Assessing Fruit Freshness with Deep Learning: A Case Study on Banana Using GoogLeNet and Transfer Learning

Harilal J[1], Edukondalu Duggeboina[2], Pitta Satya Surekha[3]

[1,2,3]Assistant Professor, Department of ECE, Malla Reddy Engineering College and Management Sciences, Hyderabad, Telangana

Abstract

Freshness is a critical determinant of fruit quality, significantly impacting consumers' health and purchase decisions, as well as market pricing. Consequently, the development of effective methods for evaluating fruit freshness is of utmost importance. In this research, we focus on bananas as a case study and employ transfer learning to analyze the dynamics of freshness over time, establishing a relationship between freshness and storage duration. We leverage the GoogLeNet model to automatically extract relevant features from banana images, subsequently employing a classifier module for classification. Our results demonstrate that this model can effectively detect banana freshness at a level surpassing human assessment. To assess the model's robustness, we extend its application to monitoring the freshness evolution of apples, revealing its continued utility. Based on these findings, transfer learning emerges as a precise, non-destructive, and automated method for monitoring fruit freshness. This technique holds promise for broader applications in the realm of vegetable detection.

Keywords: GoogLeNet, Transfer Learning, Autonomous Industrial Robotic, Fruit Freshness Evaluation, Banana, Apple, Freshness Monitoring, Quality Assessment.

1. Introduction

Banana freshness monitoring is an essential task for the food industry, as it helps to ensure the quality and safety of bananas [1]. Autonomous industrial robotic arms have the potential to streamline this process by automatically identifying fresh and ripe bananas for packaging and shipping. Transfer learning is a technique in machine learning that involves leveraging a pre-trained [2] model to perform a new task. In the context of banana freshness monitoring, transfer learning can be used to train a model to classify the freshness of bananas based on visual [3] cues such as color, texture, and size. The first step in creating a transfer learning-based banana freshness monitoring system is to obtain a large dataset of labeled banana images. This dataset can be used to fine-tune a pre-trained model such as a convolutional neural network (CNN) [4] to recognize the visual features that are indicative of fresh and ripe bananas. The fine-tuning process involves updating the weights of the pre-trained model using the new dataset, which enables the model to learn the specific [5] characteristics of the banana images.

The process of transfer learning for banana freshness monitoring typically involves using a pre-trained deep neural network, such as VGG or ResNet, and fine-tuning it on a smaller dataset of banana images [6]. The fine-tuning process involves training the network on the new dataset while preserving the knowledge learned from the original [7] task. To implement a transfer learning-based banana freshness monitoring system for autonomous industrial robotic arms, several challenges must be addressed [8]. These challenges include developing a reliable method for capturing images of bananas in real-time, selecting an appropriate pre-trained network architecture, fine-tuning the network on a representative dataset of banana images, and deploying the system on the robotic arm.Overall, transfer learning has the potential to significantly improve the accuracy and efficiency of banana freshness monitoring for future autonomous industrial robotic arms, contributing to the overall quality and safety of food products [9]. Once the model is trained, it can be integrated with an autonomous industrial robotic arm to provide real-time monitoring of banana freshness. The robotic arm can be equipped with a camera to capture images of the bananas, which are then fed into the model for analysis [10]. The model can then output a classification indicating the freshness of the banana, which can be used to guide the robotic arm in selecting the appropriate bananas for packaging and shipping.

Rest of the paper is organized as follows: Section 2 details about literature survey, section 3 details about the proposed methodology, section 4 details about the results with discussion, and section 5 concludes article with references.

2. Literature Survey

Sindhu, G. R., et al. [11] comparatively analysed 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 well-known support vector machines-based classifiers. Soleh, M. S et al. (2022) [12] extended the banana (Musa sp.) shelf-life via tapioca (Manihot esculenta) starch (TS) coating formulation. The fruit coating was developed from different concentration of tapioca starch (TS) [2, 4, 6 and 8% w/v], supported for improved hydrophobicity by palm oil (PO) [0.5, 1, 1.5 and 2% v/v] and provided antioxidant properties via Premna serratifolia extract (PE) [1, 2, 3% v/v]. The effect of the fruit coating towards the banana colour, firmness, total soluble solids, and weight loss were evaluated till 8 days at room temperature. Yanusha M. et al. (2021) [13] captured the images using a professional camera. The fruit's regions were segmented using K-Means clustering and the determination of freshness was done with Support vector machine by training with the selected features from the training set of images. The accuracy level of freshness determination was calculated separately for each category in terms of days from day one to ten. Fu, Yuhang et al. (2020) [14] presented a comprehensive analysis of a variety of fruit images for freshness grading using deep learning. Several algorithms have been reviewed in this project, including YOLO for detecting regions of interest with considerations of digital images, ResNet, VGG, Google Net, and AlexNet as the base networks for freshness grading feature extraction. Fruit decaying occurs in a gradual manner, this characteristic is included for freshness grading by interpreting chronologically related fruit decaying information. Pranav, S. Bala Naga et al. (2021) [15] built a device that measures the quality of fruit and vegetables and provides an output based on its edibility. Arduino UNO (microprocessor) along with MQ2, MQ4 (gas sensors Mǐngǎn Qǐ lai 2, 4) and IR (Infra-Red) sensors are used to detect the concentration of Methane (CH 4) and Ethylene (C 2 H 4) in ppm (Parts Per Million). It was found that the excess ripening after which the fruit starts decomposing has a concentration of 300ppm (Ethylene) for all fruits and vegetables.

Karakaya, Diclehan, et al. (2019) [16] comparatively analysed 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. Cheah, Ui Shaun et al. (2021) [17] proposed a mobile application that can detect freshness in fruits. To do this, this project utilizes Deep Learning technologies in conjunction with a mobile application to predict the freshness of fruits. Although there are several applications that can perform fruit freshness prediction, they require the user to have several external devices to accurately predict its freshness. Therefore, this project will focus on developing an application that can do fruits freshness prediction accurately without needing extra devices. Evans, David.M et al. (2022) [18] aproached freshness as a matter of concern. Drawing on extensive fieldwork across sites of food production and consumption in the UK and Portugal, we identify four enactments of freshness. The analysis zooms in on the specific case of plastic food packaging and uses these enactments to consider a series of questions about realities and the relationships between them. Since packaging is an issue that readily overflows to encompass a broader suite of propositions about food, we argue that freshness is a suitable focus around which to assemble hybrid forums to debate future possibilities. Arya, Prabha Shanker, et al. (2021) [19] discussed the level of freshness of fruits based on factors which could be classified and examined such as ripeness, leak, humidity etc. Later we proposed a model discussing the Freshness of fruits in various units from A to F such as input from signals of sensors, IOT Sensing electrodes, signals, output unit in form of voltage, temperature, colour etc, database units and informing unit. A deep learning-based prediction algorithm is being used computed in opencv and Kaggle database is used. Later the accuracy of the detection came out to be 97.5 %. Ai, Binling et al. (2021) [20] cellulose film synthesized from delignified banana stem fibers via an ionic liquid 1-Allyl-3-methylimidazolium chloride ([AMIm][Cl]) were evaluated as packing material for mangos preservation. The moisture vapor transmission rate and gas transmission rate of the synthesized cellulose film were 1,969.1 g/ (m2·24 h) and 10,015.4 ml/ (m2·24 h), respectively, which are significantly higher than those of commercial PE films.

3. Proposed Methodology

Figure 1 shows the proposed block diagram for banana fruit freshness detection. Initially, the image pre-processing operation is performed, which normalizes the images. Then, the dataset is spitted into 80% for training, and 20% for testing. Here, transfer learning based GoogleNet is used to train the model, which learns the detailed probability specific features about the dataset. Then, the accuracy is calculated using confusion matrix evaluation on test data. Then, the test banana image is applied, where freshness class is identified.

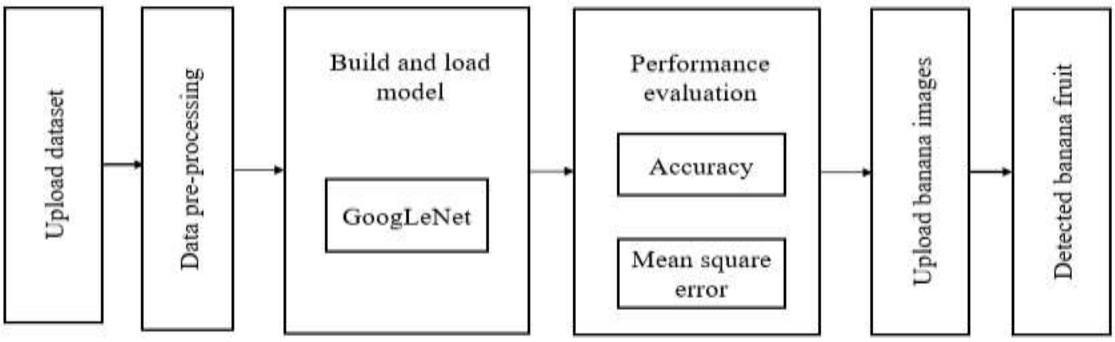


Figure1: Block diagram of proposed system.

3.1 Image pre-processing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model. When creating a machine learning project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task. A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data pre-processing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

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 Figure 2 architecture, every box represents a layer,

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

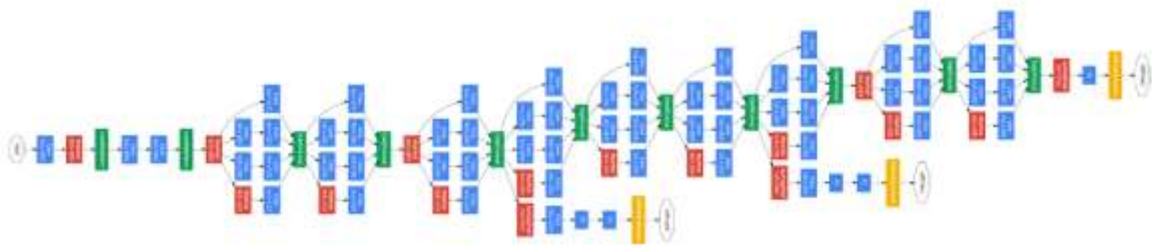


Figure 2: GoogleNet Architecture.

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.

3.3 CNN Layer basics

According to the facts, training, and testing of GoogleNet involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1]. Convolution layer as depicted in Figure 3 is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$.

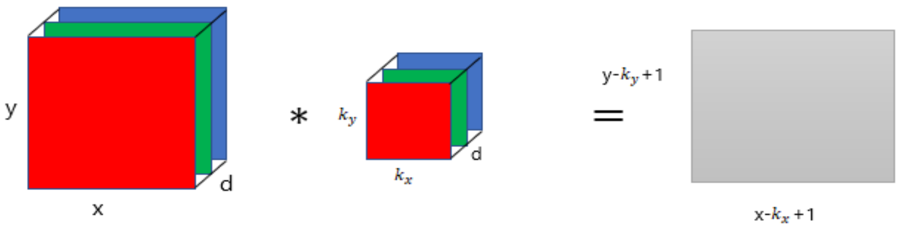
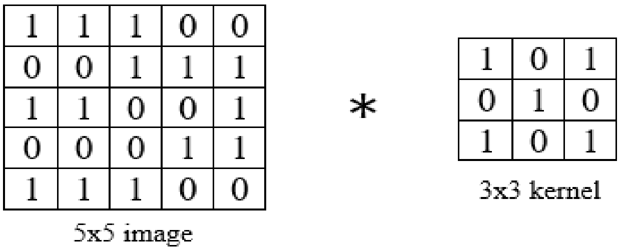
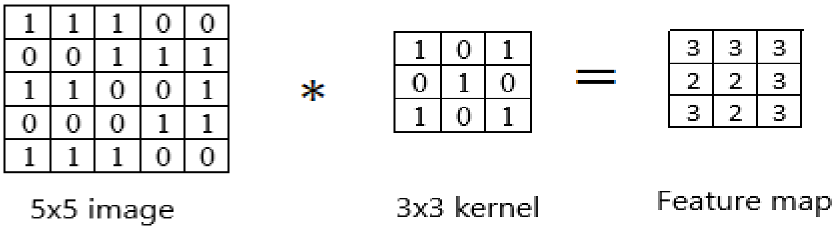


Figure 3: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x-k_x+1),(y-k_y+1),1\right)$, which is referred as feature map. An example of convolution procedure is demonstrated in Figure 4. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.



(a)



(b)

Figure 4: Example of convolution layer process (a) an image with size $\mathbf{5}\times\mathbf{5}$ is convolving with $\mathbf{3}\times\mathbf{3}$ kernel (b) Convolved feature map

ReLU layer: Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x)=\max\{0,x\} \tag{1}$$

Max pooing layer: This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

SoftMax classifier: Generally, SoftMax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has as shown in Figure 5. In Figure 6, and we must predict what is the object that is present in the picture. In the normal case, we predict whether the crop is A. But in this case, we must predict what is the object that is present in the picture. This is the place where softmax comes in handy. As the model is already trained on some data. So, as soon as the picture is given, the model processes the pictures, send it to the hidden layers and then finally send to softmax for classifying the picture. The softmax uses a One-Hot encoding Technique to calculate the cross-entropy loss and get the max. One-Hot Encoding is the technique that is used to categorize the data. In the previous example, if softmax predicts that the object is class A then the One-Hot Encoding for: Class A will be [1 0 0], Class B will be [0 1 0], and Class C will be [0 0 1].

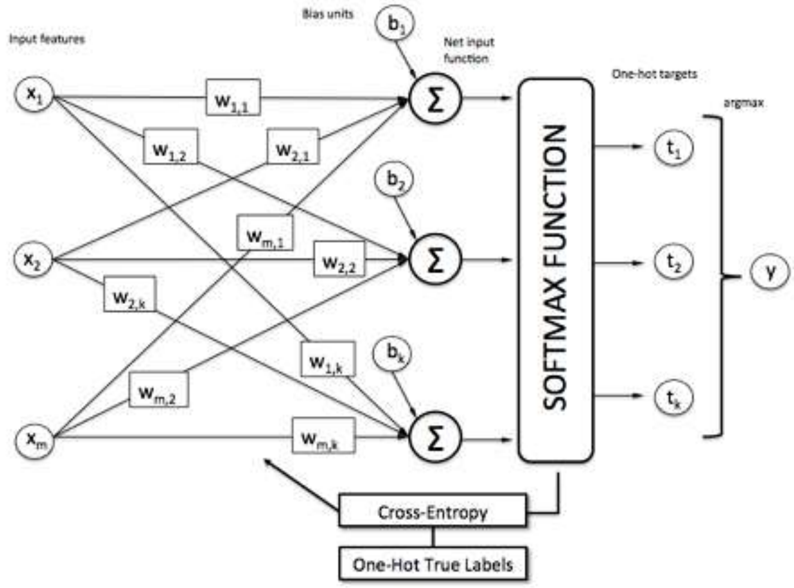


Figure 5: OSA prediction using SoftMax classifier.

From the diagram, we see that the predictions are occurred. But generally, we don't know the predictions. But the machine must choose the correct predicted object. So, for machine to identify an object correctly, it uses a function called cross-entropy function. So, we choose more similar value by using the below cross-entropy formula.

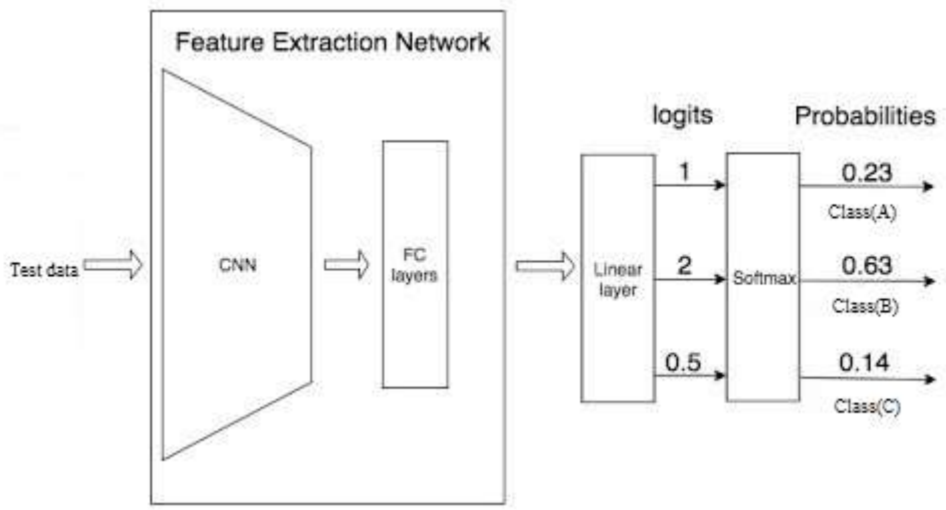


Figure 6: Example of SoftMax classifier.

In Figure 7, we see that 0.462 is the loss of the function for class specific classifier. In the same way, we find loss for remaining classifiers. The lowest the loss function, the better the prediction is. The mathematical representation for loss function can be represented as: -

$$LOSS = np.sum(-Y * np.log(Y\_pred)) \quad (2)$$

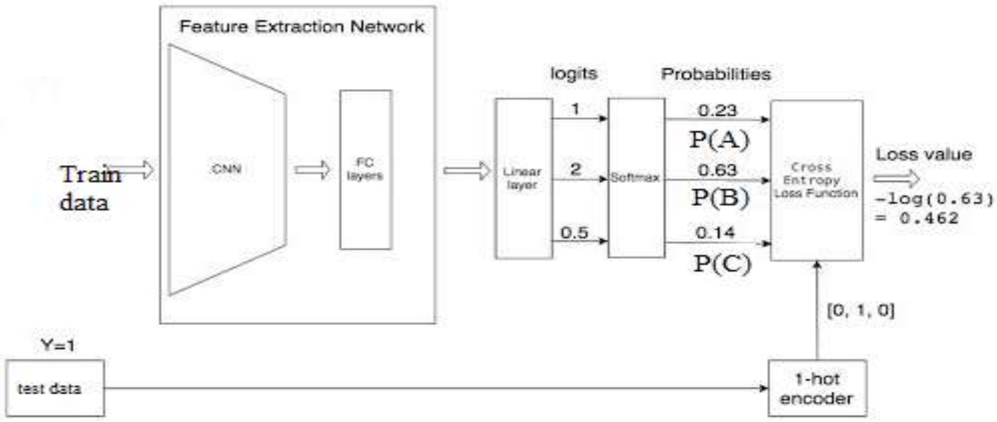


Figure 7: Example of SoftMax classifier with test data.

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 and Discussions

In Figure 8, we can see GoogLeNet model generated. Here, the multiple layers are displayed with the sizes. In Figure 9, x-axis represents EPOCH or iterations, 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 'Predict the Change' button and upload test image from the test folder or else you can try any image downloaded from Google and then model will predict it changes.

Figure 8: GoogLeNet model generated and loaded.

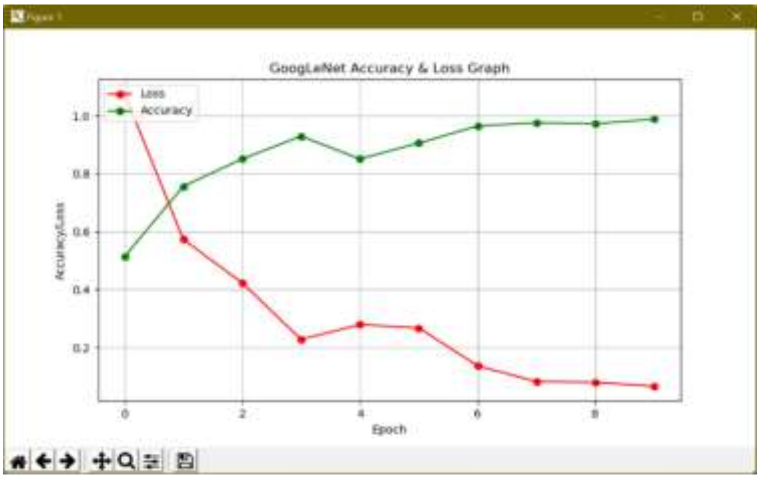


Figure 9: GoogLeNet Accuracy & Loss Graph

Figure 10 shows the predicted outcome as over ripe; Figure 11 shows the predicted outcome as green, Figure 12 shows the predicted outcome as ripe, and Figure 13 shows the predicted outcome as over ripe.

Figure 10: Banana Change Predicted As:Over Ripe

Figure 11: Banana Change Predicted As: Green

Figure 12: Banana Change Predicted As: Ripe

Figure 13: Banana Change Predicted As: Over Ripe

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.

References

[1]. Petluru, Surya, and Pradeep Singh. "Survey on Fruit Classification Using Deep Learning Techniques." Information Systems and Management Science: Conference Proceedings of 4th International Conference on Information Systems and Management Science (ISMS) 2021. Cham: Springer International Publishing, 2022.

[2]. Mukhiddinov, Mukhriddin, Azamjon Muminov, and Jinsoo Cho. "Improved Classification Approach for Fruits and Vegetables Freshness Based on Deep Learning." Sensors 22.21 (2022): 8192.

[3]. Singh, Vijay Prakash, S. N. Talbar, and Deepali M. Bongulwar. "SORTING OF FRESH FRUITS USING TRANSFER LEARNING."

[4]. Aherwadi, Nagnath, et al. "Prediction of Fruit Maturity, Quality, and Its Life Using Deep Learning Algorithms." Electronics 11.24 (2022): 4100.

[5]. Mehendran, Yanusha, Thangathurai Kartheeswaran, and Nihal D. Kodikara. "Banana Freshness Identification Using Image Processing Techniques." 2022 7th International Conference on Business and Industrial Research (ICBIR).

[6]. Gautam, Neha, and Nisha Chaurasia. "Forecasting of Fruits Stock Life using CNN-based Deep Learning Techniques: A Comprehensive Study." (202

[7]. Archana G., and Bharti Joshi. "Pragmatic Analysis of Fruit Processing Models for Quality Evaluation from a Statistical Perspective." 2022 2nd Asian Conference on Innovation in Technology (ASIANCON). IEEE, 2022.

[8]. Mamidi, Shanmukha Sai Rohit, et al. "Implementation of Machine learning Algorithms to Identify Freshness of Fruits." 2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT). IEEE, 2022.

[9]. Almeyda, Estefani, and William Ipanaqué. "Recent developments of artificial intelligence for banana: Application areas, learning algorithms, and future challenges." Engenharia Agrícola 42 (2022).

[10]. Saranya, N., K. Srinivasan, and S. K. Pravin Kumar. "FBCNN-TSA: An optimal deep learning model for banana ripening stages classification." Journal of Intelligent & Fuzzy Systems Preprint: 1-17.

[11]. Sindhu, G. R., and M. Prasad. "SURVEY PAPER ON FRUIT FRESHNESS ANALYSIS."

[12]. Soleh, M. S., et al. "Physicochemical Characterization and Shelf-Life Extension of Banana (Musa sp.) via Tapioca starch (Manihot esculenta)/Premna serratifolia Leaves Extract Coating Formulations." IOP Conference Series: Earth and Environmental Science. Vol. 995. No. 1. IOP Publishing, 2022.

[13]. Yanusha.M Freshness Identification of Banana using Image Processing Techniques. Diss. 2021.

[14]. Fu.Yuhang. Fruit freshness grading using deep learning. Diss. Auckland University of Technology, 2020.

[15]. Pranav, S. Bala Naga, et al. "Freshness Estimator for Fruits and Vegetables Using MQ Sensors." 2021 International Conference on Advances in Computing and Communications (ICACC). IEEE, 2021.

[16]. Karakaya, Diclehan, Oguzhan Ulucan, and Mehmet Turkan. "A comparative analysis on fruit freshness classification." 2019 Innovations in Intelligent Systems and Applications Conference (ASYU). IEEE, 2019.

[17]. Cheah, Ui Shaun. Mobile application for fruits freshness/ripeness detection. Diss. UTAR, 2021.

[18]. Evans, David M., et al. "The ontological politics of freshness: Qualities of food and sustainability governance." Environment and Planning A: Economy and Space 54.3 (2022): 461-476.

[19]. Arya, Prabha Shanker, and Mohit Gangwar. "A Proposed Architecture: Detecting Freshness of Vegetables using Internet of Things (IoT) & Deep Learning Prediction Algorithm." 2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N). IEEE, 2021.

[20]. Ai, Binling, et al. "Biodegradable cellulose film prepared from banana pseudo-stem using an ionic liquid for mango preservation." Frontiers in Plant Science 12 (2021): 625878.