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Classification of Fruits using Convolutional Neural Network

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ABSTRACT
Automated assessment of fruit freshness is indispensable in the agricultural sector. Traditionally, fruit grading relies on human inspection, a method prone to inconsistency and susceptibility to external influences. Hence, there is a pressing need for a swift, precise, and automated system tailored for industrial applications. This study employs a deep learning approach for fruit freshness classification. The proposed Convolutional Neural Network (CNN) model utilizes the "Fruit Fresh and Rotten for Classification" dataset sourced from Kaggle. This dataset comprises images depicting three varieties of fresh fruits (Apple, Banana, and Oranges) along with their corresponding rotten counterparts. Leveraging deep learning, the CNN model extracts key characteristics or attributes from these fruit images. Subsequently, a softmax function categorize the images into fresh and rotten classes. The performance of the proposed CNN model is evaluated using the dataset, yielding an impressive accuracy of 95%. These results demonstrate the efficacy of the CNN model in fruit classification. Additionally, this study explores four Transfer Learning methods for fruit classification. A comparative analysis of classification performance underscores the superior efficiency of the Convolutional Neural Network model over transfer learning approaches. In this paper, they introduce a novel dataset comprising high-quality images of fruits. Furthermore, they present the outcomes of numerical experiments conducted to train a neural network for fruit detection. Additionally, they elucidate the rationale behind selecting fruits for this project by proposing several potential applications that could benefit from such a classifier.

Keywords
CNN, Agriculture, Transfer Learning Models

1. INTRODUCTION
This paper introduces the Fruits dataset, a comprehensive collection of images showcasing a diverse range of popular fruits and vegetables. the dataset comprises various images representing distinct fruits and vegetables, with ongoing updates as new items become available to the authors.

The importance of a high-quality dataset cannot be overstated, particularly in the realm of developing robust classifiers. Many existing image datasets, such as the widely recognized CIFAR dataset, incorporate both the target object and background noise. However, this amalgamated context presents challenges, especially when background alterations are involved, potentially leading to misclassifications.

In addition to introducing the Fruits dataset, this paper addresses the development of a specializes deep neural network for fruit identification from images. This endeavour is part of a broader initiative aimed at creating classifiers capable of recognizing an extensive array of objects—an attempt aligned with the prevailing trends in augmented reality technology. The ramifications of such technology extend across various domains, encompassing autonomous navigation, object modelling, process control, and human- robot interactions. Of particular interest is the potential deployment of autonomous robots capable of executing intricate tasks surpassing those of conventional industrial robots. For instance, these robots could conduct aisle inspections in retail settings to identify misplaced items or shelves with low stock. Moreover, they could be endowed with the capability to interact with products autonomously, facilitating problem-solving. Another promising application lies in autonomous fruit harvesting, a domain where existing research predominantly focuses on specific fruit or vegetable types. This paper endeavour to broaden this scope by developing a network capable of classifying a diverse range of fruit species, thus enhancing its applicability across multiple scenarios.

Fruit identification serves as the initial focal point of this project for several reasons. Firstly, certain fruit categories, such as the citrus genus encompassing oranges and grapefruits, present inherent challenges for differentiation, making them suitable candidates for assessing the effectiveness of artificial intelligence in classification tasks. Additionally, fruits are omnipresent in retail environments, rendering them an ideal starting point for the broader project outlined earlier.

The structure of this paper unfolds as follows: The first segment briefly delineates notable advancements in deep learning for fruit recognition, followed by an elucidation of deep learning concepts. Subsequently, the creation and contents of the Fruits dataset are expounded upon. underlying its selection. Following this, the architecture of the employed neural network is detailed, accompanied by descriptions of the training and testing datasets and performance evaluation metrics. The paper concludes with a discussion on potential avenues for enhancing project outcomes, complemented by the inclusion of source code in the Appendix.

2. RELATED WORK
They delve into previous endeavors utilizing neural networks

and deep learning for fruit recognition. One notable approach, outlined and, focuses on recognizing and quantifying fruits within cluttered greenhouse environments. Specifically targeting peppers, which exhibit complex shapes and varying colors akin to the plant canopy, this method aims to locate and count green and red pepper fruits amidst large, dense pepper plants. The training and validation datasets employed in this study comprise various images encompassing over plants and their respective fruits. The approach entails a two- step process: initially locating the fruits within a single image and subsequently combining multiple views to enhance detection accuracy.

The first step involves identifying points of interest, applying a sophisticated high-dimensional feature descriptor to patches surrounding these points, and employing a bag-of- words approach for patch classification.

Another innovative approach, detailed, revolves around detecting fruits from images using deep neural networks. Here, the authors adapt a Faster Region-based Convolutional Network (Faster R-CNN) with the objective of creating a neural network suitable for deployment in autonomous fruit-harvesting robots. The network is trained utilizing both RGB and near-infrared (NIR) images. The fusion of RGB and NIR models is explored through two distinct methodologies: early fusion and late fusion. Early fusion involves incorporating four channels at the input layer—three for the RGB image and one for the NIR image. Conversely, late fusion employs two independently trained models, various image generation has also emerged as a valuable tool for training and evaluating fruit recognition models.

These synthetic datasets are used to train computer vision models, which can then be fine-tuned on smaller empirical datasets for improved performance. By leveraging synthetic data, researchers can overcome limitations such as data scarcity and variability in real-world image collections.

Predicting fruit yield is another important application of neural networks in agriculture. In [4], researchers use backpropagation neural networks to predict apple yield for the upcoming season. By extracting features from images, such as the total cross-sectional area of fruits and foliage, the model can estimate fruit yield with reasonable accuracy. This predictive capability can assist farmers in planning and optimizing their harvest operations.

Understanding the impact of camera angles on fruit detectability is also crucial for developing effective fruit recognition systems. Paper [10] investigates how the angle of the camera affects fruit detectability in images. Through empirical analysis, the researchers determine that certain camera angles, particularly front views and zenith angles of 60 degrees upwards, result in higher fruit detectability. This insight can inform the design and deployment of fruit recognition systems to maximize detection performance in real-world scenarios.

Additionally, several studies explore the use of color, shape, and texture features for fruit detection. Papers such as [28, 38, 16] highlight the challenge of accurately classifying similar fruits of different species. These studies propose combining multiple features, such as texture, shape, and color, to improve the accuracy of fruit detection algorithms. By leveraging complementary information from different feature modalities, researchers aim to enhance the robustness and reliability of fruit recognition systems.

Lastly, [37] introduces an algorithm for night-time green grape detection using advanced level-set models and Hough line detection. By combining principles from level-set modeling with innovative techniques for stem detection, the algorithm achieves accurate detection of green grapes in low- light conditions. This capability has implications for improving the efficiency and effectiveness of grape harvesting operations, particularly in nocturnal settings.

Overall, these studies demonstrate the diverse applications and advancements in using neural networks and deep learning for fruit recognition in agriculture. From orchard environments to predictive modeling and synthetic data generation, researchers are leveraging cutting-edge techniques to address key challenges and enhance productivity in the agricultural sector.

3. METHODOLOGY

The dataset contains a various image of fruits: fresh fruits and rotten fruits. These images were collected, sorted, and labelled by experts to ensure accuracy.

Within the dataset, there are six different categories: three for fresh fruits and three for rotten fruits. These categories help them to distinguish between fruits that are in good condition and those that have started to spoil.

To train the classification model, they divide the dataset into three parts: a training set, a validation set, and a test set. The training set is used to teach the model how to classify fruits based on their freshness, while the validation set helps us fine-tune the model's parameters to improve its accuracy. Finally, the test set is used to evaluate the model's performance on new, unseen data.

A Convolutional Neural Network (CNN) is a type of model used for recognizing and classifying images. One of the main benefits of using CNNs is that they require less preprocessing compared to other algorithms. They automatically process the input data, train the model, and extract important information without needing much manual intervention.

The main goal of a CNN is to understand the data in a structured way without losing important features. This makes CNNs great for handling large datasets. A CNN consists of three main layers, but the number of layers can vary based on the complexity of the problem being solved. In more complex applications, there are usually more layers.

The image passes through these layers in a sequence: first is the convolutional layer, then the pooling layer, and finally the fully connected layer, which generates the output. In the convolutional layer, filters are applied to the original image to extract features. Most of the user-specified parameters, like the number and size of filters, are determined in this layer.

Pooling layers, usually using a technique called max pooling, are used to reduce the size of the network. They take the output from the convolutional layer and shrink it down. The fully connected layers are the last layers in the network. They take the output from the previous layers and classify the input image into different labeled classes using an activation function called softmax.

In simple terms, a CNN learns to understand images by breaking them down into smaller pieces, extracting important features, and then making predictions based on those features. It's like teaching a computer to recognize patterns in pictures!

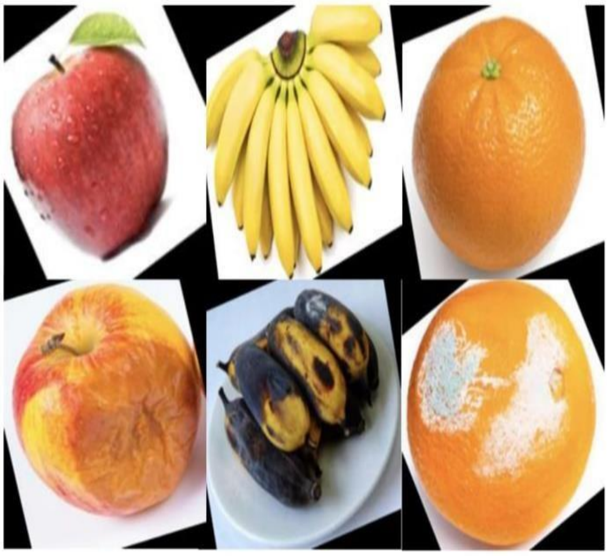

Fig.2: Example of Images in Dataset

The first convolutional layer (Convolution 1) uses Rectified Linear Unit (ReLU) activation function, enhancing learning speed and performance. Convolution layers 1 to 5 are followed by max pooling layers of 2 x 2 size and stride 2, aiding in feature extraction. Convolution layer 6 employs various filters with a kernel size of 3.

Subsequently, a fully connected layer processes the features after flattening the feature map using a flatten layer. A dropout layer is inserted to prevent overfitting. The classification outcomes are then forwarded to the softmax classifier layer. The model employs a categorical cross- entropy loss function and utilizes the Adam optimizer with a learning rate of 0.0001 for efficient optimization.

In summary, the proposed CNN architecture effectively processes fruit images, leveraging convolutional and pooling layers for feature extraction, followed by fully connected layers for classification.

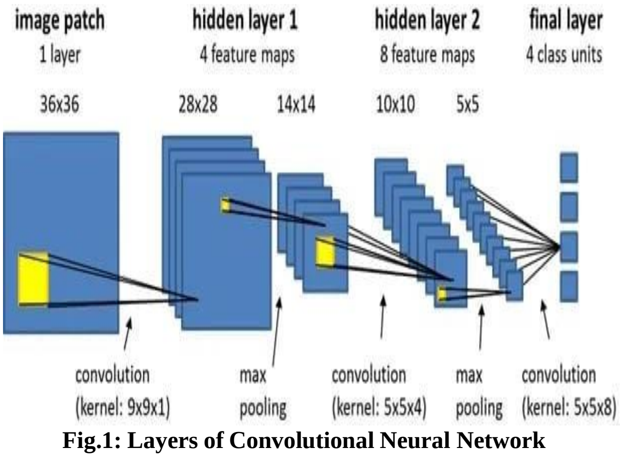

Fig.1: Layers of Convolutional Neural Network

AlexNet, a Convolutional Neural Network developed by Alex Krizhevsky and colleagues in 2012, is renowned for its thorough research and balanced performance in terms of speed and accuracy. It comprises eight layers, including five Convolutional Layers and three Fully Connected Layers, all with assigned weights. The model employs data augmentation and dropout techniques to mitigate overfitting.

With a requirement of 227 x 227 x 3 input images, AlexNet utilizes Rectified Linear Unit (ReLU) activation function after each convolutional and fully connected layer to enhance the model's ability to capture nonlinear features. The final fully connected layer, with 1000 neurons, feeds into the softmax function for classification across 1000 classes. The architecture of AlexNet is depicted in Figure 4, showcasing its foundational design.

The VGG model, devised by Simonyan and Zisserman in 2014, emphasizes the significance of depth in Convolutional Neural Network (CNN) architecture. The depth of the VGG network determines its name; VGG16 comprises 16 layers, while VGG19 comprises 19 layers.

VGG networks are built on the idea of employing numerous convolutional layers with small filters. They typically consist of multiple convolutional layers (varying depending on the specific architecture), along with five max pooling layers, three fully connected layers, and a softmax layer for classification.

4. RESULTS AND DISCUSSION

The batch size refers to the number of data samples processed together in one iteration during the training of a classification model. Choosing the right batch size is crucial as it impacts

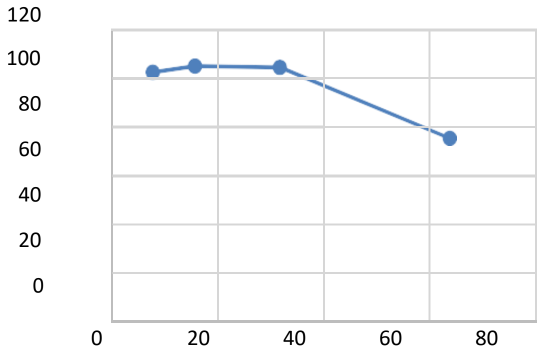

Fig 3: Results

The process begins with Data Collection, where images of various fruits, both fresh and rotten, are gathered. These images form a dataset that will be used for training and testing the model. Next, in the Image Pre-processing step, the collected images undergo processing to ensure they are suitable for training a Convolutional Neural Network (CNN). This processing includes resizing, normalization, and potentially augmenting the images to enhance the dataset's diversity. The pre-processed images are then prepared for the next phase, Data Manipulation, where they are split into three sets: the Train Set for training the model, the Test Set for evaluating the model's performance during training, and the Validation Set for validating the model's performance during and after training. We observed that increasing the batch size from 8 to 16 resulted in improved accuracy of the model. However, beyond a batch size of 16, the accuracy began to decline, dropping further with batch sizes of 32 and 64.

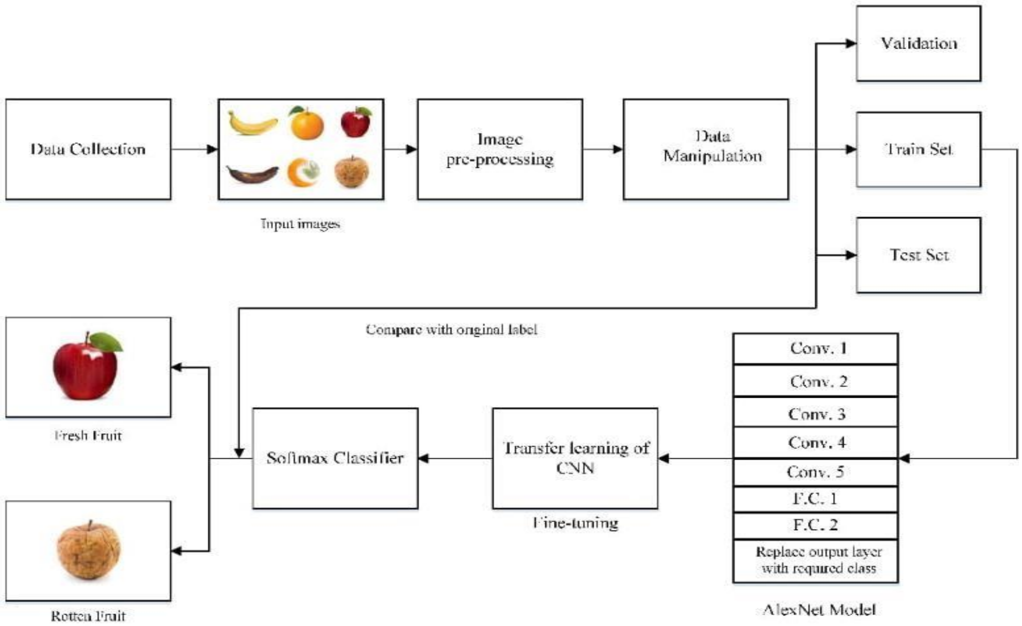

Fig 3: Overall Process of the Model

The training process involves iterating over the entire dataset multiple times, each iteration known as an epoch. In this study, a model was trained over 25 epochs, where each epoch represents one complete pass through the dataset. The model was trained using various numbers of epochs: 5, 15, 20, and 25, with a fixed batch size of 16, a learning rate of 0.0001, and utilizing the Adam optimizer.

Optimizing a model's performance is crucial in reducing its loss function by adjusting the weight parameters. This process involves updating the network's parameters to minimize the disparity between real and predicted values. In our study, we evaluated four commonly used optimizers: stochastic gradient descent (SGD), Adam, Adagrad, and RMSprop. The objective was to identify the optimizer that yields the highest accuracy for our neural network model.

5. CONCLUSION

The automated categorization of fruits into fresh and rotten categories is a crucial task within the agriculture industry. In this study, they conducted a comparative analysis between a convolutional neural network (CNN)-based model and various pre-trained transfer learning models for fruit categorization. Specifically, we evaluated the performance of AlexNet, LeNet-5, VGG-16, and VGG-19 transfer learning models. The study aimed to assess the efficacy of the proposed CNN model against established transfer learning approaches and investigate the impact of different hyperparameters. The findings indicate that the proposed CNN model consistently outperforms transfer learning methods in terms of classification accuracy for fruit categorization. Notably, the CNN model achieved an accuracy of 96.23%.

6. FUTURE SCOPE

The comparison of accuracy between the proposed CNN model. We emphasize that manual fruit classification methods are prone to errors and are time-consuming. However, the implementation of our proposed model offers a promising solution to mitigate these challenges, providing more accurate and efficient fruit Future plans may include the development of an automated system equipped to identify numerous fruit varieties, offering substantial advantages to fruit growers. Moreover, crafting a mobile application capable of capturing fruit images and distinguishing between fresh and rotten specimens could prove highly beneficial

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