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Review Article

Recent Advancement in Postharvest Loss Mitigation and Quality Management of Fruits and Vegetables Using Machine Learning Frameworks

Abha Singh [iD],[1] Gayatri Vaidya [iD],[2] Vishal Jagota [iD],[3] Daniel Amoako Darko [iD],[4] Ravindra Kumar Agarwal [iD],[5] Sandip Debnath [iD],[6] and Erich Potrich [iD][7]

[1]*Department of Basic Science, College of Science and Theoretical Study, Dammam-Female Branch, Saudi Electronic University, Riyadh, Saudi Arabia*

[2]*Department of Studies and Research in Food Technology, Davangere University, Davangere, Karnataka, India*

[3]*Department of Mechanical Engineering, Madanapalle Institute of Technology & Science, Madanapalle, Andhra Pradesh, India*

[4]*Institute for Environment and Sanitation Studies, University of Ghana, Accra, Ghana*

[5]*Department of Food Technology, Centre for Health and Applied Sciences, Ganpat University, Mehsana, Gujarat, India*

[6]*Department of Genetics and Plant Breeding, Palli Siksha Bhavana (Institute of Agriculture), Visva-Bharati University, Sriniketan, Birbhum, West Bengal, India*

[7]*Department of Chemical Engineering, Amapá State University, Macapá-AP, Brazil*

Correspondence should be addressed to Vishal Jagota; vishaljagota@mits.ac.in and Daniel Amoako Darko; dadarko@ug.edu.gh

Agriculture is an important component of the concept of sustainable development. Given the projected population growth, sustainable agriculture must accomplish food security while also being economically viable, socially responsible, and having the least possible impact on biodiversity and natural ecosystems. Deep learning has shown to be a sophisticated approach for big data analysis, with several successful cases in image processing, object identification, and other domains. It has lately been applied in food science and engineering. Among the issues and concerns addressed by these systems were food recognition; quality detection of fruits, vegetables, meat, and aquatic items; food supply chain; and food contamination. In precision agriculture, Artificial Intelligence (AI) is a commonly used technology for estimating food quality. It is especially important when evaluating crops at different phases of harvest and postharvest. Crop disease and damage detection is a high-priority activity because some postharvest diseases or damages, such as decay, can destroy crops and produce poisons that are toxic to humans. In this paper, we use Convolutional Neural Networks (CNNs)-based U-Net, DeepLab, and Mask R-CNN models to detect and predict postharvest deterioration zones in stored apple fruits. Our approach is unique in that it segmented and predicted postharvest decay and nondecay zones in fruits separately. This review will focus on postharvest physiology and management of fruits and vegetables, including harvesting, handling, packing, storage, and hygiene, to reduce postharvest loss (PHL) and improve crop quality. It will also cover postharvest handling under extreme weather conditions and potential impacts of climate change on vegetable postharvest and postharvest biotechnology on PHL.

1. Introduction

The postharvesting (PH) is the process by which the plant is separated instantly from the ground. The harvesting is totally depending upon the maturity of any plants. There is a large amount of wastage remaining which is a big problem after harvesting. During the process of harvest, some grains and fruits are also damaged and wasted which is also known as postharvest loss (PHL) [1]. In recent years, there has been a substantial increase in the use of computer vision in industry, with applications in natural capital mapping on the ground and in the air, crop monitoring, precision farming,

robotics, and autonomous guiding [2, 3]. Many researchers are working on the minimization of this type of loss. Food poisoning count in PHL refers to measured quantitative and qualitative food loss in the postharvest system. From agricultural harvesting to crop processing, marketing, and meal preparation, to the consumer's final decision to eat or discard the food, this system is comprised of interrelated activities [4]. Because the loss or inefficiency kinds are comprised of both aspects in various amounts, they cannot be unambiguously labelled as either preventable or wholly unavoidable. Seepage and degradation during storage and transportation result in handling, storage, and transportation losses. Primary crops, processing commodities, and animal products are all affected. When a crop is taken from the ground or separated from its parent plant, it begins to decompose immediately. Whether a crop is sold fresh or used as a component in a processed food product, postharvest treatment is the most important factor in determining its quality.

AI in the food and beverage industry appears to be ruled by innovative start-ups and tech company alliances developing machine learning algorithms to handle specific challenges. AI may also help by avoiding unnecessary food waste and lowering edible wasted food. AI is one of the most significant technological developments of the Industry 4.0 era, with the once-in-a-lifetime potential to transform the food system from a unidirectional to a circular paradigm. Artificial intelligence-based systems, often known as autonomous systems, are widely employed in nearly every element of technology. It enables the world to solve problems more efficiently, computerize the food industry, and modify food things. As we know, the demands for processed and packed food are increasing for saving the time in their busy life schedule. The processed food is prepared in the industries, the raw food material is transported from fields to the industries, and the wastage of grains and raw materials occurs [5]. The fact that computer vision systems provide massive amounts of information on the origin or characteristics of event detection explains the wide variety of applications. Additionally, this technology allows the researcher to study scenes in sections of the electromagnetic spectrum where the human eye is not sensitive, such as the violet (UV) and indigo (IR) spectral ranges [6, 7]. Many researchers are developing the models and machine learning algorithms for reducing the PHL [8]. Many agencies' initiatives to address food insecurity now include interventions in PHL reduction. PHL is becoming more widely acknowledged as an important component of a comprehensive strategy for reaching agriculture's full potential in meeting the world's growing food and energy demands. In the food supply chain, food losses occur during the production, postharvest, and processing stages. Poor infrastructure, logistics, a lack of technology, insufficient skills, knowledge, managerial ability of supply chain actors, and a lack of markets are the primary causes of food losses [9]. The Food Corporation of India (FCI) claims that every year, 23 million tonnes of food cereals, 12 million tonnes of fruits, and 21 million tonnes of vegetables are lost, totaling 240 billion rupees in value [10]. The quality of a fruit or vegetable,

whether fresh or processed, is determined by a number of physicochemical attributes that make it just about appealing to consumers, such as maturity, size, mass, shape, colour, presence of dirt and diseases, involvement or absence of stem, involvement or absence of seeds, and sugar content [11, 12]. According to the Ministry of Food Processing, India wastes agricultural output worth 580 billion rupees per year [13]. There are many agencies and organizations taking steps to control the fruit and grain wastages by applying precision agriculture, implementing artificial intelligence, and machine vision technologies in conventional agricultural practices [14–17].

The most prevalent causes of postharvest losses include rotting, mechanical damage, improper handling, inappropriate temperature and partial humidity management, and hygiene difficulties during handling. Postharvest loss (PHL) has the potential to impair food security and nutrition by affecting the four pillars of food security: availability, access, usage, and stability. When losses are reduced, accessibility and availability improve. Farmers profit from reduced agricultural losses by improving their nutrition or boosting their earnings. Moreover, food poisoning from production is on the increase around the globe. Microbial contamination, chemical residues, antibiotics, and toxic metals in agricultural goods are increasingly major concerns that have a severe influence on human health and the environment. As a result, it is vital to provide safe and healthful meals by adhering to certain health regulations. Food products naturally change colour or texture after harvesting, depending on their ripeness and processing tanks (humidity and temperature, fungal infections, volatile ingredient presence, storage time, and so on). Likewise, the colour of such a patch on the face of this other similar fruit can match the colour of a specific area of the skin of either a healthy fruit [18, 19]. Because food is the most important component for survival on this planet, the quality of fruits and vegetables has an impact on health care and health-related disorders. An inclusive range of infections can be caused by unsafe food. You may have read in the news about food contamination or adulteration causing health concerns. Food poisoning is a huge public health concern all over the world [20]. According to the National Family Health survey, acute diarrhea affected almost 2 lakh children under the age of five. Food-borne disease may cause death as well as harm to commerce and tourism, as well as loss of profits, unemployment, and lawsuits, all of which can stymie economic progress. As a result, food safety and quality have become a global concern. Raw and processed food quality is a public health hazard that must be addressed. Food quality and food safety have become highly important since the last decade, both internationally and in India. This is due to a number of variables including more people are dining outside their homes due to rapidly changing lives and eating habits. Food is made in mass and handled by a large number of people in commercial settings; therefore, there is a higher risk of contamination. Manual sorting techniques provide a significant risk of human error, and employees' assessments may be affected by psychological factors such as weariness or acquired habits [21, 22]. Additionally, food is cooked many
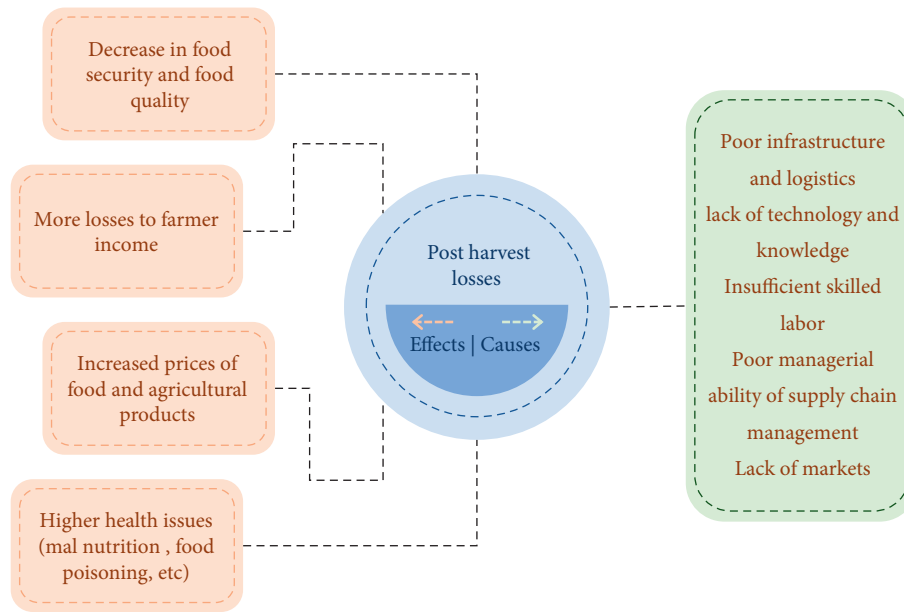
FIGURE 1: Causes and effects of postharvest losses on agricultural and food processing industry.

hours ahead of time and may deteriorate if not properly preserved. Pollution in the air, soil, and water, as well as agricultural pesticide usage, all contribute toxins. Food analysis for diverse components both nutrients and contaminants is also necessary due to the usage of additives such as preservatives, colorants, flavoring agents, and other chemicals such as stabilizers. There are many types of pollution such as pollution in the atmosphere, soil, and water, as well as pesticide usage in agriculture, which contribute toxins in the natural resources. Food analysis for diverse components both nutrients and contaminants is also required due to the usage of additives such as preservatives, colorants, flavoring agents, and other chemicals such as stabilizers. The effect and cause of postharvest losses have been shown in Figure 1.

To incorporate quality into every part of food production and delivery, as well as to secure the supply of hygienic, healthy food, and to promote commerce within and between nations, effective food standards and control systems are essential. For maintaining the food quality and standards, there are many food organizations such as Bureau of Indian Standards (BIS) and grading systems such as Agmark and ISI mark FSSAI. Agmark is a voluntary programme for certifying agricultural goods (raw and processed) in order to protect consumer health. It is a method of ensuring food safety by being proactive [23].

To enhance the quality of the food chain or delivery, as well as to secure the supply of sanitary, wholesome food, and to boost commerce within and between nations, effective food standards and control systems are essential. We created an approach that might be used for other fruits and vegetables in the future, with the goal of making generalizations into a full noninvasive and nondestructive strategy for assessing food shelf life. In recent times, a lot of developments have been done in agricultural and food processing industry to mitigate PHL. However, a systematic review is

missing in public domain which discusses about the role of deep learning algorithm in tackling the concern f PHL. A systematic review will help the future researchers to strengthen the orientation to make the progress more faster. The present work discusses about various deep learning, machine learning models, frameworks, and modified algorithms which are helpful in mitigating PHL more efficiently for various fruits and vegetables.

2. State-of-the-Art Review

2.1. Machine Learning Frameworks for PHL Mitigation. Many organizations' attempts to address food poverty are increasingly seeing PHL reduction programmers as a critical component. PHL is becoming more widely recognized as a critical component of a comprehensive plan for realising agriculture's full potential in meeting the world's growing food and energy demands. To meet the task of feeding the world's growing population, reducing PHL, as well as making better use of today's crops, boosting agricultural output, and bringing new land into production on a long-term basis, is vital. The report is unrealistic in terms of reducing food waste [24, 25]. In these days, the consumption of packed food increases according to the needs of the people, hence the number of food industries also increases. The food industries are unable to work lonely, and it needs a complex network for their success, i.e., farmers and their products for the raw material for the preparation of food and other eatable things in the industries and transporters for the transportation of the food from one place to the other with the help of vehicles. After the COVID-19 pandemic, the people are aware about the quality and hygiene of the food materials. Therefore, the food industries prefer to provide the best quality food products, but this seems to be difficult; hence, they wanted to emerge the artificial intelligences and IoTs in their field. Many researchers are working on the AI in
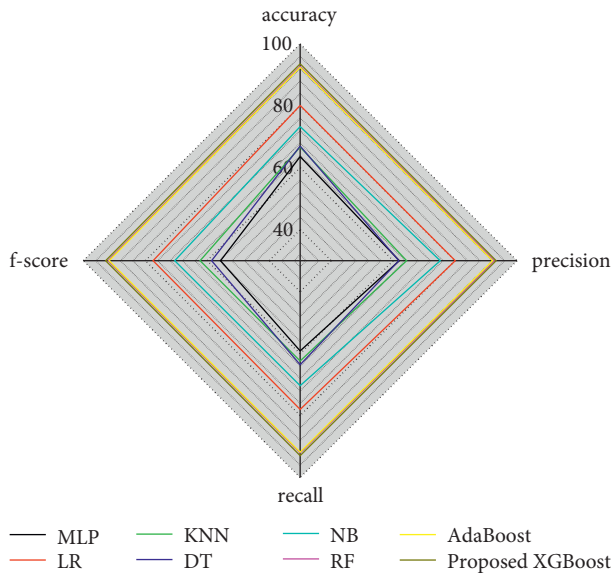
Figure 2: Performance parameter comparison of model XGBoost with other conventional models.

Figure 3: Performance comparison of support vector regression and Gaussian process for different classifier algorithms.

food industries such as Alfian et al.'s [26] works on the AI frameworks in this field which help to maintain the freshness of perishable foods and fruits. The researcher and their coworkers emerge radio frequency identification technology (RFID) and IoT sensors for tracing the condition of materials during the transportation, and these models are also able to identify the diseases and rotten fruits and bad quality food materials, humidity, and temperature during the process of food supply chain and helps in correctly identifying the target places. The RFID technique is also applicable in large scale as it performs a vital role in the healthcare system, manufacturing, companies, malls, etc. [27]. There are various types of AI models used in food industries such as XBoost model which is able to track in movement and direction of targeted places which are based on the received signal strength (RSS) and SinceNet. The working of the RSS is hanged on the distance amid the probes and label, and it uses two antennae. The XBoost models are a collection of set of deterioration hierarchy and classification sets, and it provides a series of improvement in the form of loss of role and gradient boosting (helps in to boost the other models for the better performance, to find the residual error). The function of the model consisted of two parts: training loss and regularization. The researcher compares the XBoost with other AI models to recognize the best performance following accuracy, precision, and recall metrices; the other models that are used for the comparison are k-nearest neighbor (KNN), multilayer perception (MLP), logistic regression (LR), random forest (RF), decision tree (DT), and AdaBoost. This improved system is worked on the basis of RFID and IoT sensor system. The RFID identification technique is used without any contact; hence, we can say that it is a contactless technique which is used for the identification of any objects, animals, and tracing of targeted places. As shown in Figure 2, the researcher proves the best performance by comparing with the other algorithms. Figure 2
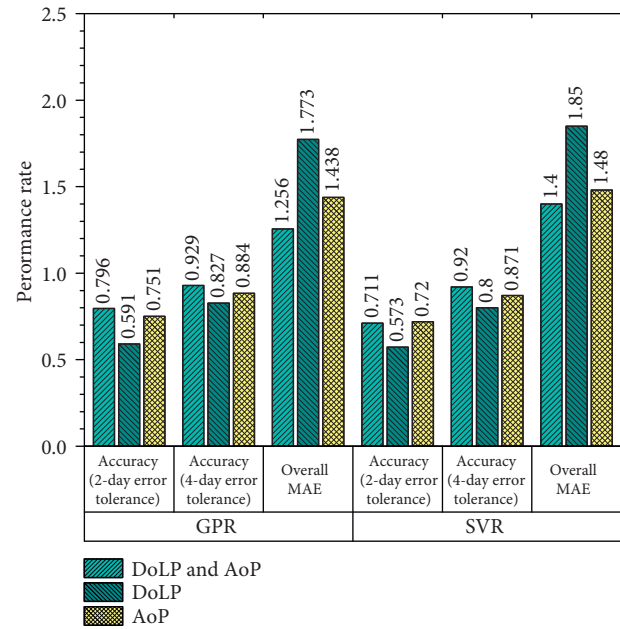
shows that the XBoost algorithm of AI has highest values of accuracy, i.e., 93.5%, precision rate 93.2%, and recall rate 92.5%. Hence, we can say that the XBoost frameworks are for the identification of condition of food material and fruits and temperature and humidity.

During the transportation, they are more prone to rotting of fruits hence the caring of fruits; the quality of fruits and food materials are more important, and it can be possible by applying the artificial intelligence and IoTs. Takruri et al. [26] proposed AI models such as Division-of-Focal-Plane (DoFP) based on the machine learning polarization camera for capturing the polarized images for the detection of the freshness of the fruits and vegetables such as apples, and these images work on the basis of machine learning. The images from these types of cameras are used for the reconstruction of the degree of linear polarization (DoLP) and angle of polarization (AoP) images. Then, the restored pictures are able for further processing through machine learning that helps in finding the age of an apple. The images through the DoFP-ML are best for finding the healthiness and accurate age of apples with 92.5% accuracy, by which we consume the fruits before they rotten. This method is nonoffensive and nonharmful that uses the computational methods such as SVR (support vector regression) and Gaussian process regression (GPR). There are some others methods that are also available for the detection of quality, for example, chromatography, spectrophotometry, and electrophoresis, but these methods are having some limitations such as time-consuming and very costly, and it always needs a trained person for proceeding. Some methods (acoustic) by which the measurement happens electrically help in identifying the elasticity and softening of the tissues of fruits. The most common method is the optical method because it is easy to use, simple in application, and can be

used without any damage. The light polarization method is also applicable in material classification and shape rebuilding to study the food properties and biomedical imaging. The researcher performs the experiments which are grounded on Division of time (DoT). The photos of apples and other fruits utilized in these methods were captured using a regular CMOS camera with a linear polarizer. The fluctuations were tracked using Stokes' Degree of Polarization (DoP) and Degree of Linear Polarization (DoLP). This concept was challenging to develop in terms of hardware because it required two polarization filters and a standard CMOS camera. In addition, a totally linearly polarized light was expected, making DoLP assessment inconclusive. As shown, using both DoLP and AoP as input-pair features to the GPR system resulted in the overall accuracy of 79.6% within a 2-day mistake acceptance and 92.9 percent within a 4-day error acceptance.

The accuracy of the GPR structure remained advanced once the self-determining variables (DoLP and AoP) were employed as a couple than when were cast off as a sole input feature, similar to the SVR classification as shown in Figure 3. Trials on actual facts revealed that the suggested DoFP-ML structure can accurately evaluate the phase of apples up to 92.57 percent of the time. Even before the external rot shows, the DoFP-ML approach that has been suggested can be used to detect apples that are unfit for consumption. We plan to investigate the feasibility of applying the suggested technique to other fruits and vegetables in the future, with the goal of generalising it into a comprehensive noninvasive and nondestructive approach for assessing the shelf life of food items. This will help large shops manage their food storage more effectively [28].

2.2. Machine Learning Classifiers for Food Quality Control.
In the Mediterranean region, trade is a major source of income. Around 9.4 million tonnes of olive pods are harvested each olive year around the world. There are 805 million olive trees in the Mediterranean region, accounting for 98 percent of all olive trees on the planet. 60 million metric tonnes of seed oil and 2 million metric tonnes of olive oil are consumed every year. Jade oil and virgin olive oil are two of the most popular ingredients in Mediterranean cooking. Because this sort of oil is often more expensive than vegetable oils, adulteration with lower cost or lower quality oils could save money. There are two other methods used for the identification of olive oils, i.e., E-nose (made up of 32 odor sensors) and machine learning algorithms (classifier) such as Naïve Bayesian, k-nearest neighbors (k-NN), linear discriminant analysis (LDA), decision tree (DT), artificial neural network (ANN), and support vector machine (SVM) for identifying the quality of olive oils, and we can control olive oil quality more quickly and at a lower cost without the condition for a test center or examination. To manage the tarnishing of jade oil foodstuffs and to protect the devotion of customers and manufacturing in overall, we must continue to be careful as the electronic nose is used, or the detection of different types of aromas with low-charge E-nose is tremendously valuable in a diversity of fields
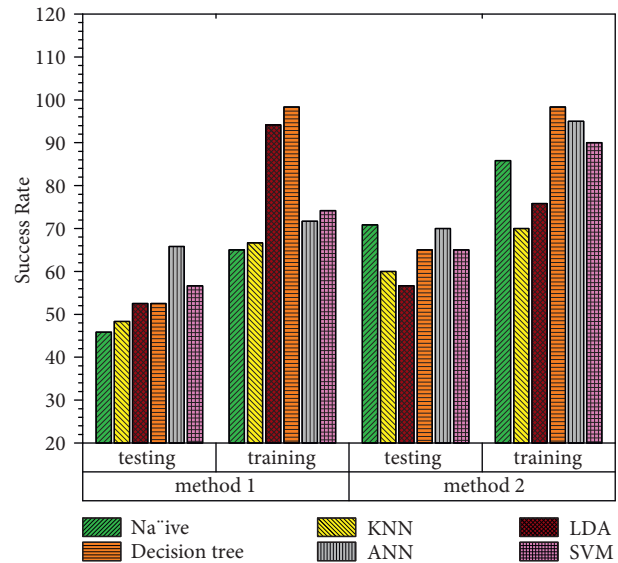

FIGURE 4: DL algorithm success rate comparison during training and testing for different methods.

including diet, make-ups, medicines, and ecological sciences. E-nose is also aimed at the analysis of drinks and fruits with the help of a principal component analyzer (PCA); some researchers work on the uses of E-nose and several types of ML frameworks, and some advanced sensors arrays are used to differentiate between the Spanish wines and grape wines, and the canonical discriminant analyzer (CDA) is valuable for the identification of the fragrance of honey. These algorithms are basically used for the deep classification and identification of olive oils. We wish to save time and money by automating the real-time olive oil quality checking procedure in this application. Our goal is to create a control device that can be carried about with you. We wish to build a portable control device that uses machine learning classifiers like Nave Bayesian, Next-door Nationals (NN), Decision Tree, Artificial Neural Networks (ANN), and Support Vector Machine (SVM). Without the requirement for a laboratory or analysis, we can undertake a more quick and less expensive quality check of olive oil.

As shown in Figure 4, by comparing both methods, E-nose and machine learning algorithm, we can find the accurate methods. From the above discussion, it can be concluded that the first method with naïve Bayes is the best method to control the quality of olive oil [29].

The machine learning algorithms and models useable to analyze the qualities and productivity of oranges also help in maintaining the consistency of the orange economy. Temperature, climate, humidity, and other terrestrial novel traceability essentials have an impact on ensuring the quality and safety of commodities. Additionally, when food safety issues arise, orange traceability may assist in swiftly identifying the source of the problem, which is beneficial not just to consumers but also to producers. There are many difficulties seen to find the best quality and taste, but every orange is having different tastes even harvested from the same place at the same time; this is due to the presence of a
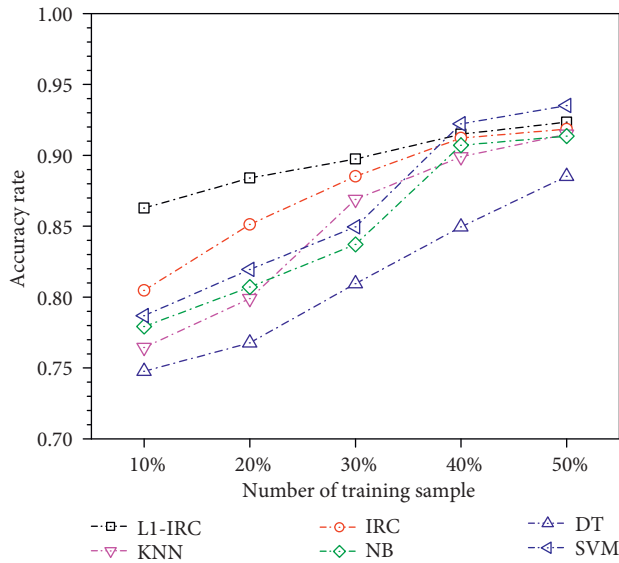
Figure 5: Comparison of L1-IRC model with existing models for different sizes of training samples.

Figure 6: Accuracy, classification, and misclassification rate of different models with MFC inception V3.

diverse amount of chemicals. Many modern technologies have been used in tracing the origins of agriculture-based products, such as isotope ratio mass spectrometry (IRMS), which has been used to identify meat, wine, as well as juice. Other one is the nuclear magnetic resonance (NMR) spectroscopy, which has been used to identify the honey and butter processing areas, along with gas chromatography (GS), which has been adapted for the classification of the main origin of wine and cheese. NIR spectroscopic analysis technology has been popularized and widely employed in the agricultural sector for maintaining product quality testing and identifying origin as a rapid, accurate, convenient, and nondestructive analysis method. It is seen as a potential alternative to traditional chemical analysis, leveraging the theoretical framework of sparse representation to develop a near-infrared spectroscopy also known as NIR approach based on L1-IRC. This approach picks and classifies features using the L 1-standard regularization adaptive learning method. The experimental result shows that, when compared to a typical learning algorithm, the IRC works on the standard hypothesis, which includes a certain category of patterns available in a specific one-dimensional subspace generated by data images from the same category, as well as the classification pattern, which can be described as a linear combination of training samples from the same category. Face image recognition was the first application of the IRC algorithm. A 2-D discrete signal investigation objective can be viewed as the face image. Face recognition, like NIR spectroscopy, resides in the feature dimension and requires the extraction of important features. IRC is used in face recognition, particularly when certain noise, such as illumination, is present. When the sample is insignificant, the original IRC technique is proven to be insufficient for the subdata due to fewer samples, subjected to offsetting of a training sample offset, which frequently produces a high error during reconstruction. An IRC approach based on the
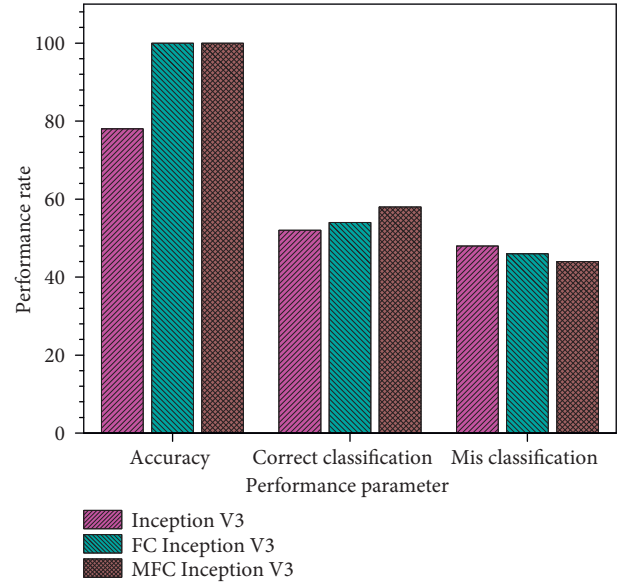
L1 norm is tested using the oranges in the beginning of identification model of NIR spectroscopy. Using the regularization method described in the preceding part, the algorithm computes the IRC model. Reedy constraints are used to make them more effective. NIR spectrum image data set for C-type origin have been provided for oranges.

The identification analysis experiment employs the L1-normalized IRC algorithm (L1-IRC) and the NIR spectrum for oranges and several other fruits. The present work predicts the fresh data set on the original IRC algorithm, decision tree (DT), closest neighbor classifier (KNN), naïve Bayes (NB), and support vector machine (SVM) models. Figure 5 demonstrates the average accurate rate findings for NIR spectral origins by using various machine learning techniques and training sample sizes. The above discussion states that NIR computation approach based on L1-IRC has been able to achieve higher recognition accuracy with a minimal number of data images and produces much better output than other comparative models, and this is due to the use of small-sized samples at the same time [30].

2.3. Machine Learning for Pest Control, Fruits Diseases, and Damage Detection.

After China, India is the world's second-largest fruit producer. It is also the most fruit-exporting country. Fruit markets have the biggest economic weightage/share in the agriculture market as a whole, whether seen from a worldwide or local perspective. Farmers grow fruits and sell them to industries or local market sellers, or they export them to worldwide markets. These fruits are under the processes in the industries which provide different types of products and processed food such as pickles, jams, and juices; hence, the quality of fruits is more important. The quality of the fruit has a direct impact on the profitability of the business. The basic need of industries is the selection of

good quality fruits with high accuracy in less time. Manual fruit categorization, sorting, and grading may be arduous, monotonous, back-aching, and error-prone, all of which have a direct impact on stakeholders' profit margins. Fresh fruit quality traits are divided into three categories depending on the presence of product characteristics: exterior, internal, and concealed. Quality attributes in the exterior category include appearance (sight), feel (touch), and flaws. A quality attribute in the internal class is odor, taste, and texture. Fruits are classed as either excellent or bad, according to stakeholder needs. The authors suggest a strategy for improving the accuracy of a deep neural network model for fruit classification and addressing the problem of misclassification. The misclassification issue was explored using popular CNN models densenet161, InceptionV3, MobileNetV2, and VGG19. Two distinct models, FC InceptionV3 and MFC InceptionV3, are created using transfer learning. The results were then compared, and it was discovered that MFC InceptionV3 based on MNet achieved 99.92 percent accuracy and reduced misclassification by 5.98 percent compared to the original InceptionV3 and 4.17 percent compared to FC InceptionV3 as shown in Figure 6. The Fuzzy Rule-Based Approach for Disease Detection (FRADD) is a new approach for detecting and classifying apple fruit disease (also known as apple scab). FRADD (Fuzzy Rule-Based Approach for Disease Detection) is a novel method for identifying and diagnosing apple fruit disease (also known as apple scab). To recognize photos of citrus illnesses, DenseNet-16, a novel simple, effective, and lightweight model has been presented. The suggested model was 93.33 percent accurate in its categorization. The proposed method included the use of three machine learning algorithms: K-means, SVM, and ANN. Color and texture cues are used to classify the solution presented.

Fruits are classed as excellent or terrible, depending on the needs of stakeholders. A paradigm is provided to enhance the precision of the deep machine learning algorithm for fruit classification while also addressing the issue of misclassification. The discrimination problem was explored using popular CNN algorithms densenet161, InceptionV3, Inception v2, and VGG19. For the purposes of this study, we concentrated on only one system, InceptionV3, for further analysis. Two separate models, FC InceptionV3 and MFC InceptionV3, are constructed utilizing transfer learning. The results were then compared, and it was discovered that MFC InceptionV3 based on MNet achieved 99.92 percent accuracy and reduced misclassification by 5.98 percent when compared to the original InceptionV3 and 4.17 percent when compared to FC InceptionV3 [31].

Deep learning is becoming a frequently utilized and useful technique in a variety of study domains, however not yet in agriculture. The Residual Network (ResNet) along with its upgraded version as well as ResNeXt is utilized in identifying internal mechanical mutilation in blueberries with the help of HIS aging technique data in this study. Blueberries are very soft and delicious fruits with high economic values. Due to its softness, it suffers from pathogenic diseases after harvesting, even at their initial stage of damage. This is directly affecting the income of the producer.
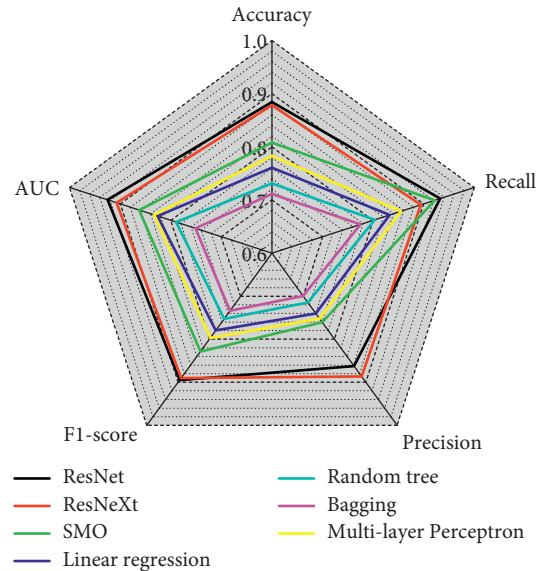

FIGURE 7: Radar graph representing the comparative analysis of performance parameters of various models.

After damage, the colour of it changes and dark pigments are formed. The damaged fruits can be separated by normal human vision, but it takes lots of time; hence, the deep learning algorithms or frameworks are essential for the classification between the healthy and unhealthy blueberries. Hypercubes' initial structure and dimensions are modified for deep CNN training. Convolution layer filters have been adjusted to guarantee that the framework is relevant to hypercube. Moreover, five classic machine learning techniques are used as comparative experiments: Several Sequential Minimal Optimization (SMO) such as Linear Regression (LR) as well as Random Forest (RF) along with Bagging and Multilayer Perceptron (MLP). There are only two deep learning methods (ResNet and ResNeXt) that are achieving better results than the others such as traditional machine learning algorithms because these models attain accurate classification. There are some other methods used for the classification such as hyperspectral imager and thermal imager; these methods are nondestructive type of technique that is applied for recognizing the internal stages of fruits and vegetables. There is no denying that deep learning is an unstoppable general movement for agriculture's future. Deep learning had been applied in agricultural engineering by several researchers. There are some works mentioned about convolutional neural network (CNN) utilization for classification purpose, and their conclusions revealed that the deep learning architecture can provide a great concert for detecting defect areas on cucumbers, tomatoes, melons, and other soft fruits with surface defects. The results after the CNN framework attains high accuracy and high recognition rate with 94%. When employing spectral data to identify sound and damaged blueberries, most classic machine learning systems use nonlinear models. These spectral data, on the other hand, are unable to capture structural changes produced by external load forces, and we want more representational picture characteristics. CNN

uses convolutional layers to extract image characteristics implicitly, making it an ideal option for extracting depth information using hypercube, thereby allowing the creation of robust as well as trustworthy classifier.

Figure 7 shows the comparison between the algorithms with respect to 5 metrices: accuracy, recall, precision, F1 score, and AUC. Both deep learning models outperform standard approaches in general. Compared to other classifiers, ResNet and ResNeXt obtain an additional 8% accuracy. The F1-score is a performance metric that considers both accuracy and recall. The area that is below the ROC curve is used to produce AUC, which may be used to compare the two classifiers. Both deep learning models outperform the other methods in terms of F1-score and AUC.

3. Conclusion and Future Scope

We have provided many ways for PHL mitigation and quality control utilizing various machine learning algorithms in this work. The integration of IoT sensors into a traceability system for the perishable food supply chain in minimizing PHL has been demonstrated in the models discussed. This analysis is based on substantial data to show the effect of DLML and IoT in precision agriculture and food processing in reducing PHL losses in fruits. To compare and contrast the accuracy outcomes of various machine learning methods, various models have been critically reviewed and discussed in terms of their accuracy, recall, precision, and F1 score. The discussed models made use of RBG images, infrared images, and hyperspectral images for developing training and testing data sets followed by feature extraction and classification. We hope that this research would aid in better quality control and cost analysis for food quality. The findings of this study reveal that the recommended methods for identifying and classifying quality control of various fruits and vegetables are faster and far less expensive than traditional ways. Other data reduction and hybrid algorithms can be used in future projects, and their performance can be compared based on accuracies. The information offered in this paper discusses the possibilities of alternative techniques for controlling citrus postharvest infections. We plan to investigate whether the proposed technique may be used on additional fruits and vegetables in the future, with the goal of generalising it into a comprehensive noninvasive and nondestructive approach for assessing the shelf life of food items. This will assist large retailers in effectively managing their food storage. In the future, we plan to examine various ensemble learning algorithms in diverse contexts in order to increase performance and expand our experimental results to include more data sets. The proposed model's classification accuracy was 93.33 percent. When the results were compared, MFC InceptionV3 based on MNet obtained 99.92 percent accuracy and reduced misclassification by 5.98 percent compared to the original InceptionV3 and 4.17 percent compared to FC InceptionV3. The deep learning model has shown good results. In the future, AI may also help by avoiding unnecessary food waste and lowering edible food waste. AI is one of the most significant technological developments of the industry 4.0 eras, with the once-in-a-lifetime potential to transform the food industry from a linear to a circular paradigm.

Data Availability

The data are available on request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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