An Intelligent Approach to Determine Banana Ripeness Stages using Deep Learning Models

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***Abstract*— Fruit ripeness classification is important in agriculture, food processing industry, supermarkets, Ayurveda, and many more. The manual identification is tedious, time-consuming, and laborious. Hence, deep learning techniques have gained popularity recently as a computer vision method for automatically classifying fruit ripeness simplifies feature engineering work. Differentiating between the visual characteristics of fruits at different stages of ripeness is a difficult task for machine learning systems. In this proposed work, two CNN models such as InceptionV3 and VGG19 are used to invent the best deep-learning model to categorize bananas into their three distinct ripeness stages. The experiments are carried out using self-created datasets consisting of 687 image samples of three different stages. The first dataset consists of individual banana image samples and the second dataset contains banana bunch sample images. The CNN models are trained and tested in the range of 80:20. It is observed that VGG19 achieves better accuracy than InceptionV3 in predicting three ripening stages of banana fruit with an accuracy of 98.1% and 97.5%.**

Keywords*— *Banana fruit, Transfer learning, Ripeness stages, Classification, Deep learning

I. Introduction

Fruit ripeness identification is essential to determine the food products can be prepared at different stages of maturation in the food processing sector. India is the nation that produces the most bananas and economically significant fruit worldwide, contributing to global food security. The banana fruit is very nutritious having various medicinal properties that are consumed at different growth stages. During the different phases, fruits undergo significant physical and biochemical changes that have a direct impact on their quality and marketability[13]. These changes include variations in color, texture, taste, and aroma. The accurate prediction of banana ripeness is important to improve harvesting systems and storage methods. Traditional ripeness prediction methods rely on measuring biological parameters such as color, hardness, soluble solids, and acidity. However, traditional methods frequently fall short in terms of accuracy and efficiency. They are time-consuming and subjective, making them prone to human error[22].

Bananas, in particular have a short shelf life due to rapid aging. As bananas transition through different ripening stages, from unripe to overripe, their physical characteristics, such as color, texture, and aroma undergo significant changes[24]. These changes not only affect consumer preferences but also impact post-harvest handling, storage, and distribution practices in the banana industry. The fruit peel's visual appearance changes as it ripens, going from greenish-yellow to dark dots on a yellow background and finally taking on a muddy brown color. In view of this problems, an intelligent technique for assessing banana ripening stages is not only novel but also vital. This strategy might make use of new technologies based on machine learning and deep learning models to produce more accurate, objective, and rapid banana ripeness evaluations.

Traditionally, the assessment of banana ripeness has relied heavily on subjective human judgment, which can lead to inconsistencies and inefficiencies in quality control and supply chain management. However, with the emergence of advanced technologies in artificial intelligence and computer vision, there is an opportunity to revolutionize ripeness classification through automated methods. Artificial intelligence and deep learning approaches has shown impressive results in problems involving image recognition and categorization. Particularly convolutional neural networks (CNNs) have demonstrated promising result in precisely recognizing and classifying objects in images[23]. By leveraging deep learning algorithms, researchers and practitioners can develop intelligent systems capable of discerning subtle differences in banana ripening stages with high precision and reliability. In this study, we focus on the development of an intelligent identification system for classifying the ripening stages of bananas using deep learning techniques. Specifically, we explore the effectiveness of two widely used CNN architectures, VGG19 and InceptionV3, in categorizing bananas into three distinct ripening stages: unripe, ripe, and overripe. Our research builds upon existing literature on deep learning applications in agricultural contexts, particularly in fruit ripeness assessment and quality control.

To facilitate our investigation, we have compiled a dataset consisting of 687 high-resolution images of Golden Finger bananas at various ripening stages. The dataset includes diverse images of both individual bananas and banana bunches, captured in varying sizes, shapes, and color

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characteristics of different ripening stages. The objective is to evaluate the accuracy and resilience of our deep learning models in differentiating between banana ripening stages through thorough testing and analysis. The research conclusions may improve the decisions to be made at every stage of the banana supply chain, from packing and production to retailing and consumption[14].

In the subsequent sections, we discuss about the dataset description, literature review, model architecture, and experimental evaluation using various performance metrics. Furthermore, discussion about the implications of findings for the agricultural industry and explore avenues for future research and innovation in automated fruit quality assessment[25]. The research contributes to the ongoing discourse on the intersection of deep learning and agriculture, offering novel insights and practical solutions for improving the efficiency and sustainability of banana production and distribution systems [4].

II. RELATED WORK

Rybacki et al.,[1] created an automatic categorization model DateNET in response to the growing demand for premium date palm fruits. The model's effectiveness in classifying fruits was demonstrated by its integration of geometric characteristics and color difference, which resulted in validation accuracies of 85.24% for color-based classification, 87.62% for geometry-based classification, and a noteworthy 93.41% when both criteria were considered. Baglat et al.,[2] utilized shallow and deep learning for non-destructive banana ripeness detection was examined. Analysis was done on parameters such as sample sizes, banana ripeness stages, banana capture devices, and reported results. Based on the features of the datasets, the investigations were divided into three groups: sensor-based, substantially augmented, and non-augmented. Manohar et al.,[3] proposed a real-time face mask detection system, employing CNN for 99% accuracy, ensures computational efficiency in enforcing COVID-19 safety measures in public spaces. Rajesh et al.,[5] Different stages of tomato ripeness is investigated using a fuzzy logic-based method that achieved 95.6%, 94.2% and 93.1% for color, size and form parameters. This automated, effective, and non-destructive method promised significant improvements in precision farming. Nassiri et al.,[6] addressed the drawbacks of conventional methods. The method achieved a high accuracy of 95.7%, in classifying tomato maturity based on weight, volume, and diameter using fuzzy logic. Aherwadi et al.,[7] proposed innovative research that addresses a crucial need in the banana industry by significantly enhancing quality assessment, reducing post-harvest losses, and improving supply chain efficiency. Araujo et al.,[8] suggested a creative and effective method for utilizing computer vision technology to categorize the various stages of banana ripening. By addressing the shortcomings of conventional methods, their novel approach would minimize post-harvest losses and improve quality evaluation. Hamza et al.,[10] introduced a novel approach for apple ripeness estimation using a fuzzy inference system (FIS) optimized with the gradient method. Their system is based on the observation that apple color changes gradually from green in the unripe stage to red in the ripe stage, achieving an average accuracy of 90.80%. Azarmdel et al.,[11] presented a novel and effective approach for classifying mulberry fruit based on ripeness using image processing and artificial intelligence techniques. A total of 577 mulberries were graded based on geometrical properties. Further, conventional models are used for classification. The ANN model with correlation-based Feature selection Subset (CFS) achieved the highest accuracies. Altaheri et al., [12] used deep learning to introduce a real-time fruit classification system. The deep neural networks with transfer learning are trained and tested using 8000 image samples. Villaseñor et al.,[15] introduced an approach for automating and improving tomato maturity assessment using a vision system and fuzzy logic. The approach utilized fuzzy logic to classify tomato maturity based on color, texture, and shape, achieving high accuracy rates of 94.4%, 93.8%, and 92.2% respectively. Peng et al.,[16] proposed a novel and effective approach for fruit recognition and classification enabling the development of a fruit-picking robot capable of handling multiple types of fruits. These outcomes set the groundwork for multi-class fruit picking robot. Dong et.al.,[18] developed a quality evaluation using a color distribution analysis method for automatically evaluating the maturity and quality of harvested dates based on their color. They used 2D histograms of colors in each grading category to determine the co-occurrence frequency, the dataset used in their experiment was Medjool dates collected from an orchard in Arizona, U.S.A., and has achieved an accuracy of 90%. Surya et al.,[19] emphasized the classification of banana fruit maturity with different methods of image processing. Van et.al.,[20] evaluated a model-based approach that classifies tomato fruit during development and ripening based on physiological maturity. By considering the fruit's physiological maturity, their technique approach enables the user to interpret other detrimental physiological markers, like firmness decline or ethylene generation, on a more realistic time scale.

The literature highlights the advancement made towards the fruit classification, ripeness and quality detection, ripeness stages and disease prediction in the field of agricultural crops. While the significant progress made still there is a scope towards proposing a model that predicts different stages of Banana fruits using single and banana bunch image samples. Also, improving the datasets with real time capturing will standardize to focus on real world problems.

The Proposed methodologyogy highlights:

- The primary dataset, along with 2 classes of Bunch and Single fruit.
- The model demonstrates the capability to predict ripeness stages for both Single and Bunch images in real-time, providing instantaneous insights.
- Integration of transfer learning techniques, leveraging pre-trained models to tailor them for the precise task of classifying banana ripeness stages.
- Exploring into employing explainable AI techniques to uncover the underlying features influencing ripeness

stage predictions, thereby enhancing the model's interpretability and reliability.

III. Dataset

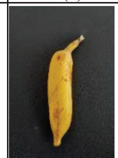
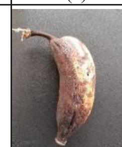
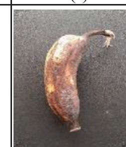
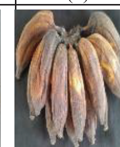
To build a datasets, Banana fruits is taken from the market and placed individually on black color sheet. The images are captured in day light between 10 a.m. and 3 p.m. using Samsung A13 smartphone camera with a 50-megapixel resolution. A smartphone holding stand is used to place mobile device at a distance of 35cm during the indoor image-capturing procedure. The images are captured from different angles and directions. The amount of natural light in the space was carefully regulated to avoid direct light, which may have caused reflections and shadows in the background.

A black background also highlights clarity and gets rid of visual clutter and impediments. Every image has been scaled to measure 227 × 227 × 3. The two datasets collected comprise image samples of individual bananas and the other featuring bunches of bananas. As shown in Table 1, the images of banana fruits are divided into three stages for example, overripe, ripe, and unripe. 687 samples in all, 114 in each category under investigation. The visual characteristics of the banana fruit at different ripeness stages is illustrated in Table 1 and Table 2.

TABLE I. Key visual characteristics of Banana fruit at different ripening stages

Ripening Stage	Description
Unripe	Green Skin Yellow Stripe
Ripe	Green Skin with a well-defined yellow stripe
Over ripe	Yellow in colour and may or may not have presence of small light green areas

TABLE II. Image samples of Banana fruit at different ripeness stages

Stages	Sample 1	Sample 2	Sample 3	Sample 4
Unripe	 (a)	 (b)	 (c)	 (d)
Ripen	 (e)	 (f)	 (g)	 (h)
Over Ripen	 (i)	 (j)	 (k)	 (l)

IV. Methodology

The proposed method intends to project the significance of deep learning models in classifying the ripening stages of Banana Fruit. Two deep learning models such as InceptionV3 and VGG19 are employed to evaluate the suitable model. Initially, the preprocessing techniques used that includes normalization and augmentation to standardize image quality and enhance the models' ability to recognize patterns. Then, the deep learning models, VGG19 and InceptionV3 are subjected to fine-tuning hyperparameters and leveraging transfer learning for efficient training.

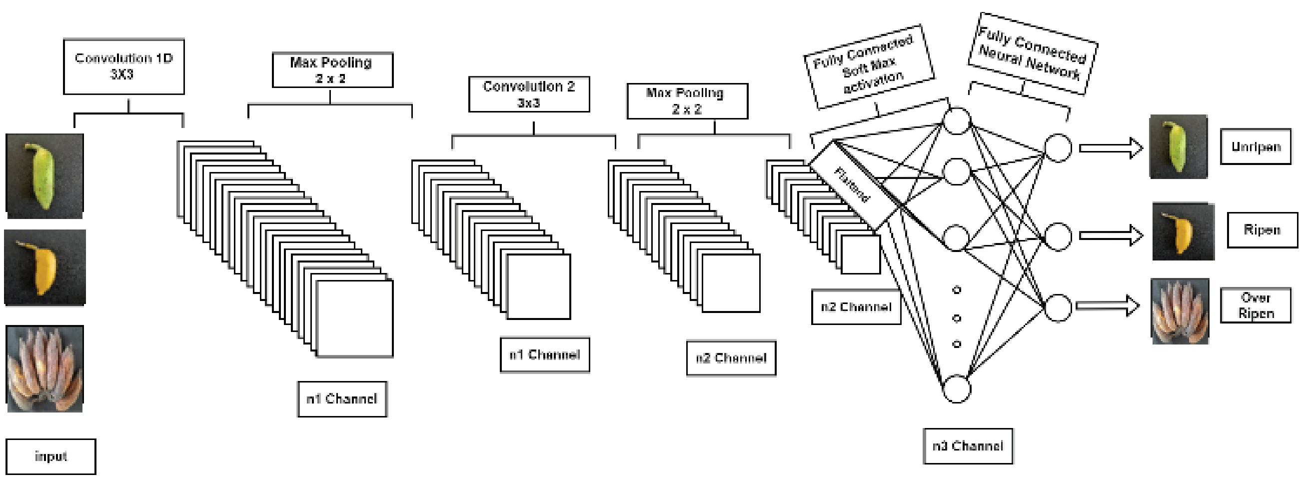


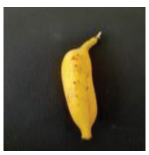
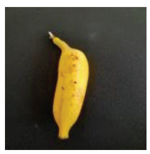
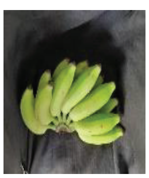
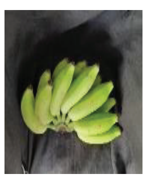
Fig. 1. Architecture diagram of the proposed model

Finally, the validation is carried out to evaluate the performance of two deep learning models. The experiments are evaluated using the self-created dataset that consists of individual bananas and bunches of banana image samples of different ripening stages. 80% of the total image samples were utilized for model training, and the remaining 20% were used for model testing [18]. In Figure 1, the suggested workflow paradigm is displayed.

A. Preprocessing

Basic image preprocessing is applied before inputting the images into the VGG19 and InceptionV3 models for classification. The original images are subjected to resizing to a consistent size of 255x255 pixels. The scaling procedure is critical since it ensures images supplied into the models have the same dimensions, which is required by most convolutional neural networks. Further, color representations are adapted which is a crucial characteristic in training deep learning models. Inception V3 requires BGR (Blue-Green-Red) color space, whereas VGG19 prefers RGB (Red-Green-Blue). To meet the needs of each model, the images were transformed into the correct color space[22]. This conversion provided model compatibility and allowed for more accurate feature extraction during categorization. This conversion is crucial because it influences how the model learns from images and improves model efficacy and accuracy.

TABLE III. SAMPLE OF ORIGINAL AND AUGMENTED IMAGES

Original image	Rotate	Flip	Zoom
 (a)	 (b)	 (c)	 (d)
 (e)	 (f)	 (g)	 (h)
 (i)	 (j)	 (k)	 (l)
 (m)	 (n)	 (o)	 (p)

Augmentation is a method commonly used to artificially expand a dataset by applying various transformations to the original images, thereby introducing diversity and improving the model's robustness. Table 3 provides detailed information on the original dataset and the augmented dataset post-transformation of the two datasets. In the proposed work, basic image augmentation such as rotate, flip and zoom are applied. The original images are rotated 180 degrees in a clockwise, vertical flipped and the images are enlarged by performing the crop operations.

B. VGG 19

VGG19 is a convolutional neural network (CNN) architecture that belongs to the Visual Geometry Group (VGG) family. Specifically, VGG19 consists of 16 convolutional layers organized into five convolutional blocks, each followed by max-pooling layers. All convolutional layers in the model use 3x3 filters, and as one moves further into the network, the number of filters rises to 512 in the final layers. VGG19 has three fully connected layers with 4096 neurons each after the convolutional blocks., followed by an output layer with 1000 neurons for class probabilities. VGG19 is known for its ability to learn hierarchical features, leveraging its architecture's depth and simplicity. The model is effective in capturing intricate patterns and variation in datasets, making it a valuable tool in various applications, including image classification tasks.

C. Inception V3

Inception V3 is a convolutional neural network (CNN) model recognized for its advanced architecture with inception modules designed for parallel feature processing at different scales. The model pre-processes images by resizing them to a consistent size of 299x299 pixels and adjusting colour representation to meet InceptionV3's requirements. Transfer learning is implemented by fine-tuning pre-trained InceptionV3 models on datasets like ImageNet, allowing the model to inherit knowledge and features. Hyperparameter tuning experiments optimize configurations, adjusting parameters like learning rate and batch size. Using an independent testing set, evaluation metrics such as accuracy, precision, recall, and F1 score are applied to provide a thorough assessment of the model's performance in accurately classifying banana ripening stages. Overall, InceptionV3 efficiently processes diverse features, contributing valuable insights for applications in agriculture and food industry.

D. Model Trainning and Validatation

We employed transfer learning techniques as a cornerstone for training the VGG19 and InceptionV3 models on the pre-processed banana ripening dataset. This approach allowed the models to inherit knowledge and features learned from diverse image data, providing a powerful starting point for our task. During training, fine-tuning the model parameters using gradient descent-based optimization algorithms is done ensuring that the models adapted to the unique characteristics of our dataset. Continuous monitoring of performance metrics such as accuracy, loss, and validation error guided the optimization process, allowing us to strike a balance between model convergence and avoidance of overfitting. The utilization of transfer learning not only expedited the training process but also enhanced the models' ability to discover new patterns in banana ripening stages, contributing to the development of accurate and efficient classification models.

E. Hyperparameter Tunning

In the pursuit of enhancing model performance, our research incorporated extensive hyperparameter tuning experiments aimed at optimizing the configuration of the VGG19 and InceptionV3 models. The learning rate, batch size, and regularization strategies were the critical parameters that are fine-tuned to optimize classification accuracy while reducing overfitting on the validation set. A key hyperparameter, the learning rate, was adjusted to balance the stability and speed of the model's convergence, ensuring efficient training without compromising generalization. Batch size adjustments were made to optimize memory usage and computational efficiency during training. Through an iterative process of experimentation and validation, hyperparameter configurations yielded the most robust and well-generalized models for accurate banana ripening stage classification.

F. *Model Evaluatation and validatation*

After training, VGG19 and InceptionV3 models are evaluated using an independent test set. The assessment criteria, such as classification accuracy, offered a reliable way to categorize banana ripening stages. This quantitative analysis enabled us to assess overall performance and identify individual strengths and predictions in addition to quantitative assessments. This qualitative examination sought to find misclassifications that quantitative measurements alone could not completely represent. By evaluations, it results a significant recommendation for further refining and optimization of banana ripening categorization models. Table 4 provides of validation results of deep learning models.

V. RESULTS AND DISCUSSIONS

In the study conducted with InceptionV3 and VGG19, models were trained using the Adam optimizer with a learning rate set to 0.001. The sparse categorical cross-entropy loss function was employed, suitable for scenarios where the labels are integers. The training process for both models involved 20 epochs, representing 20 complete passes through the entire dataset. Additionally, early stopping was not explicitly mentioned, but it can be a valuable regularization technique to monitor the validation loss and prevent overfitting. The choice of Adam optimizer, sparse categorical cross-entropy loss, and a modest learning rate align with common practices in deep learning, aiming to strike a balance between efficient optimization and effective generalization across diverse classes or categories[9].

The VGG19 model attained an accuracy of 98.1%, where the model classifies 98% of single images and 98.2% for bunch images, while the InceptionV3 model demonstrated performance with an accuracy of 97.5%. InceptionV3 classifies 97.4% for single banana datasets and 97.6% for bunch datasets. These accuracy illustrate the models ability to categorize instances in the dataset, performance of the selected architectures, optimization method, and hyperparameters were able to extract and extract pertinent characteristics from the input data. The accuracy of the models was determined using eq (1).

$$\text{Accuracy} = ((TP+TN+FP))/\text{Total samples} \quad (1)$$

where,

TP = True Positive (correctly predicted class 1)

TN = True Negative (correctly predicted class 0)

FP = False positive (Incorrectly predicted class 1)

FN = False Negative (Incorrectly predicted class 0

A. *Visualizations*

Figure 2 represents the validation and training accuracy of VGG19 and InceptionV3 models. Performance is evaluated for 20 epochs, in the initial epochs the accuracy ranges from 85% to 95%. Through the multiple runs the models depicted the highest accuracy of 98.1% for VGG19 and accuracy 97.5% for InceptionV3 models.

Fig. 2. Training vs Validatation accuracy graph for VGG19 and InceptionV3

The VGG19 model demonstrates its highest validity at 84.8%, with a peak accuracy of 98.1%.

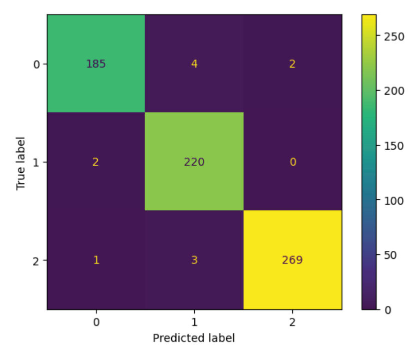


Fig. 3. Confusion Matrix for VGG19 Model

In the confusion matrix of the VGG19 model, it was observed that 674 images were correctly classified, while the remaining 12 images were misclassified.

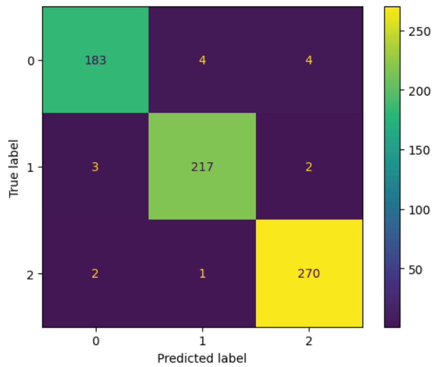
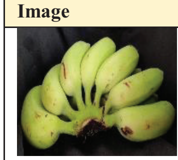
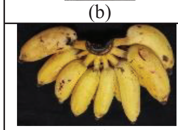


Fig. 4. Confusion matrix for InceptionV3

In the confusion matrix of the InceptionV3 model, it was observed that 670 images were correctly classified and 16 were misclassified.

TABLE IV. VALIDATION RESULTS

Image	**Validation Results**
 (a)	The predicted class is Golden_finger_stage_1
 (b)	The predicted class is Golden_finger_stage_3
 (c)	The predicted class is Golden_finger_stage_2
 (d)	The predicted class is Golden_finger_stage_3
 (e)	The predicted class is Golden_finger_stage_2
 (f)	The predicted class is Golden_finger_stage_1

B. Validatation

Validation is a way of evaluating a trained model's effectiveness on an unseen set of images that was not utilized during training. The model picks the random samples from the test images and predicts the image category by the knowledge learned during training. This technique aids in understanding the model's ability to generalize its learning to new, previously unknown data. It is a critical stage in determining the efficacy of deep-learning models. Table 4 describes the validation results for the datasets for the model VGG19 and InceptionV3.

VI. CONCLUSION

In conclusion, the study employing InceptionV3 and VGG19 models achieved a successful three-stage classification system, accurately distinguishing between unripe, ripened, and over-ripen states. The models demonstrated high accuracies of 98.1% for VGG19 and 97.5% for InceptionV3. This robust classification system holds promise for practical applications, particularly in agricultural automation and monitoring. The success of this study opens avenues for future work, with potential applications in areas such as robotic harvesting and real-time agricultural monitoring. The selected architectures and optimization strategies underscore the model's effectiveness in capturing and learning pertinent features of the image samples.

REFERENCES

[1] Rybacki P, Niemann J, Derouiche S, Chetehouna S, Boulaares I, Seghir NM, Diatta J, Osuch A. Convolutional Neural Network (CNN) Model for the Classification of Varieties of Date Palm Fruits (Phoenix dactylifera L.). Sensors. 2024; 24(2):558. https://doi.org/10.3390/s24020558.

[2] Baglat P, Hayat A, Mendonça F, Gupta A, Mostafa SS, Morgado-Dias F. Non-Destructive Banana Ripeness Detection Using Shallow and Deep Learning: A Systematic Review. Sensors. 2023; 23(2):738. https://doi.org/10.3390/s23020738

[3] Nayak, R., & Manohar, N. (2021, July). Computer-Vision based face mask detection using CNN. In 2021 6th international conference on communication and electronics systems (ICCES) (pp. 1780-1786). IEEE.

[4] Kaur, P., & Gosain, A. (2022). Issues and challenges of class imbalance problem in classification. International Journal of Information Technology, 14(1), 539-545.

[5] Rajesh, J., et al. "Application of Fuzzy Logic in Smart Agriculture to Recognise Tomato Fruit Ripeness," IJFANS International Journal of Food and Nutritional Sciences, vol. 11, no. 1, 2022.

[6] Nassiri, Seyed Mehdi, Amir Tahavoor, and Abdolabbas Jafari. "Fuzzy logic classification of mature tomatoes based on physical properties fusion." Information Processing in Agriculture 9.4 (2022): 547-555.

[7] Aherwadi, N. G., Mittal, U., Singla, J., & Hossain, M. S. (2022). Prediction of Fruit Maturity, Quality, and Its Life Using Deep Learning Algorithms. MDPI Electronics, 11(12), 1948

[8] Araujo, Matheus T., et al. "Banana Ripening Classification Using Computer Vision: Preliminary Results." International Conference on Systems, Signals and Image Processing. Cham: Springer International Publishing, 2021

[9] Zeeshan, M., Prabhu, A., Arun, C., & Rani, N. S. (2020, July). Fruit classification system using multiclass support vector machine classifier. In 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC) (pp. 289-294). IEEE.

[10] Hamza, Raja, and Mohamed Chtourou. "Design of fuzzy inference system for apple ripeness estimation using gradient method." IET Image Processing 14.3 (2020): 561-569.

[11] Azarmdel, H., Jahanbakhshi, A., Mohtasebi, S. S., & Muñoz, A. R. (2020). Evaluation of image processing technique as an expert system in mulberry fruit grading based on ripeness level using artificial neural networks (ANNs) and support vector machine (SVM). Postharvest Biology and Technology, 166, 111201

[12] H. Altaheri, M. Alsulaiman and G. Muhammad, "Date Fruit Classification for Robotic Harvesting in a Natural Environment Using Deep Learning," in IEEE Access, vol. 7, pp. 117115-117133, 2019, doi: 10.1109/ACCESS.2019.2936536.

[13] Jain, R., Kingsly, I., Chand, R., Raju, S. S., Srivastava, S. K., Kaur, A. P., & Singh, J. (2019). Methodology for region level optimum crop plan. International Journal of Information Technology, 11, 619-624.

[14] Nair, B. B., Akash, S., Smaran, R., Hemanth, V., & Bhat, S. (2022, July). Stage Wise Prediction of Covid-19 Pneumonia from CT images using VGG-16 and SVM. In 2022 International Conference on Inventive Computation Technologies (ICICT) (pp. 457-463). IEEE.

[15] Villaseñor-Aguilar, Marcos J., et al. "Fuzzy classification of the maturity of the tomato using a vision system." Journal of Sensors 2019 (2019).

[16] Peng, H., Shao, Y., Chen, K., Deng, Y., Xue, C., 2018. Research on Multi-class Fruit Recognition Based on Machine Vision and SVM. IFAC-PapersOnLine 51 (17), 817–821. https://doi.org/10.1016/j.ifacol.2018.08.094.

[17] Nashwa El-Bendary, Esraa El Hariri, Aboul Ella Hassanien, Amr Badr,Using machine learning techniques for evaluating tomato ripeness, Expert Systems with Applications, Volume 42, Issue 4,2015,Pages 1892-1905,ISSN 0957-4174,https://doi.org/10.1016/j.eswa.2014.09.057.

[18] Dong Zhang, Dah-Jye Lee, Beau J. Tippetts, Kirt D. Lillywhite,Date maturity and quality evaluation using color distribution analysis and back projection,Journal of Food Engineering,Volume 131,2014,Pages 161-169,ISSN 0260-8774,https://doi.org/10.1016/j.jfoodeng.2014.02.002.

[19] Surya Prabha, D., and J. Satheesh Kumar. "Assessment of banana fruit maturity by image processing technique." Journal of food science and technology 52 (2015): 1316-1327.

[20] B. Van de Poel, I. Bulens, M.L.A.T.M. Hertog, L. Van Gastel, M.P. De Proft, B.M. Nicolai, A.H. Geeraerd,Model-based classification of tomato fruit development and ripening related to physiological maturity,Postharvest Biology and Technology, vol. 67, pp. 59-67, 2012.

[21] M. Zeeshan, A. Prabhu, A. C and N. S. Rani, "Fruit Classification System Using Multiclass Support Vector Machine Classifier," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 289-294, doi: 10.1109/ICESC48915.2020.9155817.

[22] Pushpa, B. R., AV, S. H., & Ashok, A. (2021, July). Diseased leaf segmentation from complex background using indices based histogram. In 2021 6th International Conference on Communication and Electronics Systems (ICCES) (pp. 1502-1507). IEEE.

[23] Dasari, S. K., & Prasad, V. (2019). A novel and proposed comprehensive methodology using deep convolutional neural networks for flue cured tobacco leaves classification. International Journal of Information Technology, 11, 107-117.

[24] Puri, D., Kumar, A., Virmani, J., & Kriti. (2019). Classification of leaves of medicinal plants using laws' texture features. International Journal of Information Technology, 1-12.

[25] Saxena, A. K. (2013). On the Importance of Ensembles of Classifiers. BVICAM's International Journal of Information Technology (BIJIT), 5(1), 569-576.