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Food spoilage alert system by deploying deep learning model

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***Abstract*---**Food waste due to rotting is unquestionably an important resource issue that must be addressed as soon as possible in the next age. Recent technological advancements, such as cloud technology, Deep Learning (DL) may aid in the reduction of food waste. To address the rising issue of food spoilage in everyday situations in the most effective way possible, a DL model is built to distinguish between fresh and rotten fruit. The dataset required for this inquiry was obtained from Kaggle. The raw dataset is pre-processed so that it may be used with the DL model. Detection systems, controllers, and transmission elements make up the functional model. These modules interact with the items, such as the fruits, to collect data, which is then processed using a DL technique, such as CNN, and if there is any degradation in the food, an alert message is sent to the registered user.

***Keywords*---**Food, DL, Cloud, Alert system, Train, Test.

Introduction

In recent years, food waste has grown to be a severe issue, and researchers are working to find new ways to reduce it. A major problem has been recognized as the protracted durability of agricultural production, need, and delivery systems. Meals have always been in high demand because they are the most basic kind of sustenance for all living things. The Internet of Things (IoT), which integrates whatever, everywhere, at any time, can enhance food supply chain operations [1]. This technology could be used to evaluate and check the status of food, as well as to communicate data with others from customers. FSC's use of IoT technology is still very much in inception, and much work is still to be done. To prevent food waste, food hygiene and safety are critical. Meals should be standardized in terms

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of uniformity. As a result, by establishing quality control systems, the quantity of waste in supermarkets can be reduced. It will also help with disease prevention and treatment. These devices monitor environmental factors to assure food quality. Freeze and ventilation system storage had already been employed to monitor the effects of the atmosphere. The most prevalent cause of food contamination is inefficient food handling activities due to poor environmental factors during food storage and preparation, although it can occur throughout the manufacturing process as well. Modern technologies are emerging to make the lives of the working class easier. Technological advances are being made to better satisfy the requirements of an expanding, urbanizing, and globalizing civilization. Food quality has become increasingly important in the lives of humans. Food quality is determined by two factors: cleanliness and long-term stability. Temperature fluctuations can cause food to spoil, so keep an eye on the condition of your food. Eating undercooked or pink animal meat, which rots and turns toxic when swallowed, almost invariably causes health concerns. A food's colour can reveal a lot about its quality. In addition to other food-related diseases, food poisoning can be caused by decaying or unfit-for-use food. A food spoiler detector can detect the gas released by rotten or otherwise unfit for consumption food.

Fruits are popular and in high demand in today's market, particularly among those concerned about their health. Because fruits are a dietary supplement that contains a variety of elements that are beneficial to your health. Fruit can help you lose weight by replacing your main meals with it. Furthermore, because the fruits do not require any preparation before consumption, they are a popular choice among consumers. Each fruit originates or is grown in a different section of the world depending on the species and the environment conducive to yield. As the world's population grows, so does the demand for goods and services. As a result, a diverse range of fruits can now be found all over the world. It can take days or even weeks to transport fruit from one location to another, causing it to rot. Transportation technology has advanced dramatically in recent years, and it is now lightning fast. Certain factors, such as high temperatures and excessive humidity, may cause fruit to rot faster than usual. It's also possible that bacteria will spread from one fruit to the next, causing other fruits to perish. As a result, before consuming decaying fruit, it must first be removed from its packaging or fruit crate [2].

DL is being used to monitor and assess food spoilage data to prevent food degradation caused by weather and atmospheric effects. Because of the finding of hazardous substances in fruits and vegetables, health-conscious consumers are increasingly concerned about food waste, but they are also concerned with the quality of the product itself. DL is used to monitor and analyse food spoilage, which saves time and produces consistent and trustworthy results.

The goal of the project [3] is to detect rotten food using appropriate sensors and to monitor gases emitted by the specific food item in question. As soon as a microcontroller detects this, it delivers an alarm over the internet of things, allowing for immediate remedial action. This is widely used in the food industry, where food detection is currently performed by hand. This model will be enhanced using machine learning (ML) so that we can predict how long it will take for food purchased from a specific vendor to degrade. Increased competition among shops for the sale of healthier and fresher foodstuffs will lead to a safer environment for all customers. It is the goal of this research [4] to use Azure Custom Vision API to identify rotting in rice. A correlation coefficient of 1 was found between the readings from the gas sensors and the images taken during data collection, indicating a very strong connection. Detection accuracy of 85% was achieved when the researchers tested the system with 20 different samples of rice, including 10 samples of damaged rice and 10 samples of not spoiled rice. Using a Raspberry Pi 3B and a camera module, the system is programmed in Python and runs in its container. Researchers in [5] employed computer vision to design an architecture that can tell the difference between fresh and decayed fruits. Images of Apples, Bananas, Guavas, and Oranges are processed using the VGG16 (CNN) model. Decision Trees, Support Vector Machines (SVMs), and Logistic regression models are used to classify the data. It was the Support Vector Machine that had the most accurate classification, at 99%.

Bacteria can swiftly spread if the fruit is not properly kept. Fruits must be inspected before they are delivered to consumers to guarantee their safety. Because of the time and energy required to inspect manually with the human eye, the human examination has a lower degree of reliability and precision. To address this issue, the article [6] suggests using CNN for feature extraction and categorization of deteriorating fruits. This inquiry will focus on bananas, apples, and tangerines. The validation accuracy of this paper is 98.89 percent. The training stage lasts a total of 212.13 minutes. As a result, classifying a single fruit image takes roughly 0.2 seconds. Author [7] devised a model to halt the progression of rottenness. Based on the images provided, the proposed model distinguishes between fresh and rotting fruits. This endeavour, which featured a lot of fruit, included the usage of apples, bananas, and oranges. To capture features from fruit shots, a CNN is employed, and the images are classified using the pooling, and MobileNetV2 architectures. While validated on a Kaggle database, the accuracy of the proposed model is 99.46 percent in training examples and 99.61 percent in test sets when utilizing MobileNetV2. Max pooling achieved 94.49 percent training accuracy and 94.97 percent validation accuracy. Aside from just that, the average pooling achieved 93.06 percent training accuracy and 93.72 percent validation accuracy. "According to the results, the proposed CNN model can identify between fresh and rotting fruits.

Methodology

The methodology of the research work is detailed in the chapter with the help of a flow chart shown in figure 1. The three important phases in this research are data acquisition and process, model development, and interfacing of mobile apps and the cloud. First, the data with fresh and rotten images are collected. The data count should be high to make the model trained on different samples. Next based on the model architecture the data is resized and resampled without reducing the important features of the image. Then the DL model is constructed. The CNN is picked in this research for classifying the fruits. The model is trained and validated in the training phase. Then it is validated using the metrics called accuracy and loss. After analysing the results of the model, it will be shifted to the test phase. In this phase, the model quality is checked by giving different samples. In the test phase again, the model is validated using several metrics.

After this stage, the DL mode is deployed in the cloud. By using hardware, the real picture of fruits is captured and sent to the cloud. Based on the model stored, the cloud sends the notification and status of the acquired fruits to the mobile application. This helps the customer to know about the quality of their food in their home and helps to make arrangements based on the information in the mobile application.

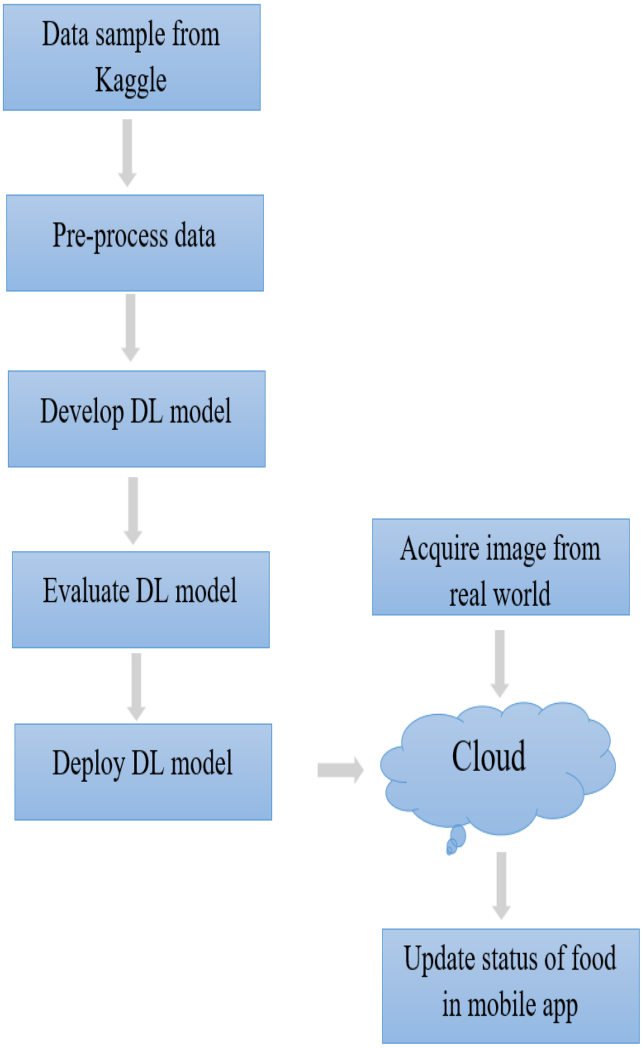


Fig. 1. Workflow

Data collection and pre-process

The dataset consists of a variety of fruits: apples, bananas, and oranges, which are divided into two categories: fresh and rotting, and was obtained via Kaggle [8]. The dataset used in this study contains 9000 images. The total number of images in the training set is 5400, the validation set is 1800, and the test set is 1800. Table 1 displays the samples from the dataset for each class. The details of data slicing are shown in Table 2. As a result, the entire dataset has been reduced in size and converted to NumPy arrays, allowing the CNN model to be generated considerably faster. Finally, the pictures in the modified dataset are categorized by class. When using CNN to train a dataset, picture augmentation is done in real-time, but validation is done on a test set in parallel.

Table 1. Sample image

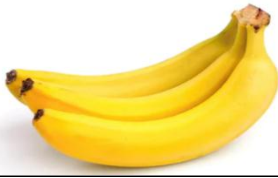
Food Item	Fresh	Rotten
Apple		
Orange		
Banana		

Table 2
Data splitting

Fruit	Train	Valid	Test
Fresh Apple	900	300	300
Rotten Apple	900	300	300
Fresh Orange	900	300	300
Rotten Orange	900	300	300
Fresh Banana	900	300	300
Rotten Banana	900	300	300

Model design and evaluation

DL is a well-known subfield in ML =. It is capable of dealing with a wide variety of data. Using a CNN, a DL model can be used to design an image categorization network [9]. Figure 2 illustrates the underlying CNN structure. Computers store images in the form of a connected series of pixels. Numerous patterns may be seen in the image, including the image's shadow and edge. Convolution is a technique that can be used to detect these patterns. Matrix-based representations of image pixels are used during the calculation procedure. To recognize patterns, one should multiply a “filter” matrix by the image pixels. The initial pixel of the matrix can be used to execute convolution, beginning with a subset dependent on the filter size of the matrix. The filter's size affects the multiplier. When all pixels in the image have indeed been examined, it goes onto another pixel in the image as well as continues the process. Many variables are exchanged throughout this convolving procedure. The following layer receives a convolutional feature map. The pooling layer is the following CNN layer type in the model. For instance, the feature map will be smaller and hence less likely to be overfitted by this layer. The most critical and final layer is one that is completely integrated. A single vector is produced, which can be utilized as a source for the next level, by "flattening" the outcome of the preceding layer throughout this. Batch Normalizations are employed to normalize characteristics gathered at every level. Additionally, dropouts can be exploited to accelerate calculation.

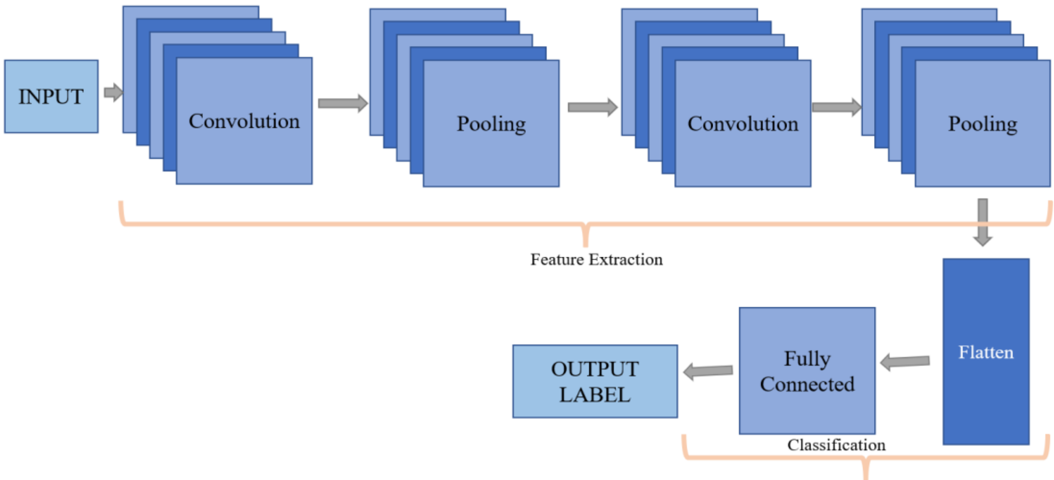


Fig. 2. CNN architecture

The evaluation metric is critical in choosing the optimal classifier during classification training and testing. As a result, selecting the appropriate evaluation metric is critical for differentiating and reaching the optimum classifier. During the training phase, many dynamic classifiers use accuracy as a measurement to distinguish the ideal response. However, there are various faults in the accuracy, including less individuality, making specific, less information quality, and bias toward dominant class data [10]. Additional measures offered in this paper are used to identify the optimal solution.

Depending on the purpose of the research, various studies used different assessment methods. We used more often and regularly used assessment metrics in the area of object classification, which is listed in table 3 utilizing formulas.

Table 3
Model metrics

Metrics	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN} * 100$
TNR	$\frac{TN}{TN+FP} * 100$

TPR	$\frac{TP}{FN+TP} * 100$
FPR	$\frac{FP}{TN+FP} * 100$
FNR	$\frac{FN}{FN+TP} * 100$
Precision	$\frac{TP}{FP+TP} * 100$

Where the forecast and actual outcomes are rotten fruit in true positive (TP), while the forecast and actual outcomes are fresh fruit in the true negative (TN), the forecast outcomes are rotten and actual outcomes are fresh fruit in false positive (FP), the forecast is fresh fruit and actual outcomes are rotten fruit in false-negative (FN), and the predicted and actual outcomes are fresh fruit in false positive (FP).

IoT and mobile app design

After analysing earlier studies on food degradation prevention, it was determined that the barriers include technology with limited flexibility, in both terms of price and ease of use. This study presents a mobile monitoring system that is customizable, inexpensive, and quick to use. The project made extensive use of cutting-edge technology such as edge IoT, DL, and a user-friendly Python-based graphical user interface. Sensor data were collected for two different types of fruit: fresh and rotting. Additionally, CNN learning systems have been created to assess the stock's degradation based on image information. The Python-based graphical user interface, which is displayed on top of the microcontroller screen, enables real-time monitoring and control of sensor data, as well as the transmission of alert messages. The device has two purposes: it determines the decaying stage of the product and alerts the user to certain fruits and vegetables' environmental conditions. A software expertise system was designed that accurately alerts the user to newly updated environmental conditions based on available data. Wi-Fi is utilised to transfer the data received from the microcontroller to the Firebase server. A mobile application that uses Firebase to analyse storage fruits and receive warning messages in case of fruits rotten.

The primary challenges of the Internet of Things include successfully extracting significant data from vast quantities of data created by legitimate sensor observation, converting it to a suitable format, and minimizing cloud services and energy consumption. The combination of cloud computing and edge computing paradigms, as well as recent breakthroughs in on-chip embedded technologies, may be able to solve these issues [11]. It is now possible to trace the whereabouts of the food from everywhere in the world thanks to the development of a mobile application. It retrieves data from the Firebase and makes it available on mobile. The mobile app was created using the web-based Kodular which is an open platform. All that is required of the user is a single sign-in with the particular device using a suitable login method.

Result and Discussion

The ultimate goal of this research is to detect the spoilage of the fruits using DL algorithms. In this research both fresh and rotten apple, banana, and orange images are used to train and test the DL model to detect the rotten fruit from the fresh fruit. The dataset is initially divided into two parts training and testing set. The training set contains 1200 images each of fresh apple, banana, and orange and 300 images each of rotten apple, banana, and orange. Accuracy, Precision, True positive rate, True Negative rate, False positive rate, and False-negative rate are the performance metrics evaluated in this study to analyse the DL model. These performance metrics contribute to the creation of the best DL model with a low error rate to detect the rotten fruit from the fresh fruit. The pre-processed images are evaluated using the CNN algorithm. Figures 3 and 4 given below show the plot of loss percentage of spoiled food and the plot of accuracy percentage of spoiled food respectively using the CNN DL algorithm.

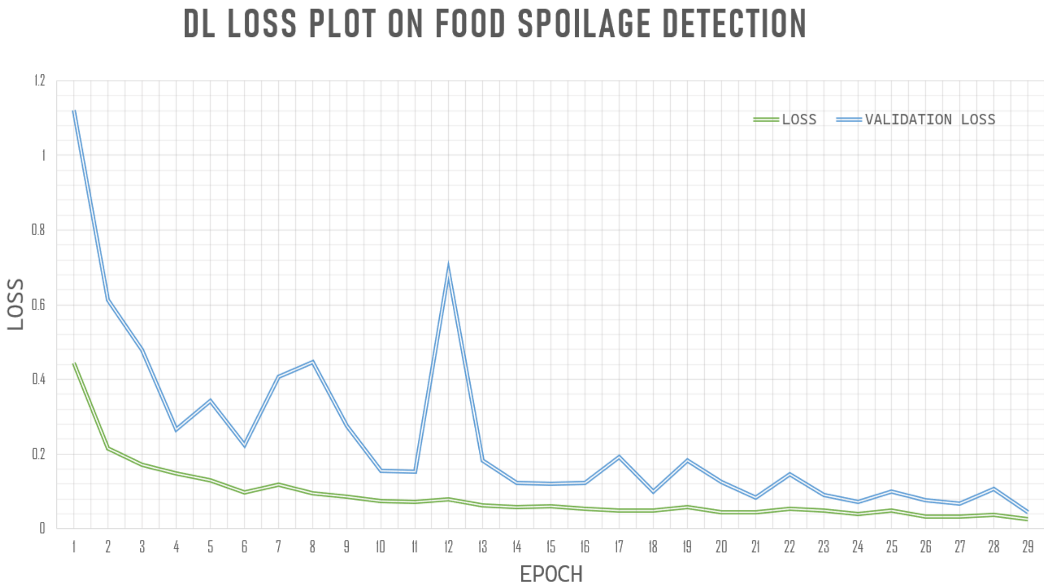


Fig. 3. DL Loss plot on food spoilage detection

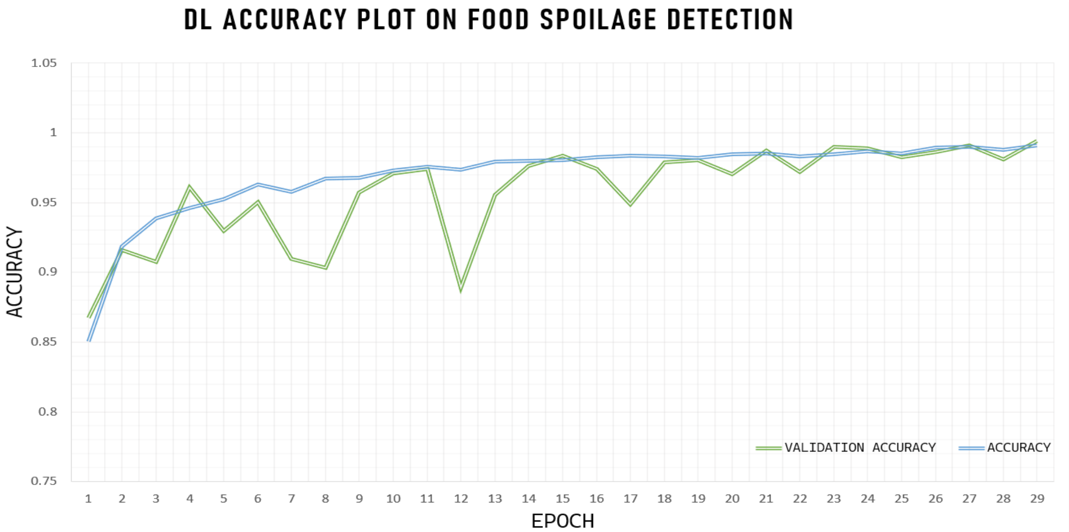


Fig.4. DL Accuracy plot on food spoilage detection Figure 5 given below shows the result of test data using the CNN DL algorithm. From the plot, it is given that the accuracy of the model is 95.2% and the precision is about 94.5 %. The True positive rate is given as 95.8% and the True negative rate is about 94.6%. The False positive rate is about 5.3 % and the False-negative rate is about 4.1%.

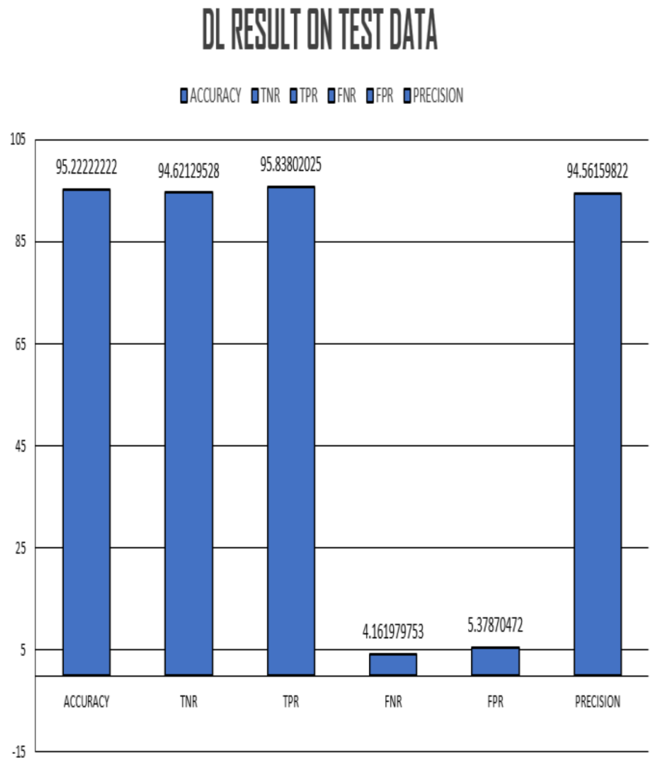


Fig. 5. DL result on test data

The user-friendly mobile application is the final purpose of this research in detecting the rotten fruits from the fresh fruits. The DL model detects the rotten fruit among the fresh fruit precisely and this is conveyed to the consumer through an SMS text message that the certain fruit is rotten. Figure 6 given below shows the notification of the SMS sent to the consumer's mobile phone that Apple is affected. Once the application is opened it shows orange and banana as fresh fruit indicating that they aren't rotten and the apple is rotten.

Fig. 6 Image of the mobile application

Conclusion

According to the United Nations Environmental Program, around 1.3 metric tonnes of edible food are wasted each year. As a result, this paper proposes a DL technique that can distinguish between fresh and rotting fruits and delivers a message alert to the user. As a result of the notification, users will be able to remove away spoiled fruits and eat food before it expires, reducing waste and allowing customers to obtain new fruit on time. This study employs the CNN DL algorithm and produces an accuracy rate of 95.2%, which is much higher than other traditional models presently in use. Even though the customer wasn't at home, the smartphone app receives real-time notifications, with the help of cloud computing technology.

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