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Maturity Detection of Scotch Bonnet Pepper (*Capsicum chinense*) using Image Processing

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Abstract— Proper classification of harvests is crucial to maximize crop yield, ensure high-quality exports, determine storage conditions and export quality. This study presents the development of a real-time image processing algorithm to detect the maturity stage of scotch bonnet peppers (*Capsicum chinense*) using Convolutional Neural Networks (CNNs). The algorithm classifies the peppers into three stages: unripe, moderately ripe, and ripe. It is achieved by training a CNN on a labeled dataset of scotch bonnet images at various maturity stages. The architecture of the CNN is trained on a dataset of labeled images using TensorFlow and Keras, leveraging these robust frameworks for efficient construction and optimization of the neural network. The developed algorithm demonstrates 89.04% testing accuracy and 91.6% training accuracy, showcasing its effectiveness in real-time maturity detection. This cost-effective, reliable, and intelligent solution has significant practical implications for the agricultural industry. It can reduce postharvest losses and production costs, ensuring the delivery of high-quality products to consumers while optimizing storage conditions and export quality. Additionally, the algorithm, developed using Python, is versatile and can be extended to other crop types, making it a valuable tool for the agricultural sector.

Index Terms—Convolutional neural networks, Crop maturity detection, Image processing, Scotch bonnet

1 Introduction

Agriculture, as a fundamental pillar of the global economy, holds immense potential across various regions worldwide, significantly contributing to economic stability and growth. Application of advanced technologies in agriculture is highly needed with the increasing demand for agricultural products. The computer science and its subfields have vast practical applications, which make them ideal for interdisciplinary studies. For instance, image processing has proven so successful that it is now widely used in other fields, including medicine, forensics, engineering, remote sensing, agriculture, and more [1], [2]. In recent decades, image processing has become an essential area in agriculture, and there is a necessity to develop computer vision applications to enhance productivity in the field [3]. The art of processing real-time images and generating images with enhanced information and other valuable parameters is known as image processing [4].

Scotch bonnet is very hot, averaging 100,000-350,000 SHU on the scoville scale according to Caicedo-Lopez et al. [5], which ranks spiciness and is used in diverse range of raw and cooking applications such as hot sauces, jam, canned pickle and dry powder in which it is used for aroma in cooking and health benefits

[6]. It has been observed that the quantity of scotch bonnet production, and export has shown remarkable growth due to high demand in world market. Scotch bonnet is found to be light green in its unripe state and gradually turns to bright red, orange or brown once it matures depending on variety [7]. The proper classification of harvested pepper as ripe, unripe or the stage of maturity is very important in the export sector as the market demand vary. Scotch bonnet is a pepper with good nutritional value and a convenient crop due to its non-seasonality and short harvesting period. The classification of scotch bonnets is done manually by human operators, which could lead to personal errors.

Artificial Intelligence has made a significant growth in closing the gap between the capabilities of machines and human. Using image processing, challenges in agricultural production can now be solved effectively and efficiently due to advancements in deep learning technology [8]. Numerous projects were put on earlier for categorizing, detecting maturity and diseases of fruits and vegetables. However, those research were conducted utilizing machine learning algorithms while more advanced technology can be used with a system which focuses on the deep learning algorithms, mainly utilizing Convolution Neural Network (CNN). CNN is a deep learning approach that detects features without needing manual intervention and hence it is very powerful and efficient model which perform with rich accuracy as sated by Kamilaris and Prenafeta-Boldú [9]. Convolutional Neural Network (CNN) is a method that has gained popularity because to its exceptional effectiveness in extracting useful features from raw images without the need for human interaction and its simplicity in classifying them. In the modern agriculture sector, there are several existing researches that are based on image processing and machine learning approaches to recognize the crop quality, detect fruit maturity, detect crop diseases and classify the fruits. Most of the existing algorithms have been developed by using MATLAB software, Python and OpenCV as the programming languages [10], [11]. The process for recognizing the maturity stage uses deep learning techniques of image processing which does not require manual feature extraction, giving more accurate results [12]. In this study, a classification model constructed by applying the convolutional neural network approach, utilizing pre-trained set of image databases is used. There is limited research on image processing in the field of agriculture. A few studies have been conducted on crop disease detection and maturity detection, but most of them were based on machine learning using MATLAB software [13]. However, no much research studies were conducted using deep learning techniques based on CNN. Furthermore, there has been little emphasis focused globally on monitoring the maturity of scotch bonnet which has a significant market value and growing market. Therefore, identifying the maturity stage of scotch bonnets using CNN would pave the pathway for significant technological advances in the field of agriculture.

The research study uses Convolution Neural Network to train and develop an image processing algorithm, which is capable of detecting the maturity stages of scotch bonnet automatically. Identifying the maturity stage of a scotch bonnet will aid in determining the export quality and the storage conditions and ultimately providing a good quality product for the consumers. As a result, it can reduce postharvest loss and production cost of the export quality product. Furthermore, this application will be less time consuming, intelligent, cost effective, reliable, smart and non-destructive solution for identifying the maturity stage. The results of this research is not limited to scotch bonnet as its implications are valuable for any agriculture-based economy seeking to leverage technological innovations for growth and efficiency.

2 MATERIALS AND METHODS

2.1 Data Collection

A dataset of scotch bonnet peppers at three maturity levels, namely ripe, moderately ripe, and unripe, was collected using a high-resolution (12 MP) mobile camera. The images were captured in a specially designed photo box with controlled white lighting conditions to ensure consistency in lighting and image quality. The dataset consisted of 100 images, with 40 depicting unripe peppers, 30 showing ripe ones, and 30 featuring moderately ripe peppers. The dataset was divided into training and testing groups, with 86 images used for training and 14 images for testing. Additionally, 15% of the images were reserved for model testing. The images were stored in JPEG format and were manually labeled to indicate the maturity stage of each scotch bonnet pepper.

2.2 CNN-Based Feature Extraction and Classification Model

An affordable approach in categorizing scotch bonnet peppers based on their ripeness involves the development of a Convolutional Neural Network (CNN). To ensure successful classification, it is crucial to extract appropriate features. The basis for classification includes surface color, size, and shape features of scotch bonnet peppers [14], [15]. The maturity level of the pepper was determined by its surface color and size. The CNN was utilized to extract color, size, and shape features from the scotch bonnet surfaces, leveraging its automatic feature extraction capabilities. In the initial layer of the system, a 3x3 convolutional layer transformed the input image into a matrix, resizing it to (x, y) pixels. The input image matrix underwent conversion into a normalized matrix using batch normalization, which employed a maximum pixel algorithm. The output from batch normalization was then forwarded to the 2x2 max pooling layer, producing a significant 2x2 matrix crucial for feature extraction [16]. Following the max pooling layer was the flatten layer, functioning as a neural network that learns from the data to make necessary predictions [17]. Preceding the output layer was the dense layer, responsible for the essential classification to predict the pepper into one of three classes. The dropout layer provided the final output, with one dropout for each class ripe, moderately ripe, and unripe. Since the classification involved three classes, the system incorporates three dropout layers.

The specific CNN model was created using the TensorFlow and Keras library with the python programming language on Jupyter notebook, with the aid of the Anaconda navigator coding platform. In the system, an image was provided as input. The input image was fed to CNN. In CNN, the image was segmented for easy analysis. Feature extraction was provided by CNN to automatically extract all the necessary features through the pool of network. Based on the feature extraction, training was done. The general CNN architecture of our approach is shown in Fig. 1. The testing data was passed for two stage classification based on features: size, and surface color. The output stage determined whether scotch bonnet is ripe, unripe or moderately ripe. The classification output along with the classified image was shown on the Jupyter notebook cell.

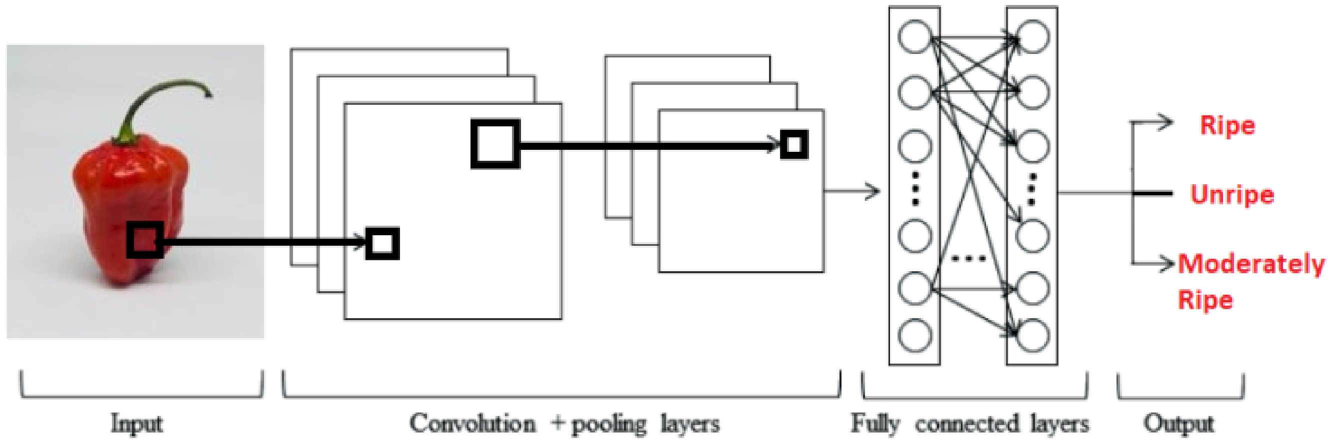


Fig. 1. CNN Architecture of the model

3 RESULTS AND DISCUSSION

3.1 Overall Model Performance

The CNN-based crop maturity detection algorithm achieved a training set accuracy of 89.04% and a testing set accuracy of 91.67%. As the model accuracy revealed, the algorithm performed better on the testing set compared to the training set, indicating that it can generalize well to new, unseen data. Therefore, these results suggest that the CNN-based scotch bonnet crop maturity detection algorithm can classify the maturity levels of scotch bonnet pepper with high accuracy. However, it should be noted that the testing accuracy was higher than the training accuracy in the overall model testing, which suggests that the model may be slightly overfitting to the training data. Therefore, to further improve the CNN model, it could be applied with additional data augmentation techniques or regularization methods [18]. In addition to that, using more wide range of data set for each can solve the issue of overfitting to the training data.

The results obtained after completing the model train is shown in Fig. 2. The graph represents the relationship between the accuracy and the number of epochs, for both train accuracy and validation accuracy. The accuracy for each of the epoch is shown for each of the train and validation. The Fig. 3 shows both train and validation loss of the CNN model. The graph depicts the relationship between loss and the number of epochs, showing both the train and validation loss. This indicates how accurate the model's predictions were for the given data. The achieved train and validation loss values are relatively low, indicating good performance of the model.

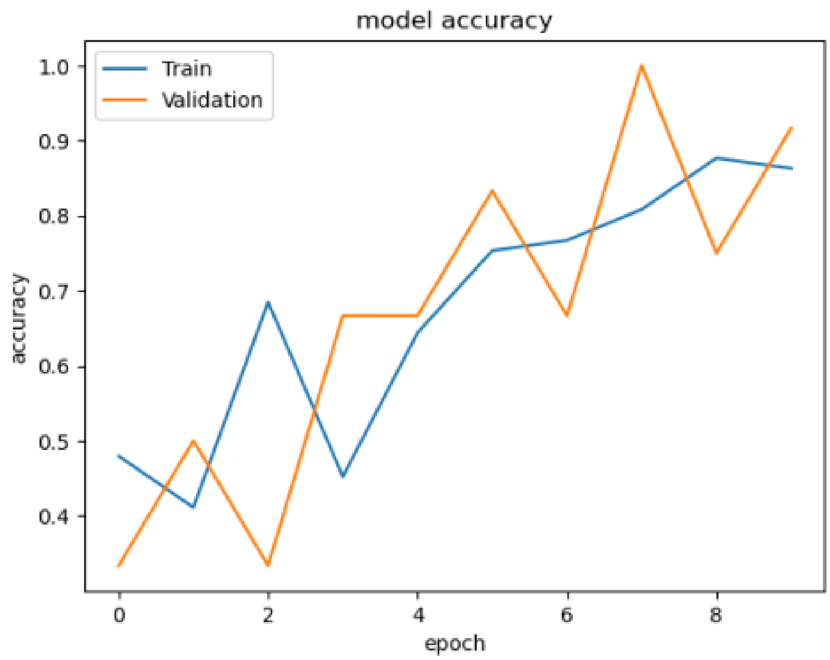


Fig. 2. Model accuracy graph of the proposed model

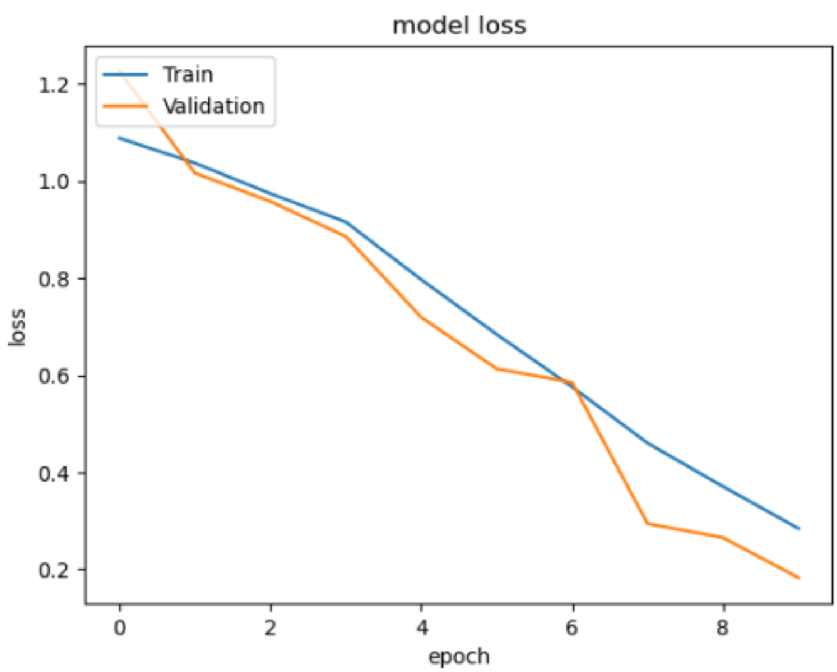
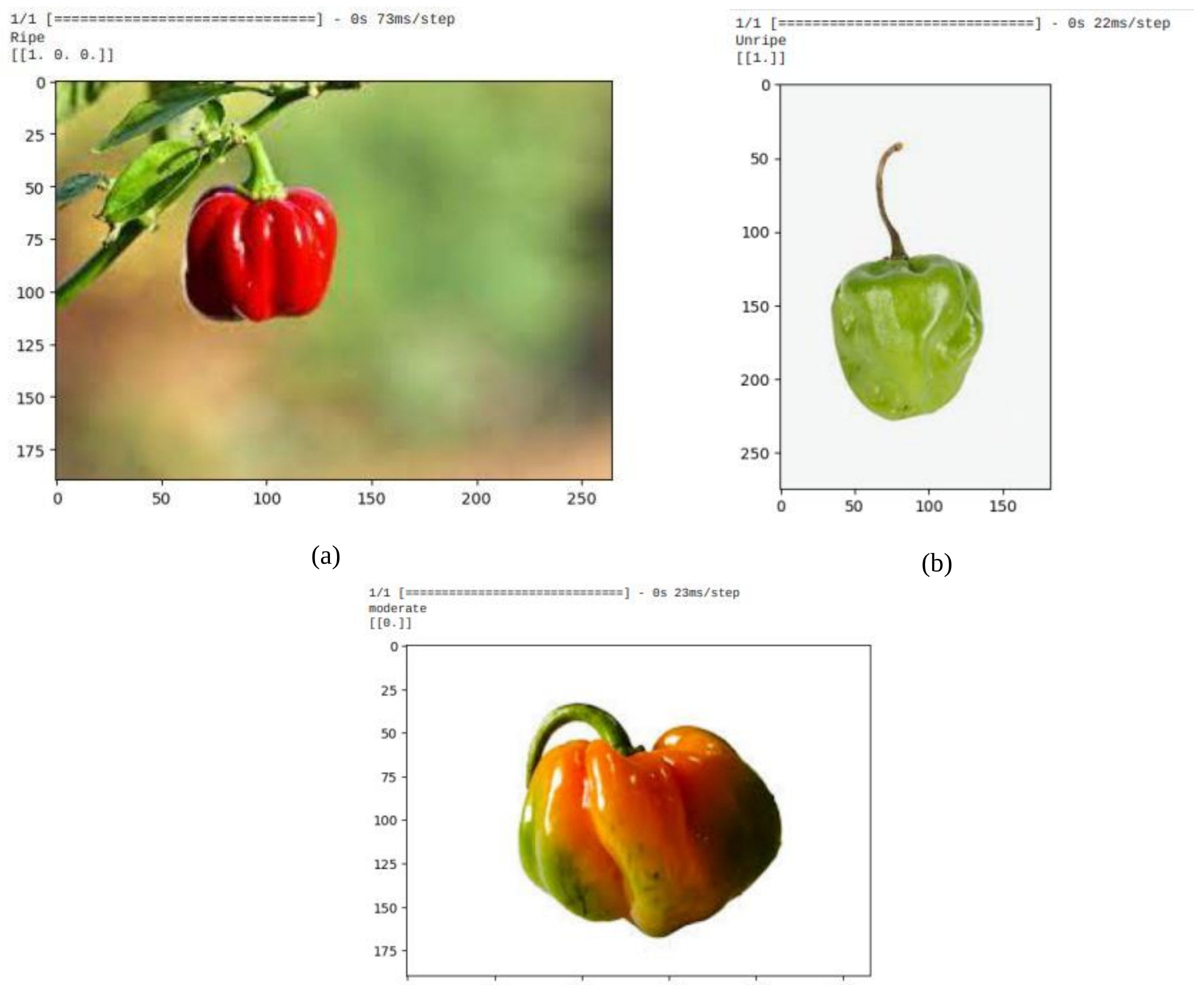


Fig. 3. Model loss graph of the proposed model

3.2 Maturity Stage Prediction

The developed Convolutional Neural Network (CNN) model is used to predict the maturity stage of scotch bonnet peppers (ripe, unripe, or moderately ripe) by processing a test image and returning a probability distribution over the possible classes. Fig. 4 shows the output of the CNN model maturity stage prediction in the Jupyter notebook cell display where the image classifies along with its actual class. The given input image is properly classified as ripe scotch bonnet pepper by the CNN model.



(a) (b) (c)

Fig. 4. Maturity stage prediction results in Jupyter notebook cell for ripe (a), unripe (b) and moderately ripe (c) stages of scotch bonnet

The model provides reliable predictions for maturity stages, ensuring the efficiency and effectiveness of the algorithm. As Kamalaris and Prenafeta-Boldú [9] were also stated, this research study has proven that CNN offers superior performance in precision agriculture in the crop maturity stage detection related work compare to other image processing techniques. While the scope of this research study is relatively limited, it is shown particularly noteworthy accuracy when compared to similar problem-solving studies [19].

As the system algorithm is able to obtain overall model performance with 91.67% of accuracy, it indicates that the scotch bonnet crop maturity detection through image processing algorithm based on CNN can effectively and precisely categorize the maturity stages of scotch bonnet peppers with a notable level of accuracy. Furthermore, the ability to determine the maturity stage of a scotch bonnet is crucial in ensuring the export quality and storage conditions, and ultimately delivering a high-quality product to consumers. As a consequence, it has the potential to decrease postharvest losses and production costs associated with exporting high-quality products [20], [21]. In addition, this approach offers several benefits, such as being efficient, cost-effective, reliable, non-destructive, and intelligent, making it a smarter and less time-consuming solution for accurately identifying the maturity stage. With further development and refinement, these mechanisms could be applied to other crops and help to address important problems and pressing challenges in agriculture and food security.

4 CONCLUSION

The image processing-based automatic harvest grading system addresses the need for accurate classification of harvest, minimizing economic losses by reducing human error and effort. This research developed a Convolutional Neural Network (CNN) algorithm to classify scotch bonnet peppers into three maturity stages: ripe, unripe, and moderately ripe. With 89.04% testing and 91.6% training accuracy, the system provides reliable classification, aiding farmers and exporters in optimizing harvest timing and ensuring export quality. The results demonstrate the potential of automated systems in improving efficiency of agricultural practices through real-time image processing solutions.

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