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AI Based Food Quality Recommendation System

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ABSTRACT- Deep learning has been evidenced to be a cutting-edge technology for big data scrutiny with a huge figure of effective cases in image processing, speech recognition, object detection, and so on. Lately, it has also been acquainted with in food science and business. In this paper, a fleeting overview of deep learning and detailly labelled the structure of some prevalent constructions of deep neural networks and the method for training a model is provided. Various techniques that used deep learning as the data analysis tool are analyzed to answer the complications and challenges in food sphere together with quality detection of fruits & vegetables. The precise difficulties, the datasets, the pre-processing approaches, the networks and frameworks used, the performance attained, and the evaluation with other prevalent explanations of each research are examined. We also analyzed the potential of deep learning to be used as a cutting-edge data mining tool in food sensory and consume explores. The outcome of our review specifies that deep learning outclasses other approaches such as physical feature extractors, orthodox machine learning algorithms, and deep learning as a capable tool in food quality and safety inspection. The cheering outcomes in classification and regression problems attained by deep learning will fascinate more research exertions to apply deep learning into the arena of food in the forthcoming. The main aim of this work is to facilitate our learning and implement that in real life. Food quality and food security are always issues which are always overlooked. In modern times, this has morphed into more significant concerns relating to optimization of on- demand supply chains and profitability of agri-businesses. But now with the advanced systems and technology, it is possible to resolve this issue efficiently using the power of AI.

KEYWORDS: Artificial Intelligence based Predictive Analysis of Customer Churn, Comparative Graphs, Deep Learning, Heroku, Machine Learning.

I. INTRODUCTION

A healthy diet is important for human health. Natural products are widely used as food and can also be processed to meet consumer demand. Types, compositions, nutrients, and process style of food (natural products and processed food) are issues related to healthy eating. The fact is that people in different regions have different eating habits. Knowing the properties of food (types, compositions, nutrients and process style and so on) is very important for consumers around the world to observe the quality and safety of food. Quick, accurate and automatic determination of food characteristics is a practical demand in daily life. Modern techniques including electronic noise computer vision, spectroscopy and spectral imaging are widely used to identify food features. These methods can obtain large amounts of digital information related to food characteristics. Data analysis of these methods is very important because large amounts of data contain a lot of unnecessary and irrelevant information. How to deal with such a large amount of data and extract useful features from the acquired data is an important and vital issue, and bringing these technologies into real-world applications (APPs) is also a challenge.

Many data analysis methods have been developed to deal with the large amount of data, for modeling such as partial least squares (PLS) artificial neural network (ANN), support vector machine (SVM), random forest, k-nearest neighbor (KNN), and so on. For feature extraction, such as principal component analysis (PCA), wavelet transform (WT), independent component correlation algorithm (ICA), scale-invariant feature transform, speedup robust features, histogram of oriented gradient, and so on. These methods have shown their great value in dealing with this data. Deep learning, as an effective machine learning algorithm, has been extensively studied and now attracts attention in various fields such as remote sensing, agricultural production, medical science, robotics, health care, human activity recognition, speech recognition. In-depth representation data has shown significant benefits in representation learning, transfer learning, dealing with large amounts of data and achieving superior performance and high accuracy. Sensory neural networks (CNN) and its derivative algorithms have been identified as key methods in many surveyed articles that can automatically learn the in-depth features of input digital information for subsequent classification or regression tasks. Large amounts of data collected by CNN can be successfully processed for devices for food quality and safety assessment (spectroscopy, electronic nose, digital camera, etc.). CNN has been found to be an effective in image analysis (two-dimensional data) and has expanded

to one-dimensional and three- dimensional data to handle more diverse data formats [4].
Nowadays, in-depth study in the field of food has been introduced by analyzing RGB images and food spectra images. However, since deep learning understanding and APP is a very difficult subject for researchers and workers in the food industry, researchers are on the way. This Research focuses on studying the various image recognition techniques used to identify an object in the frame using Artificial Intelligence. Our Aim is to design and Implement a 'Machine Learning Model' with CNN Layer and pooling Layer to train the model for measuring the quality of food (i.e., Apple, Banana, Oranges) and thereafter testing the model to achieve the best accuracy. To achieve this goal first review of various methodologies for measuring and improving food quality using CNN, KNN, SVM, ANN is provided and conclude if a machine/deep learning approach would reveal a greater rate of improved food quality. Then a novel CNN model is proposed to measure and enhance food quality with enhanced accuracy and reduced time and space complexity and proposed model is compared with existing food quality model to evaluate the significance.

II. LITERATURE REVIEW

Determining the quality of fruits and vegetables is currently a hot and challenging research area. In recent years, the classification of intensive learning types with image processing or spectral sensory methods has been widely used as a tool to determine the quality of effective and destructive fruits such as nutrients [8]. Rodriguez et al. [1] focused on the separation of plum varieties during the early maturation period using intensive learning techniques. And then performed the classification using CNN. Alexnet architecture was chosen as the CNN model. Exclusive - Classification accuracy ranged from 91% to 97% on the various datasets collected. Aziza et al. (2017) applied CNN to Mangos teen to identify defective surfaces. One hundred and twenty RGB images were obtained with manual labels and then cropped to 512 × 512 pixels in size as a dataset for modelling and evaluation. CNN has been combined with quadruple cross validation to solve the binary classification problem. The proposed method can reach a classification accuracy of 97.5% for mangos teen defect surface detection.
Tan et al. [2] Airbase Alert System for Apple pests and diseases with the aim of capturing Artificial Intelligence (AI). CNN applied to the Apple skin lesion image collected through the Infrared Video Sensor Network. The image pre-processing method used in this research adjusts the intensity value of each raw image to a constant brightness interval and processes these adjusted images with rotation translation from four different angles so that trend disturbances and brightness differences are detected. The size of the image database can be expanded to 4000. After resizing and resizing to 28 * 28 pixels by the PCA method, images were trained using the five CN layer CNN models defined by the authors, and the detection accuracy was up to 97.5%. The proposed network introduced parallel diversity with traditional neural networks such as multilayer perceptron (MLP) (68.75%) and KNN (62.50%).

Some damage or lesions on the surface of the fruit are visible to the naked eye and the symptoms are clearly visible even in RGB images [9]. Such identification tasks can be solved by combining machine learning and computer vision. However, it is challenging for researchers to properly detect mechanical damage under the skin of dark black pigmented berries using RGB imaging technology (e.g., blueberries). Spectroscopy techniques are often applied as non-destructive measurement methods to indicate the internal condition of the fruit. Wang, et. al. [3] introduced the Hyper Spectral Image Sensing and Deep Learning method as a solution to identify damaged blueberries. Corrected and damaged samples were scanned by the Hyper Spectral Transmittance Imaging System (wavelength: 328.82 to 1113.54 Nm) to capture the Hypersonic Cube. Each sample was resized to 32 × 32 with 151 channels by clipping, syntax splitting, resizing and total layout. The adjusted structures of Resnet and Resnext were used for classification with fine-tuned parameters and obtained 0.8844 and 0.8952, respectively, for accuracy, as well as for the scores of 0.8784 and 0.8905, respectively, which gave a lower minimum than the traditional classification. Optimization (SMO) (0.8082 / 0.8268), Linear Regression (LR) (0.7606 / 0.7796), Random Forest (RF) (0.7314 / 0.7529), Badging (0.7113 / 0.7339), and MLP (0.7827 / 0.797). Although this is adequate for traditional machine learning, the authors specifically report that the size of the raw database does not meet the need for intensive learning. In addition to the sufficient amount of samples, in-depth learning methods also require adequate flexibility information of each sample.
Mesa et al. [5] researched the potential of the CNN method of artificially harvesting bananas through hyperspectral sensing and RGB imaging. It should be noted that only RGB images (120 images from each class: artificially / normally extracted, 30 images for training and testing) are used to train and evaluate Alex Net's transformation. Significant classification accuracy of 90% has been done for the model used for this binary classification problem. Lin et al. [6] points out the obstacles of a deep learning APP based APP. His goal is to develop a system for detecting diseased fibers using spectral analysis. At least partial class discrimination analysis (PLS and DA) and DBN (full spectral range of 420 channels, 54 image features and 474 features fusion) during training based on data in high form dimensional form. Both methods have shown excellent performance. However, training on data after dimension reduction, which includes only six optimal features, showed that the PLS model performed better than the DA model Deep Confidence Network (DBN) model. Considering the size of the data-occupied storage space, computing speed and other requirements for hardware, common models, and low-channel spectrophotometers have many advantages over industrial APPs.
A new in-depth learning structure has been established by Kim et al. [7] to assess the stability and solubility of pears. There are one hundred and eighty peer chambers, 15 of which are collected daily to obtain WIS / NIR spectral data and labelled with their reference solidity and soluble solid content values. SAE has been trained to extract high extract level properties of raw spectra. Then, the collected traits

were included in the FNN to assess these two traits of the pear. When training for the SAE model, the pixel SA level spectra of interest (ROI) were used to ensure that the dataset was large enough. The average spectrum was calculated to minimize the effects of interference and considered as inputs to the trained SAE N FNN model. Results obtained with RP2 of 0.890, RMSEP of 1.81N, RPDP of 3.05 for stability and RP2 of 0.921, RMSEP of 0.22%, and RPDP of 3.68 for soluble solid content indicate intensive learning and visual and infrared combination. Vis / NIR) spectral sensing can be used as an effective non-destructive method to determine fruit quality. Studies of these surveys suggest that some of the fruit varieties and their physical and chemical indicators (persistence, nutrient content, degree of damage, degree of disease, natural maturity, etc.) are reflected in the spectral information of the RGB image or specimens [10]. Can be learned and discriminated against through in-depth learning models to assess quality and safety parameters.

III. PROPOSED MODEL

Practically, to achieve the objective of image recognition for measuring the food quality, CNN plays a crucial role. Therefore, this section describes the process and steps to be flowed to implement and design such a model which can give us an accuracy better than the previous developed models using Pytorch framework. The Suggested model is defined with 4 integrated work stages: data acquisition, data pre-processing, training the model and testing the model to calculate the accuracy. Figure 1 presents the framework of the proposed model.

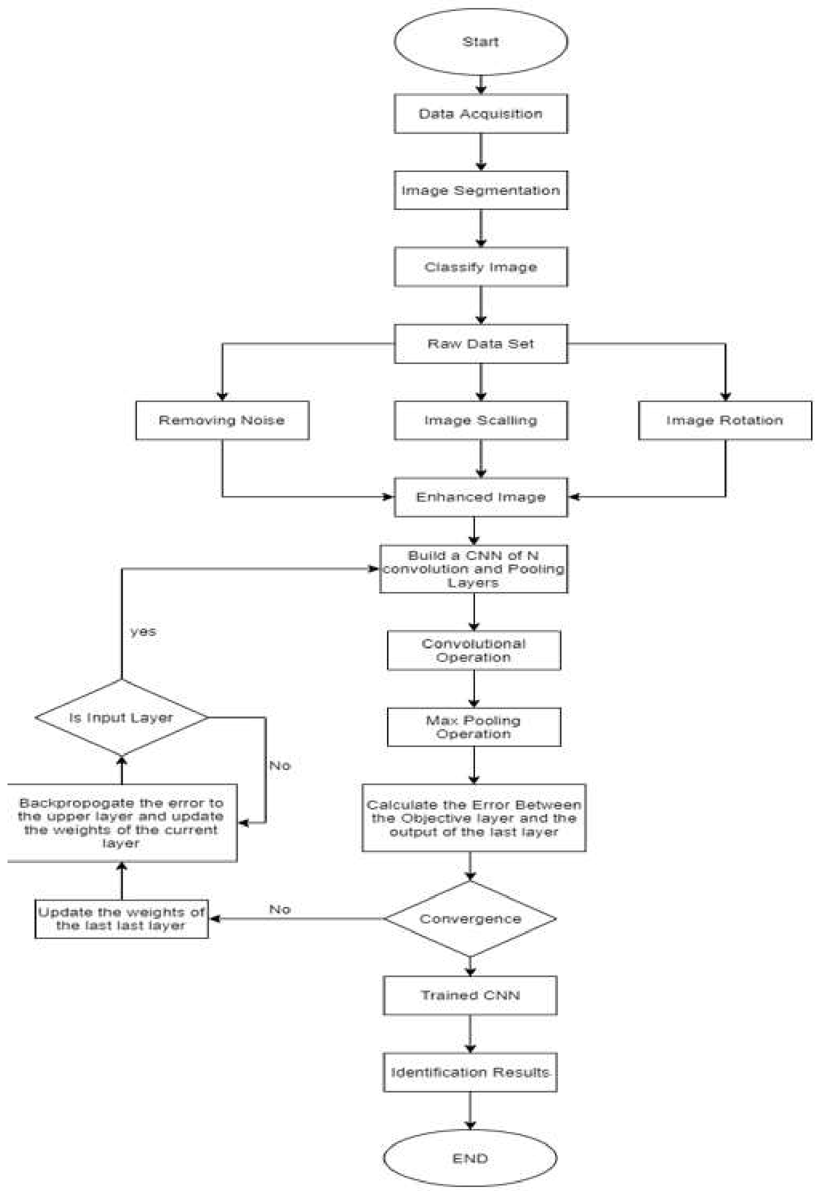

Figure 1: Framework of Proposed Methodology

A. Features of the Proposed Model

- It uses Pytorch Framework which reduces the line of Codes and hence helps in improving the time and space complexity of the project.
- It is trained over a large dataset. As CNN is supposed to give a higher accuracy with larger data but it increases the time for training of the model.
- The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision [11]. For example, given many pictures of Apple and Orange it learns distinctive features for each class by itself. CNN is also computationally efficient.

B. Data Set

The dataset is obtained from Kaggle which has three types of fruits-apples, bananas, and oranges with 6 classes i.e., each fruit divided as fresh and rotten. The total size of the dataset used in this work is 13,599 images. The total number of training images are 9811, the validation set (Taken from the training dataset) contains 1090 images belongs to 6 classes, and the test set contains of 2698 images which belong to 6 classes. Figure 2 represents the no. of images in dataset per class and figure 3 shows the sample data set.. Now the entire dataset of images is reshaped to 32x32 size to make it easier and faster to train the model. Finally, the converted dataset of images is labelled according to each class they belong to. Whereas, when training the dataset using transfer learning the image augmentation is applied, validation is done in parallel while training and tested upon the test set.

Categories	Image Distribution					
	Fresh Apple	Fresh Banana	Fresh Oranges	Rotten Apple	Rotten Banana	Rotten Oranges
Testing	395	381	388	601	530	403
Training	1693	1581	1466	2342	2224	1595

Figure 2: No. of images in dataset per class

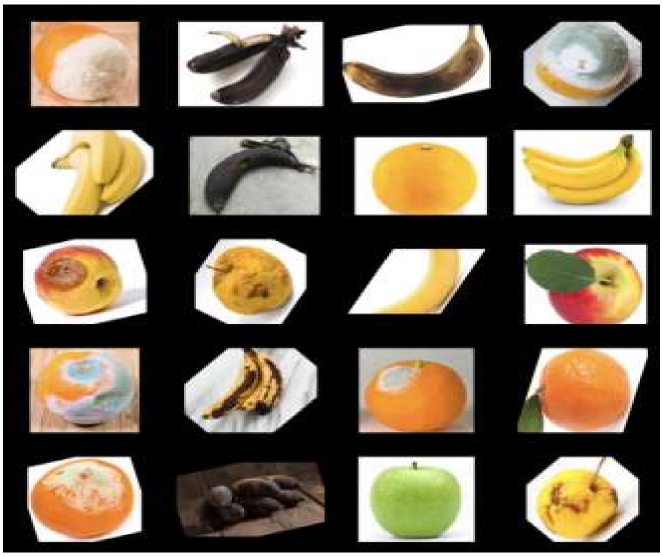

Figure 3: Sample Image of dataset

one variance. For rescaling the images to 32x32 size we have used cv2. A small size is chosen to reduce the training time.

```
[8]  img_t, _ = dataset[1000]
     img = img_t.permute(1,2,0)
     plt.imshow(img);
```

Clipping input data to the valid range for imshow with RGB data

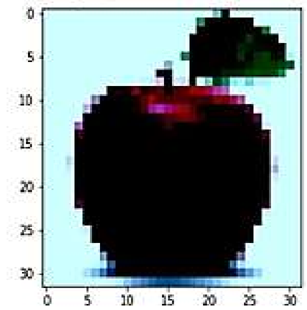

Figure 4: A random image in RGB after transformation

IV. RESULTS AND DISCUSSION

The dataset which is acquired from Kaggle is just images in separate folders such as: freshapples, freshbanana, freshoranges, rottenapples, rottenbanana and rottenoranges. These folders are common subfolders in train and test folders. A lot of effort in solving any machine learning problem goes in to preparing the data. PyTorch provides many tools to make data loading easy and hopefully, to make code more readable. So, a custom dataset FruitsDataset is created which inherits Dataset class and overrides the above methods in which we labeled the images as well by following a clever approach which is if the image path name contains word “rotten” then it’s “rotten” and if it contains word “fresh” then it’s labeled as “fresh”. Figure 4 depicts a random image transformation.Two methods are used for this- ToTensor method to convert the numpy images to torch images and normalize method so that the images have zero mean and

During the data loader process a simple for loop is used to iterate over the created dataset. However, we are losing a lot of features by using a simple for loop to iterate over the data. In particular, we are missing out on: i) Batching the data ii) Shuffling the data and iii) Load the data in parallel using multiprocessing workers. Torch.utils.data.DataLoader is an iterator which provides all these features. A separate loader is developed for training and validation with sampling. Using this data indices is created for training and validation splits to train in batches of size 64 with randomly shuffled data to reduce skewness of the data and get better results. Then in the training phase preprocessed data is used to incrementally improve our model’s ability to predict whether a given drink is wine or beer. In some ways, this is like someone first learning to drive. At first, they don’t know how any of the pedals, knobs, and switches work, or when any of them should be used. However, after lots of practice and correcting of their mistakes, a licensed driver emerges. Moreover, after a year of driving, they've become quite adept. The act of driving and reacting to real-world data has adapted their skills. In the same way model gets trained and improves over time when provided with more real-world data. So for the training part, first of all the nn.module is redefined class to create our custom NN using nn.functional library. Then the number of parameters is checked for training. A snapshot of the training model is shown in figure5. We also checked on which machine we're training to make sure it is on GPU or TPU else the training time would be huge. We defined our training loop in which in every iteration it gets rid of gradients from last round and performs backward step to compute all the gradients and then update the model. We also used *tqdm_notebook module* to keep track of the progress. And saving the tensor using *torch.save* in *.pt* format.

```
en=(FloatProgress(value=0.0, max=50.0), HTML(value='')))
15:28:18.387151 Epoch 1, Training Loop 0.6246137977951635
15:29:28.878808 Epoch 2, Training Loop 0.5140579421154774
15:30:38.389913 Epoch 3, Training Loop 0.4745591817981135
15:31:48.309941 Epoch 4, Training Loop 0.4456824127339969
15:32:59.546547 Epoch 5, Training Loop 0.4080729340984873
15:34:12.960751 Epoch 6, Training Loop 0.3676542927966501
15:35:26.465913 Epoch 7, Training Loop 0.3313259861453116
15:36:49.535537 Epoch 8, Training Loop 0.3047165835868872
15:38:06.812159 Epoch 9, Training Loop 0.2815546602228262
15:39:24.792931 Epoch 10, Training Loop 0.26149793616394057
15:40:45.361064 Epoch 11, Training Loop 0.24843892259319333
15:42:01.885836 Epoch 12, Training Loop 0.24484657643850173
15:43:18.278993 Epoch 13, Training Loop 0.23538611883664654
15:44:31.225062 Epoch 14, Training Loop 0.22873013858159963
15:45:41.738022 Epoch 15, Training Loop 0.2223207966907181
15:46:52.395908 Epoch 16, Training Loop 0.21599870098985896
15:48:03.080191 Epoch 17, Training Loop 0.21554553487005024
15:49:14.727210 Epoch 18, Training Loop 0.20566486115873295
15:50:24.363609 Epoch 19, Training Loop 0.2041858326453362
15:51:34.917070 Epoch 20, Training Loop 0.19697247777324522
15:52:44.953817 Epoch 21, Training Loop 0.1950111598800705
15:53:54.836141 Epoch 22, Training Loop 0.18968439074980953
15:55:04.841142 Epoch 23, Training Loop 0.18745125941660282
15:56:15.038263 Epoch 24, Training Loop 0.18232614359390126
15:57:25.128909 Epoch 25, Training Loop 0.17733189202573177
15:58:34.656606 Epoch 26, Training Loop 0.17812858037922505
15:59:44.726780 Epoch 27, Training Loop 0.1693306589213681
16:00:53.756109 Epoch 28, Training Loop 0.16847655924893642
16:02:03.445965 Epoch 29, Training Loop 0.16266518874760091
16:03:12.656087 Epoch 30, Training Loop 0.16085760145774722
```

Figure 5: Training of the Model

Model is validated each time and calculated the training and validation accuracy to get an idea of how the model is performing in training phase. Some random pictures are also checked (as shown in figure 6) to confirm if the model is actually learning or not.

```
print('Actual: {}'.format(label))
print('Prediction: {}'.format(out))

Clipping input data to the valid range for imshow with RGB data (
Actual: 0
Prediction: tensor([[ 4.0472, -3.8361]], grad_fn=<AddmmBackward>)
```

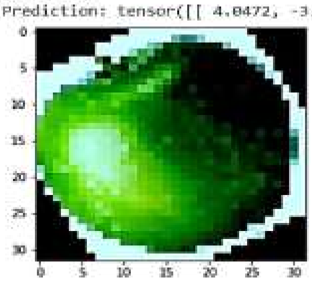

Figure 6: Checking Random Sample Predictions

In model evaluation step a model's performance are divided into 2 categories: namely, holdout and cross-validation. Both methods use a test set (i.e. data not seen by the model) to evaluate model performance. It's not recommended to use the data we used to build the model to evaluate it. This is because our model will simply remember the whole training set and will therefore always predict the correct label for any point in the training set. While evaluating the model, the same transformation is applied on the test dataset and on training dataset to make all the pictures of equal size. And then the model is evaluated on the test dataset and kept doing some minor changes in the code and dataset to get better accuracy as shown in Figure 7.

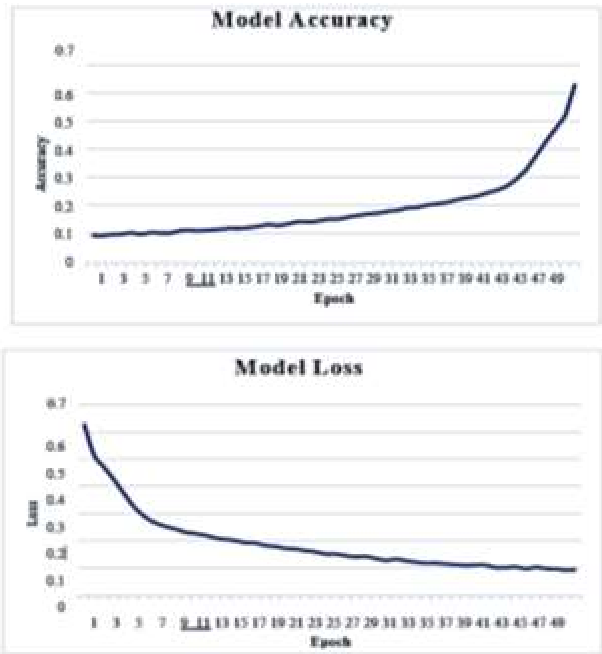

Figure 7: Model accuracy and Model Loss Curve s for CNN Models based on Data Augmentation at 50 Epochs.

Category			Predicted					
Observed	Types		Rotten			Fresh		
			Apple	Banana	Orange	Apple	Banana	Orange
	Rotten	Apple	581	0	0	20	0	0
		Banana	0	513	0	0	17	0
		Orange	0	0	390	0		13
	Fresh	Apple	13	0	0	382	0	0
		Banana	0	13	0	0	368	0
		Orange	0	0	13	0	0	375

Figure 8: Confusion Matrix over the predicted and observed values

Figure 8 depicts the Confusion Matrix over the Predicted and Observed Values of Rotten and Fresh Food images and figure 9 visualized it, on basis of this the Accuracy can be Calculated.

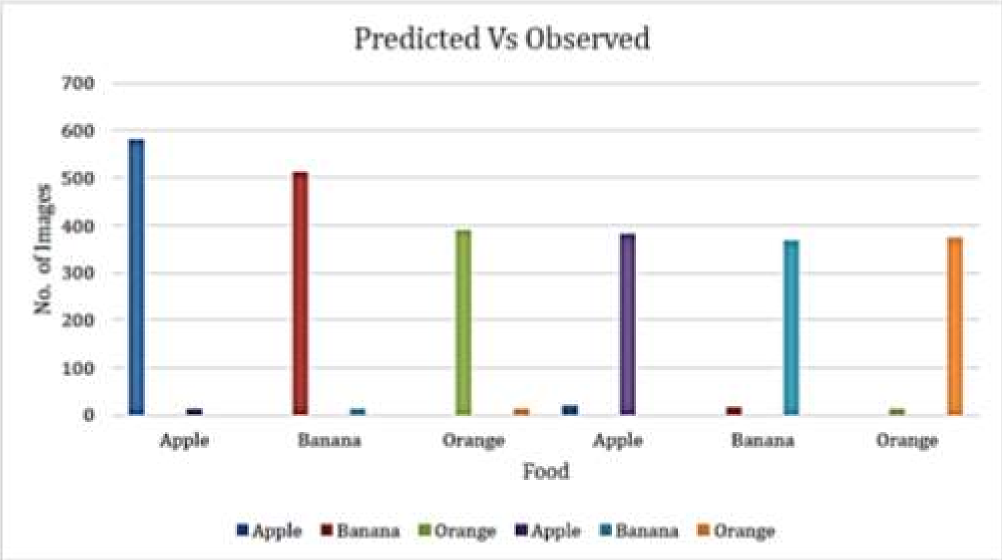

Figure 9: Visualization of Confusion Matrix

V. COMPARATIVE ANALYSIS WITH EXISTING TECHNIQUES

This section describes a generalized comparison between the proposed model and existing models in the literature and table 10 depicts how our proposed model is different from the already developed model.

Table 10: Comparison between different Models

Proposed Model (CNN)	Existing Model using same Technology (CNN)	Existing Models using Different Technology (Conventional)
Our model is Developed using Pytorch Framework which reduces a lot of code because of a large bundle of inbuilt API's	Had Big dumps of Codes which requires lots of space	Need to Write 1000 of lines of code.
As the Code is less Requires less time to Execute than the previously developed CNN models	Requires More time to Execute because of large Code.	Execution Time Is Same as That of our Proposed Model because Conventional Techniques Executes Faster Than CNN.
CNN works Better Over Large Dataset.(Our Model uses a dataset of 10,000+ Labelled Images)	These Models Uses a Smaller Dataset Which Reduces the Accuracy of the Model.	Conventional Methods Although can't work on large dataset and on smaller dataset also Gives less Accuracy.

VI. CONCLUSION AND FUTURE SCOPE

Classification of fresh and rotten fruits in agricultural areas is very important. In this work, a model based on CNN is introduced and focused on building transfer learning models for the performance of fresh and rotten fruit taxonomy. The effects of various hyper-parameters i.e. batch-size, optimizer and learning rate are questioned. The results demonstrated that the proposed CNN model could strongly classify fresh and rotten fruit and produce better accuracy than the transfer learning model. Therefore, the proposed CNN model can automate the process of the human brain in classifying fresh and rotten fruits with the help of the proposed robust neural network model and thereby minimize human errors in classifying fresh and rotten fruits. 96.79% accuracy was obtained for the proposed CNN model. The proposed CNN model provides high accuracy within the classification task of fresh and rotten fruits. Here the proposed model's accuracy is compared against the transfer learning models. Three kinds of fruits are selected from various kinds of fruits. The dataset is obtained from Kaggle with 6 classes i.e., each fruit is split as fresh and rotten. We used PyTorch and OpenCV to coach our model and got pretty good accuracy of 96.8%. This paper introduces a robust CNN model which has enhanced accuracy for fresh and rotten fruits classification. This can be extended to open domains in the future. Currently it has only 3 fruits, it may add more in the future.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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