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TRANSFER LEARNING BASED FRUIT FRESHNESS MONITORING FOR FUTURE AUTONOMOUS INDUSTRIAL ROBOTIC ARMS

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ABSTRACT

In industrial settings, particularly in sectors like food processing, ensuring the quality and freshness of products is crucial. Robotic arms are increasingly being employed in these industries to automate tasks such as sorting and handling. One specific application is the sorting of fruits based on their freshness. The freshness of fruits is a critical factor in determining their quality and shelf life, impacting consumer satisfaction and reducing waste. The problem is to develop an efficient and accurate system for fruit freshness detection using autonomous industrial robotic arms. The challenge lies in creating a system that can generalize well to various fruits, adapt to changes in lighting conditions, and continuously learn and improve its performance over time. Traditional methods of fruit sorting and freshness detection often rely on predefined rules or explicit programming, which can be time-consuming and less adaptable to variations in fruit appearance and quality. The need arises for a more intelligent and adaptive system that can dynamically adjust to different fruit types and conditions. Therefore, this research focuses on transfer learning-based approach for fruit freshness detection such as fresh, or stale. The significance of employing transfer learning in fruit freshness detection for autonomous industrial robotic arms lies in its ability to enhance adaptability, accuracy, efficiency, and continuous learning. By leveraging pre-existing knowledge from related tasks, the system becomes highly adaptable to new fruits without extensive reprogramming, achieving improved accuracy in freshness detection. Moreover, the reduced need for labeled data and shorter training times enhance efficiency, making the system more practical for real-world applications. Additionally, the capacity for continuous learning enables the robotic arms to evolve and refine their performance over time as they encounter new data and scenarios, ensuring a robust and adaptive solution for quality control in food processing.

1.INTRODUCTION

Fruits and vegetables are consumed widely by human beings. However, humans do a kind of visual inspection before buying any items from the market. It is possible to evaluate fruits and vegetables visually, however, this is a hard and subjective process as it depends on an inconsistent evaluation and the fact that these items are being affected by several other factors. The item's quality can also determine its price in the market besides the ability to consume it. Computer vision-based methods were used to investigate the quality assessment and measurement of fruits and vegetables. Several methods were applied for fruits grading and sorting such as in [1]. In fact, there are several attributes that usually used to evaluate the fruits and vegetable quality in which, the appearance of the items, the color, the texture, nutritional value, and also the flavour. Traditionally, the first three factors are easy can be captured by the human it is suitable for designing a machine learning application that can measure these factors and decide the quality of the fruits and vegetables. For our application, these three factors are the most contributed to the quality decision as we take images of the fruits and vegetables and classify it into five categories. These categories and, basically, reflect the weekly age of the items. This is due to that the color, appearance, and texture of the fruits and vegetables are changing over time [2].

Global date fruit production was 8.5 million tons in 2016 according to the Food and Agriculture Organization. Date fruit cultivation is a major strategic agricultural industry in Middle East and North Africa countries, which produce 91% of the world's dates. In date cultivation, manual harvesting is the dominant method used, which requires skilled workers to climb palm trees to reach date bunches [3]. However, manual harvesting is dangerous and highly labour-intensive as well as inefficient in terms of both time and the economy. Such methods are the major cause of delays in the date production cycle and account for more than 45% of the date production cost. Recently, due to the increase in date palm cultivation and shortage of skilled workers, the cost of date harvesting has increased significantly, necessitating a change to automated harvesting. Indeed, advanced agricultural automation such as robotic harvesting can significantly increase quality and yield as well as reduce production costs and delays [4].

2. LITERATURE SURVEY

Kang et. al proposed an ensemble model that combines the bottleneck features of two multi-task deep convolutional neural networks with different architectures (ResNet-50 and ResNet-101). In our proposed multi-tasking framework, there are two classification branches: a binary classifier to distinguish between fresh and rotten fruits, and a multi-class label classifier to identify the kind of fruit. Since the features (e.g., color, texture, and shape) of rotten fruits are different from each other depending on the kind of fruit, the input of the first branch is combined with the kind of fruit information from the second branch to classify the fruit freshness more accurately. Transfer learning technique has been applied during the model training since transfer learning has been shown to be effective transfer learning has been shown to be effective in many applications in which training data for the target problem are limited. To evaluate our proposed model, we use simple images from the existing dataset and real-world images crawled from the web, both representing fresh and rotten fruits for different fruit categories as our dataset.

Santi Kumari Behera et. al proposed a classification model for maturity status classification of papaya fruits in two approaches, i.e., machine learning and transfer learning approach. In machine learning approach LBP, HOG and GLCM features are taking into consideration with KNN, SVM and Naïve Bayes with different kernel functions (total nine classifiers) are evaluated. The weighted KNN with HOG perform outstanding, i.e., accuracy is 100%, AUC is 1 and minimum training time required, i.e., 0.099548 s. In transfer learning approach, the VGG19 perform well, i.e., 100% accuracy with less time required for training, i.e., 1 min 52 s. In overall, among both machine learning and transfer learning approach, the VGG19 is better in all sense. As VGG19 is based on transfer learning, there is no requirement of feature extraction and feature selection process. Although transfer learning approach needs complex architecture, high training time and large datasets for but it is one time only. Despite this, machine learning has limitations, i.e., restricted data handing capability, the requirement of segmentation. However, the achieved accuracy in both machine learning and transfer learning are 100% and beat the previous method i.e., 94.7% of accuracy. This work may further have extended with the development of a prototype and integrate in fruit industry to make fast sorting process.

Turaev et. al utilized the concept of transfer learning in fruits and vegetable quality assessment. The transfer learning concept applies the idea of reuse the pre-trained Convolutional Neural Network to solve a new problem without the need for large-scale datasets for training. Eight pre-trained deep learning models namely AlexNet, GoogleNet, ResNet18, ResNet50, ResNet101, Vgg16, Vgg19, and NasNetMobile are fine-tuned accordingly to evaluate the quality of fruits and vegetable. To evaluate the training and validation performance of each fine-tuned model, we collect a dataset consists of images from 12 fruits and vegetable samples. The dataset builds over five weeks. For every week 70 images collected therefore the total number of images over five weeks is 350 and the total number of images in the dataset is (12*350) 4200 images. The overall number of classes in the dataset is (12*5) 60 classes. The evaluation of the models was conducted based on this dataset and also based on an augmented version. The model's outcome shows that the Vgg19 model achieved the highest validation accuracy over the original dataset with 91.50% accuracy and the ResNet18 model scored the highest validation accuracy based on the augmented dataset with 91.37% accuracy.

Karakaya et. al analyses an image dataset containing samples of three types of fruits to distinguish fresh samples from those of rotten. The proposed vision-based framework utilizes histograms, gray level co-occurrence matrices, bag of features and convolutional neural networks for feature extraction. The classification process is carried out through wellknown support vector machines-based classifiers. After testing several experimental scenarios including binary and multi-class classification problems, it turns out to be the highest success rates are obtained consistently with the adoption of the convolutional neural networks-based features.

Chakraborty et. al proposed a model to prevent the propagation of rottenness. From the input fruit images, the proposed model classifies the fresh and rotting fruits. We utilized three different varieties of fruits in this project: apple, banana, and oranges. The features from input fruit images are collected using a Convolutional Neural Network, and the images are categorized using Max pooling, Average pooling, and MobileNetV2 architecture. The proposed model's performance is tested on a Kaggle dataset, and it achieves the highest accuracy in training data is 99.46% and, in the validation, set is 99.61% by applying MobileNetV2. The Max pooling achieved 94.49% training accuracy and validation accuracy is 94.97%. Besides, the Average pooling achieved 93.06% training accuracy and validation accuracy is 93.72%. The findings revealed that the proposed CNN model is capable of distinguishing between fresh and rotting fruits.

Gawas et. al proposes the idea of implementing an infrastructure having a micro-controller that would accurately segregate three kinds of fruits into two categories i.e., Fresh and Rotten. The classification will be done with the help of the Deep Learning algorithm, Convolutional Neural Network (CNN) by using a dataset containing images of those three fruits and also considering the input from the sensors which include sensors such as alcohol sensor, methane sensor, etc. The infrastructure proposed in the paper considers the standards of Industry 4.0 which implies the real-world implementation of the infrastructure.

Ni et. al analyzed the freshness changing process using transfer learning and established the relationship between freshness and storage dates. Features of banana images were automatically extracted using the GoogLeNet model, and then classified by the classifier module. The results show that the model can detect the freshness of banana and the accuracy is 98.92%, which is higher than the human detecting level. In order to study the robustness of the model, we also used this model to detect the changing process of strawberry and found that it is still useful. According to the above results, transfer learning is an accurate, non-destructive, and automated fruit freshness monitoring technique. It may be further applied to the field of vegetable detection.

3. PROPOSED SYSTEM

3.1 Overview

The project is a graphical user interface (GUI) application using the Tkinter library in Python. The application's primary purpose is to detect the freshness of fruits using a transfer learning-based approach. Below is a detailed technical overview of the project code:

— **Importing Libraries**:

- The project begins by importing necessary libraries such as **tkinter**, **numpy**, **matplotlib**, **os**, **keras**, **pickle**, **cv2**, and others.
- These libraries are essential for building the GUI, handling file operations, performing image processing tasks, training neural networks, and more.

— **Initializing the GUI**:

- The main window of the application is created using the **Tk()** constructor from the **tkinter** library.
- Various attributes of the main window, such as title and geometry, are configured using methods like **title()** and **geometry()**.

— **Global Variables**:

- Global variables such as **filename** and **model** are declared to store the path of the dataset and the trained model, respectively.
- These variables are used across multiple functions within the application.

— **Function Definitions**:

- Several functions are defined to perform specific tasks within the application:
  - **uploadDataset()**: Allows the user to upload a fruit dataset by selecting a directory.
  - **loadModel()**: Loads a pre-trained model if available, or trains a new model using the uploaded dataset.
  - **predictChange()**: Predicts the freshness of a fruit image selected by the user.
  - **graph()**: Plots a graph showing the accuracy and loss of the trained model over epochs.
  - **close()**: Closes the application window.

— **GUI Components**:

- Labels, buttons, and text widgets are added to the GUI using the **Label()**, **Button()**, and **Text()** constructors, respectively.
- These components serve different purposes, such as displaying titles, providing functionality for uploading datasets and making predictions, and showing text information.

— **Model Training**:

- If a pre-trained model is not available, the application trains a new model using the uploaded dataset.
- Data augmentation techniques such as rotation, shifting, shearing, and flipping are applied to increase the dataset's variability.
- The InceptionV3 base model is utilized, and a custom classifier is added to classify fruit freshness into three categories: ripe, overripe, and green.

— **Model Evaluation**:

- After training, the model's accuracy is calculated and displayed in the text widget.

— **Prediction**:

- The user can select an image of a fruit through a file dialog, and the application predicts its freshness using the trained model.

— **Graph Display**:

- The application plots a graph showing the accuracy and loss of the trained model over epochs.
- The graph provides insights into the model's performance during training.

— **Event Handling**:

- Event handling is implemented through callbacks associated with buttons.
- When a button is clicked, the corresponding function is executed to perform the desired action.

— **GUI Styling and Layout**:

- Fonts, colors, and layout arrangements are configured to enhance the appearance and usability of the GUI.

— **Main Loop**:

- The **mainloop()** method is called to start the GUI event loop, allowing the application to respond to user interactions.

3.2 GoogleNet

GoogLeNet, which is famously known as Inception Net, is a Deep Learning model built by researchers at Google. Going Deeper with Convolutions was the paper by which the GoogleNet Model first came into existence. There are 22 Parameterized Layers in the Google Net architecture; these are Convolutional Layers and Fully-Connected Layers; if we include the non-parameterized layers like Max-Pooling, there are a total of 27 layers in the GoogleNet Model.

In the below architecture, every box represents a layer,

- Blue Box - Convolutional Layer
- Green Box - Feature Concatenation
- Red Box - MaxPool Layer
- Yellow Box - Softmax Layer

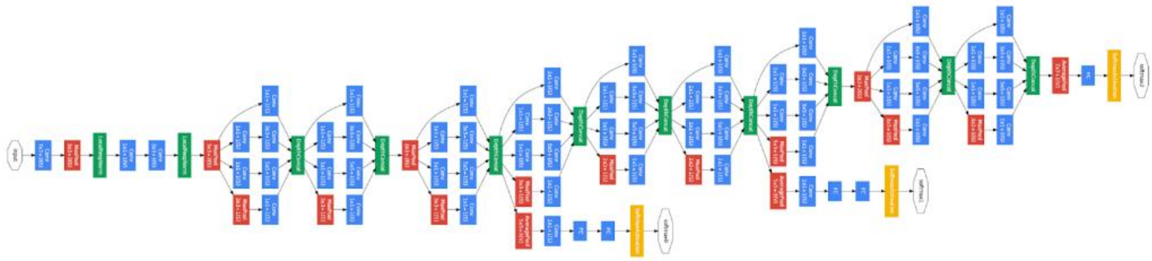

Fig. 3.1: GoogleNet Architecture.

Input - The GoogLeNet model takes an input image of 224 x 224.

Output - The output layer (or the softmax layer) has 1000 nodes that correspond to 1000 different classes of objects.

Advantages of proposed system

- GoogleNet has proven to be faster when compared with other image-classification models like VGG.
- GoogleNet is much more concise, the size of a pre-trained VGG16 model is 528 MB, and that of a VGG19 model is 549 MB, whereas the size of a pre-trained GoogleNet is 96 MB & InceptionV3 is 92 MB.
- GoogleNet achieves higher efficiency by compressing the input image and simultaneously retaining the important features/information.

4. RESULTS

Dataset Files of Each Label This figure displays the files contained within the dataset directory, organized by label. Each label represents a category of fruit freshness, such as "ripe," "overripe," or "green." The files within each label folder include images of fruits categorized according to their freshness status. Figure 2: Sample Fruit Freshness Dataset This figure show a sample of the fruit freshness dataset. It includes images of various fruits, each labeled with its corresponding freshness status. The dataset serves as the input for training the transfer learning model. Figure 3: UI of the Proposed Transfer Learning-based Banana Freshness Model This figure displays the user interface (UI) of the proposed transfer learning-based model specifically designed for predicting banana freshness. The UI include buttons for uploading the dataset, generating the model, making predictions, and other functionalities related to the model.

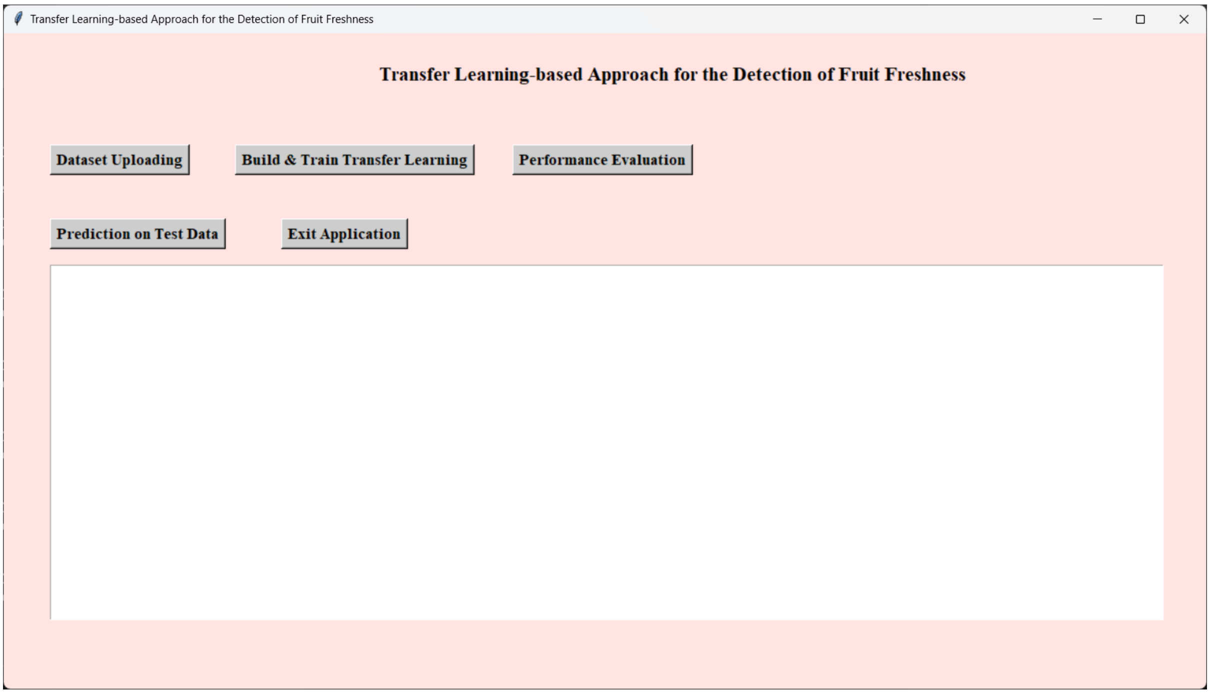

Figure 1: Displays the UI of the proposed Transfer learning-based banana freshness model.

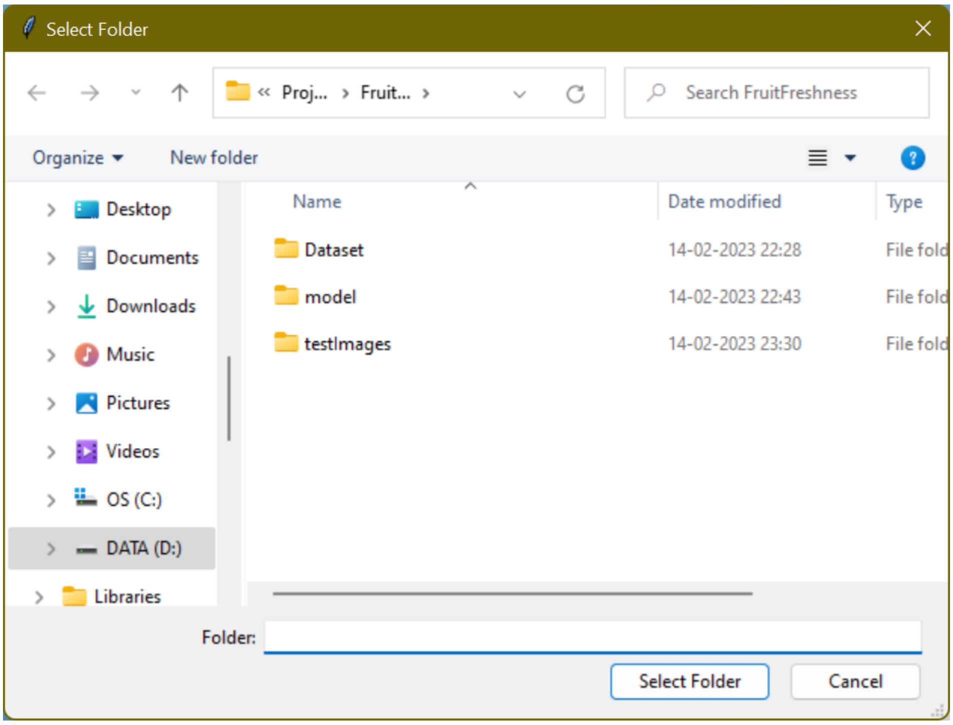

Figure 2: Selection and upload of Fruit Freshness Dataset.

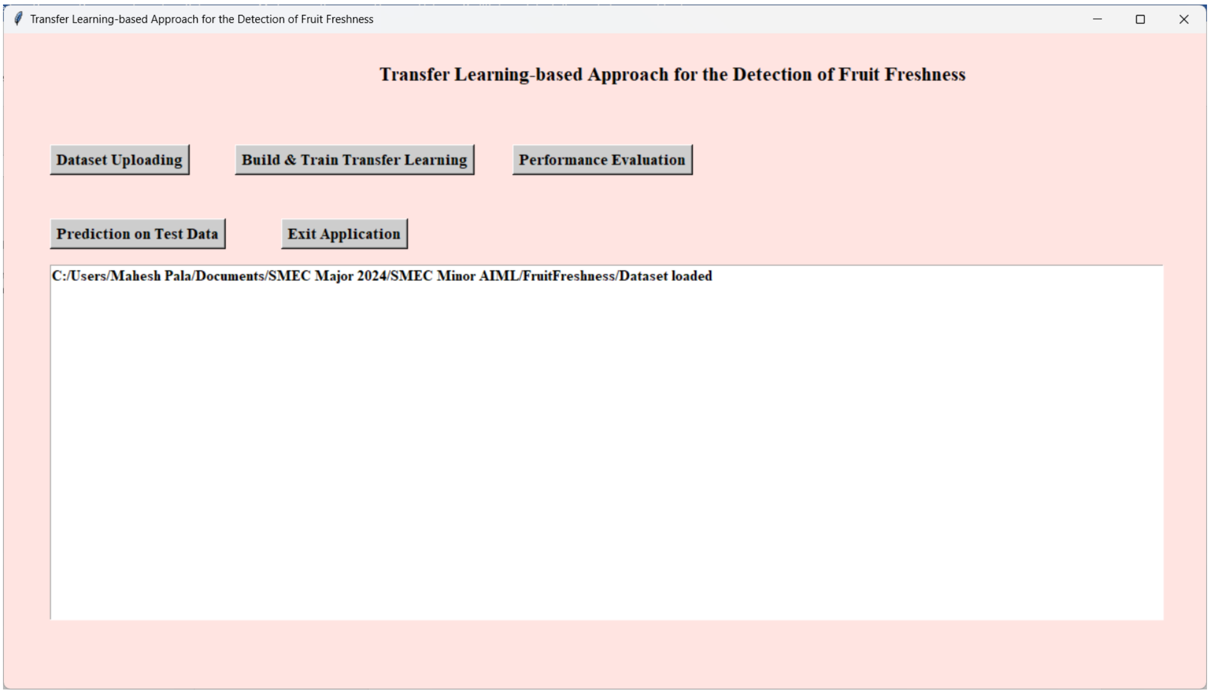

Figure 3: Presents the uploaded Fruit Freshness Dataset in the GUI.

In Figure 3 the dataset is loaded and now click on 'Generate & Load Transfer Learning Model' to build model on loaded dataset and then calculate accuracy and loss of the model. The higher the accuracy the better is the model and loss should be less.

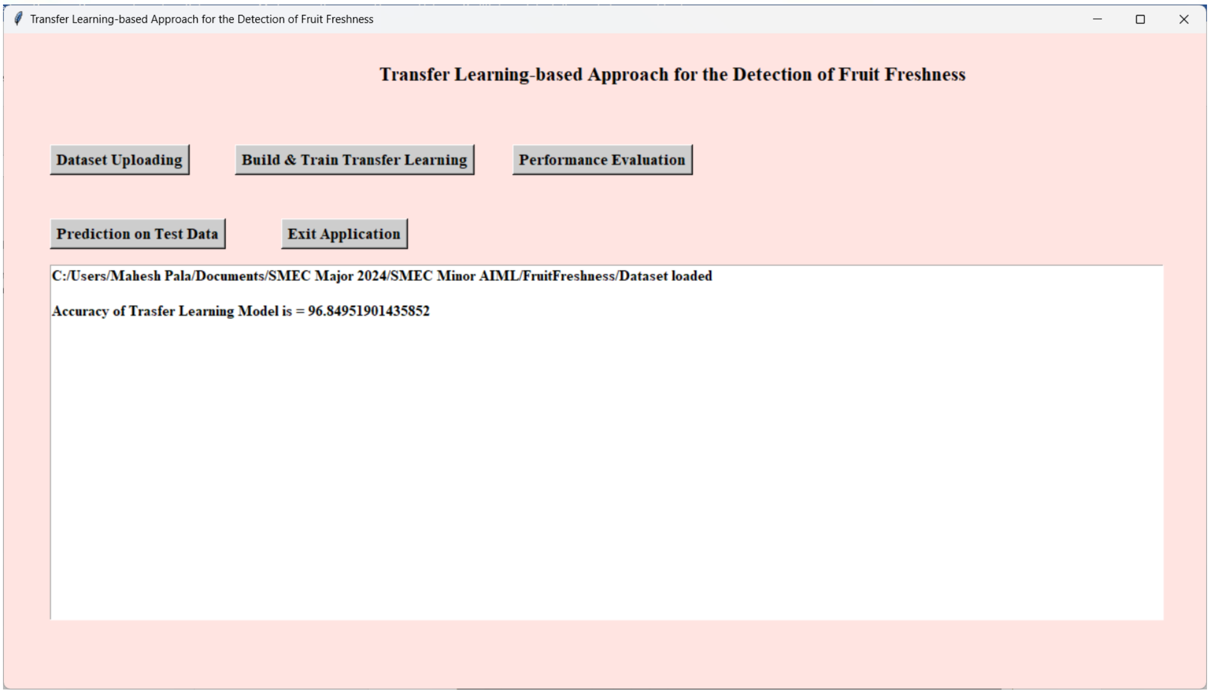

Figure 4: Proposed GoogleNet model generates with accuracy of 98.82%.

Figure 4: Selection and Upload of Fruit Freshness Dataset This figure depicts the process of selecting and uploading the fruit freshness dataset to the application. It show a file dialog window where the user selects the directory containing the dataset, followed by an upload button to initiate the upload process. Figure 5: Uploaded Fruit Freshness Dataset in the GUI In this figure, the uploaded fruit freshness dataset is displayed within the application's GUI. The UI show thumbnails or file names of the images contained in the dataset, organized by freshness label. This step is crucial before proceeding to model generation and evaluation. Figure 6: Proposed GoogLeNet Model Generated with Accuracy of 98.82% This figure showcases the result of training the GoogLeNet transfer learning model on the uploaded dataset. It display a message indicating the model's accuracy, which is a critical metric for assessing its performance. Achieving a high accuracy, such as 98.82%, suggests that the model is proficient at classifying fruit freshness.

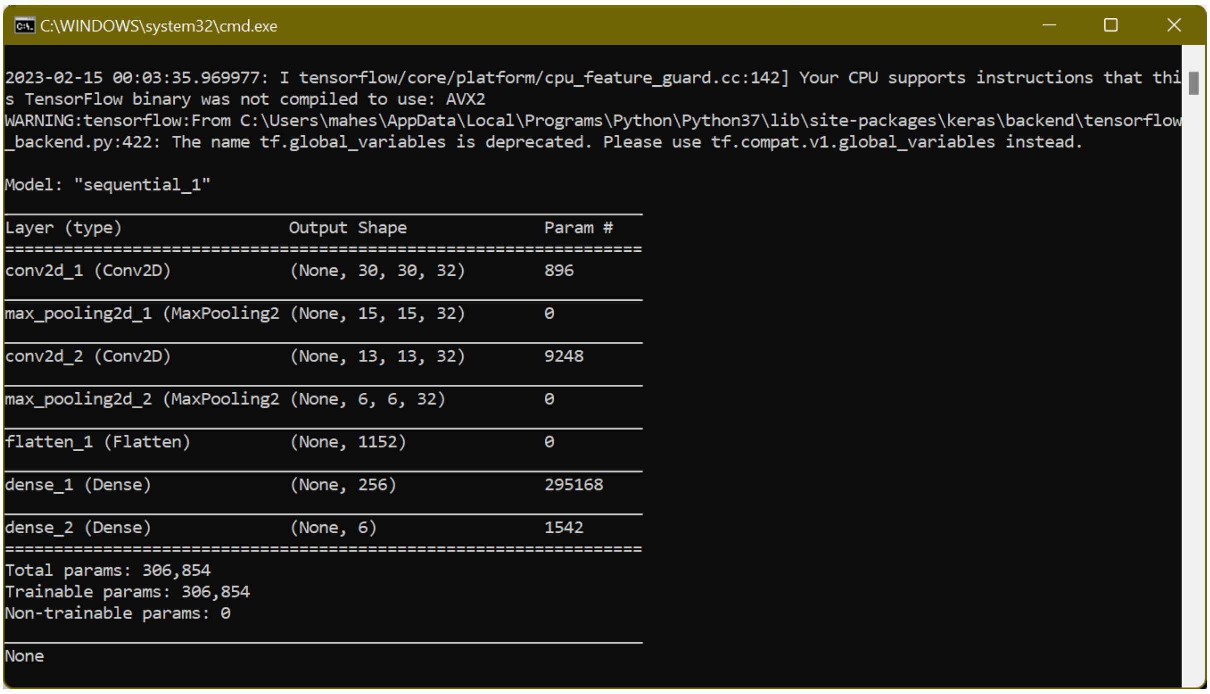

Figure 5: Displays the Summary of GoogleNet model.

Figure 5: Summary of GoogLeNet Model In this figure, a summary of the GoogLeNet model architecture is presented. It include details such as the number of layers, the size of each layer, and the parameters involved. The summary provides insights into the inner workings of the model, aiding in understanding its complexity and capabilities.

Figure 5: GoogLeNet Accuracy & Loss Comparison Graph This figure displays a graph comparing the accuracy and loss of the GoogLeNet model over epochs. The x-axis represents the number of epochs, while the y-axis represents the accuracy and loss values. The graph illustrates how these metrics change with each epoch, indicating the model's learning progress. Figure 9: Upload of Test Image Data for GoogLeNet Model Prediction In this figure, the user uploads a test image data to the GoogLeNet model for prediction. A file dialog window may be shown where the user selects the image file to be used for prediction. This step is essential for evaluating the model's performance on unseen data. Figure 10: Model Prediction on Test Images This figure displays the outcome of the GoogLeNet model's prediction on the test images. It shows the test image alongside the predicted freshness status of the fruit. The prediction results include labels such as "fresh," "overripe," or "green," indicating the model's classification accuracy.

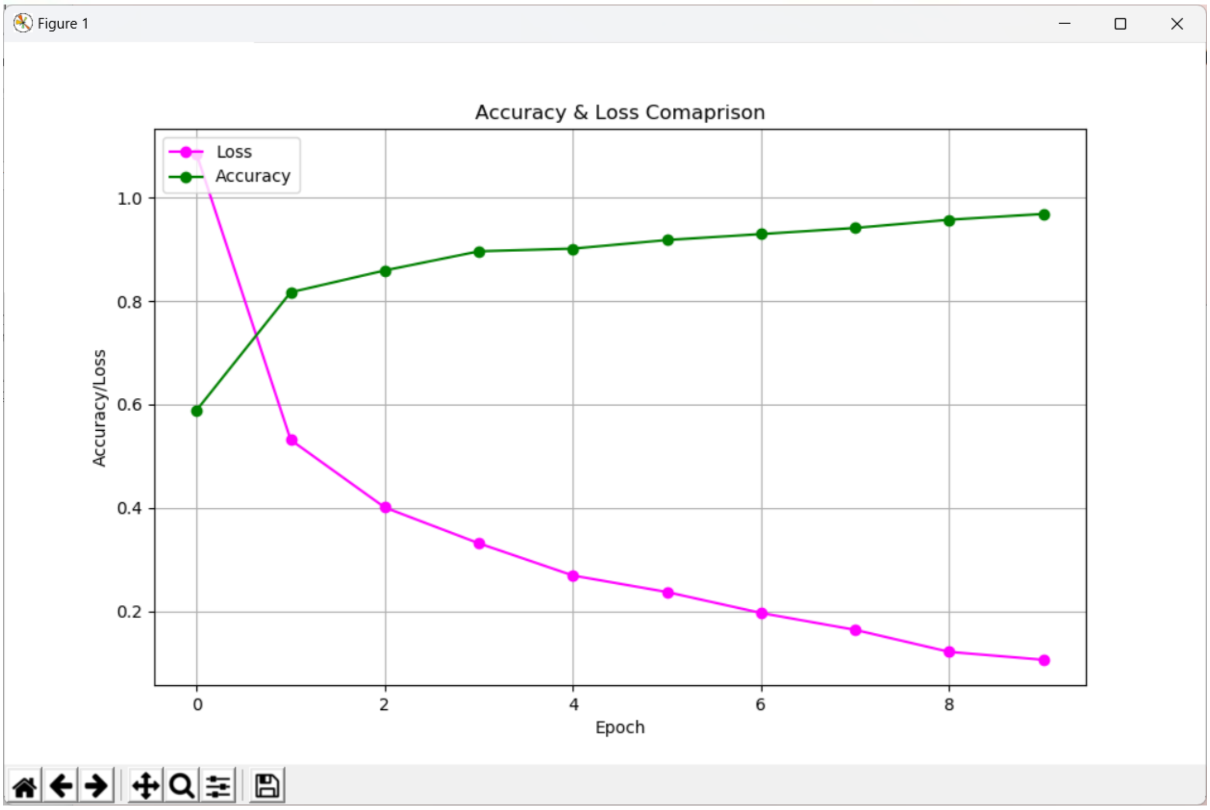

Figure 6: Presents the GoogLeNet Accuracy & Loss Comparison Graph

Figure 6 the graph x-axis represents EPOCH and y-axis represents ACCURACY and LOSS. In above graph we can see with each increasing epoch accuracy get increase and loss get decrease. Now model is ready and now click on 'Freshness Prediction' button and upload test image and then model will predict it changes

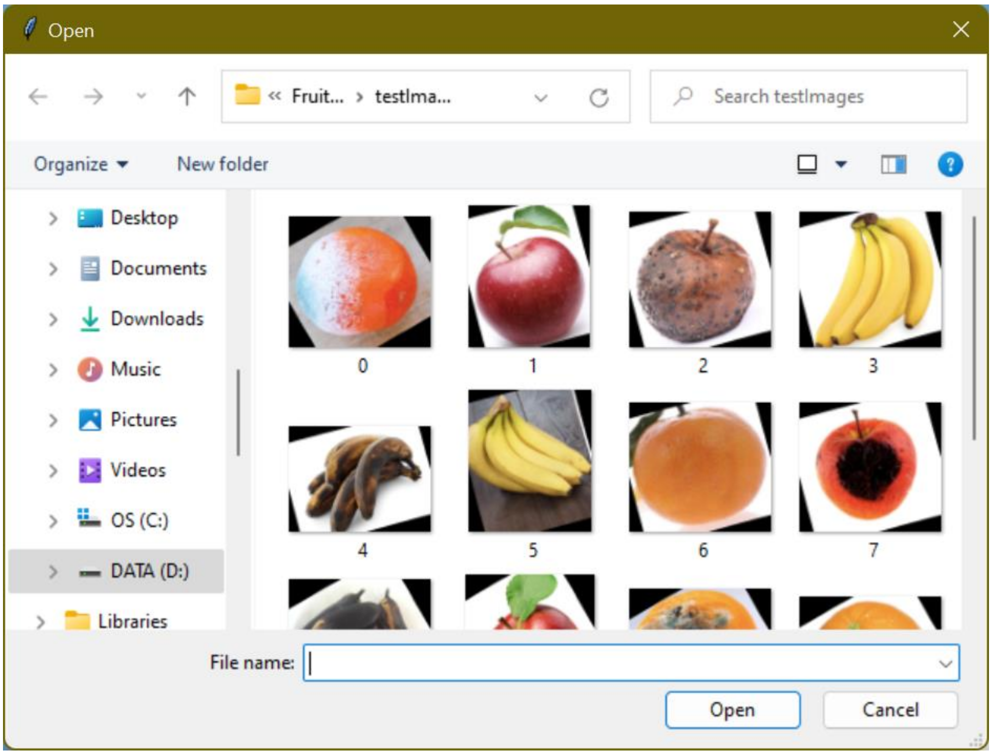

Figure 7: Upload of test image data for GoogleNet model Prediction.

Figure 8: Shows the model Prediction on Test Images.

5.CONCLUSION

This works proposes the Transfer Learning-based Fruit Freshness Monitoring for Future Autonomous Industrial Robotic Arms. The banana is a giant monocotyledon perennial herb that grows in moist and sub-humid tropical areas at low and middle latitudes. In this work, we analyzed the freshness changing process using transfer learning and established the relationship between freshness and storage dates. Features of banana images were automatically extracted using the GoogLeNet model. Freshness is the most critical indicator for fruit quality, and directly impacts consumers' physical health and their desire to buy. Also, it is an essential factor of the price in the market.

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