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DETECTING FOOD QUALITY WITH MACHINE LEARNING METHODS

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Abstract

The proposed method of using a convolutional neural network (CNN) for fruit freshness detection is an efficient and nondestructive approach. Traditional methods for food quality detection can be time-consuming, time-intensive, and require specialized equipment and investigators to operate. By utilizing machine learning, specifically CNNs, the detection process can be streamlined and automated. CNNs are a type of deep learning algorithm commonly used for image identification tasks. They have shown excellent performance in various computer vision applications, including object detection and classification. In the context of fruit freshness detection, CNNs can analyze the visual characteristics of fruits and determine their freshness based on visual cues such as color, texture, and surface defects. The advantage of using CNNs for fruit freshness detection is that they can learn complex patterns and features directly from the input data without relying on explicit rules or predefined features. This makes CNNs well-suited for detecting subtle differences in fruit appearance that may indicate freshness or spoilage. By training the CNN on a large dataset of labeled fruit images, the model can learn to differentiate between fresh and spoiled fruits. The paper you mentioned likely presents experimental results that demonstrate the effectiveness of CNNs in identifying fruit freshness. These results would validate the proposed approach and provide evidence that machine learning can be a valuable tool in the field of food quality detection. Additionally, the paper may discuss the challenge of over fitting, which is a common issue in machine learning where the model becomes too specialized to the training dataset and performs poorly on new, unseen data. Overall, using CNNs for fruit freshness detection offers several benefits, including improved efficiency in food circulation, reduced storage and labor costs, and enhanced food safety. By leveraging the power of machine learning, this approach has the potential to revolutionize the way fruit quality is assessed and monitored throughout the supply chain.

Keywords: CNN, Freshness Detection, Food Quality, Visual Defects, Machine Learning, Improved Efficiency.

INTRODUCTION

Food analysis plays a vital role in addressing food safety concerns. By analyzing various aspects of food, such as its composition, contaminants, pathogens, and adulterants, scientists and researchers can assess its safety and quality. This information helps in

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identifying potential risks, implementing preventive measures, and ensuring compliance with regulatory standards.

Based on the information so far it seems that research in the field of fruit quality control and monitoring has been directed towards three main areas:

Supply Chain Management: Wang et al. proposed a food traceability system that enables real-time quality tracking, monitoring, and information sharing throughout the supply chain. This system can help identify the source and quality of fruits, ensuring transparency and accountability.

Internet of Things (IoT) and Big Data: Pal and Kant utilized big data collected through IoT devices to swiftly identify and remove poor-quality food from the supply chain. This approach not only reduces food waste but also improves transportation efficiency by optimizing the selection and handling of fruits based on their quality data. Elavarasi et al. suggested the use of IoT for monitoring fresh fruits during transportation, aiming to minimize wastage and ensure their quality and freshness.

Thermal Heterogeneity Analysis: Wu and Defraeye focused on studying thermal heterogeneity in large collections of packed fruits. They investigated the differences in quality evolution among fruits based on their thermal profiles. By understanding the thermal characteristics of fruits, it becomes possible to optimize storage and transportation conditions to maintain fruit quality and minimize spoilage.

These research directions demonstrate efforts to enhance fruit quality control and monitoring throughout the supply chain. By integrating technologies such as traceability systems, IoT, big data analysis, and thermal analysis, researchers aim to ensure the freshness, safety, and efficiency of fruit production, transportation, and storage. These advancements can contribute to reducing food waste, improving consumer confidence, and meeting the increasing demand for fresh and high-quality fruits. According to web research data (from ourworldinda-ta.org), these kinds of fruits' growth in production from 1995 to2020 are shown in Table 1. Te production of these fruits increased dramatically over 25 years, the average of the absolute change increased by about 240 million tons, and the average of the relative change increased by about 403. With a dramatic increase in the production of fruits, fruit selection, transportation, and quality control have become an important issue. Fresh fruits are an important part of the human diet and contain essential minerals, vitamins, and dietary fibers therefore, finding an efficient and nondestructive method to identify the quality of fruits has become a hot research direction in recent years. According to the current research, there are about three directions.

Based on the Supply Chain. Wang et al. proposed a food traceability system, which not only enables quality tracking but also allows quality monitoring and information sharing in real time. Pal and Kant used big data collected by the Internet of things to quickly remove poor-quality food from the supply chain while reducing food waste and improving transportation efficiency. Due to the increasing demand for fresh fruit, Elavarasiet al suggested that by using the Internet of things, fresh fruits can be monitored to avoid wastage during transportation. Wu and Defrayed researched thermal

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heterogeneity and associated differences in quality evolution for large collections of packed fruits and investigated the thermal heterogeneity and applications.

Production of fruits from 1995-2020 at Simla, India summarized in the given Table below.

Table 1

Fruits Name	1995	2020	Absolute change	Relative change (%)
Apple	77075584	69813253	292737669	379.81
Kiwi	3551185	29777027	26235842	740.88
Banana	104571703	565151188	460579484	440.44
Grapes	198602103	360302582	161700479	81.42
Orange	70741342	334086151	263344809	372.26

Artificial intelligence techniques, such as machine learning and data analytics, can be applied to analyze large amounts of data collected throughout the food supply chain. By harnessing the power of AI, Dora et al. aimed to improve several aspects of the food supply chain, including:

1. Transparency: AI can help capture, process, and analyze data related to various stages of the food supply chain. This enables stakeholders to have a better understanding of the origin, handling, and quality of food products. Improved transparency can facilitate accountability and trust among consumers, suppliers, and regulators.
2. Traceability: By integrating AI technologies, it becomes possible to track and trace food products throughout the supply chain. This allows for better identification of potential issues, such as contamination or quality deterioration, and enables timely interventions and recalls if necessary.
3. Food Safety and Quality: AI problem solving methods (PST)can be employed to analyze data and identify patterns or anomalies that may indicate potential food safety risks. By detecting and addressing these risks early on, it becomes possible to prevent or mitigate food borne illnesses and ensure higher standards of food safety. Additionally, AI can assist in assessing and stabilizing the quality of food products, optimizing storage conditions, and reducing waste.

By leveraging artificial intelligence in the food supply chain, Dora et al. aimed to address challenges related to food safety, quality, and waste. These advancements can lead to improved efficiency, reduced risks, and enhanced consumer confidence in the overall food supply system.

The data we give highlights numerous researches that investigated the use of hyper spectral imaging and novel equipment for detecting fruit quality. These studies show that these strategies are successful and have the potential to improve food safety and quality control.

Zhang et al. devised an mechanism for hyper spectral reflectance imaging system for spotting early rottenness in apples in the case of hyper spectral imaging. By combining spectrum analysis, picture processing, and chemo metrics, they reached a high detection

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accuracy of 98%. Wang et al. detected internal mechanical damage in blueberries using hyper spectral transmittance data and convolution neural networks, attaining good accuracy and F1 scores.

Weng and Neethirajan reported on portable micro fluidic devices for food safety and quality control, which enable the detection of numerous pollutants and chemical components in food. Yousef et al. proposed using sensors integrated in food packaging materials to detect microbial contamination in real time. Alfan et al. proposed Utilizing Internet of Things (IoT) and radio frequency identification (RFID) technologies to regulate temperature and humidity during food storage and transportation.

There are further projects that focus on using convolutional neural networks (CNNs) to detect fruit quality. Azizah et al. and Suistika et al. investigated CNN models for strawberry and mangos teen classification that are both automatic, respectively. CNNs were highlighted by Hameed et al. as a promising strategy for the classification of fresh produce, including fruits and vegetables. Jahan Bakhshi et al. proved the benefits of CNNs in quality assessment of photos of sour lemons.

While hyper spectral imaging and new equipment have potential benefits for detecting fruit quality, they also have drawbacks, such as significant investment prices and the requirement for specialized subject expertise. Large collections of hyper spectral pictures can also be difficult to establish. To overcome these issues, your paper's recommended technique involves employing CNNs to classify fruit freshness based on RGB photos. This method, which makes use of CNNs' capacity to interpret visual information reflected in RGB images, is well recognized as an efficient and nondestructive method for fruit quality assessment.

Overall, these researches highlight the importance of investigating innovative technologies and methodologies for enhancing fruit quality detection, such as hyper spectral imaging, new equipment, and CNNs. The goal is to improve traceability, efficiency, and accuracy in monitoring the freshness and safety of fruits throughout the supply chain by utilizing these technologies. Convolutional Neural Network is a type of neural network

ResNets are a form of convolutional neural network (CNN) architecture that pioneered the concept of residual learning. ResNets use skip connections to address the problem of vanishing gradients in deep neural networks. Each layer of a typical CNN learns to extract certain properties from the input data. However, as the network grows deeper, the gradients might become very small, making effective learning impossible. ResNets solve this problem by creating residual connections, also known as shortcut or skip connections.

Residual connections enable the network to carry information directly from one layer to the next without alteration. ResNets give the network the ability to pick up on differences by learning residual mappings. between a layer's input and output. When compared to learning the whole mapping directly, these leftover mappings are easier to optimise.

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A ResNet's design is often made up of numerous residual blocks. Each residual block is made up of several convolutional layers and shortcut connections. A residual block's output is obtained by adding the input to the the convolutional layers' output. This summation technique permits the network to more effectively propagate gradients and facilitates the learning of deeper representations.

DenseNets are densely connected convolutional networks

Another type of CNN architecture that facilitates maximal information flow across layers is densely connected convolutional networks (DenseNets). Each layer in DenseNets is connected to every other layer in a feed-forward method.

Information travels layer by layer in classic CNNs, and features from older layers may not reach later layers directly. DenseNets work around this limitation by creating dense connections between layers. A DenseNet layer gets feature mappings from all preceding layers, resulting in a dense connection pattern.

There are various advantages to dense connectivity. They let the network to access features from prior levels, which helps improve gradient flow and information propagation. Dense connections also lower the amount of network parameters by reusing characteristics rather than learning new ones from scratch. DenseNets are often made up of numerous dense blocks, each with multiple convolutional layers and dense connections. The number of feature maps between dense blocks is controlled by transition layers, which contain pooling procedures. DenseNets facilitate feature sharing, gradient flow, and information exchange by exploiting dense connections, resulting in improved learning and performance.

In summary, ResNets and DenseNets are sophisticated CNN designs that handle deep learning difficulties. DenseNets use dense connections to enable maximum information flow and feature reuse between layers, whereas ResNets use residual connections to facilitate learning of deeper representations. These designs have performed admirably in a variety of computer vision tasks, including picture categorization and feature extraction. In convolution neural network, when deeper networks are able to start con-verging, a degradation problem has been exposed: with the network depth increasing, accuracy gets saturated and then degrades rapidly [22]. This problem is called degradation. He et al. [22] developed an improved version of CNN called Res Nets. In Res Nets, a deep residual learning framework to solve the degradation problem is proposed.

In summary, ResNets and DenseNets are sophisticated CNN designs that handle deep learning difficulties. DenseNets use dense connections to enable maximum information flow and feature reuse between layers, whereas ResNets use residual connections to facilitate learning of deeper representations. These designs have performed admirably in a variety of computer vision tasks, including picture categorization and feature extraction.

ResNets (Deep Residual Networks)

When deeper networks begin to converge in convolutional neural networks, a degradation issue is identified. As network depth increases, accuracy becomes saturated and

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subsequently rapidly deteriorate. This is referred to as deterioration. He et al. [22] created ResNets, an upgraded form of CNN. ResNets proposes a deep residual learning architecture to overcome the degradation problem, which can be realised through "shortcut connections".

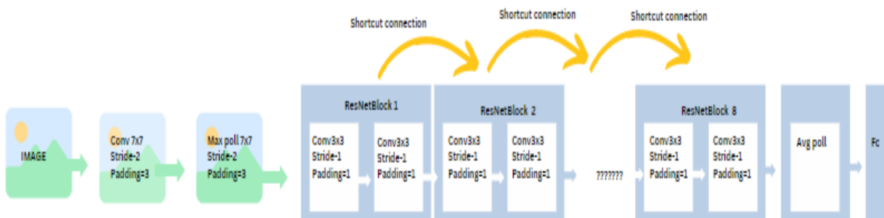

Fig 2: Shortcut connection in deep residual networks.

ResNets (Deep Residual Networks). When In convolutional neural networks, a degradation issue emerges as deeper networks start to converge. As network depth increases, accuracy becomes saturated and subsequently rapidly deteriorate. This is referred to as deterioration. He et al. [22] created ResNets, an upgraded form of CNN. ResNets proposes a deep residual learning architecture to overcome the degradation issues, which can be realised through "shortcut connections" [23-25].

Dense Convolution Networks (DenseNets) are a type of neural network

Huang et al. created the dense convolutional network model. Figure 3 shows that Dense Nets concatenate feature maps learnt by multiple layers, so that the feature maps of the input for each layer are the output of all preceding layers' feature maps.

Evolution Metrics and parameters: In the machine learning field almost all research scholars use precision, recall F1 score to evaluate models.

$$Precision=tp/(tp+fp)$$

where tp =true positive value of samples which are classified correctly.

Fp=false positive which is no of negative samples which are classified incorrectly.

False Negative, or fn, refers to the number of positive samples that are mistakenly classified as negative.

$$Recall=tp/(tp+fn)$$

F1=2*precision*recall/(precision*recall)

This table displays the parameters utilised in the techniques of this paper.

Dataset- Several sources, including Kaggle (kaggle.com), provided the dataset used in this article so that a high-quality network could be trained. All datasets are RGB photos with three freshness levels (fresh, medium, and rotten) and six fruit varieties (apples, bananas, cucumber, lemon, orange, and tomatoes). The total number of these RGB

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photos is over 40,000, as indicated in Table 3. 3.2. Tree-Classification Experiment. This three-classification experiment seeks to assess freshness without taking into account the type of fruit. As a result, the dataset was separated into three sections: fresh, medium, and rotten, with 70% of all photos used for training and the remaining 30% for testing. Figure 4 depicts the results. Dense Nets provide various appealing advantages over other CNNs, such as adding dense blocks to improve feature selection.

Experiment with eighteen classifications- The eighteen-classification experiment aims to classify all fruit types, whether they are fresh or not. The dataset was consequently split into eighteen parts: fresh tomato, medium tomato, rotten tomato, fresh apple, medium tomato, rotten tomato, fresh banana, medium banana, rotten banana, fresh cucumber, medium cucumber, rotten cucumber, fresh lemon, medium lemon, rotten lemon. The remaining 30% of images are used for testing, with the first 70% being used for training. Table 4 gives a summary of recent publications that employ machine learning to identify fruit quality. The results are shown there. The techniques used in this work, ResNets and DenseNets, perform better than others, as seen in the table.

Resents and Denseness start off with just RGB photographs as input data, but many other techniques use hyper spectral, laser backscattering, or infrared movies to increase the accuracy of model evaluation. Second, while the trials in this work stretch the classification numbers to three and eighteen, other research studies only have a binary classification problem. This suggests that the machine learning model must have a better classification impact. The study concludes by listing important parameters and their values, including precision, recall, and F1score, which show that this paper's approaches are superior to others. In the discipline of machine learning, overstating is a critical factor in assessing whether a model is good or terrible. A statistical modeling error called overstating happens when a function is too close to a set of finite data.

ResNets and DenseNets' loss function values for training and testing are shown. These data demonstrate that Res Nets and Dense Nets do not exhibit overfitting and deliver good results on both the training and test sets.

CONCLUSIONS AND FUTURE WORK

The authors present two machine learning models, Resents and Denseness, for the quick and constructive detection of fruit quality in this work. The authors ran trials on a large dataset and evaluated the models' precision-based performance, recall, and the F1 score. The results show that the chosen models outperformed others and continually improved performance indicators while exhibiting no evidence of over fitting.

One critical point raised by the authors is data imbalance, which occurs when the number of photos in each class is not equal. This can result in categorization bias in favour of the dominant class. To overcome this issue, the authors propose future study on employing data augmentation techniques and generative adversarial networks (GANs) to alleviate data imbalance and improve machine learning model performance.

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Furthermore, the scientists state that future study will focus on overcoming RGB image restrictions such as illumination and occlusion. These difficulties may have an impact on the accuracy of fruit quality identification, and the authors want to address them in future study.

The authors note that the study's data are available upon request from the corresponding author in regards to its accessibility. Finally, the authors state that they have no conflicts of interest linked to this study.

Overall, the work describes the application of ResNets and DenseNets for fruit quality assessment, emphasises the necessity to resolve data imbalance, and offers future research possibilities to improve the models and overcome RGB image restrictions.

References

1) H. Yousef, H.-M. Su, S. M. Imani, K.M. C. D. Alkhaldi, andT. F. Didar, “Intelligent food packaging: a review of smart sensing technologies for monitoring food quality,” ACSSensors, vol. 4, no. 4, pp. 808–821, 2019.

2) X. Weng and S. Neethirajan, “Ensuring food safety: quality monitoring using microfuidics,” Trends in Food Science &Technology, vol. 65, pp. 10–22, 2017.

3) J. Wang, H. Yue, and Z. Zhou, “An improved traceabilitysystem for food quality assurance and evaluation based onfuzzy classifcation and neural network,” Food Control, vol. 79, pp. 363–370, 2017.

4) C. Leneveu-Jenvrin, F. Charles, F. J. Barba, and F. Remize,“Role of biological control agents and physical treatments inmaintaining the quality of fresh and minimally-processedfruit and vegetables,” Critical Reviews in Food Science and Nutrition, vol. 60, no. 17, pp. 2837–2855, 2020.

5) A. Pal and K. Kant, “IoT-based sensing and communications infrastructure for the fresh food supply chain,” Computer, vol. 51, no. 2, pp. 76–80, 2018.

6) G. Elavarasi, G. Murugaboopathi, and S. Kathirvel, “Freshfruit supply chain sensing and transaction using iot,” inProceedings of the 2019 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), pp. 1–4, IEEE, Tamilnadu, India, January2019.

7) W. Wu and T. Defraeye, “Identifying heterogeneities incooling and quality evolution for a pallet of packed fresh fruitby using virtual cold chains,” Applied Termal Engineering, vol. 133, pp. 407–417, 2018.

8) M. Dora, A. Kumar, S. K. Mangla, A. Pant, and M. M. Kamal, “Critical success factors infuencing artificial intelligence adoption in food supply chains,” International Journal of Production Research, vol. 60, no. 14, pp. 4621–4640, 2021.

9) B. Zhang, S. Fan, J. Li et al., “Detection of early rottenness on apples by using hyperspectral imaging combined with spectral analysis and image processing,” Food Analytical Methods, vol. 8, no. 8, pp. 2075–2086, 2015.

10) Z. Wang, M. Hu, and G. Zhai, “Application of deep learning architectures for accurate and rapid detection of internal me-chanical damage of blueberry using hyperspectral transmittance data,” Sensors, vol. 18, no. 4, p. 1126, Article ID 1126, 2018.

11) T. Wang, J. Chen, Y. Fan, Z. Qiu, and Y. He, “See fruits: design and evaluation of a cloud-based ultra-portable nirs system for sweet cherry quality detection,” Computers and Electronics in Agriculture, vol. 152, pp. 302–313, 2018.

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12) H. Yousef, M. M. Ali, H.-M. Su, C. D. Filipe, and T. F. Didar,"Sentinel wraps: real-time monitoring of food contamination by printing dnazyme probes on food packaging," ACS Nano,vol. 12, no. 4, pp. 3287–3294, 2018.

13) G. Alfan, M. Syafrudin, U. Farooq et al., "Improving efficiency of rfd-based traceability system for perishable food byutilizing iot sensors and machine learning model," Food Control, vol. 110, Article ID 107016, 2020.

14) C. Gonzalez Viejo, S. Fuentes, A. Godbole, B. Widdicombe, and R. R. Unnithan, "Development of a low-cost E-nose to assess aroma profles: an artifcial intelligence application toassess beer quality," Sensors and Actuators B: Chemical,vol. 308, Article ID 127688, 2020.

15) L. M. r. Azizah, S. F. Umayah, S. Riyadi, C. Damarjati, andN. A. Utama, "Deep learning implementation using convolutional neural network in mangosteen surface defect detection," in Proceedings of the 2017 7th IEEE international conference oncontrol system, computing and engineering (ICCSCE), pp. 242–246, IEEE, Penang, Malaysia, November 2017.

16) R. Sustika, A. Subekti, H. F. Pardede, E. Suryawati,O. Mahendra, and S. Yuwana, "Evaluation of deep convolutional neural network architectures forstrawberry quality inspection," International Journal of Engineering and Tech-nologies, vol. 7, no. 4, pp. 75–80, 2018.

17) G. Ciocca, P. Napoletano, and R. Schettini, "Learning cnn-based features for retrieval of food images," in Proceedings of the International Conference on Image Analysis and Pro-cessing, pp. 426–434, Springer, Lecce, Italy, May 2017.

18) K. Hameed, D. Chai, and A. Rassau, "A comprehensive reviewof fruit and vegetable classification techniques," Image and Vision Computing, vol. 80, pp. 24–44, 2018.

19) A. Jahanbakhshi, M. Momeny, M. Mahmoudi, andY. D. Zhang, "Classification of sour lemons based on apparent defects using stochastic pooling mechanism in deep convolutional neural networks," Scientia Horticulturae, vol. 263, Article ID 109133, 2020.