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FruitNet: Utilisation of an Artificial Intelligence Algorithm for the Implementation of a Fruit Quality Classification Application

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ABSTRACT: A long-standing component of Bangladeshi agriculture is the growing of fruits. A new era has begun in the cultivation of fruits. Fruits provide us with nutrients. The vitamins and minerals included in it are beneficial. It happens that fruits become bad at both the consumer and packaging ends. In order to steer clear of these spoiled fruits, we devised this study project. We want to use state-of-the-art computer vision and deep learning algorithms to detect rotten or fresh produce. Everyone is now savvy and dependant on one another's generation. Artificial intelligence and gadget learning are pervasive. In light of this, I built a gadget here. In this case, I'm using the CNN version in Python to distinguish between spoiled and unspoiled fruit. Using image data, this gadget can detect the percentage of spoiled and fresh fruit. Using this gadget to detect spoiled fruit might simplify our work with large farms and juice factories. We are hoping it will speed up the process and make our work more accurate, this study aimed to forecast the quality of fresh products (fruits). We thought that Computer Vision may help us handle the challenge of forecasting the true state of fruits based on their exterior look and internal quality characteristics, which is rather challenging. The fruit domains that were used in this research were orange, banana, and apple. Classifying fruits and detecting or localizing them are the two primary steps in the development process. In addition, data photos of two distinguishing freshness states, 'Fresh' and 'Rotten,' were gathered in order to construct predictions about the freshness states of these fruits. To build and train the classification model, the use of a CNN style of architecture. The model's performance was evaluated and analyzed with the goal of making incremental improvements utilizing the regularization technique and the transfer learning strategy.

KEYWORDS: Fruit Cultivation; machine learning; Transfer learning; CNN

I. INTRODUCTION

Machine learning has seen significant adoption in recent years for use in operational aspects of many types of businesses. Major areas of use include driverless vehicles, virtual assistants, video surveillance analysis, and many more. But there are also less obvious uses for these technologies that have a significant influence on the day-to-day running of some businesses. The categorization of fruits and vegetables is one example of this less obvious use. Machine learning has attracted a lot of attention for its potential benefits in fruit classification, the most prominent of which being fruit identification and categorization.

The best researcher for AI and deep learning studies is the one who specializes in picture categorization and recognition. These days, we rely on this kind of advanced analysis for the majority of our day-to-day needs. It will, therefore, touch on almost every facet of ordinary life. Perhaps it will grow and spread much more in the future. For a lot of problems, picture classifiers and recognizers will be the answer. Image processing using a deep learning technique has the potential to resolve a great deal of the problems that people face on a daily basis. Nowadays, Convolutional neural networks (CNNs) and relapse calculation methods have many more practical

applications and product problems to handle. Supermarkets often mislead customers into buying unhealthy organic food and other items simply because they don't label them. A deep learning image processing system allows us to classify items according to their condition.

Apples, bananas, and oranges are some of the fruits we're studying and utilizing to demonstrate how an image processing system can accurately identify their state. The worst-case scenario is that we can't handle fresh fruits. Consequently, a large portion of the population lacks the necessary expertise to buy such items. People will receive good understanding about these things when they use our strategy from this aspect. We could use any number of algorithms, but for this project we're sticking with a specific variation of (CNN). Just as with bananas and oranges, we can now tell whether an apple is fresh or spoiled. Compared to previously, it will make our lives simpler. We can achieve everything that humans might imagine with picture recognition and categorization systems. Almost anything, from fruits to chemicals and everything in between, may be processed with this technology.

Some data-intensive parts of farming have seen the use of machine learning as smart farming has progressed. Field data collection, processing, monitoring, prediction, and other related functions are all part of these systems. Research on farming methods and practices that help manage scarce resources and adapt to climate change has also benefited from these systems. As a result of all these studies and uses, farmers are now able to grow crops with greater quantity and quality. Figure 1.1 illustrates a few components of smart farming.

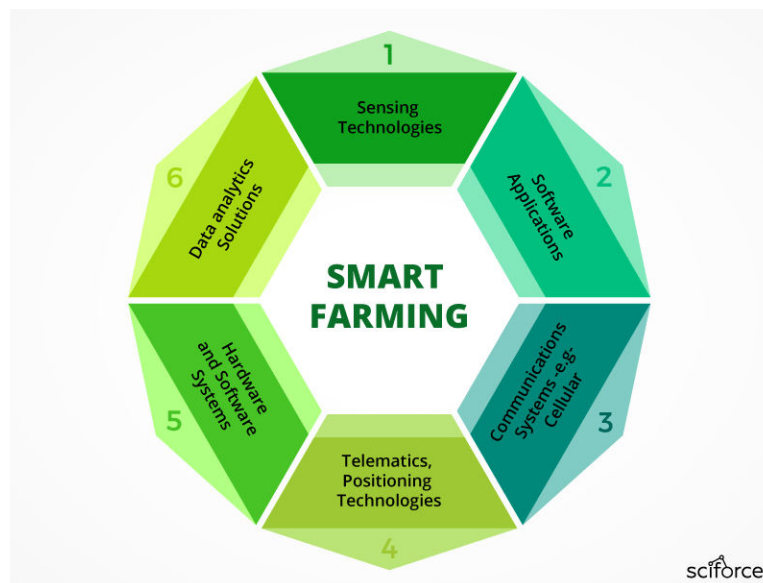


Fig 1.1: Several parts of integrated farming

Among the several ways in which machine learning has benefited industrial-scale farming is via the development of fruit categorization systems. These systems have found practical use in the analysis and prediction of agricultural productivity as well as in the identification of diseases and defects. Researchers have also made use of these systems to better study and address issues that impact the agriculture sector.

Off the field, machine learning has helped experts make better judgments about the transportation, preservation, and inspection of agricultural goods. The produce inspection team at Amazon employs fruit detection technology to consistently grade their goods, much as in other warehouses (Day one Team, 2019). Computer vision scientists working with Amazon have also used AI to create systems that can detect whether produce is about to spoil or if it is delicious. In order to collect data, all of the product is routed through a network of sensors and cameras. After then, AI systems are given this data and told to draw conclusions.

II. RELATED WORK

Many industries, including healthcare, agriculture, and more, have benefited from deep learning's revolutionary changes. Deep learning is now the subject of much study. Looking at medicinal plants through a Bangladeshi lens, the author [1] classified them using deep neural networks. Despite working with little data, they improved accuracy. To identify plant diseases, the author [2] relied on extensive training. They used a very rudimentary design for this.

A machine vision method was used by the authors [3] to detect anomalies in the skin of fruit. The main advantage and assistance for color categorization comes from assistance Vector Machine (SVM), a machine learning method used for recognition and classification. For a smaller selection of datasets, support vector machines (SVMs) provide excellent and appropriate results. To a large extent, the features that are drawn determine how accurate the machine learning categorization approach is. Also, the characteristics that will be used by the machine learning algorithm are chosen. When applied to this specific viewpoint, deep learning models allow us to effortlessly enhance our performance. Models like this are useful for picture classification in massive datasets. Writer [4] Processing images aids in defect and non-defect categorization. We may use this to identify surface issues on banana and apple fruits. At the outset, the researchers manually sort the fruits into two categories: fragile and faulty. The CNN model is fed these pre-processed pictures for categorization. This model has a 97.5% accuracy rate. This technique provides a theoretical foundation for maximum productivity. The results of this study demonstrate that the technology can detect damaged regions automatically and is both effective and non-destructive. The criteria for finding Apple mistakes may be readily satisfied by this approach. Conventional algorithms do a poor job of error detection compared to CNN-based models [5]. A research was conducted to identify flaws in the fruit skin using an artificial vision system [7]. The classification was done using the Support Vector Machine (SVM) approach, with color being the main characteristic for categorization. Support vector machines (SVMs) provide respectable outcomes for small datasets. The success or failure of a machine learning classification depends heavily on the features used for extraction and those fed into the algorithm. Making use of deep learning models allows us to enhance performance. These models are useful for picture classification in massive datasets. Classifying fruits as defective or not may be aided by image processing [8].

We find that the suggested CNN model achieves very high levels of accuracy when it comes to the clean and rotten culmination kind of tasks. This is where the correctness of the suggested version is compared to the styles of switch mastering. From among many possible outcomes, three types of culmination are selected. The dataset was obtained from Kaggle and contains six training examples, where each fruit is categorized as either clean or spoiled. Compared to switch mastering models, this paper's CNN model achieves better accuracy for clean and rotten culmination type tasks. The authors also examine the effect of critical hyper parameters to achieve better results and avoid overfitting.

After a thorough examination of the relevant literature, we have decided to use a convolutional neural network (CNN) method. This particular approach works wonders when applied to organic goods, such as fruits and vegetables. Additionally, it aligns with our goals and the nature of our job, and it is comparable to our working viewpoint.

- With the right training, convolutional neural networks (CNNs) outperform existing image identification and classification algorithms in terms of accuracy, reaching 95% or higher.
- With the right information about progress, we can incorporate it into our future work plan with ease. On top of that, there are a plethora of readily available resources on the internet.
- It's effective on almost all products, but when it comes to fruit quality, it outperforms other algorithms. Moreover, it is simple to tell whether fruit has gone bad.
- Using CNN layers allows us to get respectable outcomes with high accuracy,

Since convolutional neural networks (CNNs) are our principal classification model, we shall employ Deep Learning layers using CNNs. On the backend, we build the model using Tensorflow and Keras. Utilizing the internal database and Anaconda is our primary objective. We have decided on Google Collab because to its widespread usage and its ease of installation. To maximize its performance during runtime, I used colab and Google GPUs. Consequently, in order to access the database using Google disk, we need to mount the disk.

In addition, we want to build a system that can distinguish between ripe and spoiled fruit and then use that data to inform future comparisons. For that reason, we built the CNN layer using the Merge, Con2d, and Trigger layers. Fruits like apples and bananas, which are easy to utilize, are used for the first time. Objects that are hard to locate cannot be classified using a classifier since doing so would reduce accuracy and performance. If we use fruits like mangoes,

bananas, and apples, we should receive rather accurate results. Compare your excellent and negative scores as accurately as possible. We can discern the level of goodness or badness in this fruit and determine whether it is edible, suggesting that we have a decent range of good to bad.

III. METHODOLOGY

3.1 Hidden Layer Neural Network (CNN)

The CNN that was used for this evaluation consists of fully connected layers, one maximum pooling layer, and sixteen hidden convolutional layers. Figure 5.1 shows a reasonable convolutional neural network (CNN) illustration. The Rectified Linear Unit (ReLU) is used in this configuration to perform activation tasks in the fully connected and convolutional layers, and the SoftMax initiation capacity in the yield layer for class probability assessment. These studies use scikit-learn for organization and evaluation, with Tensor Flow-supported Keras as the framework for deep learning. Because of this, we are able to reduce the amount of standard codes written. This also helps us complete the research function more quickly.

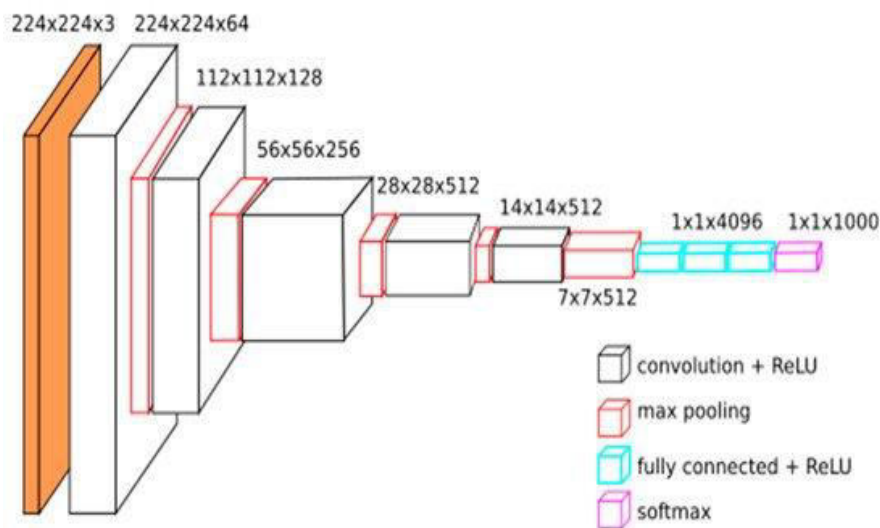


Fig 3.1: Layout of a CNN

Multiple convolutional layers, arranged alternately between pooling and normalization levels, made up the CNN network. Inputs and sets of filters are used to calculate convolution at every convolutional level. A methodical approach was taken to the teaching process. The Convolutional, Batch Normalization, Rectifier Linear Unit (ReLU), Pooling, Convolutional neural networks (CNNs) consist of Fully Linked and Convolutional levels).

Similar to a multi-layer perceptron (MLP), a common CNN design consists of FC levels, sub-sampling (pooling) layers, and several convolution layers.

3.2 Advantages of Using CNNs

When compared to traditional neural networks, convolutional neural networks (CNNs) provide many benefits in computer vision applications:

1. Consideration of CNN is primarily driven by its weight sharing feature, which lessens the quantity of trainable network parameters, hence assisting the network in improving generalization and preventing overfitting.
2. The model's output is both structured and heavily dependent on the derived features since the feature extraction and classification layers are learned simultaneously.
3. Compared to other neural networks, CNN makes large-scale network installation more simpler.

3.3 CNN network architecture

Multiple layers, or "multi-building blocks," make up the CNN architecture. What follows is an exhaustive description of the CNN design, down to the layer level, describing what each layer does.

1. A convolutional neural network's (CNN) backbone is the convolutional layer. Kernels, which are a collection of convolutional filters, are its building blocks. In order to create the feature map, these filters are convolved with the input picture, which is represented as N-dimensional metrics.

Kernel definition: A grid of integers or discrete values may best depict the kernel. For every value, a kernel weight is allocated. To begin training a convolutional neural network (CNN), the kernel is first given a random string of values to use as weights. In addition, there are other methods used to initialize the weights. The kernel learns which features are most valuable to extract by adjusting these weights throughout training.

First, the CNN input format is explained, and then the convolutional operation is performed. Traditional neural networks use vector formats as input, but convolutional neural networks (CNNs) take multi-channeled images as input. For example, although RGB images have three channels, grayscale images only have one. An example of a grayscale picture with a random weight-initialized kernel will help us comprehend the convolutional procedure. A horizontal and vertical sweep of the whole picture is first performed by the kernel. On top of that, the kernel and the input picture are "dot-producted" simultaneously by adding and multiplying their values to create a single scalar value. When sliding becomes impossible, the process is repeated. The calculated dot product values reflect the output feature map, therefore keep that in mind. In Figure 8, we can see the primary calculations done at each step. Light blue represents a tiny, about equal-sized chunk of the input image, whereas light green denotes the kernel. The output feature map takes as input the sum of the two variables, which is represented by a vibrant orange color, after multiplication.

Unlike the last example, which applied padding to the input image, this one adds a stride of one to the kernel, representing the required step-size across all vertical or horizontal locations. Also, don't forget that you may experiment with various stride values. Additionally, increasing the stride value results in a feature map with reduced dimensions. On the other hand, padding has a significant impact on the input picture's border size information. Contrarily, border side features fly out of control quite quickly. Padding has an effect on both the input image size and the output feature map size. Using Convolutional Layers Has Many Benefits.

Sparse Connectivity: The neurons in an FC neural network talk to each other across all layers. The sparse sparsity of the weights between adjacent layers is a key component of convolutional neural networks (CNNs). Because very few weights or connections are required, and even less memory is required to hold them, this approach is memory-effective. Additionally, the computational cost of matrix operation is much higher than that of CNN's dot (.) operation.

No two neurons in neighboring layers of a convolutional neural network (CNN) share weights because each weight in a CNN acts on a single pixel from the input matrix. Learning a single set of input weights instead of learning the weights of individual neurons could significantly cut down on training time and other costs.

The second algorithmic layer, the pooling layer, subsamples the feature maps. These maps are created using the convolutional techniques. To rephrase, this technique shrinks feature maps from their initial, bigger versions. Even when pooling, it retains the majority of the data that is most indicative of the dominant feature. Stride and kernel are size-assigned before the pooling technique, same to how the convolutional operation is carried out. Multiple pooling layers are available, each of which may have a unique pooling technique. The following pooling methods fall under this umbrella: tree, gated, average, min, and max pools; global average (GAP) and global max pools. The three most popular and well-known algorithms for pooling data are max, min, and GAP.

An activation function that is not linear Transforming input into output is the fundamental goal of all activation functions in neural networks. A neuron's input value is determined by adding its weighted input value to its output value, which also includes the output of any bias present. A neuron's activation state is therefore determined by the output produced by the activation function in response to an input.

Next to the CNN's weighted levels are the learnable layers, which include convolutional and FC layers, and finally, the non-linear activation layers. The activation layers' non-linear performance guarantees a non-linear translation from

input to output, which in turn allows the CNN to learn more complicated things. An further crucial quality that the activation function must possess in order to allow error back-propagation for network training is the ability to differentiate.

Many convolutional neural network (CNN) layouts include the Fully Connected Layer at the network's very base. Here, we use the so-called Fully Connected (FC) technique, which involves connecting all of the neurons in the previous layer to each node in this layer. The CNN uses it as its classifier. Its basic function is similar to that of a classic multiple-layer perceptron neural network as it is a feed-forward ANN. The preceding convolutional or pooling layer provides the input for the FC layer. This vector input is created by first flattening the feature maps.

Analysis of Losses: In the last part, we discussed the various CNN layers. Additionally, the final classification is the responsibility of the output layer, which is the last layer of a convolutional neural network (CNN). At the output layer, the CNN model uses a couple of loss functions to determine the predicted error over all of the training data. This error emphasizes the difference between the predicted and observed outcomes. The next step in the CNN learning process is to optimize it.

On the other hand, the error is determined by the loss function using two parameters. The estimated output, also known as the prediction, of the CNN is the first parameter. The label, standing in for the finished item, serves as the second argument here. Many different forms of loss functions are used in a broad range of issues.

IV. EXPERIMENTAL RESULTS

4.1 Setup for the Experiment

Typically, we'll evaluate the suggested model of our work's output and provide a logical explanation of our findings in this area. With Tensor flow 2.0.1, we trained our model. The first stage was to set the basic parameters for our model. Assign 45 as the batch size. We have a training data ratio of 80% and a testing data ratio of 20%. Then, we used the Adam [6] optimizer to put together our model, and the resulting learning rate was 0.0001. Afterwards, use fit() to begin training.

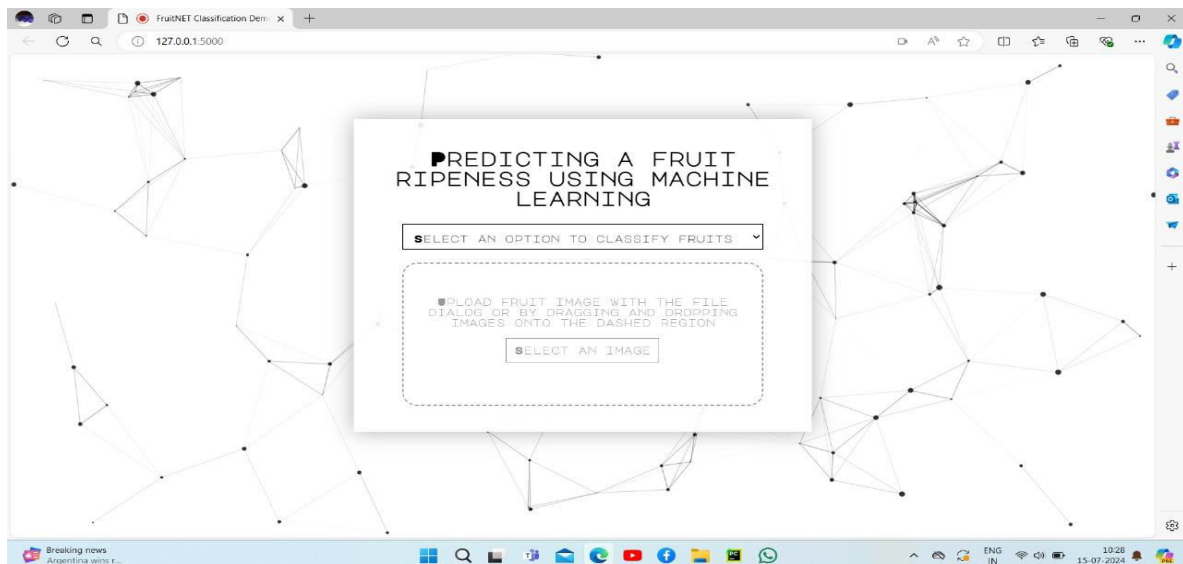


Fig 4.1: Home Page

Predicting a ripeness of fruit using machine learning whether it's a fresh fruit or rotten fruit as shown in below fig 4.2 and 4.3.

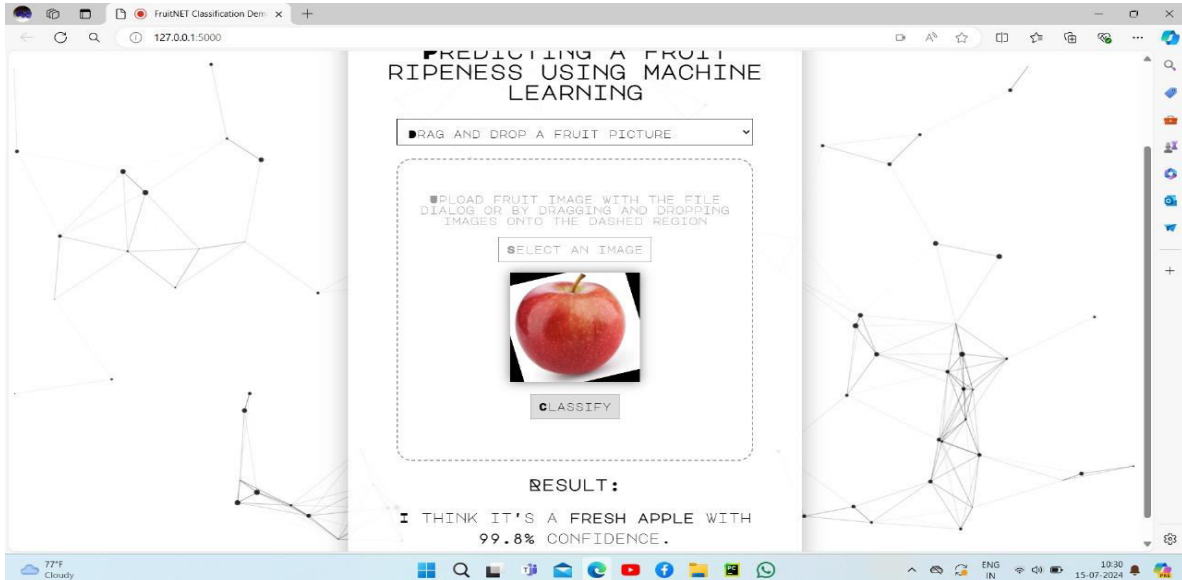


Fig 4.2: Classifying a fruit ripeness as fresh fruit

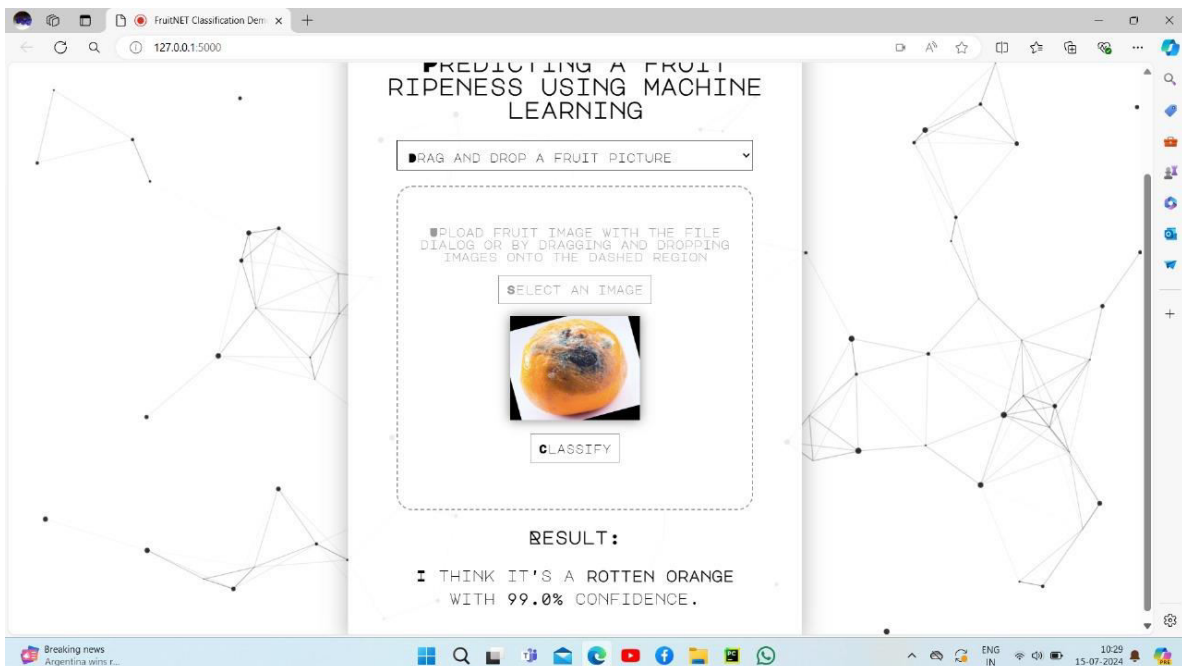


Fig 4.3: Classifying a fruit ripeness as rotten fruit

4.2 Assessment of Work Performance

Our model achieved a 98.04% accuracy rate after 10 epochs of training. Figure 4.4 shows our model's accuracy curve; it shows that our training accuracy was 98.04% and our validation accuracy was 98.21%.

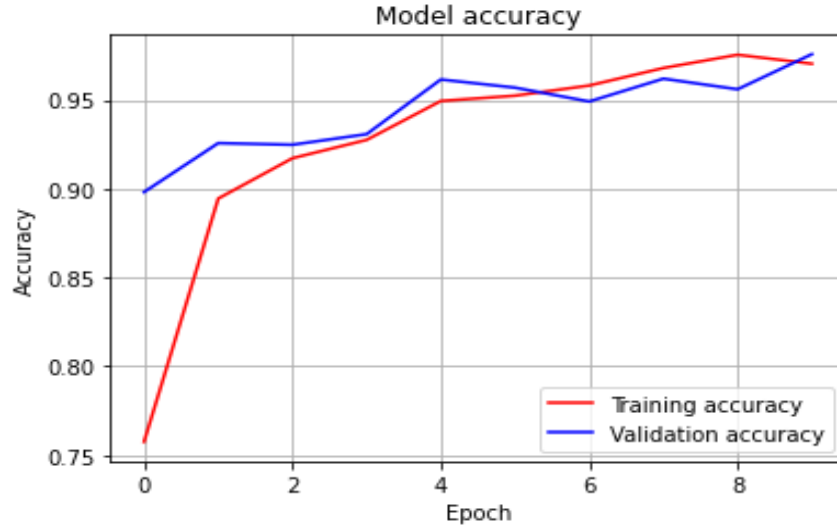


Fig4.4:Accuracy in training compared to validation

Fig-4.5 shows our model's loss curve. Our training loss was 0.0545 and validation loss 0.0797.

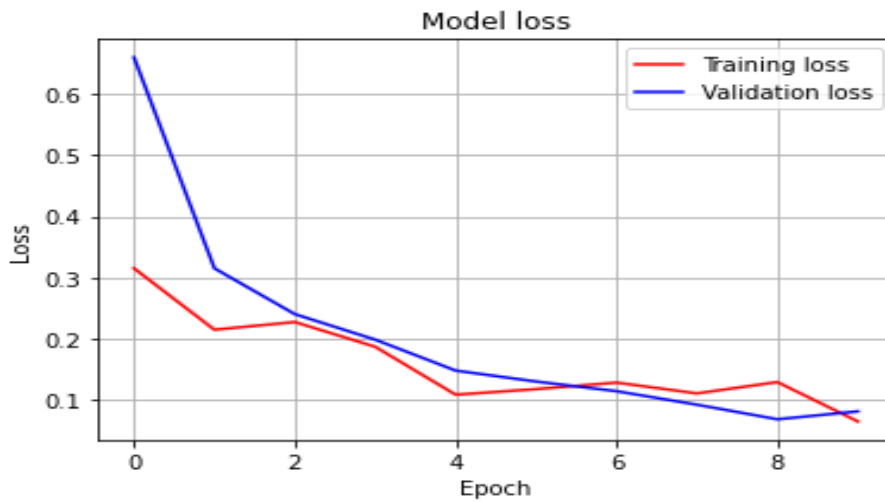


Fig 4.5: Different types of loss: training and validation

When tested, our model achieves an accuracy of 97.39% and a loss of 0.0765. The first, second, and Max-pool convolutional layers are shown in Figure 4.6.

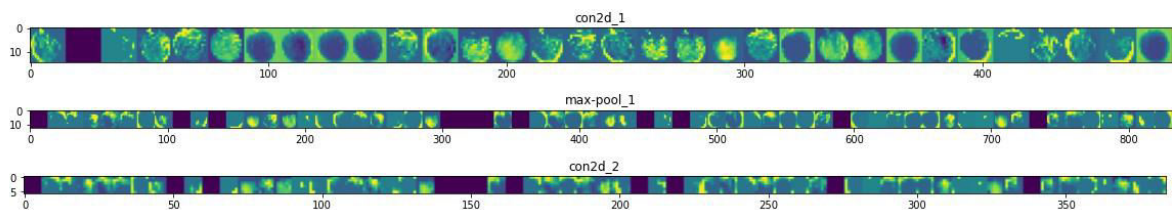


Fig 4.6: Visualizing Layers

4.3 Discussion of Results

We achieved our goal after running our dataset and constructing the model using the supplied data. After all of the testing and training, we can say that our model is quite effective; it distinguishes between fresh and spoiled fruit with a 98% success rate. After considering many comparisons and datasets, we have concluded that our model is suitable for further research.

V. CONCLUSION AND FUTURE WORK

We have a better chance of succeeding if we can tell ripe fruits from spoiled ones. Knowing which fruits are healthy and which ones aren't would undoubtedly benefit individuals. Like I said before, about 95% of our countrymen are growing up in a world where they don't know how to properly choose and purchase fruit products. Therefore, we demonstrate three primary fruits in our work to help you determine whether a fruit is fresh or spoiled. Our CNN-based algorithm accurately detects ripe or spoiled fruit with little to no room for mistake. By operating flawlessly, the complex neural network model may decrease error. More data sets that we have previously used will be used, so we can claim that it will be effective. Additionally, it provides us with a respectable degree of precision. The accuracy for the suggested model that was presented was 98.04%.

Improving the precision of the neuronal organization is, in our view, one of the main goals for the future. As is commonplace in deep learning, a massive amount of source data is needed to construct a model that is both more resilient and more accurate in its assessment of the novelty of organic products.

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