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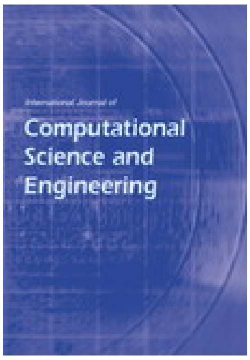

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Development of a sorting system for mango fruit varieties using convolutional neural network

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Abstract: Mango is a tropical fruit with numerous varieties, these varieties intermix during harvest and post-harvest procedures thereby causing complications and inability to accurately identify specific varieties at the retail stage. Accuracy of existing sorting techniques does not fit well to real-world scenarios. This research introduces an enhanced sorting system for mango fruits to address these challenges. Our approach involved building a comprehensive database by photographing six distinct mango fruit varieties prevalent in South-West Nigeria using a digital camera. The captured images underwent quality enhancement through histogram equalisation and noise reduction via median filtering. The convolutional neural network framework was used in the creation of a model named AdeNet to facilitate feature extraction and classification within the system. The experimental result achieved 99.0% accuracy and F1-score of 97.6% which is better than the performance of existing mango sorting techniques. The work will enhance the efficiency of mango industries.

Keywords: artificial intelligence; convolutional neural network; CNN; deep learning; machine learning; mango fruit; automatic sorting system.

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1 Introduction

The agricultural sector plays a pivotal role in the economic framework of any nation (Tanveer et al., 2016). Fruits contribute significantly to this sector, their fleshy and edible components contain essential vitamins, minerals, and chemicals that make them serve as crucial raw materials in various industries (Carlos et al., 2023). Mango (*Mangifera indica L.*) is a highly perishable tropical fruit that was originally propagated naturally through open-pollination of seedlings (Uddin et al., 2016) thereby resulting in the available varieties. The mango landscape encompasses numerous identified varieties, each enjoying substantial demand in both local and international markets (Faye et al., 2022; Carlos et al., 2023). These varieties exhibit distinctions in colour, size, shape, weight, peel content, length, sweetness, pulp, and physicochemical properties thus influencing their applications, demand, pricing, and market (Shyam et al., 2013; Nayeli et al., 2014; Abdalla and Faustin, 2017).

Though consumers often select mangoes based on external appearances, the ultimate purchasing decision hinges on the taste of the variety (Nguyen and Nguyen, 2020). Identifying mango varieties efficiently poses a challenge for many individuals (Igbari et al., 2019; Kiatkamjon et al., 2012). In practice, experts are frequently consulted to discriminate between mango varieties by relying on their domain knowledge and visual observation skills (Alaa et al., 2019; Longxin et al., 2023). The post-harvest procedures for mango involve a sequence of activities such as cleaning, sorting, grading, and packing as outlined by Leo and Deepa (2015). Accurate sorting of mango varieties is essential for ensuring the efficiency of the supply chain, customer satisfaction, and quality control, as highlighted by Rohan et al. (2018). Nonetheless, sorting mango fruits based on their variety poses a considerable challenge due to variations within the same class and similarities across different classes among mango varieties, as noted by Girish et al. (2020).

The traditional manual sorting approach, relying on human eye pattern recognition for sorting tons of mango fruits prove to be laborious, inefficient, monotonous, inconsistent, tedious, and unreliable. This method results in high costs, subjectivity, time-consuming processes, and significant annual wastage of fruits (Ohnmar, 2019; Najva and Abdul, 2023). Despite the advancements in machinery for various stages of agricultural processing, the mechanical sorting of mango fruits still relies on human efforts, presenting a cumbersome technological challenge (Tabada and Beltran, 2019). Therefore, it becomes imperative to devise an efficient and cost-effective automated machine-based solution for distinguishing between mango fruits of different varieties based on their distinctive features (Leo and Deepa, 2015; Valous and Sun, 2012). Such a solution would alleviate stress, save time, and yield consistent and objective results (Hakim and Rizwan, 2022). In recent years, the automatic identification and classification of fruit and plant categories have become significant research areas in the agricultural sector (Wei et al., 2022). Researchers have increasingly embraced computer vision and artificial intelligence techniques to address challenges related to pattern recognition, image classification, and pattern understanding in agriculture (Alexandre and Mauricio, 2017; Prasad et al., 2015).

Image classification involves systematically organising data into groups and categories based on visual content (Jaswal et al., 2014; Gayatri et al., 2023). Machine learning, a branch of artificial intelligence (Philip et al., 2023) utilises algorithms to predict the actual class of an image or its probability of belonging to different classes (Karis et al., 2016). Deep learning, a type of machine learning with multiple layers and nonlinear processing units (Krishna et al., 2018) can directly perform classification tasks from images, sound, and text using its unique computing method (Adebisi et al., 2020). Deep learning employs neural network (NN) architecture to automatically extract global features and contextual details from images. Among the various deep learning algorithms for image classification, convolutional neural network (CNN) offers superior performance in pattern and image classification (Taye, 2023; Prasad et al., 2015; Shaohan et al., 2021). The CNN is an artificial neural network (ANN) featuring a feed-forward architecture as elucidated by (Aamir et al., 2019). It possesses the capability to automatically learn simple edges and shapes from raw data, while more intricate shapes are identified through feature extraction (Adejumobi et al., 2023). The fundamental layers in the CNN architecture includes the convolutional layer, fully connected layer, and max-pooling layer (Philip et al., 2023), with assigned significant tasks (Krizhevsky et al., 2012; Rohrmanstorfer et al., 2021).

Over time, researchers have developed numerous CNN models for image classification tasks (D'Angelo et al., 2023), exhibiting substantial performance improvements compared to traditional methods (Edna, 2023; Saboora et al., 2020). However, the precision of these CNN models rely on complex architectures and extensive image databases. Training such intricate structures necessitates substantial data and powerful graphics processing units (GPUs) (Hakim and Rizwan, 2022; Xingguang et al., 2023). Moreover, selecting the optimal model for a classification application involves striking a balance between accuracy, memory usage, and speed. To address these challenges, it is essential for scientists to develop lightweight networks to reduce redundancy in the network (Sachi and Rashmi, 2023; Nguyen and Nguyen, 2020). While some existing CNN models have demonstrated impressive performance in automating mango classification, there remains a need to enhance accuracy for real-life applications.

This paper aims to improve the technical support for the sorting of mango fruit varieties by improving the performance accuracy. Our work involved the creation of a sorting system designed for six distinct mango fruit varieties (Alphonso, German, Julie, Jumbo, Kerosene, and Peter mangoes). Initially, we captured images of these mango fruit varieties to construct our database. For effective classification, we created a CNN model named AdeNet, and integrated it into our developed mango sorting system. The system underwent training and testing using our generated dataset. In the experimental results, our developed system demonstrated impressive metrics, achieving an accuracy of 99.0%, precision of 97.1%, recall of 97.0%, F1-score of 97.6%, and AUC of 98.8%. These outcomes signify a performance improvement compared to existing works utilising CNN models. In previous research, the performance of CNN models was improved by exploiting the model's architecture based on depth, the deeper the network, the better its performance. However, the novelty of our work is in the use of a shallow architecture (two convolutional layers and one fully connected layer) to achieve improvement in accuracy. Compared with other classification methods based on CNN, our proposed method achieved novelty in performance in terms of accuracy, F1-score and AUC values. The primary contributions of this paper include the generation of a dataset for mango fruit varieties in South-West Nigeria, the development of a reliable and efficient sorting system for mango fruit varieties, accompanied by an enhancement in accuracy. This research has significant implications for mango industries by streamlining sorting processes, minimising fruit waste, and ensuring that customers receive the specific mango type of their choice.

The structure of this paper is outlined as follows: in Section 2, a thorough examination of related work in image classification is provided, emphasising the classification of mango fruit varieties. Section 3 introduces our proposed methodology for sorting mango fruits, covering the generation of our dataset, the design and configuration of a customised CNN model, and the details of the training and testing procedures applied in our approach. Moving on to Section 4, we presented the experimental results and discuss our study's findings in terms of accuracy, precision, recall, F1-score, and AUC. Finally, Section 5 encapsulates our conclusions drawn from the research outcomes, while also pinpointing potential areas for future exploration in this field.

2 Related works

Leo and Deepa (2015) sorted Alphonso mango from other varieties using seven hue moment for the shape analysis. The result achieved overall accuracy of 83.33%. Misigo and Miriti (2016) classified apple fruit varieties using Naive Bayes. Colour and size features were extracted, RGB images were transformed to grayscale images and the images were filtered. The features extracted were fed into the Naive Bayes algorithm for classification. In the result sensitivity, precision, specificity and accuracy of 77%, 100%, 80% and 91% were obtained correspondingly. Qaiser et al. (2018) classified mango varieties using texture and shape features. The features were attracted using correlation, angular second moment, inverse difference moment, contrast and variance. The system achieved a classification accuracy of 83%. Santi et al. (2019) classified mango fruits using support vector machine and statistical features. The background removal and fruit detection were done using K-means clustering, the feature extraction was done using grey level co-occurrence matrix while support vector machine was used for the classification. The system attained an accuracy of 90%.

Figure 1 Flow diagram for the proposed work

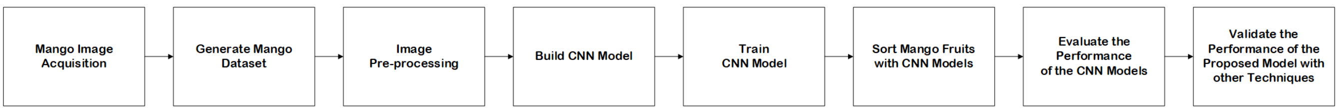
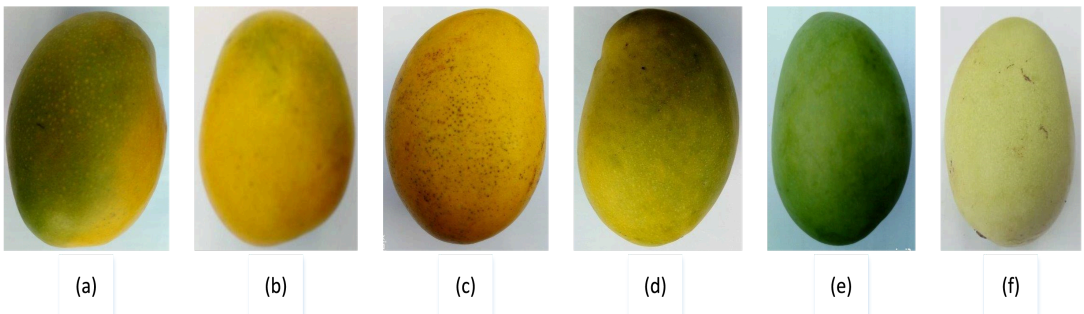


Figure 2 Side view of six mango fruit varieties, (a) German mango (b) Julie mango (c) Jumbo mango (d) Alphonso mango (e) Peter mango (f) Kerosene mango (see online version for colours)



Amin et al. (2019) sorted date fruits using deep convolutional neural network. The authors constructed a CNN model from VGG-16 architecture by introducing max-pooling, dropout, batch normalization and dense layers. The CNN model was able to achieve an overall accuracy of 96.98%. Ohnmar (2019) classified mango varieties using the Naive Bayes algorithm. At first, RGB images were converted to HSV before the region of interest was segmented using edge detection and morphological operation. The features extracted were given as inputs to a Naive Bayes classifier to classify the test images. Accuracy of 94% was achieved by the system. Badar et al. (2019) proposed a machine learning model for the identification of mango varieties based on shape and texture features. The work achieved an overall accuracy of 70%. Girish et al. (2020) classified mango varieties using transfer learning techniques. A deep learning approach with inception-V3 model was used for the training and the classification. The model achieved an overall test accuracy of 97.6%. Farhana and Mohidul (2020) classified mango varieties using correlation distance. Firstly, RGB images were converted to grayscale images. The features were extracted using variance analysis to form feature vector and the mango fruits were recognized using correlation measure. The model achieved an accuracy of 91% and misclassification rate is 9%.

Nguyen and Nguyen (2020) introduced an innovative mango grading system based on external features by utilising a combination of a computer vision system and weight measurement. Four machine learning models, namely random forest (RF), linear discriminant analysis (LDA), support vector machine (SVM), and K-nearest neighbours (KNN), were employed. Mango weight was captured using a load-cell sensor, and external features were obtained through a camera. The experiment resulted in an accuracy exceeding 87.9%, emphasising the significance of combining features for accurate mango classification. Tanveer et al. (2016) focused on classifying mango leaves through digital image analysis. The work involved extracting binary, RST, spectral, histogram, and texture features, with LMT and KNN employed for classification. The results indicated that LMT achieved classification accuracy rates ranging from 80.33% to 88.33%, while KNN demonstrated a maximum overall classification accuracy rate between 88.33% and 97%.

Wei et al. (2022) improved a lightweight model with a visualisation approach to classify mango defects. The research employed convolution process visualisation to adjust the squeeze model's structure. By visualising the feature extraction characteristics of deep and shallow networks in the SqueezeNet model, eight extrusion network models were constructed. After training and evaluation, model 4 exhibited superior performance, attaining a 95.64% accuracy and an F1 score of 0.9587 compared to the other models. Anuradha and Khelchandra (2023) undertook the classification of renal ultrasound images to identify three kidney disorders. Image features were extracted using intensity histogram, grey level co-occurrence matrices, and grey level run length matrices. The self-organising NN (SONN) was employed to cluster input patterns into four groups, while classification was executed using the multilayer perceptron (MLP) with a generic algorithm. The proposed hybrid method achieved impressive metrics, including a precision of 93.9%, recall of 93.0%, F1 score of 93.0%, and an overall accuracy of 96.8%.

Jui-Feng et al. (2023) employed the AlexNet-spatial pyramid pooling network (SPP-Net) in conjunction with a segmentation algorithm based on a mask region-based CNN (R-CNN) for the classification of graded mangoes. The designed system comprised a user interface module, an object detection module generating mango shape masks and bounding boxes, an image preprocessing module cropping the mango and colouring the background, and the grade classification modules utilising AlexNet-SPP-Net. Experimental results demonstrated that the proposed method outperformed the traditional AlexNet-based approach. In a study by Figueroa-Flores and San-Martin (2023), the performance of pre-trained deep learning models (InceptionV3, VGG19, ResNet152, and MobileNetV2) was compared in the classification of flowers. ResNet152 exhibited the highest performance with an accuracy of 95.87%, precision of 95.73%, sensitivity of 95.23%, specificity of 95.87%, F1-score of 95.85%, and an AUC of 96.02%. Rohit et al. (2023) classified user activities and addresses issues related with illegal transactions using supervised machine learning models. The datasets were trained using ensemble, decision tree, instance-based learning and Bayesian. GridSearchCV was used to optimise the CV accuracy of the classification models. In the result, A CV accuracy below 85% was achieved. Extra trees had the best performance while Gaussian naïve Bayes performed worst.

Ulligaddala and Aakanksha (2023) classified spam email using sentiment analysis. TF-IDF, information gain and Gini index were the classifiers used. In the experimental analysis, Gini index FS technique, word2vec FE and SVM classifier show the highest accuracy of 95.17% in e-mail spam detection. Longxin et al. (2023) classified fault in novel freight train image using CNN model. In the work an object detection model was designed to reduce dependence on texture and colour, then a fault classification model was developed to classify the segmented image. In the experimental result, a mean accuracy rate of 92.55% was achieved. Reviewing the existing literature, several methods have been applied for the classification of fruits. Many early authors predominantly relied on traditional feature extraction and classification techniques. This method failed to achieve high classification accuracy. The emergence of deep learning techniques has significantly improved classification performance. From reviewed literature, it was observed that the techniques that used CNN models achieved high classification accuracy. This justified that the automatic feature extraction and classification by CNN models has the potential to achieve state of art results than other techniques.

From the reviewed studies, most of the work used unbalanced dataset for the training of CNN models while others validated their experiments on a limited dataset, consequently, there is a pressing need to use balanced dataset and validate models with a more extensive dataset to enhance accuracy in mango classification. Also, none of the reviewed work utilised area under the curve (AUC) as an evaluation metric, incorporating AUC as a metric would offer insights into the classifier's pictorial ability to distinguish between varieties in a multiclass image classification problem. Hence, this work aims to improve on the accuracy of existing mango sorting techniques by employing a dataset captured in an uncontrolled environment and developing a CNN model to fit well in real-world applications.

3 Experimental method

This section outlines the methodology employed for the automated sorting of mango fruits based on variety. The proposed methodology encompasses image acquisition, image pre-processing, training and testing stages. The experimentation of an efficient image classification task using deep learning techniques would require both hardware and software materials, this includes a desired dataset, a deep learning model, a robust hardware resources such as GPU or a central processing unit (CPU), and a software library that would serve as the development environment. The flow diagram for this proposed methodology is illustrated in Figure 1. The subsequent sub-sections delve into the intricacies of each of these steps.

3.1 Image acquisition

The utilisation of a CNN model requires a substantial amount of dataset to achieve high accuracy. Accessing such diverse image data for real-world applications proves challenging, except for major companies like Google or Facebook as noted by Stefan et al. (2021). In the context of this research, we conducted data collection focusing on six mango fruit varieties (Alphonso, German, Julie, Jumbo, Kerosene, and Peter mangoes) from designated markets in the southwestern part of Nigeria specifically (Osun, Ekiti, Lagos, Ondo, Ogun, and Oyo States). The collected mangoes exhibited diverse maturity levels (unripe and ripe) and sizes (big, medium, and small). The image capturing was carried out using a 16-megapixels digital camera (Samsung Galaxy, 1/2.3” BSI-CMOS sensor) under uncontrolled environmental conditions, encompassing different times of the day, varied illumination, and orientations. A total of 6,744 images were used to generate our dataset (1,124 per variety). To create a test set, 100 images were extracted from each mango variety, resulting in a total of 600 images (approximately 9% of the data). The training dataset totalling 6,144 images underwent further division into two sets: a training set consisting of 4,300 images (approximately 70% of randomly selected data) and a validation set comprising 1,843 images (approximately 30% of randomly selected data). A selection of these captured images is depicted in Figure 2.

3.2 Image pre-processing

In deep learning, the quality of images in the dataset significantly influences the model's performance. It is important to facilitate the uniform processing of all images irrespective of their original resolution. Hence, it is imperative to ensure that the resolution of each captured image aligns with the specific input value required by the CNN model. In this subsection, all images within our database were captured at a pixel resolution of 3264 × 2448. The images underwent cropping and resizing by standardising them to 640 × 480 pixels. Subsequently, the images were subjected to de-noising through median filtering and their quality was improved using histogram equalisation. These processed images were stored as Joint Photographic Experts Group (JPG) files.

3.3 Convolutional neural network model

CNNs typically consist of designated elements that vary across different models. These elements basically containing input layer, convolutional layer, pooling layer, and fully connected layer are organised to form the model's architecture. The convolution layer forms the core of a CNN model and it consumes a significant portion of the processing time. The number of layers in a CNN model plays a crucial role in determining the testing time, the training time, and the overall network performance. Recent years have witnessed a growing interest in enhancing the efficiency and performance of CNN models, leading to notable advancements in novel architecture designs. This progress has resulted in a reduction in the number of parameters, optimisation of the training process, and substantial improvements in classification accuracy as noted by Figueroa-Flores and San-Martin (2023). Scientists have successfully developed numerous CNN models with varying architectures to enhance classification accuracy over the years. Despite these advancements, challenges persist, including the selection of an appropriate architecture for a specific task, the demand for substantial data, and the need for extensive computational resources, as highlighted by Najva and Abdul (2023). Consequently, the exploration of lightweight CNN architectures with reduced computational requirements and improved performance presents a promising research area.

3.4 Mathematical concept

In this section, we delve into the mathematical foundations underlying the primary operations within a CNN. The pivotal operations include feature extraction accomplished through the convolution operation, the classification utilising the fully connected layer, and the prediction employing the softmax layer. For an input image denoted as $f(x, y)$, the image undergoes convolution with filters to generate output feature maps. Every feature map represents a distinct feature identified by the corresponding filter. The expression for the output feature map is represented as shown in equation (1).

$$x_j^l = mf\left(\sum\nolimits_{i\in M} x_i^{l-1} * k_{ij} + b_j^l\right) \tag{1}$$

where x_i^{l-1} is the i^{th} input feature map of the $(l-1)^{\text{th}}$ layer, x_j^l is the j^{th} output feature map at the l^{th} layer and M is the set of feature maps at the $(l-1)^{\text{th}}$. k_{ij}^l is the convolution kernel between the l^{th} input map at layer $(l-1)^{\text{th}}$ and the j^{th} output map at the l^{th} layer. Rectified linear unit (ReLU) activation function is used to apply nonlinearity to the convolutional layer as shown in (2).

$$f(x)_{ReLU} = \max(0, x) \tag{2}$$

For an input image, the size of the output feature map can be determined using equations (3) to (7)

$$O = \frac{H - K + 2P}{S} + 1 \tag{3}$$

where O denotes the output's height/length, H denotes the input height/length, K denotes the filter size, P represents the padding while S is the stride. The padding is determined using equation (4).

$$P = \frac{K-1}{2} \tag{4}$$

Weights and bias are parameters in every layer of the CNN. They are calculated using equations (5), (6) and (7).

$$W = K^2 * C * N \tag{5}$$

$$B = N \tag{6}$$

$$P = W + B \tag{7}$$

where W equals the number of weights, B is the number of bias, N is the number of kernels, and C is the number of channels in the input image. K is the size of the filter while P is the number of parameters in a layer.

The softmax classifier is a traditional multi-classifier that employs an exponentially enhanced technique for generating predictions. For a composite feature $O = X1, X2, X3, \ldots, Xi$, O is processed by the fully connected layer to acquire feature vector $O_k = x1, x2, x3, \ldots, xk$. k is the number of class while O_k serves as the input to the softmax classifier to output classification label y_m, where $m \in [1, k]$. The principle of the softmax classifier is shown in equations (8) to (10)

$$y_m = \max(h(O_k)) \tag{8}$$

$$y_m = \max([h(x1), h(x2), \ldots, h(x_k])) \tag{9}$$

$$h(x_m) = \frac{e^{x_m}}{\sum_{i=1}^{k} e^{x_i}} \tag{10}$$

where $h(x_m)$ is the probability that the current image belongs to class y_m.

3.5 Building the proposed CNN model

This subsection delves into the analysis and the processes involved in constructing our CNN model. CNN architecture can be created through the stacking of basic layer elements such as convolutional, pooling and fully connected layers (Aamir et al., 2019). For our proposed architecture, we stacked convolutional layer, pooling layer, batch normalisation layer and fully connected layer. For the feature extraction segment, we used a convolutional layer as layer-1, a batch normalisation layer as layer-2, a rectified linear unit layer as layer-3 and a max pooling layer as layer-4. Another convolutional layer was used as layer-5, a batch normalisation layer as layer-6, a rectified linear unit layer as layer-7 and a max pooling layer as layer 8. For the classification segment, we used a fully connected layer as layers-9 and a softmax layer as layer-10. Figure 3 illustrates the architecture of our proposed model named AdeNet, Conv1 and Conv2 represent convolutional layers, Pool1 and Pool2 indicate pooling layers, FC3 denotes the fully connected layer, and the output layer is a softmax layer. Each layer has its own weights, hyperparameters, and biases. In the architecture, each convolutional layer was trailed by a batch normalisation layer, a ReLU layer and a max pooling layer. There are 512 neurons in the first fully connected layer and there are six neurons in the softmax layer to calculate the class scores. Our proposed architecture was implemented in Python programming with PyTorch library. When an image of size 224 × 224 × 3 serves as input for our developed AdeNet model, the output feature map will be determined using equations (3) to (7). The configuration obtained is as shown in Table 1.

Figure 4(a) illustrates the process flow for constructing a CNN model, while Figure 4(b) depicts the process flow for training the CNN model.

3.6 Training our built CNN model

This subsection highlights the training procedure for our built AdeNet model. The training of a CNN model is computationally intensive, the process involves the utilisation of the training dataset to initialise the weights. In our approach, we commenced by importing PyTorch libraries. Subsequently, the images in our dataset underwent cropping and resizing to match our model's input size (224 × 224 pixels). We employed the Totensor function to convert the images into a format usable by PyTorch. The images were then normalised and transformed. The DataLoader was employed to load both the validation and training datasets into the device (CPU). The specific hyperparameters utilised in our experiments were configured as detailed in Table 2. Afterwards, we initiated the training process. During the training process, the performance of the developed model was evaluated using the validation dataset. Upon the completion of the training, the model was saved.

Figure 3 Architecture of the proposed AdeNet model (see online version for colours)

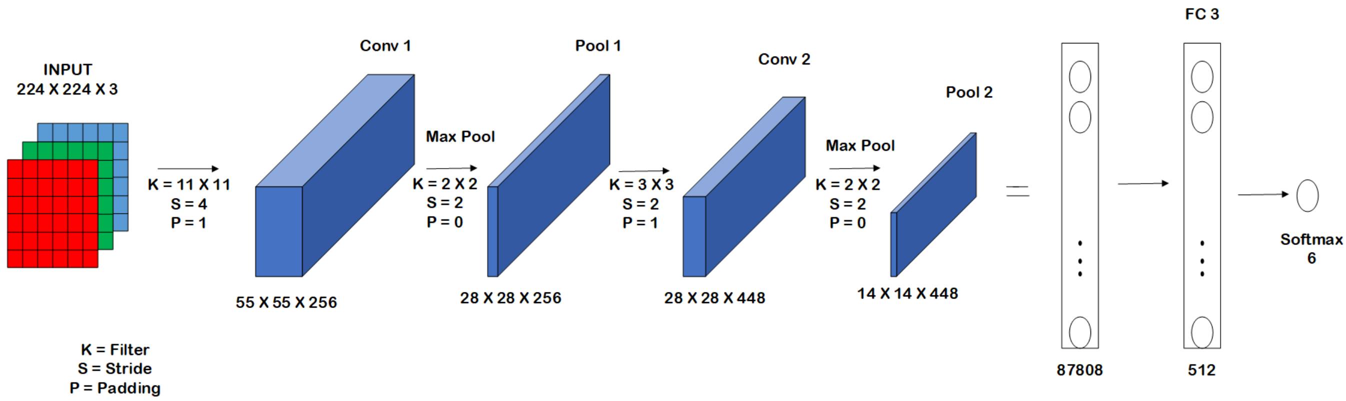
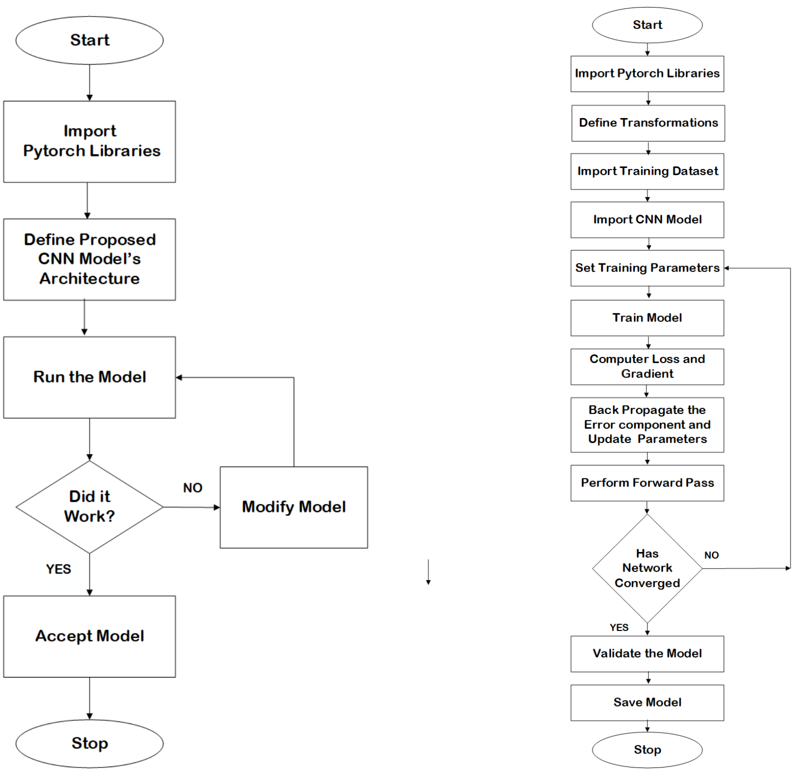


Figure 4 (a) Flowchart for building CNN model (b) Flowchart for training CNN model

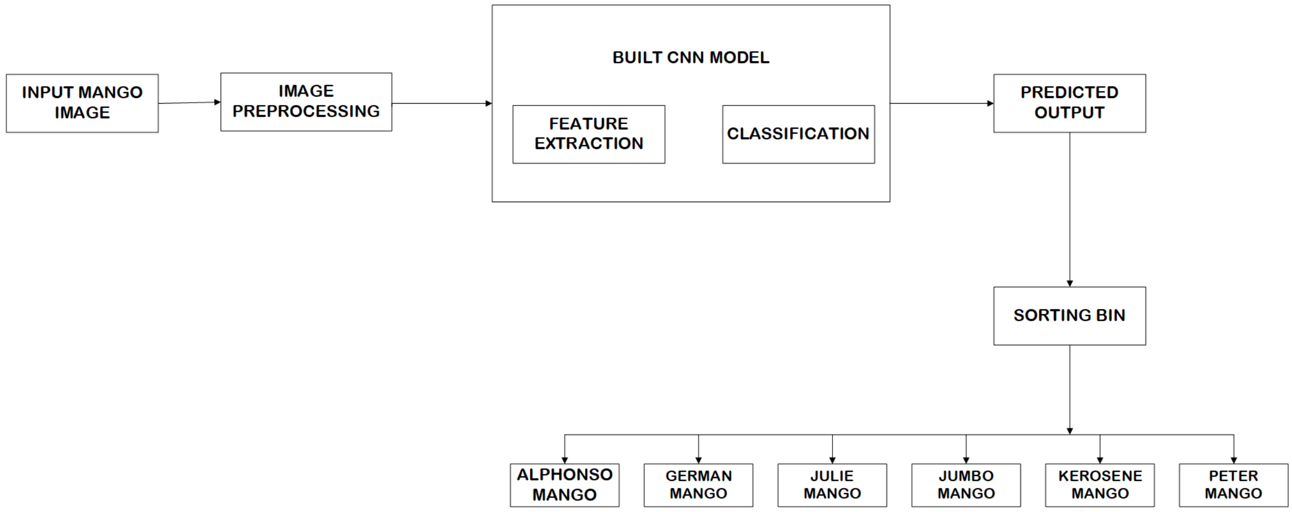


(a) (b)

Table 1 Configuration of the proposed CNN model

Layer	*Type*	*Size of input feature map*	*Dimension of filter*	*Depth of layer*	*Stride*	*Padding*	*Size of output feature map*	*Parameters*
0	Input	224 × 224 × 3	-	-	-	-	-	0
1	Convolutional	224 × 224 × 3	11 × 11	256	4	1	55 × 55 × 256	93,184
2	Batch normalisation	-	-	256	-	-	55 × 55 × 256	1,024
3	ReLU	-	-	-	-	-	-	0
4	Max-pooling	55 × 55 × 256	2 × 2	-	2	-	28 × 28 × 256	0
5	Convolutional	28 × 28 × 256	3 × 3	448	1	1	28 × 28 × 448	101,824
6	Batch normalisation	-	-	448	-	-	28 × 28 × 448	115,136
7	ReLU	-	-	-	-	-	-	0
8	Max-pooling	28 × 28 × 448	2 × 2	-	2	-	14 × 14 × 448	0
9	Fully connected	-	-	512	-	-	512	44,958,208
10	Softmax	-	-	6	-	-	-	3,078

Figure 5 Block diagram of the developed mango fruit sorting system



3.7 Testing our built CNN model

This subsection illustrates the testing of our developed model. Model testing is important, as it determines the performance of a trained CNN model by testing it on a dataset it has never seen before. When testing a trained model, the full-scale network will be employed to generate predictions. To test our developed model, we set the testing hyperparameters afterwards the model was switched to evaluation mode. Our experiment was conducted on a workstation with 8 GB of memory, an Intel(R) Core™ i3-2330 CPU @ 2.20GHz processor, and Windows 10, 64-bit Operating System.

3.8 Mango fruit sorting

In this subsection, we incorporated our built AdeNet model into our developed mango sorting system as illustrates in the schematic diagram in Figure 5. To test the performance of our developed mango fruit sorting system, we used it to sort the test dataset into the corresponding varieties.

Table 2 Experimental values for hyperparameters

Hyperparameter	*Value (%)*
Optimisation algorithm	Stochastic gradient descent (SGD)
Momentum	0.9000
Initial learning rate	1×10^{-3}
Epochs	50
Batch size	32

3.9 Evaluation metrics

The effectiveness of a CNN model is primarily assessed by its performance on test data. Evaluation metrics serve as crucial indicators for gauging the success of an experiment, as highlighted by Niklas and Davidsson (2007). The confusion matrix visually portrays the classifier's performance by illustrating the distinctive classes within the dataset. Each column corresponds to the true class, while each row corresponds to the predicted class. The off-diagonal elements signify misclassifications, whereas the diagonal elements represent correctly classified observations. From the confusion matrix, additional measures such as accuracy, precision, recall, and F1-score can be computed.

Accuracy, a commonly utilised metric calculates the percentage of correctly classified samples. It is represented by equation (11).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

Precision measures the prediction power of an algorithm, it determines how many of the predicted positive cases were truly positive. It is represented by equation (12)

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

Recall, often referred to as sensitivity represents the true-positive rate of the specified class.

$$Recall = \frac{TP}{TP + FN} \tag{13}$$

F1-score is a metric that combines both recall and precision. It is represented by equation (14)

$$F1\text{-}score = 2 \times \frac{precision \times recall}{precision + recall} \tag{14}$$

where TN – true negative, FN – false negative, FP – false positive and TP – true positive. A precision value of 1, a recall value of 1, F1 score of 1 and 100% accuracy is an expected value for a machine learning model.

The receiver operating characteristic (ROC) curve represents a probability curve that illustrates the relationship between the false positive rate (FPR) plotted on the x-axis and the true positive rate (TPR) plotted on the y-axis at various threshold values. Equations (15) and (16) present the formulas for the true positive rate and false positive rate respectively.

$$True\ positive\ rate\ (TPR) = \frac{TP}{TP + FN} \tag{15}$$

$$False\ positive\ rate\ (FPR) = \frac{FP}{FP + TN} \tag{16}$$

where TN, FN, FP, and TP denote true negative, false negative, false positive, and true positive respectively. AUC summarises the ROC curve, it is a measure of the capacity of the classifier to distinguish between classes. AUC is given mathematically by equation (17).

$$AUC = \frac{1}{C(C-1)} \sum_{i=1}^{C} \sum_{j=1}^{C} AUC_{ij} \tag{17}$$

where C represents the number of class, AUC_{ij} represents the binary AUC between class j and i. AUC value that is close to 1 is desirable. For this work, accuracy, precision, recall, F1-score and AUC were the evaluation metrics used to measure the efficacy of our developed mango sorting system.

4 Results and discussion

4.1 Training result of the built CNN model

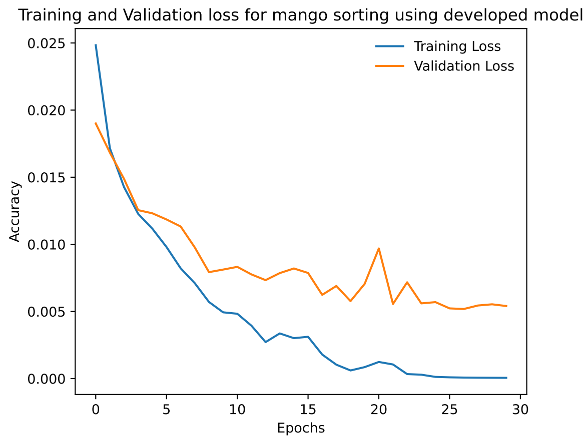
The result obtained from the training of our developed AdeNet model is detailed in this subsection. The developed model underwent training for 30 epochs. Throughout the training process, we observed that both the validation loss and training loss initially exhibited high values. However, with an increasing number of epochs, these values gradually diminished. At the conclusion of the training, we achieved a validation loss of 0.00541 and a training loss of 0.00006. Figure 6 illustrates the plot of validation loss against training loss. As depicted in Figure 6, the training loss is lower than the validation loss at the 30th epoch, this indicates that the model did not over-fit and it successfully learnt the features of the images.

4.2 Testing result for the developed mango fruit sorting system

This subsection presents the test result obtained by our developed system in the sorting of mango fruits into varieties. The confusion matrix result obtained is as shown in Figure 7(a) while Figure 7(b) shows the ROC result obtained.

Observations from confusion matrix in Figure 7(a) reveal that the Kerosene variety achieved a 100% accurate sorting, potentially due to its distinct colour feature. The pale peach skin colour of Kerosene mango sets it apart from other varieties. Similarly, Peter mango achieved a 100% accurate sorting, likely attributed to its size feature. Peter mango consistently exhibited the smallest and uniform size compared to other varieties. Julie mango achieved a 98% accurate sorting, with 1% of Julie samples mistakenly sorted as Alphonso mango and 1% as German mango. This misclassification can be attributed to the similarities among Alphonso, German, and Julie varieties. Alphonso mango achieved a 97% accurate sorting, with 3% of Alphonso samples incorrectly sorted as Jumbo mango. German mango achieved a 96% accurate sorting, with 3% of German samples mistakenly sorted as Julie mango and 1% as Alphonso mango. Jumbo mango achieved a 91% accurate sorting, with 6% of Jumbo samples mistakenly sorted as Alphonso mango, 2% as German mango, and 1% as Julie mango. These results affirm the intra-breed differences and inter-breed similarities among mango fruit varieties.

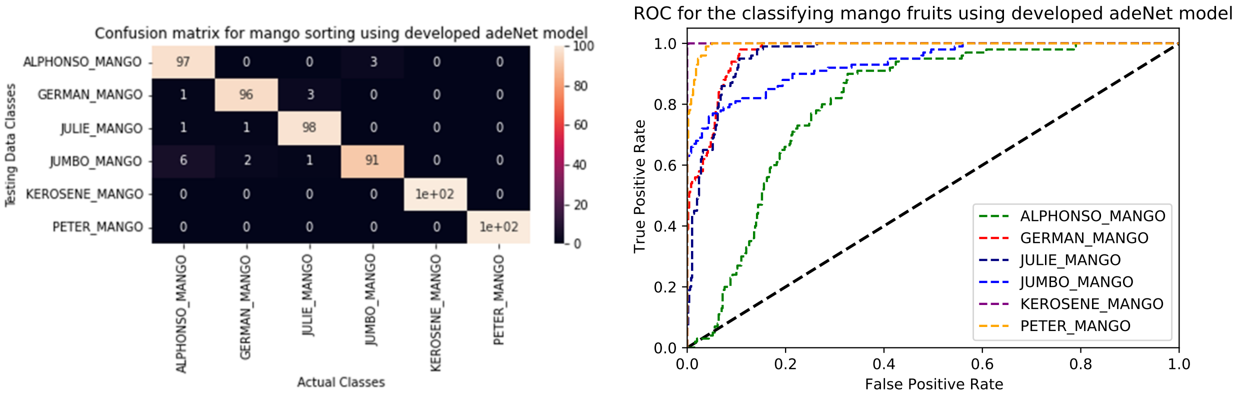
Figure 6 Training loss and validation loss plot (see online version for colours)



From the ROC curve in Figure 7(b), it is evident that the positive class for each variety was well separated from other varieties. The performance of the developed system was evaluated by utilising equations (11), (12), (13), (14), (15), and (17) to determine accuracy, precision, recall, F1-score, and AUC as detailed in Table 3. Table 3 provides an assessment of the mango sorting system's performance. Kerosene mango had the highest performance of 100% in terms of accuracy, precision, recall, F1-score, and AUC. Peter mango also had 100% for all the metrics except an AUC value of 99%. The performance of the other four mango fruit varieties also varied across the metrics. This result suggests that the use of more than one evaluation metric is important for a clearer picture of the performance of a CNN model. From Table 3, the performance of the developed mango sorting system was determined by calculating the average accuracy, average precision, average recall, average F1-score and average AUC as shown in Table 4.

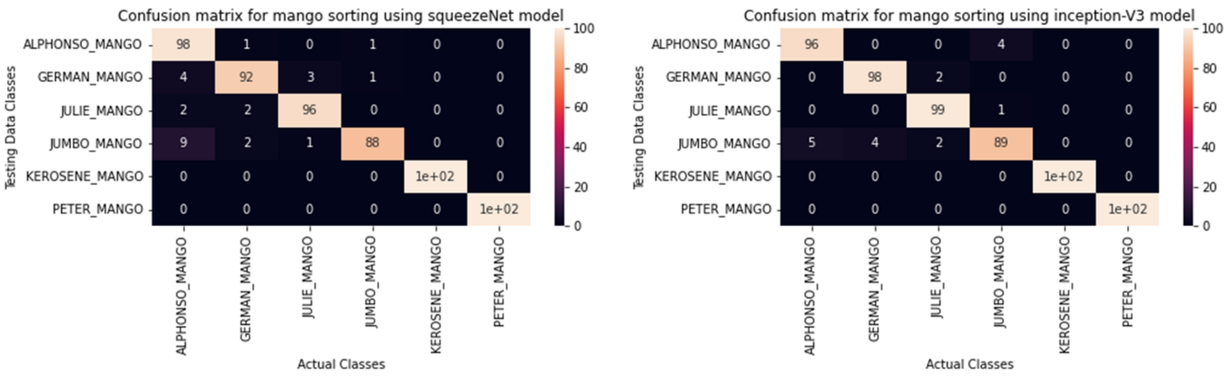
In an ideal situation, a precision value of 1, a recall value of 1, F1-score of 1, AUC of 1 and 100% accuracy is the projected value for a deep learning model. From Table 4, the developed system is 99.0% accurate. The mean AUC of 98.8% indicated excellent separation capability for all the six mango varieties. Additionally, a recall of 97.0% signified the system's ability to correctly classify 97.0% of positive samples while a precision of 97.1% indicates the prediction power of the system. Hence, the developed system can be trusted in its ability to sort mango fruit varieties.

Figure 7 (a) Confusion matrix and (b) ROC plot for mango sorting using developed model (see online version for colours)



(a) (b)

Figure 8 Confusion matrix for, (a) SqueezeNet model (b) Inception-V3 model (see online version for colours)



(a) (b)

Table 3 Performance evaluation per variety

Parameters	*Alphonso mango*	*German mango*	*Julie mango*	*Jumbo mango*	*Kerosene mango*	*Peter mango*
Accuracy (%)	98.2	98.8	99.0	98.0	100.0	100.0
Precision (%)	92.4	97.0	96.1	96.8	100.0	100.0
Recall (%)	97.0	96.0	97.0	97.4	100.0	99.4
AUC (%)	99.0	98.0	99.0	97.0	100.0	99.0

Table 4 Performance of the developed mango sorting system

Performance evaluation metrics	*Average result (%)*
Accuracy (%)	99.0
Precision (%)	97.1
Recall (%)	97.0
F1-score (%)	97.6
AUC (%)	98.8

4.3 Discussion and comparison

In this subsection, we tried to prove the effectiveness, quality and robustness of our developed model by comparing our achieved result with that of relevant and recent existing studies from literature. The comparison is presented in Table 5.

From Table 5, it was noted that our proposed approach outperformed the existing works in the literature. From the comparative analysis of existing literature, it was noted that various databases and CNN models were employed for image classification. Consequently, we validated the performance of our developed system against two established classic pretrained models, Inception-V3 and SqueezeNet using the same training and testing parameters. The corresponding confusion matrices are presented in Figures 8(a) and 8(b).

From the confusion matrixes, equations (11), (12), (13), (14), (15) and (17) were used to determine accuracy, precision, recall, F1-score, and AUC respectively. Furthermore the average accuracy, average precision, average recall, average F1-score, and average AUC obtained from the Inception-V3 and SqueezeNet models were compared with the result of our developed model. The comparative result is as shown in Table 6.

Table 5 Comparison of our work with existing literature

S/N	*Author*	*Classifier used*	*Dataset*	*Classification performance (%)*
1	Santi et al. (2019)	Support vector machine	Images of mango fruits	Accuracy 90%
2	Ohnmar (2019)	Naïve Bayes	Images of mango fruits	Accuracy 94%
3	Amin et al. (2019)	VGG-16	Images of date fruits	Accuracy 96.98%
4	Girish et al. (2020)	Inception-V3	Images of mango fruits	Accuracy 97.6%
5	Wei et al. (2022)	SqueezeNet model	Images of mango fruits	Accuracy 95.64%, F1-score 95.9
6	Anuradha and Khelchandra (2023)	Self-organising neural network (SONN) and multilayer perceptron (MLP)	Renal ultrasound images	Accuracy 96.8%, precision 93.9%, recall 93.0%, F1-score 93.0%
7	Figueroa-Flores and San-Martin (2023)	ResNet152	Images of mango fruits	Accuracy 95.87%, precision 95.73%, F1-score 95.85%, AUC 96.02%
8	Rohit et al. (2023)	Extra trees	Criminal users' activity dataset	CV accuracy below 85%
9	Ulligaddala and Aakanksha (2023)	Sentiment analysis	e-mail spam dataset	Accuracy of 95.17%
10	Longxin et al. 2023	CNN model	Images of freight train	Mean accuracy rate of 92.55%
11	Developed system	AdeNET model	Images of mango fruits sourced from South-West Nigeria	Accuracy 99.0%, precision 97.1%, recall 97.0%, F1-score 97.6%, AUC 98.8%

Table 6 Validating the performance of our proposed model with classic CNN models

Model	*Proposed AdeNet model*	*Inception-V3*	*SqueezeNet*
Accuracy (%)	99.0	98.8	98.6
Precision (%)	97.1	96.5	95.9
Recall (%)	97.0	96.5	95.7
F1-score (%)	97.6	96.5	95.7
AUC (%)	98.8	98.3	97.2

Examining Table 6, it is evident that all the three models demonstrated proficient performance in sorting mango fruit varieties. However, our developed AdeNet model outperformed Inception-V3 and SqueezeNet models in terms of accuracy, precision, recall, F1-score and AUC. These results underscore the state-of-the-art capabilities of our developed system, positioning it as a viable solution for the automated sorting of mango fruits. This could be as a result of the insertion of a dropout layer before the fully connected layer.

5 Conclusions

This research aimed to develop a sorting system with improved performance for mango fruit varieties. The methodology involved the creation of dataset from six commercially available mango fruits in southwestern part of Nigeria, the creation of a novel CNN model to perform the feature extraction and classification within the developed system and the evaluation of the performance of the developed system. The advantage of the developed system is that its architecture has a shallow depth and the experimental result showed better performance when compared with similar existing works. This research has contributed to knowledge in the area of generating dataset for the mango fruit varieties, and developing a novel CNN model with improved performance for image classification. The developed system can be applied in the fruit processing sector and it can be deployed in mobile devices as mango fruit variety identifier. Regardless of the performance achieved by the developed system, the limitation of this work is that its best performance can only be achieved when it is used to sort the mango fruit varieties it was trained with. The following recommendations are made for the improvement of this research in the future: increasing the number of mango fruit varieties, increasing the number of mango fruit samples in the training and test dataset, and training the system for a greater number of epochs. Compare with other classical CNN models, our developed model is reliable.

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