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An In-Depth Repository of Fruit Disease Identification using Deep Learning Analysis

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ABSTRACT: Fruit disease identification is facilitated by the use of Artificial Intelligence (AI) methods in the agricultural sector. Early illness prediction helps in taking the right management measures. This is a significant development in the fight against sickness and the production of high-quality goods to satisfy the world's need. At this point, we may take preventative measures to limit the spread of illness in plants, and the results from those plants will ultimately benefit the expanding human population. Many fruit datasets are accessible for study of plant stems and roots in the public domain. This information may be used effectively even by those without a strong background in agriculture. This study introduces nine new Convolutional Neural Network models for image-based plant leaf classification, including a deep convolutional neural network and eight previously developed models. Two methods of data augmentation are used to the collection of fruit disease images in order to increase its size and depth. There are three distinct color augmentation methods and six distinct position augmentation methods that may be used to enhance the data.

KEYWORDS: fruit disease detection, segmentation, feature extraction, feature selection, deep learning, convolutional neural network

I. INTRODUCTION

Image classification is a very active research direction in many areas and plays a very important role. Image recognition serves various uses including video analysis, face recognition, image classification, etc. Deep learning (DL) is a subdomain of machine learning (ML) that has shown excellent results in image identification [1]. DL utilizes the multi-layer structure to process image characteristics which significantly increase image recognition efficiency [2]. In other words, the application of image recognition and DL is becoming a concept within the field of logistics and supply chain. For instance, image recognition can better facilitate logistics and transportation and solve the errors in many fully automated transport vehicles due to large-scale track identification errors [3]. Another application of DL is the classification of fruits. DL can effectively extract image characteristics and then introduce classification.

Current computer vision (CV) developments have shown outstanding results in many areas of life. Fruit detection and classification has demonstrated to be a complex and a challenging task. For some economic sectors, both for wholesale and retail markets, research in fruit processing is very important including the processing industry. These factors have motivated researchers who developed various methods to process fruits automatically, either to identify them or to estimate their quality efficiently. Over the past few years, agricultural industries such as food processing, marketing, packaging, and fruit classification have become more focused research direction. Processing and sorting of unique crop plants such as orange, cherry, apple, mango, and citrus are labor and time intensive due to a number of varieties of same fruit, for instance, more than 7,000 apple varieties are produced worldwide (<http://usapple.org>). Automation can thus minimize labor costs and quickly increase productivity. In early research, scientists suggested different methods from CV in order to manually extract features from fruit and ML for classifying the CV features. Through CV algorithms, color, form, size, and texture characteristics of fruit are used for classification algorithms [4–6]. Most of them utilized preprocessing or feature extraction through CV in conjunction with different classifiers. However, most evolved classifiers are not robust for all fruit types which results in higher misclassification rates. For quality evaluation and robotic harvesting, fruit detection and classification has seen some implementation of DL methods, but these

methods are having limited classes and small datasets. Literature analyses of new methods to classify fruits were published in 2017 by Liu et al. [7]. They conducted a search on the recent published work in the area of fruit detection and classification. They selected, among others, eleven publications that were significant. Among the selected publications, just 4 works discuss DL or other conventional ML methods [8–11]. This demonstrates that while convolutional neural networks (CNNs) were of great interest at that time, still many studies on fruit detection and classification did not utilize CNNs. They also suggested that DL models should be more commonly used, especially CNNs, because they have shown state-of-the-art performance on image classification in biomedical and health informatics.

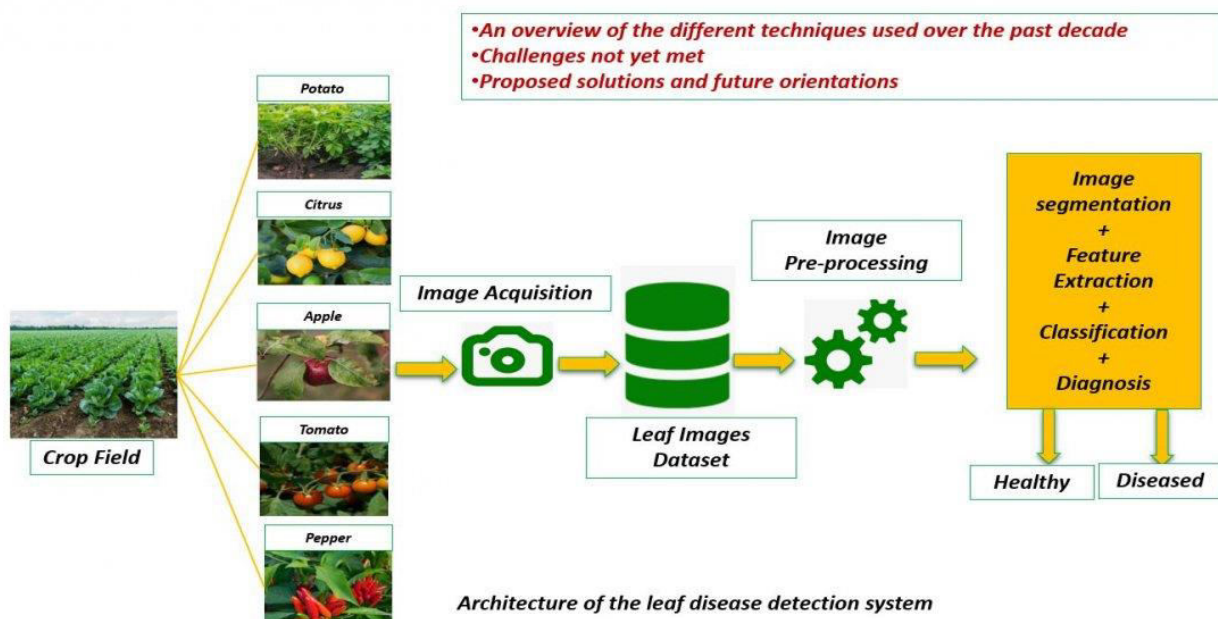


Fig 1:

In the area of object detection and image recognition, CNN has become a highly important model for study. CNN’s ability to extract attributes automatically from an input image made it more robust to use. In CNN, the image can be fed into the network directly in contrast to conventional CV-based feature extraction algorithms, and thus it eliminates preprocessing and extraction processes. Convolutional layers (CLs), pooling layers (PLs), and fully connected (FC) layers are the three layers that make a classic CNN. After winning the ImageNet award, CNN gained much attention [12]. The various CNN models developed by many scholars by varying width and depth of layers were then discussed in [13–15]. Detection and classification of fruits is a relatively complex problem due to the great variety of intraclass forms, colors, and textures. These limitations have led to a shortage of automated fruit classification systems for multiple classes. A more complex information system of fruit automated detection and classification may be useful in picking right fruit with the correct nutrition. It can support children and people with visual impairments and develop self-checking supermarkets. We identify fruit classification tasks as class determination by their particular type in order to define the study areas of our review.

II. BACKGROUND

DL is described as research direction in ML for the creation of complex models that solve complex tasks. DL models have been developed using supervised learning techniques and based on artificial neural networks. The fact that these models are proven capable of understanding the problem that needs to be resolved in the hierarchy of concepts is an essential component of DL [6]. CV is one of the areas in which DL achieved state-of-the-art performance. More precisely, on problems like optical character recognition [7], object detection [8], semantic segmentation [9], and image classification [2], DL models were found to achieve the best results. Thus, presently, most of the practical solutions for these concerns are DL based.

In current history, a number of papers have shown tremendous progress in modelling frameworks with DL for image recognition. With the CNN, the authors in used DL for the identification of fruit objects and achieved an outstanding degree of both learning and recognition. In, the studies evaluated two CNN architectures, namely, MobileNet and Inception, as the classifiers of ten classes of fruit. They claimed that MobileNet was propagating images with about the same accuracy significantly faster [22]. However, clementines and kiwifruits were difficult to predict which may be due to the option of training and testing a number of images taken with a video camera mounted to the conceptual retail market systems and simultaneously obtained from ImageNet. Abdul Hamid et al. [23] introduced a comparative analysis between the bag of features (BoF), AlexNet, and a CNN for fruit recognition. The results showed that all three methods were very reliable, but the most rapidly available prediction for recognition was the CNN technique. In turn, two deep neural networks, with excellent results in the precise fruit classification of both bases, were proposed and tested in utilizing simple and more complex datasets. A number of computational experiments have been presented in to train various CNN architectures to detect fruit. For a similar reason in, a 13-layer CNN was proposed.

There is significant evidence of attempts to develop an automated fruit detection and classification system. Fruit identification faces a variety of challenges due to its irregular form, size, and varying color. A lot of research has been undertaken to define strategies for coping with these problems. Virtually every physical component of fruits is known to be feasibly classifiable. ML methods have been investigated and continuously developed for this role, both by the empirical network and neural network (NN). In this respect, most attempts are made to combine image analysis as feature details with ML framework for classification/recognition. These efforts identify and represent a physical feature in a vision-based machine representation called the description of features or feature description. These characteristics are then given to converge on a qualitative result as the input to the classification algorithm. Numerous techniques for the description and classification of features have been studied, but substantial overhaul and enhancement are required to achieve an efficient classification. A thorough reconsideration for all associated questions of features, sensors, and classification algorithms is important for an effective system of detection and classification for fruit.

II. METHODS

Taking hint from the work of Zhang et al. [135] on plant leaf disease recognition, we saw that the authors constructed a three-channel CNN framework which accepts three color components, thereby reducing the known DL requirement of large dataset in training and achieving a high detection accuracy. Such idea should be adopted in designing a fruit detection and classification system, thereby overcoming the issues of the small availability of training datasets. Looking at the acquisition of dataset used, most researchers focused on the images generated in the visible range, whereas a lot of information is contained in the electromagnetic wave outside the visible range, and thus researchers should pay attention to the information such as multi-spectral, near infrared, and visible light during dataset acquisition.

Looking at the current trend in DL, in the field of fruit detection and classification, researchers widely adopt the supervised learning method, thereby requiring that the datasets for training must be large. Manually labelling of the datasets takes a lot of time and manpower, and thus researchers are recommended to venture into the unsupervised mode of learning. Deploying trained DL models on mobile platforms are unsuitable due to the large amount of memory needed during testing as well as the time consumption of the models. It is very critical for researchers to study how to reduce complexity as well as study fast executing models without affecting the result. Generally, hyperparameter selection has been a big problem in deep learning especially in new task. It affects the model result positively and negatively, thus having greater effect on the final training results.

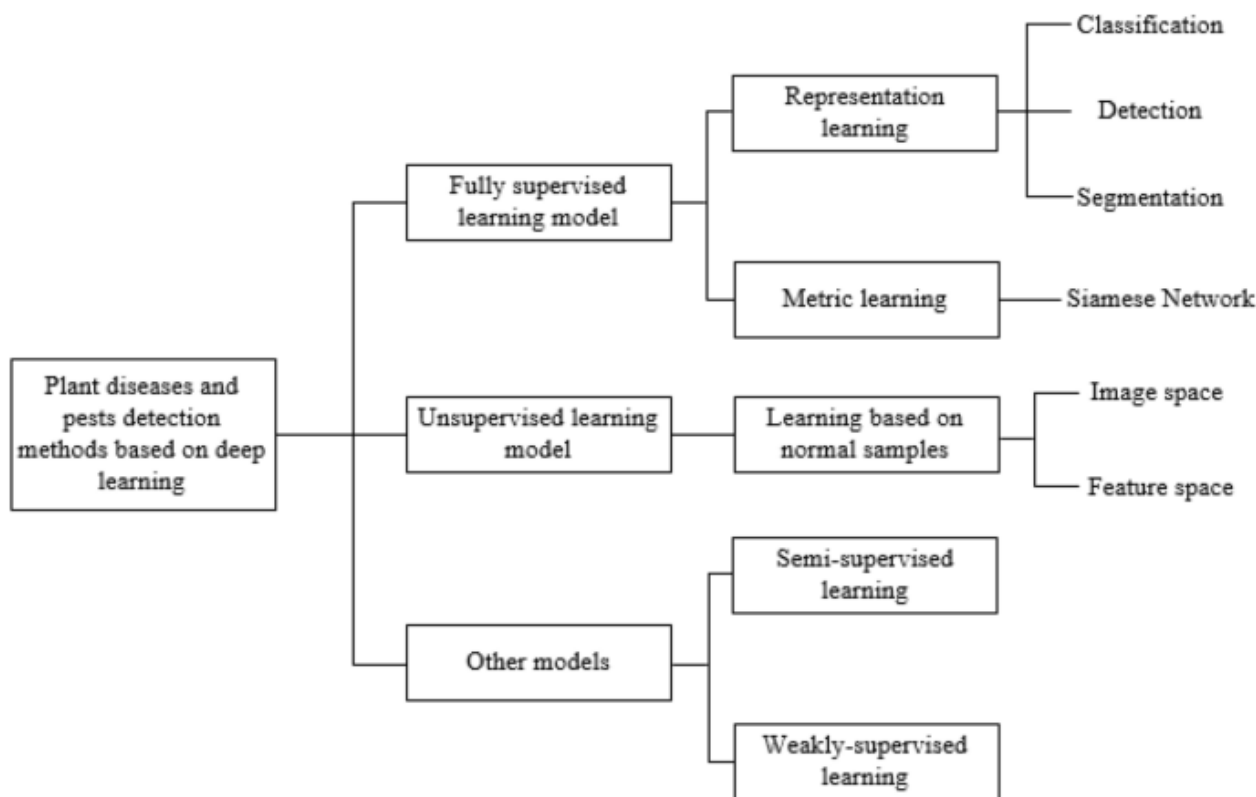


Fig 2: Work Flow

Attention mechanism (AM) has gained a lot of attention in computer vision fields such as object detection and classification [136]. There is need to incorporate AM into DL frameworks for the task of fruit detection and classification since AM has a high capacity to pick features. Knowing that CNN and RNN-based models are widely used in fruit detection and classification, we suggest the use of AM to extract the fruit features which are difficult to distinguish due to their size, shape, and color and enable them into another CNN for information fusion. The goal of AM which is to predict the weight vector for feature maps by model learning makes the integration one of the possible best solutions to tackle the issue of fruit detection and classification.

IV. RESULT ANALYSIS

In order to give basic understanding of what is meant by DL model to beginner researchers who do not necessarily have skills in computer science especially in the area of agriculture, we present the practical implementation of a simple DL model (CNN) for a fruit classification task. We used the PyTorch framework in our implementation. PyTorch is a famous open-source learning machine library based on torches that have a wrapper in C. It is an alternative to the open-source machine library, TensorFlow. It was primarily developed and published under the modified BSD license by the Facebook AI Research lab (FAIR). It stores data as a 3D-based storage system called tensor rather than vector, like TensorFlow. PyTorch supports many languages, but Python is extensively the most recognized language of all. PyTorch is a more flexible library for developing DL-models. However, Keras and Tensorflow provide built-in architectures with less flexibility. In DL-based research, PyTorch offers maximum versatility and speed.

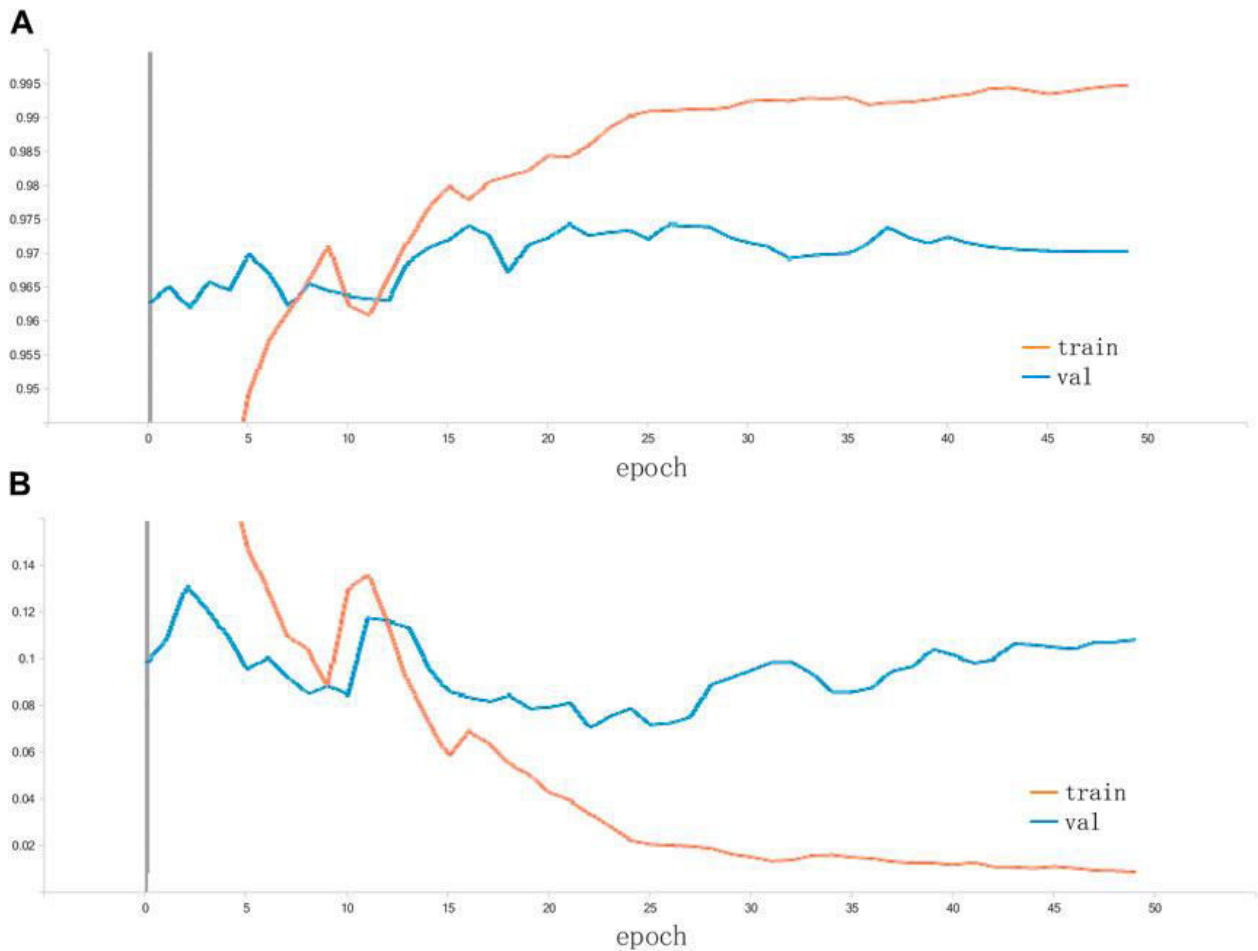


Fig 3: Result analysis

We employed the Fruit 360 dataset in our experiment as it is currently the widely used dataset in fruit classification by researchers. We maintain the set value for the training and testing sets as originally done by the owner. shows our model configurations. We set our hyperparameters (learning rate, no. of epochs, batch size, and dropout) to 0.001, 40, 15, and 0.5, respectively. We made use of the Adam optimizer which is an extension of the stochastic gradient descent. Adam optimizer has seen a wider adoption in CV for DL applications. Indicates that after 15 epochs, our network achieved a validation accuracy of 100%. To avoid overfitting, we applied dropout (0.50) to the network from which we observed that the validation loss graph decreases alongside the training loss. illustrates the details of the employed classifiers, whereas the implementation details of the CNN architecture. shows the model training and validation loss. We plotted the model loss curves against the number of epochs.illustrates the training vs the validation accuracy of the model. With the help of the dropout, we were able to overcome overfitting. Our model achieved an overall classification accuracy of 95%.

V. CONCLUSION

In this study, we studied and analyzed various deep learning methods proposed by numerous researchers in the domain of fruit detection and classification. While studying different automated approaches for fruit detection and classification, we noticed that previous review papers focused on the application of computer vision techniques in the area. However, deep learning models were not given much attention despite their state-of-the-art performances on many image classification problems. To fill this gap, we conducted an up-to-date review of the recently published literature in the domain of fruit detection and classification that utilized deep learning models. Additionally, a detailed study was presented considering feature description, detection, and classification algorithms as well as different

datasets for fruit detection and classification. Moreover, after critical analysis of the reviewed methods, open challenges in terms of datasets, feature representation, and classification algorithms were identified to overcome.

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