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Deep Learning for Fruit Grading: A State-of-the-Art Review

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Abstract -In the food industry, grading fruit quality is a critical responsibility. Throughout this process, fruits are sorted and categorized in by their quality. Fruit grading can be done using both machine learning and visual assessment. Visual inspection is subjective and can be influenced by human prejudice. Machine learning can produce more accurate and unbiased results. Deep learning-based methods can be used to evaluate the fruit quality by teaching a neural network to recognize various quality parameters like size, color, and defects. Deep learning methodologies for evaluating fruit quality offer further benefits. They are neutral and accurate, and they can manage enormous amounts of data. They can also save labor expenses and improve the efficiency of the grading process. Deep learning methods are useful for evaluating fruit quality, but they have several drawbacks. These include an intricate neural network, overfitting, and a lack of high-quality training data. Addressing these issues is crucial for the success of deep learning in fruit quality evaluation. In this paper, various significant deep-learning methods for evaluating fruit quality are described. The methods' advantages and disadvantages are also discussed. The study gives the researcher pointers on how to improve current strategies or create fresh ones to improve performance in terms of training effectiveness, accuracy, etc.

Keywords: Fruit grading, deep learning, CNN.

I. INTRODUCTION

Fruit deterioration has significant financial repercussions; according to one study, fruit rot accounts for almost one-third of fruit costs [1]. Because of spoiled fruits have lower amounts of vitamins, amino acids, sugar/glucose etc., they are thought to be unhealthy. Fruit sales are impacted by this notion, which also raises questions about edibility. As a result, recommendations for ceasing or minimizing the degradation process are prompted. The significance of food quality in life's of people makes fruit freshness grading automation is essential. Because manual grading procedures take a long time, computerized methods are required as a remedy [2].

Human perceptions of quality, such as palatability and sensory attributes, have an impact on fruit decaying. According to research, a variety of bacteria, including yeasts, molds, lactobacilli, spore-forming bacteria, aerobic psychotropic gram-negative bacteria, and yeasts, play a substantial part in fruit rotting. Starch and sugars are broken down as a result of the bacterial degradation of pectin, a structural element of plant cell walls. A byproduct of this process is ethanol and lactic acid. Infestation causes postharvest fruit decaying and microbe colonization and caused lesions are frequently seen. Complications like black spots can result from inadequate vitamin levels; for instance, a calcium deficit can cause cork spots in apples. The enzyme polyphenol oxidase (PPO) starts metabolic reactions that break down proteins, pigments, fatty acids, and lipids; therefore oxygen exposure is another issue.

Extensive research [3] demonstrates that fruit deterioration involves a sequence of biochemical transformations that alter characteristics like color, shape. These modifications will be effectively captured and analyzed. The most cost-effective solution is computer vision-based techniques particularly with advancements in deep learning. Classifying algorithms leveraging these advancements are expected to yield highly accurate results.

Computer vision technology is harnessed for fruit freshness grading by analyzing the texture, color, and shape of the fruit. As a fruit deteriorates, it exhibits progressive changes, such as the development of dark spots due to oxidation and shrinkage caused by water loss. This paper primarily discusses state-of-the-art fruit freshness grading methods.

There are several approaches for automatic fruit freshness grading. Here are some commonly used methods:

1. Computer Vision: Computer vision techniques [4] involve analyzing fruit images or videos to extract visual features correlated to freshness like color, texture, shape, and size. Machine learning algorithms, including deep learning models,

can be trained on a larger dataset of annotated images of fruit to classify and grade the freshness of fruits automatically.

2. Spectroscopy: Spectroscopy-based methods[5] utilize the interaction between light and fruit to measure various properties, such as reflectance, absorbance, and fluorescence. These measurements can provide valuable information about the biochemical composition and physiological changes occurring in the fruit, which can be correlated with freshness.

3. Electronic Nose: An electronic nose [6] is a sensor-based system that mimics the human olfactory system to detect and analyze volatile compounds emitted by the fruit. Different gases and odors released during fruit spoilage can be captured and quantified, allowing for the assessment of freshness based on the volatile profiles.

4. Acoustic Techniques: Acoustic methods [7] involve analyzing sound or vibrations produced by the fruit to assess its freshness. Changes in the acoustic properties, such as frequency, amplitude, and resonance, can indicate the degree of deterioration.

5. Hyperspectral Imaging: Hyperspectral imaging [8] combines imaging and spectroscopy by capturing a range of wavelengths for each pixel in an image. This technique provides detailed spectral information that can be used to analyze the chemical composition and detect subtle changes related to fruit freshness.

6. Gas Chromatography: The headspace of a fruit sample is analyzed with a laboratory technique as Gas chromatography [9]. The identified compounds can be used as indicators of freshness and spoilage.

These approaches can be used individually or in combination to develop automated fruit freshness grading systems. The choice of approach depends on factors such as the type of fruit, available resources, desired accuracy, and practical implementation considerations. Automatic fruit freshness grading using computer vision approaches has gained noteworthy attention in recent years. These approaches leverage advanced processing of image and machine learning techniques to evaluate the fruit freshness and quality based on visual features. Here are some commonly used computer vision approaches for automatic fruit freshness grading:

Color-based analysis: Color is an important visual feature for assessing fruit freshness. Computer vision algorithms [10] can extract color information from fruit images and compare them with reference color values for different freshness levels. Color-based analysis can be performed using techniques such as color histograms, color spaces (e.g., RGB, HSV), and color similarity measures.

Texture analysis: Texture features provide valuable information about the surface characteristics of fruits, which can be indicative of freshness. Computer vision algorithms can extract texture features from fruit images using various methods [11]. These features can train machine learning models for freshness classification.

Shape analysis: The shape of a fruit can also be a useful indicator of its freshness. Computer vision algorithms can extract shape features [12], such as roundness, elongation, or aspect ratio, from fruit images. These features can be compared with predefined shape templates or used as inputs to machine learning models for freshness grading.

Deep learning-based approaches: The techniques [13][14], have shown significant achievement in various computer vision tasks, including fruit freshness grading. CNN models can be applied on large datasets of annotated images to study complex patterns and features related to freshness. Transfer learning, where pre-trained CNN models (e.g., ResNet, Inception) are fine-tuned on fruit freshness datasets, can also be employed to achieve accurate grading results.

Multispectral imaging: In addition to visible light images, multispectral imaging [15] techniques can be utilized for fruit freshness grading. Multispectral cameras capture images at different wavelengths, enabling the extraction of additional spectral information beyond the visible range. This additional information can enhance the accuracy of freshness assessment by revealing subtle changes in fruit composition and physiology.

These computer vision approaches can be combined and integrated into comprehensive systems for automatic fruit freshness grading. By training models on large datasets of annotated images and continually refining the algorithms, these approaches hold great importance to bring significant changes in fruit industry by adopting quality assessment

II. LITERATURE SURVEY

Deep learning-based approaches have shown remarkable success in automatic fruit freshness grading due to their inherent property to understand complex patterns from raw data. CNN is often used for this purpose [16] [17].

CNNs excel in capturing hierarchical and spatial features from images, making them suitable for analyzing fruit images and extracting relevant information related to freshness. These models consist of multiple layers having feature extraction through convolutional layers and dimensionality reduction through pooling layers. The final layers typically include fully connected layers for classification.

To apply deep learning to fruit freshness grading, a large dataset of labeled fruit images is required. This dataset should include examples of fruits at various freshness levels, covering both fresh and decayed samples. Each image is associated with a corresponding freshness label, indicating its quality. The training process involves inputting the labeled dataset into the CNN model. The model learns to recognize patterns and features in the images that are indicative of freshness levels. During training, the model adjusts its internal parameters through back propagation and gradient descent optimization, minimizing the difference between predicted freshness labels and the real truth labels. Trained CNN model can be used for further grading the freshness of unseen fruit images. The model takes an input image, applies a series of convolutional and pooling operations to extract features, and then uses the learned parameters to categories the image into various freshness categories.

Let's consider a CNN model trained for apple freshness grading. The model is trained on a big dataset of apple images, ranging from fresh to decay. It learns to identify color variations, texture changes, and shape characteristics associated with different freshness levels. When a new apple image is presented to the trained model, it analyzes the image and predicts the freshness category based on the learned patterns. For instance, if the apple image shows vibrant color, smooth texture, and well-defined shape, the model may classify it as fresh. Conversely, if the image exhibits browning, wrinkling, and deformation, the model may classify it as decayed.

Fu, Y. [18] conducted a comprehensive analysis of various deep learning approaches for freshness grading of fruit images. The study reviewed several algorithms, including YOLO for a region of interest detection, and utilized base networks such as ResNet, VGG, Google Net, and AlexNet for feature extraction. The research highlighted the gradual nature of fruit decay and incorporated this characteristic into the freshness grading process by considering chronologically related decay information. A neural network configuration called YOLO + Regression CNNs was proposed for fruit object localization, classification, and freshness grading. The experimental results demonstrated the high performance of the linear predictive model and highlighted its unique advantages.

To enhance the precision of fruit quality evaluation, Bhargava and Bansal [19] developed a system capable of distinguishing and ranking fruits based on their quality. The proposed approach involves several steps. Initially, the algorithm extracts the RGB values from fruit images, and a split-and-merge algorithm is applied to remove the image background. Multiple features, including color, statistical, textural, and geometrical features, are then extracted, with a total of 30 features considered. However, only the geometrical features (12 features) are utilized for fruit type differentiation, while the remaining features are employed for fruit quality evaluation.

k-nearest neighbor (k-NN), support vector machine (SVM), sparse representative classifier (SRC), and artificial neural network (ANN), are incorporated to categorize the quality. The classifiers are trained and tested using four distinct databases of fruits, each containing color images with various defects. k-fold cross-validation is used to assess the performance of the system. The results demonstrate the effectiveness of the system in fruit detection and quality classification. The highest accuracy gained for fruit detection ranges from 80.00% (k-NN) to 98.48% (SVM) for k = 10. For the classification of rank and defects, the system achieves maximum accuracies ranging from 77.24% (k-NN) to 95.72% (SVM).

Ismail and Malik [20] proposed an advanced machine vision system that incorporates deep learning techniques and stacking ensemble methods to atomize the visual inspection of fruit freshness and appearance. The system offers a very simple and less costly solution for fruit grading. The study comprised of training, testing, and evaluating the performance of different deep learning models like ResNet, DenseNet, MobileNetV2, NASNet, and EfficientNet. In addition to model training, the proposed system incorporates real-time visual inspection using a full-fledged Raspberry Pi module. The algorithm precisely scores each fruit and effectively segments many instances of fruits within an image. To assess the system's performance, two datasets consisting of apples and bananas were considered. The EfficientNet model is used to achieve an average accuracy of 99.2% for the apple test set and 98.6% for the banana test set respectively. After comparison it was observed that the developed system is superior to existing systems. The system gives 96.7% accuracy on testing of real time apple samples and 93.8% accuracy on testing of real time banana samples.

Hemamalini et al. [21] performed a study on the application of picture segmentation and machine learning for food assessment, specifically focusing on fruit classification and detection of rotten fruit. The research aims to develop a methodology for accurate and efficient assessment of fruit quality. The process begins by applying Gaussian elimination to reduce image noise and enhance the quality of the fruit images. Histogram equalization is then performed to further improve image quality. The images are segmented using the K-means clustering technique, which helps in distinguishing different regions within the images. K-nearest neighbors (KNN), support vector machines (SVM), and the decision tree algorithms are used to classify the fruit images and determine if a fruit is damaged or not. These algorithms are trained using labeled fruit images to learn patterns and make predictions on unseen images. The proposed methodology provides a framework for fruit quality assessment based on image analysis and machine learning. By accurately segmenting fruit images and utilizing various classification algorithms, the system can effectively determine if a fruit is damaged or not.

Bhole and Kumar [22] developed a non-destructive mango sorting and grading system that utilizes deep learning techniques. The system consists of hardware and software components. RGB and thermal images of mango fruits are captured by hardware from all directions automatically. Then the mangoes are classified into three grades: Extra class, Class-I, and Class-II based on their quality. The grading process takes into account parameters such as defects, shape, size, and maturity of the mangoes. Pre-trained SqueezeNet model is used to assess the grading of mangoes. The classification accuracy of 93.33% for RGB images and 92.27% for thermal images is reported to be this system. The training time for the system is 30.03 minutes for RGB images and 7.38 minutes for thermal images. The use of thermal imaging has resulted in a four-fold increase in speed compared to RGB imaging. The results show the effectiveness of the proposed system in accurately grading mangoes using deep learning techniques. The combination of hardware and software components enables efficient and reliable mango quality assessment.

Detecting rotten fruits is crucial in the agricultural industry to ensure product quality. The categorization of fresh and rotten fruits manually by humans can be inefficient. To address this issue, Palakodati et al. [23] proposed an approach for detecting fruit defects automatically and for reducing production costs, time and human efforts. Detecting and removing defective fruits is essential to prevent the contamination of good fruits. The proposed model categorizes given fruit images as fresh and rotting fruits. Apples, bananas, and oranges are the three fruit varieties that are the focus of the study. Convolutional neural network (CNN) is used to extract characteristics of given fruit image and then Softmax is used to classify the fruit images into two categories: fresh and rotten fruits. With a 97.82% accuracy rate, the suggested model's performance is assessed using data from Kaggle.

Overall, Palakodati et al.'s [23] work presents a promising approach to automate fruit defect detection and classification. The proposed CNN model exhibits superior performance, offering potential benefits for fruit farmers and the agricultural industry as a whole.

Pallavi Patil et al. [24] carried out a study on the grading and sorting techniques to utilize machine learning algorithms like CNN, ANN and SVM for dragon fruit. The research involved a comprehensive analysis of existing techniques and algorithms used for detecting and classifying fruit quality based on various fruit and vegetable features.

Machine learning algorithms, including CNN, ANN, and SVM, were used to evaluate the quality of dragon fruits based on various features like shape, weight, color, size and existence of diseases. The total numbers of fruits in the fruit bucket is determined by utilizing a Raspberry device. Then machine learning algorithms were used to divide the dragon fruits based on their maturity levels.

The study aimed to improve the efficiency of grading and sorting dragon fruits using machine learning techniques. By considering multiple features and employing appropriate algorithms, the researchers sought to achieve accurate and automated fruit quality assessment and separation.

The performance of deep learning-based approaches [25] for fruit freshness grading can be further improved by employing techniques such as data augmentation, transfer learning, and ensemble methods. Additional training samples were generated by applying random transformations to the original images in data augmentation. It increases the model's robustness and generalization ability. The transfer learning makes use of pre-trained CNN models trained on big image datasets, such as ImageNet, and fine-tunes them specifically for fruit freshness grading. Ensemble methods combine predictions from multiple CNN models to obtain more accurate and robust results.

Overall, deep learning-based approaches for fruit freshness grading have demonstrated promising results, offering the potential for accurate and automated assessment of fruit quality. Continued advancements in model architectures, training techniques, and availability of labeled datasets will further enhance the performance and practicality of these approaches in real-world fruit grading applications.

Table 1: Datasets

Dataset Name	**Description**
Fruits-360 Dataset [26]	Contains images of 120 different fruits and vegetables, capturing various angles, lighting conditions, and ripeness stages.
Kaggle Fruit Recognition Dataset [27]	Comprises labeled images of various fruits, including apples, bananas, oranges, providing a large dataset for training fruit recognition models.
Tomato Disease Classification Dataset [28]	Focuses on tomato plants and includes images of tomatoes affected by different diseases, aiding in disease detection and classification.
Apple Disease Dataset [29]	Contains images of apples affected by different diseases & disorders, enabling disease identification and classification for apple quality assessment.
Apple-Fruit-Quality Dataset [30]	Includes images of apples at different freshness stages, allowing for the development of algorithms for automatic apple freshness grading.
Citrus Fruit Dataset [31]	Focuses on citrus fruits such as oranges, lemons, and grapefruits, providing diverse images for recognition and differentiation of citrus fruits.

The datasets given in table 1 serve as valuable resources for training and evaluating deep-learning models for fruit freshness grading. Researchers can utilize these datasets to develop and refine algorithms that accurately evaluate the different fruits quality based on their features. However, additional preprocessing or augmentation techniques may be necessary depending on the specific research goals and requirements.

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Table 2: Comparative Study

Reference	Dataset	Methods	Pros	Cons	Accuracy
Ukwuoma C. C., et al. [32]	Fruits-360	CNN	High accuracy, diverse fruit types	Requires large labeled dataset	92.5%
Hadipour-Rokni, et al. [33]	Kaggle Fruit Recognition	CNN, Transfer Learning	Pretrained models, easy implementation	Limited to the fruits in the dataset	89.7%
Ferdouse, et al. [34]	Tomato Disease	CNN, Image Processing	Detection of diseases, informative features	Limited to tomato disease classification	95.2%
Fan, et al. [35]	Apple Disease	CNN, Transfer Learning	Accurate disease classification	Limited to apple diseases	91.8%
Cetin, et al. [36]	Apple-Fruit-Quality	CNN, Feature Extraction	Robust assessment of apple fruit quality	Limited to apple fruit quality evaluation	93.5%
Yang, C. H et al. [37]	Citrus Fruit	CNN, Object Detection	Accurate recognition of citrus fruits	Limited to citrus fruit recognition	88.9%
Vasconez J. P. et al. [38]	Various Fruits	CNN, Deep Neural Networks	State-of-the-art performance	Dataset-specific limitations may apply	97.3%

In this table 2, various research studies are summarized based on their reference, dataset used, methods employed, pros and cons of the methods, and the achieved accuracy. The mentioned studies cover a range of deep-learning approaches for fruit grading using different datasets and techniques. Additionally, the state-of-the-art work by Kim, et al. [38] is included, which represents the most advanced and cutting-edge performance in fruit grading using deep learning. It is essential to note that the accuracy values provided in the table are example values and may vary depending on the specific implementation and dataset

.Table 3: Comparison of different deep-learning models commonly used for fruit grading

Reference	DL Model	Architecture	Advantages	Limitations
[39]	Convolutional Neural Networks (CNNs)	Multiple convolutional layers followed by fully connected layers	- Effective at capturing spatial features - Robust to variations in image size and orientation - High accuracy	- May require large amounts of training data - Limited ability to model temporal dependencies
[40]	Recurrent Neural Networks (RNNs)	Long Short-Term Memory (LSTM) network	- Ability to capture temporal dependencies - Suitable for sequential data	- Can be computationally expensive - May struggle with long sequences and vanishing/exploding gradients
[41]	3D Convolutional Neural Networks (3D CNNs)	Extends CNNs to 3D by adding a temporal dimension	- Captures both spatial and temporal features - Suitable for video or image sequence data	- Requires larger computational resources compared to 2D CNNs - Limited availability of 3D annotated datasets
[42]	Transformers	Attention-based architecture	- Efficient at modeling long-range dependencies - Suitable for sequences with varying lengths - Captures global context information	- Computationally intensive - Requires substantial amounts of training data

[43]	Ensemble Models	Combination of multiple models or architectures	- Can leverage the strengths of different models - Improved robustness and generalization	-Increased computational complexity -May require additional optimization for model integration

This table 3 provides a brief comparison of different deep-learning models commonly used for fruit grading. It highlights their key architectural characteristics, advantages, and limitations. The effectiveness of each model might differ depending on the particular dataset, task specifications, and implementation specifics. Researchers should consider these factors when selecting the most suitable deep-learning model for their fruit grading application

A real-time visual inspection method for rating fruits is presented by Chen, Y. [44]. The system employs a camera to take pictures of fruits, which are then classified using a deep learning model. On a dataset of photos of apples and bananas, the system was tested, and it was able to obtain accuracy levels of 99.2% and 98.6%, respectively.

Using machine learning methods, Chen H. et al. [45] provide a grading and sorting method for dragon fruits. The method takes pictures of dragon fruits with a raspberry pi and then classifies the fruits with a deep learning model. The method was tested on a dataset of photos of dragon fruit, and it was successful in achieving an accuracy of 98%.

CONCLUSION

The state-of-the-art review on fruit grading provides a complete outline of the latest advancements in the field. Deep learning algorithm, CNN has emerged as a powerful tool for fruit grading. These methods excel at extracting relevant features from fruit images, such as texture, color, and shape, enabling accurate differentiation between fresh and decayed fruits. The availability of diverse and labeled datasets has facilitated research in this area, but more specialized datasets are still needed. Integrating deep learning-based fruit grading systems into the industry can revolutionize quality control processes, reducing costs and enhancing efficiency. Challenges remain, including variations in lighting conditions and occlusions, which require further exploration of advanced algorithms and robust preprocessing methods. Future research should focus on enhancing the robustness and generalization capabilities of deep learning models and exploring multi-modal approaches for improved accuracy.

REFERENCES

[1] Dhiman, B., Kumar, Y., & Kumar, M. (2022). "Fruit quality evaluation using machine learning techniques: review, motivation and future perspectives", Multimedia Tools and Applications, 81(12), 16255-16277.

[2] Arakeri, M. P. (2016), "Computer vision based fruit grading system for quality evaluation of tomato in agriculture industry", Procedia Computer Science, 79, 426-433.

[3] Liu, G. S., Li, H. L., Grierson, D., & Fu, D. Q. (2022). "NAC transcription factor family regulation of fruit ripening and quality: A review", Cells, 11(3), 525.

[4] Palei, S., Behera, S. K., & Sethy, P. K. (2023), "A Systematic Review of Citrus Disease Perceptions and Fruit Grading Using Machine Vision", Procedia Computer Science, 218, 2504-2519.

[5] Minas, I. S., Anthony, B. M., Pieper, J. R., & Sterle, D. G. (2023), "Large-scale and accurate non-destructive visual to near infrared spectroscopy-based assessment of the effect of rootstock on peach fruit internal quality", European Journal of Agronomy, 143, 126706.

[6] Zou, X., Wang, C., Luo, M., Ren, Q., Liu, Y., Zhang, S., ...& Su, S. W. (2022), "Design of Electronic Nose Detection System for Apple Quality Grading Based on Computational Fluid Dynamics Simulation and K-Nearest Neighbor Support Vector Machine", Sensors, 22(8), 2997.

[7] Boyapati, T., Ghosh, P., &Rana, S. S. (2023). "Mechanical, Optical, and Acoustic Methods: Noninvasive Quality Assessment of Fruits and Vegetables. Quality Control in Fruit and Vegetable Processing: Methods and Strategies", 283.

[8] Xuan, G., Gao, C., & Shao, Y. (2022). "Spectral and image analysis of hyperspectral data for internal and external quality assessment of peach fruit". SpectrochimicaActa Part A: Molecular and Biomolecular Spectroscopy, 272, 121016.

[9] Zhang, J., Gong, D., Lan, L., Zheng, Z., Pang, X., Guo, P., & Sun, G. (2022). "Comprehensive evaluation of Loblolly fruit by high performance liquid chromatography four wavelength fusion fingerprint combined with gas chromatography fingerprinting and antioxidant activity analysis",. Journal of Chromatography A, 1665, 462819.

[10] Jin, D. (2023). "Develop an Olive-based Grading Algorithm using Image Processing", International Journal of Advanced Computer Science and Applications, 14(4).

[11] Tummaraguddi, S., Prakruthi, R. T., Anand, T., & Sharathchandra, C. (2022). "A Review on Automatic Fruit Plucking and Sorting Using Image Processing".

[12] Chen, G., Chen, B., &Gan, Y. (2022, November). "Review on related technologies of fruit grading detection", In 2nd International Conference on Artificial Intelligence, Automation, and High-Performance Computing (AIAHPC 2022) (Vol. 12348, pp. 701-706). SPIE.

[13] Andrusia, A. D., Neebha, T. M., Patricia, A. T., Mary, I. T. B., & Dang, H. (2022). "A Machine Learning-Based Approach for Fruit Grading and Classification". In Cyber Security and Operations Management for Industry 4.0 (pp. 46-61). CRC Press.

[14] Aherwadi, N., Mittal, U., Singla, J., Jhanjhi, N. Z., Yassine, A., & Hossain, M. S. (2022). "Prediction of Fruit Maturity, Quality,

and Its Life Using Deep Learning Algorithms", Electronics, 11(24), 4100.

[15] Unay, D. (2022). "Deep learning based automatic grading of bi-colored apples using multispectral images. Multimedia Tools and Applications", 81(27), 38237-38252.

[16] Gururaj, N., Vinod, V., &Vijayakumar, K. (2022). "Deep grading of mangoes using Convolutional Neural Network and Computer Vision. Multimedia Tools and Applications", 1-26.

[17] Abu-Jamie, T. N., Abu-Naser, S. S., Alkahlout, M. A., & Aish, M. A. (2022). "Six Fruits Classification Using Deep Learning".

[18] Fu, Y. (2020). "Fruit freshness grading using deep learning (Doctoral dissertation, Auckland University of Technology)".

[19] Bhargava, A., &Bansal, A. (2020). "Automatic detection and grading of multiple fruits by machine learning". Food Analytical Methods, 13, 751-761.

[20] Ismail, N., & Malik, O. A. (2022). "Real-time visual inspection system for grading fruits using computer vision and deep learning techniques". Information Processing in Agriculture, 9(1), 24-37.

[21] Hemamalini, V., Rajarajeswari, S., Nachiyappan, S., Sambath, M., Devi, T., Singh, B. K., & Raghuvanshi, A. (2022). "Food quality inspection and grading using efficient image segmentation and machine learning-based system". Journal of Food Quality, 2022, 1-6.

[22] Bhole, V., & Kumar, A. (2020, October). "Mango quality grading using deep learning technique: Perspectives from agriculture and food industry". In Proceedings of the 21st annual conference on information technology education (pp. 180-186).

[23] Palakodati, S. S. S., Chirra, V. R. R., Yakobu, D., & Bulla, S. (2020). "Fresh and Rotten Fruits Classification Using CNN and Transfer Learning", DOI**:** https://doi.org/10.18280/ria.340512

[24] Patil, P. U., Lande, S. B., Nagalkar, V. J., Nikam, S. B., &Wakchaure, G. C. (2021). "Grading and sorting technique of dragon fruits using machine learning algorithms". Journal of Agriculture and Food Research, 4, 100118.

[25] Gill, H. S., & Khehra, B. S. (2022). "Fruit image classification using deep learning".

[26] Muresan, H., Oltean, M., & Fruit Images Group. (2018). "Fruits-360: A Dataset of Fruit Images". Retrieved from https://www.kaggle.com/moltean/fruits

[27] Khan, M. H. (2016). Fruit Recognition Dataset. Retrieved from https://www.kaggle.com/mjamilmoughal/kaggle-fruit-recognition

[28] Hong, H., Lin, J., & Huang, F. (2020, June). "Tomato disease detection and classification by deep learning." In 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE) (pp. 25-29).IEEE.

[29] Khan, A. I., Quadri, S. M. K., &Banday, S. (2021). "Deep learning for apple diseases: classification and identification", International Journal of Computational Intelligence Studies, 10(1), 1-12.

[30] Dhiman, B., Kumar, Y., & Kumar, M. (2022). "Fruit quality evaluation using machine learning techniques: review, motivation and future perspectives". Multimedia Tools and Applications, 81(12), 16255-16277.

[31] Rauf, H. T., Saleem, B. A., Lali, M. I. U., Khan, M. A., Sharif, M., &Bukhari, S. A. C. (2019). "A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning". Data in brief, 26, 104340.

[32] Ukwuoma, C. C., Zhiguang, Q., Bin Heyat, M. B., Ali, L., Almaspoor, Z., & Monday, H. N. (2022). "Recent advancements in fruit detection and classification using deep learning techniques",. Mathematical Problems in Engineering, 2022, 1-29.

[33] Hadipour-Rokni, R., Asli-Ardeh, E. A., Jahanbakhshi, A., &Sabzi, S. (2023). "Intelligent detection of citrus fruit pests using machine vision system and convolutional neural network through transfer learning technique". Computers in Biology and Medicine, 155, 106611.

[34] Ferdouse Ahmed Foysal, M., Shakirul Islam, M., Abujar, S., & Akhter Hossain, S. (2020). "A novel approach for tomato diseases classification based on deep convolutional neural networks", In Proceedings of International Joint Conference on Computational Intelligence: IJCCI 2018 (pp. 583-591). Springer Singapore.

[35] Fan, X., Luo, P., Mu, Y., Zhou, R., Tjahjadi, T., &Ren, Y. (2022). "Leaf image based plant disease identification using transfer learning and feature fusion", Computers and Electronics in Agriculture, 196, 106892.

[36] Necati Çetin et. Al. (2022). "Using hyperspectral imaging technology and machine learning algorithms for assessing internal quality parameters of apple fruits", Chemometrics and Intelligent Laboratory Systems, 230, 104650.

[37] Yang, C. H., Xiong, L. Y., Wang, Z., Wang, Y., Shi, G., Kuremot, T., & Yang, Y. (2020). "Integrated detection of citrus fruits and branches using a convolutional neural network", Computers and Electronics in Agriculture, 174, 105469.

[38] Vasconez, J. P., Delpiano, J., Vougioukas, S., &Cheein, F. A. (2020). "Comparison of convolutional neural networks in fruit detection and counting: A comprehensive evaluation", Computers and Electronics in Agriculture, 173, 105348.

[39] Saedi, S. I., & Khosravi, H. (2020). "A deep neural network approach towards real-time on-branch fruit recognition for precision horticulture", Expert Systems with Applications, 159, 113594.

[40] Gill, H. S., & Khehra, B. S. (2022). "Fruit image classification using deep learning"

[41] Hu, Z., Tang, J., Zhang, P., & Jiang, J. (2020). "Deep learning for the identification of bruised apples by fusing 3D deep features for apple grading systems", Mechanical Systems and Signal Processing, 145, 106922.

[42] Shahi, T. B., Sitaula, C., Neupane, A., & Guo, W. (2022). "Fruit classification using attention-based MobileNetV2 for industrial applications",. Plos one, 17(2), e0264586.

[43] Kang, J., &Gwak, J. (2022). "Ensemble of multi-task deep convolutional neural networks using transfer learning for fruit freshness classification",Multimedia Tools and Applications, 81(16), 22355-22377.

[44] Chen, Y., Wang, X., & Zhang, L. (2021). "Real-time visual inspection system for grading fruits using computer vision and deep learning techniques", IEEE Access, 9, 112577-112586.

[45] Chen, H., Zhang, X., & Liu, J. (2021). "Grading and sorting technique of dragon fruits using machine learning algorithms", IEEE Access, 9, 112587-112596.