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A scheme based on deep learning for fruit classification

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ABSTRACT

Grading and classifying fruits are critical due to automated machine learning systems. In computer vision, different fruits have large complexity and similarity to identify the fruit types. In this study, we developed an efficient and reliable fruit grading system. It is very difficult to classify fruits from images with established conventional approaches. We used a Convolutional Neural Network (CNN) methodology involving comparing a custom-built CNN and the VGG pre-trained models. In the research results, the VGG model accuracy is of 99.98 percent. This research proved the effectiveness of the deep model in the challenges of fruit classification and set a foundation for its application in automated grading systems.

1. Introduction

Agriculture field development plays an important role in the food supply in the world. Fruit classification and grading is the area of agriculture, which relies on manual Labor. The deep methods incorporated into the fruit classification system can significantly benefit the industry. Artificial Intelligence (AI) [1] offers solutions for automating agricultural objectives, and yield production for profit. Machine learning methods for fruit production encourage the supply chain for producers, distributors, and retailers too.

Currently, IoT-based deep methods make it possible to analyze production and sales data in the agriculture sector. Apples, bananas, pineapples, strawberries, and oranges fruits are rich sources of essential vitamins and nutrients. However, the growing demand for fruit grading requires auto-systems to improve cost-effectiveness in the supply chain of fruits in the market. Deep learning model as like Convolutional Neural Networks (CNNs), is the best solution for fruit classification.

The fruit industry plays a vital role in the agro-supply chain eco-system and needs to automate the fruit grading process to make it cost-effective and efficient. Deep Neural Network (DNN) methods are very effective in complex feature extractions for fruit classification. Deep learning models can be trained efficiently to classify complex images on open source large datasets available at Kaggle's Fruit360. DNN schemes are very vital to classifying fruits for classification in auto-systems[2] in complex situation and efficiently classify complex images [3, 4].

CNN is more effectively used in image classification [5-7], and it is highly capable of capturing intricate visual features in computer vision. The CNNs model used and proved the best in image classifications [8],[9] despite this, full accuracy remains a challenge. However, the CNNs model in different variants continues to make it perfect accuracy [10-13] and efficiency in auto-systems.

In this research study, we made a fruit classification system using a deep learning scheme that offers superior performance as compared to traditional machine learning schemes. We utilized a custom-built VGG model in research and achieved optimal accuracy, which showed in the confusion matrix. And have made a user-friendly application, for getting images and providing the results accurately.

The research study will benefit supply-chain systems of fruit industry potentially, and deep learning in solving real-world challenges in the agriculture sector.

2. Literature Review

In agro-field ecosystems, fruit classification is a complex job in fruit identifications due to their similar features [3]. In research studies, researchers used many deep learning models, like CNN, VGG16, VGG19, and Support Vector Machines (SVM), etc. to classify fruit images [14-17]. A hybrid classification method was also proposed for internal classification by fruit images at 256x256 pixel sizes and also can removed the background elements using a split-and-merge algorithm. A k-fold multi-layer cross-validation technique yielded classification accuracies of 89% for FSCABC-FNN, 88% for SVM, and 87% for PSO-FNN [24-26].

Transfer learning schemes have gained attention due to their ability to apply pre-trained models to new tasks in deep learning. In fruit harvesting, autonomous systems typically employ early and late blending methods. However, fruit detection remains challenging due to issues like fruit overlap and high density in the images. A region extraction method based on a discriminatory search algorithm is used at the initial detection step, followed by region selection via entropy analysis. These regions are fed into a Convolutional Neural Network (CNN) for training and recognition. CNNs have demonstrated significant effectiveness in object classification, particularly in agricultural applications. For example, [27] utilized CNNs for plant disease detection and classification from leaf images, achieving impressive results. The paper proposed a novel approach by developing a recognition model for plant disease based on leaf image classification using Deep Neural Networks (DNNs) [28-31] and achieved an accuracy of 96.3%.

The automatic recognition of fruits can also be implemented through vision-based systems, such as a voice-controlled robotic arm classification scheme using transfer learning [7]. This method used data augmentation techniques to prevent overfitting [32-34]. Other researchers have proposed various techniques for fruit detection using different algorithms and tools. For instance, [8] employed a DNN classifier alongside a radial Hough-like operator, which aimed to identify regions in the image effectively. However, some limitations persisted, particularly for near-spherical fruits like grapes and apples [6, 18, 19, 27-29, 35, 36]. Another study [9] developed a system for identifying fruits and vegetables in the merchandising market using video cameras to capture images. The network employed multiple propagation times and was tested with different neural networks, achieving varying accuracies.

One of the most notable advancements in fruit recognition is to use of deep learning models, particularly the CNNs models. A study [10] utilized the Fruit-360 dataset, trained a CNN model using TensorFlow, and achieved a training accuracy of 99% and a test accuracy of 95%. The researchers were also interested in applying this technology to robotics within the agricultural industry. Another study [11] presented a commercial source trace system for automatic fruit recognition using Deep Convolutional Neural Networks (DCNNs). However, challenges remain, as noted by [8, 12, 20-23, 30, 33, 36-43],with automatic fruit recognition facing difficulties due to the similarities between different fruit types and environmental factors like lighting. Previous research was often limited by the availability of datasets, which only included 15 categories of fruits with 44,406 images. These images were directly input into DNN models for training and recognition without further feature extraction, relying on region classification fusion for the final decision [31, 46, 60].

Researchers have generally focused on fruit classification based on specific features such as shape, size, and density. For instance, [12] proposed a model that recognized fruits automatically by identifying different types based on their properties. This system involved three phases: image data preprocessing, feature extraction, and classification. The feature extraction process employed the Scale-Invariant Feature Transform (SIFT) technique. At the same time, classification was done using K-Nearest Neighbors (K-NN) and SVM, achieving high accuracy with a dataset of 178 images. The model demonstrated that color and shape could effectively identify fruit properties. According to [13], accuracy is critical in fruit detection. In their research, the Fruits-360 dataset was used to train CNN models, successfully evaluating 17,823 fruit images across 25 categories. The feature extraction process highlighted the importance of optimizing parameters and layers within the CNN model. Various combinations of hidden layers and epochs were tested to maximize the accuracy of fruit classification.

3. Methodology and Design

The Fruit classification application is used to classify the fruits of different groups can be identified automatically in computer vision. Precise fruit classification systems are essential to a fully automated harvesting robot.

3.1.1 Proposed framework

The proposed model of the CNN has been described in Fig. 1, showing the processing of the tested scheme.

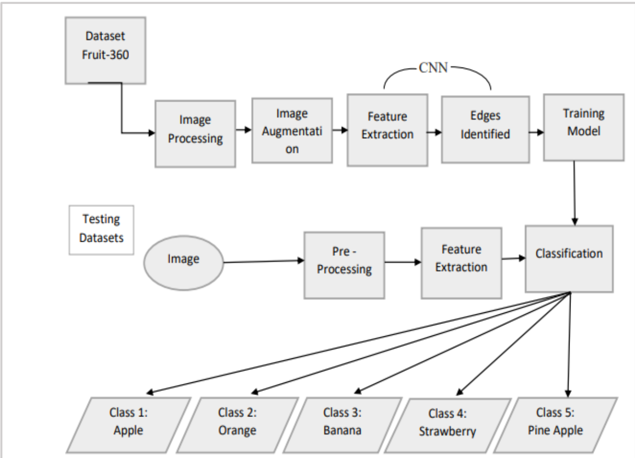

Fig. 1. Proposed Framework Classification Using CNN

3.1.2 Fruit-360 dataset

Dataset augmentation is a technique used to increase the size and diversity of the dataset without collecting additional samples. In this study, various augmentation techniques were applied to the original dataset to generate new variations of the images, ensuring the model can generalize better. These techniques include:

- Image flipping (horizontal/vertical)
- Rotation (e.g., 0°, 90°, 180°)
- Scaling (zooming in/out)
- Cropping
- Translation (shifting images)
- Adding noise
- Color adjustments (brightness, contrast, saturation)

Before augmentation, the dataset consisted of 17,823 images, covering 25 categories. After applying the augmentation techniques, the size of the dataset increased to 53,469 photos, providing a more diverse set of training data for improved performance and generalization in fruit classification.

In this study, we utilized the high-quality Fruit-360 dataset (version: 2019.06.29.0) publicly available on GitHub and Kaggle. Sample images from the Fruit-360 dataset are illustrated in Fig. 2, with the different fruit categories, each treated as a separate object for classification purposes. The dataset consists of 75,937 images of fruits and vegetables, organized into two categories: training and testing sets. Specifically, the training set includes 56,781 images (each depicting one fruit or vegetable per image), while the testing set comprises 19,053 images. Each image is standardized to a resolution of 100 x 100 pixels. A white sheet of paper was used as a backdrop for the fruits, although variations in lighting conditions resulted in non-uniform background colors.

We employed a flood fill-type algorithm to extract the fruit images from the background. Using a high-quality, standardized dataset is critical for achieving better accuracy in testing the classifier model, as noisy datasets can lead to incorrect object classification. This dataset selected 22 different categories of fruits for classification purposes.

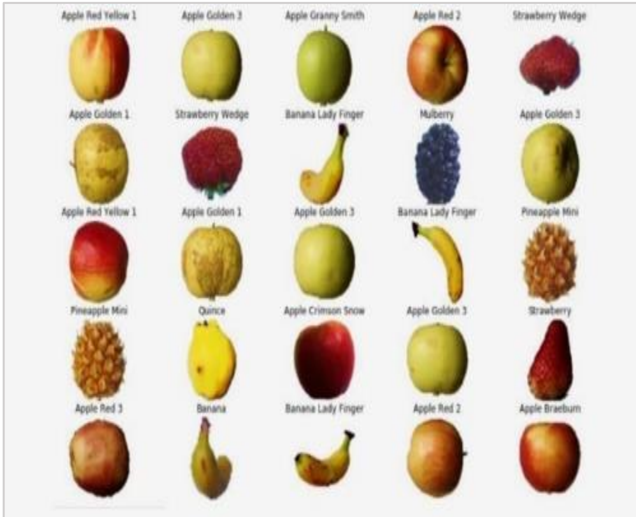

Fig. 2. Sample Images From The Fruit-360 Dataset Classification

In Fruit-360, each fruit described in Fig 2 is further categorized into different types, each treated as a distinct object for classification.

Deep learning is a powerful tool for handling complex, high-dimensional data such as images. In this study, the goal was to solve one of the most critical challenges in computer vision—accurate image classification—particularly in the context of fruit grading. Traditional machine learning methods often struggle with feature extraction, which requires manual intervention and limits scalability. By using deep learning, specifically Convolutional Neural Networks (CNNs), we can automate feature extraction and improve performance on complex datasets like Fruit360. This approach enables models to learn and adapt to intricate visual patterns (like color, texture, and shape) that distinguish fruits, overcoming challenges posed by similarity and complexity in visual data.

The proposed research design is composed of stages, like data acquisition to create a diverse dataset. In this stage, data preprocessing is done in which we make cleaning, normalization, and transformation of data images. It added in the model requirements like resizing and noise reduction. The second stage is featuring extraction. which is fed into a deep-learning model to train it. After training, the model has been tested and evaluated finding the model's accuracy and precision ratios. Finally, the model continues to a post-processing step to refine outputs for deployment in real-world applications.

Relatively smaller datasets. This study used models like VGG because they have been pre-trained on large image datasets, capturing valuable features that can be transferred to the fruit classification task. The used model improves efficiency and ensures better generalization on the test dataset, as demonstrated by the performance metrics of 99.98% accuracy.

The incentive for this research is to create an automated, scalable, and reliable fruit grading system, which has significant practical implications for the agriculture and food industries. By improving the speed and accuracy of fruit classification, this technology can reduce manual labor, enhance quality control, and ensure consistency in grading, ultimately benefiting both producers and consumers. Using deep learning in this context also opens up opportunities for further applications in other areas requiring fine-grained image classification, such as medical imaging and industrial inspection.

3.1.3 Image processing

Image processing is a field of computer vision and machine learning techniques that perform some operations on images to train the model for applications. Image processing enhanced the quality of the image to remove defects and reduce the size of the image as required for the training dataset. We used the image normalization technique; normalization is a process that changes the range of pixel intensity values.

3.1.4 Image augmentation

Image augmentation works with random image alteration or transformation techniques that enhance the size and quality of images from the dataset and improve the model's performance. The augmentation process can be applied to the CNN model scheme's random rotation, horizontal flip, or random zoom. We used CNN to generalize unseen image data and avoid overfitting the model testing process. This overfitting may refer to high variance where required regularization techniques and data augmentation are to overcome the overfitting in the proposed CNN model. Building a robust and valuable deep learning model that may reduce the validation error is necessary. Data Augmentation can extract the feature from the given datasets. It depends on the size of the data. In classification, it is more difficult at this stage when the model is a training process.

Convolutional neural networks (CNN) are deep learning algorithms for image classification. This CNN network model scheme contains convolutional, pooling, ReLU, fully connected, and loss layers. In a typical CNN model, each convolutional layer is followed by a Rectified Linear Unit (ReLU) layer and a pooling layer. Additionally, it has a dropout layer to avoid overfitting problems. Finally, the model has one or more fully connected loss layers with the SoftMax function.

In the Fruit-360, each fruit has different categories, and each is considered a separate object. The number and types of fruit images are:

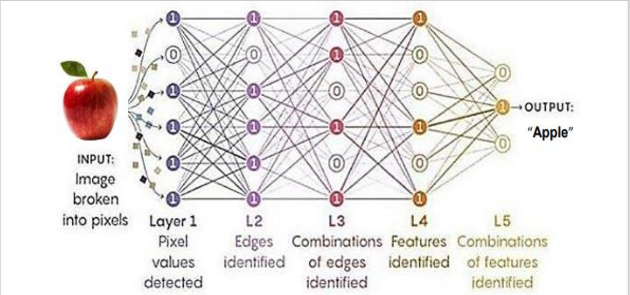

Fig. 3. The Model Of Working Architecture

Fig. 3 shows the input image broken down into individual pixels in Layer 1, where the pixel values are processed. In Layer 2, the model detects and identifies edges within the image based on the pixel values. Moving to Layer 3, combinations of these detected edges are formed, providing more structure to the image. In Layer 4, these combinations of edges are further processed into features. Finally, in Layer 5, combinations of these features lead to the identification of the object in the image. The model outputs the recognized object, such as an "Apple." This layered process is typical of deep learning models used for image classification, where each layer builds upon the previous one to achieve a refined understanding of the image.

3.1.5 Convolutional layers

The essential component of CNN is the convolutional layer. The convolutional layer uses a 3D core (also known as a dimensional-specific filter) of groups of neurons to perform heavier lifting, such as object extraction and recognition. The proposed researchers [16] used interactive systems, including facial 3D and 2D recognition. The depth of the filter is selected based on the number of color channels and the color image with RGB. To convert this kernel to an embodiment, focus the kernel on the pixels of the image, take the multiplier values for each pixel, multiply, add, and assign them to the pixels. The output of the composite layer is generated by overlaying the resulting activation map and is used to determine the input for the next layer. For example, a 32 x 32 image has a trigger tag size of 28 x 28. As the complexity increases, each image becomes smaller, the image size decreases dramatically, information is lost, and problems are raised exponentially. The solution is to align the whole image without adding color fill and without losing the convolution kernel. This operation is called filling itself. The ReLU level is an activation function that allows the model to solve nonlinear problems and perform a maximal activation function. It does not reduce the network size but improves the nonlinear characteristics.

3.1.6 Pooling layers

We used a pooling layer in the CNN model to reduce the images' spatial dimension and computation cost. Moreover, this layer is also used to control overfitting problems. The size 2 x 2 filters with a stride two effectively managed the model problem of overfitting.

3.1.7 Fully connected layer

The neuron of this layer is connected or linked with the previous layer, which means a fully connected layer from a regular neural network with operations behind cumulative levels being the same as for a fully connected layer.

3.1.8 Loss layers

This layer shall be the last layer of a network, used to discipline the network for taking off from the expected output. In this layer, various loss functions, such as softmax, are exercised to predict classes from multiple disjunct categories of images.

3.1.9 Techniques for avoiding overfitting

a) Dropout: This layer helps to avoid overfitting and prevent complex co-adaptations on training data. The dropout set is between 0.25 to 0.5.

b) Batch Normalization Layer: We must normalize this layer's activation, gradient propagation, network training, and optimization problems. We have used the layer between the Convolutional layer and the ReLU layer to get speedy training and reduce any sensitivity to the training model network for the initialization process.

c) Custom Build Model: The mode script is shown in Fig 4. It is also essential to notice the best results in the training and validation datasets.

```
from keras.layers import Flatten, Conv2D , BatchNormalization , MaxPooling2D
from keras import backend as K

model = Sequential()
inputShape=(96 , 96, 3)
ChanDim = -1

if K.image_data_format() == 'channels_first':
  inputShape=(3 , 96 , 96)
  ChanDim = 1
model.add(Conv2D(16 ,(3,3) ,input_shape=inputShape,padding='same',activation='relu'))
model.add(BatchNormalization(axis=ChanDim))
model.add(Conv2D(16 , (3,3) , padding='same', activation='relu'))
model.add(BatchNormalization(axis=ChanDim))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(32 ,(3,3) ,padding='same',activation='relu'))
model.add(BatchNormalization(axis=ChanDim))
model.add(Conv2D(32 , (3,3) , padding='same', activation='relu'))
model.add(BatchNormalization(axis=ChanDim))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))

model.add(Conv2D(64 ,(3,3),padding='same',activation='relu'))
model.add(BatchNormalization(axis=ChanDim))
model.add(Conv2D(64 , (3,3) , padding='same', activation='relu'))
model.add(BatchNormalization(axis=ChanDim))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512 , activation='relu'))
model.add(BatchNormalization(axis=ChanDim))
model.add(Dropout(0.50))
model.add(Dense(22 , activation='softmax'))

Epoch 20/20
339/339 [==============================] - 55s 164ms/step - loss: 0.0012 - acc: 0.9998 - val_loss: 0.0012 - val_acc: 1.0000
```

Fig. 4. Custom-Build Model Script

It is also important to note the best results in the training dataset and the validation dataset. We trained the dataset using a different combination of layers and CNN architecture and observed the accuracy of both training and validation data. It took several configurations to train the model to get accuracy on the validation and training sets of images to maintain and achieve the best network configuration for classifying fruit images.

Table 1

Model performance on the training and validation set accuracy

Authors and Model	Accuracy of Training Set	Accuracy of Validation Set
Muresan, H., and Oltean, M. (2018) DNN/CNN [68]	99%	99.7%
Sakib, S., Ashrafi, Z., and Siddique, M. A. B. (2019) -CNN [69]	99.%	99.79%
Joseph, J. L., Kumar, V. A., and Mathew, S. P. /CNN [70]	93%	95.35%

Aldakhil, L. A., and Almutairi, A. A. (2024)/CNN [71]	99%	99.17%
Proposed Approach Custom VGG	99.999%	100%

As demonstrated in Table 1, our custom-built VGG model achieves an accuracy of 99.9% to 100%, outperforming or matching the accuracy of other SOTA methods. This comparison proves our approach is competitive and compelling for fruit classification tasks.

We observed the accuracy of both the training and testing datasets using CNN's different architectures. Finally, we implemented the VGG_Custom Build Model of CNN, which gave the best accuracy of 99.98% on the training and 100% on test sets.

4. Experimental Analysis

This study applied a CNN model to the Fruit-360 dataset to achieve the best classification results. We experimented with different combinations of hidden layers and varying input parameters, such as the number of epochs and batch sizes of 50 and 32. Our deep model achieved optimal accuracy in the training and test phases. The highest classification accuracy of 100% on test images was achieved in cases 7 (VGG Custom Build Model) and 4 (GoogleNet) where our model got between 9- 20 epochs on the test set.

In contrast, the GoogleNet model, with greater complexity, achieved its best accuracy between 14 to 20 epochs. The next highest test accuracy was observed in case 3 (99.8%) at epoch 6, case 2 (99%) at epoch 5, case 1 (99.8%) at epoch 9, case 5 (99%) at epoch 9, and case 6 (97%) at epoch 7. These results provide a comprehensive visualization of the performance of deep learning models on the dataset. Over time, during training, we used the Matplotlib library to make graphical statistics, expressing the accuracy and loss of both training and validation datasets. We used two techniques to reduce the overfitting problem, so we did not counter the overfitting problem during training. Therefore, the overfitting issue did not arise during the training model processing. In addition, loss of verification and training was observed in all seven cases. The best results were found on the same VGG. And GoogleNet custom build models are that there is the slightest difference between training and validation. Training and validation losses also play an essential role in dataset formation as they are misclassified due to their high accuracy but high loss rate.

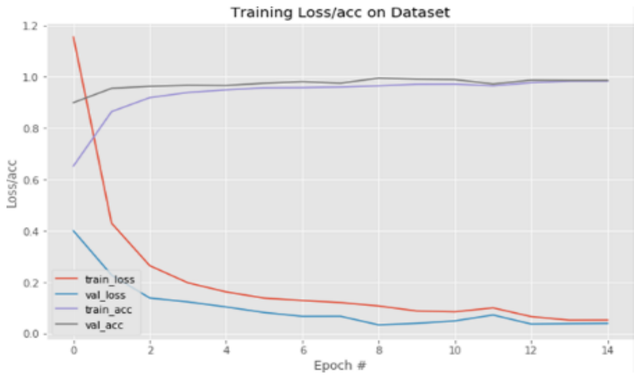

Fig. 5. VGG16 Model for Training Loss and Accuracy

We have found that the VGG. The Custom Build Model is the best, giving the highest accuracy and the lowest loss for training and validation, so we finally implemented it.

Fig. 6. VGG19 Model – Training Loss and Accuracy

5. Model Evaluation

In this research study, we used to identify the valid and predicted classes through confusion matrix specifications; in this connection, rows represent the valid class, whereas columns represent the predicted class to justify the scheme accuracy. These results are shown in Fig4, Fig6, and Fig7, the diagonal entries of the confusion matrix to check the performance of the classification CNN model. Moreover, for best accuracy, other metrics are used to compare the model's performance, such as precision, recall, and F1-score.

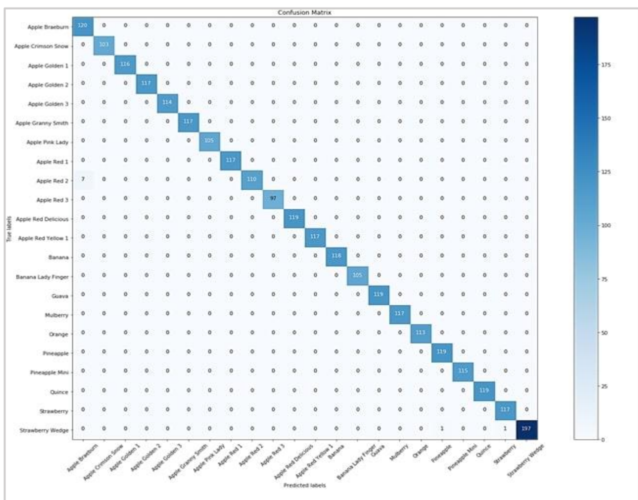

Fig. 7. Confusion Matrix Analysis

- Precision: In this metric, "Precision = T.P.P.P. / (TP+FP)", we can measure how many predicted values are correctly classified, proper labels of the fruit image class, and optimistic prediction by the trained model scheme.
- Recall: In this metric, "Recall = T.P.P.P. / (TP+FN", we accurately measured the amount of retrieved information or the correct data sample predicted by the trained model.
- F1-Score: In this metric, "1-score = 2x Precision * Reca", we combined the precision and recall values relative to a specific positive class label. It can be achieved between best and worst cases at 1 or 0 specifications.
- Support: In this metric, we find out how much the accurate responses' actual number of data samples lie in that class.

	precision	recall	f1-score	support
Apple Braeburn	0.94	1.00	0.97	120
Apple Crimson Snow	1.00	1.00	1.00	103
Apple Golden 1	1.00	1.00	1.00	116
Apple Golden 2	1.00	1.00	1.00	117
Apple Golden 3	1.00	1.00	1.00	114
Apple Granny Smith	1.00	1.00	1.00	117
Apple Pink Lady	1.00	1.00	1.00	105
Apple Red 1	1.00	1.00	1.00	117
Apple Red 2	1.00	0.94	0.97	117
Apple Red 3	1.00	1.00	1.00	97
Apple Red Delicious	1.00	1.00	1.00	119
Apple Red Yellow 1	1.00	1.00	1.00	117
Banana	1.00	1.00	1.00	118
Banana Lady Finger	1.00	1.00	1.00	105
Guava	1.00	1.00	1.00	119
Mulberry	1.00	1.00	1.00	117
Orange	1.00	1.00	1.00	113
Pineapple	0.99	1.00	1.00	119
Pineapple Mini	1.00	1.00	1.00	115
Quince	1.00	1.00	1.00	119
Strawberry	0.99	1.00	1.00	117
Strawberry Wedge	1.00	0.99	0.99	199
accuracy			1.00	2600
macro avg	1.00	1.00	1.00	2600
weighted avg	1.00	1.00	1.00	2600

Fig. 8. Model Classification Report

If we look at Table 1 and compare it with previous studies, our approach using a VGG custom-build model achieves the highest accuracy, ranging between 99.9% and 100%.

In contrast, Muresan and Oltean (2018) [68] used a combination of CNN and RNN, reaching 99% accuracy, while Sakib et al. (2019) [67] employed a CNN with a slightly higher accuracy of 99.79%. Joseph et al. (2021) [66] also used a CNN but reported a lower accuracy of 94.35%. Our custom

VGG model's superior performance demonstrates its effectiveness in handling the dataset, surpassing the accuracy of other CNN and RNN-based approaches.

6. Software Utilized for Implementing the Fruit Classifier Deep Learning (F.C.D.L.) Application

We have implemented the state-of-the-art proposed scheme for fruit classification. It is freely available and can be used by Windows, Linux, and Mac OS systems. This model was designed and implemented with the open-source distribution of R and Python to facilitate package management and easy deployment for everyone. Moreover, the package version is handled by Conda and Anaconda distribution. Anaconda Navigator is easily accessible and provides a graphical user interface (GUI).

7. UI Implementation

After getting a trained model, this research study has been implemented and tested in real-time. The GUI interface allows users to interact with the system, icons, and buttons instead of text-based use. This model design has a visual composition and temporal behavior, which aims to increase the usability of the interactive design application; this is expressed in Fig. 7.

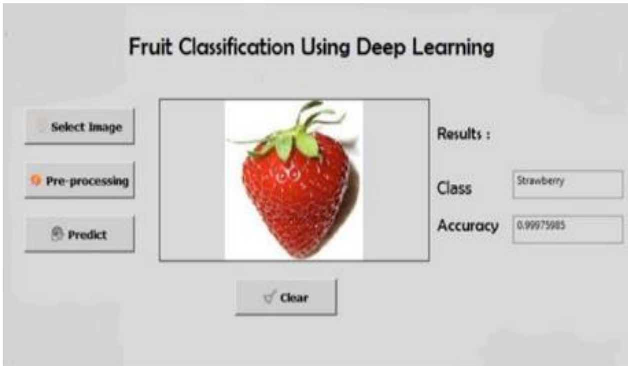

Fig. 9. User Interface Design Outlook

8. Conclusion and Limitations

Image classification and computer vision remain crucial areas of study, with significant progress yet to be made in achieving human-level accuracy. Despite advances, there are still challenges in the field, especially in accurately classifying objects with high similarity, such as fruits. Deep Convolutional Neural Networks (CNNs) have emerged as one of the most promising approaches for image classification. However, distinguishing between similar fruit images continues to take time and effort. In this study, we applied a deep learning-based classification method using a custom-built VGG model to classify fruits from the Kaggle Fruits-360 dataset, which includes 22 classes and 14,480 images. These images were divided into training and testing datasets, with 10,848 images used for training and 3,632 for testing. In the proposed scheme, we incorporated dropout and batch normalization techniques into the CNN architecture to improve performance and prevent overfitting. In results, the proposed custom-built VGG model achieved test accuracy of 100 percent with a low validation loss of 0.0012. This tested model, we integrated into a user-friendly GUI application, making it accessible for practical use. In comparison to previous studies, our custom VGG model consistently outperformed state-of-the-art methods, achieving an accuracy range of 99.9% to 100%, as highlighted by our comparison with authors [66], [67], and [68]. While our approach has achieved remarkable accuracy, there remain opportunities for future research.

- Model Limitations: We study that and found that one major limitation in our proposed model, is overfitting, when we applied to small or less diverse datasets. In the complex data, due to the large number of parameters in deep learning models like VGG a risk exists there as the model memorizes the training data rather than capturing general patterns. When the dataset lacks sufficient diversity, the model might not perform well on real-world data.
- Generalizability: It remains a challenging task when dealing the deep models in complex data sets. Deep learning models are often sensitive to changes in data distribution. It may require additional fine-tuning and careful selection of hyperparameters and data augmentation techniques to improve robustness.

In future work, resolve the issues by regularization methods such as dropout and expanding the dataset to enhance the model's generalization capabilities.

9. Acknowledgement

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