResNet-50 backbone achieves good accuracy for the objective, especially in detecting extremely minute rust disease items on the leaves.

H.Ayaz et al. [25] study several Deep CNN (DCNN) applications for apple disease classification leveraging deep generative images to improve accuracy. To do this, their work gradually adjusts a baseline model by utilizing an end-to-end trained DCNN model with fewer parameters and higher recognition accuracy than current models (e.g., ResNet, SqeezeNet, and MiniVGGNet). They conducted a compari- son research with state-of-the-art CNN as well as traditional approaches presented in the literature, and the comparative findings demonstrate the superiority of mentioned model.

This research indicates that convolution neural networks have been successfully used in the field of agricultural and plant disease identification. In this paper, a relatively new CNN-based proposed framework is used to detect apple leaf diseases.

III. Proposed Work

A. Dataset

The dataset preparation process is divided into two stages:

1) Data collection: collecting diseased apple leaf images from various fields and orchards and ii) data annotation: labelling images based on their symptoms. Both of these tasks need a significant amount of time and are resource intensive.
2) Data Collection: For this study, we studied on five com- mon diseases: scab, rot, powdery mildew, apple cedar rust, and apple blotch. We also made certain that each variety's leaf im- ages and videos were included in our dataset. The images and videos of apple crop disease utilised in this study were taken from the Jubbal-Himachal Pradesh, University of Kentucky College of Agriculture, Food and Environment, University of Nebraska–Lincoln and Plant Village collection dataset avail- able in the public domain. The dataset contains 7909 high- quality, real-life images which are divided

into six categories as shown in the Figure 7. The images are taken in various light conditions and with different positions, at different times a day, with different backgrounds.We also performed manual inspec- tion of these images and removed all duplicate, low quality, damaged and those images which were beyond recognition due to severe disease attack.Table I lists the class wise breakup of images for training and testing. These images were used for training and testing the models.

3) Data Annotation: Data annotation is a vital step in the success of the deep learning models. In data annotation, each spot/object in an image is manually labelled with its tag or label as shown in the Figure 7. There are several tools available for image annotation and in this study we have used makesene.ai website. Makesense.ai is a webiste which is opens source and free to use under GPLv3 license image annotation tool. There is no need to install any software and dont need to store the images also,just drap and drop the images .It Support multiple label types - rects, lines, points and polygon .It generates many annotations output file formats like YOLO, VOC XML, VGG JSON, CSV. It makes the process of preparing a dataset much easier and faster.

Fig. 6: Annotation of Images

Data Augmentation: Data Augmentations are required to supplement and enrich training data. Following the collection and annotation of about 7909 photos, several data augmentation methods were used to enrich and diversify the dataset. This improves the generalizability of deep models and eliminates the problem of overfitting. The dataset was enlarged via data augmentation technology to mimic changes in illumination, exposure, angle, and noise throughout the preprocessing stage. With additional images and variety provided by data augmentation approaches, the model may learn as many relevant features as necessary during training, avoiding overfitting and ensuring improved performance. Images are processed by raising and lowering the brightness, increasing and decreasing the contrast, increasing and decreasing the sharpness. The real shooting angles were recreated utilising rotation (90 degrees, 180 degrees, and 270 degrees), flipping (horizontal and vertical), mirroring, and symmetry operations. At the same time, the dataset is further strengthened by adding the interference of suitable Gaussian pepper noise, to imitate the noise that may occur during the image collecting process, which can decrease the over- fitting issue in the CNN training phase. Following the data augmentation, the size of the training dataset grew by 3 times.

4) Data Normalization: Normalization is the process of converting the values of numeric columns in a dataset to a similar scale without distorting the ranges of values or losing information. Some algorithms require normalisation to accurately model the data. Given how sensitive the deep neural network is to the input feature range, a broad range of eigenvalues will induce model training instability. The dataset is adjusted to enhance CNN convergence performance and learn minor distinctions between images [?].In this paper, a Z score is used for data normalization. The following formula is used to convert the values in the column:

$$X' = \frac{X - Xm}{\sigma}$$

Sno	Class	Total Images	No. for Training	No. for Test
1	Apple Scab	1386	1086	300
2	Healthy	1381	1105	276
3	Apple Cedar Rust	1288	1030	258
4	Powdery Mildew	1321	1056	265
5	Blotch	1295	1036	259
6	Apple Rot	1238	990	248

Table 1: Statistics of the Images in the Dataset Collected

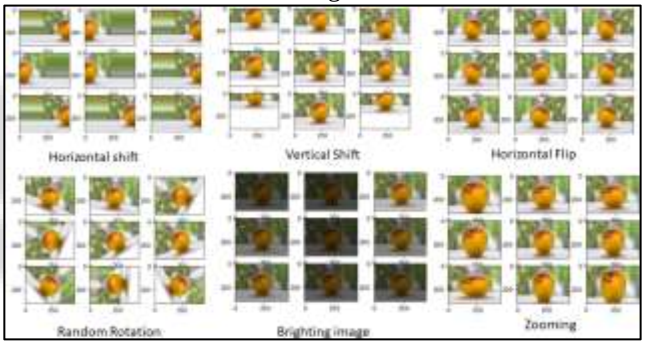

Fig. 7: Effect of different augmentation operations on original image

where X is the original feature vector, Xm is the mean of that feature vector, σ is its standard deviation. The data has been standardised to zero mean by removing the mean and dividing by the standard deviation of the channel pixel values, and all image pixel values are within the range of [-1,1] [?].

5) Resizing and Rescaling: To operate effectively, convolu- tional neural networks require similar image sizes. Of course, images in the actual world are rarely uniform. Resize the pictures that are varied in scale to the same size . Images must fit the network’s input size to train it and draw conclusions on new data. Rescale or trimming the data to the appropriate size if needed to alter the size of your images to fit the network . The larger the fixed size, the less shrinking is required. Less shrinkage means less distortion of the image’s features and patterns. This will lessen the impact of deformations on classification accuracy. Large pictures, on the other hand, not only take up more memory space but also result in a bigger neural network. As a result, both the spatial and temporal complexity of the system are increased. It should be

apparent by now that deciding on set image size is a tradeoff between computing efficiency and accuracy.

B. Dividing the Dataset

The dataset of 3200 images is split into two distinct subsets for the training and testing of the Deep CNN network. The training dataset accounts for 80% of the entire dataset, while the testing dataset accounts for 20% and the testing set is further divided into validation datasets, which accounts for 10% . All of the images are randomly shuffled throughout the train test split to maintain a balanced dataset. The dataset is divided into a batch size of 32. In training, we have 80 batches and each batch has 32 images and an invalidation dataset and testing dataset, we have 10 batches. So the total number of images in training belonging to 4 classes is 2560 and in testing and validation, we have 320 and 320 images. The validation set is used to adjust the hyper-parameters of the model and perform a preliminary evaluation of the model. Lastly, the testing set is used to evaluate the generalisation ability of the final model. The aforementioned data augmentation techniques are applied to the training dataset, while the validation and testing datasets are not augmented.

C. Modeling

The task of classifying and localising items in an image or video is known as object detection. The fast development of deep learning algorithms in recent years has substantially increased the pace of object detection. Object detectors performance has substantially improved because of improved deep learning models and increased computer power, resulting in numerous achievements. Object detection techniques may be divided into two types: region proposal-based approaches, often known as two-stage approaches, and single-stage ap- proaches based on regression or classification. Many people favour single-stage object detection algorithms because they are faster. The overall pipeline is shown in Figure 9 and Framework for classification and detection system is presented in Figure 10.

Object detection has gone a long way in the last decade or two, but there are still several major problems to address. High intra-class variance, low inter-class variation, and model efficiency are among the challenges. To respond to these challenges, research have come up with innovations like novel region proposals, multi-scale feature maps, split grid cells, a new loss function, and so on. These advancements have improved the performance of object detecting systems. However, one current difficulty that has piqued the interest of researchers is the identification of tiny objects. Most modern object detectors, including single-stage and two-stage tech- niques, have had difficulty identifying small objects.

The detection and categorization of diseases is an object detection issue in which many symptoms must be recognized and located. These symptoms can range in size from a few millimetres to a few centimetres, making detection challenging for most modern detectors. Nguyen et al. (2020) did study on multi-scale objects using several models with different backbone networks to determine which model and backbone network is best for tiny items. On a small object dataset, Faster R-CNN with ResNet-101+FPN backbone got the best mAP (mean Average Precision) of 41.2 percent.Yolov3 608 608 with Darknet-53 achieved 33.1 percent mAP, as in single-stage techniques. According to the results, Faster RCNN appears to be the best option for our problem, but since Yolov4 and Yolo5 was released, which increased accuracy over Yolov3 while simultaneously decreasing inference time by a significant margin, we chose to test both techniques. We also chose another well-known detection model, SSD (Single Shot Detector), which outperformed Yolo models on the MS COCO dataset. All three algorithms are the most effective detection approaches available.

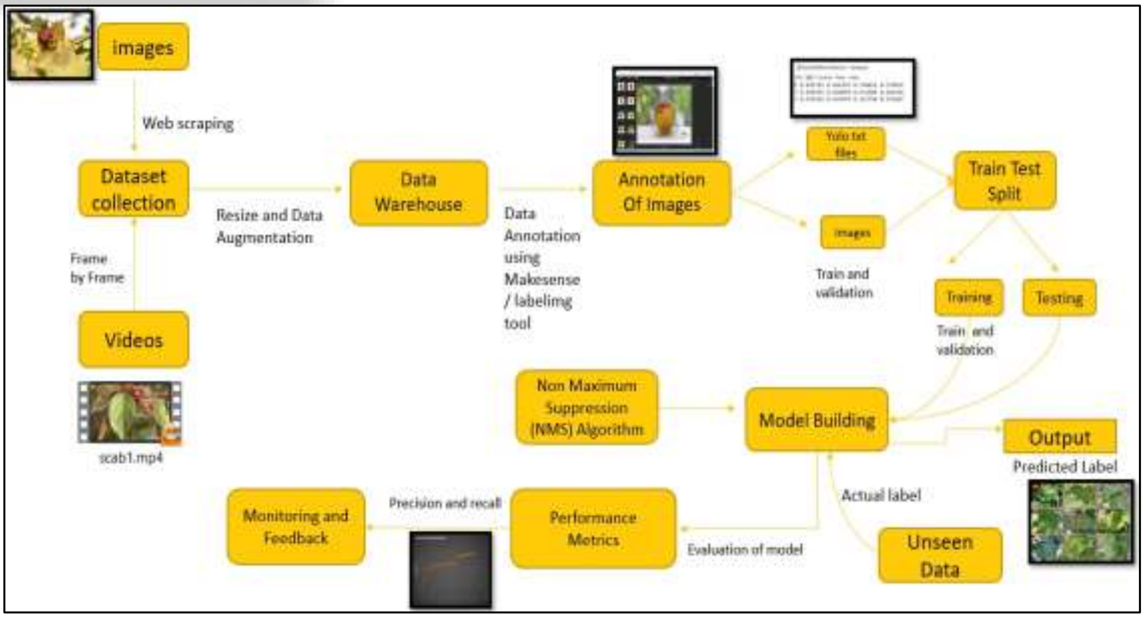

Fig. 8. Pipeline of overall methodology

1) Yolo v4: You Only Look Once (YOLO) is a set of one-stage object detection algorithms that were initially introduced in 2016. Yolov4 and Yolov5 are the most current members of the family and are improved versions of Yolov3. YOLO models are extremely performant and efficient, producing cutting-edge outcomes in a variety of object detection ap- plications. Yolo v5 is now one of the top real-time ob- ject detection algorithms in terms of

both mAP and perfor- mance. YOLO v4 combined many universal features (features that are independent of the dataset, model, or task) such as Weighted-Residual-Connections (WRC), Selfadversarial- training (SAT), Cross mini-Batch Normalization (CmBN), Cross-Stage-Partialconnections (CSP), and Mish-activation function, Mosaic data augmentation, DropBlock regularisa- tion, and CIoU loss

Yolov4 implements CSPDarknet53 as its backbone model and has implemented several unique methods for improving performance. Yolo v4 featured two new data-augmentation methods: Mossaic and SelfAdversarial Training (SAT). Mos- saic mixes four training pictures into one, such that batch normalisation calculates activations from four separate images rather than one on each layer. It also aids in maintaining a modest batch size with the same amount of images. Another augmentation approach is self-adversarial training, in which an input image is first manipulated to generate deception, and then the network is taught to recognise an item from this altered image in the next step.In this manner, the Yolo v4 model conducts an adversarial attack against itself. Yolo v4 also included the CIoU loss for the bounding box, which takes into account the distance between the centre points, aspect ratio, and overlapping area of the boxes. CIoU results in faster convergence and improved performance.

2) Yolo v5: Yolov5 is a state of the art cutting-edge, real-time object detector, and it is built on continuous improvements from Yolov1–Yolov4. It has consistently outperformed on two official object detection datasets: Pascal VOC (visual object classes) [26] and Microsoft COCO (common objects in context) [27]. The network architecture of Yolov5 is shown in Figure 11. In this research we select Yolov5 as our initial learner for three reasons. Yolov5 first implemented cross stage partial network (CSPNet) into Darknet, resulting in CSPDarknet as its backbone. CSPNet overcomes the problem of repeated gradient information in large-scale backbones by integrating gradient changes into the feature map, reducing model pa- rameters and FLOPS (floating-point operations per second), ensuring not only inference speed and accuracy, but also model size. The detection speed and accuracy of apple crop disease detection and classification are critical, and the compact model size impacts its inference efficiency on resource-limited edge devices.

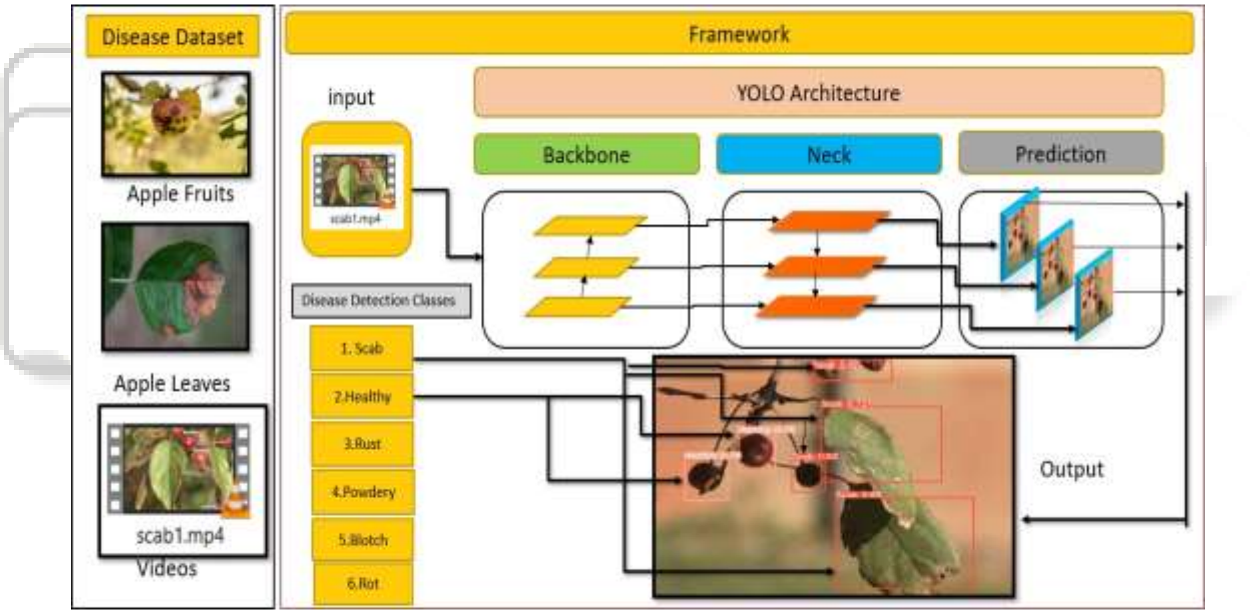

Fig. 9. Framework for classification and detection system

Second, to improve information flow, the Yolov5 used a path aggregation network (PANet) as its neck. PANet uses a novel feature pyramid network (FPN) topology with an improved bottom-up route, which increases low-level feature propaga- tion. Simultaneously, adaptive feature pooling, which connects the feature grid and all feature levels, is employed to ensure that important information in each feature level propagates straight to the next subnetwork. PANet improves the utilisation of accurate localization signals in lower layers, which can obviously improve the object's position accuracy.Third, the Yolo layer, the head of Yolov5, creates three distinct sizes (18 × 18, 36 × 36, 72 × 72) of feature maps to accomplish multi- scale prediction, allowing the model to handle tiny, medium, and large objects. The model can track size changes in the process of identifying the micro sized diseases in the apple leaves and fruits, thanks to multi-scale detection.

3) Faster RCNN: Faster R-CNN (Ren et al., 2015) is an upgraded version of Fast-RCNN, a region-based object detector (Girshick R, 2015). It first runs an image through a backbone network (CNN), and then on the final feature map of Convolution layers, a fully convoluted network called region proposal network (RPN) is trained, which outputs a set of bounding boxes as well as their objectless scores, which determine the likelihood of an object. We applied a ResNet101+FPN-based Faster RCNN in our experiment. ResNet101 is a Convolutional Neural Network with 101 layers. It achieves the best speed/accuracy ratio. The Feature Pyramid Network (FPN) (Lin et al., 2017) builds a

pyramid of feature maps at various sizes that may be used to detect tiny objects.

4) SSD:

D. *Implementation and Training*

The Yolov5 act as object detectors, to detect apple crop disease locations in images by generating candidate boxes, respectively. Then, the non-maximum suppresion algorithm is employed to eliminate redundant boxes, preserving boxes with top confidence.

Detailed training strategy of models is:

The various layers and functions used in the CNN model architecture are discussed below:

1) 2D Convolution Layer: The 2D convolution layer, which is commonly abbreviated as conv2D, is the most frequent form of convolution utilised [?]. In a conv2D layer, a filter or kernel performs elementwise multiplication by “sliding” across the 2D input data. As a consequence, all of the findings will be summed into a single output pixel. The kernel will turn a 2D matrix of features into a new 2D matrix of features for each point it slides over [?].
2) Max-Pooling Layer: Pooling is a characteristic that many Convolutional Neural Networks (CNN) designs use. A pooling layer’s main goal is to”accumulate” characteristics from maps created by applying a filter to a picture ?. Its formal purpose is to gradually shrink the spatial dimension of the representation to minimise the number of parameters and computations in the network. Maximum pooling is the most frequent type of pooling.

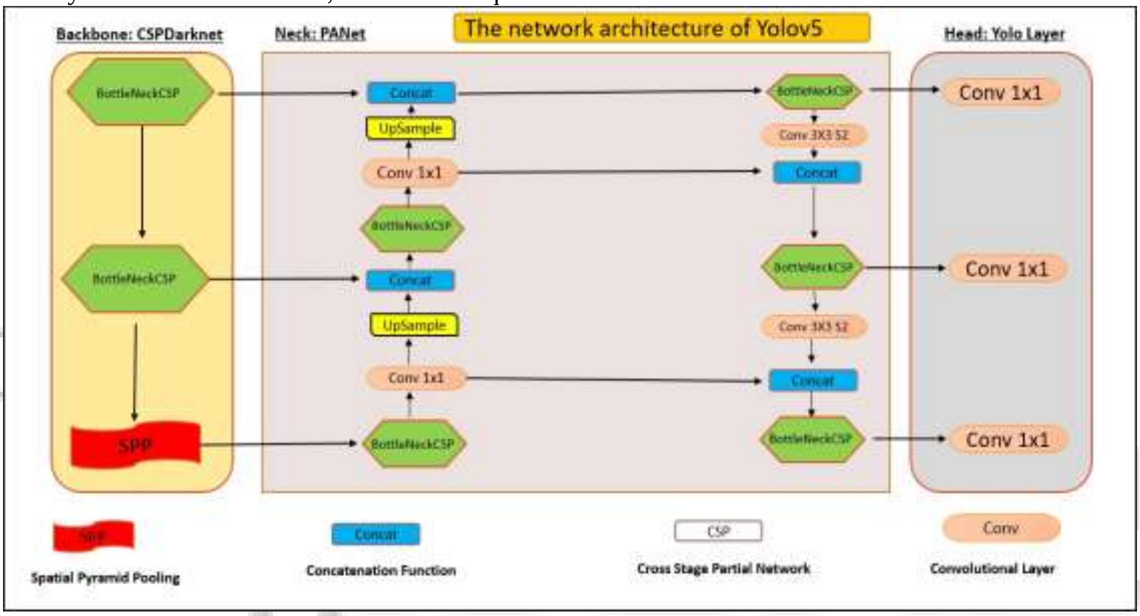

Fig. 10. The network architecture of Yolov5. It consists of three parts: (1) Backbone: CSPDarknet, (2) Neck: PANet, and (3) Head: Yolo Layer. The data are first input to CSPDarknet for feature extraction, and then fed to PANet for feature fusion. Finally, Yolo Layer outputs detection results (class, score, location, size).

Algorithm : Non-Maximum Suppression (NMS)

INPUT : $B = \{b1,...,bn\}$, $S = \{s1,...,sn\}$, Nt
B is the list of initial detection boxes
S contains corresponding detection boxes
Nt is the NMS threshold

```
Begin:
                    D ← { }
while B ≠ empty do
                m ← argmax S
                M ← b_m
                D ← D ∪ M; B ← B − M
for b_i in B do
if iou(M, b_i) ≥ N_t then
                B ← B − b_i; S ← S − s_i
end
end
        end
        Return D, S
End
```

Fig. 11. Algorithm: Non-Maximum Suppression (NMS)

Sno.	Label	No. of Images	No. for Training	No. for Test
1	Apple Scab	1386	1086	300
2	Healthy	1381	1105	276
3	Apple Cedar Rust	1288	1030	258
4	Powdery Mildew	1321	1056	265
5	Blotch	1295	1036	259
6	Apple Rot	1238	990	248

Fig. 12. Statistics of the images in the dataset collected. The images were used for training and testing the models

3) Softmax Regression: The Softmax regression is a type of logistic regression that converts an input value into a vector of values that follow a probability distribution with a total sum of one. The output values are in the range [0,1], which is convenient since it allows us to avoid binary classification and fit as many classes or dimensions as possible into our neural network model?. Softmax is frequently referred to as a multinomial logistic regression because of this.
4) ReLU Activation Function: The rectified linear activation function, or ReLU for short, is a piecewise linear function that, if the input is positive, outputs the input directly, else, it outputs zero. Because a model that utilises it, is faster to train and frequently produces superior performance, it has become the default activation function for many types of neural networks? The vanishing gradient problem is solved by using a rectified linear activation function, which allows models to learn quicker and perform better. When building multilayer Perceptron and CNN, RELU activation is the default activation function.

Sno.	Video Name	Label	Frames
1	Video1	Scab	900
2	Video2	Healthy	725
3	Video3	Rust	850
4	Video4	Powdery Mildew	960
5	Video5	Blotch	700
6	Video6	Apple Rot	1500

Fig. 13: Statistics of the videos in the dataset collected. The videos were only for detection. They did not participate in the model training

IV. RESULT ANALYSIS

A. Quantitative Results

This section presents performance evaluation of classification and detection model. On a test set, we tested the proposed model. The results of multi-class classification and object detection were recorded, and average numbers were computed. Figure 6 depicts the model's performance in the form of a Confusion matrix (CM). Table II summarises the overall accuracy, precision, recall, and F-measure derived by the equations presented below.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall \ \frac{TP}{TP + FN}$$

$$F\ 1Score \ \frac{2 \times Precision \times Recall}{Precision + Recall}$$

class	Precision	Recall	F1- Score
Scab	.95	.88	.91
Healthy	.92	.95	.93
Rust	.90	.90	.90
Powdery Mildew	.89	.88	.89
Blotch	.90	.89	.90
Rot	.92	.91	.91
Average	.91	.90	.91
Overall Accuracy	93%		

Table 2: Class-Wise Results of Classification Model

The abovementioned performance metrics are the most commonly used metrics to measure the performance of classification models. The classification model attained an average accuracy of 93 percent, precision of 91 percent, and recall of 90 percent respectively. The Figure 14 depicts the precision metrics with respect to epoch values and figure 15 depicts the recall metrics with respect to epoch values. As it is observed from the figures 14 and 15 that the performance metrics precision, recall increase with epoch values and reaches upto 95 percent.

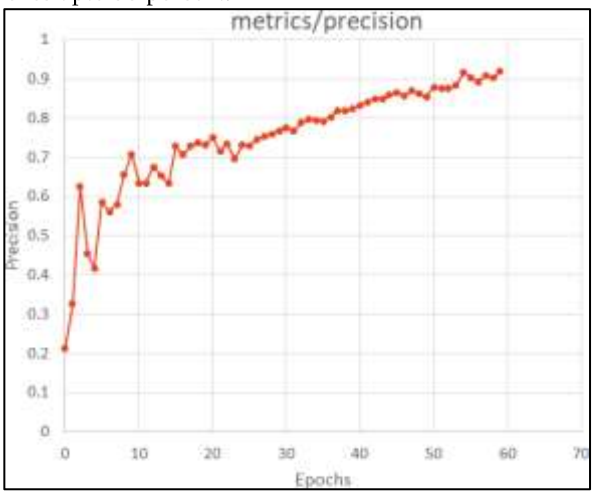

Fig. 14: Precision VS Epochs

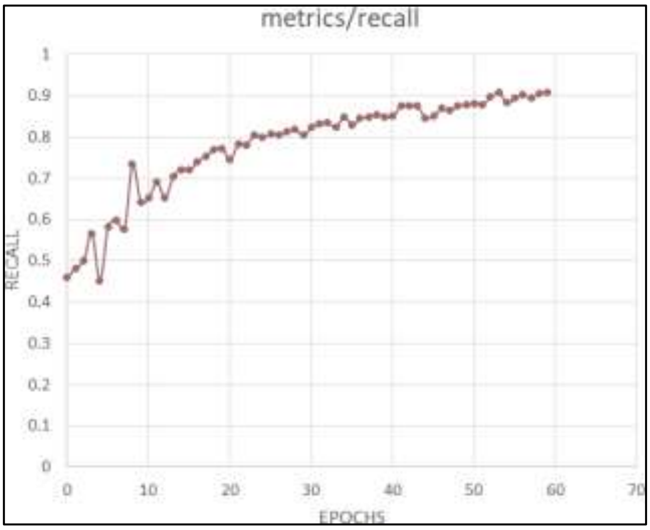

Fig. 15: Recall VS Epochs

When presented with multiple classes with minimal vari- ance, a classifier's performance might suffer dramatically. Images of leaves afflicted with different diseases and at varying intensities might confound the classification model, resulting in poor performance. In the confusion matrix, for example, it can be observed that certain rust cases have been labelled as scab. This can happen if certain rust areas develop brown or black papery spots over time, giving the appearance of another symptom such as scab. According to the results, the model achieved best precision score for Powdery mildew (PWM), Rot category while as Rot is the worst performing category. Rot disease spots vary immensely in shape and size. They can be black or brown or sometimes white in colour. As the number of spots grow they can turn from light brown to red lesions with a blood red halo. On the other hand Powdery Mildew appears as white powder on leaves, branches which very often covers whole leaf, stem surface thus easily identifiable.

Fig. 16: Testing Results on Video 1: Apple Scab

Fig. 17: Testing Results on Video 3: Apple Rust

Fig. 18: Testing Results on Video 4: Apple Powdery Mildew

B. Qualitative Results

The model's findings were evaluated on an augmented dataset with the fixed hyperparameters but modest variations in number of convolution layers, kernel size, activation function, number of max pooling layer setup, resize and rescaling, various normalization techniques are selected and tested , batch size, epochs, and train-test split by altering the validation size [?]. After all trying all combinations with these parameters and performing the testing on the model, here in Tabel III, We find the best accuracy with the following hyperparameters:

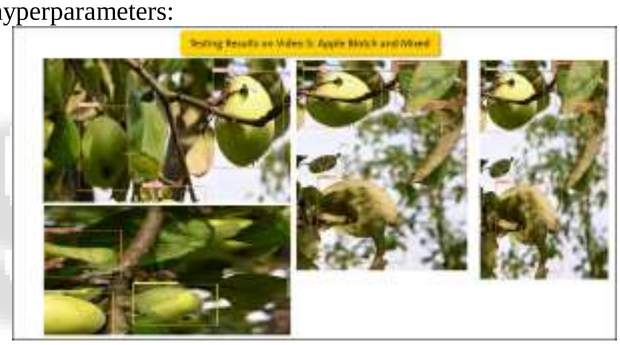

Fig. 19. Testing Results on Video 5: Apple Blotch and Mixed

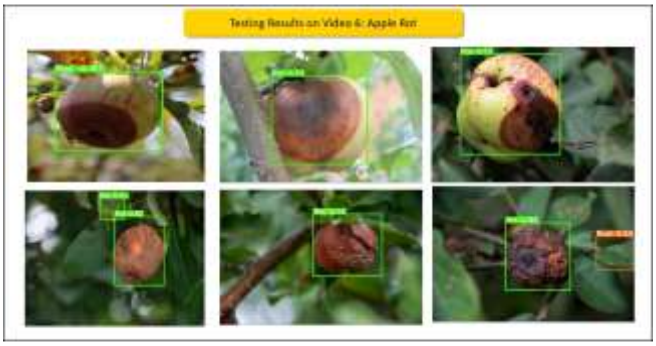

Fig. 20. Testing Results on Video 4: Apple Rot

S No.	Hyperparamete	Description
1	Image Size	256 * 256
2	Channels	3
3	Epochs	50
4	Train Test Split	0.8:0.2
5	Validation Split	0.1
6	Shuffle	True
7	Data Augmentation 1	Random, Zooming, Flippig
8	Data Augmentation 2	Shearing, Rotation

9	Activation Function	Relu
10	Output Activation Fn	Softmax
11	Kernel Size	(3,3)
12	Maxpooling	(3,3), 6 Layers
13	Con2D Layers	6 layers
14	Trainable Parameters	183812
15	Optimizer	Adam
16	Metrics	Accuracy
17	Batch Size	32
18	Loss Function	Sparse Categorical Cross Entropy

Table 3: Best Accuracy Hyperparameters

After adjusting all of the variables, the best results are achieved with test 7. (batch size, epochs, and train-test split and number of convolutional layers, kernel size) shown in Table III. It shows that test 7 is the best option for a stable, bias-free model with excellent accuracy across almost all classes. As a consequence, our deep learning model has a 98.58% accuracy on the test dataset and 97.81% on the validation dataset. The prediction of apple-leaved diseases is shown in Fig?? with the confidence percentage. The average accuracy of the prediction of apple leaves is 97.31%.

Aside from that, there are just a few observations that can be made after observing Apple leaves disease detection accuracy. Some observations are as follows:

When compared to 24, a batch size of 32 produces considerably superior outcomes [?]. It is preferable to split training and testing in an 80/20% ratio rather than a 60/40% split.At approximately 50 epochs, the deep learning model begins to converge and has a minimum error. Although a dropout of 0.1 offers better accuracy than a dropout of 0.2, the dropout of 0.2 is significantly more resistant to bias owing to overfitting of training data [?], especially when the dataset only includes a few hundred samples.

The accuracy of the CNN model increases as we increase the number of the epochs up to 50 during the neural network training and avoids overfitting to the training data [?]. The below snippet Fig?? plots the graph of the accuracy of the CNN model vs. the number of epochs taken into consideration.

Test Loss	Test Acc	Val Loss	Val Acc
0.03	98.58	0.08	97.81

Table 4: Deep Learning CNN Model Metrics Values

The CNN model achieved a maximum accuracy of 98.58 percent on the test dataset and 97.81 percent on the validation dataset with 50 epochs, as shown in the modal accuracy plot in Fig?? and modal loss shown in the Fig ?? We can observe from the loss plot that the model performs similarly on both the train and validation datasets (labeled test). If these parallel plots begin to diverge consistently, it may be time to cease training at a previous epoch. The model test loss, test accuracy, validation loss, and validation accuracy is shown in Table IV

V. CONCLUSION

This study concentrated on discovering diseases in apples using images of their leaves. As a deep learning-based technique to address the disease diagnostic issue, we present a convolutional neural network architecture trained on the dataset described in the dataset collection section. Once an image is presented, all that is left to do is run the code, and the system will be able to accurately predict the disease class from which the apple tree is suffering. The CNN network's whole design is discussed in the proposed work section. The CNN network can diagnose plant diseases better than an expert's eye with only a little fine-tuning.

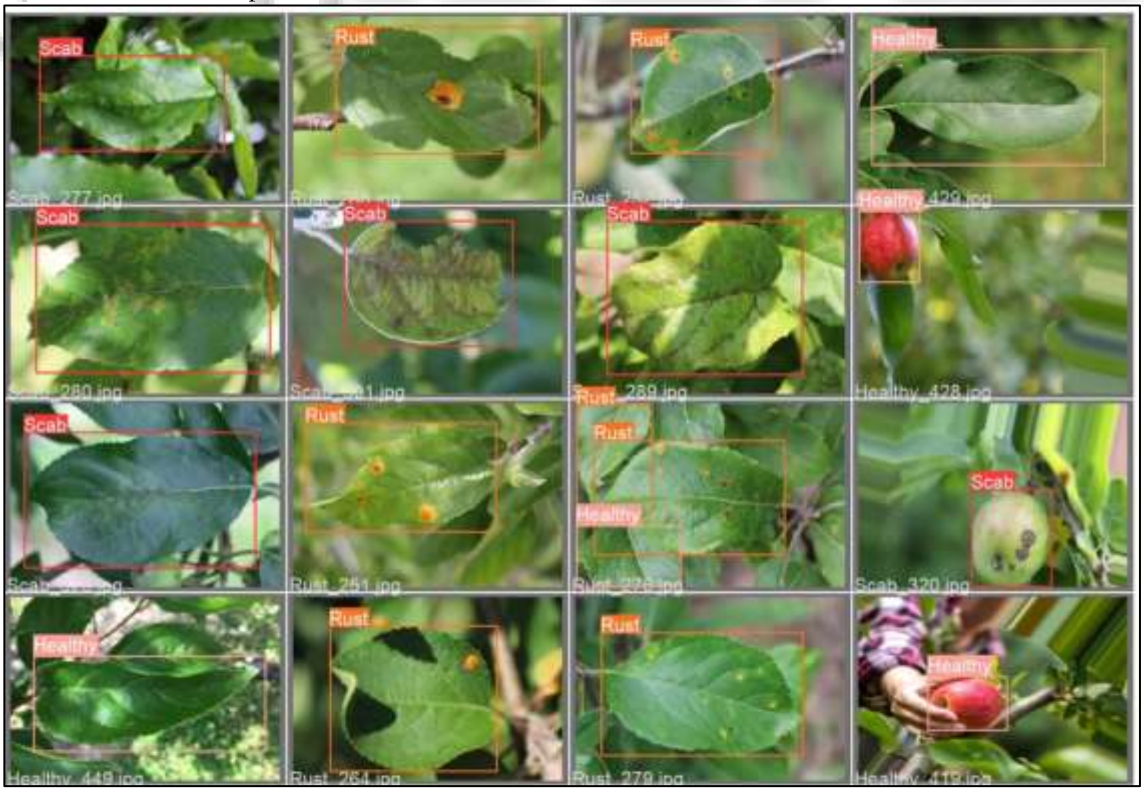

Fig. 21. Prediction of Apple Leaf Diseases

Table III shows how to fine-tune the CNN model by adjusting parameters such as the dropout amount, batch size, and train-test partition. With a 97.81% accuracy, the model was able to recognize Apple Black Rot, Apple Cedar Apple Rust, Healthy Apple, and Apple Scab. These consistently high accuracy findings show that the state-of-the-art CNN is superior to the expert's eye in diagnosing plant diseases.

Fig. 22. Prediction of Apple Leaf Diseases

VI. FUTURE SCOPE

The method described in this paper can be implemented in more fruit disease detection situations and the future to further test the suggested model's performance. The prospect of expanding this study to hand-held technologies is extremely intriguing, given the exponential increase in mobile computing technologies and the development of specific mobile-platform Neural Processing Units. Furthermore, this technique can let us collect data on the fly and test it on a variety of real-world samples while concurrently refining the model and adding new inputs.

So this deep learning-based CNN modal can be converted into a web-based application and mobile application so that farmers can use it directly as other mobile apps in their smartphones. In the future, This CNN modal can be used with the transfer learning approach and can be used with the pre-trained modals of convolutional neural networks such as VGG, Inception, and ResNet to assess and enhance the modal's performance.

REFERENCES

[1] Y. Abbaspour-Gilandeh, A. Aghabara, M. Davari, and J. M. Maja, "Feasibility of using computer vision and artificial intelligence tech- niques in detection of some apple pests and diseases," Applied Sciences (Switzerland), vol. 12, 1 2022.

[2] K. Bhat, S. Peerzada, and A. Anwar, "Alternaria epidemic of apple in kashmir," African Journal of Microbiology Research, vol. 9, no. 12, pp. 831–837, 2015.

[3] M. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep learning for tomato diseases: classification and symptoms visualization," Applied Artificial Intelligence, vol. 31, no. 4, pp. 299–315, 2017.

[4] R. Hassan, "Grim omen for apple growers as scab noticed on trees after plenty of rain," https://kashmirreader.com/2021/04/19/grim-omen-for-apple-growers-as-scab-noticed-on-trees-after-plenty-of-rain/, 21 April, 2021.

[5] A. Abbas, S. Jain, M. Gour, and S. Vankudothu, "Tomato plant disease detection using transfer learning with c-gan synthetic images," Comput- ers and Electronics in Agriculture, vol. 187, 8 2021.

[6] A. C. Vela´squez, C. D. M. Castroverde, and S. Y. He, "Plant–pathogen warfare under changing climate conditions," Current Biology, vol. 28, no. 10, pp. R619–R634, 2018.

[7] N.-D. Nguyen, T. Do, T. D. Ngo, and D.-D. Le, "An evaluation of deep learning methods for small object detection," Journal of Electrical and Computer Engineering, vol. 2020, 2020.

[8] J. JJMCOE, "Detection and classification of apple fruit diseases using k-means clustering and learning vector quantization neural network." 2017.

[9] S. Xing, M. Lee, and K. K. Lee, "Citrus pests and diseases recognition model using weakly dense connected convolution network," Sensors (Switzerland), vol. 19, 7 2019.

[10] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, "A robust deep-learning- based detector for real-time tomato plant diseases and pests recognition," Sensors (Switzerland), vol. 17, 9 2017.
[11] B. Liu, Y. Zhang, D. He, and Y. Li, "Identification of apple leaf diseases based on deep convolutional neural networks," Symmetry, vol. 10, 1 2018.
[12] "Apple leaf diseases recognition based on an improved convolutional neural network," Sensors (Switzerland), vol. 20, pp. 1–14, 6 2020.
[13] J. Liu and X. Wang, "Tomato diseases and pests detection based on improved yolo v3 convolutional neural network," Frontiers in Plant Science, vol. 11, 6 2020.
[14] M. Turkoglu, D. Hanbay, and A. Sengur, "Multi-model lstm-based convolutional neural networks for detection of apple diseases and pests," Journal of Ambient Intelligence and Humanized Computing, 2019.
[15] C. B. Murthy, M. F. Hashmi, N. D. Bokde, and Z. W. Geem, "Investi- gations of object detection in images/videos using various deep learning techniques and embedded platforms-a comprehensive review," 5 2020.
[16] H. Zhu, H. Wei, B. Li, X. Yuan, and N. Kehtarnavaz, "A review of video object detection: Datasets, metrics and methods," pp. 1–24, 11 2020.
[17] G. B.V. and U. D. G., "Identifying and classifying plant disease using resilient lf-cnn," Ecological Informatics, vol. 63, 7 2021.
[18] S. Kumar, V. Chaudhary, M. Supriya, and K. Chandra, "Plant disease detection using cnn," pp. 2106–2112, 2021.
[19] F. R. Albogamy, "A deep convolutional neural network with batch normalization approach for plant disease detection," IJCSNS International Journal of Computer Science and Network Security, vol. 21, p. 51, 2021. [Online]. Available: https://doi.org/10.22937/IJCSNS.2021.21.9.6
[20] P. Bansal, R. Kumar, and S. Kumar, "Disease detection in apple leaves using deep convolutional neural network," Agriculture (Switzerland), vol. 11, 7 2021.
[21] H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik, and Z. Alrahamneh, "Fast and accurate detection and classification of plant diseases," pp. 975–8887, 2011.
[22] H. Sun, H. Xu, B. Liu, D. He, J. He, H. Zhang, and N. Geng, "Mean- ssd: A novel real-time detector for apple leaf diseases using improved light-weight convolutional neural networks," Computers and Electronics in Agriculture, vol. 189, 10 2021.
[23] J. S. H. Albayati and B. B. U¨ stu¨ndag˘, "Evolutionary feature optimization for plant leaf disease detection by deep neural networks," International Journal of Computational Intelligence Systems, vol. 13, pp. 12–23, 1 2020.
[24] G. Storey, Q. Meng, and B. Li, "Leaf disease segmentation and detection in apple orchards for precise smart spraying in sustainable agriculture," Sustainability (Switzerland), vol. 14, 2 2022.
[25] H. Ayaz, E. Rodr´ıguez-Esparza, M. Ahmad, D. Oliva, M. Pe´rez- Cisneros, and R. Sarkar, "Classification of apple disease based on non- linear deep features," Applied Sciences (Switzerland), vol. 11, 7 2021.
[26] M. Everingham et al., "Fatta, ha, 2007. konversi format citra rgb ke format grayscale menggunakan visual basic. yogyakarta, seminar nasional teknologi 2007 (snt 2007)." Challenge, vol. 111, no. 1, pp. 98–136, 2010.
[27] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dolla´r, and C. L. Zitnick, "Microsoft coco: Common objects in context," in European conference on computer vision. Springer, 2014, pp. 740–755.