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Smart Disease Detection System for Citrus Fruits Using Deep Learning with Edge Computing

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Abstract: In recent decades, deep-learning dependent fruit disease detection and classification techniques have evinced outstanding results in technologically advanced horticulture investigation. Due to the comparatively limited image processing capabilities of edge computing devices, implementing deep learning methods in actual field scenarios is currently difficult. The use of intelligent machines in contemporary horticulture is being hampered by these restrictions, which are emerging as a new barrier. In this research, we present an efficient model for citrus fruit disease prediction. The proposed model utilizes the fusion of deep learning models CNN and LSTM with edge computing. The proposed model employs an enhanced feature-extraction mechanism, with a down-sampling approach, and then a feature-fusion subsystem to ensure significant recognition on edge computing devices with retaining citrus fruit disease detection accuracy. This research utilizes the online Kaggle and plan village dataset which contains 2950 citrus fruit images with disease categories black spots, cankers, scabs, Melanosis, and greening. The proposed model and existing model are tested with two features with pruning and without pruning and compared based on various performance measuring parameters, i.e., precision, recall, f-measure, and support. In the first phase experimental analysis is performed using Magnitude Based Pruning and in the second phase Magnitude Based Pruning with Post Quantization. The proposed CNN-LSTM model achieves an accuracy rate of 97.18% with Magnitude-Based Pruning and 98.25% with Magnitude-Based Pruning with Post Quantization, which is better as compared to the existing CNN method.

Keywords: citrus fruit disease; deep learning method; edge computing; pruning feature; CNN; LSTM

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1. Introduction

In the past few years, fruit disease classification has been the topic of intense dispute among researchers all around the globe. The establishment of systems that can limit human appearance is the goal of computerized assessment and categorization. In the current situation, precise examination of fruits and veggies is prominent. The FAO-2022 report estimates that 197,198 million tonnes of citrus fruit will be produced globally, with oranges comprising more than 50% of that production. Producing quality fruits at a lower cost while ensuring they are free of disease-causing insects and viruses is a goal for farmers [1]. This goal can be achieved by using the right automated standards and proactive maintenance methods. Fruit diseases pose a serious threat to citrus growing in the present era. Since a few tainted fruits could spread the disease to just the opening sequence throughout data-processing or delivery, the citrus industry needs quick and automated disease screening throughout post-harvesting [2].

The advancement of image processing by AI-based techniques, i.e., machine learning, and deep learning have great resilience and consistency at low prices, high precision, and speed capability to evaluate citrus fruits disease and quality under bad weather and typical ecological factors. The edge computing significant gains have experienced a difficult development process for IoT solutions [3]. The conventional neural network's (CNN) scope is limited in order to meet increasing demands due to its rigid establishment of effectiveness. Deep learning forecasts mainly focus on a set of variables, which can help to produce a large weight matrix. These models demanded a significant of computational and memory resources to train and validate. However, it is difficult to implement these criteria on low-cost devices or technology with few resources to deal with [4].

1.1. Background Research

The learning categories, i.e., supervised and unsupervised can be utilized in deep learning methods. The performance measures differ based on the specific application area wherein deep learning has been employed. The complexity of the Hyperparameter selections makes it difficult to design an effective DNN model or choose the best DNN model for a particular application [5]. It can be beneficial for the DNN modeling planner or the developer to have a sound knowledge of the choices among speed, precision, storage, cost, and other running processes [6]. There are numerous uses for deep learning methods on edge devices, including object recognition, language processing, networking protocols, the Internet of Things, voice recognition, and image segmentation. Numerous quick-performing DNN inference architectures have been created in order to help these services achieve their latency constraints. Figure 1 shows the techniques of rapid analysis in fruit disease classification.

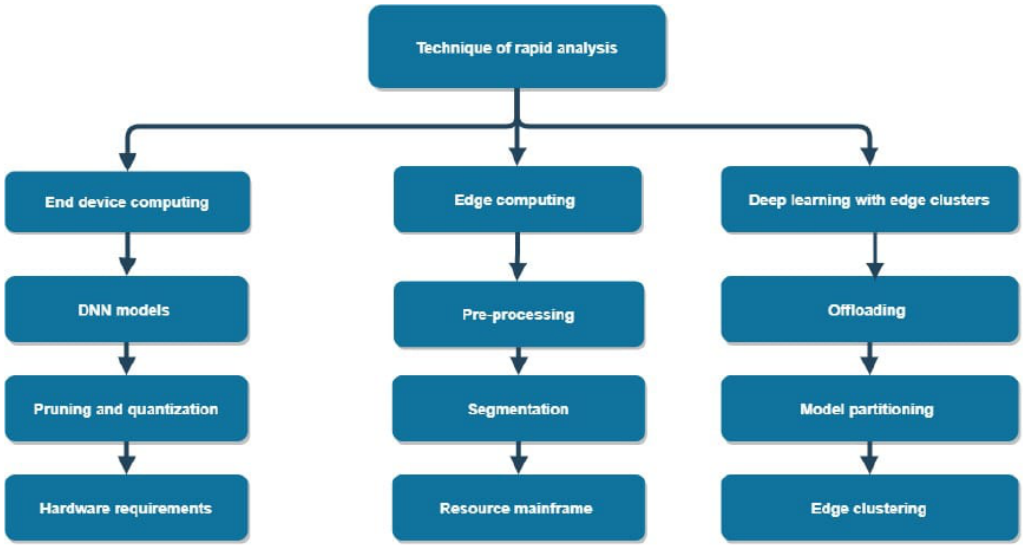


Figure 1. Techniques of rapid analysis in fruit disease classification.

1.2. Method for Fast Interference

Three significant experimental models are addressed in this examined in this section: There are three types of computations: (a) on-device mathematical computation, wherein DNNs can run just on edge devices; (b) Architecture based on an edge server, in which the input is collected from the edge nodes and directly transferred with one too many edge computing servers for calculation; and (c) Architecture based on joint computation feature among end computing devices, cloud, and edge computing servers. There have been a lot of studies carried out on how to make deep learning run more quickly on devices with limited resources [7].

These initiatives can help the entire edge ecological system by minimizing the latencies of a DNN since operating on edge devices or edge computing platforms servers. Machine

learning investigators concentrate on modeling the system with a smaller set of variables in the Convolutional neural network, lowering storage and operation delay while striving to maintain high precision when constructing DNN algorithms for resource-constrained systems. DNNs can also be allowed on edge nodes by reducing the number of layers and lowering the model. Typically, these techniques aim to reduce the size of the current DNN modeling while preserving as much precision as possible in comparison to the previous model. Parameter reduction, parameter filtering, and information extraction are some common techniques for prototype compression. Here is a quick summary of these strategies [8].

1.3. Quantization and Pruning Techniques

Using low-bit width values instead of expensive floating-point operations such as multiplication and division, variable reduction compresses the parameters of a conventional DNN. The lowest crucial aspects are eliminated in the pruning process (close to 0). There have been both separate and combined considerations of the quantized and pruning methodologies [9].

This research presents efficient fruit disease identification and classification model using deep learning-based CNN and LSTM techniques with edge computing. The key contribution of the research includes.

- Citrus fruits dataset with various diseases is gathered from various online sources and submitted to edge computing devices for categorization. Edge computing devices which have a limited number of resources are unable to run complex DNN-based applications.
- This research utilizes a light processing-based CNN-LSTM model with edge computing for Citrus fruit disease classification. We have also quantized and pruned the edge network. So that the proposed model can able to run on limited resources.
- The proposed model utilizes three phases. Phase 1 includes data collection, and data pre-processing, and phase 2 includes re-scaling of images, data augmentation, and image segmentation by K-mean clustering and canny edge detection, also applying CNN-LSTM for model training. Phase 3 is the final process which includes testing of the images and classification. In this phase, experimental analysis is performed using Magnitude-Based Pruning, and in the second step Magnitude-Based Pruning with Post Quantization.
- The Online Kaggle dataset is utilized in this research. The proposed model and existing CNN model are compared based on various performance parameters, i.e., precision, recall, f-measure

The organization of the article is as follows: the dataset used for the implementation of the model is described in Section 2. In Section 3, the proposed edge computing configuration, including pre-processing, data augmentation, classification, pruning, and quantization processes is defined. The outcome and performance evaluation are included in Section 4. Section 5 concluded the proposed work.

2. Literature Review

Citrus fruit analysis, i.e., fruit quality, disease identification, and classification are hot areas of research. This section covers the comparative analysis of various existing works in the field of citrus fruit disease classification.

Edge Computing is a hot topic that the research community is closely associated with because of its implications for science, technology, and industry. The incorporation of the ETSI guidelines has significantly strengthened the case for edge computing. However, many of the present MEC biological studies fall short, which prevents and invalidates their implementation [10]. A wide range of innovative rapid prototyping, functionalities, and implementation seems to be critical to overcome this discrepancy. Early initiatives can prove the functionality, restrictions, connected techniques, and application frameworks for multi-edge factors affecting the adoption of edge computing [3]. A large amount of

IoT statistics is forwarded to the cloud through the cloud-based architecture for strategic decision, research, and data processing. It could cause not just limited availability on the data center but also increased communication overhead, possibly negating the benefits of the cloud. To deal with these challenges, investigators are looking for new distributed network models for IoT-based computing devices and networks, and technology.

One such method that is receiving a lot of attention among both academia and industry experts is edge computing. The fundamental idea behind the edge computing technique is to shift the processing of digital information from remote servers to relatively close machines. It is encouraging to see the advancement of more massively parallel, low-latency, and efficient edge computing devices and IoT-edge systems [4]. To determine an optimal technique to determine image imperfections on the citrus fruit skin, an associated with advanced PCA with B-Spline illumination clarification assessment was incorporated. Machine learning and computer vision methods carry out image processing. The proposed model helps to estimate and retrieve useful information for fruit disease images concerning [5].

Various IoT-based devices and sensors are widely used to collect fruit images. Typically, hyperspectral functionality provided obtained 2D statistics at a period and checked all over three-dimensional. Premised on the filtering method multispectral imagers as well as imaging systems are classified into two types: optical filtration and digitally configurable filters [6]. The most frequently used image transmission process is a 3-CD webcam with illumination gray walls accented with gray files [7]. Numerous image fusion strategies, such as pixel level, quantitatively, and metaphorical level, were formed in recent decades. Image enhancement is being used by investigators to recognize orange fruit disease [8]. The terms near-infrared spectrograph and spatial frequency acquisition refer to two distinct edge devices, namely the segments, and sub-FT-spectrometer. A multivariate regression prototype was utilized to evaluate these two small and medium companies and FT-spectrometers [9].

Image enhancement can be employed to detect and classify diseases at a lower cost. In the proposed model an enhanced Image principal component analysis is implemented to apply reduction on orange images. The Edge detection module in the proposed model mainly extracts seven attributes from the orange fruit image dataset. Next, then, a method of deep learning is employed to detect orange fruit conditions at their earliest stages of growth [10]. The study suggested an image processing technology for evaluating the various imperfections in citrus fruits and detecting malformations in fruit. A failure mark's symptoms reveal the character of the disorder and suggest the ideal treatment regimen [11]. To find the desired diseased region, segmentation is conducted using DE color change. In addition, color statistics and texture analysis were used to classify the disorder [12].

Lime and orange citrus fruit with pharmacological decays have lower economic potential. The investigator proposes a method of image handling to recognize types of diseases on X-ray image data of lemons and oranges fruit. The image sequence was automatically classified using K - means and Naive Bayes similar techniques [13]. The researchers utilized the partial least squares analysis to look into the connection between granulation psychological disorder incidence and quality characteristics [14]. The categorization of infectious illnesses affecting citrus fruits has been incorporated using heuristic methods that combine Deep Convolutional neural networks& random forest methodologies [15].

A modern AlexNet infrastructure that utilized deep learning has been used to detect diseases successfully. This method was divided into four major steps: pre-processing, edge detection, object recognition, and categorization [16]. The characteristics of the input object were first improved through pre-processing. After that, the images and videos were categorized using the Based segmentation method. An Alex-Net framework was initially presented as just a filtration feature. A random forest method was finally utilized for the categorization of citrus fruit diseases. Ten independent factors were employed as the neural network's feedback to identify the feature set [17].

RNNs are a type of Neural Network model that uses the immediately preceding step in the process outcome is utilized as direct input within the initial stage. The most popular uses of RNNs include the classification of sequences, emotions, images, and videos [18].

RNNs are a type of network wherein node links establish a sequentially ordered graph. It resembles a linked sequence of items from a deep network. Each one is communicating with the individual ahead of them in sequence. An RNN is trained to recognize patterns and behaviors, whereas a CNN is trained to recognize patterns throughout space [19].

SVM classifiers [20] were utilized to classify citrus fruit after modifying the existing CNN method for the classification procedure. Feature values were accumulated utilizing k-mean cluster analysis. The multi-class problems damage the overall system effectiveness even though they decreased the rate of false positives. The researchers [21,22] developed a segmentation technique to incorporate prediction models. It has enhanced the segmentation algorithm in identification for sensing the three separate types of disorders. Images of lemon fruits with softness and bacterial blight were used in the testing. In order to categorize the binary classification diseases, backpropagation architectures were used. Although this remedied the multi-class problem, the data processing is extremely complex. Table 1 represents the comparative analysis of the performances of different detection model using various kind of pruning techniques.

Table 1. Comparison between different compression Models.

	Detection Model/Type	Pruning Technique	Accuracy without Pruning	Accuracy with Pruning	Loss Ratio	Image Original Size MB	Image Size After Pruning MB	Size Reduction %
[11]	Classic MNIST	Kernel-based	97.98	98.19	0.0478	58.14	12.9	77.84%
[12]	MNIST with BSF	Kernel-based	98.47	97.58	0.1278	12.8	1.83	91.23%
[13]	CIFAR-10	Kernel-based	79.12	78.32	0.6713	29.7	8.99	67.78%
[14]	CIFAR-10 with BSF	Kernel-based	73.28	76.73	0.7117	3.89	3.21	17.86%
[15]	ResNetmodel	Channel-based	94.86	93.10	0.87	90.12	50.23	65.77%
[16]	VGG-16 model	Compressed-based (ρ_{cih} = 0:50)	88.78	86.91	0.097	NA	32.78	87.91%
[17]	LSTM model	Load Balance -based	More than 90%	More than 90%	NA	22 × X	11 × 11	94.65%
Proposed Model	CNN with LSTM and Edge computing	Magnitude-based Pruning	97.1	96.75	0.147	55.244	29.228	48.188%
		Magnitude Based Pruning with Post Quantization method	98.25	88.92	NA	55.48	81. 14	85.92

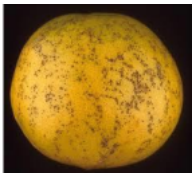
3. Materials and Methods

The complete process of implementing the proposed model for detecting the disease in a multi-class framework is further explained. The flow of steps is divided into several necessary modules into subsections explained in detail below, beginning with image collection and image processing for the training of the CNN-LSTM model with compression technique over an edge computing environment.

3.1. Dataset

Fruit diseases lead to depleted marketability and quality in the field of farming, which becomes the root cause of global loss of financial return. Citrus is a significant provenance of vitamins A and C all around the world. Citrus illnesses, on the other hand, harm the quality and yield production of citrus fruit. Citrus fruits such as lemons, grapefruit, oranges, and limes are liable to a diversity of citrus diseases such as scabs, anthracnose, black spots, HLB, and all other bacterial deformities. At all phases of object detection investigation, from the training process through monitoring the effectiveness of detection systems, adequate datasets are necessary. The image samples taken from the online dataset were collected from three sources, i.e., World Wide Web, plant village, and Kaggle. Table 2 represents different classes of citrus fruits that we have used for the classification model.

Table 2. Citrus Fruit Disease Classes.

Disease Class	Details	Sample	Ratio
Huanglongbing (HLB)	It is just a citrus fruit disease that has dramatically affected the dimension and pattern of the nation's modern agriculture. Its negative impacts are still affecting the economy as the infection progresses all across the world's largest citrus fruit-producing countries. The syndrome affects a wide range of symptoms that can be found in any place on the main plant, it affects the properties of citrus fruit.		14.4
Blackspot disorder	A bacteria and fungi disease known as the black spot is characterized by gloomy, gangrenous splodges or patches on the citrus fruit rind. This also causes premature seed size and decreases agricultural output. Fruity black spot is a fungus-caused citrus fruit disorder. This fungal infection attacks citrus crops in tropical areas, lowering fruit levels and quality.		15.3
Melanose disorder	Melanose can attack any citrus fruit variety. Melanose can directly affect plants of every age and harm their fresh fruit, twigs and leaves, small branches, as well as, in certain cases, the primary trunk. The loss is superficial that has no bearing on the individual's character of the fruit.		12.1
Citrus Canker disorder	The bacterium "axonopodispv. citri" causes the citrus disorder. Canker has a major negative effect on citrus trees' health and vitality, having caused leaves and fresh fruit to fall off before their time even though it is not toxic to human beings. Although a fruit only with canker disease is healthy to eat, its promotional campaign as fresh produce is declined. Citrus canker-causing virus can infect leaves via root systems or mutilate initiated by weather-related bruises or aphids such as the fruit leaf node.		17.3
Scab disorder	The parasitic fungus "Elsinoe-fawcettii" causes scabs. The scabs are initially grey or pale pink and darken to maturity level. They're more popular on citrus fruits instead of on leaves.		16.4
Healthy	Numerous fruit varieties, including lemons, lime, and oranges, are classified as citrus. Citrus fruit grows on annual herb trees and bushes. Individuals have thick skins as well as pulpy flesh that is segmented.		27.8

3.2. Proposed Model

The existing deep learning models, i.e., DNN, and CNN are unable to perform well on edge computing devices due to limited resources. It can be resulting long delays in processing, high latency, poor accuracy, and high computation time. In this research, we are presenting a CNN-LSTM with edge computing for citrus fruit disease early detection and classification. To identify or categorize citrus fruit diseases in a multi-classification way, it is crucial to develop a more robust and efficient model. In this research, the fruit sample images (healthy and 5 categories of unhealthy) were collected from online data sources, i.e., Kaggle, of plant disease.

Figure 2 illustrates the broad sense architecture of the proposed CNN-LSTM system model. Under this system, edge computing servers seem to be relatively close to the client computers/device, as well as the data transmission delay between the client computers and the edge computing servers seems to be significantly smaller for a cloud remote server. The major part in training A cloud can be implemented on edge servers to provide end users

with quality service, and data acquired might be continuously transferred electronically to alter the system.

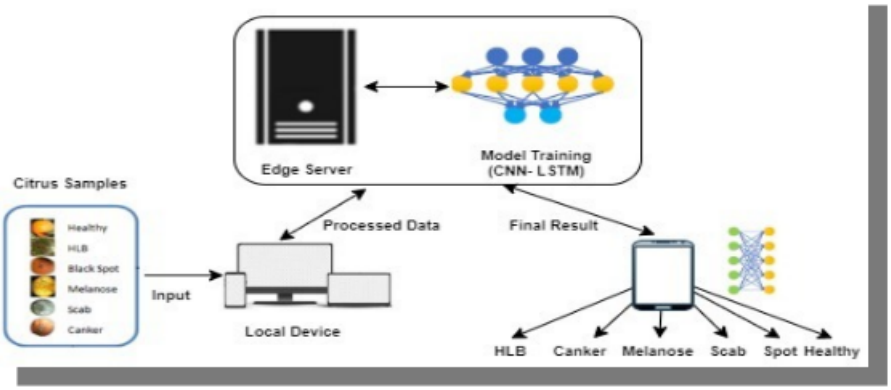


Figure 2. Architecture of the proposed model over edge computing.

Figure 3 the working steps of the proposed model. Figure 3 provides a brief explanation of how citrus fruit diseases are classified. The proposed model utilizes three phases. Phase 1 includes data collection, and data pre-processing, and phase 2 includes re-scaling of images, data augmentation, and image segmentation by K-mean clustering and canny edge detection, also applying CNN-LSTM for model training. Phase 3 is the final process which includes testing of the images and classification. In this phase, experimental analysis is performed using Magnitude-Based Pruning, and in the second step Magnitude-Based Pruning with Post Quantization. The key steps include (a) Data pre-processing, (b) Augmentation, (c) Training phase, (d) pruning process, (e) Quantization process, and (f) Measuring the performance and analysis.

After applying the image processing technique such as rescaling, data augmentation, and k-means clustering algorithm, the processed images are fed into the proposed DNN model. The proposed CNN-LSTM model mainly contains four modules.

- Its first module is composed of a collection of relevant nodes.
- The second module deploys edge computing services and resources,
- The third module contains a classification algorithm and prediction model, and also includes a pruning method with quantization features, and
- The final module deploys application programs over edge computing devices.

Each of the modules has its functionality. A link among platform-based both local as well as remote processes is provided by the third phase component. The information is gathered domestically first from public platforms, and after a pre-processing is applied to eliminate the non-relevant features. Various groupings have been created similarly to offer better accessibility to possible application circumstances. Users have access to the console's services and applications via module 4 which is the final module. As a result, the layer is responsible for providing the client with complete access to each of the resources delivered by an edge computing device. This component gives network virtualization processing the ability to access the tasks that require, analyzing and evaluating the results. An online dataset, which consists of various fruit (citrus fruit) diseases, is sent to the native collector device. CNN with LSTM and edge computing-based proposed model is utilized with magnitude pruning and quantization for an internet connection is made. The visualization layer enables remote access to deep learning model outcomes.

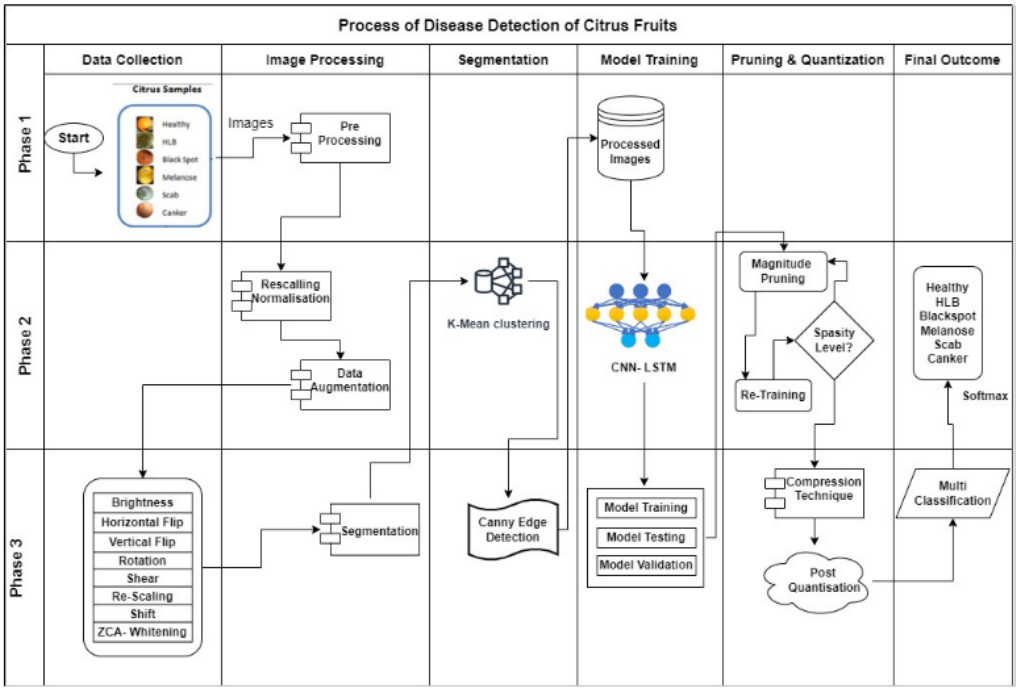


Figure 3. Working of Proposed CNN LSTM model.

The edge computing servers lighten the load on the communications infrastructure when compared with the most sophisticated cloud architectures. A few issues caused by poor contrast, including such colored lights as well as flashing, etc., can be removed by pre-processing the input images. As limited disparity images reduce the histopathological segmentation's precision in the domain of image processing, data preprocessing plays an important role. Because each of the images within the learning algorithm is sparse but also have distinct size, and widths, so we need to normalize it to the comparable image aspect in order to determine the optimal one. As a result, all fruit images within the training dataset have been scaled to (256 × 256). Each image has an RGB color mode, a 32-count filter, a [3,3]-sized kernel, [2,2]-sized strides, and [2,2]-sized pools. The CNN method with LSTM can also be used by edge computing servers for feature extraction and classification to acquire additional data without incurring labeling costs. In addition, information augmentation is used to improve the functionality of the constructed proposed model CNN-LSTM [23].

3.3. Pre-Processing and Segmentation

In order to update the properties of each learning algorithm, feature selection methods are generally a necessary and even critical step. In reality, unscaled statistics make visualizations challenging and, quite saliently, they can impair the forecasting effectiveness of several machine learning methods. The correlation of several gradient-based estimation techniques is also affected and even prevented by this kind of statistic.

On each image, in this case, we used a rescaling methodology. Additionally, it helps to enhance the capabilities of CNN models through the incorporation of data augmentation features As a result, 8 standards are been added to complement our training dataset and testing dataset. These standards include (a) Horizontal flip process, (b) Vertical flip, (c) Brightness improvement, (d) Rescaling process, (e) Shear, (f) ZCA-Whitening, (g) Rotation in different angles, (h) Height shift, and (i) Width shift [24].

After employing the augmentation functions, the 2556 citrus specimens that were at first obtained, along with six classes, expanded to 20,448. For image quality analysis a segmentation process plays a vital role. Image segmentation is the division of a digital picture into several separate areas, each of which contains pixels that have comparable

characteristics. To extract the target area (Segment) from the Citrus image, a K-Means technique is used. The data collected is clustered or divided into the K clusters and components predicated on the K-centroids. It reduces the total squared intervals among each point and also the centroid. An edge retrieval technique called the "Canny-edge" method is used after K-means clustering. The Edge detection by the Canny method is an image acquisition method that employs noise suppression while detecting an image's edges. Figure 4 represents outcome of the segmentation technique applied on citrus fruit samples. the Algorithm 1 consist of various steps that have to be followed for image processing and segmentation.

Algorithm 1: Proposed Algorithm for Image Processing.

Input: Citrus fruit

(1) Input the colored image(Img)
(2) Perform Pre-processing Resizing (256 × 256)
(3) Performed Data Augmentation using
(4) Convert each image from RGB color space to HSV
(5) Applied K-means clustering, where cluster (k) = 4
(5.1) Select k as the desired quantity of clusters to be discovered.
(5.2) Decide which k clusters to arbitrarily allocate the data points across.
(5.3) then determine the clusters' centers.
(5.4) Determine the separation between the data points and the clusters' centers.
(5.5) Reroute the data points towards the closest clusters according to their distance first from the center.
(5.6) Recalculate cluster center once more.
(5.7) Continue steps 5.4 to 5.6 as necessary to achieve the specified number of repetitions or until the measured values do not impact the clusters.
(6) Regenerate the clustered Image
(7) Performed Canny Edge Detection method
(7.1) Noise reduction;
(7.2) Gradient calculation;
(7.3) Non-maximum suppression;
(7.4) Double threshold;
(7.5) Edge Tracking by Hysteresis.
(8) Stop

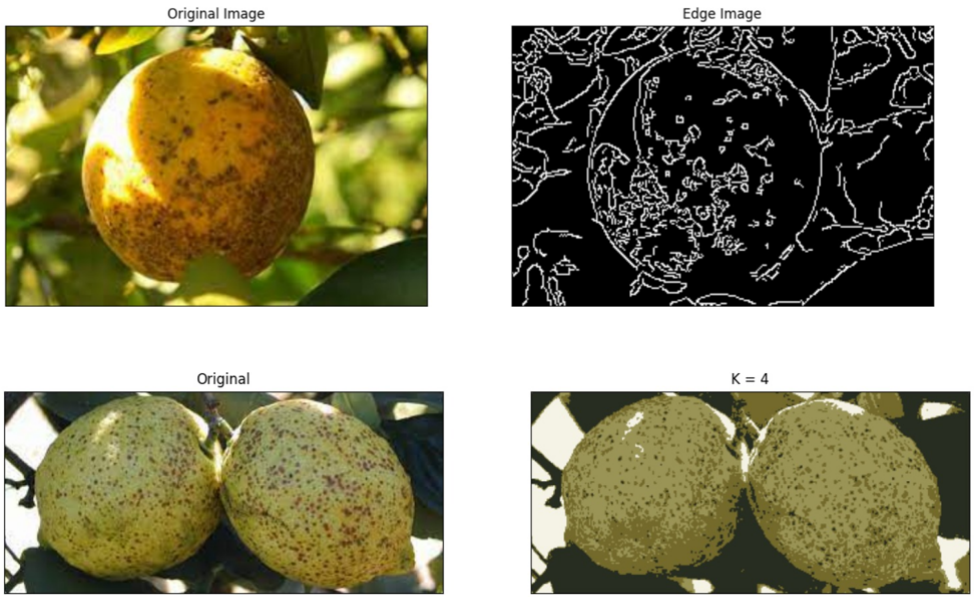


Figure 4. *Cont.*

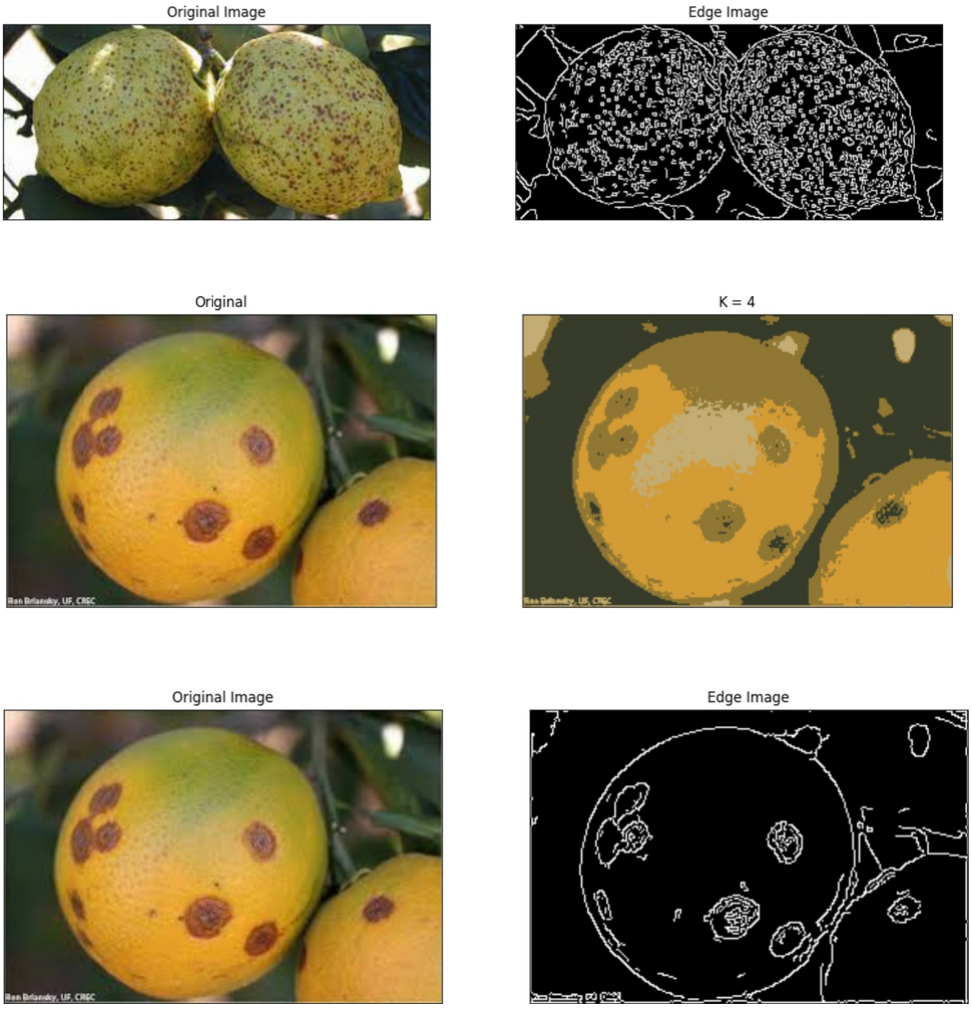


Figure 4. Represent the Segmentation Results on the Image Samples.

4. Experimental Results and Discussion

The efficiency of the model is evaluated and determined with 80-20 cross-validation. Firstly, the model is predicted with the baseline CNN model and different evaluation parameter is calculated. Then the proposed CNN-LSTM model is evaluated using an SGD optimizer to enhance the parameter of cross entropy. Table 3 represented the confusion matrix generated from the proposed CNN-LSTM model for each class of citrus fruit diseases. Table 4 shows the values of accuracy, precision, recall, and f-score achieved from the proposed model for each class of disease.

Table 3. Classification Result of the Proposed Deep Model on a Prepared Dataset.

Fruit Class	Canker	Blackspot	Scab	Greening	Melanosis	Healthy
Healthy	1	6	0	0	0	107
Melanosis	2	0	0	8	62	1
Scab	1	7	37	0	0	0
Blackspot	0	72	0	0	9	0
Greening	0	3	2	29	0	4
Canker	58	0	1	3	2	2

Table 4. Class-wise Accuracy, Recall, Specificity, and F-Score of the Proposed Model.

Fruit Class	Accuracy	Precision	Recall	F-Score
Canker	97.08 %	88%	94%	91%
Scab	97.32 %	82%	93%	87%
Melanosis	94.65%	85%	85%	85%
Greening	95.13%	76%	72%	74%
Blackspot	95.38%	89%	88%	88%
Healthy	99.05%	99%	94%	96%

Table 5 represents the comparison of different parameters evaluated through different approaches. The evaluation parameter used for determining the efficiency of the model is the accuracy, loss, precision, recall, F-score, and model size. Firstly, different evaluation parameters are derived from the baseline CNN model without using any compression technique. Then, all the evaluation parameter is determined by using the proposed CNN-LSTM model without using the pruning technique. After that, we determine the different parameters by employing the proposed CNN-LSTM model along with a magnitude-based pruning algorithm. Then, the proposed CNN-LSTM model along with pruning and post-quantization technique is implemented on the given data set and different evaluation parameters were determined.

Table 5. Comparison of Various Parameters Before and After Compression Techniques

Evaluation Parameter	Without Pruning CNN Model	Without Pruning CNN-LSTM Model	With Pruning CNN-LSTM Model	Pruning + Post Quantization CNN-LSTM Model
Accuracy %	96.98	98.87	96.13	94.35
Loss	0.1713	0.0831	0.165	0.1867
Precision %	94.09	96.65	96.05	94.16
Recall %	93.4	97.74	94.13	93.44
F-Score %	94.88	97.72	92.71	93.71
Size MB	56.65	52.82	28.16	20.62

It is observed from the table that the accuracy achieved using the baseline model without using the compression technique is 96.93 and the loss achieved is 0.17. The accuracy achieved by the proposed CNN-LSTM model without compression technique is 98.87 and the loss is less in this scenario which is 0.0831. It is observed that the reduction in model size by using the proposed model is 6.67%. Then the proposed model is implemented by using a magnitude-based pruning technique and it is observed that the reduction achieved in the model size is 50.29%. The size of the model can further be reduced by using the post-quantization technique without compromising the accuracy of the model. The Figure 5 represents the test accuracy and the training accuracy of the baseline CNN model and Figure 6 represents the training and test loss obtained of the baseline CNN model without compression technique. In the Figure 5 x-axis represents the number of epochs and y-axis represents the accuracy obtained during the testing and training phase. Similarly, in Figure 6 x-axis represents the number of epochs and y-axis represents the loss obtained during the testing and training phase.

The Figure 7 represents the test accuracy and the training accuracy of the proposed CNN-LSTM model and Figure 8 represents the training and test loss obtained from the proposed CNN-LSTM model without compression technique. In the Figure 7 x-axis represents the number of epochs and y-axis represents the accuracy obtained during the testing and training phase. Similarly, in Figure 8 x-axis represents the number of epochs and y-axis represents the loss obtained during the testing and training phase.

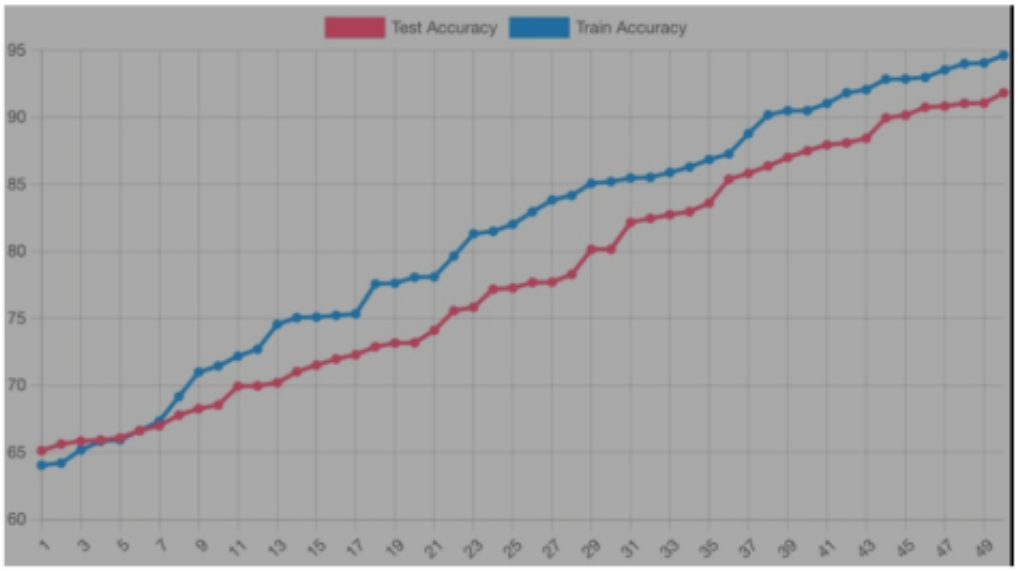


Figure 5. Accuracy Curve of Baseline CNN model.

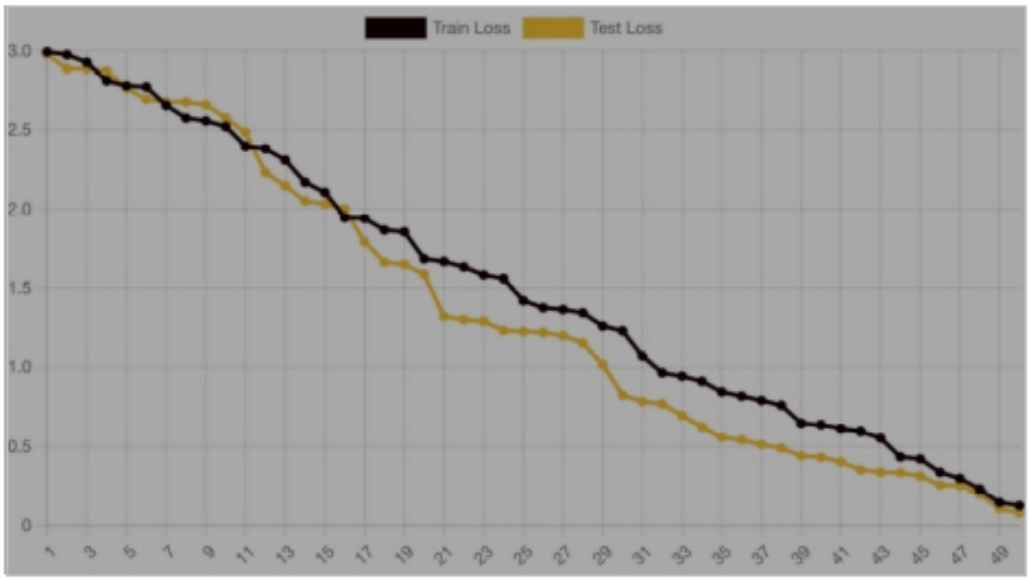


Figure 6. Loss Curve of Baseline CNN model.

The Figure 9 represents the test accuracy and the training accuracy of the proposed CNN-LSTM model magnitude-based pruning and Figure 10 represents the training and test loss obtained from the proposed CNN-LSTM model with magnitude-based pruning. In the Figure 9 x-axis represents the number of epochs and y-axis represents the accuracy obtained during the testing and training phase. Similarly, in Figure 10 x-axis represents the number of epochs and y-axis represents the loss obtained during the testing and training phase.

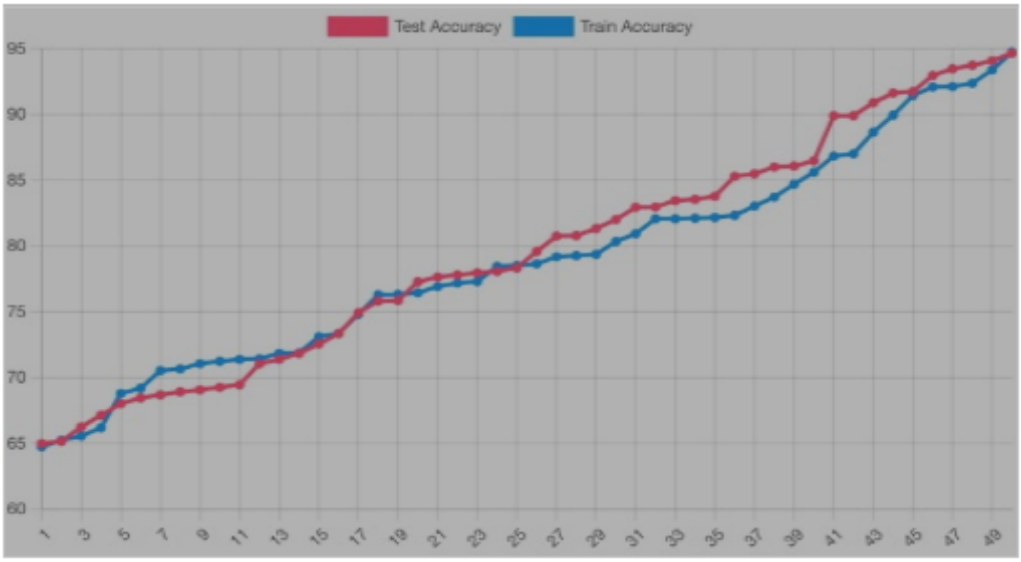


Figure 7. Accuracy Curve of Proposed CNN-LSTM model.

The Figure 11 represents the test accuracy and the training accuracy of the proposed CNN-LSTM model with magnitude-based pruning followed by post-quantization technique and Figure 12 represents the training and test loss obtained from the proposed CNN-LSTM model with magnitude-based pruning followed by post quantization technique. In the Figure 11 *x*-axis represents the number of epochs and *y*-axis represents the accuracy obtained during the testing and training phase. Similarly, in Figure 12 *x*-axis represents the number of epochs and *y*-axis represents the loss obtained during the testing and training phase.

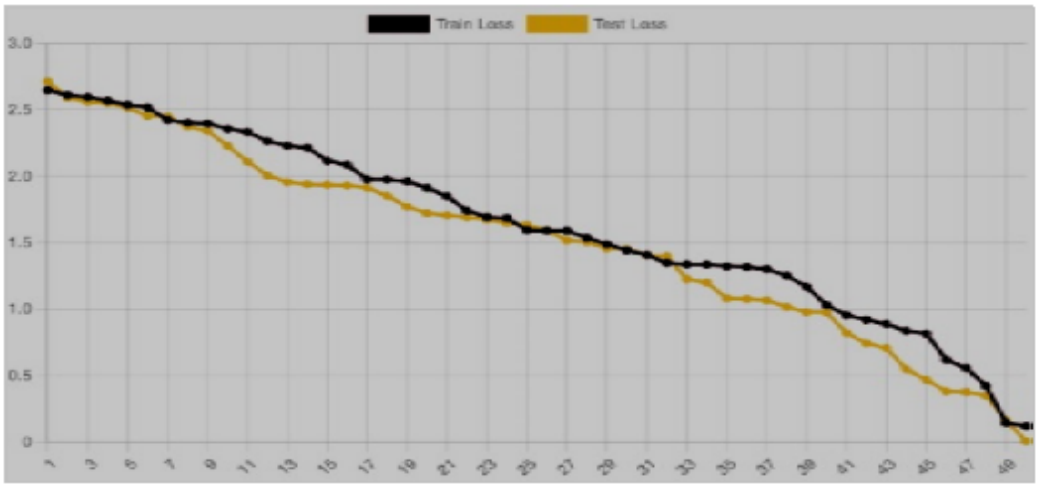


Figure 8. Loss Curve of Proposed CNN-LSTM model.

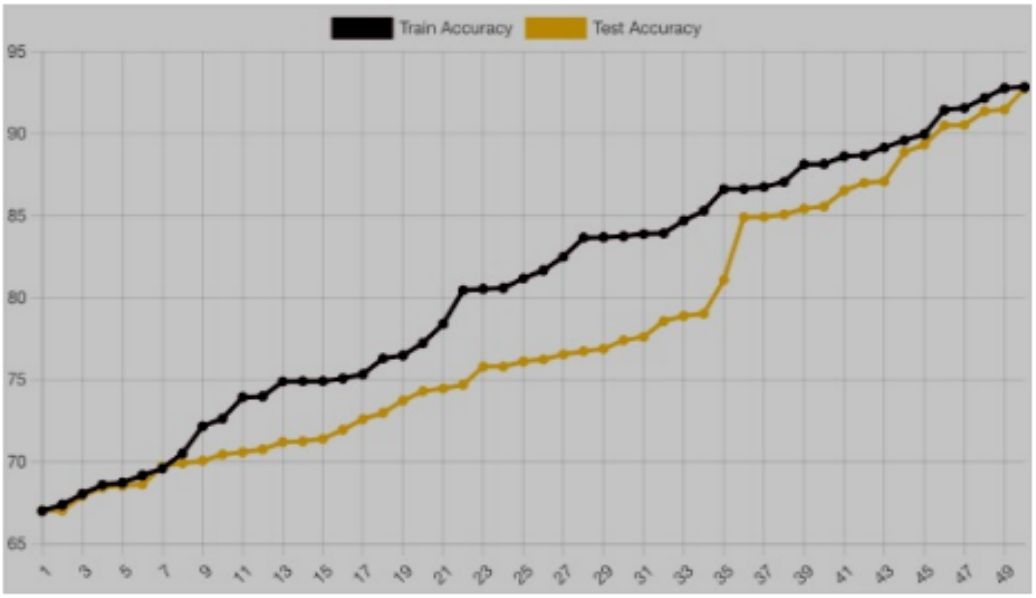


Figure 9. Accuracy of Proposed CNN-LSTM model with pruning.

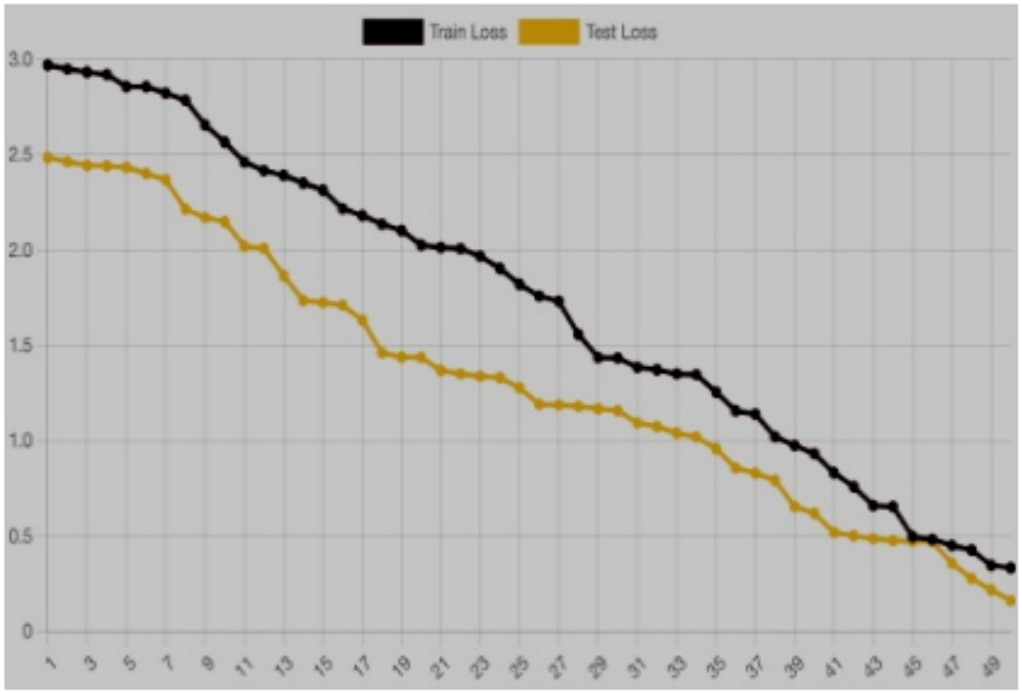


Figure 10. Loss Curve of Proposed CNN-LSTM model with pruning

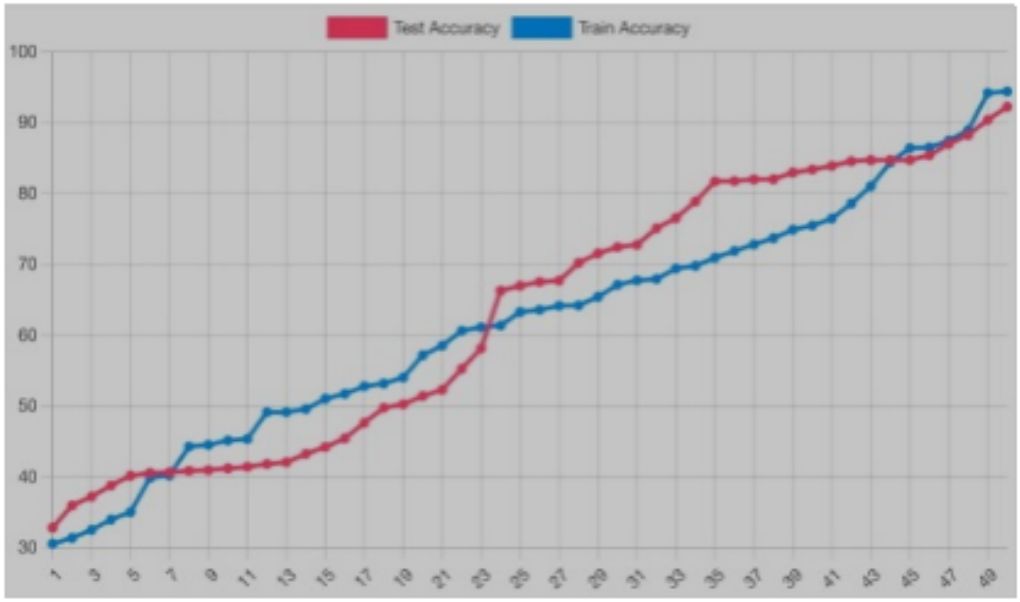


Figure 11. Accuracy of Proposed CNN-LSTM model with pruning and quantization

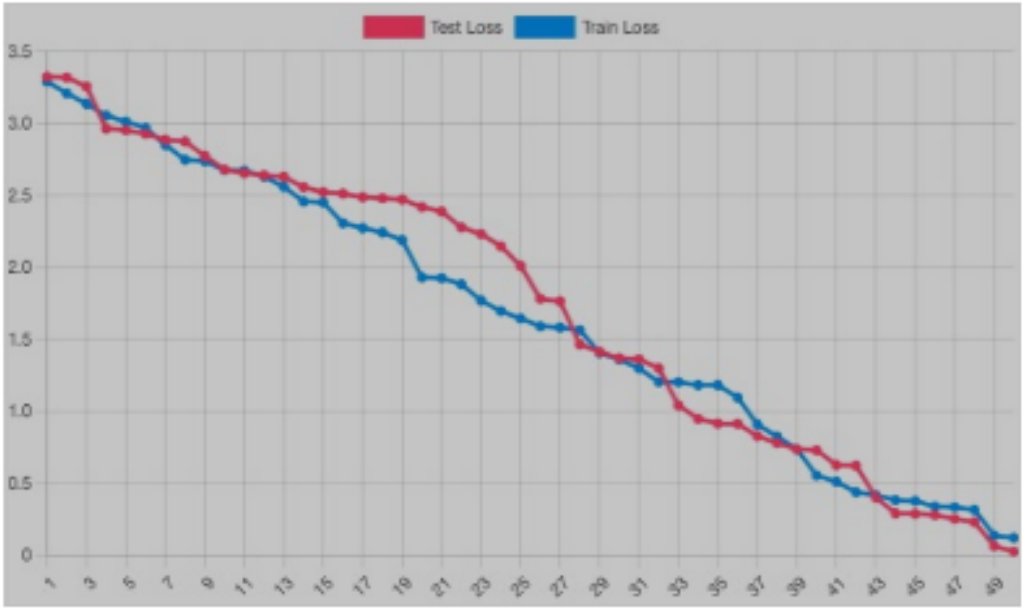


Figure 12. Loss Curve of Proposed CNN-LSTM model with pruning and quantization

Figure 11 test accuracy and the training accuracy of the proposed CNN-LSTM model with pruning and post quantization and Figure 12 graph represents the training and test loss obtained by the baseline model.

5. Conclusions and Future Work

The Implication of the Research

Sustainable farming: Providing the farmers with direct access to disease information at the earliest feasible time. Improve the citrus industry's economy by predicting diseases by enhancing fruit disease detection's value in a limited resource environment. The parameter quantization compresses the parameters of the existing DNA by converting from floating point numbers to low-bit numbers by avoiding Complex and expensive floating point multiplication computation. On the other hand, pruning helps in removing the least

significant or less important parameter which is approaching zero. By combining the pruning and quantization the size of the deep model was considerably reduced. Particularly for edge and mobile devices prone deep models can be used on it devices without further modifications. Offloading the computation of deep CNN from end systems to the more powerful system such as edge servers or the cloud is considerably useful. Nevertheless, for the applications such as agriculture, and medicine, forecasting the clouds are not suitable for edge servers as these applications require short responsive time.

Citrus fruit disease analysis plays a vital role in fruit production. It motivates the research to develop an efficient fruit disease detection model. Edge computing devices are widely used in the agricultural sector. Due to higher resources/computing a traditional CNN-based-fruit disease detection model is not much efficient for edge computing devices with limited resources. This research presents a hybrid model using CNN and LSTM with edge computing.

The proposed CNN-LSTM model is competent for functioning on low-resource platforms, and significant size reductions. This allows CNN-LSTM to run quickly on platforms with limited capabilities. In the experimental analysis, the online Kaggle dataset for fruit disease is utilized. The proposed model and existing CNN models are compared based on various performance-measuring parameters. The experiments were performed using Magnitude-based pruning with quantization and without pruning for proposed and existing methods.

Based on experimental outcomes it is observed that the accuracy achieved using the baseline model without using the compression technique is 96.93 % and the loss achieved is 0.17. The accuracy achieved by the proposed CNN-LSTM model without compression technique is 98.87 % and the loss is less in this scenario which is 0.0831. It is observed that the reduction in model size by using the proposed model is 6.67%. Then the proposed model is implemented by using a magnitude-based pruning technique and it is observed that the reduction achieved in the model size is 50.29%. Size of the model can further be reduced by using the post-quantization technique without compromising the accuracy of the model.

The outcomes are predicted to encourage the utilization of pruning with quantization a valid method for a compression ratio of CNN-LSTM advance models for execution in limited resource circumstances. The limits of the approach are evident when the edge network involves elements of the same type. This research can be further developed by applying it to real-time agricultural images in future research.

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Abbreviations

CNN	Convolutional Neural Network
DNN	Deep Neural Network
IoT	Internet of Things
PCA	Principal Component Analysis
DL	Deep Learning
HLB	Huanglongbing
ETSI	European Telecommunications Standards Institute
MEC	Multi-access Edge Computing
SGD	Stochastic gradient descent
LSTM	Long short-term memory
HSV	Hue, Saturation, Value
RGB	Red, Green, Blue

References

1. Mangla, M.; Mehta, V.; Mohanty, N.; Sharma, N.; Preetham, A. Statistical growth prediction analysis of rice crop with pixel-based mapping technique. *Int. J. Artif. Intell. Soft Comput.* **2022**, *7*, 208–227. [CrossRef]
2. Zhang, M.; Jin, Y.; Qiao, H.; Zheng, F. Product quality asymmetry and food safety: Investigating the 'one farm household, two production systems' of fruit and vegetable farmers in China. *China Econ. Rev.* **2017**, *45*, 232–243. [CrossRef]
3. Cruz, P.; Achir, N.; Sorbonne, U.; Nord, P.; Viana, A.C. On the Edge of the Deployment: A Survey on Multi-Access Edge Computing. *ACM Comput. Surv.* **2022**, *55*, 1–34. [CrossRef]
4. Kong, L.; Tan, J.; Huang, J.; Chen, G.; Wang, S. Edge-Computing-Driven Internet of Things: A Survey. *ACM Comput. Surv.* **2022**, *55*, 1–41. [CrossRef]
5. Mahajan, S. Image acquisition techniques for assessment of legume quality. *Trends Food Sci. Technol.* **2015**, *42*, 116–133. [CrossRef]
6. Simon, C.; Mansouri, A.; Marzani, F.S.; Boochs, F. Integration of 3D and multispectral data for cultural heritage applications: Survey and perspectives. *Image Vis. Comput.* **2012**, *31*, 91–102. [CrossRef]
7. Pydipati, R.; Burks, T.F.; Lee, W.S. Statistical and neural network classifiers for citrus disease detection using machine vision. *Trans. ASAE* **2014**, *48*, 2007–2014. [CrossRef]
8. Bulanon, D.M.; Burks, T.F.; Alchanatis, V. Image fusion of visible and thermal images for fruit detection. *Biosyst. Eng.* **2009**, *103*, 12–22. [CrossRef]
9. Malegori, C. Talanta Comparing the analytical performances of Micro-NIR and FT-NIR spectrometers in the evaluation of acerola fruit quality , using PLS and SVM regression algorithms. *Talanta* **2017**, *165*, 112–116. [CrossRef]
10. Saha, R. Orange Fruit Disease Classification using Deep Learning Approach. *Int. J. Adv. Trends Comput. Sci. Eng.* **2020**, *9*, 2297–2301. [CrossRef]
11. Behera, S.K.; Jena, L.; Rath, A.K.; Sethy, P.K. Disease Classification and Grading of Orange Using Machine Learning and Fuzzy Logic. In Proceedings of the IEEE International Conference on Communication and Signal Processing, Tamilnadu, India, 3–5 April 2018; pp. 678–682.
12. Ali, H.; Lali, M.I.; Nawaz, M.Z.; Sharif, M.; Saleem, B.A. Symptom based automated detection of citrus diseases using color histogram and textural descriptors. *Comput. Electron. Agric.* **2017**, *138*, 92–104. [CrossRef]
13. Dael, M.V. A segmentation and classification algorithm for online detection of internal disorders in citrus using X-ray radiographs. *Postharvest Biol. Technol.* **2016**, *112*, 205–214. [CrossRef]
14. Theanjumpol, P.; Wongzeewasakun, K.; Muenmanee, N. Non-destructive identification and estimation of granulation in ' Sai Num Pung' tangerine fruit using near infrared spectroscopy and chemometrics. *Postharvest Biol. Technol.* **2019**, *153*, 13–20. [CrossRef]
15. Ranjit, K.N.; Raghunandan, K.S.; Naveen, C.; Chethan, H.K.; Sunil, C. Deep Features Based Approach for Fruit Disease Detection and Classification. *Int. J. Comput. Sci. Eng.* **2019**, *7*, 2347–2693.
16. Senthilkumar, C.; Kamarasan, M. An Effective Classification of Citrus Fruits Diseases using Adaptive Gamma Correction with Deep Learning Model. *Int. J. Eng. Adv. Technol.* **2020**, *9*, 2249–8958. [CrossRef]
17. Huijun, L.; Xiangfeng, W. Rapid shelf-life identification model of citrus based on near infrared spectroscopy. In Proceedings of the International Symposium on Knowledge Acquisition and Modeling, Wuhan, China, 21–22 December 2008; pp. 298–301.
18. Wang, Z. 1-Methylcyclopropene suppressed the growth of Penicillium digitatum and inhibited the green mould in citrus fruit. *J. Phytopathol.* **2021**, *169*, 83–90. [CrossRef]
19. Lan, Y. Comparison of machine learning methods for citrus greening detection on UAV multispectral images. *Comput. Electron. Agric.* **2020**, *171*, 105234–105234. [CrossRef]
20. Cevallos-Cevallos, J.M.; Futch, D.B.; Shilts, T.; Folimonova, S.Y.; Reyes-De-Corcuera, J.I. GC-MS metabolomic differentiation of selected citrus varieties with different sensitivity to citrus huanglongbing. *Plant Physiol. Biochem.* **2012**, *53*, 69–76. [CrossRef]
21. Stegmayer, G.; Milone, D.H.; Garran, S.; Burdyn, L. Automatic recognition of quarantine citrus diseases. *Expert Syst. Appl.* **2013**, *40*, 3512–3517. [CrossRef]

22. Wadhwa, S.; Rani, S.; Verma, S.; Shafi, J. Citrus black spot detection using hyperspectral image analysis. Energy Efficient Consensus Approach of Blockchain for IoT Networks with Edge Computing. *Sensors* **2022**, *22*, 3733. [CrossRef]
23. Pan, W.; Qin, J.; Xiang, X.; Wu, Y.; Tan, Y.; Xiang, L. A Smart Mobile Diagnosis System for Citrus Diseases Based on Densely Connected Convolutional Networks. *IEEE Access* **2019**, *7*, 87534–87542. [CrossRef]
24. Jahanbakhshi, A.; Momeny, M.; Mahmoudi, M.; Zhang, Y.D. Classification of sour lemons based on apparent defects using stochastic pooling mechanism in deep convolutional neural networks. *Sci. Hortic. (Amst.)* **2020**, *263*, 109133–109133. [CrossRef]

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