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Rotten Fruit Detection Using Artificial Intelligence

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ABSTRACT:

Detecting rotten fruits has become crucial in the agricultural industry as it ensures the separation of spoiled produce from fresh ones, thus maintaining trust and credibility among consumers. Machine learning and Artificial Intelligence are rich in algorithms. These algorithms help in various fields. Unhealthy fruits may cause damage to the other healthy fruits if not classified properly and can also affect productivity. The above issue has been discussed in this paper. A Convolutional Neural Network (CNN) based Deep Learning Technique was proposed to enhance the prediction model for identifying rotten fruits. This model aims to classify fruit images as either fresh or rotten. The study focused on three fruit types: Apple, Banana, and Oranges. A dataset consisting of fresh and rotten fruits was collected and used for training, validation, and testing purposes. The CNN architecture was employed to build the predictive model. The dataset that is downloaded from Kaggle is evaluated for the performance of the proposed model and produces an accuracy of 96.88%. By leveraging the power of CNNs, this improved model can effectively analyze and classify fruit images, providing accurate predictions regarding their freshness or spoilage. Such advancements contribute to the agricultural industry's ability to deliver high-quality products to consumers and reduce potential health risks associated with consuming rotten fruits.

Keywords: CNN, fresh fruits, rotten fruits, Artificial Intelligence, Deep Learning.

1.Introduction:

Fruit health detection and assessment are essential for ensuring the quality, safety, and marketability of fruits in the agricultural industry. Traditional manual inspection methods have been surpassed by innovative approaches leveraging Artificial Intelligence (AI) advanced technologies. By accurately evaluating factors such as diseases, pests, ripeness, firmness, and sugar content, these methods enhance decision-making throughout the supply chain.

The assessment of the health of fruits using artificial intelligence (AI) has gained significant attention in recent years. The quality and healthiness of fruits are critical factors for both producers and consumers [1]. The assessment of fruit health using AI involves the application of machine learning algorithms, and image processing methods to analyse fruit images and extract meaningful information. The primary objective of fruit health assessment using AI is to develop robust and efficient methods for fruit quality control. Detection of defected fruits and the classification of healthy and unhealthy fruits represent one of the major challenges in the agricultural fields [2]. Unhealthy fruits may cause damage to the other healthy fruits if not classified properly and can also affect productivity. Traditionally this classification is done by men, which was labour-intensive, time taking, and not an efficient procedure. Additionally, it increases the cost of production also.

Ongoing efforts aim to address challenges such as fruit variability, environmental factors, and the need for robust models that handle multiple diseases simultaneously. By ensuring high-quality and safe fruits while optimizing production processes and reducing costs, fruit health detection and assessment hold immense potential for meeting consumer demands and benefits the fruit industry. Hence, we need an automated system which can reduce the efforts of humans, increase production, and reduce the cost of production and time of production.

2. Methodology:

Deep neural networks, particularly convolutional neural networks (CNNs), have been demonstrated to be good at recognizing image patterns [3]. The Primary Objective of Assessment of health of fruits using AI is to develop efficient methods for classifying the fruits. We used CNN model for analyzing our data for assessment of health of fruits

Convolutional Neural Network (CNN):

The CNN architecture comprises several fundamental components.

2.1 Convolutional layers:

The convolutional layer is responsible for extracting features from input images in a convolutional neural network (CNN). It performs the mathematical operation of convolution by sliding a filter of size MXM over the input image. The filter calculates the dot product between itself and the corresponding parts of the input image, capturing local patterns and features. This process allows the network to learn and detect important visual patterns, such as edges, textures, and shapes, which are crucial for higher-level image understanding and classification tasks [10].

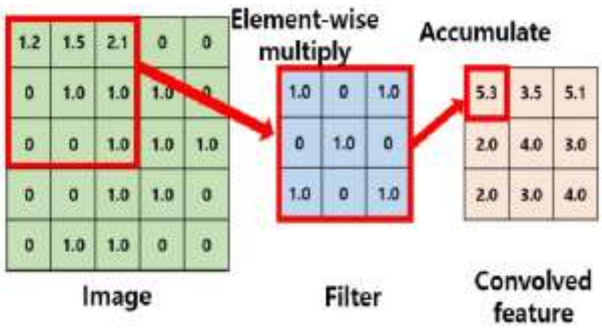

Fig 1: Convolution Operation

The output of the convolutional layer in a CNN is known as the feature map, which provides information about the image, including corners and edges. This feature map is then passed on to subsequent layers to learn additional features of the input image. The convolutional layers in CNNs are advantageous because they preserve the spatial relationship between pixels, allowing the network to capture local patterns and spatial dependencies. This property enables CNNs to effectively learn and represent complex visual information in images.

2.2 Pooling layers:

In convolutional neural networks (CNNs), the Convolutional Layer is often followed by a Pooling Layer. The main purpose of the Pooling Layer is to reduce the size of the convolved feature map, thereby reducing computational costs and controlling overfitting.

The Pooling Layer operates independently on each feature map and decreases the spatial dimensions. By doing so, it reduces the number of connections between layers and compresses the information from the previous layer. This compression helps in summarizing the features generated by the Convolutional Layer.

There are different types of pooling operations that can be applied, including Max Pooling, Average Pooling, and Sum Pooling. In Max Pooling, the largest element within each predefined section of the feature map is selected. This retains the most prominent feature in that section. Average Pooling calculates the average of the elements within each predefined section, providing a general representation of the features. Sum Pooling computes the total sum of the elements within each predefined section, capturing the cumulative strength of the features.
The Pooling Layer acts as a bridge between the Convolutional Layer and the Fully Connected (FC) Layer. It reduces the spatial dimensions while retaining important features, enabling the FC Layer to work with a more compact representation of the input. This helps in reducing the computational requirements and improving the efficiency of the network.

Overall, the Pooling Layer plays a crucial role in CNN architectures by summarizing the features obtained from the Convolutional Layer, reducing spatial dimensions, and aiding in computational efficiency and control of overfitting. The choice of pooling operation depends on the specific requirements of the task at hand and the desired properties of the extracted features.

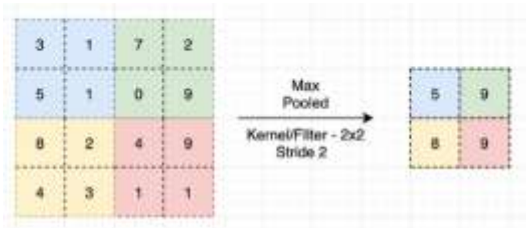

Fig2: Pooling Layer

This CNN model generalises the features extracted by the convolution layer, and helps the networks to recognise the features independently. With the help of this, the computations are also reduced in a network.

2.3 Activation function:

In convolutional neural networks (CNNs), activation functions play a crucial role in introducing non-linearity to the network's outputs. They determine whether a neuron should be activated based on the input it receives. Activation functions enable CNN models to learn and predict complex patterns by performing mathematical operations on the inputs. By applying non-linear transformations, activation functions allow the network to capture and represent intricate relationships in the data. This non-linearity is essential for CNNs to effectively handle tasks like image recognition, object detection, and semantic segmentation, where the underlying patterns are often nonlinear in nature.

2.4 Fully connected layers:

Fully connected layers combine learned features and make predictions. Neurons in these layers are connected to every neuron in the previous layer.

The FC layer consists of weights, biases, and neurons. Its primary function is to take the output from the previous layers and flatten it into a vector. This vector is then passed through the FC layer, where mathematical operations and transformations occur. The FC layer serves as a bridge between the convolutional and pooling layers and the final output layer.

The purpose of using multiple FC layers is to improve the performance and accuracy of the classification process. By connecting multiple FC layers, the network can learn more complex representations and extract higher-level features from the input data. Each FC layer performs its own set of mathematical operations, allowing the network to capture more intricate patterns and relationships within the data.

2.5 Softmax function:

The softmax layer is often the final layer in classification tasks, producing class probabilities by normalizing previous layer outputs into a probability distribution across classes [6].

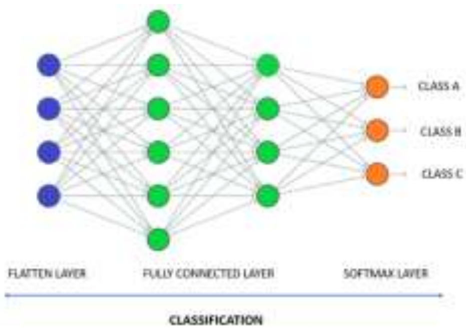

Fig 3: Fully Connected Layer

Hence, based on the above information, it is evident that the Convolutional Neural Network (CNN) model is an optimal choice for image recognition in assessing the health status of fruits due to its high accuracy.

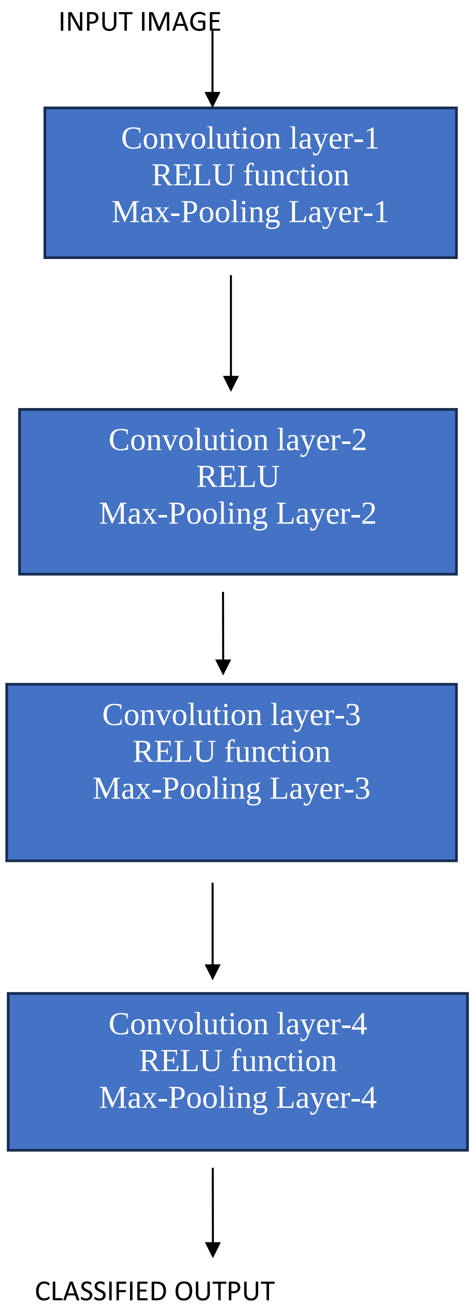

Fig 4: Architecture of proposed model

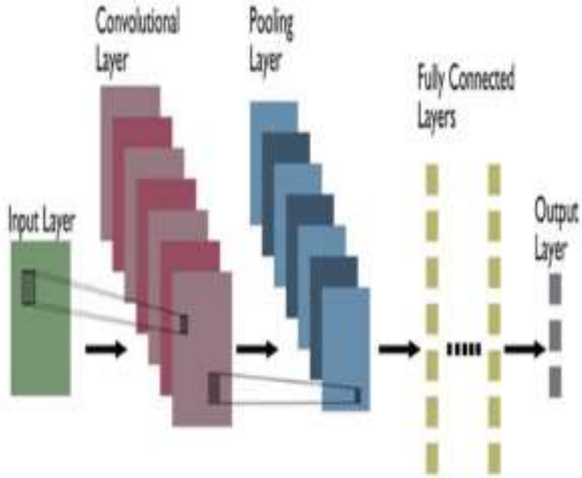

Fig5: CNN ARCHITECTURE

3.Implementation:

Assessment of health of fruits project consists of these 4 steps which are discussed below

3.1) Collection of images dataset

For this project we have used data from the Kaggle data set named as Fruits fresh and rotten for classification which consisted of 2 directories test dataset and train dataset.
Each directory consisted of 6 folders named as fresh apples, fresh bananas, fresh oranges, rotten apples, rotten bananas, rotten oranges. A total of 13,599 images were used for classification in which 7,695 images were of rotten fruits and 5,904 images were of fresh fruits [5].

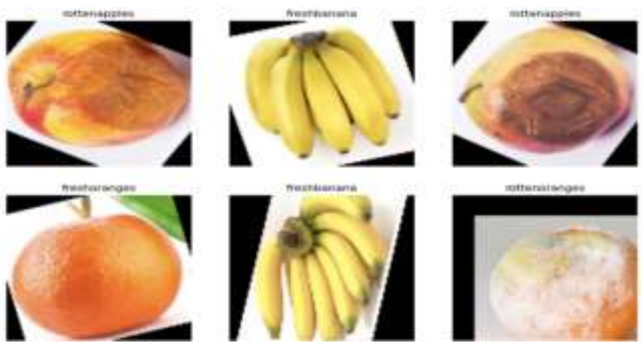

Fig6: collected dataset

3.2) Images pre-processing

Before starting to build the CNN model all the images are processed to change its size and other attributes.

All 10,901 photos of fresh and rotten fruits have been resized into 100x100 pixels and a batch size of 32 has been taken [8].

We have used random flip on layers which is used to randomly flip the input data horizontally and vertically.

We have used Random Rotation layer which randomly rotates the input data by a given degree. We have given a rotation range of 0.5 radians (approximately 28.65 degrees).

3.3) CNN Modeling

At this point, the dataset has been split into two. Each of the dataset is split into 80% (8721 images), 20% (2180 images) for training, validating the models, respectively [7].2698 images were taken for testing.

The developed model consists of four convolutional layers with Rectified Linear Unit (Re-LU) activation function, four max-pooling layers, a single flatten layer, and two dense layers. The model uses Adam optimizer and SoftMax function.

The total trainable parameter was 623,526 parameters. The developed model architecture is described below.

Model: "sequential_1"

Layer(Type)	Output Shape	Param#
rescaling (Rescaling)	(None,100,100, 3)	0
sequential (Sequential)	(None,100,100, 3)	0
conv2d (Conv2D)	(None,98,98,16)	448
max_pooling2d (MaxPooling2D	(None,49, 49, 16)	0
conv2d_1	(None,47 47, 32)	4640
max_pooling2d_1	(None,23,23,32)	0
conv2d_2	(None,21,21,64)	18496

max_pooling2d_2	(None,10,10,64)	0
conv2d_3	(None,8,8, 128)	73856
max_pooling2d_3	(None,4,4,128)	0
flatten(Flatten)	(None,2048)	0
dense(Dense)	(None,256)	524544
dense_1(Dense)	(None,6)	1542

Total params: 623,526
Trainable params: 623,526
Non-trainable params: 0

3.4) Model Evaluation

The developed model has undergone evaluation during the model testing process. This evaluation primarily focused on generating a classification report, which provides valuable insights into the performance of the models. Here the classification report consists of precision, recall, f1-score where we are getting the accuracies that is precision, recall and f1-score for each category of fruit separately.

The below table provides the classification report for each category of fruits i.e., for fresh apples, fresh bananas, fresh oranges, rotten apples, rotten bananas, rotten oranges.

	precision	recall	f1-score	support
freshapples	0.99	0.92	0.95	395
freshbanana	0.98	1.00	0.99	381
freshoranges	0.97	0.98	0.97	388
rottenapples	0.96	0.94	0.95	601
rottenbanana	0.99	1.00	0.99	530
rottenoranges	0.94	0.97	0.95	403
accuracy			0.97	2698
Macro avg	0.97	0.97	0.97	2698

weighted avg	0.97	0.97	0.97	2698

4.Result:

Thus, up to this point we have trained the model with the above dataset and developed a model which has been evaluated by using loss function called sparse Categorical cross entropy function. Adam optimizer and accuracy metrics. On evaluating the model, we have a test loss of 8.53 percent and a test accuracy of 96.88 percent. The comparison result of training and validation accuracy as well as training and validation loss is shown below [4].

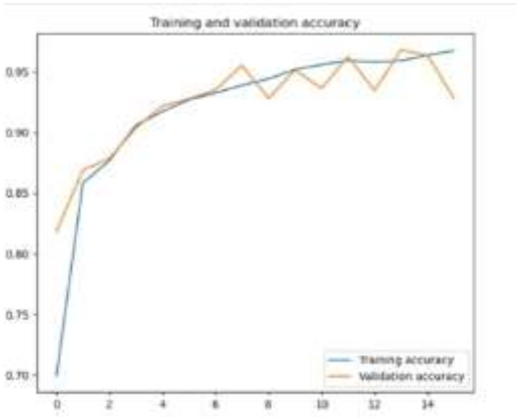

Fig7: comparison between training data and validation data accuracy

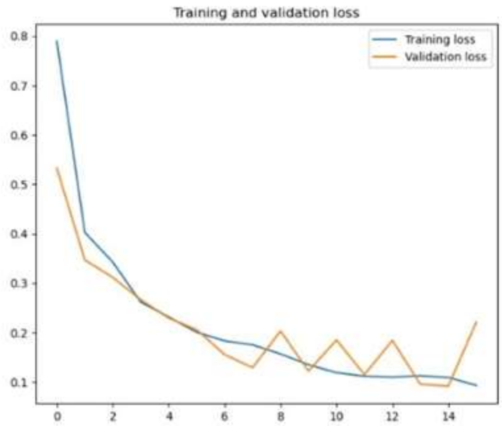

Fig 8: comparison between training data and validation data loss

Now to check whether the model is working accurately or not we have tested a few images by comparing the actual label name with their predicted label name and from the result it has been concluded that the model has been working accurately.

Fig 9: Result of the predicted data

6.Conclusion:

In conclusion, the assessment of fruit health using Convolutional Neural Networks (CNN) is a promising approach that leverages the power of deep learning and image processing techniques. This project has demonstrated the potential to revolutionize fruit quality control processes by providing automated and accurate health assessment.

By training CNN models on diverse datasets of fruit images, the project enables the extraction of relevant features for precise classification and prediction of fruit quality indicators such as freshness, ripeness, and disease presence. The utilization of CNNs offers several advantages, including their ability to learn complex patterns and generalize well to unseen fruit samples.

This project's outcomes have significant implications for various domains, including agriculture, food processing, and consumer preferences. By enabling efficient and objective fruit health assessment, it can enhance productivity, reduce waste, and provide consumers with fresher and healthier fruit options.

Moving forward, further research and development in this area can focus on refining the CNN models, expanding the dataset to encompass a wider range of fruit types, and exploring real-time implementation for practical applications. Overall, the assessment of fruit health using CNNs holds great promise in improving fruit quality control and meeting the demands of an evolving industry [9].

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