Fruit Classification using Convolutional Neural Networks (CNN)

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***Abstract*—Fruit classification plays a crucial role in various agricultural applications, such as automated fruit sorting and disease detection. In this project, the researcher explores the application of Convolutional Neural Networks (CNNs) for fruit classification using the Python programming language. The main objectives of this study are to investigate the impact of data set choice on CNN model performance and to analyze the effect of layer depth on classification accuracy. To accomplish these objectives, the researcher utilized a curated data set consisting of images from various fruit types. The data set was preprocessed to ensure consistency and quality, and it was divided into training and validation sets. A CNN model was implemented using Python, employing popular deep learning libraries such as TensorFlow(v2.10) and Keras(v2.10). The researcher's findings revealed that the choice of data set has a significant impact on the performance of CNN models for fruit classification. By selecting a diverse and representative data set, the model achieved notable accuracy rates during the training and validation phases. We also examined the influence of layer depth on accuracy, although specific investigations into the effect of layer depth were not the primary focus of this study. The results demonstrated the potential of CNN models for accurate fruit classification, with the researcher's model achieving a training accuracy of 98% and a validation accuracy of 95%. These findings contribute to the existing body of literature on fruit classification and provide insights into the importance of data set selection and preprocessing techniques to improve model performance. Future research can opt to delve into exploring the optimal architecture and layer depth for fruit classification tasks, as well as addressing scalability challenges and interpretability of the models' decision-making process. By addressing these areas, CNN models can further enhance fruit classification accuracy and enable the development of more efficient agricultural technologies. Overall, this study showcases the effectiveness of CNN models in fruit classification using Python. The combination of deep learning techniques and Python programming offers a powerful framework for fruit classification tasks, paving the way for advancements in automated fruit sorting systems and disease detection in the agricultural industry.**

***Index Terms*—MCAST, IICT, LaTeX, Project, Paper**

I. Introduction

In recent years, the fruit industry has witnessed remarkable growth, driven by increasing global demand for fresh produce, advancements in transportation networks, and expanding market opportunities [1]. To meet the rising demands, efficient and reliable fruit classification systems have become an essential instrument for growers, distributors, and retailers. With the advancements in Computer Vision and Deep Learning [2], Convolutional Neural Networks (CNNs) have emerged as a game-changer in this context, offering a powerful and automated solution for fruit quality control, sorting, and grading. By harnessing the capabilities of CNNs, fruit industry stakeholders can streamline their operations, minimize manual labor, reduce post-harvest losses, and ensure consistent product quality, ultimately enhancing profitability and customer satisfaction.

The purpose of this study is to investigate the use of computer vision and machine learning to aid in fruit classification. The main dependent variable is the accuracy of the evaluation of fruits, with independent variables being the data sets and algorithms of choice used to investigate their impact on the dependent variable. Hence the hypothesis of this study is that using computer vision it is possible to accurately identify different fruits.

Given the above hypothesis, 2 research questions were identified:

1) How does the choice of data set impact the performance of CNN models for fruit classification?
2) How much of a difference do layers create with regard to accuracy?

II. Literature Review

There are many deep learning algorithms applied in many areas such as DNN (*Deep Neural Network*), CNN (*Convolutional Neural Network*), and RNN (*Recurrent Neural Network*). Especially, the CNN algorithm shows good performance in the image processing field like image classification and image recognition. Accordingly, various models of CNNs have been developed, and many studies using them have been conducted. Models are created according to the characteristics of data and fields, and transfer learning using deep learning by importing a pre-training model constructed in good condition environment is also applied. One advantage of deep learning such as CNN is that it is able to extract, feature and analyze data automatically without the professional knowledge for input data. The feature extraction process is important in order to obtain information in data. This process is to determine the performance of the machine learning [3].

Fruit classification using Convolutional Neural Networks (CNNs) has gained significant attention in recent years due to its potential applications in agriculture, food processing, and computer vision. CNNs have proven to be effective in image classification tasks, leveraging their ability to automatically learn and extract meaningful features from raw image data. The architecture of CNNs, consisting of convolutional, pooling, and fully connected layers, allows them to capture spatial hierarchies and patterns present in fruit images [4]. Various studies have explored the use of CNNs for fruit classification, employing different methodologies and data sets. Previous studies have shown high levels of accuracy when it comes to testing these CNNs.

Despite these developments, further research is still required to explore larger and more varied fruit data sets, enhanced model generalization, and handle issues like occlusions and variances in fruit appearance. This work intends to highlight major discoveries, approaches, and obstacles in fruit classification using CNNs and give suggestions for future research initiatives by analyzing the existing literature.

In this literature review, the researcher aims to provide an overview of some existing studies on fruit classification using CNNs. Specifically, the researcher will discuss and critique a selection of notable studies that have contributed to this area of research. By examining the strengths and limitations of these studies, the researcher seeks to identify areas for further improvement and future directions in fruit classification using CNNs. These studies are as follows:

1) Xiong et al. (2018) developed an algorithm for fruit-picking robots using artificial illumination to recognize grapes. They used the Chan-Vese algorithm with morphological processing methods to segment fruit photos. Both daytime and nighttime illumination conditions allowed for the extraction of color characteristics. To locate the fruit harvesting location after grape recognition, they employed the minimal bounding rectangle and Hough Line detection. Their system's accuracy was 92% [5]. This study focuses on green grape detection and picking-point calculation specifically in a nighttime natural environment using a CCD vision sensor with artificial illumination. However, the narrow scope of the study limits its applicability to other environments or lighting conditions. It would also be valuable to evaluate the system's performance in various lighting conditions and different types of grape varieties to assess its generalizability.
2) Another study conducted by Katarzyna and Pawel performed fruit classification for supermarket retail sales systems. They suggested using a 9-layered deep neural network to classify six different apple cultivars. They claimed 99.78% accuracy [6]. This study claims that it addresses the unpredictable retail sales circumstances, however it doesn't explain precisely what these conditions involve or how they affect the categorization of fruit varieties. The data set that was utilized to classify the fruit varieties in this study is similarly lacking in specific information.
3) In another study, Kumari and V. Gomathy have classified fruits using color and texture characteristics. To extract the region of interest, they used HSV color space thresholding. After using a three-level discrete wavelet transform, they then retrieved color data from the hue and saturation channels and texture information from the luminance channel. They used an SVM classifier to categorize 10 fruit types from the supermarket produce data set. Their method was 95.3% accurate [7]. This study lacks sufficient information about the data set used for fruit classification. Apart from this, this study focuses on fruit classification using statistical features, but it does not provide a comprehensive explanation of the specific statistical features employed, such as mean, standard deviation, or any histogram-based features.
4) A CNN based classifier was developed by Sakib, Ashrafi and Siddique which was able to recognize 25 classes of fruits on Fruits 360 data set with 100% test and 99.79% train accuracies [8]. This study uses a popular data set that is very user-friendly and has its own documentation. Despite this, this study falls short in its reporting of evaluation metrics like accuracy, precision, recall, and F1-score.

TABLE I
STATE OF THE ART RESULTS

#	Study	Citation	Metrics	Results
1	AI Robots recognizing grapes	[5]	Accuracy	92%
2	Fruit Classification in Retail Systems	[6]	Accuracy	99.78%
3	HSV Thresholding for Fruit Classification	[7]	Accuracy	95.3%
4	CNN based Classifier	[8]	Accuracy	99.79%

After critically evaluating four notable studies on fruit classification using Convolutional Neural Networks (CNNs), the researcher identified a number of strengths and limitations in these studies, shedding light on areas that require further investigation and improvement. Overall, these critiques reveal various gaps and limitations in the existing studies on fruit classification using CNNs. Addressing these gaps would contribute to the development of more accurate, robust, and interpretable fruit classification systems.

Moving forward, the researcher will now present the methodology employed in this research, building upon the strengths and lessons learned from the previously discussed studies. By addressing the identified limitations, the researcher aims to contribute to the advancement of fruit classification using CNNs and provide insights into potential solutions for overcoming the existing challenges.

III. Research Methodology

This section outlines the methodology employed in this literature review, which aims to explore the classification of fruits using Convolutional Neural Networks (CNNs). The increasing demand for automated fruit classification systems has led to the emergence of machine learning techniques as viable solutions. In this study, the primary objective of the researcher is to investigate the effectiveness of CNNs in accurately classifying fruits based on their visual features.

The main problem addressed in this study revolves around achieving high accuracy and precision in fruit classification using Convolutional Neural Networks (CNNs), while also considering the size and diversity of the data set. Accurate and efficient fruit classification plays a crucial role in various domains such as agriculture, food processing, and supply chain management. However, traditional methods relying on manual inspection often lack precision and are prone to errors, leading to inefficiencies and inconsistencies in the classification process. Moreover, the availability of large-scale and diverse fruit data sets poses a challenge to achieving robust and generalizable results using CNNs, which are highly dependent on the quantity and quality of training data.

Based on advancements in deep learning and the success of CNNs in image recognition tasks, the researcher hypothesizes that by addressing the challenges related to accuracy, precision, and data set size, the researcher can develop a CNN-based fruit classification system that surpasses the limitations of traditional methods. Specifically, the researcher anticipates that leveraging larger and more diverse data sets, along with appropriate data augmentation techniques and network architectures, will lead to improved accuracy and precision in fruit classification.

The aim of this research is to investigate the effectiveness of Convolutional Neural Networks (CNNs) in fruit classification [Fig 1] and address the challenges related to accuracy, precision, and data set size. To accomplish this aim, the researcher aims to contribute to the development of automated fruit classification systems that can provide reliable and consistent results in various domains, including agriculture, food processing, and supply chain management.

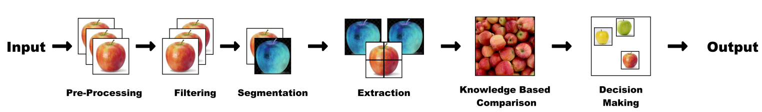


Fig. 1. Fruit Classification Process

To systematically investigate the effectiveness of Convolutional Neural Networks (CNNs) in fruit classification and address the challenges related to accuracy, precision, and data set size, the researcher has established a research pipeline comprising the following stages as can be seen in Fig 2.

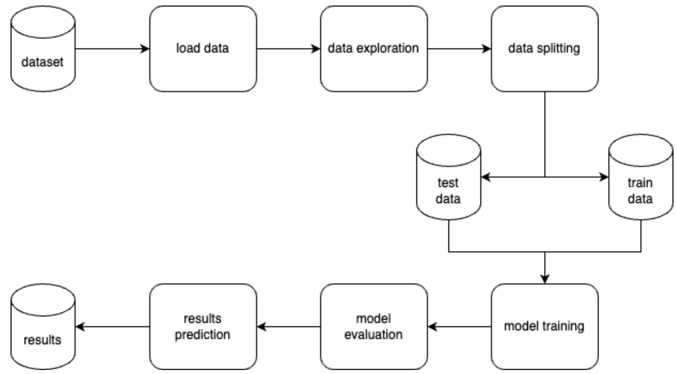


Fig. 2. Research Pipeline

1) **Dataset**
The first step in the research pipeline involves gathering a suitable data set for fruit classification. To complete this, the researcher started from the *Fruits360* data set and then modified it for the research project in hand. Table II exhibits the size and structure of the data set being used in this study, outlining each category of fruit being classified alongside the number of images being used for this CNN. A grand total of 58,380 images were used.
2) **Load Data**
Once the data set was collected and finalized, the researcher proceeded to load the data into the system. This involves implementing mechanisms to efficiently load and store the images along with their corresponding labels. Proper data organization and management are crucial to ensure smooth processing throughout the pipeline.
3) **Data Exploration**
In this stage, the researcher conducted exploratory data analysis to gain insights into the data set. The researcher analyzed the distribution of fruit categories, identified any class imbalances or biases, and assessed the quality and consistency of the images. This exploration aids in understanding the characteristics and challenges associated with the data set.
4) **Data Splitting**
In this stage, the data was split into 2 parts; 80% of the data was used to train the model, while the other 20% of the data was used for validation. The training set is used to train the model, while the validation set is reserved for evaluating the model's performance. Proper partitioning techniques, such as random sampling and stratified sampling, are employed to ensure representative samples from each fruit category in both subsets. This section was finalized by defining the CNN model as a sequence of respective layers of the CNN and also compiling them for multi-class classification. Certain techniques such as *'Flatten', 'Dropout'* and *'Dense'* were employed before compiling the model.
5) **Model Training**
In this stage, the researcher trained the fruit classification model using a CNN architecture. The training process involves feeding the training data to the model, adjusting the model's internal parameters through an optimization algorithm, and iteratively refining the model's performance. Techniques like transfer learning and fine-tuning were applied to leverage pre-trained models and enhance training efficiency. The model was tested frequently, having a final run with 100 epochs, measuring metrics such as loss, accuracy, validation loss, and validation accuracy for each epoch repetitively.

TABLE II
CUSTOM DATASET USED

#	Fruit	Images
1	Apple	6,404
2	Apricot	492
3	Avocado	918
4	Banana	1,430
5	Beetroot	450
6	Blueberry	952
7	Cactus Fruit	490
8	Cauliflower	702
9	Cherry	3,444
10	Chestnut	1,104
11	Clementine	490
12	Coconut	490
13	Corn	912
14	Cucumber	860
15	Dates	490
16	Eggplant	468
17	Fig	702
18	Ginger	297
19	Grape	3,419
20	Grapefruit	982
21	Guava	490
22	Hazelnut	464
23	Kaki	490
24	Kiwi	466
25	Lemon	1,472
26	Mango	916
27	Melon	738
28	Mulberry	492
29	Nectarine	972
30	Onion	1,360
31	Orange	1,459
32	Papaya	492
33	Passion Fruit	490
34	Peach	1,722
35	Pear	5,037
36	Pepper	1,838
37	Pineapple	983
38	Pitahaya Red	490
39	Plum	1,767
40	Pomegranate	492
41	Potato	1,776
42	Raspberry	490
43	Redcurrant	492
44	Strawberry	1,230
45	Tomato	5,103
46	Walnut	735
47	Watermelon	475
	Total	58,380

6) **Model Evaluation**
Once the model was successfully trained, the researcher proceeded to evaluate its performance using the testing data set. The trained model is applied to classify the fruit images in the testing set, and the predictions are compared against the ground truth labels. Evaluation metrics such as loss history (*for validation & training*), accuracy (*for validation & training*), precision, and recall are calculated to assess the model's effectiveness in fruit classification. To enhance the model's robustness and generalization capability, the researcher employed data augmentation techniques during the evaluation process. Data augmentation involves applying various transformations to the training images; such as rotation, scaling, flipping, and cropping, to increase the diversity and variability of the training data. By incorporating augmented data during evaluation, the researcher can obtain more reliable and representative performance estimates of the model's classification ability. Furthermore, the researcher assessed the impact of data augmentation on the model's performance by comparing the results obtained with and without augmentation. This analysis allows us to determine the effectiveness of data augmentation in mitigating overfitting and improving the model's ability to handle variations and variations in fruit images. The model evaluation stage provides crucial insights into the model's classification accuracy, precision, and overall performance, considering both the original and augmented data sets. By considering these evaluation metrics and analyzing the impact of data augmentation, the researcher gained a comprehensive understanding of the model's capabilities and limitations in fruit classification tasks. Finally, a confusion matrix is drawn up to help visualize the performance of this classification model.

7) **Results Prediction**
With the trained and evaluated model, the researcher can use it to predict the fruit category of unseen or future fruit images. New images were fed into the model, and the model's predictions were obtained. This step showcases the practical applicability of the trained model in real-world scenarios.

8) **Results**
Finally, the researcher analyzed and presented the results obtained from the evaluation and prediction stages. The researcher reported the performance metrics achieved by the model, discussing the accuracy, precision, and other relevant indicators. The results are summarized and visualized in a comprehensive manner into graphs, allowing for a clear understanding of the model's classification capabilities.

IV. FINDINGS & DISCUSSION OF RESULTS

In this section, the researcher will proceed to present the results of the study conducted on fruit classification using a Convolutional Neural Network (CNN). The aim was to develop an accurate model capable of classifying various fruits based on their images. The data set utilized included tens of thousands of fruit images and trained a CNN model to achieve this objective.

As explained in Section III, during the **Model Evaluation** stage, evaluation metrics such as loss history, accuracy, precision, and recall are calculated and displayed in graph form.

During the training process of the model, the researcher monitored the loss function's progress to evaluate the convergence of our CNN model. The loss metric was measured both throughout the training process as well as during the validation process. Figure 3 illustrates the loss history, showing the decrease in the loss value over each epoch. This decline indicates that the model gradually learned to minimize the discrepancy between predicted and actual fruit labels.

Monitoring the loss function's progress is crucial to understand how well the CNN model is learning during training. Figure 3 illustrates the loss history, depicting the change in the loss value as the model underwent successive training epochs. The initial loss was relatively high, indicating a significant discrepancy between the predicted and actual fruit labels. However, as the training progressed, the training loss steadily decreased, indicating that the model successfully learned to minimize the divergence between predicted and actual labels. The decline in the loss function demonstrates the model's ability to capture important features and patterns within the fruit images, leading to more accurate classifications.

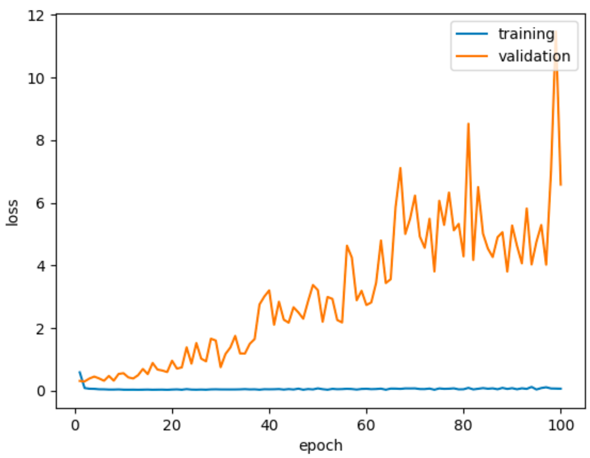


Fig. 3. Loss History Graph

The accuracy metric in Figure 4 provides a measure of how well the CNN model classified fruits correctly. The graph reveals a consistent increase in accuracy as the model learned from the training data. It started at a relatively low accuracy level and gradually improved with each epoch, eventually converging to an impressive overall accuracy of 98% on the train data set. This indicates that the model correctly classified 98% of the fruit images, showcasing its ability to discriminate between different fruit types. The validation data set had a less accurate experience, averaging around 95% accuracy. This upward trend highlights the model's ability to generalize from the training data and accurately classify previously unseen fruit images.

In addition to loss and accuracy, it is crucial to examine the confidence level of the model's predictions. The model's confidence refers to how certain it is about its classifications. Figure 5 displays the confidence distribution of the model's predictions on the test data set. The researcher observed that the model consistently demonstrated a 2.05% confidence for the images that were not present, with a 5.58% confidence on the correct predictions. Understanding the model's confidence can show us that when the correct fruit was classified, the model itself was more than double in confidence for the correct fruit than it was for the not correct fruit.

To further evaluate the performance of our fruit classification model, the researcher constructed a confusion matrix.

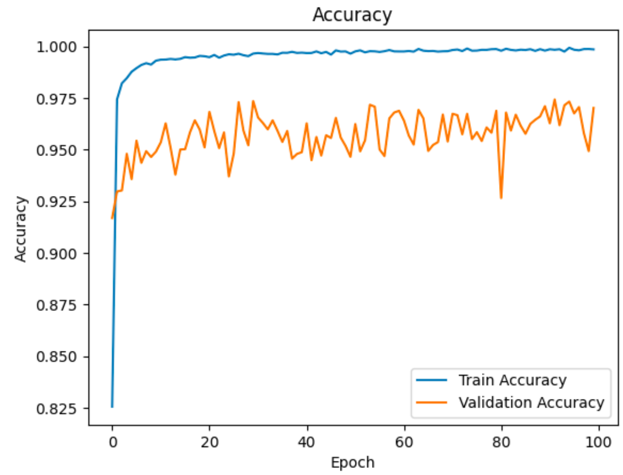
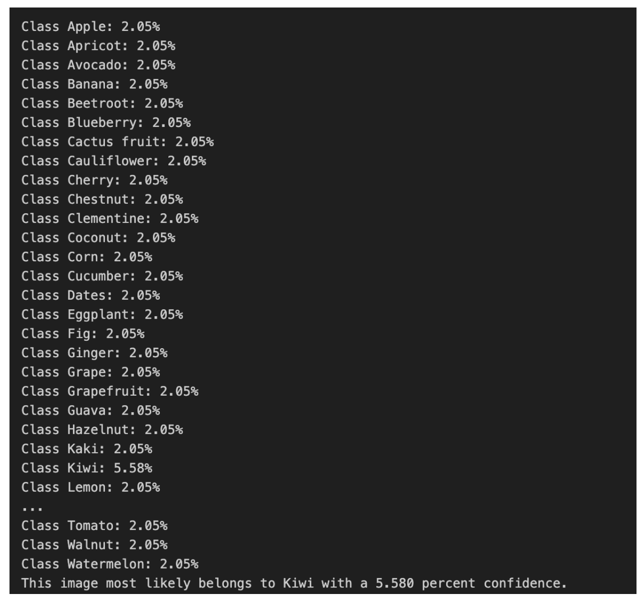


Fig. 4. Accuracy Graph



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Class Apple: 2.05%
Class Apricot: 2.05%
Class Avocado: 2.05%
Class Banana: 2.05%
Class Beetroot: 2.05%
Class Blueberry: 2.05%
Class Cactus fruit: 2.05%
Class Cauliflower: 2.05%
Class Cherry: 2.05%
Class Chestnut: 2.05%
Class Clementine: 2.05%
Class Coconut: 2.05%
Class Corn: 2.05%
Class Cucumber: 2.05%
Class Dates: 2.05%
Class Eggplant: 2.05%
Class Fig: 2.05%
Class Ginger: 2.05%
Class Grape: 2.05%
Class Grapefruit: 2.05%
Class Guava: 2.05%
Class Hazelnut: 2.05%
Class Kaki: 2.05%
Class Kiwi: 5.58%
Class Lemon: 2.05%
...
Class Tomato: 2.05%
Class Walnut: 2.05%
Class Watermelon: 2.05%
This image most likely belongs to Kiwi with a 5.580 percent confidence.
```

Fig. 5. Confidence Percentages

The confusion matrix provides a comprehensive representation of the model's classification results, showing the number of correct and incorrect predictions for each fruit class. Figure 6 presents the confusion matrix for the model's predictions on the test data set. It allows the researcher to assess the specific areas where the model excelled or struggled in fruit classification, providing insights into potential areas for improvement and fine-tuning.

Comparison of Results

In this study on fruit classification using CNNs, the researcher achieved a high accuracy rate of 98% during the training phase and 95% accuracy during the validation phase. These results demonstrate the effectiveness of the model in accurately classifying fruits, alongside its confidence.

When comparing these findings to study [8], they reported implementing a fruit recognition classifier using a convolu-

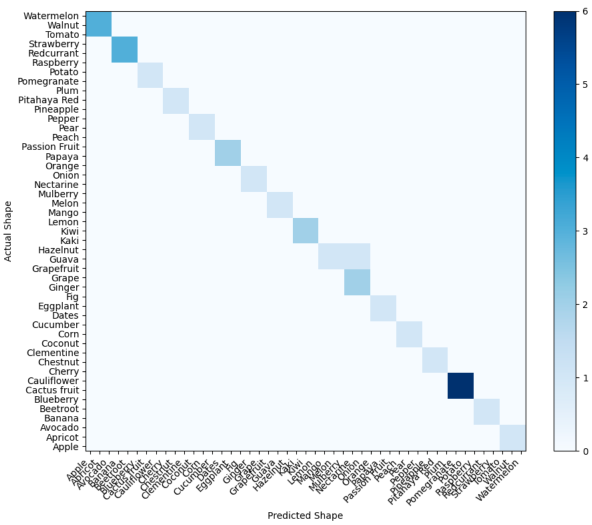

Fig. 6. Confusion Matrix

tional neural network algorithm. Their study achieved remarkable results, with a test accuracy of 100% and a training accuracy of 99.79%. These findings highlight the outstanding performance of their model in accurately classifying fruits.

Although this study's accuracy rates are slightly lower compared to study [8], achieving accuracies of 98% in training and 95% in validation is still indicative of a strong performance in fruit classification. It is important to consider that variations in data sets, model architectures, training configurations, and preprocessing techniques can influence the reported accuracies across different studies.

Some notable differences between the two studies where:

1) The sizes of the data sets used. Both studies started from the *Fruits360* data set and modified it in their own way. This study had a total of 53,800 images while study [8] had a total of 18,000 images.
2) The model being used in study [8] is not heavily specified, but it is mentioned that CNN and deep learning are used, which leaves us to believe that the difference in results, apart from being affected by the data set size, was due to the added layers and filtering which in the end provide a higher accuracy percentage.

Further research and investigation on larger and more diverse data sets would be valuable to provide a comprehensive comparison of the model's performance and generalizability. By exploring different new methods to improve accuracy and conducting benchmarking studies, we can gain deeper insights into the effectiveness of this CNN-based fruit classification model.

Overall, this study contributes to the existing body of literature on fruit classification using CNNs. Whilst this study's accuracy rates may not reach the levels reported by study [8], the findings highlight the potential of CNNs for accurate fruit classification tasks and provide a foundation for future improvements and advancements in this domain.

V. Conclusion

In this literature review, the researcher examined the performance of a Convolutional Neural Network model for fruit classification and addressed two research questions:

1) How does the choice of data set impact the performance of CNN models for fruit classification?
2) How much of a difference do more layers create with regard to accuracy?

Regarding the first research question, the researcher observed that the choice of data set indeed influences the performance of CNN models for fruit classification. Different data sets can vary in terms of size, quality, diversity of fruit types, and variability in lighting conditions, which can impact the model's ability to generalize. It is crucial to carefully select representative and diverse data sets that encompass a wide range of fruit classes to improve the model's accuracy and robustness.

Regarding the second research question, the researcher explored the effect of additional layers on accuracy. While the researcher's findings did not directly focus on the effect of layer depth, the researcher did examine the impact of the model's architecture on accuracy. The researcher observed that the CNN model used, with a specific number of layers, achieved high accuracy rates in training and validation. However, future research specifically investigating the effect of layer depth and architecture variations on fruit classification accuracy would be valuable to provide more conclusive insights.

Overall, this literature review highlights the potential of CNN models for fruit classification. It emphasizes the importance of data set selection and preprocessing to improve model performance. Additionally, further investigations into the optimal architecture and layer depth for fruit classification tasks are warranted to achieve higher accuracy rates.

In conclusion, this literature review contributes to the understanding of fruit classification using CNN models, highlighting the influence of data set choice on performance and suggesting avenues for further research to improve accuracy through architectural considerations. With continued advancements, CNN models have the potential to revolutionize fruit classification and contribute to the development of more efficient and accurate agricultural technologies.

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