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Computer Vision for Food Quality Assessment: Advances and Challenges

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ABSTRACT

One of the transformative technologies in food quality assessment provided by computer vision is an automated, precise and efficient food product evaluation. In this review, the progress, the difficult issues, and the future way of computer vision applied in food quality control are discussed. Advances in imaging technology, artificial intelligence, and deep learning have improved food inspection accuracy to real time defect detection, ripeness estimation and contamination detection. Feature extraction and classification using hyper spectral imaging and neural networks, Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) have been improved to design robust and efficient schemes for food quality assessment. Although these breakthroughs have been made, problems like food variability, dependence on large annotated databases, high implementation costs, and real time processing limitations hold back the common use. The complexity of the vision system integration in the industrial food production still remains a concern, especially for small or medium size enterprises. Future research aimed at integrating IoT and edge computing for real time monitoring, explainable AI for transparent decision making, and multimodal data fusion for accurate fusion would address the above mentioned challenges. Moreover, the creation of sustainable and low cost computer vision solutions will be crucial in ensuring availability of these solutions in different food industry sectors.

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INTRODUCTION

Developing food quality assessment methods is a vital part of the food industry where the products must comply with the safety, nutritional, and consumer preference requirements. Currently, evaluation of food quality has been done traditionally by means of human sensory analysis and laboratory based techniques which although useful, are expensive, time consuming, and can be subjective [1]. Due to the increasing need for automated, efficient, and accurate quality control methods, computer vision is shown as a powerful tool in food quality assessment. Artificial Intelligence (AI) branch named computer vision lets the machine interpret and analyze the visual information such as a human being could perceive [2]. Advanced imaging techniques and Machine Learning algorithms can be used to detect, classify and quantify food product quality attributes like color, texture, size, and shape using computer vision systems. These automated systems have a number of advantages: high speed processing, nondestructive analysis and increased consistency, making them especially suitable for large scale food production and quality control [3].

In the recent years, deep learning, image processing and sensor technology have driven significant advancements in computer vision technology. The segmentation of food processing tasks relies on Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs) and transformer based models to enhance the ability of computer vision systems to extract complex patterns and features out of food images, and therefore, increase the accuracy of quality assessment when tested on either facilitated or natural images [4]. Hyper spectral and multispectral imaging techniques have also added the ability of computer vision beyond the visible spectrum by being able to detect internal defect and do chemical composition analysis of food products. Nevertheless, several challenges exist in widely applying computer vision for food quality assessment. Computer vision models can be affected by the variability in food appearance due to natural diversity, changes in lighting conditions and the occlusion [5]. Large annotated datasets are required to train AI models which is challenging in itself, as it is a manual process and involves a huge amount of time and effort. In addition, computer vision systems need to be processed and deployed in real time in industrial environment that demands robust hardware and optimized algorithms to serve high speed food production lines [6].

This paper will review recent advances in computer vision for food quality assessment, providing an overview of chief methodologies, applications and emerging technologies. Additionally, it will describe the challenges and limitations submitted by researchers and industrial professionals in using computer vision solutions. Future research directions to improve effectiveness and the accessibility

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of computer vision based food quality assessment systems will be proposed [7]. Through the resolution of these problems, computer vision may serve as a revolution for the food quality evaluation, to guarantee food safety, reduce food waste, and increase general consumer satisfaction.

FUNDAMENTALS OF COMPUTER VISION IN FOOD QUALITY ASSESSMENT

Food quality assessment is a complex problem; computer vision provides an opportunity to process and interpret visual data with artificial intelligence embedded on a device. This comprises a number of main components such as image acquisition, image preprocessing, feature extraction and classification that collaborate in order to assess food products on the basis of visual characteristics such as color, texture, size and shape. The capture of images of food products constitutes the first step of any computer vision system. Different imaging technique is utilized according to the type of application [8]. RGB (Red–Green–Blue) cameras are conventionally used to capture the color and shape information and hyper spectral and multispectral imaging provide spectral information which is very detailed, which allows internal defect detection by means of chemical composition analysis. Foreign objects, temperature variations, and hidden defect in food items can be used using other techniques such as thermal imaging and X-ray fractal imagery. Imaging technique and how we chose to do that plays an important part in how accurate and how good a computer vision system that we build is [9].

After images are captured, there are preprocessing techniques applied to improve quality and remove noise. A commonly used preprocessing scheme, such as contrast adjustment, filtering and edge detection, are implemented to enhance the clarity of important features. To segment the background from the food product, image segmentation techniques like thresholding, watershed algorithm and deep learning based segmentation are used, thereby ensuring that the analysis of food specific features only happens [10]. To enhance the robustness of the system, preprocessing is necessary since lighting variations, shadows and occlusions will affect accuracy otherwise. Computer vision comes heavily upon the feature extraction step, where the characteristics of food products which are relevant are identified and analyzed. Traditional methods consist of extracting shape descriptors (e.g., perimeter, roundness etc...), color features (e.g., histograms, RGB values, etc...) and texute features (e.g., wavelet transform, gray level co-occurrence matrix, etc....) [11]. The feature extraction is with the aid of artificial intelligence through advancements in artificial intelligence and deep learning based, CNNs are increasingly utilized to automatically learn feature from raw image. Deep learning models can determine things like ripeness levels in fruits, marbling in meat, and surface defects in baked

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goods because these are complex patterns [12].

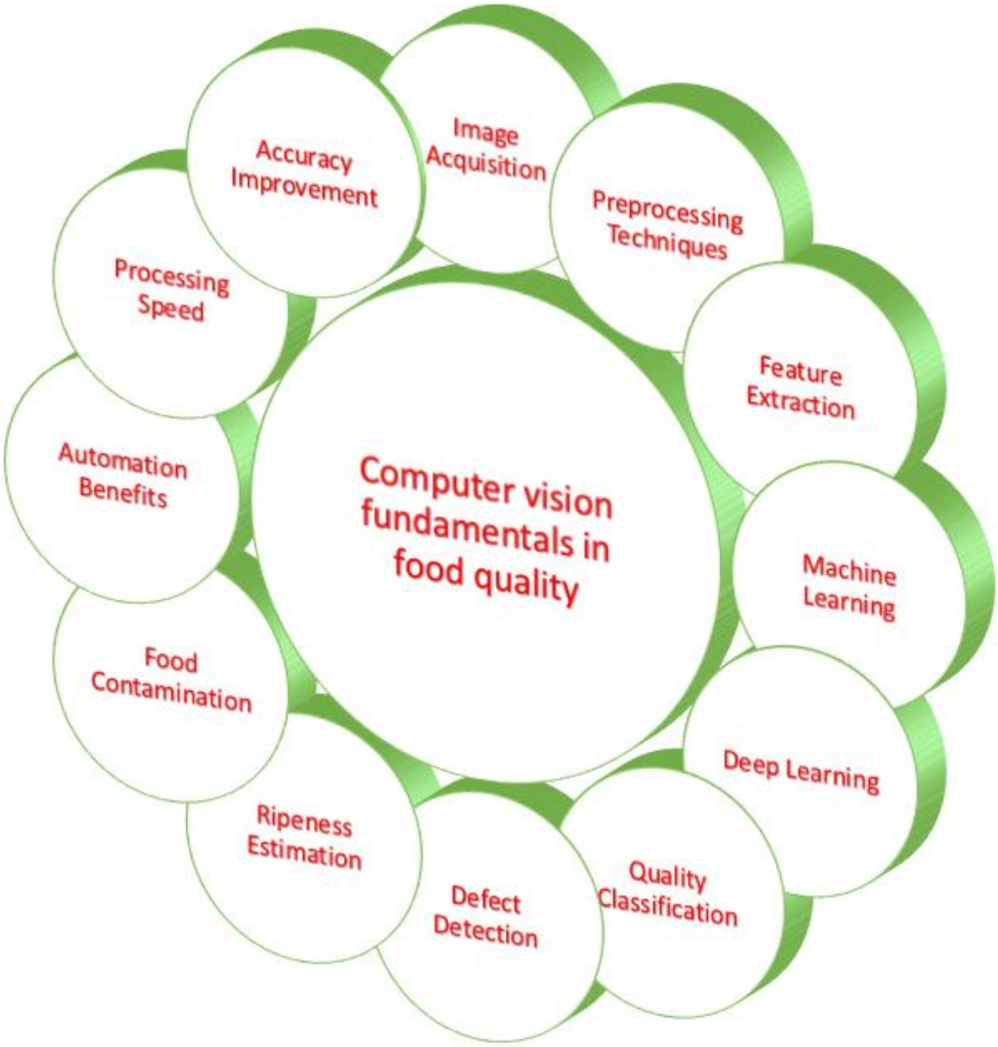

Figure: 1 showing computer vision fundamentals in food quality

Machines then learned and developed machine learning and deep learning algorithms to classify the food products based on its quality standards after feature extraction. Existing traditional classifiers such as Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbors (KNN) etc. have been used on a widespread basis. Deep learning models, including CNN, Recurrent Neural Network (RNN) and Vision Transformer (ViT), have more recently made significant improvements to accuracy in classification by learning complex features from large data sets [13]. Using these models, one can not only tell fresh from spoiled produce and detect foreign contaminants, but also predict shelf life of products. Computer vision in food quality assessment has several benefits including, automation, objectivity, and high speed of processing. However, in practice, there are challenges including variability in food appearance, the demand for large datasets, computational cost, and so forth that will need to be overcome for wider adoption. Due to the continuing development of technology,

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computer vision can be integrated with the Internet of Things (IoT) devices, as well as cloud computing, thus achieving even better application in food quality assessment systems [14].

ADVANCES IN COMPUTER VISION FOR FOOD QUALITY ASSESSMENT

Rapid advances in computer vision technology have led to more accurate, efficient and applicable food quality assessment. Recent innovations like enhanced imaging techniques and deep learning based classification models have allowed detection of even subtle quality variations in food products to guarantee their safety and reliability in the food industry. Intelligent acquisition of image is one of the major emerging techniques which is considered as one of the significant advancements in computer vision for food quality assessment [15]. Hyper spectral, multispectral and thermal imaging have added to the quality evaluation scope, but traditional RGB cameras are still widely used. For example, hyper spectral imaging is capable of detecting chemical composition and internal defect in food, and it has a wide use in applications such as bruise detection on fruits or meat freshness assessment [16].

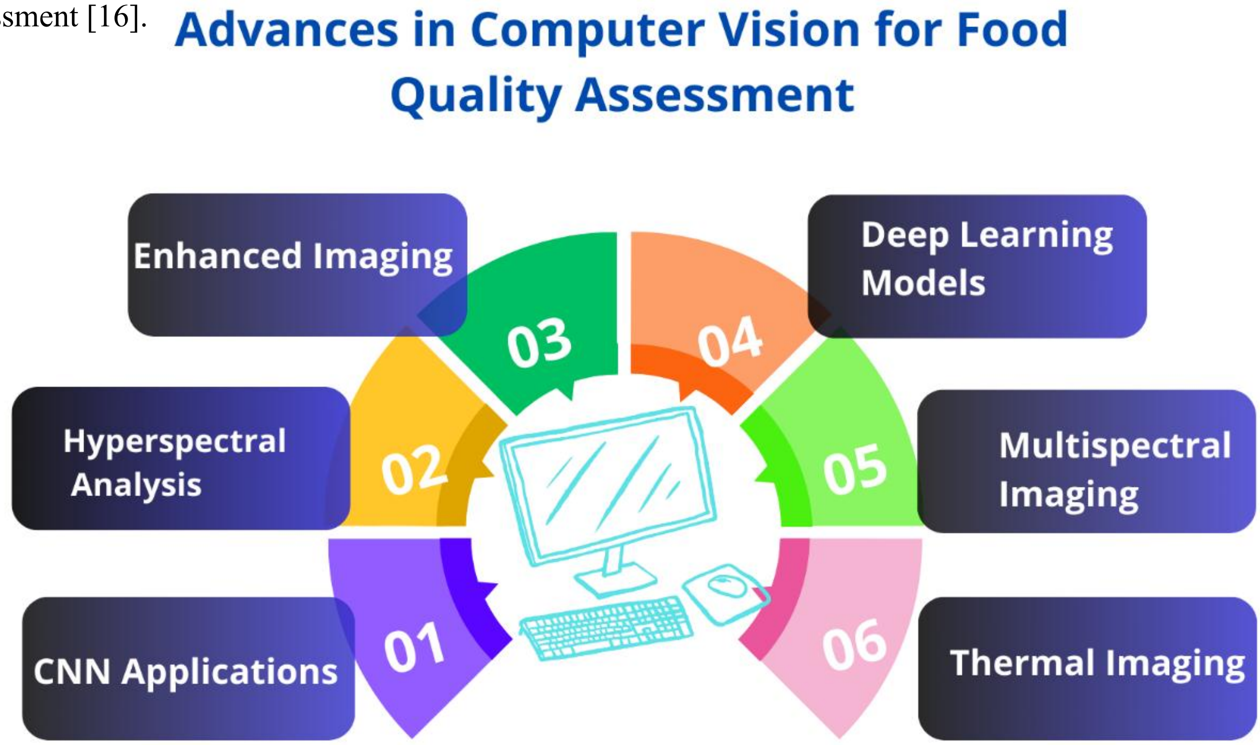

Figure: 2 showing advances in computer vision for food quality assessment

The improved imaging is complemented with improved image processing techniques to yield clearer and more usable captured images. Improved accuracy of food quality analysis is achieved by employing noise reduction algorithms, adaptive contrast enhancement and deep learning based image

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segmentation techniques [17]. With these preprocessing techniques, the lighting variation, background interference and the occlusions can be compensated so as to provide a robust and reliable performance assessment. With the advent of artificial intelligence, the feature extraction has now been incorporated in it [18]. However previous methods of food quality assessment used traditional feature extraction methods from shape, color, texture and consistency descriptors. However, the whole process has been revolutionized using deep learning based feature extraction with Convolutional Neural Networks (CNNs). A hierarchical feature learning is adopted by CNN, which allows for detecting precise defect, estimation of ripeness, identification of contamination, etc [19].

Improvement of accuracy in food quality assessment has been achieved with multimodal feature extraction, whereby multiple imaging techniques are combined. As another example, the RGB and hyper spectral imaging can be used together for both surface and interior product quality assessment, which gives overall evaluation of food products. Machine learning and deep learning application improves the classification accuracy of food quality assessment [20]. Models ranging from traditional classifiers like Support Vectors Machines (SVMs), and Decision Trees, to more advanced models such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and the vision transformers (ViTs), have supplemented and in many instances replaced these. They can analyze big data set, recognize the pattern and provide exact quality assessment with least human involvement [21].

In addition, the robustness of classification models has been further increased using deep learning architectures for example transfer learning and ensemble learning. Transfer learning enables fine tuning of models that were trained on large general datasets to a specific food quality use case thus requiring much smaller labeled data to do so [22]. In this paper, we apply GANs to the task of data augmentation by using synthetic food images to improve the accuracy with training and data scarcity problems. Various food categories have been applied with success to computer vision. It is used for grading in fruit and vegetable industry on account of size, color and ripeness. Computer vision in the meat and dairy industry allows for detecting contamination and measuring fat content as well as ensuring product consistency [23]. For processed foods and grains, it is also used for the detection of foreign objects, checking the uniformity, and monitoring texture quality. Advancements in these applications showcase the increasing importance of computer vision in regards to food quality assessment and provide faster, more accurate and automated means of food safety and quality. Nonetheless, future research and development for the problems of high computational cost, high dataset requirement, and low real time processing speed are necessary [24].

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CHALLENGES AND LIMITATIONS

Although great progress has been made in computer vision for food quality assessment, several challenges and constraints exist for its mass adoption in the food industry. The root cause of these challenges lies in the intrinsic variability of food products, technological complicacies, and in real situation implementation. In order to enhance the effectiveness, accessibility and scalability of computer vision systems for food quality control, these limitations need to be addressed [25]. Natural variability in food product is one of the primary challenges in the food quality assessment. Food items like fruits, vegetables, and meat and dairy products are not like manufactured items, which show no variation in shape, size, color, and texture. For instance, apples of the same variety can vary in hue depending on environmental conditions and different meat cuts will differ in marbling and fat distribution [26]. Having these variations in the images, the computer vision models find it hard to standardize the measures for quality assessment. However, such models based on deep learning have achieved higher adaptability but still need large and diverse datasets to accomplish such variability [27].

To train robust computer vision models, vast amounts of labeled datasets are necessary, which can be very time and money consuming to create. As for training deep learning models, datasets of high quality image with proper annotations are inevitable, unfortunately food datasets are often limited in size and diversity. Manual labeling of images for quality assessment (e.g., determining spoiled or fresh fruit, identifying defects, food item grading, etc.) is expensive, labor intensive, and requires domain expertise. These challenges can be mitigated to some extent, for instance, by using data augmentation or by generating synthetic images using Generative Adversarial Networks, but data heterogeneity remains a source of bottleneck in creating highly accurate models in the absence of standardized datasets [28].

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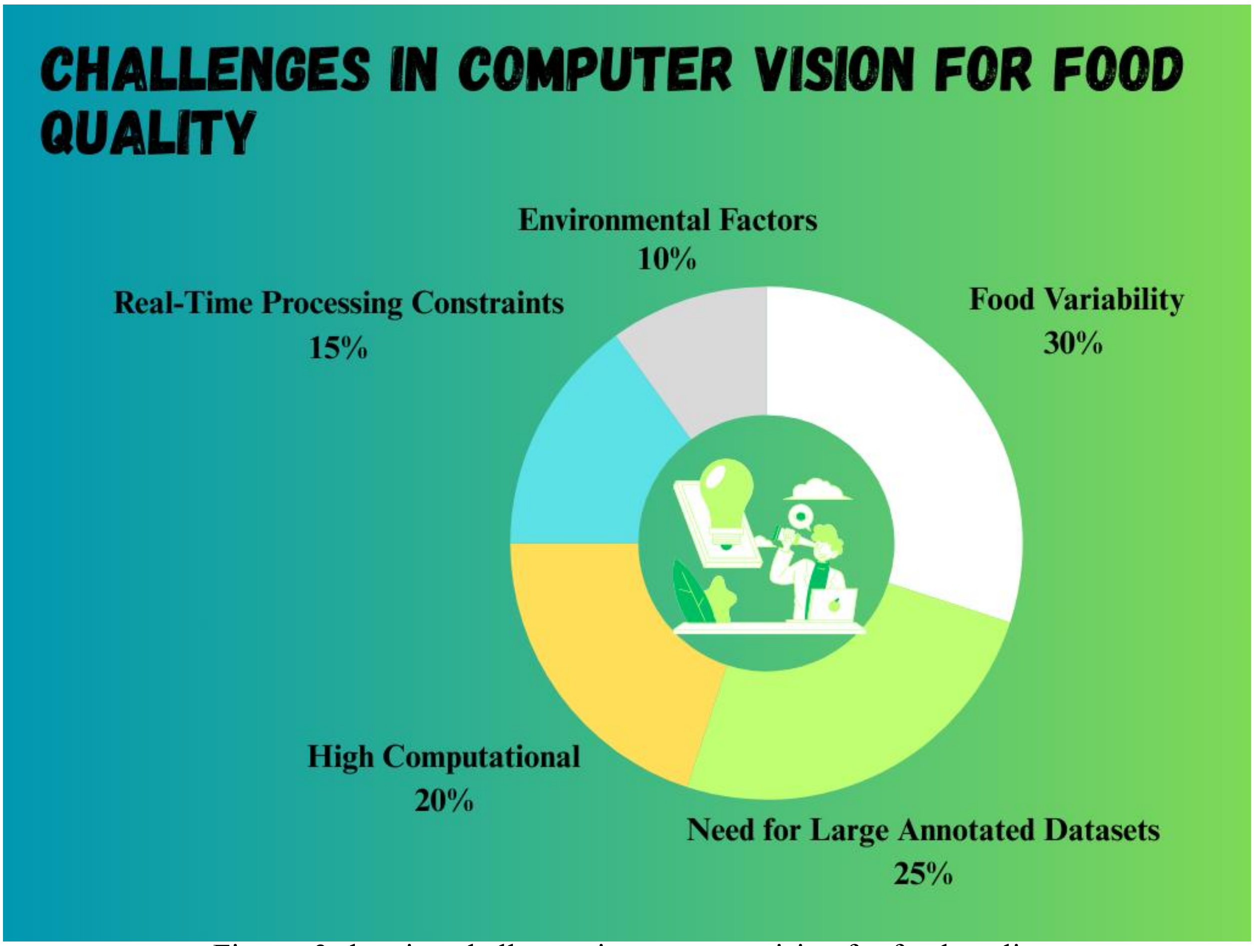

Figure: 3 showing challenges in computer vision for food quality

Computer vision systems to be implemented in food processing facilities are high technology, requiring investment in hardware to include high resolution cameras, specialized imaging sensors such as hyper spectral, and X-ray, and high performance computing infrastructure for real time processing. These costs are prohibitive to many small and medium sized food business and adoption has been only by large scale manufacturers. On the other hand, deploying and maintaining computer vision solutions in existing production lines are challenging due to the need of specialized knowledge for both food science and artificial intelligence [29]. In order to be effective in industrial food quality assessment, computer vision must work in real time and process high number of products in a rather fast moving conveyor belt. Due to the high speed of the food processing lines, rapid image acquisition, feature extraction, and decision making with acceptable accuracy are required [30]. However, deep learning models are complex which require a lot of computational power and hence leads to latencies. There is still a huge research problem in optimally designing deep learning models for real-time performance while still preserving high accuracy. Only promising solutions to that are edge computing and lightweight AI models but more to do in order to retain efficiency in industrial

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environments [31].

Most food quality assessment systems run under various environmental conditions including multiple levels of light intensity, reflections and shadows. Ambient lighting state can change the image clarity and consistency, which in turn make quality classification prone to errors [32]. However, these issues can be alleviated, albeit marginally, with the use of adaptive illumination techniques, image normalization and deep learning based image enhancement methods; however, other environmental variations still persist, particularly in open market scenarios where practicing controlled lighting is not feasible [33]. Food quality assessment has progressed significantly via computer vision, but addressing these issues ultimately ensures the success of utilizing computer vision for food quality assessment. To enhance data accessibility and efficiency, these systems require advances in AI driven adaptive learning, low cost imaging solutions, as well as optimized real time processing technique. To guarantee that computer vision remains a force multiplier in food safety, quality assurance, and automation in the food industry, these limitations must be addressed [34].

FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES

Although computer vision has undergone great development in recent decades, food quality assessment is still a problem to solve, with several challenges. Future research should focus on enhancing technologies and approaches to increase efficiency and economy as well as to gain greater accuracy. Promising directions include the embedding of IoT and edge computing, developable of explainable AI for enhanced decisions, multimodal data fusion for better accuracy, and making sustainable and low cost computer vision solutions [35]. Real time real time food quality assessment with IoT and edge computing can take an important step towards being scalable. The real time visual and environmental data can also be collected from the food production and processing environments by the IoT devices like the smart camera and sensors. In combination with computer vision, these devices allow for monitoring food quality continuously and drastically decreasing the need for manual inspections [36].

This capability can be further improved with edge computing by efficiently processing the data on the device or at the network edge instead of major cloud based systems. It reduces latency, makes decision faster and conserve bandwidth. Edge AI models can detect defects, contamination, spoilage on high speed food production lines, instantly, and take immediate corrective action [37]. Future work should be committed which can develop lightweight AI models that run efficiently on edge devices,

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in order to ensure efficiency without accuracy compromise. As deep learning models get more complex, it becomes more difficult for professionals in the food industry to trust the decisions made by the model in the way it does the job [38]. Various efforts however have been made to address this issue with explainable AI (XAI); AI driven decisions should be explained and made transparent.

XAI can be used to provide visual explanations for a food products' classification as defective or high quality for the food quality assessment. There are techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) and SHAP (Shapley Additive Explanations) that show what exactly the specific image regions or the features that contributed to a given classification decision. By ensuring food safety standards, this helps manufacturers, regulators such as food inspectors understand AI predictions and thereby improve quality control [39]. For future research, it is necessary to develop user friendly XAI tools for applications related to food quality. Multimodal data fusion, that is combining multiple data sources, is an emerging research area that can greatly improve food quality assessment. Modern computer vision systems rely mostly on visual data but with additional modalities (e.g., hyper spectral imaging, thermal imaging, and chemical sensors) can increase the accuracy of detection [40].

For instance, in a traditional RGB imaging an external appearance is evaluated, while the hyperspectral imaging is detecting internal defects and it can also detect aroma and gas emissions with an electronic nose (e-nose) to define freshness. By blending these data sources, AI models can more robustly assess from a bigger picture, lowering false positives and enhancing several classification's reliability. Novel fusion technique and machine learning model which incorporates multimodal data should be explored in future studies [41]. To have computer vision available to the food industry at large and especially to small and medium sized enterprises (SMEs), researchers need to concentrate on devising cheap solutions. The reason that highly expensive processes of imaging technologies like hyper spectral cameras and X-ray systems require specialist expertise for adoption [42].

Such developments in the future can be further focused on using low cost imaging alternatives like smartphone based computer vision systems with cloud based AI models. Furthermore, transfer learning techniques can enable us to decrease the requirement for a lot of training data and fine tune AI models for each other food product exploiting tiny labelled datasets [43]. In another approach, efforts are made to develop efficient AI models in energy which could run on affordable hardware, and can be deployed on real time, thereby enabling small businesses to perform food quality

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assessment [44].

However, future of computer vision in food quality assessment would rely on utilization of latest, cutting edge and advanced technologies to mitigate problems experienced in the existing methods. By combining IoT and edge computing, real time quality monitoring can be enabled and explainable AI enhances trust and transparency around the automated decision making. Combining multiple sources of information gives rise to multimodal data fusion which may potentially result in a more accurate food assessment [45]. Developing sustainable and reasonably priced solutions will allow computer vision technologies to become within the reach of a wider population of food producers. Computer vision offers the possibility to revolutionize food quality assessment by addressing these research opportunism and therefore ultimately benefit food safety, waste reduction, and consumer satisfaction. The evolution of AI driven food inspection systems will go on help both manufacturers of food as well as the global endeavor to provide food product safely, affordably and sustainably. As the population of world is increasing day by day and the resources are limited so it is highly necessary to find some alternative resources of food [46-47] and improve the quality of food using technologies.

CONCLUSION

It has been seen that computer vision as a transforming technology in food quality assessment which provides automation, precision and efficiency in assessment of different food products. In the past decade, improvements in imaging techniques, artificial intelligence, and deep learning have made great strides in improving accuracy of food quality inspection over previous levels. Thanks to these developments, rapid, nondestructive, and consistent evaluations are possible, diminishing dependence on the traditional manual inspections that are often time consuming, subjective, and inconsistent. Computer vision is applied to a wide range of foods, such as fruits, vegetables, meat, dairy, grains and processed foods thus showing its great versatility in the food industry.

What is one of the greatest advancements in computer vision is the usage of deep learning models, such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Vision Transformers (ViTs). Such models have added computer vision systems' capacity to process complex visual patterns, detect infinitesimal defects and classify food items with high accuracy. In addition, new imaging techniques such as hyper spectral imaging and multispectral imaging have improved the ability to assess food quality by not over restricted to the visible spectrum, which enables internal defects as well as chemical compositions of foods to be assessed. Computer vision

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has become indispensable to food manufacturers, retailers and regulators wishing to maintain high quality standards and food safety.

However, some of these advancements are hindered by several of the challenges facing the widespread adoption of computer vision technology for food quality assessment. The obstacle is still the inherent variability of food appearance arising due to natural growth conditions as well as post-harvest product handling. The issue in food items is that unlike manufactured products, they do not have standard size, color, texture and shape meaning that standard computer vision model will not achieve the same universal classification accuracy. In addition, the issue of large, annotating datasets needed for training of AI models creates substantial hurdles—due to the resource intensive and time consuming process of data collection and labelling. Additionally, the high cost of advanced imaging systems and the difficulty deploying computer vision solutions in industrial settings make them less attractive to small and medium-sized food enterprises.

The future research should focus in some aspects that are able to overcome these challenges and improve adoption computer vision in the food industry. By integrating Internet of Things (IoT) devices with edge computing, real time, scalable and automatic food quality monitoring will be possible without significant dependence on cloud based processing, enhancing efficiency. By providing human interpretable insights into AI driven decision, XAI, or explainable AI will play an important part in the increase of transparency and trust in computer vision models. The fusion of data from different imaging techniques and different data sensors for food quality assessment will increase the accuracy and robustness of the quality assessment. Furthermore, the prospects of employing these technologies in the food production systems will be accompanied by the development of cost effective, sustainable computer vision solutions and also educating more workers and technicians about these technologies to enable widespread adoption across different food production environments.

With the ability to tackle these challenges and future technological advancements, computer vision can transform the food quality assessment process making the food production processes safer, consistent, and more efficient. With continued integration of AI driven inspection systems, food safety will be further enhanced, food loss and waste will be reduced, and the trust and satisfaction of the consumer will increase. With the progress of computer vision technology, its effect will be expanding further on the food industry, and keep ensuring high quality of the food products and support the more and more demanding global food supply chain.

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