2023 International Conference on Emerging Smart Computing and Informatics (ESCI)
AISSMS Institute of Information Technology, Pune, India. Mar 1-3, 2023

Leveraging ML Techniques for Image-based Freshness Index Prediction of Fruits and Vegetables

Atharva Gokhale*
Department of Computer Engineering
Pune Institute of Computer Technology
Pune, India
atharva.gokhale251@gmail.com

Ameya Chavan
Department of Computer Engineering
Pune Institute of Computer Technology
Pune, India
chavanameya007@gmail.com

Sheetal Sonawane
Department of Computer Engineering
Pune Institute of Computer Technology
Pune, India
sssonawane@pict.edu

2023 International Conference on Emerging Smart Computing and Informatics (ESCI) | 978-1-6654-7524-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/ESCI56872.2023.10100260

***Abstract*—Freshness is a prime factor of consideration when purchasing consumables like fruits and vegetables. Studies have proven that Computer Vision can be successfully involved in classifying fresh and stale fruits and vegetables and measuring their freshness to some extent. This work attempts to determine and analyze the freshness of fruits and vegetables from their images by proposing a Machine Learning methodology. The entire study was divided into two steps. The first step focused on obtaining classification between images of fresh and stale fruits and vegetables. For this, we trained the ConvNeXt model on an open-source imagery dataset consisting of 12 classes, and it proved efficient by achieving an accuracy of 99.77%. The second step focused on analyzing how fresh a particular fruit or vegetable is from its image. We achieved this by using an open-source dataset of tomato images and extracting features specific to the texture, shape, and colour from these images. Further, we trained classification models on these extracted features and presented the results as quantitative measures with scores of 10 for each of these three factors. Thus, we attempted to achieve an in-depth freshness analysis by grading the images based on these three critical factors while defining freshness.**

***Index Terms*—computer vision, freshness analysis, classification, deep learning, feature extraction**

I. Introduction

Computer vision and image processing have enabled computers to perform many tasks which were assumed to be nearly impossible to be performed by computers in the past. One such important use case application is the determination of the freshness of consumables like fruits and vegetables merely from their digital images. With the evolution of Artificial Intelligence, many solutions have been proposed through which techniques for performing such types of analysis have been put forth. At a broad level, these studies can be classified mainly into two types. The first type can be associated with techniques that mainly involve feeding labeled data to deep learning models and obtaining classification into fresh or stale/rotten categories [1], [2]. On the other hand, the second type involves techniques that involve the selection and extraction of specific features from the data and learning from them [3], [4]. This allows freshness analysis with respect to certain important factors that are vital in deciding the freshness of consumables [4]. Both these types of studies depend mainly on the nature of the data available and the nature of insights or results required or expected from the analysis process.

The study presented in this paper has been carried out and presented in two steps. In the first step, a deep learning-based approach has been proposed to classify fresh and stale fruits and vegetables from their images. This step provides insights only regarding the fresh/stale status of the consumables. In the second step, a comprehensive analysis regarding the freshness was attempted. The approach in this step mainly focuses on giving insights regarding how fresh a given consumable is by taking suitable factors into consideration.

The following are the major contributions of the study undertaken and presented in this paper:

1) Trained a deep learning model based on one of the recent and novel architectures on an imagery dataset consisting of data belonging to 12 classes in total. This model achieved state-of-the-art results for the task of classifying fresh and stale fruits and vegetables.
2) Identified and extracted relevant features pertaining to the texture, shape, and colour from an imagery dataset of tomatoes and trained models on these features. This methodology is important for obtaining separate scores for the above-mentioned factors and providing additional and in-depth insights regarding the freshness.

The rest of the paper is structured as follows: section II summarizes multiple recent studies and approaches presented for the mentioned application scenario. Section III briefly describes the datasets used for this study along with the detailed procedure followed for carrying out the experimentation and for arriving at the results. The results obtained as outcomes of this study have been discussed in section IV while, section V presents the conclusions drawn from the study.

II. Related Work

A number of techniques have been attempted in an effort to extract useful features related to fruits and vegetables from their images to determine their freshness, ripeness, or even shelf life.

Ismail et al. [5] made use of a deep learning-based approach for classifying fruit images based on their freshness. They made use of labeled imagery data pertaining to four classes each of apple and banana and trained the EfficientNet model on it separately. They achieved training accuracies of 98.6% and 99.2% and test accuracies of 93.8% and 96.7% on banana and apple data, respectively. Similar to this, Jana et al. [1] considered an imagery dataset consisting of images of only apples and proposed a Convolutional Neural Network (CNN) for classifying between the fresh apples and the rotten or defective ones. They obtained test accuracies of 98.46% and 98.53%, respectively, on two different datasets. Roy et al. [6] have proposed a technique for classifying rotten and fresh apples by proposing a semantic segmentation-based approach and by using the details extracted from the apple's skin. They made use of the Enhanced UNet (En-UNet) and the UNet models for the purpose of segmentation. They achieved accuracies of 97.54% and 95.36% for the En-UNet and the UNet models, respectively.

Kaur et al. [7] made use of an Artificial Neural Network (ANN) for the task of determining the quality of vegetables from their images. They developed an algorithm that would extract suitable features from the images, like the size, colour, and shape of the vegetables, and classified the images into three categories: poor, medium, and best quality. The techniques used for extracting the features were boundary extraction, determination of minor and major axes, and pixel-based classification for determining the size, shape, and colour, respectively.

Yanusha [4] focused on determining the freshness of bananas from imagery data. They made use of the colour, shape, and texture-related features extracted from the images to identify the freshness. The freshness was expressed in terms of the number of days that passed since the fruit was separated from the tree. They made use of specific features obtained from the Gray-Level Co-occurrence Matrix (GLCM) for texture analysis and K-means clustering for performing image segmentation in order to get shape-related insights. Finally, the Support Vector Machine (SVM) classifier model was trained on the obtained features in order to predict the end result (freshness value). Sarkar et al. [8] attempted freshness determination of Amla fruits by focusing on the shape-related features of the fruit. They made use of canny-edge detection in order to obtain the geometrical features related to the shape and trained SVM and ANN models to get an accuracy of 90%.

Huang et al. [9] made use of odor information along with imagery data for the classification of spinach into four grades based on freshness. They made use of K Nearest Neighbors (KNN), SVM, and backpropagation ANN for classification and achieved a maximum accuracy of 85.42% using the KNN model. Zarnaq et al. [3] made use of a dataset consisting of colour and texture features obtained from parsley images. They made use of Linear Discriminant Analysis (LDA) for feature reduction and trained the Multilayer Perceptron (MLP) model, using which they achieved an accuracy of 97.22% which was the highest among other models. Huang et al. [10] attempted to classify among three grades of mango fruit by making use of features related to the hardness and solubility of the fruit. They obtained a test accuracy of 97.5% using the Support Vector Classification (SVC) model.

Blasco et al. [11] developed an algorithm that would make use of the colour features of the images of pomegranate fruits. They implemented the LDA technique on the RGB space of the images and obtained an accuracy of 90% for the classification between good and defective pomegranates.

From the previously proposed studies, it was observed that most approaches focusing on image-based classification for freshness made use of techniques that were capable of classifying the data into just 'fresh' or 'stale' categories. On the other hand, the number of studies aimed towards learning from specific freshness-oriented factors and presenting results in terms of 'how fresh a consumable is' is comparatively lesser in number. Thus, on identifying a research gap pertaining to the need for an in-depth analysis by considering freshness-specific factors, this study has been put forth to provide a solution for the same. Along with this, the proposed study also presents the state-of-the-art results obtained by training a deep CNN based on one of the novel architectures. This study also takes both fruit and vegetable data into consideration, whereas the majority of the previous studies specifically target only fruits.

III. Proposed Methodology

As mentioned earlier, the entire methodology for determining the freshness of fruits and vegetables from their images was divided into two main steps.

A. Datasets

1) Step 1 Dataset: For step 1 of the study, a dataset containing labeled images of fresh and stale fruits and vegetables was required. Thus, the dataset titled "Fresh and Stale Images of Fruits and Vegetables" [12] by Potdar R. was used. This is a robust dataset consisting of images of 3 fruits and three vegetables (in both fresh and stale form). The dataset consists of 14682 images in total, out of which 8805 images were used for training, 1475 images were used for validation, and the remaining 4402 images were used for testing.

2) Step 2 Dataset: For step 2, in order to perform a detailed analysis of the freshness of a fruit/vegetable from its image, a dataset consisting of labeled images corresponding to different classes was the primary requirement. Here, each class was required to represent a different or distinct level of freshness or freshness value. For this, the open-source dataset proposed by Das et al. [13] was used. This dataset includes 6470 tomato images in total, which are divided into ten different classes. The images are labeled between values 1 to 10 as per the freshness value of the tomato in the image. The label value '1' represents the freshest tomato, whereas the value '10' represents the least fresh one. The intermediate classes between 1 and 10 represent decreasing freshness with respect to increasing label values.

B. Workflow

1) Step 1: Identifying the fruit/vegetable as fresh or stale: Fig. 1 represents the overall workflow for feeding the data to the model and obtaining the classification.

The main focus in the first step of the study was to classify the image of a given fruit/vegetable as 'fresh' or 'stale.' For

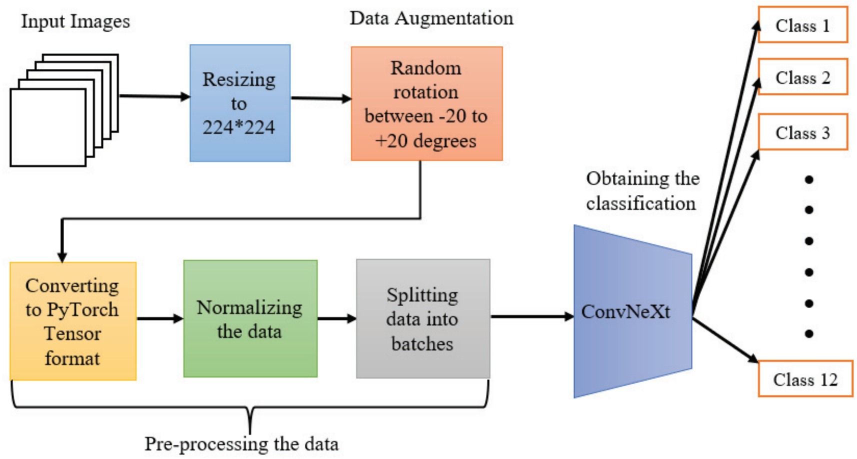

Fig. 1. Workflow representing the data preparation and feeding the data to the ConvNeXt model.

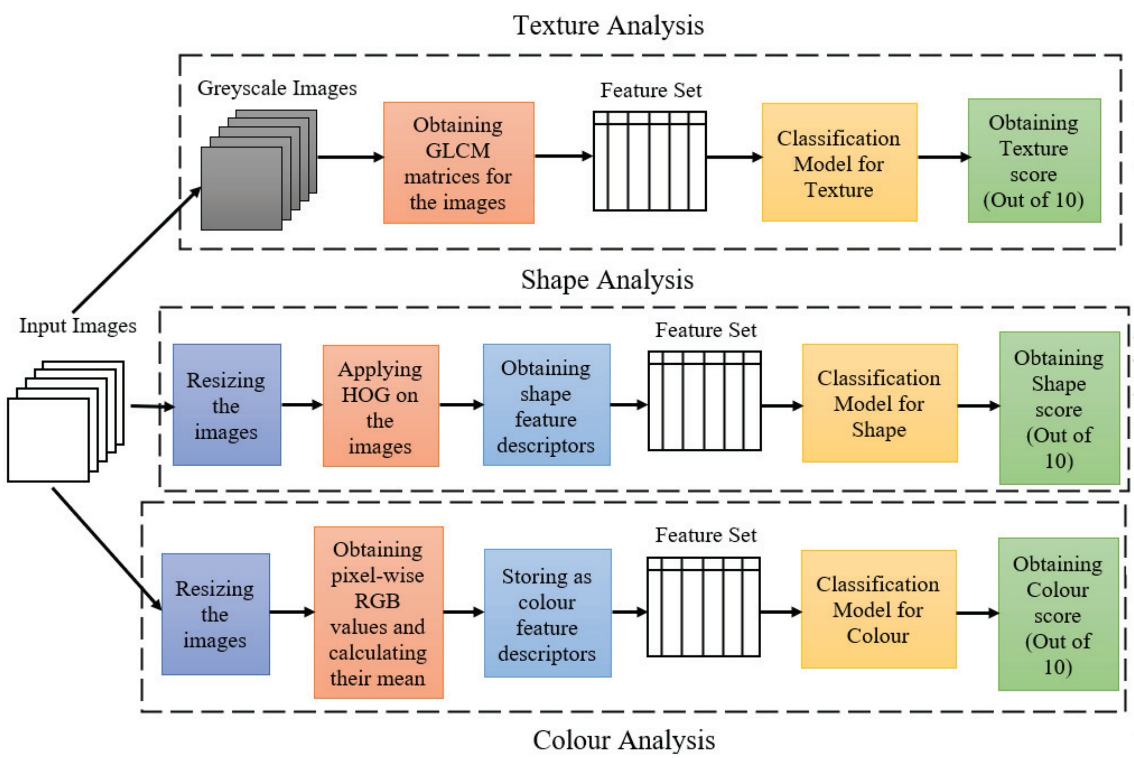

Fig. 2. Workflow representing the method used for obtaining scores for texture, shape, and colour from the images.

example, if the model is fed with an image of an orange, the model can classify it into either "fresh orange" or "stale orange." By using the dataset mentioned in subsection III-A1, we trained a deep convolutional neural network on the image data, which was capable of extracting the suitable features from the data and learning from them.

ConvNeXt [14] is a deep CNN model which has been proposed recently with a view to modernizing the standard Convolutional Networks. As shown in fig. 1, the images in the dataset had to undergo some pre-processing steps before they could be fed to the model. The images were resized to 224*224 before augmenting them. The augmentation step included obtaining rotated images by a random value between -20 to +20 degrees. Since the images were in RGB format, the mean and standard deviation values for the three separate channels were used for the normalization process. Further, the data was fed to the model for training. Transfer learning was implemented in order to include the model's pre-trained weights for enhancing the learning process and the model's performance.

2) Step 2: Comprehensive freshness analysis: Step 2 of this study aimed to obtain detailed insights regarding the freshness of the fruit/vegetable under consideration. Fig. 2 represents the overall workflow for processing the images for obtaining the analysis with respect to the texture, shape, and colour of the tomatoes from their images. As mentioned earlier, the techniques for the identification of the shape, the colour, and the texture were applied to the tomato dataset mentioned in section III-A2.

1) Texture Analysis:
Gray Level Co-Occurrence Matrix (GLCM) analysis is one of the most promising techniques in image processing, which is used for analyzing textures in images [15]. We made use of this technique in order to obtain the features related to the texture of the tomatoes from their images. Table I shows the GLCM features used along with the importance of each feature while training the Random Forest model.

TABLE I
IMPORTANCE OF GLCM FEATURES WHILE TRAINING THE MODEL

Sr. No.	Feature	Feature Importance
1	Correlation	0.220676
2	Contrast	0.170235
3	Dissimilarity	0.170034
4	Homogeneity	0.163927
5	ASM	0.138150
6	Energy	0.136977

Thus, on converting the dataset images to grayscale, the values pertaining to the above-mentioned features were obtained and stored as a set of features along with the corresponding labels for the images. For every image, these values were calculated at the pixel level, and then, the summarized values for each of the features for each image were stored. Further, this feature set was used for training the Random Forest classifier model in order to classify between the images based on the texture. The result of classification for a given image was the score (out of 10) for the texture of the tomato in the corresponding image.

2) Shape Analysis:
We used a Histogram of Oriented Gradients (HOG) based approach for grading the available tomato data based on the shape. HOG is one of the most simple techniques which are widely used for object detection with a focus on identifying the shape of the objects [16]. This technique can be used for forming feature descriptors which can be used for training models for shape classification [4], [16]. Since the dimensions of the feature descriptors depend on the size of the images, defining constant image size for all the images is an essential step before applying the HOG technique. Thus, we resized all the images to a size of 128*128, and as a result, we obtained the HOG feature descriptors of size 8100. Later, we trained the Random Forest classifier model on this feature set in order to obtain the required classifications, i.e., a score (out of 10) for the shape.

3) Colour Analysis:
An approach similar to the HOG technique of obtaining the feature descriptors for classification was used for the colour-based analysis of the data. The images were resized to a size of 128*128, and separate Red, Blue, and Green channel-based analysis was performed for each image. We obtained pixel-wise RGB values, computed the mean of these three values, and stored it in the descriptor for that specific image and hence created a feature set for training a classification model on it. The descriptor obtained for every image was of size 16384. Further, we trained the Random Forest classifier model on the obtained feature set for classification and obtaining scores (out of 10) for every image based on the colour of the tomato in that particular image.

IV. RESULTS AND DISCUSSION

A. Step 1 Results

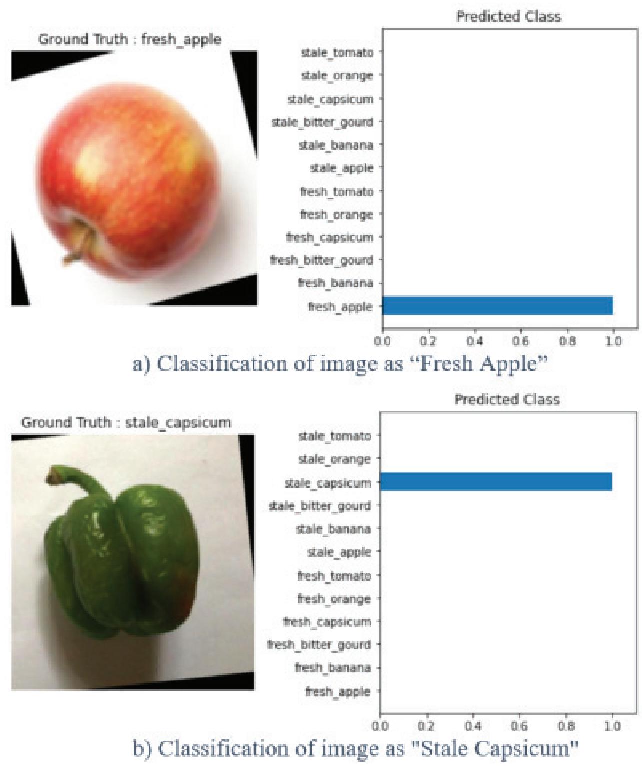

Fig. 3. Results of Image Classification by the ConvNeXt model

Fig. 3 shows two sample images of a fresh apple and a stale capsicum, respectively which the model has classified.

The ConvNeXt model was trained on the dataset for 20 epochs in total after setting all the relevant hyperparameters. We achieved a training accuracy of 99.535% and a validation accuracy of 99.261% for this model. Following this, the model was tested on a test dataset comprising 4402 images in total, and the test accuracy obtained on this was 99.774%.

Table II represents the class-wise values for the performance parameters: accuracy (ACC), adjusted F-score (AFS), area under ROC curve (AUC), false negative rate (FNR), false positive rate (FPR), and true positive rate (TPR). These values have been obtained by testing the ConvNeXt model on the test dataset. The classes have been represented as 0: fresh apple, 1: fresh banana, 2: fresh bitter gourd, 3: fresh capsicum, 4: fresh orange, 5: fresh tomato, 6: stale apple, 7: stale banana, 8: stale bitter gourd, 9: stale capsicum, 10: stale orange, 11: stale tomato.

TABLE II
CLASS-WISE PERFORMANCE OF CONVNEXT ON TEST DATA

Classes	ACC	AFS	AUC	FNR	FPR	TPR
0	0.999	0.997	0.997	0.006	0.0	0.994
1	1.0	1.0	1.0	0.0	0.0	1.0
2	0.999	0.999	0.999	0.0	0.0	1.0
3	1.0	1.0	1.0	0.0	0.0	1.0
4	0.999	0.998	0.999	0.0	0.001	1.0
5	0.999	0.998	0.998	0.003	0.0	0.996
6	0.999	0.999	0.999	0.0	0.001	1.0
7	1.0	1.0	1.0	0.0	0.0	1.0
8	0.999	0.996	0.995	0.009	0.0	0.99
9	1.0	1.0	1.0	0.0	0.0	1.0
10	0.998	0.994	0.994	0.012	0.0	0.987
11	0.999	0.998	0.998	0.003	0.0	0.996

Table III summarizes some of the latest studies on this topic and presents a concise comparison between the proposed study and the other relevant studies. It can be observed that the novel ConvNeXt model has achieved state-of-the-art results.

TABLE III
COMPARISON WITH OTHER SIMILAR STUDIES

Ref.	Model	Classes	Accuracy	Data
[2]	Proposed CNN	6	97.14	fruits
[17]	Proposed CNN + categorization with: a) Max pooling b) Avg pooling c) MobileNetv2 layers	6	94.97 93.72 99.61	fruits
[6]	Enhanced UNet	2	97.54	fruits
[18]	ANN	3	96.50	fruits
[19]	ResNet50	6	98.89	fruits
[5]	EfficientNet	8 4	99.20 98.60	fruits
[20]	Improved ResNet	2	95.60	veg
This	**ConvNeXt**	**12**	**99.77**	**fruits+veg**

B. Step 2 Results

TABLE IV
MODEL PERFORMANCES IN COMPREHENSIVE FRESHNESS ANALYSIS STEP

Factor	Features	Model	Accuracy
Texture	GLCM features	Random Forest	99.70%
Shape	HOG descriptors	Random Forest	99.98%
Colour	Colour (RGB) descriptors	Random Forest	74.89%

Table IV shows the results obtained for the model trained for the texture, shape, and colour analysis respectively.

Table V represents the model accuracy obtained by training with each of the mentioned image sizes. It can be noted that the highest accuracy has been obtained for a feature descriptor size of 22500.

TABLE V
CHANGE IN ACCURACY WITH DIFFERENT FEATURE SET SIZES

Sr. No.	Image Size	Feature Set Size	Accuracy
1	32*32	1024	65.21%
2	64*64	4096	73.52%
3	128*128	16384	74.89%
4	150*150	22500	**78.89**%
5	170*170	28900	66.79%

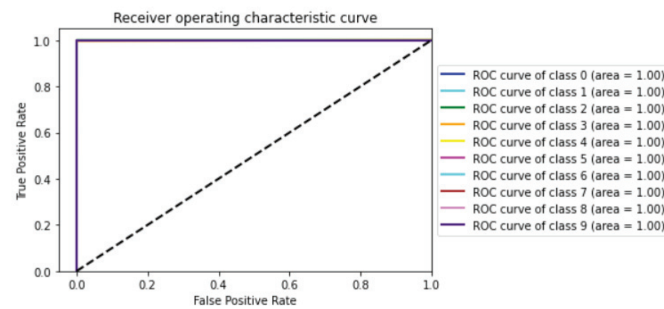

Fig. 4. Class-wise ROC curves for classification based on texture

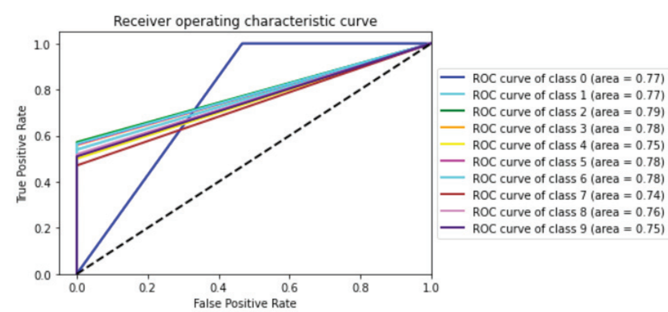

Fig. 5. Class-wise ROC curves for classification based on colour

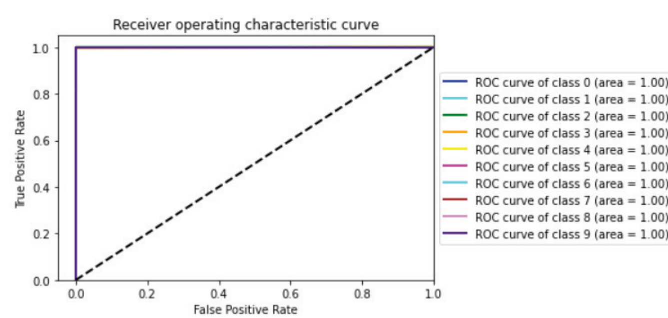

Fig. 6. Class-wise ROC curves for classification based on shape

Fig. 4, 5, and 6 represent the class-wise ROC curves obtained for the Random Forest models for texture, colour, and shape, respectively. For the ROC curves for texture and shape, the lines for most classes seem to coincide due to similar accuracies. Since each line represents the ROC curve

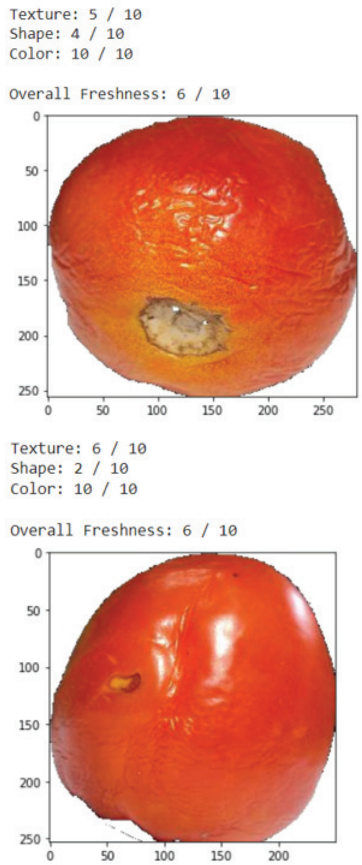

Fig. 7. Results of comprehensive freshness analysis

for an individual class, the area under each curve represents the classification accuracy for that specific class. Fig. 7 represents two sample tomato images along with their respective scores for texture, shape, and colour and also the overall freshness score. The overall freshness score has been determined by calculating the mean of the three individual scores.

V. Conclusion

Freshness determination in the case of consumables like fruits and vegetables is an important task, and Computer Vision based techniques have proven to be novel ways to achieve this goal in a more straightforward and more accurate manner. We proposed a two-step methodology while attempting the same. In the first step, we used a labeled imagery dataset with 12 classes for classification using the novel ConvNeXt model. Using this method, we achieved state-of-the-art results as the model achieved a test accuracy of 99.77%. Whereas in the second step of the study, we tried to perform a comprehensive analysis of the freshness of tomatoes using a labeled dataset of graded tomato images. This was achieved by extracting features relevant to the texture, shape, and colour of the tomatoes and training separate models on these features to obtain individual grades/scores for the tomatoes based on these factors, which would contribute to providing important and more profound insights about their freshness.

References

[1] S. Jana, R. Parekh, and B. Sarkar, "Automated sorting of rotten or defective fruits and vegetables using convolutional neural network," in *Proceedings of International Conference on Computational Intelligence, Data Science and Cloud Computing*, pp. 43–55, Springer, 2021.

[2] T. B. Kumar, D. Prashar, G. Vaidya, V. Kumar, S. Kumar, and F. Sammy, "A novel model to detect and classify fresh and damaged fruits to reduce food waste using a deep learning technique," *Journal of Food Quality*, vol. 2022, 2022.

[3] M. H. Zarnaq, M. Omid, M. S. Firouz, M. Jafarian, and P. Bazyar, "Freshness and quality assessment of parsley using image processing and artificial intelligence techniques," *Agricultural Engineering International: CIGR Journal*, vol. 24, no. 2, 2022.

[4] M. Yanusha, *Freshness Identification of Banana using Image Processing Techniques*. PhD thesis, University of Colombo School of Computing, 2021.

[5] N. Ismail and O. A. Malik, "Real-time visual inspection system for grading fruits using computer vision and deep learning techniques," *Information Processing in Agriculture*, vol. 9, no. 1, pp. 24–37, 2022.

[6] K. Roy, S. S. Chaudhuri, and S. Pramanik, "Deep learning based real-time industrial framework for rotten and fresh fruit detection using semantic segmentation," *Microsystem Technologies*, vol. 27, no. 9, pp. 3365–3375, 2021.

[7] M. Kaur and R. Sharma, "Ann based technique for vegetable quality detection," *IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)*, vol. 10, no. 5, pp. 62–70, 2015.

[8] T. Sarkar, A. Mukherjee, K. Chatterjee, V. Ermolaev, D. Piotrovsky, K. Vlasova, M. A. Shariati, P. E. Munekata, and J. M. Lorenzo, "Edge detection aided geometrical shape analysis of indian gooseberry (phyllanthus emblica) for freshness classification," *Food Analytical Methods*, vol. 15, no. 6, pp. 1490–1507, 2022.

[9] X. Huang, S. Yu, H. Xu, J. H. Aheto, E. Bonah, M. Ma, M. Wu, and X. Zhang, "Rapid and nondestructive detection of freshness quality of postharvest spinaches based on machine vision and electronic nose," *Journal of food safety*, vol. 39, no. 6, p. e12708, 2019.

[10] X. Huang, R. Lv, S. Wang, J. H. Aheto, and C. Dai, "Integration of computer vision and colorimetric sensor array for nondestructive detection of mango quality," *Journal of Food Process Engineering*, vol. 41, no. 8, p. e12873, 2018.

[11] J. Blasco, S. Cubero, J. Gómez-Sanchís, P. Mira, and E. Moltó, "Development of a machine for the automatic sorting of pomegranate (punica granatum) arils based on computer vision," *Journal of food engineering*, vol. 90, no. 1, pp. 27–34, 2009.

[12] R. Potdar, "Fresh and stale images of fruits and vegetables dataset," 2021. Kaggle Datasets.

[13] S. Das, S. Kar, and A. A. Sekh, "Fgrade: A large volume dataset for grading tomato freshness quality," in *International Conference on Computer Vision and Image Processing*, pp. 455–466, Springer, 2020.

[14] Z. Liu, H. Mao, C.-Y. Wu, C. Feichtenhofer, T. Darrell, and S. Xie, "A convnet for the 2020s," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 11976–11986, 2022.

[15] B. Sebastian V, A. Unnikrishnan, and K. Balakrishnan, "Gray level co-occurrence matrices: generalisation and some new features," *arXiv preprint arXiv:1205.4831*, 2012.

[16] R. Ebrahimzadeh and M. Jampour, "Efficient handwritten digit recognition based on histogram of oriented gradients and svm," *International Journal of Computer Applications*, vol. 104, no. 9, 2014.

[17] S. Chakraborty, F. J. M. Shamrat, M. M. Billah, M. Al Jubair, M. Alauddin, and R. Ranjan, "Implementation of deep learning methods to identify rotten fruits," in *2021 5th International Conference on Trends in Electronics and Informatics (ICOEI)*, pp. 1207–1212, IEEE, 2021.

[18] T. Sarkar, A. Mukherjee, and K. Chatterjee, "Supervised learning aided multiple feature analysis for freshness class detection of indian gooseberry (phyllanthus emblica)," *Journal of The Institution of Engineers (India): Series A*, vol. 103, no. 1, pp. 247–261, 2022.

[19] C. C. Foong, G. K. Meng, and L. L. Tze, "Convolutional neural network based rotten fruit detection using resnet50," in *2021 IEEE 12th Control and System Graduate Research Colloquium (ICSGRC)*, pp. 75–80, IEEE, 2021.

[20] Y. Xu, Y. Zhai, Q. Chen, S. Kong, and Y. Zhou, "Improved residual network for automatic classification grading of lettuce freshness," *IEEE Access*, vol. 10, pp. 44315–44325, 2022.