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RESEARCH ARTICLE

A Review on Automated Detection and Assessment of Fruit Damage Using Machine Learning

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ABSTRACT Automation improves the quality of fruits through quick and accurate detection of pest and disease infections, thus contributing to the country's economic growth and productivity. Although humans can identify the fruit damage caused by pests and diseases, the methods used are inconsistent, time-consuming, and variable. The surface features of fruits typically observed by consumers who seek their health benefits affect their market value. The issue of pest and disease infections further deteriorates fruits' quality, becoming a mounting stressor on farmers since they reduce the potential revenue from fruit production, processing, and export. This article reviews various studies on detecting and classifying damages in fruits. Specifically, we review articles where state-of-the-art approaches under segmentation, image processing, machine learning, and deep learning have proved effective in developing automated systems that address hurdles associated with manual methods of assessing damage using visual experiences. This survey reviews thirty-two journal and conference papers from the past thirteen years that were found electronically through Google Scholar, Scopus, IEEE, ScienceDirect, and standard online searches. This survey further presents a detailed discussion of previous research done in the past while emphasizing their strengths and limitations as well as outlining potential future research topics. It also reveals that much as the use of automated detection and classification of fruit damage has yielded promising results in the horticulture industry, more research is still needed with systems required to fully automate the detection and classification processes, especially those that are mobile phone-based towards addressing occlusion challenges.

INDEX TERMS Fruit damage detection, classification, deep learning, image analysis, segmentation.

I. INTRODUCTION

A. BACKGROUND OF CITRUS FRUIT DAMAGE DETECTION

The horticulture industry plays a vital role in the economic growth of a nation [1]. Like other African nations, the horticulture industry remains the backbone of Uganda's economy to achieve inclusive development, with more than 60% of the population engaged in the sector providing approximately 24% of gross domestic product (GDP) [2]. However, pests have intensified over time, becoming a mounting stressor on farmers due to damages caused to plants grown [3].

The potential revenue from fruit production, processing, and export for farmers has been impacted by fruit loss caused by pests and diseases [4]. Fruit analysis for a variety of aspects is essential to increasing quality and reducing waste. Automated computer vision and image processing techniques have been applied to pre- and post-harvesting procedures to enable prompt analysis of damage inflicted on fruits. Fruits have great relevance for humans because of their nutritional

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value, such as being a source of vitamins A, C, B1, and B-9 [5], [6]. This has greatly improved research in the analysis and processing of fruits, as it feeds into horticulture industries, thus improving the economic sectors of different nations. Various studies have attempted to develop methods that automate fruit processes such as detection, classification, and estimation of quality yields, among others [7]. Usually, the damage inflicted on fruits is due to pests and disease infections, affecting their quality for use in the production and marketing sectors. The fruit industry depends on early identification of fruit damages and the causing conditions to prevent them from spreading from one fruit to another, which results in extreme fruit yield declines and substantial economic losses [6], [8].

Annually, a large proportion of export fruit is rejected due to signs of damage caused by pests and disease infections. This causes losses to farmers as quarantine restrictions are imposed by fruit-importing countries that, in turn, hamper horticulture trade, especially between African and developed nations [9]. These pests have become a significant constraint in production and marketing, with their management cited as a challenging issue worldwide [6], [9]. For instance, an ICIPE-led African Fruit Fly Programme assessment revealed that out of 1.9 million tonnes of mangoes produced in Africa annually, about 40% are wasted due to fruit fly damage [9]. As a result of such damages to fruits, diseases and pests have imposed substantial danger to farming, causing deterioration of the quality of fruits and sometimes even endangering the orchards [10]. This has called for the need to alleviate challenges associated with manual methods of assessing and investigating fruit quality, which is based on the visual experiences of trained professionals. These methods are inconsistent, time-consuming, labour-intensive, tedious, cost-intensive, and subjective [11], [12], [13] yielding low efficiency and unstable accuracy, thus the need for timely and automated identification systems to quickly and accurately detect and diagnose fruit damage infections and reduce such losses and associated costs [14]. Research done on the use of non-destructive techniques (NDTs) in evaluating damage to fruits has led to better accuracy from rich information collected at different wavelengths. NDTs detect the internal state of objects without destroying them [15]. However, these techniques rely on costly equipment, making them unsuitable for field use [12], [16] when capturing fruit images and identifying associated damages. These techniques are based on physical properties that correlate well with certain quality factors of fruits without rupturing the tissue [17]. This has led to the need to use low-cost tools for detecting surface defects such as black spots, cankers, scabs, greening, rot, discolouration, and bruising [18] using conventional machine learning techniques that use shallow learning. Machine learning is a preferred and efficient technique to perform various tasks such as segmentation and classification [19]. However, state-of-the-art deep learning techniques have also been recently used [20], [21] due to their ability to extract features directly from datasets [22].

Generally, fruit damage detection is considered a vital area of research. Several authors are researching ways to improve the quality of fruits and further reduce waste from pests and disease infections.

B. OVERVIEW OF AUTOMATED APPROACHES FOR FRUIT DAMAGE DETECTION

The automated inspection of quality in fruits using computer vision and machine learning is becoming of paramount importance to address challenges associated with a visual inspection that is inconsistent, destructive, and involves tiresome processes that require skilled labour for orchard management [23] when assessing damages [24]. Due to these challenges, automated systems have been developed [14] using image processing, machine learning, and state-of-the-art deep learning-based approaches with precise technologies in some cases used to avoid damage aggravation that could further result in fatal losses [14], [24].

The automated approaches that use conventional machine learning techniques use hand engineering of features to extract features, which are fed as inputs to models [25] such as SVM [26] and Fuzzy learning [27] among others. The performance of these models depends on extracted features such as textural, colour, and shape, a task that is challenging when identifying those features since they are invariant due to different imaging conditions that are found in fields such as rotation, scale, and translation. Recent research is directed towards using state-of-the-art deep learning-based approaches due to their ability to extract features within different semantic levels that give good adaptability to various working scenes [22] learning features directly from bigger datasets where models such as CNN [28], YOLO-V4, EfficientNet, MobileNet-V2, ResNet-50, DenseNet-169 [23] have been developed for damage detection of fruits in orchards and at post-harvest levels. The concept of automated feature extraction exhibited by deep learning models has improved the performance of models when performing tasks such as detection and classification to improve accuracy while developing robust models [23].

Machine learning has also been integrated with other cutting-edge technologies, like the Internet of Things (IoT), to enrich agricultural production across the entire ecosystem.

C. IOT (INTERNET OF THINGS) FOR FRUIT DETECTION AND STATUS MONITORING OF FIELDS

The use of IoT in agriculture, also referred to as Agricultural IoT applies IoT technology in the agricultural production chain, which brings together sensing, computing, and implementing devices to aid in automating specific farming operations [29]. The use of machine learning-based approaches and the Internet of Things (IoT) in horticulture during orchard management has the prospect of revolutionizing agriculture by fostering decision-making through the analysis of data collected by IoT sensors used to transmit data from an aground point to a destination point where farmers acquire alert notifications about the status of their fields [30]. IoT in horticulture has helped in realising the success of automation of processes such as communication of one orchard to another to aid in managing big farms [31].

IoT, one of the emerging technologies in agriculture, has been applied in many areas, such as intelligent agricultural machinery, growth monitoring, and plant life information monitoring. This information relates to air temperature, air humidity, CO2 concentration, light intensity, soil temperature, humidity, and soil PH as collected by various sensors to obtain real-time environmental information about the field [32]. Thanks to developments in the domains of hardware and algorithm optimization, real-time fruit identification and damage evaluation are now achievable. This is particularly important in industrial settings where rapid processing is crucial for efficiency. Recent research has indicated several developments that indicate the impact of integrating image processing, machine learning, deep learning, and IoT-based technologies in the areas of fruit detection and assessing associated damages for the best utilization of sensor datasets collected. For instance, Behera et al. [33] developed a framework that uses both image processing and IoT system with components including a camera, a mobile phone IoT gateway, and an image processing system for on-tree fruit monitoring, including counting and size estimation, with a coefficient correlation of 0.994 and 0.997, respectively. Onishi et al. [34] also designed an apple-picking robot that uses a single-lens multi-box detection approach to detect fruits on the tree and then a stereo camera for detection of the position of the fruits. Kang and Chen [35] also developed a framework for detecting apples to be harvested in orchards using a harvesting robot vision sensing system that detects and localises fruits to be detached from trees. An auto-label generation module was used, and a deep-learning-based fruit detector (LedNet) which adopts feature pyramid network and atrous spatial pyramid pooling for enhanced detection performance of the model with LedNet attaining 0.821 and 0.853 on recall and accuracy respectively on apple detection in orchards. Furthermore, Wang et al [36] developed an apple growth monitoring system in an orchard for apple size remote estimation throughout the entire growth period using image datasets acquired regularly with a remote apple growth monitoring hardware system built with a spherical video camera. Segmentation of images was done using an edge detection network with fused convolutional features. The system attained an F1 score of 53.1% and a mean average absolute error of the apples' horizontal diameters of 0.90 mm.

D. NON-DESTRUCTIVE METHODS IN EVALUATING FRUIT DAMAGE

Non-destructive methods have been explored in the detection of pest and disease infections in fruits, despite their costly nature [37]. For instance, hyperspectral imaging (HSI) has been seen as a promising technology to detect fruit fly infestations when they are still in small numbers. Saranwong et al. [38], developed an approach that uses partial least squares discriminant analysis models to detect fruit fly eggs and larvae in intact mangoes using different wavelengths and obtained an error rate of 4.2%. Haff et al. [4] further applied HSI using hyperspectral data to assess fruit fly larvae infestation in mangoes using Bayesian discriminant analysis for classification obtaining classification rate for infested and healthy fruits as 99.1% and 94.3%, respectively. Jamshidi et al. [39] investigated the use of visible / near-infrared spectroscopy in conjunction with pattern recognition methods (PCA-DA) to detect internal infestation in pomegranate fruits caused by Carob Moth larvae. The method attained a classification rate of 90.6%. Vélez Rivera et al. [13] also developed an HSI system to detect mechanical damage induced in mango fruit at an early stage. Naive Bayes, Decision Trees, Linear Discriminant Analysis, and K-Nearest Neighbor classifiers categorized mangoes as damaged or sound obtaining accuracy of 67.46, 84.63, 89.27, 89.76 and 94.87 respectively on the first day and the scores increased over seven days after damage induction. K-NN and LDA were the best at performance obtaining 97.5% and 95.54% by day 3.

The commonly used Non-destructive techniques in evaluating fruit damage are discussed below:-

1) Biospeckle technique
   This technique is a relatively new non-invasive, non-destructive, low-cost, and simple optical method that works based on optical properties to study biological materials. It has various biological or non-biological processes when laser light is incident on a substance. Biospeckle is a situation that occurs when a biological material is illuminated by coherent light, causing light to be backscattered from an optically coarse surface. From the observation plane, bright and dark areas are displayed. Using laser light when the objects are illuminated, the optical intervention effect is observed, which is granular in appearance, with light and dark speckles formed due to constructive and destructive interference, discretely of scattered laser light [40]. This technique has been used in fruit damage assessment to examine the quality properties of plants such as damage, ageing, or disease infections [41].
2) X-ray imaging
   This is a non-invasive machine vision technology that detects internal defects of fruits during food inspection using electromagnetic radiation that works with wavelengths that range from 0.01 to 10nm with a powerful ability to penetrate through fruit products with the potential to inspect internal disorders of fruits in high-resolution [42]. This imaging technology has a competitive edge since it can penetrate through most objects with a frequency and energy range of 30-30000 Peta Hz and 0.12-120 keV, respectively. It computes the levels of fruit damage through defect volume calculation though it's quite an expensive imaging technique hindering its use in agricultural products. It is further associated with the risk of X-ray leakage, posing

a health hazard to operators with difficulties acquiring fruit images from many angles in real-world applications making it difficult to compute for volumes [43].

3) Hyperspectral imaging
This is used in analysing a wide spectrum of light instead of just assigning primary colours (red, green, blue) to each pixel, with the light that strikes each pixel broken down into many different spectral bands to provide more information on what is imaged. It captures spectral information from an object at a high spatial resolution. In HSI, the unique colour signature of an object can be detected. Unlike other optical technologies that can only scan for a single colour, HSI can distinguish the full-colour spectrum in each pixel. Therefore, it provides spectral information in addition to 2D spatial images. In fruits, it captures images across a wide range of wavelengths, providing a spectrum for each image pixel. Analysis of the spectral information using hyperspectral imaging provides detailed information about the chemical composition, structural properties, and quality of the fruit [44]. However, it is a time-consuming technique requiring complex data processing with low flexibility of multivariate models [18].

4) Spectroscopy
Spectroscopy is an imaging technique that studies the interaction of light and matter. Various types of spectroscopy exist that rely on the ability of atoms and molecules to absorb or emit electromagnetic radiation. This interaction is according to a certain wavelength and associated with radiation energy with the spectral wavelength normally denoted by a spectrum series representing wavelength or frequency. Classifications of spectroscopy are according to:- the type of radiation energy, type of material, nature of interaction and so on. As a non-destructive method, it evaluates fruit damage without causing any physical harm to the fruit by analysing the interaction of light with the fruit and providing information about the chemical composition, structural properties, and quality of the fruit [44]. It has been used in several applications such as the detection of hollow-heart in citrus fruit, and assessing the quality parameters such as colour, sugar content, and acidity. Some of the commonly used spectroscopy techniques include visible and infrared spectroscopy, visible and ultraviolet spectroscopy, and near-infrared spectroscopy (NIRS). These techniques are based on the principle that different wavelengths of light interact differently with the fruit, depending on the chemical and physical properties of the fruit.

5) Thermal Sensing
This is one of the non-destructive techniques that have emerged as powerful tools in analysing agriculture and food industries through monitoring temperatures. Thermal imaging analysis works by converting the radiation pattern of a sample based on the temperature differences in the objects being studied [45]. Thermal imaging creates a bit-map called a thermogram by detecting infrared radiation emitted from an object. It has been used in many areas including post-harvest quality, crop yield, temperature monitoring, pathogen detection, chilling damage to the fruits, crop maturity estimation and crop yield estimation among others [46]. Defects such as chilling injuries do not change fruit colour yet most of the current algorithms for traditional computer vision systems are based on manually designed features that involve colour or texture and thus are not suitable for detecting such defects hence the need for other imaging systems such as thermal imaging which obtains up to 4X speed in training time compared to RGB images [22].

This study aims to identify, analyze, classify, and discuss the current state-of-the-art techniques for detecting fruits in orchards and assessing associated damages as reported in scientific literature indexed in databases such as Scopus or Web of Science. In summary, this article, therefore, focuses on the following specific contributions:

1) Systematic collection and analysis of research works about automated fruit damage detection through the application of machine learning, deep learning, and image processing approaches.
2) Identifying and delineating the integration of IoT components with deep learning-based techniques in horticulture while addressing privacy concerns for farmers stemming from the management of large datasets.
3) Lastly, we then give recommendations for diverse avenues aimed at enhancing automated assessment and monitoring in orchards.

The remainder of this work is structured as follows: Section II discusses the research methods, where the search strategy, inclusion, and exclusion criteria to obtain relevant studies are specified. Section III introduces the literature review. The different sub-sections are created, indicating the reviews under each of them. Section IV then discusses the challenges and privacy issues inherent to the automation of fruit detection and associated damages. Section V briefly illustrates standard databases with data sets that can be used by researchers to study the automation of fruit detection. A comparison is also done, specifying the different parameters under each of the databases. VI then shows the metrics commonly used in evaluating model performance. Section VII then discusses the main findings, current challenges, and recommendations. Section VIII presents the conclusions of this review and IX the future work researchers can explore.

II. RESEARCH METHODS

This section serves to introduce the strategy and methods utilized to find pertinent research for this review article. The articles reviewed have been analyzed to identify current research trends and directions by detecting the unexplored research areas, and those areas that have not been extensively explored.

A. SEARCH STRATEGY

This survey reviewed articles related to the application of image processing and analysis, machine learning and deep learning in the automated detection of fruits and assessment of damages inflicted on them. Many articles were obtained electronically through scientific databases including Google Scholar, IEEE, Scopus, and ScienceDirect. General internet searches were also conducted to obtain datasets that hadn't been put into specific repositories. Such information is hard to find, and yet searching more broadly helps in retrieving it if using previous strategies that search from specific databases has failed. This is because people sometimes make information available through sources such as sites that are related to subjects, including research groups or projects. Such information is best retrieved using general internet searches done across the internet.

From the sources searched, several articles were retrieved, and the most relevant were filtered, leaving 32 of them as guided by the inclusion and exclusion criteria. The automated identification of damages and defects in fruits starts with detecting fruits being analyzed. As such, literature about the techniques that have been used in the past to detect fruits, especially while still on trees, has been reviewed, as indicated in Table 4. More literature about the use of conventional machine learning and deep learning for automated damage detection in fruits has been explored, as seen in Tables 2 and 3 respectively.

The keywords used in the search criteria of articles extracted from different databases selected include a set combination of the following keywords:

1) Deep learning, quality assessment and fruit damage
2) Fruit damage detection, machine learning, image processing.
3) Fruits defect detection, image analysis, machine learning.

B. INCLUSION AND EXCLUSION CRITERIA

The inclusion/exclusion criteria are used in this work to help strengthen the search process towards attaining quality and relevant information for the study being researched. The inclusion/exclusion criteria were mainly focused on literature about automated fruit and damage detection in fruits using machine learning-based approaches. This was done in studies that used techniques that analysed the features of fruits at both pre- and post-harvest stages. However, because such damage detection first originates from detecting the fruits themselves, studies about automated detection of fruits, especially when still in the orchards, are further reviewed. Hence, articles that did not meet these criteria were excluded. Poster papers were also excluded from the review to avoid duplicating the information obtained, especially in the full-text articles retrieved. The search spanned 2010 to date, with all articles outside the range left out. This search looked at articles only authored in the English language. An overview of a full description of the inclusion and exclusion criteria used in this work is described in Table 1.

C. DATA EXTRACTION, AND ITS ANALYSIS

After attaining relevant information from articles that met the inclusion criteria, different data elements were extracted and populated in a tabular structure with columns representing authors & year research was done, research goal, dataset, features used, techniques/models, and performance evaluation metrics. This is illustrated in Table 2 and Table 3 enumerating those studies done under machine learning and deep learning respectively that have looked at automated detection of fruits and associated defects/damages on them. Furthermore, a general survey is done to identify past reviews on automated fruit detection, and associated damages, fruit classification, and quality classification.

III. LITERATURE REVIEW

The literature under this survey has been organised into different sub-sections:

1) III-A Existing surveys on automated detection of fruits and damages
2) III-C:- Application of image analysis techniques for fruit damage detection
3) III-D:- Classical machine learning for fruit damage detection
4) III-E4:- Application of CNN architectures and techniques for fruit detection and associated damages

A. EXISTING SURVEYS ON AUTOMATED DETECTION OF FRUITS AND DAMAGES

Numerous reviews have been done in the past aiming at in-field fruit detection, damage assessment, grading quality of fruits [7], [11], [56], and fruit yield estimation [57] using image processing machine learning, deep learning-based approaches, and non-destructive techniques [42]. For instance, Naik and Patel [58] presented a review of the process of fruit classification and grading using machine vision and classification techniques. Feature extraction methods:- Speeded Up Robust Features, Histogram of Oriented Gradient and Local Binary Pattern were also discussed, with features:- color, size, shape and texture being the commonly extracted ones to be fed into classifiers like K-nearest neighbour (KNN), Support Vector Machine (SVM), Artificial Neural Networks (ANN) for specifying quality of fruits. Gongal et al. [59] also reviewed machine learning techniques ANN, KNN, SVM, Bayesian classifier, and K-means clustering for detecting fruits on trees. The study further summarizes sensors and systems developed to localize fruits, with major challenges in the application of computer vision for robotic fruit harvesting and crop-load estimation discussed. Dubey and Jalal [60] then surveyed various approaches used in fruit and vegetable segmentation and classification using image processing machine learning approaches in the identification of fruit disease. The review considered a single type of fruit and one type of disease. Bhargava and Bansal et al. [5] also presented a review of various preprocessing, segmentation, feature extraction, and classification techniques with the use of machine learning and image processing approaches

TABLE 1. Inclusion and Exclusion Criteria.

No	Inclusion	Exclusion
1	The paper should be written and published in English language	Papers authored that are written in other languages other than English
2	Papers published in peer-reviewed journals or conference proceedings	Papers published in non-peer review journals or conferences
3	Papers published from 2010 to date	Papers published before 2010
4	The paper shows work carried out on fruit damage and defect detection. The machine learning approaches and systems used should be included in the paper.	Articles using machine learning for non-invasive detection of damages in fruits.

for determining fruits and vegetable quality using colour, texture, size, shape, and defect features. A comparison of the performance of various algorithms by different researchers in the evaluation of fruit and vegetable quality was also done with a recommendation to consider capturing images from different directions. Dhiman et al. [11] further reviewed fruit quality evaluation, emphasizing popular machine learning techniques. The review revealed that shape, size, color, or texture features are commonly extracted and then fed into classification techniques including a k-nearest neighbor, support vector machine, and neural network for fruit quality assessment. Syal et al. [61] also stress the procedure of fruit detection as the extraction of handcrafted features such as colour, texture, and shape that are fed into machine learning models. Generally, the use of traditional machine learning approaches for fruit detection and damage assessment follows steps including image preprocessing, feature extraction, and training of the models, with color and texture features being the common inputs to the models built. However, since deep learning models outperform traditional machine learning due to their ability to autonomously learn hierarchical features from raw data and the automatic extraction of features, they have superior performance in complex tasks such as managing unstructured and large datasets. Because it has provided state-of-the-art results in smart farming applications [57], several researchers have embraced its use. Specifically, here we discuss reviews in fruit detection and their assessment for quality. A review by Kamilaris et al. [62] on the application of deep learning approaches in the agricultural field indicated improved detection accuracy than other image processing techniques in the field of agriculture. Studies have indicated great use of CNN in various areas of the agriculture sector, such as disease detection [57]. Naranjo-Torres et al. [7] reviewed the application of state-of-the-art CNN models, including AlexNet, VGG16, and GoogLeNet to various tasks in fruit image processing, including fruit detection, their classification, grading, and quality assessment. Results indicated an observation in the great use of CNN for fruit recognition with the recommendation that for complex tasks, the number of layers is increased for improved feature extraction when working with both pre-trained and new models using datasets with different types of images. Authors in [63] also reviewed approaches used in automated feature detection and classification of fruits, with a focus on watermelon. They gave an overview of the methods for the automatic recognition of fruits and their classification using machine learning and evolutionary computational techniques in the analysis of sensed data in the agro-industry. The study further developed an automated watermelon recognition system using images, acoustic, and spectroscopy methodologies. Wang et al. [64] reviewed CNN-based detection methods applied to the entire production process of fresh fruit including fruit flower detection, fruit detection, fruit harvesting, and fruit grading. The CNN architecture's object detection was elaborated from the data acquisition process to model training while comparing the different detection methods at each phase of fruit production. The findings here suggest that detection customized to specific characteristics of each production stage may address environmental challenges and optimise multitask operations in fresh fruit production. Maheswari et al. [57] reviewed fruit yield estimation approaches using deep learning semantic segmentation architectures. The various steps such as fruit detection, counting, sampling, capturing annotation, augmentation, performance evaluation of models, and challenges associated with these approaches involved in fruit yield estimation are discussed. Findings suggest that transfer learning and optimizing weights to train the architecture in fruit detection and related tasks improve performance. Kumar and Mohan [65] also reviewed the application of deep learning models for fruit detection and localization to aid in tree crop load estimation. This work looked at approaches ranging from extrapolating tree image counts to orchard yield estimation while dealing with occlusion. The study recommended the use of standard metrics and publicly available image datasets to enable comparison of models and make transfer learning possible.

This review emphasizes the use of machine learning and deep learning in fruit detection and damage assessment. It encapsulates the progress achieved so far in automated fruit damage detection and damage assessment. It further incorporates a novel dimension that explores the latest developments, including the integration of IoT and machine learning. It then examines challenges and privacy issues, components that limited reviews have attempted to explore in the past.

B. AUTOMATED DETECTION OF DAMAGE IN FRUITS

Automated detection of fruit pests and disease infections is necessary to determine their quality. This is done by detecting various features that represent such infections and

TABLE 2. Conventional machine learning for fruits damage detection.

Author	Goal of study	Dataset	Feature	Technique	Performance measure
Bakar *et al.* [26]	Detecting external skin defects of mangoes	500 mango images	colour and texture	Support Vector Machine	Accuracy - 90.4%
Wang *et al.*. [47]	Detecting orange skin defects	650 orange images	Colour	Linear SVM, RGB colour Space, Fisher LDA	Precision - 96.70%
Nandi *et al.*. [27]	Classifying mangoes using surface defects	2184 images	Colour	Support Vector Regression, Multi-Attribute Decision Making & Fuzzy incremental learning, Thresholding	Accuracy - 90%
Golzarian *et al.* [48]	Grouping mangoes based on the size of dark spots on the skin surface	60 images	Texture	K-means clustering	ROC curve - 93.3%
Truong *et al.* [49]	Using machine learning to grade the quality of mangoes based on external features	4983 of images	Texture	Random forest	Accuracy - 98.1%
Behera *et al.* [50]	Identify disease on apple, mango, orange, tomato and pomegranate fruits	230 images	Colour, texture, shape and appearance	Multi-class SVM, K-means clustering, Gray-Level Co-occurrence Matrix	Accuracy - 92.17%
Sahu *et al.* [51]	Identify surface defects and detect maturity of mango fruits	28 images	Shape, size and colour	Image analysis algorithms developed using MATLAB	N/A
Nadarajan *et al.* [52]	Detecting bacterial canker disease in mangoes	100 image frames from a video	Colour	Watershed algorithm, template matching	N/A
Ahmed *et al.* [53]	Segmentation of lesions in mango fruits	500 images	Colour, texture and edge	K-means, thresholding, edge-based, Texture and Colour-based segmentation	Accuracy - 98%
Dubey *et al.* [54]	Apple fruit disease recognition	431 images	colour and texture	K-means clustering	Accuracy - 93%
Habib *et al.* [55]	Identifying papaya disease	128 images	colour and texture	K-means clustering, SVM classifier	Accuracy - 90%

recognizing symptoms of pests and diseases as soon as they appear on the growing fruits. These infections can develop on fruits in the field and after harvest, leading to major losses in yield and quality [60].

The edible and economic values of horticulture products are affected when the damage affects fruits. This has made quality detection in the horticulture industry a hot field to research [15]. The growing demand for high-quality fruits during the inspection process has led to many developments in the use of automated computer vision approaches since they are cost-effective and non-destructive [60] using image processing techniques. Image preprocessing applies a series of techniques to the raw input image to enhance its quality and suppress undesirable features for better processing and accurate feature detection [28]. In the fruit industry, this would enhance the visual quality of image datasets that are input into the model. Preprocessing is applied to image datasets to deal with problems such as distortion, noise, brightness effects, illumination, and poor contrast that affect the accuracy of models [66]. Images used in building models are first preprocessed using several techniques. This allows the training of models with consistent and uniform datasets. Such techniques include those listed below under the following categories:

1) IMAGE PREPROCESSING

(a) Image resizing

Resizing the images helps reduce computational costs and achieve better generalisation of the model. All images are resized to the same scale before they are fed into the designed model for detection and classification tasks [67]. The sizes of the acquired images are normally different, so it is necessary to have them normalised first. Techniques such as OpenCV BICUBIC interpolation are used for this task using the OpenCV framework to attain higher processing time and better output quality for the models built.

(b) Normalisation

The image datasets collected are normalised by subtracting the mean and dividing by the standard deviation to improve contrast and reduce the impact of lighting variations. Using RGB images, the mean and standard deviation of the training dataset computed are used to normalise image datasets so that the resulting data has a zero mean and unit variance [67].

(c) Image enhancement
Enhancing the image improves the visibility of image features and reduces noise using techniques including contrast stretching, histogram equalisation, and sharpening.

Histogram Equalization
This improves the contrast of the collected images by assigning pixel intensity values to the input image so that the output images contain a uniform intensity distribution. This is achieved by effectively spreading out the most frequent intensity values.

Contrast stretching
This is an image enhancement technique that improves contrast in images by stretching the range of pixel intensity values it contains to span a desired range of values.

Sharpening
This enhances the edge and fine details of an image, thus making it appear sharper and clearer.

2) IMAGE ANALYSIS

Image analysis uses preprocessed image datasets for the extraction of useful information from the data. Some of the techniques used here include:

(a) Image segmentation
Segmentation is an approach that splits an image into several parts to detect regions of interest by combining similar pixels together [68]. This technique is used in the horticulture industry to extract regions of interest by separating diseased regions from healthy ones. Segmentation techniques include handcrafted feature-based methods such as threshold-based ones, including edge-based, region-based, cluster-based, and Watershed [69]. Intelligence-based ones include artificial neural networks and deep learning methods.

(b) Feature extraction
This is the process where the features are automatically or manually selected that contribute most to the desired output of a model. Redundant features in the acquired image datasets decrease the performance of models since they learn based on irrelevant features. Extracting features uses approaches such as texture, colour, and shape. Colour descriptors include approaches such as the RGB colour histogram, opposition histogram, hue histogram, transform colour distribution, colour moment, and colour moment invariants, among others, whereas convexity, compactness, width, length, roundness, border encoding, elongation, length or width ratio, Fourier descriptor, and invariant moments are used for shape. Qualitative and quantitative analysis are common approaches to assessing texture. Statistical texture gives great accuracy and is commonly used.

(c) Feature Selection
This is the process of selecting a subset of extracted features that result in the best performance of the model. Sometimes, these features come with noise, and others might not be utilised by models. Thus an optimum set of features must be determined, possibly by trying all combinations, especially when using conventional machine learning. However, when they become many, they increase the computational complexity of the models. They are classified into the filter, wrapper, and embedded [70]. However, state-of-the-art deep learning models do not require manual selection of the features.

(d) Data Augmentation
This technique is used to increase the number of training images to prevent overfitting:- a condition that occurs when a small number of samples are used as training data in model development. Augmentation also makes model generalisation better. Data augmentation techniques include rotation, translation, zooming, shearing, flipping horizontally or vertically, brightness, and contrast are commonly used [28], [67], [71]. Because huge datasets are normally needed in building deep neural networks, augmentation solves this problem and further prevents overfitting by generating large datasets to achieve sufficient generalizability to obtain generalised models.

C. APPLICATION OF IMAGE ANALYSIS TECHNIQUES FOR FRUIT DAMAGE DETECTION

Various studies have used different image analysis techniques in processing image datasets into fundamental components to extract meaningful information.

1) Using segmentation
Ahmed et al. [72] developed an approach to segment lesions in mango fruits using various segmentation techniques, and then computed the lesion area. Using the K-means algorithm, higher accuracy was attained compared to thresholding, edge-based, Texture and colour-based segmentation. Nadarajan and Thamizharasi [52] also proposed a method that detects bacterial canker disease in mangoes using a watershed algorithm for segmentation, template matching for finding diseased areas, and cross-correlation to identify segmented areas. This template-matching approach does not work well with large datasets. Dubey and Jalal [54] further proposed a system for apple fruit disease recognition using a local binary pattern approach using image segmentation with K-means clustering. Texture and colour features were extracted from normal and diseased apple fruits with 104 Apple Blotch, 107 Apple rot, 100 Apple scabs and 120 Normal Apple images using CCV, LBP and GCH feature extraction techniques attaining the highest accuracy of 93.14% using CLBP feature. Habib et al. [55] attempted a study to recognise papaya disease using k-means clustering to segment the diseased region

from the healthy sections using a dataset comprised of 128 images, both faulty and fault-free. Statistical and grey-level co-occurrence matrix features were extracted and fed into the SVM classifier, attaining more than 90% classification accuracy. Figure 1 illustrates the effect of the segmentation technique on infected fruit images.

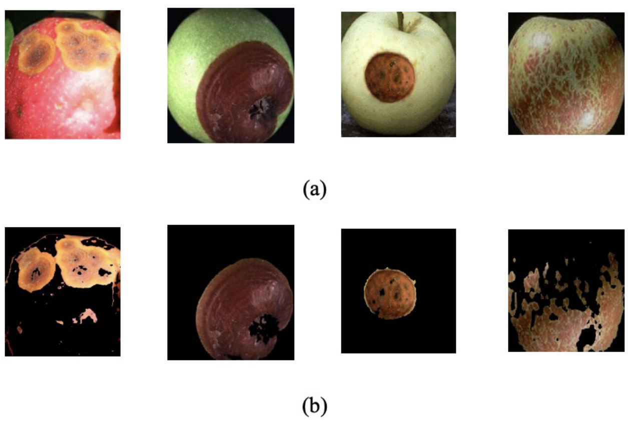

FIGURE 1. Results of image segmentation task. (a) before segmentation and (b) after segmentation with the K-means technique. [60].

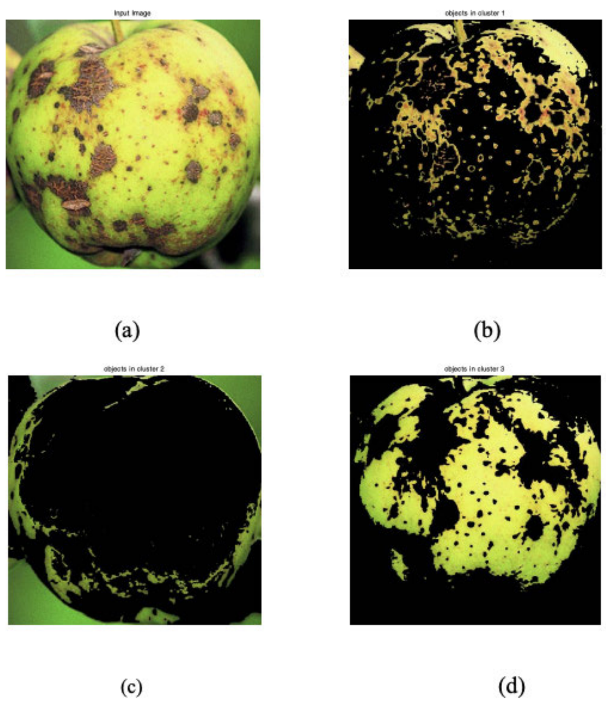

FIGURE 2. Results of segmentation using K-Means clustering with images showing (a) infected apple fruit, (b) first cluster, (c) second cluster, (d) third cluster respectively. [60].

2) Using Feature extraction
Features that are colour-based on the RGB and HSV spaces, texture, and shape are extracted to develop efficient models and systems. These features have been used in fruits and vegetables to perform various tasks, such as classification and detection, and to identify diseased and healthy parts. For instance, in a study by Dubey et al. [54] for apple fruit disease recognition, several methods, including local binary patterns, global colour histogram, colour coherence vector, border/interior classification, completed local binary patterns (CLBP), and improved sum difference histogram (ISDH) were used, with the CLBP attaining more accurate results for the classification of apple fruit diseases.

3) Augmentation for automated detection of fruit damages
Augmentation techniques have been observed to have several positive effects on building models and how they perform. They introduce variations in datasets, address class imbalance issues, and make the model robust to noise. For instance, in a study by [28] using a deep neural network model to classify citrus fruits into healthy and diseased ones, augmentation resulted in a higher performance of the model compared to where no augmentation was applied. Nithya et al. [73] also demonstrated the effects of augmentation in a study where CNN was being employed to identify defects in mangoes. Higher accuracy was attained in the case where augmented datasets were applied. Figure 9 further depicts the effects of augmentation.

D. CLASSICAL MACHINE LEARNING FOR FRUIT DAMAGE DETECTION

Whereas deep learning-based approaches have attained substantial attention and gained notable success in the field of computer vision, classical machine learning techniques continue to be valuable and effective in fruit damage detection and thus cannot be overlooked. Machine learning-based models do not need a large annotated dataset or resource-intensive requirements such as GPUs and thus can attain satisfactory performance using smaller training datasets. On the other hand, deep learning models require complex architectures with many parameters, requiring significant computational resources and time-consuming training procedures. Furthermore, optimization tasks are quite complicated using deep learning [74].

As such, several researchers still embrace the detection of damage to fruits using machine learning. For instance, Sharif et al. [66] proposed an approach for detecting and classifying anthracnose, black spot, canker, scab, greening, and melanose diseases in citrus plants using 670 images collected from Citrus Diseases Image Gallery Dataset. The images were first preprocessed to deal with brightness effects, illumination, and poor contrast issues using the top-hat filter and Gaussian function. The weighted segmentation technique was then used to detect lesion spots in the infected images. A feature selection method consisting of a PCA score, entropy, and skewness-based covariance vector was employed to extract colour, texture, and geometric features stored in a codebook. The features were then fed into a multi-class support vector machine (M-SVM) for citrus disease classification, attaining a classification accuracy of 97%. Bakar et al. [26] proposed a method that detects external skin defects (stem end rots, black spots, the presence of scales, and resin canal discolouration in mangoes using colour features from 500 digital camera images. Steps including image preprocessing for background removal and segmentation for recognition of defected areas are performed to obtain features fed into an SVM classifier, obtaining an accuracy of 90%. Textural features were not exploited to increase the accuracy of the system. Color systems other than RGB were also not explored [75].

Wang et al. [47] proposed a system that detects orange fruit skin defects. A colour histogram was extracted from the image dataset, and Fisher-Linear Discriminant Analysis (LDA) was then applied for vector dimension reduction and linear SVM to identify defects in the fruit. 650 images of orange were used, with 300 of them being defective. The evaluation of 61 images achieved a recall rate of 96.70%. This system is not able to distinguish between different kinds of defects.

Sambrani et al. [76] developed an image processing algorithm that classifies infestation of mango by the weevil as very lightly, lightly, moderately, severely, and uninfected using X-ray images by computing the percentage of the affected area on the surface of the fruit. Bakar et al. [26] then evaluated the severity of the detected skin defects (stem end rots, black spots, presence of scales, and resin canal discolouration on the mango by computing the pixel area in percentage rates of the segmented boundary region and using SVM to grade them using rates of the severity of damages inflicted on the mango. The authors in [48] used k-means clustering to group mangoes based on the size of dark spots on the skin surface. An image dataset taken with a digital camera was obtained, and segmentation was performed to extract regions of interest. The classification was then done to categorise mangoes as grade 1: a defect size of less than 5% of the total area; grade 2:- a defect region with a size between 5 and 15%; and grade 3: a defect area with a size greater than 15% but less than 25%. The ROC curve was then used to assess the accuracy measure, obtaining a score of 93.33%. Truong Minh Long and Truong Thinh [49] developed an approach to evaluate the internal quality of a mango using external features combined with weight, length, width, and defects to predict the volume and density. The internal quality of mango was evaluated as high if its density was higher than the average level. Grading was then done using various classifiers, with random forest achieving the highest accuracy of 98.1%.

Sahu and Manohar Potdar [51] developed an automated approach to identify surface defects, including scars and dark spots, and further detect the maturity of mango fruits based on shape, size and colour features. Digital images were preprocessed for conversion into grayscale, background removal, and filtering before defect identification using the developed image analysis algorithm. A small dataset of 28 images was used, with half of it defective and the others healthy. Nandi et al. [27] graded mangoes based on maturity in terms of actual days to rot and quality using surface defects. Image frames from a video of mangoes on a conveyor belt were preprocessed for noise removal, followed by feature extraction. Pixel identification was used for defect identification using the thresholding method. In defective pixels, the blue value is very high compared to healthy ones. The number of defective pixels is computed to establish the percentage of defect area when assessing damage. Support Vector Regression was used to predict maturity, and Multi-Attribute Decision Making was adopted for quality. Fuzzy incremental learning was then used to grade based on both maturity and quality. An accuracy of 90% is obtained for surface defects. However, only one side of the image was considered without the rotational view.

The above studies indeed indicate the potential of automated damage detection in fruits using conventional machine learning. They have exhibited good performance, as realized by the accuracy measures obtained, among other metrics used. However, these techniques are criticised for hand-engineering features and not being robust enough to handle huge datasets, calling for the need to explore state-of-the-art deep learning-based approaches in the identification of fruits [77] and detection of damages inflicted on them.

E. DEEP LEARNING FOR FRUIT DAMAGE DETECTION

1) DEEP NEURAL NETWORKS

A deep neural network (DNN) is an artificial neural network with multiple layers between the input and output layers. It consists of various layers of neurons that perform automated hierarchical learning of the data representation via non-linear transformations, unlike in traditional neural networks. Data is passed cumulatively across a long chain of layers, which brings about the term "deep," with each layer fully or partially connected to the preceding one. DNNs are characterized by no need for hand engineering of features with the learning of features done automatically, where DNN model performance improves with properties including the amount of input data, model size, and several computations that have made DNN attain state-of-the-art performance on supervised learning tasks.

2) CONVOLUTIONAL NEURAL NETWORK (CNN)

A convolutional neural network, or ConvNet, is just a neural network that uses convolution. CNN is a class of deep neural networks commonly applied in the analysis of visual imagery. It is a set of deep neural networks (ANNs) with numerous layers between the input and output layers that learn feature representation from datasets. CNNs are created as a function with images as input and thus have a contrasting architecture from classic ANNs. The model takes images as inputs on the input layer, applies a convolution operation, and then extracts features. This process reduces the input dimension, which affects the model's accuracy during feature extraction. CNN is divided into feature extraction and classification. Feature extraction has two sections: the pooling layer and the convolutional layer. The classification consists of flattening and fully connected layers. CNN works in a hierarchical manner, whereby the first Convolutional layer is reused in the next convolution [78]. It has various components, including the following:

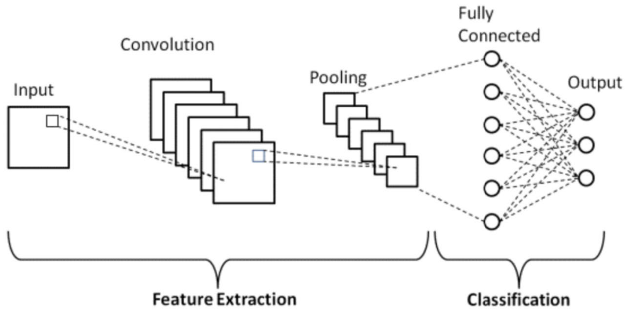

FIGURE 3. **Convolutional Neural Networks.**

1) CNN Layers.
   The CNN architecture consists of many layers, also known as building blocks. These are described below:
   a) Convolutional Layer
      A convolutional layer is the main building block of a CNN. It consists of a set of convolutional filters/feature detectors, also known as kernels, whose parameters are to be learned throughout the training of datasets. The size of the filters is usually smaller than the actual image. This layer applies convolutional operations to the input data (images expressed as N-dimensional metrics) to extract features by applying a set of filters to the input data, which slides over the data and computes dot products to produce a feature map. These filters are learned during the training process and help the network identify important features such as edges, corners, and shapes in the input data [79].
      i) The Kernel Description
         This is a grid of discrete numbers. Each number is called the kernel weight. Random numbers are assigned to act as the weights of the kernel at the beginning of the CNN training process. The weights are then adjusted at each training era thus the kernel learns to extract significant features.
      ii) Convolutional Operation
         Convolution is performed by the kernel going over the input image, working out matrix multiplication element after element, with the result for each receptive field (the area where convolution takes place) written down in the feature mAP which in turn contributes to the input of the next layer. The convolution operation is to extract high-level features, such as edges, from the input image.
   b) Pooling Layers
      These layers reduce the dimensionality of feature maps by shrinking large ones (feature maps) to create smaller ones. This maintains the majority of the dominant information/features at every step of the pooling stage. Several pooling methods exist for utilisation in various pooling layers, including tree pooling, gated pooling, average pooling, min pooling, max pooling, global average pooling (GAP), and global max pooling. The most common is max pooling, which selects the maximum value from a group of features. This also makes the network more robust to variations in the input data
   c) Fully Connected Layers
      This layer is located at the end of each CNN architecture. These layers connect every neuron in one layer to every neuron in the next layer. They are typically used at the end of the network to produce the final output. The fully connected layers take the flattened output of the previous layers and apply a set of weights to produce a final output, which can be used for classification or regression tasks.
2) Activation function
   This is a transformation function that maps the input signals into output signals that are required for the neural network to function. Popular types of activation functions include linear activation, sigmoid functions (logistic and hyperbolic tangent functions), rectified linear units (ReLU) also known as piecewise linear functions, exponential linear unit and softmax.
3) Hyperparameters
   These include filter kernel, batch size, padding, learning rate, and optimizers.
   - **Optimizers**. These are used to produce maximum performance from a network model. Examples include Adam, rmsprop, Nesterov and Sobolev gradient-based optimizers
   - **Padding**. This is the number of pixels added to an image when the kernel of a CNN is processing it.
   - **Striding**. Stride is how far the filter moves in every step in one direction. Striding skips some areas when the kernel slides over, such as skipping every 2 or 3 pixels to reduce spatial resolution and make the network more computationally efficient.
4) Loss Functions
   These are used in the output layer to compute the predicted error created across training samples in the CNN model. This error reveals the difference between the actual output and the predicted one.

3) CNN DEEP LEARNING ARCHITECTURES

CNN architectures are key factors used in building deep learning algorithms, with model architecture considered an important factor for enhancing the performance of different applications that implement them. Several variants exist for the different architectures due to the modifications that have been made from 1989 until today. These modifications include structural reformulation, regularisation, and parameter optimizations. An understanding of the features of the various architectures, including input size, depth, and robustness, is critical in helping researchers identify the most suitable ones for application development [79]. The most popular architectures used in fruits and their damage detection are presented below:

1) AlexNet

This is the very first successful deep CNN architecture on ImageNet, consisting of eight layers:5 convolutional layers and 3 fully connected layers with dropout, ReLU nonlinearity, and max-pooling. AlexNet was first proposed by Krizhevesky et al. [80] with CNNs by then restricted to handwritten digit recognition tasks, an issue that was addressed by increasing the number of feature extraction stages from five to seven to enable its use in different image categories. Its learning ability was limited due to hardware restrictions, an issue that was further overcome using two GPUs used in parallel in training AlexNet [67].

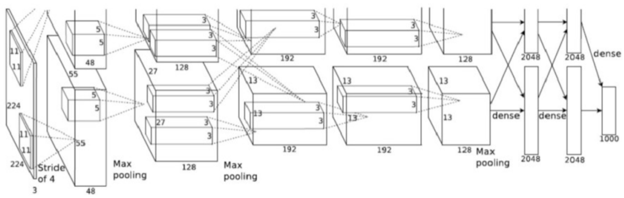

FIGURE 4. The AlexNet Architecture.

2) VGG Net

VGG (Visual Geometry Group) Net is a deep convolutional neural network architecture that was proposed in 2014 by researchers from the University of Oxford. It improved AlexNet by replacing the large-sized convolutional kernels with multiple 3 × 3 and 1 × 1 kernels and further increasing the depth of the network [81]. The 1 × 1 convolutions inserted in the middle of the convolutional layers enabled VGG to regulate the network complexity. VGG then achieved significant outcomes for localization and image classification tasks with enlarged depth, homogeneous topology, and simplicity attained though the computational cost was excessive due to its utilisation of many parameters approximated to 140 [79]. Generally, a VGG consists of 5 "VGG blocks", that are composed of a sequence of convolutional layers, each followed by ReLU nonlinearity, and a max-pooling layer. It has variants, including VGG11, VGG16, and VGG19, among others, that are named according to the number of convolutional and fully connected layers used in the model [67]. For instance, VGGNet-16 consists of 16 layers, while VGGNet-19 has 19 hidden layers [82].

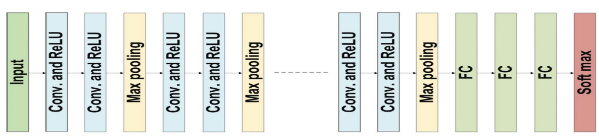

FIGURE 5. The VGG Architecture.

3) GoogleNet

GoogleNet, also known as Inception v1, is a deep convolutional neural network architecture that was proposed by Google researchers in 2014 to attain high-level accuracy with decreased computational cost using the inception block (module) concept in the CNN context by combining multiple-scale convolutional transformations while employing merge, transform, and split functions for feature extraction [79]. It has a deeper and wider architecture than AlexNet and its model weight is lighter than VGG-16 and VGG19 [83]. It uses "global average pooling" instead of "fully connected" layers, reducing its weight size. It is a tiny architecture when compared to AlexNet and VGGNet, which reduces the number of parameters in the network and helps to prevent overfitting.

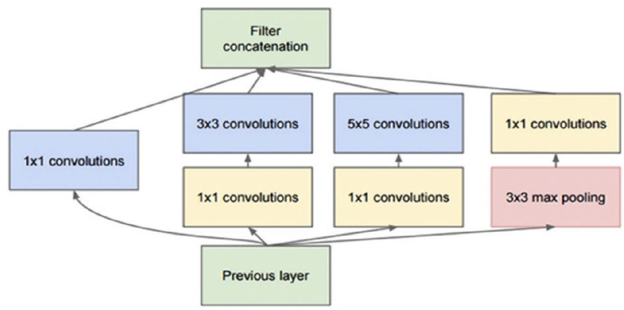

FIGURE 6. The inception module in GoogLeNet [83].

4) YOLO Architecture

YOLO algorithm identifies objects and their positioning using the bounding box approach by looking at the image only once, hence the name You Only Look Once (YOLO). YOLO architecture is inspired by GoogLeNet. It has 24 convolution layers, followed by 2 fully connected layers. Of the 24 convolutional layers, only four convolutional layers are followed by max-pooling layers. The YOLO-based algorithm uses a 1 × 1 convolutional and global average pooling [84].

It has several variants, such as YOLOv1, YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv7, and YOLOv8, the latest [85]. YOLO-based models are best used for object detection and image segmentation. They are preferred for being fast, accurate detectors compared to many similar models.

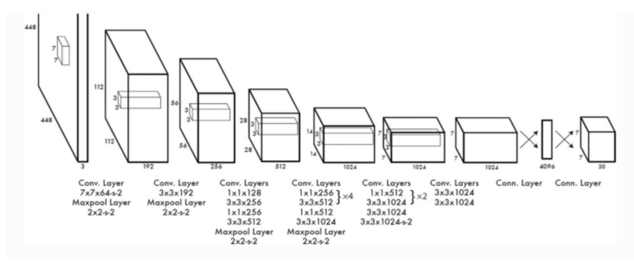

FIGURE 7. YOLO Architecture for object detection and segmentation [84].

5) ResNet

This architecture was created to enhance the performance of CNN architectures like VGGNet, GoogLeNet, and AlexNet [86]. It was first introduced by Microsoft

Research in 2015 using skip connections to design an ultra-deep network free of the vanishing gradient problem often encountered when training deep neural networks [86]. This architecture has residual blocks containing multiple convolutional layers and shortcut connections. The residual connections allow the output of one layer to be added to the input of another layer, effectively creating a "skip connection," which allows information to bypass layers, which could be causing the vanishing gradient problem. ResNet is deeper than the VGG network but with a smaller model size due to the use of "global average pooling" in place of the "fully connected" layers found in VGGNet.

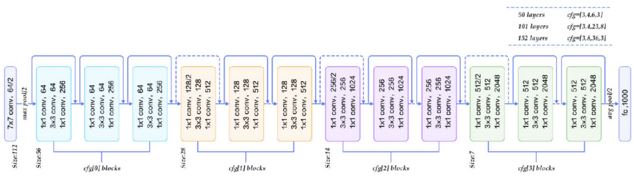

FIGURE 8. **An illustration for ResNet Architecture.**

Several variants of ResNet exist [79] based on the number of layers, starting with 34 layers up to 1202 layers, with ResNet50 being the most prominent with 49 convolutional layers plus a single FC layer.

4) APPLICATION OF CNN ARCHITECTURES AND TECHNIQUES FOR FRUIT DETECTION AND ASSOCIATED DAMAGES

Deep learning techniques have been used effectively in conjunction with imaging techniques and non-invasive approaches in the field of horticulture to address problems including post-harvest grading, classification, and maturity detection, and damage detection. These methods have been seen to yield better performance compared to traditional machine-learning approaches in analyzing and processing image data, spectral data, or sound data [15]. Hadipour et al. [87] proposed a study to detect citrus fruit damage due to Mediterranean fruit fly larvae using convolutional neural networks through transfer learning. Techniques including ResNet-50, GoogleNet, VGG-16 and AlexNet as well as optimization algorithms: SGDm, RMSProp and Adam were used to classify healthy and damaged fruits, with the VGG-16 model in conjunction with SGDm attaining the highest accuracy of 98.33% in the early outbreak of infestation class. However, the AlexNet model in conjunction with SGDm had the best result with the highest detection accuracy of 99.33% in the third class. A dataset of 1519 images of three classes, including before pest infestation, at the beginning of fruit infestation, and eight days after the second stage, is used. Zhang et al. [23] proposed a deep learning algorithm for the identification of five common types of citrus diseases:- canker, anthracnose, sunscald, greening, and melanose in orchards using detection networks YOLO-V3, YOLO-V4, and optimised YOLO-V4 to locate citrus fruits and classification networks MobileNet-V2, ResNet-50, DenseNet-169, and EfficietNet-B4 for classifying fruits into corresponding types of diseases. These were evaluated on a dataset of 1524 images taken in diverse orchard conditions, including distinct time intervals, scales, angles, and lighting conditions. The algorithm adopted an optimised YOLO-V4 model for detection, and then the EfficientNet model for classification attained a higher performance in terms of accuracy and F1 score of 0.890 and 0.872, respectively. Kukreja and Dhiman [28] then proposed a deep neural network model that classifies citrus fruits into healthy and diseased ones. Dense CNN was used to detect defects in citrus fruit using a dataset of 150 images. Using a dense CNN model with augmentation techniques such as rotation, width shift, height shift, rescaling, shear, zoom, horizontal shift, vertical shift, and brightness resulted in 1200 images attaining a higher performance of 89.1%.

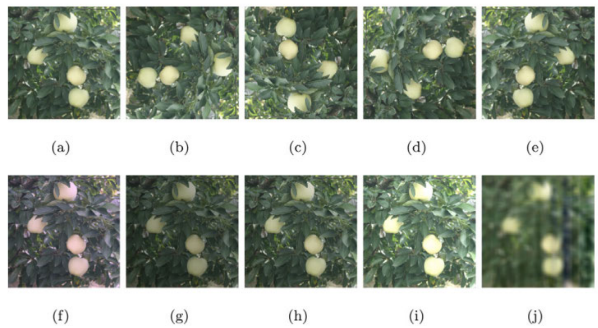

FIGURE 9. **Results of image augmentation techniques (a) original image, (b) clockwise rotation of 90Â°, (c) clockwise rotation of 180Â°, (d) 270Â° clockwise rotation, (e) horizontal mirror, (f) colour balance processing, (g-i) brightness transformation, and (j) blur processing [88].**

Pathmanaban et al. [18] proposed an approach to classify damaged and diseased Guava fruit from healthy ones using CNN to assess fruit quality. The study used both thermal and digital images. 4129 images were collected in total. These included depth-damaged, chilling injuries and diseased images. Thermal images were obtained using a thermal imaging system to record the surface temperatures of maturity-indexed and damaged fruits. The prediction accuracy of the developed CNN model was approximately 99.92%. Tian et al. [89] attempted a study to detect and classify bruised strawberries from healthy ones using 2903 thermal images obtained using an active thermal imaging system. 2903 thermal images obtained over 5 consecutive days were used, with temperature differences between the bruised area and the unbruised area analyzed. Optimized CNN, Pre-trained Inception V3, Resnet 50 and VGG19 models were evaluated for the classification of unbruised and bruised strawberries, with an accuracy of 0.98 for optimized CNN being higher than the accuracy of the pre-trained models.

Guo et al. [90] proposed an approach for early segmentation of healthy and anthracnose-diseased areas of the mango using 108 images. The red, green, and blue colour information of the pixels under two types of illumination

(RGB and UV) is analyzed. A combination of four different methods: RGB-threshold, RGB-linear discriminant analysis, ultraviolet-A illumination (UV)-LDA, and UV-threshold are then used to assess sugar mango images using R, G, and B features whose pixels are extracted from the area of interest. Accuracy and precision values of 0.97 and 0.95, respectively, using UV-LDA and 0.86 and 0.82 for RGB-LDA are obtained.

Authors in [91] proposed a deep learning model for the detection of severity levels of citrus fruit diseases using 3309 public images for lemons, oranges, grapefruit, and limes, collected and preprocessed by rescaling and annotation. Graph-based segmentation was used to extract regions of interest, and then a deep neural network model was trained to detect targeted areas of the disease with severity levels as high, medium, low, and healthy. Transfer learning using the VGGNet architecture was used as a multi-classification framework for each class of severity, achieving an accuracy of 98%. Several other deep architectures can be explored on a dataset in a real environment.

Dhiman et al. [92] proposed a CNN-based model to differentiate healthy fruits and leaves from damaged ones with citrus diseases including black spots, canker, scab, greening, and Melanose. The proposed CNN model extracts texture based on colour and shape from 2293 images from the citrus dataset in [93], with normalisation, pixel scaling, and data normalisation pre-processing procedures applied using Keras ImageDataGenerator class and API. The CNN model then classified diseased from healthy fruits attaining an accuracy of 94.55%. The authors in [94] then developed an intelligent system using a densely connected convolutional networks (DenseNet) model for the diagnosis of HLB, Anthracnose, Canker, Black spot, Sandpaper rust, and Scab diseases of citrus plants using fruit and leaf citrus diseases. Colour, texture, edge and shape features were extracted for use in the model. The developed system is realized using the WeChat applet in the mobile device that enables end-users to upload images of citrus fruits and receives results and comments about diagnosis attaining accuracy exceeding 88%. Liu et al. [68] further developed ResNet50, DenseNet201, InceptionV3, and MobileNetV2-based deep learning models for recognition of citrus diseases including Huanglong, Anthracnose, Canker, Black spot, Sandpaper rust and Scab with MobileNetV2 attaining highest accuracy of 87.28%.

Khan et al. [8] proposed a study to detect and classify apple and banana leaf diseases. Procedures including contrast stretching to increase the visibility of diseased regions identified by the segmentation process using the correlation coefficient method (using a combination of colour & texture features), and then extraction of Deep features using VGG-VD-16 and CaffeAlexNet models, and a multiclass SVM classifier for classification of the six types of apple and banana diseases studied: (1) apple scab, (2) apple rot, (3) banana sigota, (4) banana cordial leaf spot, (5) banana diamond leaf spot, and (6) fruit spot, were performed. 6309 images of bananas and apples were used for testing. Classification accuracy of 98.60% and 96.00% precision rate was obtained. Behera et al. [50] proposed an approach that identifies disease in Apple, Mango, Orange, Tomato and Pomegranate fruits using the Multi-class Support Vector Machine (MSVM) classifier. The grey-level co-occurrence matrix technique extracts features from the colour, texture, shape and appearance of defects and K-means clustering for segmentation of images captured with a mobile phone. Anthracnose and Fruit Rot identification achieved an accuracy of 92.17% with the severity predicted as a percentage of the affected area and differentiated by level of risk:- low risk, moderate risk and high risk as per the percentage of infection using the Fuzzy Logic approach. A small dataset of around 230 for health and defective groups was used in this study.

Costa et al. [22] developed a system that detects the quality of tomato fruit using colour, size and defect features using 38,884 healthy & 4959 defective tomato images. Damages detected include; longitudinal cuts, dark spots, rain bruises, punctures, bruises, and rain spots. Deep residual neural network (ResNet) classifiers were trained to detect external defects using feature extraction and fine-tuning from JPEG images. Fine-tuning outperformed feature extraction. The best model was ResNet50 with a precision of 94.6% and recall of 86:6% obtained. In [95], an approach is developed that assesses the severity stages of diseases of the leaf from PlantVillage, a database of more than 50,000 RGB images of healthy and diseased crops, using deep convolutional neural networks with deep VGG16 model-trained with transfer learning obtaining best accuracy of 90.4%. The number of spots using their diameters is used for assessment of the severity of the damage. Imaging systems that use infrared were not explored.

Kumar et al. [96] developed a CNN model to detect and classify fresh and damaged fruits using 8400 images of apples, oranges and bananas attaining 97.14% accuracy. Nithya et al. [73] also developed an automated system to identify defects in mangoes using a CNN model containing 50 good and 50 defective Kent mangoes augmented using scaling and rotation techniques which resulted in 800 images. An accuracy of 98.5% was obtained. Chen et al. [97] developed a system that uses a detecting drone to recognize T. papillosa pests in the orchard using the YOLOv3 model and Tiny-YOLOv3 neural network models built using 5473 images on an embedded system NVIDIA Jetson TX2 in real-time and determine pests' positions used to plan the optimal pesticide spraying route for the agricultural drone attaining accuracy of 95%.

F. AUTOMATED DETECTION OF FRUITS USING CNN ARCHITECTURES

Normally, fruits are first localized using several techniques before damage identification. Several studies have been attempted in the detection of fruits and the estimation of their yields. For instance, in [99] a method is proposed for the

TABLE 3. Table showing Deep learning approaches for automated damage detection in fruits.

Author	Goal of Study	Dataset	Feature	Technique	Performance Measure
Zhang *et al.*. [23]	Automated identification of citrus diseases in orchards using deep learning	1524 images	Colour and texture	YOLO-V3, YOLO-V4, optimized YOLO-V4, MobileNet-V2, ResNet-50, DenseNet-169, and EfficientNet-B4	Accuracy 0.890, F1score 0.872
Khan *et al.* [8]	Detection and classification of apple and banana diseases	6309 Apple and Banana images	Colour and texture	SVM and Deep CNN Contrast Stretching, Genetic Algorithm for feature selection	Accuracy- 98.60%, Precision- 96.00%
Costa *et al.* [22]	Detection of external defects on tomatoes using deep learning	38,884 healthy and 4959 defective tomato images	Size and colour	ResNets DNN	Precision- 94.6%
Hadipour *et al.* [87]	Intelligent detection of citrus fruit pests using a machine vision system and CNN through transfer learning technique	1519 images	colour and texture	ResNet-50, GoogleNet, VGG-16 and AlexNet, as well as Optimization algorithms: - SGDm, RMSProp and Adam	Accuracy 98.33% [VGG-16 + SGDm] [AlexNet model + SGDm] - Accuracy 99.33%
Vinay *et al.* [28]	A Deep Neural Network based disease detection scheme for Citrus fruits	1200 images	Texture and shape	Dense CNN With augmentation (using rotation, width shift, height shift, Re-scaling, shear, zoom, horizontal shift, vertical shift, and brightness)	Accuracy- 89.1%
Dhiman *et al.* [91]	Detection of severity levels of citrus fruit diseases	3309 public images of lemons, oranges, grapefruit and limes	Diameter, colour, and shape and the surface area of diseased portion	Deep neural network and VGGNet architecture	Accuracy- 98%
Wang *et al.* [95]	Automatic image-based plant disease severity estimation using deep learning	50,000 RGB images of healthy and diseased crops	Diameter of spots	Deep CNN	Accuracy- 90.4%
Ahmad Jahanbakhshia [98]	Classification of sour lemons based on apparent defects using deep CNN	341 sour lemon	Shape	HOG, LBP., KNN, ANN, Fuzzy, SVM, DT, CNN	100% with CNN
Chen *et al.* [97]	Detecting T. papillosa pests in the orchard	5473 images	Shape	YOLOv3	Accuracy 95%

detection and counting of mangoes in RGB images. Semantic segmentation is carried out followed by object detection for counting mangoes using MangoNet, a deep CNN-based architecture. 11,096 image patches obtained from 40 images are used to train MangoNet. The analysis is carried out using the accuracy and F1-score evaluations attaining results of 73.6% and 84.4% respectively.

Hu [100] proposed a model for fruit yield assessment using video frames captured in an apple orchard. Yolov7 was used with an attention module to detect and count apple fruits using a cascaded multi-object tracking technique with SURF extraction of appearance descriptions. The model uses two attention mechanisms namely; convolutional block attention module and coordinate attention, trained and tested on a dataset of 4246 apple images using tracking methods based on Kalman filtering and motion trajectory prediction. The yolov7-CA model achieved a 91.3% mAP and 0.85 F1 score.

Pichhika and Subudhi. [101] developed a model named MangoYOLO5 to detect seven varieties of on-tree mangoes using 20,429 images captured using UAVs and achieved an average accuracy of 92% which is 3.4% better than the YOLOv5s.

Chen et al. [88] proposed an improved YOLO-V3 model by incorporating the DenseNet method to detect apples at different growth stages while in the orchards. The stages are:- young, expanding, and ripe with each stage having 1600 images. The proposed model attained better performance with an F-score of 0.817 which was higher than that of the original YOLO-V3 and the Faster R-CNN with VGG-16 net models, with detection in videos recommended.

Shi et al. [102] proposed an attribution-based pruning method for pruning detection networks that can be fine-tuned to detect mangoes accurately in real time. Designing channel and spatial masks to generalize the attribution method, the convolutional kernels that are firmly correlated with a specific target output in the original YOLOv3-tiny network can be detected. The pruning method can compute the convolutional kernel attributions and fine-tune the network by retaining the important pre-trained parameters to extract special mango features. Compared to the YOLO-based network without pruning, the computational cost of the proposed network was reduced by 83.4%, with only 2.4% loss in accuracy

Xiong et al. [103] further proposed a method that uses UAV images to detect green mangoes on the tree to estimate their count on the tree. ROIs of images were labelled and then the YOLOv2 model was used for detection. A precision of 96.1% and a recall rate of 89.0% were achieved. UAV image acquisition in this study was manual, and thus semi-automation or full-automation of image acquisition can be considered for different mango cultivars.

Yijing et al. [104] further developed a method for fig fruit recognition and localization based on a comparison of YOLOv4, Faster R-CNN and YOLOv3 algorithms achieving 92.35%, 86.09% and 79.50% accuracies respectively using a dataset of 913 images differing in terms of fruit ripeness, and degree of shading. These algorithms can be used in the detection of other fruits since they succeeded in fig fruits that have more dense branches and leaves.

Stein et al. [105] then proposed an approach for detecting mango fruits in an orchard using Faster R-CNN with a dataset obtained from 522 trees using 71,609 images obtained from an unmanned ground vehicle (Shrimp) achieving an F1 score of 0.881. Naranjo-Torres et al. [7] then used improved faster R-CNN to detect 820, 822 and 799 apple, mango, and orange fruit images obtaining precision values of 92.51, 88.94, and 90.73% respectively.

Chen et al. [106] developed an approach that uses YOLOv4 to detect citrus fruits - Kumquats, Nanfeng tangerines, fertile oranges, and tangerines. The study used the canopy algorithm and K-Means++ algorithm to automatically select the number and size of the prior frames from RGB images collected. An improved YOLOv4 achieved higher performance compared to YOLOv4, YOLOv3, and Faster R-CNN. Images of occlusion less than 50% and more than 50% were considered with better performance attained where occlusion is less.

Ganesh et al. [57] developed an approach for detecting and segmenting oranges in an orchard. Image datasets using different colour spaces - RGB, HSV, and combined RGB and HSV, were used as input to the Mask R-CNN model. The best performance was obtained with an F1 score of 0.88, a precision of 0.97, and a recall value of 0.60 using combined RGB and HSV colour space.

Bargoti and Underwood [53] proposed an approach that uses Faster R-CNN to detect fruits including mangoes, almonds and apples in their orchards using a tiling approach that overcomes the GPU memory bottleneck by performing detections using smaller sliding windows over the larger images. The approach attained F1 scores of 0.904, 0.775 & 0.908 for Apple, Almond and mango using 729, 385 & 1,154 images respectively for training the model. Images were obtained using a Hand-held DSLR camera and a Research ground vehicle Shrimp. Detection output from the R-CNN model can be integrated with yield mapping in future studies.

Kang and Chen [35] then developed a deep-learning-based framework for apple fruit detection and segmentation of the fruits and branches in orchards using various neural network frameworks using an auto label generation module that utilised the multi-level pyramid and clustering-based classifier to enable fast labelling data and a deep-learning-based fruit detector "LedNet" that utilised FPN and ASPP techniques for improved performance of feature extraction and detection. Using LedNet with resnet-101, higher performance of 0.841 & 0.864 and 0.821 & 0.853 using LedNet with light-weight backbone on recall and accuracy respectively for orchard fruit detection. More automatic labelling generation techniques are needed to reduce human interventions in model training.

Apolo-Apolo et al. [107] developed a model for citrus fruit detection using faster R-CNN architecture. UAV was used to capture images from 20 sample trees. Features extracted from the images using CNN were given as input to the region proposal network. The proposed model achieved more than 90% precision and an F1 score of more than 89%. Detection in real-time from UAV videos should be explored to reduce the processing time required to obtain accurate results. Table 4 illustrates an overview of previous studies done in the automated detection of fruits in orchards.

IV. CHALLENGES AND PRIVACY ISSUES IN AUTOMATION OF FRUIT DETECTION TASKS

The automation of fruit detection and damage assessment is data-driven. Therefore, several challenges that have faced this sub-domain are data-centered. Ensuring that there are sufficient high-quality datasets is crucial for the effective building of machine learning models. However, this data is not available in most cases [26]. Preprocessing and annotation to obtain a high-quality dataset also require extensive labour as well as financial and time inputs, making it difficult or even impossible to construct robust datasets that can be used in automating agricultural tasks [108]. The annotation task should thus be automated to address the said challenge [109]. Recently, large amounts of agricultural data related to farms have been collected. With advances in digital devices such as drones, robots, smartphones, and satellites that are connected through technologies such as the Internet of Things and combined with big data analytics, it is now possible to collect massive agricultural datasets and analyse them [110]. Nevertheless, these big datasets collected raise privacy risks for farmers ranging from identification, reputation loss, unauthorized access, and sharing of their data with third parties, among others [111], [112]. This has

TABLE 4. Deep learning approaches for automated detection of fruits.

Author	Goal of Study	Dataset	Feature	Technique	Performance Measure
Yijing *et al.* [104]	Fig fruit recognition and localization	913 images	Shape, colour, Texture	YOLO v4, Faster R-CNN and YOLO v3	Accuracies of 92.35%, 86.09% and 79.50% respectively
Xiong *et al.* [103]	Detect green mangoes on the tree to estimate their count on the tree	360 UAV images	Colour, Edge	YOLOv2	Precision- 96.1%, Recall- 89.0%
Ganesh *et al.* [57]	Orange fruit detection using faster mask R-CNN	150 images RGB and HSV.	Colour	Faster mask R-CNN	F1 score and precision:- 0.88 and 0.97
Bargoti *et al.* [53]	Detecting mango, Apple and almond fruits in orchards	729, 385 and 1,154 Tree images of Apple, almond and mangoes obtained using: a hand-held DSLR camera and a ground vehicle	Colour	Faster R-CNN	F1 score -. 0.904, 0.775 and 0.908 for Apple, Almond and Mango respectively
Kestur *et al.* [99]	Detecting and counting mangoes in orchards	40 images	Shape	Semantic segmentation, CNN	F1-score - 73.6% and 84.4% using 11096 image patches from the 40 images.
Stein *et al.* [105]	Detecting mango fruits in an orchard	71,609 images	Shape	Faster R-CNN	F1 score of 0.881
Wenkang *et al.* [106]	Detecting citrus fruits - Kumquats, Nanfeng tangerines, fertile oranges, and tangerine	1750 images	Shape	YOLOv4, Improved YOLOv4, YOLOv3, Faster R-CNN	Accuracy of 93.58% with improved YOLO under occlusion of < 50%, 90.82% where occlusion is > 50%
Apolo-Apolo *et al.* [107]	Citrus fruit detection	UAV images from 20 sample trees	Shape	Faster R-CNN	Precision - 90%

caused a lack of trust in the way data is being managed in a wide range of industries, causing great concern for societal biases in the farming sector. There is a worry that the "willingness to share agricultural data," a vital concept and a timely contribution to smart farming, will be affected. As such, the issue of consent by farmers to share their data is needed. Currently, data transactions are governed by contracts and licensing agreements, although they are complex [113] for farmers to understand. They should thus seek clarification in case of ambiguity before consent, as determining data ownership in automated systems can be a challenging legal and ethical issue. These licence agreements are being introduced to govern the way farmers' datasets are collected and managed using smart farming technologies [114]. More so, most of the data licences are non-negotiable as they involve the use of a "clickwrap" agreement whereby clicking of an "I agree" symbol implies farmers consent to the terms of the software or data licence with agricultural technology. These software licences are being embedded into farming equipment, and farmers rarely understand them as they are not often discussed at the time of purchase. In most cases, turning on machinery or downloading the technology means agreeing to terms of data usage. Due to limited standardized data protection practices in the farming industry, there have been inconsistent legal data and use agreements that need to be normalized. Furthermore, there is complexity in data-driven technologies that makes it hard for most farmers to understand how to leverage them [112]. As such, farmers should strive to advance their digital skills to know their rights and have control over their data.

Besides challenges around obtaining high-quality annotated datasets, machine learning models further require complex architectures with various hyperparameters, making the process of building these models computationally intensive. More so, having access to high-performance computing resources is a limiting factor for building deep learning-based applications [74], [115].

V. STANDARD FRUIT IMAGE DATASETS

1) CitGVD
This is a comprehensive database of citrus genomic variations. It was developed as the first citrus-specific comprehensive database dedicated to genome-wide variations, including single nucleotide polymorphisms (SNPs) and insertions/deletions (INDELs). The current version (V1.0.0) of CitGVD is an open-access resource centred on 1,493,258,964 high-quality genomic variations and 84 phenotypes of 346 organisms curated from in-house projects and public resources [116].
2) MinneApple
MinneApple provides a set of image datasets obtained in orchards with annotations of the fruit on trees, labelled using polygonal masks for each object instance, to advance the state-of-the-art in fruit detection, localization, segmentation, and counting in orchard environments. Additionally, it also provides data for patch-based counting of clustered fruits. The

Minneapple dataset contains over 41,000 annotated object instances in 1000 images, and a detailed overview of the dataset is presented together with the baseline analysis for tasks of bounding box detection, segmentation, fruit counting, and yield estimation [117].

3) On-tree mango instance segmentation dataset
This is an image dataset created for on-tree mango detection and segmentation tasks. The images are annotated using the VGG Image Annotation (VIA) tool with polygon region annotation. The image and JSON annotation files in COCO annotation format for train and text image sets are also provided in two directories, with the first directory (Folder 1) described as tiled-images: Total 542 (train + test) tiled images of 640 × 540 pixels (Honey Gold and Keitt cultivars), and Folder 2 as individual-mango-snips: Total 1200 (train + test) snips (Honey Gold and Keitt cultivar) [118].

4) Fruits-360
Fruits-360 is an image dataset with a collection of 120 different types of fruits, including oranges, lemons, limes, and grapefruits, taken in a controlled environment with different angles and variations in lighting. The dataset has over 90,000 images for fruit recognition tasks, with each fruit having multiple images taken under different conditions, including light and angles. The images are of various sizes, ranging from 100 × 100 pixels to 512×512 pixels, and are in the RGB colour format. With a training set of 67,000 images and 23,000 test sets, the metadata for each image, such as fruit type, weight, size, and quality. The dataset has been used for benchmarking by different research studies and competitions [119].

5) A Citrus Fruits and Leaves Dataset
This is an image dataset of citrus fruits, leaves, and stems with images of healthy and infected plants. Diseases include Black spots, Cankers, scabs, Greening, and Melanose. These images were taken in December from the Orchards. This is the period when fruits were about to ripen and maximum diseases were found in the plants. The dataset contains 759 images, each containing 256*25 dimensions with 72 dpi resolution. Citrus fruits were 150 and 609 Citrus Leaves images. This dataset is especially helpful to researchers who use machine learning and computer vision for studies in the early detection of plant diseases [93].

6) ACFR Orchard Fruit Dataset
This data set contains images and annotations of mangoes, almonds, and apples for detection tasks. The images were acquired in the daytime in an orchard using a Shrimp (an unmanned ground vehicle) with the sensor mounted on an all-round research ground vehicle. The images were obtained from different farms across Australia, with the vehicle moving through numerous lines of the orchards, capturing image data from the trees. A total dataset of 3232 images was collected with the mango class having 1154, 270, and 270 images for the training, testing, and validation sets while the almond class had 385, 100, and 100 images, respectively. The Apple class had 729, 112, and 112 images for training, testing, and validation, respectively.

7) InterFruit
This is an image dataset containing 3,139 images of common fruits in 40 different classes. This image dataset is used for tasks such as classification. These fruits are collected from sources including:- Baidu, JD.com, Google, and Taobao. The images were cropped to 300 × 300 pixels. 70% of each class were randomly set aside for training and 30% for testing [120].

A. OVERVIEW OF COMPARISON OF THE DATASETS

Among the datasets cited in this study, CitGVD is the only web-based bioinformatics platform for citrus-related studies that has been curated for genome-wide variations and related gene annotations. Other datasets have mainly been curated for the tasks of detection, localisation and classification of fruits using image data, which are vital steps that improve yield estimation [121]. Table 5 provides a comparison of the datasets based on different parameters such as the size of the datasets, type of fruit, and annotation done on the images among other tasks.

Fruits-360 has the largest dataset with over 90,000 RGB images of different sizes of 100 × 100 pixels to 512 × 512 pixels [119].

VI. METRICS FOR ASSESSING PERFORMANCE EVALUATION

The major metrics used for performance evaluation of the machine learning segmentation, classification and deep learning models in the detection and evaluation of fruit damages include Accuracy, Precision, Recall and Specificity [87], [96]. The mentioned metrics are cited to have been used in most studies reviewed. Their description is included below:-

1) Accuracy
This is the measure of the number of correctly classified classes over the total number of classes for classification results. It is computed as:-

$$Accuracy = \frac{tp + tn}{tp + fp + tn + fn} \quad (1)$$

2) Precision
This measures the total number of positively predicted classes that belong to the number of positive classes. To evaluate the precision value, the total number of TP cases successfully classified is divided by the total number of TP and FP examples.

$$Precision = \frac{tp}{tp + fp} \quad (2)$$

3) Sensitivity / Recall
This is an indicator that shows the number of correct predictions made out of all the optimistic predictions

TABLE 5. A comparison of MinneApple, On-tree mango instance segmentation, Fruits-360, Citrus Fruits and Leaves, ACFR Orchard Fruit, and interFruit datasets.

Dataset	Size	Annotation used	Fruit Category	Diversity	Ares for use
MinneApple	1000 images with over 41,000 annotations	Bounding box, Segmentation	Apples on trees in the orchard	Different Apple varieties	Detection, segmentation, fruit counting and yield estimation of Apple fruits
On-tree mango instance segmentation dataset	1742 images	Polygon region annotation	Mangoes	Mangoes of different stages captured at different conditions	on-tree Mango fruit instance detection and segmentation
Fruits-360	90,000 images	Bounding box	Several-fruits with over 80 classes	120 Different varieties of the same fruit including oranges, lemons, limes, grapefruits among others	Detection and classification
ACFR Orchard Fruit	1120 Apple images, 1964 mango images and 620 Almond images	Pixel-wise annotation and Bounding Box	Apple, almond and mangoes	Various fruit types from different farms at different environmental conditions	Fruit detection, classification and segmentation in an orchard
interFruit	3,139 images	Bounding box	Various fruits	Different fruit types	Identification and classification
Citrus Fruits and Leaves	150 Citrus fruits and 609 Citrus Leaves images	Bounding box	Citrus fruits	Citrus fruits, leaves, and stems of healthy and infected plants	Detection and classification tasks

that could be made. The recall is obtained by taking the total amount of TP and FN and dividing it by the number of TP.

$$Recall = \frac{tp}{tp + fn} \tag{3}$$

4) Specificity
This measure is used to calculate the fraction of negative patterns that are correctly classified.

$$Specificity = \frac{tn}{tp + tn} \tag{4}$$

5) F1 score
The F1 score is a metric that symmetrically represents precision and recall in one metric. It measures the harmonic mean of precision and recall scores. The highest possible value that can be achieved for the F-score is 1.0, which indicates perfect precision and recall, and the lowest value can be 0.

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{5}$$

From the above-represented metrics, TP, TN, FN, and FP are defined as:

1) TP: The number of infected images that the system has correctly detected.
2) TN: The number of healthy images that the system has correctly detected.
3) FN: The number of healthy images identified by the system as infected fruit.
4) FP: The number of infected images that the system has detected as healthy.

VII. DISCUSSION

From this review, it is observed that research in the field of automated fruit detection and assessment has grown over the years. There is a remarkable shift in research directions within the domain of fruit monitoring. This is being driven by integrating deep learning techniques with IoT to process big datasets generated by sensors in use towards real-time monitoring of the status of orchards. Generally, there is a big growth in the use of deep learning models (pre-trained or developed from scratch) for fruit detection and quality monitoring as compared to the use of traditional machine learning approaches. Several variants of these models exist, and their choice depends on the nature of the task being addressed, the suitability of the architecture, and the availability of resources, among other factors. However, despite these advancements, it should be noted that traditional machine learning is still relevant due to constraints such as limitations in accessing computing resources needed by deep learning models, which still makes machine learning methods relevant in addressing resource-related challenges.

In this review, it has been revealed that colour, texture, shape, and size are the most commonly extracted features, with deep learning models being the most efficient in assessing fruit damage. Out of the 32 articles surveyed in this study, 36.36% of these were on automated detection of fruits, 33.33% on automated damage detection using traditional machine learning, and 30.30% using deep learning for damage detection, with deep-learning CNN models being most prevalent [122]. From Table 3, deep-learning approaches have shown notable advantages in processing large datasets [15]. For instance, Khan et al. [8] attained up to 98.6% using Deep CNN in the detection of apple and banana diseases using a dataset of 6309 images. 98% was attained by Alberto et al. [91] in the detection of severity levels of citrus fruit diseases using VGGNet with a dataset of 3309 and 88.1% by Stein et al. [105] in detecting mango fruits in the orchard using Faster R-CNN with a dataset of 71,609 images. On the other hand, traditional machine learning models accommodate smaller datasets, with the largest used being 2184 images by Nandi et al. [27] who classified mangoes using surface defects as observed in Table 2. Large datasets generally improve learning by models and thus performance, yet these huge datasets are not always available [26], [51] and when available, they are not open source [22]. This makes it hard to reproduce studies done and make further investigations into results attained for improvement [7]. Research further indicates that deep learning-based fruit detection models are largely developed using fully supervised approaches. Consequently, a model trained on one distinct domain species and fruit type may not seamlessly be transferred to another, underscoring the need for domain adaptation methods. Moreso, several studies [12], [90] have reported that automated detection and classification of fruit damages has mostly been post-harvest, with limited studies done that access damage on fruits while still on trees in the fields. This would assist farmers in estimating fruit damage and predicting profits and losses for their yields while still in orchards.

It should be noted that various CNN architectures exist. However, their choice of what researchers can adopt in developing applications depends on the selection of their parameters and hyper-parameters, as they affect the performance of the developed models [79]. This selection process is currently manual as it is handled by a trial-and-error approach, which is time-consuming for large models [7].

For both post-harvest and orchard-based assessment of fruits, YOLO-based algorithms [23], [103], [104], [106] and Faster R-CNN [53], [57], [104] have been seen to be the most dominant techniques in the automated detection of fruits, with ResNet-50 and VGG-16 models widely used to identify associated damages [23], [87]. However, much as CNN is the most predominant architecture that has been used in fruit damage detection, limited studies have used ensembles despite their strength in yielding good performance [86].

For the developed models, metrics commonly used in their evaluation are accuracy, recall, precision, specificity, and the F1 measure. The datasets, pre-processing techniques, models, and associated hyper-parameters used and adopted by different researchers are also different, which makes it hard for future researchers to generalize results. Current research in deep learning CNN architectures is directed towards the development of efficient block architectures that are lightweight and specifically designed for generating efficient compressed DNN models that are deployable on mobile and embedded devices due to their limited resources towards a more convenient accuracy-speed trade-off [75], [123]. Machine learning-based techniques have also been widely used in the damage identification of fruits, with the main challenge realized being the hand engineering of features and models not being robust enough to work with big datasets generated [25]. Other challenges faced in automated fruit detection include occlusion in orchards that obscures the necessary parts and features to be detected in plants and fruits [106]. Research is underway to deal with this issue. For instance, Hosang et al. [25] developed an approach that uses an object proposal technique that is capable of generating numerous potential object regions, a feature that addresses occlusion by considering alternative locations for objects of interest being studied. There is also a challenge in the detection of some defects, such as chilling injuries. This is because fruits affected with such defects don't change colour or texture, and yet most of the current algorithms for traditional computer vision systems are based on manually designed features that involve colour or texture and thus are not suitable for detecting such defects, calling for the need for other imaging modalities such as thermal imaging [106] that capture heat radiation emitted by objects, enabling the detection of temperature variations. Thermal imaging can further help to overcome challenges related to lighting variations encountered when capturing images and occlusions, as it is not affected by ambient lighting conditions.

VIII. CONCLUSION

This survey reviewed the progress that has been made in the field of automated damage and defect detection in fruits. Several approaches based on computer vision, image processing, machine learning, and deep learning techniques for identifying fruit damage have been reviewed. Major phases observed in such automated detection tasks are image acquisition and pre-processing, annotation, segmentation, feature extraction, and damage identification, with deep learning-based techniques being the most preferred as they replace hand-crafted feature learning techniques. In this survey, it is generally noted that pre-processing techniques improve the performance of developed models, with shape, texture, and colour seen as the most prominent extracted features fed into the learning models that detect and classify the damages on fruits. ResNet-50 and VGG-16 are the most used CNN architectures in fruit damage detection and thus can be recommended for implementing an effective, accurate automated system utilized for damage detection and classification. Generally, the overall benefits of deep learning models have been observed and are thus recommended in smart farming.

IX. FUTURE RESEARCH

Annotation of the images collected from the trees in the orchards is a very tedious task that still needs further innovative studies to save time spent manually labelling the data using experts who are scarce in most cases. Furthermore, future research should venture into automated detection and classification of fruit damages on different varieties of fruits while still in orchards [12], [90], and automate the optimization of costs incurred on fruits in fields such as applying pesticides to exact locations where infestations are reported in agricultural farms [97]. Future work should also look into developing machine learning models that can run on edge devices, allowing for on-site processing and reducing the need for larger computational resources to aid in remote and resource-constrained areas.

Research should also focus on developing automated solutions based on standard frameworks that implement deep learning models to detect damages in fruits and address the challenge of occlusion. The use of CNN architectures in conjunction with optimizers is seen to yield good performance in assessing damage and defects in fruits. As such, future research should adopt this practice in related studies. More studies should also focus on using existing models to detect fruits in videos and yield estimation [88].

Future research should further explore the use of IoT systems and UAVs with environmental parameters such as temperature and humidity acquired with the ground segment gadgets embedded. Multi-sensor fusion for thorough monitoring using sensors with different bands should also be explored for accurate image analysis of damages inflicted on fruits and plants in orchard management [124]. Research should also look more into the development of machine learning algorithms that predict conditions in which early pest and disease outbreak infestations can occur in orchards based on IoT datasets. More so, due to the big data generated by IoT devices [125] deployed in agricultural fields, research should focus on more innovative approaches to developing database systems efficient in managing these datasets. The security and privacy of these datasets should also be an area of concern to avoid data breaches and losses through several efforts, such as hacking [126].

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this piece of work.

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REFERENCES

[1] A. P. Siregar and N. P. A. Widjanarko, "The impact of trade openness on economic growth: Evidence from agricultural countries," *J. Asian Finance, Econ. Bus.*, vol. 9, no. 3, pp. 23–31, 2022.

[2] D. Bamwesigye, A. Doli, K. J. Adamu, and S. K. Mansaray, "A review of the political economy of agriculture in Uganda: Women, property rights, and other challenges," *Universal J. Agricult. Res.*, vol. 8, no. 1, pp. 1–10, Jan. 2020.

[3] E. Andersson and E. Isgren, "Gambling in the garden: Pesticide use and risk exposure in Ugandan smallholder farming," *J. Rural Stud.*, vol. 82, pp. 76–86, Feb. 2021.

[4] R. P. Haff, S. Saranwong, W. Thanapase, A. Janhiran, S. Kasemsumran, and S. Kawano, "Automatic image analysis and spot classification for detection of fruit fly infestation in hyperspectral images of mangoes," *Postharvest Biol. Technol.*, vol. 86, pp. 23–28, Dec. 2013.

[5] A. Bhargava and A. Bansal, "Fruits and vegetables quality evaluation using computer vision: A review," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 33, no. 3, pp. 243–257, Mar. 2021.

[6] Y. Nagpal, V. Jindal, V. Kukreja, A. Bansal, and A. Singh, "Multiclassification of seven citrus fruits diseases using the deep learning approach," in *Proc. 10th Int. Conf. Rel. INFOCOM Technol. Optim. (ICRITO)*, Oct. 2022, pp. 1–5.

[7] J. Naranjo-Torres, M. Mora, R. Hernández-García, R. J. Barrientos, C. Fredes, and A. Valenzuela, "A review of convolutional neural network applied to fruit image processing," *Appl. Sci.*, vol. 10, no. 10, p. 3443, May 2020.

[8] M. A. Khan, T. Akram, M. Sharif, M. Awais, K. Javed, H. Ali, and T. Saba, "CCDF: Automatic system for segmentation and recognition of fruit crops diseases based on correlation coefficient and deep CNN features," *Comput. Electron. Agricult.*, vol. 155, pp. 220–236, Dec. 2018.

[9] C. M. Nankinga, B. E. Isabirye, H. Muyinza, I. Rwomushana, P. C. Stevenson, A. Mayamba, W. Aool, and A. M. Akol, "Fruit fly infestation in mango: A threat to the horticultural sector in Uganda," *Uganda J. Agricult. Sci.*, vol. 15, no. 1, pp. 1–14, 2014.

[10] J.-F. Vayssières, S. Korie, and D. Ayegnon, "Correlation of fruit fly infestation of major mango cultivars in borgou with abiotic and biotic factors and assessment of damage," *Crop Protection*, vol. 28, no. 6, pp. 477–488, Jun. 2009.

[11] B. Dhiman, Y. Kumar, and M. Kumar, "Fruit quality evaluation using machine learning techniques: Review, motivation and future perspectives," *Multimedia Tools Appl.*, vol. 81, no. 12, pp. 16255–16277, May 2022.

[12] O. P. Chauhan, S. Lakshmi, A. K. Pandey, N. Ravi, N. Gopalan, and R. K. Sharma, "Non-destructive quality monitoring of fresh fruits and vegetables," *Defence Life Sci. J.*, vol. 2, no. 2, p. 103, May 2017.

[13] N. Vélez Rivera, J. Gómez-Sanchis, J. Chanona-Pérez, J. J. Carrasco, M. Millán-Giraldo, D. Lorente, S. Cubero, and J. Blasco, "Early detection of mechanical damage in mango using NIR hyperspectral images and machine learning," *Biosyst. Eng.*, vol. 122, pp. 91–98, Jun. 2014.

[14] N. Vélez-Rivera, J. Blasco, J. Chanona-Pérez, G. Calderón-Domínguez, M. de Jesús Perea-Flores, I. Arzate-Vázquez, S. Cubero, and R. Farrera-Rebollo, "Computer vision system applied to classification of 'Manil' mangoes during ripening process," *Food Bioprocess Technol.*, vol. 7, no. 4, pp. 1183–1194, Apr. 2014.

[15] B. Yang and Y. Xu, "Applications of deep-learning approaches in horticultural research: A review," *Horticulture Res.*, vol. 8, no. 1, pp. 1–31, Dec. 2021.

[16] L. Doitsidis, G. N. Fouskitakis, K. N. Varikou, I. I. Rigakis, S. A. Chatzichristofis, A. K. Papafilippaki, and A. E. Birouraki, "Remote monitoring of the bactrocera oleae (Gmelin) (diptera: Tephritidae) population using an automated McPhail trap," *Comput. Electron. Agricult.*, vol. 137, pp. 69–78, May 2017.

[17] J. F. I. Nturambirwe and U. L. Opara, "Machine learning applications to non-destructive defect detection in horticultural products," *Biosyst. Eng.*, vol. 189, pp. 60–83, Jan. 2020.

[18] P. Pathmanaban, B. K. Gnanavel, and S. S. Anandan, "Guava fruit (Psidium guajava) damage and disease detection using deep convolutional neural networks and thermal imaging," *Imag. Sci. J.*, vol. 70, no. 2, pp. 102–116, Feb. 2022.

[19] H. M. Rizwan Iqbal and A. Hakim, "Classification and grading of harvested mangoes using convolutional neural network," *Int. J. Fruit Sci.*, vol. 22, no. 1, pp. 95–109, Dec. 2022.

[20] K. K. Patel, A. Kar, and M. A. Khan, "Monochrome computer vision for detecting common external defects of mango," *J. Food Sci. Technol.*, vol. 58, no. 12, pp. 4550–4557, Dec. 2021.

[21] B. Zheng and T. Huang, "Mango grading system based on optimized convolutional neural network," *Math. Problems Eng.*, vol. 2021, pp. 1–11, Sep. 2021.

[22] A. Z. da Costa, H. E. H. Figueroa, and J. A. Fracarolli, "Computer vision based detection of external defects on tomatoes using deep learning," *Biosyst. Eng.*, vol. 190, pp. 131–144, Feb. 2020.

[23] X. Zhang, Y. Xun, and Y. Chen, "Automated identification of citrus diseases in orchards using deep learning," *Biosyst. Eng.*, vol. 223, pp. 249–258, Nov. 2022.

[24] T. R. B. Razak[1], M. B. Othman, M. N. B. A. Bakar, K. A. B. Ahmad, and A. R. Mansor, "Mango grading by using fuzzy image analysis," in *Proc. Int. Conf. Agricult. Environ. Biol. Sci.*, May 2012, pp. 1–5.

[25] R. Holmes, P. J. Hofman, and L. Barker, ''Mango quality assessment manual: A guide to assessing the post-harvest quality of Australian mangoes,'' Dept. Employment, Econ. Develop. Innov., 2009.

[26] M. N. A. Bakar, A. H. Abdullah, N. A. Rahim, H. Yazid, N. S. Zakaria, S. Omar, W. M. F. W. Nik, N. A. Bakar, S. F. Sulaiman, M. I. Ahmad, K. Ahmad, N. M. Maliki, and S. R. Romle, ''Defects detection algorithm of harumanis mango for quality assessment using colour features extraction,'' *J. Phys. Conf. Ser.*, vol. 2107, no. 1, Nov. 2021, Art. no. 012008.

[27] C. S. Nandi, B. Tudu, and C. Koley, ''A machine vision technique for grading of harvested mangoes based on maturity and quality,'' *IEEE Sensors J.*, vol. 16, no. 16, pp. 6387–6396, Aug. 2016.

[28] V. Kukreja and P. Dhiman, ''A deep neural network based disease detection scheme for citrus fruits,'' in *Proc. Int. Conf. Smart Electron. Commun. (ICOSEC)*, Sep. 2020, pp. 97–101.

[29] K. E. Morgan, ''Automation in agriculture,'' *Outlook Agricult.*, vol. 4, no. 6, pp. 295–301, Dec. 1965.

[30] V. R. Pathmudi, N. Khatri, S. Kumar, A. S. H. Abdul-Qawy, and A. K. Vyas, ''A systematic review of IoT technologies and their constituents for smart and sustainable agriculture applications,'' *Sci. Afr.*, vol. 19, Mar. 2023, Art. no. e01577.

[31] M. R. M. Kassim, ''IoT applications in smart agriculture: Issues and challenges,'' in *Proc. IEEE Conf. Open Syst. (ICOS)*, Nov. 2020, pp. 19–24.

[32] J. Xu, B. Gu, and G. Tian, ''Review of agricultural IoT technology,'' *Artif. Intell. Agricult.*, vol. 6, pp. 10–22, Jan. 2022.

[33] S. K. Behera, P. K. Sethy, S. K. Sahoo, S. Panigrahi, and S. C. Rajpoot, ''On-tree fruit monitoring system using IoT and image analysis,'' *Concurrent Eng.*, vol. 29, no. 1, pp. 6–15, Mar. 2021.

[34] Y. Onishi, T. Yoshida, H. Kurita, T. Fukao, H. Arihara, and A. Iwai, ''An automated fruit harvesting robot by using deep learning,'' in *Proc. JSME Annu. Conf. Robot. Mechtron.*, vol. 2018, no. 1, pp. 1A1–B03, 2018.

[35] H. Kang and C. Chen, ''Fast implementation of real-time fruit detection in apple orchards using deep learning,'' *Comput. Electron. Agricult.*, vol. 168, Jan. 2020, Art. no. 105108.

[36] D. Wang, C. Li, H. Song, H. Xiong, C. Liu, and D. He, ''Deep learning approach for apple edge detection to remotely monitor apple growth in orchards,'' *IEEE Access*, vol. 8, pp. 26911–26925, 2020.

[37] A. A. Adedeji, N. Ekramirad, A. Rady, A. Hamidisepehr, K. D. Donohue, R. T. Villanueva, C. A. Parrish, and M. Li, ''Non-destructive technologies for detecting insect infestation in fruits and vegetables under postharvest conditions: A critical review,'' *Foods*, vol. 9, no. 7, p. 927, Jul. 2020.

[38] S. Saranwong, W. Thanapase, N. Suttiwijitpukdee, R. Rittiron, S. Kasemsumran, and S. Kawano, ''Applying near infrared spectroscopy to the detection of fruit fly eggs and larvae in intact fruit,'' *J. Near Infr. Spectrosc.*, vol. 18, no. 4, pp. 271–280, Aug. 2010.

[39] B. Jamshidi, E. Mohajerani, H. Farazmand, A. Mahmoudi, and A. Hemmati, ''Pattern recognition-based optical technique for non-destructive detection of ectomyelois ceratoniae infestation in pomegranates during hidden activity of the larvae,'' *Spectrochimica Acta Part A, Mol. Biomolecular Spectrosc.*, vol. 206, pp. 552–557, Jan. 2019.

[40] R Pandiselvam, V. P. Mayookha, A. Kothakota, S. V. Ramesh, R. Thirumdas, and P. Juvvi, ''Biospeckle laser technique—A novel non-destructive approach for food quality and safety detection,'' *Trends Food Sci. Technol.*, vol. 97, pp. 1–13, 2020.

[41] L. Yan, J. Liu, and S. Men, ''The biospeckle method for early damage detection of fruits,'' *Modern Phys. Lett. B*, vol. 31, nos. 19–21, Jul. 2017, Art. no. 1740034.

[42] Y. He, Q. Xiao, X. Bai, L. Zhou, F. Liu, and C. Zhang, ''Recent progress of nondestructive techniques for fruits damage inspection: A review,'' *Crit. Rev. Food Sci. Nutrition*, vol. 62, no. 20, pp. 5476–5494, Jul. 2022.

[43] N. K. Mahanti, R. Pandiselvam, A. Kothakota, P. Ishwarya, S. K. Chakraborty, M. Kumar, and D. Cozzolino, ''Emerging non-destructive imaging techniques for fruit damage detection: Image processing and analysis,'' *Trends Food Sci. Technol.*, vol. 120, pp. 418–438, Feb. 2022.

[44] M. M. Ali, N. A. Bachik, N. 'A. Muhadi, T. N. Tuan Yusof, and C. Gomes, ''Non-destructive techniques of detecting plant diseases: A review,'' *Physiol. Mol. Plant Pathol.*, vol. 108, Dec. 2019, Art. no. 101426.

[45] M. Mohd Ali, N. Hashim, S. A. Aziz, and O. Lasekan, ''Emerging non-destructive thermal imaging technique coupled with chemometrics on quality and safety inspection in food and agriculture,'' *Trends Food Sci. Technol.*, vol. 105, pp. 176–185, Nov. 2020.

[46] K. Hameed, D. Chai, and A. Rassau, ''A comprehensive review of fruit and vegetable classification techniques,'' *Image Vis. Comput.*, vol. 80, pp. 24–44, Dec. 2018.

[47] L. Wang, A. Li, and X. Tian, ''Detection of fruit skin defects using machine vision system,'' in *Proc. 6th Int. Conf. Bus. Intell. Financial Eng.*, Nov. 2013, pp. 44–48.

[48] M. R. Golzarian, M. Shamili, O. D. Irani, and P. Azarkish, ''Detection of surface defects caused by mechanical damages on mangos of Kelk-e Sorkh variety with the use of color image processing,'' *Iranian Food Sci. Technol. Res. J.*, vol. 12, no. 5, pp. 652–662, 2016.

[49] N. Truong Minh Long and N. Truong Thinh, ''Using machine learning to grade the mango's quality based on external features captured by vision system,'' *Appl. Sci.*, vol. 10, no. 17, p. 5775, Aug. 2020.

[50] S. K. Behera, A. K. Rath, A. Mahapatra, and P. K. Sethy, ''Identification, classification & grading of fruits using machine learning & computer intelligence: A review,'' *J. Ambient Intell. Humanized Comput.*, pp. 1–11, 2020.

[51] D. Sahu and R. M. Potdar, ''Defect identification and maturity detection of mango fruits using image analysis,'' *Amer. J. Artif. Intell.*, vol. 1, no. 1, pp. 5–14, 2017.

[52] A. S. Nadarajan and A. Thamizharasi, ''Detection of bacterial canker disease in mango using image processing,'' *IOSR J. Comput. Eng.*, vol. 19, no. 2, pp. 1–8, Apr. 2017.

[53] S. Bargoti and J. Underwood, ''Deep fruit detection in orchards,'' in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2017, pp. 3626–3633.

[54] S. R. Dubey and A. S. Jalal, ''Detection and classification of apple fruit diseases using complete local binary patterns,'' in *Proc. 3rd Int. Conf. Comput. Commun. Technol.*, Nov. 2012, pp. 346–351.

[55] M. T. Habib, A. Majumder, A. Z. M. Jakaria, M. Akter, M. S. Uddin, and F. Ahmed, ''Machine vision based papaya disease recognition,'' *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 32, no. 3, pp. 300–309, Mar. 2020.

[56] Z. Iqbal, M. A. Khan, M. Sharif, J. H. Shah, M. H. U. Rehman, and K. Javed, ''An automated detection and classification of citrus plant diseases using image processing techniques: A review,'' *Comput. Electron. Agricult.*, vol. 153, pp. 12–32, Oct. 2018.

[57] P. Maheswari, P. Raja, O. E. Apolo-Apolo, and M. Pérez-Ruiz, ''Intelligent fruit yield estimation for orchards using deep learning based semantic segmentation techniques—A review,'' *Frontiers Plant Sci.*, vol. 12, Jun. 2021, Art. no. 684328.

[58] S. Naik and B. Patel, ''Machine vision based fruit classification and grading—A review,'' *Int. J. Comput. Appl.*, vol. 170, no. 9, pp. 22–34, Jul. 2017.

[59] A. Gongal, S. Amatya, M. Karkee, Q. Zhang, and K. Lewis, ''Sensors and systems for fruit detection and localization: A review,'' *Comput. Electron. Agricult.*, vol. 116, pp. 8–19, Aug. 2015.

[60] S. R. Dubey and A. S. Jalal, ''Application of image processing in fruit and vegetable analysis: A review,'' *J. Intell. Syst.*, vol. 24, no. 4, pp. 405–424, Dec. 2015.

[61] A. Syal, D. Garg, and S. Sharma, ''A survey of computer vision methods for counting fruits and yield prediction,'' *Int. J. Comput. Sci. Eng.*, vol. 2, no. 6, pp. 346–350, 2013.

[62] A. Kamilaris and F. X. Prenafeta-Boldú, ''Deep learning in agriculture: A survey,'' *Comput. Electron. Agricult.*, vol. 147, pp. 70–90, Apr. 2018.

[63] D. Caceres-Hernandez, R. Gutierrez, K. Kung, J. Rodriguez, O. Lao, K. Contreras, K.-H. Jo, and J. E. Sanchez-Galan, ''Recent advances in automatic feature detection and classification of fruits including with a special emphasis on watermelon (Citrillus lanatus): A review,'' *Neurocomputing*, vol. 526, pp. 62–79, Mar. 2023.

[64] C. Wang, S. Liu, Y. Wang, J. Xiong, Z. Zhang, B. Zhao, L. Luo, G. Lin, and P. He, ''Application of convolutional neural network-based detection methods in fresh fruit production: A comprehensive review,'' *Frontiers Plant Sci.*, vol. 13, May 2022, Art. no. 868745.

[65] M. S. Kumar and S. Mohan, ''Selective fruit harvesting: Research, trends and developments towards fruit detection and localization—A review,'' *Proc. Inst. Mech. Engineers, Part C, J. Mech. Eng. Sci.*, vol. 237, no. 6, pp. 1405–1444, Mar. 2023.

[66] M. Sharif, M. A. Khan, Z. Iqbal, M. F. Azam, M. I. U. Lali, and M. Y. Javed, ''Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection,'' *Comput. Electron. Agricult.*, vol. 150, pp. 220–234, Jul. 2018.

[67] S.-L. Wu, H.-Y. Tung, and Y.-L. Hsu, ''Deep learning for automatic quality grading of mangoes: Methods and insights,'' in *Proc. 19th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2020, pp. 446–453.

[68] Z. Liu, X. Xiang, J. Qin, Y. Tan, Q. Zhang, and N. N. Xiong, "Image recognition of citrus diseases based on deep learning," *Comput. Mater. Continua*, vol. 66, no. 1, pp. 457–466, 2020.
[69] D. Kaur and Y. Kaur, "Various image segmentation techniques: A review," *Int. J. Comput. Sci. Mobile Comput.*, vol. 3, no. 5, pp. 809–814, 2014.
[70] S. Das, "Filters, wrappers and a boosting-based hybrid for feature selection," *Icml*, vol. 1, pp. 74–81, Jun. 2001.
[71] P. P. Patel and D. B. Vaghela, "Crop diseases and pests detection using convolutional neural network," in *Proc. IEEE Int. Conf. Electr., Comput. Commun. Technol. (ICECCT)*, Feb. 2019, pp. 1–4.
[72] M. Ahmed, A. Raghavendra, and D. M. Rao, "An image segmentation comparison approach for lesion detection and area calculation in mangoes," *Int. Res. J. Eng. Technol.*, vol. 2, 2015.
[73] R. Nithya, B. Santhi, R. Manikandan, M. Rahimi, and A. H. Gandomi, "Computer vision system for mango fruit defect detection using deep convolutional neural network," *Foods*, vol. 11, no. 21, p. 3483, Nov. 2022.
[74] M. Knott, F. Perez-Cruz, and T. Defraeye, "Facilitated machine learning for image-based fruit quality assessment," *J. Food Eng.*, vol. 345, May 2023, Art. no. 111401.
[75] A. D. Le, D. A. Pham, D. T. Pham, and H. B. Vo, "AlertTrap: A study on object detection in remote insects trap monitoring system using on-the-edge deep learning platform," 2021, *arXiv:2112.13341*.
[76] S. Sambrani, S. Dhumwad, B. Navalli, H. Shivraj, and S. Kanakaraddi, "Detection of stone weevil in mango fruit using non-destructive technique," *Int. J. Emerg. Technol. Comput. Sci. Electron.*, vol. 14, no. 2, pp. 204–208, 2015.
[77] F. Liu, L. Snetkov, and D. Lima, "Summary on fruit identification methods: A literature review," in *Proc. 3rd Int. Conf. Econ. Social Sci. Arts, Educ. Manage. Eng. (ESSAEME)*. Atlantis Press, Jul. 2017, pp. 1–5.
[78] T. Oriana, A. Siddika, and Sk. Md. M. Ahsan, "A naive ConvNet model for defect identification and grading of mangoes," in *Proc. 5th Int. Conf. Electr. Inf. Commun. Technol. (EICT)*, Dec. 2021, pp. 1–6.
[79] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M. A. Fadhel, M. Al-Amidie, and L. Farhan, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions," *J. Big Data*, vol. 8, no. 1, pp. 1–74, Mar. 2021, doi: 10.1186/s40537-021-00444-8.
[80] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Commun. ACM*, vol. 60, no. 6, pp. 84–90, May 2017.
[81] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," 2014, *arXiv:1409.1556*.
[82] A. Ramdani and S. Suyanto, "Strawberry diseases identification from its leaf images using convolutional neural network," in *Proc. IEEE Int. Conf. Ind. 4.0, Artif. Intell. Commun. Technol. (IAICT)*, Jul. 2021, pp. 186–190.
[83] C. Szegedy, "Going deeper with convolutions," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2015, pp. 1–9.
[84] T. Diwan, G. Anirudh, and J. V. Tembhurne, "Object detection using YOLO: Challenges, architectural successors, datasets and applications," *Multimedia Tools Appl.*, vol. 65, pp. 1–33, Dec. 2022.
[85] P. Jiang, D. Ergu, F. Liu, Y. Cai, and B. Ma, "A review of YOLO algorithm developments," *Proc. Comput. Sci.*, vol. 199, pp. 1066–1073, Jan. 2022.
[86] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 770–778.
[87] R. Hadipour-Rokni, E. A. Asli-Ardeh, A. Jahanbakhshi, I. E. Paeen-Afrakoti, and S. Sabzi, "Intelligent detection of citrus fruit pests using machine vision system and convolutional neural network through transfer learning technique," *Comput. Biol. Med.*, vol. 155, Mar. 2023, Art. no. 106611.
[88] Y. Tian, G. Yang, Z. Wang, H. Wang, E. Li, and Z. Liang, "Apple detection during different growth stages in orchards using the improved YOLO-V3 model," *Comput. Electron. Agricult.*, vol. 157, pp. 417–426, Feb. 2019.
[89] B. Guo, B. Li, Y. Huang, F. Hao, B. Xu, and Y. Dong, "Bruise detection and classification of strawberries based on thermal images," *Food Bioprocess Technol.*, vol. 15, no. 5, pp. 1133–1141, May 2022.
[90] L. R. Alberto, C. E. C. Ardila, and F. A. P. Ortiz, "A computer vision system for early detection of anthracnose in sugar mango (Mangifera indica) based on UV—A illumination," *Inf. Process. Agricult.*, vol. 10, no. 2, pp. 204–215, Jun. 2023.
[91] P. Dhiman, V. Kukreja, P. Manoharan, A. Kaur, M. M. Kamruzzaman, I. B. Dhaou, and C. Iwendi, "A novel deep learning model for detection of severity level of the disease in citrus fruits," *Electronics*, vol. 11, no. 3, p. 495, Feb. 2022.
[92] A. Khattak, M. U. Asghar, U. Batool, M. Z. Asghar, H. Ullah, M. Al-Rakhami, and A. Gumaei, "Automatic detection of citrus fruit and leaves diseases using deep neural network model," *IEEE Access*, vol. 9, pp. 112942–112954, 2021.
[93] H. T. Rauf, B. A. Saleem, M Ikram U. Lali, M. A. Khan, M. Sharif, and S. Ahmad C. Bukhari, "A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning," *Data brief*, vol. 26, p. 104340, Oct. 2019.
[94] W. Pan, J. Qin, X. Xiang, Y. Wu, Y. Tan, and L. Xiang, "A smart mobile diagnosis system for citrus diseases based on densely connected convolutional networks," *IEEE Access*, vol. 7, pp. 87534–87542, 2019.
[95] G. Wang, Y. Sun, and J. Wang, "Automatic image-based plant disease severity estimation using deep learning," *Comput. Intell. Neurosci.*, vol. 2017, pp. 1–8, Jul. 2017.
[96] C. C. Ukwuoma, Q. Zhiguang, M. B. Bin Heyat, L. Ali, Z. Almaspoor, and H. N. Monday, "Recent advancements in fruit detection and classification using deep learning techniques," *Math. Problems Eng.*, vol. 2022, pp. 1–29, Jan. 2022.
[97] C.-J. Chen, Y.-Y. Huang, Y.-S. Li, Y.-C. Chen, C.-Y. Chang, and Y.-M. Huang, "Identification of fruit tree pests with deep learning on embedded drone to achieve accurate pesticide spraying," *IEEE Access*, vol. 9, pp. 21986–21997, 2021.
[98] A. Jahanbakhshi, M. Momeny, M. Mahmoudi, and Y.-D. Zhang, "Classification of sour lemons based on apparent defects using stochastic pooling mechanism in deep convolutional neural networks," *Scientia Horticulturae*, vol. 263, Mar. 2020, Art. no. 109133.
[99] R. Kestur, A. Meduri, and O. Narasipura, "MangoNet: A deep semantic segmentation architecture for a method to detect and count mangoes in an open orchard," *Eng. Appl. Artif. Intell.*, vol. 77, pp. 59–69, Jan. 2019.
[100] J. Hu, C. Fan, Z. Wang, J. Ruan, and S. Wu, "Fruit detection and counting in apple orchards based on improved YOLOV7 and multi-object tracking methods," *Sensors*, vol. 23, no. 13, p. 5903, Jun. 2023.
[101] H. C. Pichhika and P. Subudhi, "Detection of multi-varieties of on-tree mangoes using MangoYOLO5," in *Proc. 11th Int. Symp. Electron. Syst. Devices Comput. (ESDC)*, vol. 1, May 2023, pp. 1–6.
[102] R. Shi, T. Li, and Y. Yamaguchi, "An attribution-based pruning method for real-time mango detection with YOLO network," *Comput. Electron. Agricult.*, vol. 169, Feb. 2020, Art. no. 105214.
[103] J. Xiong, Z. Liu, S. Chen, B. Liu, Z. Zheng, Z. Zhong, Z. Yang, and H. Peng, "Visual detection of green mangoes by an unmanned aerial vehicle in orchards based on a deep learning method," *Biosyst. Eng.*, vol. 194, pp. 261–272, Jun. 2020.
[104] W. Yijing, Y. Yi, W. Xue-fen, C. Jian, and L. Xinyun, "Fig fruit recognition method based on YOLO V4 deep learning," in *Proc. 18th Int. Conf. Electr. Eng./Electron. Comput. Telecommun. Inf. Technol. (ECTI-CON)*, May 2021, pp. 303–306.
[105] M. Stein, S. Bargoti, and J. Underwood, "Image based mango fruit detection, localisation and yield estimation using multiple view geometry," *Sensors*, vol. 16, no. 11, p. 1915, Nov. 2016.
[106] W. Chen, S. Lu, B. Liu, G. Li, and T. Qian, "Detecting citrus in orchard environment by using improved YOLOV4," *Sci. Program.*, vol. 2020, pp. 1–13, Nov. 2020.
[107] O. E. Apolo-Apolo, J. Martínez-Guanter, G. Egea, P. Raja, and M. Pérez-Ruiz, "Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV," *Eur. J. Agronomy*, vol. 115, Apr. 2020, Art. no. 126030.
[108] D. Wang, W. Cao, F. Zhang, Z. Li, S. Xu, and X. Wu, "A review of deep learning in multiscale agricultural sensing," *Remote Sens.*, vol. 14, no. 3, p. 559, Jan. 2022.
[109] N. Mamat, M. F. Othman, R. Abdulghafor, A. A. Alwan, and Y. Gulzar, "Enhancing image annotation technique of fruit classification using a deep learning approach," *Sustainability*, vol. 15, no. 2, p. 901, Jan. 2023.
[110] J. Kaur, S. M. Hazrati Fard, M. Amiri-Zarandi, and R. Dara, "Protecting farmers' data privacy and confidentiality: Recommendations and considerations," *Frontiers Sustain. Food Syst.*, vol. 6, Oct. 2022, Art. no. 903230.

[111] B. B. Chichaibelu, H. Baumüller, and M. A. Matschuck, "Protecting the data of African agricultural producers: A review of national laws, compliance and perceptions," *Law, Innov. Technol.*, vol. 15, no. 2, pp. 617–661, Jul. 2023.

[112] S. Linsner, F. Kuntke, E. Steinbrink, J. Franken, and C. Reuter, "The role of privacy in digitalization—Analyzing perspectives of German farmers," *Proc. Privacy Enhancing Technol.*, vol. 2021, no. 3, pp. 334–350, Jul. 2021.

[113] F. Zampati, "Ethical and legal considerations in smart farming: A farmer's perspective," *Towards Responsible Plant Data Linkage, Data Challenges Agricult. Res. Develop.*, p. 257, 2023.

[114] L. Wiseman, J. Sanderson, A. Zhang, and E. Jakku, "Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws impacting smart farming," *NJAS-Wageningen J. Life Sci.*, vol. 90, p. 100301, 2019, Art. no. 100301.

[115] G. Menghani, "Efficient deep learning: A survey on making deep learning models smaller, faster, and better," *ACM Comput. Surveys*, vol. 55, no. 12, pp. 1–37, 2023.

[116] Q. Li, J. Qi, X. Qin, W. Dou, T. Lei, A. Hu, R. Jia, G. Jiang, X. Zou, Q. Long, L. Xu, A. Peng, L. Yao, S. Chen, and Y. He, "CitGVD: A comprehensive database of citrus genomic variations," *Horticulture Res.*, vol. 7, no. 1, p. 12, Dec. 2020.

[117] N. Häni, P. Roy, and V. Isler, "MinneApple: A benchmark dataset for apple detection and segmentation," *IEEE Robot. Autom. Lett.*, vol. 5, no. 2, pp. 852–858, Apr. 2020.

[118] C. Neupane, A. Koirala, and K. B. Walsh, "In-orchard sizing of mango fruit: 1. comparison of machine vision based methods for on-the-go estimation," *Horticulturae*, vol. 8, no. 12, p. 1223, Dec. 2022.

[119] M. Oltean, "Fruits 360 dataset," *Mendeley Data*, vol. 1, Oct. 2018.

[120] W. Liu, "Interfruit: Deep learning network for classifying fruit images," *bioRxiv*, 2020.

[121] C. Clark, "Applying faster R-CNN and mask R-CNN on the minneapple fruit detection challenge," *BNAIC/BeneLearn*, p. 411, 2020.

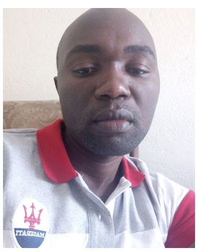
[122] X. Yang and M. Sun, "A survey on deep learning in crop planting," in *Proc. IOP Conf. Series, Mater. Sci. Eng.*, vol. 490. Bristol, U.K., IOP Publishing, 2019, p. 062053.

[123] F. Xiao, H. Wang, Y. Xu, and R. Zhang, "Fruit detection and recognition based on deep learning for automatic harvesting: An overview and review," *Agronomy*, vol. 13, no. 6, p. 1625, Jun. 2023.

[124] G. Ristorto, A. Bojeri, G. Scarton, G. Giannotta, and G. Guglieri, "DroneONtrap project—Integration of IoT technologies and drones for health status and pests monitoring of orchards," in *Proc. IEEE Int. Workshop Metrol. Agricult. Forestry*, Nov. 2021, pp. 12–16.

[125] L. He, W. Fang, G. Zhao, Z. Wu, L. Fu, R. Li, Y. Majeed, and J. Dhupia, "Fruit yield prediction and estimation in orchards: A state-of-the-art comprehensive review for both direct and indirect methods," *Comput. Electron. Agricult.*, vol. 195, Apr. 2022, Art. no. 106812.

[126] A. Srivastava and D. K. Das, "A comprehensive review on the application of Internet of Thing (IoT) in smart agriculture," *Wireless Pers. Commun.*, vol. 122, no. 2, pp. 1807–1837, Jan. 2022.



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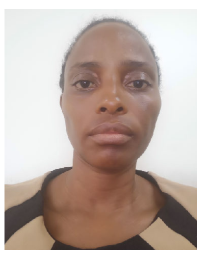

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