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Fruit Grading System for Feature Extraction and Quality Evaluation by Image Processing Technique

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Abstract: Since no deep learning fruit grading system based on digital photos has been devised, there hasn't been much progress made in determining whether or not fruit is fresh. The goal of this study is to develop methods for decreasing wasted fruit. The agriculture industry in India is crucial to the nation's economy. High quality fruit is in high demand, making fruit grading an important aspect of the agricultural industry. However, grading fruit by hand requires a lot of time and effort and is prone to mistakes. The time you spend with automatic grading is well spent. On both domestic and foreign markets, you may find a plethora of fruit. Due to their delicate nature, fruits need extra care throughout the grading process. Automation is much sought after in agricultural research with the aim of evaluating crop quality. If a country's fruits, vegetables, and harvests are of higher quality, it may see an increase in output and GDP. Price points for various types of produce are possible. Rapid and automated quality checks are in great demand in the export sector. The visual attractiveness of fruits and vegetables has a significant impact on their marketability, demand, and supply. Even though this kind of classification might provide very unpredictable results, the vast majority of classification tasks in India are still performed manually. Time is of the essence in this process. Taking the environment into account increases costs and introduces an element of uncertainty. This necessitates the employment of automated machinery for fruit sorting. In this research, we propose a method for the automated classification and analysis of digital fruit photographs. This system of grouping fruits makes it easy to compare their relative merits. The size, colour, texture, shape, and lack of flaws or illnesses all contribute to a fruit's overall quality. Quality assurance is an iterative process that occurs throughout the development of both hardware and software. Snap a photo of a tomato, and the computer will automatically sort it into the correct category.

Keywords: Computer Vision, Defect. Ripeness, Agriculture, CNN, Deep learning, Fruit freshness grading, Image processing, segmentation, classification, mangoes, ripeness, defect, agriculture

I. INTRODUCTION

India and other emerging nations rely heavily on the agricultural sector. Every year, governments around the world invest a sizable amount of money into implementing innovative technology, conducting cutting-edge research on the most effective agricultural practises, and developing innovative solutions to the devastating effects of pests, natural catastrophes, and drought [2]. People in India often inspect the quality of their produce. Sorting by eye is not only laborious and time-consuming, but it also introduces the possibility of human error. Rapid and high-precision machine vision technology has made it feasible to automate the grading process, which should increase productivity and accuracy while cutting labour costs. There has been a recent uptick in study into the feasibility of using technology to sort and grade agricultural products. Fruit cultivated on farms may be given a quality grade based on a number of factors, such as size, shape, colour, texture, and the presence or absence of deformities and illnesses. Manually inspecting fruit before shipping is not a feasible or efficient practise. Grading and sorting by eye is labour intensive, hence it is often done by hand.

Many experts in the field, as a result, reach conclusions that aren't grounded in reality and are thus erroneous. Automated sorting and grading systems may one day replace human fruit sorters [1] due to their many advantages, including higher accuracy and faster processing times. As a result of research into and development of key machine vision models for pear quality detection and sorting operations [2, 3], many computer vision-based systems have been developed for food-color-based agricultural grading applications, allowing for faster deployment of novel approaches to assessing agricultural product quality. The quality of fruit may be evaluated in real time using colour mapping [3].

Machine vision and other image processing techniques are finding increasing use in the fruit industry, particularly for quality inspection and defect sorting. Farmers assess their fruit for quality before shipping it to distant wholesale marketplaces. Fruits are often cited as a wholesome addition to a diet because of their low calorie count and high nutrient density. India's fruit industry uses 535,000 acres of land each year, producing 9.362 million tonnes of fruit [3]. Increasing agricultural exports is a major focus of trade policy. The skin of the fruit is so perishable that it must be handled carefully throughout the grading process.

The overall quality of the fruit is affected by factors such as its size, colour, shape, and amount of skin defects. Ripeness and imperfections are the two most important determinants of fruit quality. Evaluation of fruit is a time-consuming yet crucial process. Automatic grading using computers is being considered as a solution since it would lessen the workload for teachers. Some research suggests that fruit rotting is the result of a chain of biological processes that affect the fruit's structure and chemistry (and hence its nutritional value).

The quality of fruit may be judged visually or by some other method. Scent, chemistry, and overall impression are given higher weight in non-visual grading systems. The natural deterioration of fruit causes its colour to change due to a series of chemical reactions. Humans' innate acute sensitivity helps them to recognise rotten produce. It's often believed that consumption over a certain level has positive effects.

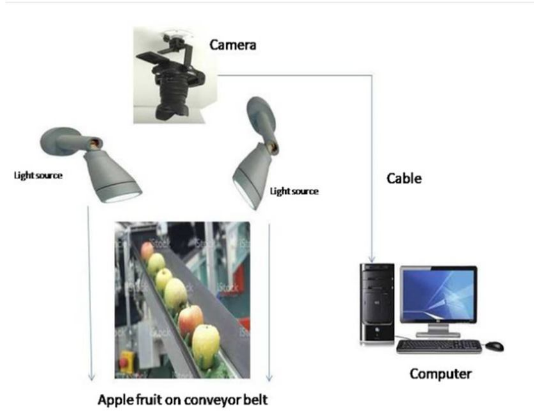

Fig1: Capturing of fruit on conveyor belt by the camera

It's a tool for figuring out whether the fruit on offer is safe for human consumption [1]. The findings suggest that bacteria may have a causal role in fruit rot. Aerobic psychoactive Gram-negative bacteria that secrete extracellular hydrolytic enzymes that damage plant cell walls are connected to this cycle, as are heterofermentative lactobacilli, spore-forming bacteria, yeasts, and moulds. Fruits are the result of the breakdown of a structural acidic heteropolysaccharide composed mostly of galacturonic acid, which is produced by biochemical processes in the cell walls of terrestrial plants. Glycolysis is the energy-generating process that occurs when polymeric carbohydrates like starch/amylum and sugar undergo anaerobic degradation [2].

Lesions are often thought to be the result of colonisation and microbial spread, which is the major cause of postharvest fruit rotting [3]. Since a shortage of calcium [4] is what triggers apple cork spots, a vitamin deficit might also lead to their appearance. When polyphenol oxidase (PPO) is exposed to oxygen, it initiates a chain reaction that degrades proteins, pigments, fatty acids, and lipids, leading to a loss of colour and a worsening of flavour and odour [5].

II. LITERATURE REVIEW

Numerous studies assessing the quality of fruits and vegetables for commercial purposes have been done over the last few decades. Apples [4, 5], dates [5, 6], mangos [6, 7], citrus fruits [8, 9], and pears [10] are just some of the fruits that have found extensive usage of machine vision-based systems for applications requiring visual assessment. Examples of machine vision systems designed for use in manufacturing settings include [8, 9] an intelligent system for packaging 2-D irregular shapes, [10] an automated system for planning and optimising lumber production using machine vision and computer tomography, and [11] flexible online visual inspections.

Several physical and chemical variables influence tomato quality. Ripeness of tomatoes may be determined by their colour and firmness [11]. Tomatoes may be classified according to their ripeness using any number of scales and colour charts, however the colorimeter test may be unreliable owing to equipment unreliability at varying ripeness stages [12] and the lack of colour uniformity throughout the tomato. A tomato classifier with an accuracy of 84% was developed by Clement et al. [13] using variables such as colour, size, and weight.

However, dimensional analysis is crucial to the success of this method. Tomatoes are at their best when they are fully mature and free of defects. The colour of tomatoes may be used in automated defect detection approaches [14, 15]. Since colour alone is insufficient for flaw detection, the main problem is that the approaches were only 90% accurate. This study also had a very small sample size.

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This complicates the task of classifiers like neural networks in assigning meaningful labels to the hidden information. Multiple methods exist for evaluating tomato quality using MRI and spectroscopic images [16, 17]. These imaging techniques, which provide clear images, help doctors make accurate diagnoses. Obtaining a picture, however, may be time-consuming and costly if many imaging techniques are used.

In [4], the authors propose an algorithm for evaluating the quality of agricultural products. Using state-of-the-art technical methods and image-processing algorithms, the system carries out delivery and quality checks.

In this work [5], the researchers use image processing to track the health of fruit from planting to picking. It's possible that a neural network model may be used to identify rotten fruit. Dates are used to indicate a grading system for fruits [6].

In order to distinguish apples from potatoes, authors [7] recommended employing colour information processing. Computer vision has been proposed [8] as a viable method for classifying bell peppers. Two examples of computer vision systems that have been used for automation purposes are the intelligent system for packaging two-dimensional irregular shapes [9] and the camera image contrast enhancement for surveillance and inspection activities [13]. Textures with intricate patterns [14] are also examined using the microscope.

There have been reports of closed-loop vision systems being used for online process control in industry [15]. A computer vision-based system was proposed as a means of evaluating apple fruit quality. Strawberries are graded on their size, their form, and their colour [16]. It's been said [17] that Apple's employment procedures make use of fuzzy logic.

In [18], the authors offer a fuzzy logic rule-based classification method for diagnosing fruit illnesses. Mrunmayee et al. [19] used neural networks to depict illnesses that might affect pomegranate plants. They recognised and labelled a variety of illnesses. It was proposed by Pranjali et al. [20] that grape vines may be used to identify diseases. They contemplated looking at grape leaves over the course of their investigation. They looked into the possibility that bacteria, viruses, or fungi were to blame for the sickness.

Using an edge detection method, Revathi et al. [21] classify cotton leaf diseases. The HPCCD method was recommended for use in disease diagnosis after a literature analysis of cotton fungal diseases. Using a technique called circulatory threshold segmentation, Jun et al. [22] developed a mechanical method for detecting disease-related flaws in oranges' skin.

TABLE I. Table of different techniques and their efficiency

Types Of Fruits	Parameters	Efficiency	References
Apples	Color feature	100% Accuracy	Suresha et al. [20]
	Color, defect, shape and size	89% Accuracy	Kavidar et al. [24]
	Stem-end/Calyx	95.24% Accuracy	Zhang et al.[25]
	Color, shape, texture and stem position	73% Accuracy	Leeman et al. [21]
Fruits	Shape, intensity, GLCM texture features	GLCM: 96% Accuracy Shape: 100% Accuracy Intensity: 92% Accuracy	Deepa [15]
	Shape and color	79-90% Accuracy	Mustafa et al. [9]
	Color and texture	Chickoo: 94% Accuracy Apple and Sweet lemon: 93% Accuracy Mango and Orange:92% Accuracy	Savakar [14]
	Texture feature	Guava and Lemon: 96% Accuracy	Khoje et al. [26]
Date	length, width and thickness	93.5%Accuracy	zariet al. [22]
	Quantity of juice, size and freshness	86% Accuracy	Alavi [19]

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III. PROPOSED METHODOLOGY

The proposed methodology for the fruit freshness grading system is shown in steps for the better understanding.

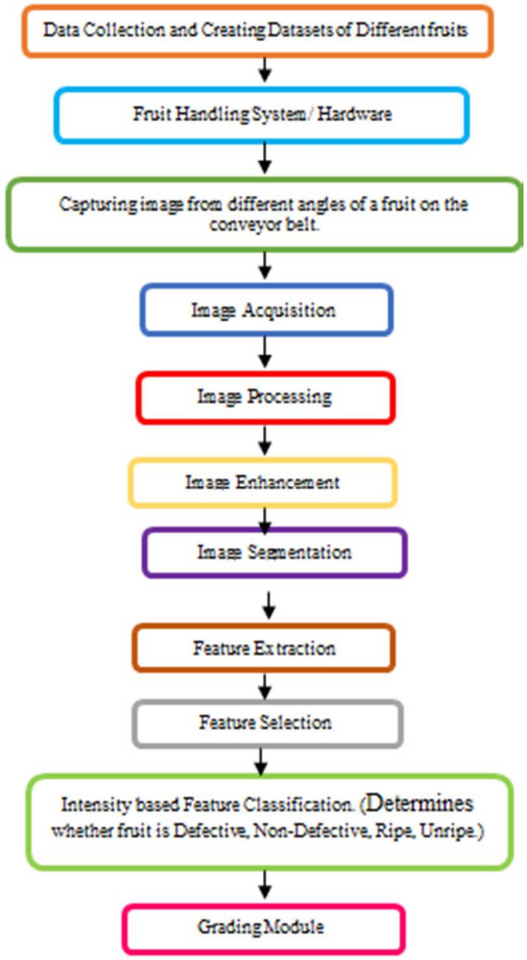

Fig2: Flow Graph of the proposed methodology

1) *Step1: Data Collection*

In order to analyse outcomes and provide answers to relevant inquiries, it is important to collect and analyse data on certain parameters within a predetermined framework. This article details the methodology we used to categorise fruits according to their apparent level of freshness. There is no publicly accessible data on fruits since this is such a novel area of study; we will need to collect this information ourselves. Here, we show how we gather data on fruits and provide evidence that it faithfully reflects the fruits' relative ripeness.

2) *Step2: Creating Datasets of different fruits*

Datasets Due to the dataset's diversity, several of the images of apples, bananas, dragon fruits, oranges, pears, and Kiwi fruits exhibit off-putting lighting or distracting background noise. First, the connection between apparent and real ripeness of fruit is investigated. Carotenoids and chlorophyll, present in small levels in young apple skin [30], degrade and alter the peel's reflectance as the apple ages. When bananas are ripe, they become yellow from a pigment called carotenoids [31]. Pectin, cellulose, and hemicellulose are what's left when water (which accounts for 60-90% of an orange's weight) is removed [32, 33]. Carotenoids and flavonoids are responsible for much of an orange's red hue. The beta-cyanins and betaxanthins in dragon fruit are responsible for its vibrant colour [34]. Kiwi fruit is green because of chlorophylls [35], but when it deteriorates, it becomes an olive brown colour from pheophytins and pyro pheophytins. The green or yellow hue of a pear comes from the high chlorophyll concentration of its skin. Dark blue to black pheophytins and pyrophytins are the byproducts of chlorophyll breakdown [35].

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3) Step3: Fruit Handling System / Hardware

The University of Agricultural Sciences in Bangalore generously donated 520 unsorted tomato images for the research. Tomatoes in the dataset span the spectrum from perfectly ripe to completely unripe. The categorization would not have been possible without input from on-the-ground specialists. Hardware for the fruit grading system was built in accordance with Figure 3. The tomatoes in Figure 4 were photographed at a resolution of 512 pixels along the longest dimension by the camera perched above the sorting machinery. MATLAB was utilised to build the image processing capabilities.

Fig3: Capturing of fruit on conveyor belt by the camera

In response to a signal from MATLAB, the microcontroller advances the conveyor belt carrying the tomatoes. The tomato has to be positioned precisely so for the greatest photo. In the image processing portion, the captured image undergoes a number of processes, including segmentation, feature extraction, and classification. The system's GUI was developed with an emphasis on ease of use. After taking the picture, it is uploaded to a computer monitor. A checkbox is provided for indicating whether or not the fruit is flawed. If that's the case, the damaged tomato will be sent to the conveyor's special area for rejects. The user may initiate the computer's ripeness check with the click of a button. The fruit on the conveyor belt is separated into containers according to its ripeness. Automatic bins are filled with high-quality tomatoes.

4) Step4: Capturing image from different angles of a fruit on the conveyor belt.

Conveyor belts come with a wide variety of characteristics that are tailored to the specific technique and product being handled. Both PVC and PU-coated vegetable and fruit belts are commercially available. There are belts that may be left on while being washed. Belts' finishes may range from moulding to sealing the edges. Inclined conveying allows for the coupling of a wide variety of belt surface types (including sidewalls, wave profiles, long or short finger profiles, horizontal or longitudinal profiles).

5) Step 5: Obtaining the Image

In order to process a picture, one must first get it from some kind of source, often some kind of hardware. Since no work can be done on the system until an image is submitted, here is where the process begins. The final product looks almost identical to the source material.

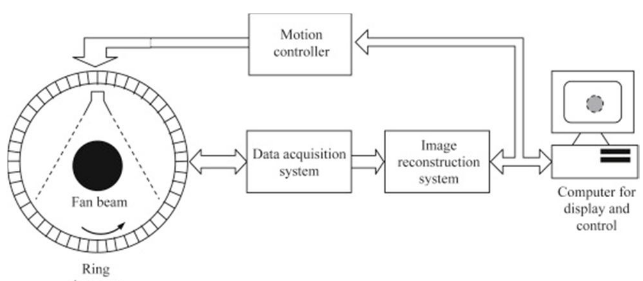

Fig4: Data Acquisition

6) Step6: Image Processing

The term "image processing" is often used to refer to a variety of methods that may be applied to a picture in order to enhance it or extract useful data from it. If you feed in a photo, you can get back a slightly different picture, or maybe only some of the information about that picture. Creating an Image Noise and specular reflections impair the camera's image of the tomato. The picture quality is degraded and the data is useless because of these impacts. To lessen the impact of background distractions like noise and glare, a median filter [18] is applied to the image.

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7) Step7: Image Enhancement

Digital image processing is the procedure of processing a digital image using an algorithm on a computer. Digital image processing, a subset of digital signal processing, has several advantages over its analogue predecessor. Separating Out the Pictures The photo of the tomatoes will now be cropped to exclude the background. To begin, we convert the image to binary using Otsu's method [18]. That tomato and that background are two separate things. The tomato area is perforated if the flaws stand out as much as the background. A complete tomato is achieved by filling up the blanks with pixels of value 1.

8) Step8: Feature Extraction

Deep learning feature extraction is a kind of machine learning. Raw data is turned into manageable numerical qualities through a process called as feature extraction, with no loss of information from the original data source. It's more efficient than training a machine learning model on raw data.

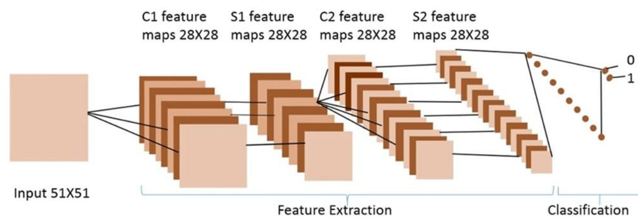

Fig5: Features Extraction

9) Step9: Feature Selection

During feature selection, the number of input variables is reduced in order to create a predictive model. In certain cases, the model's efficiency may be improved and its computational cost reduced by reducing the number of input variables.

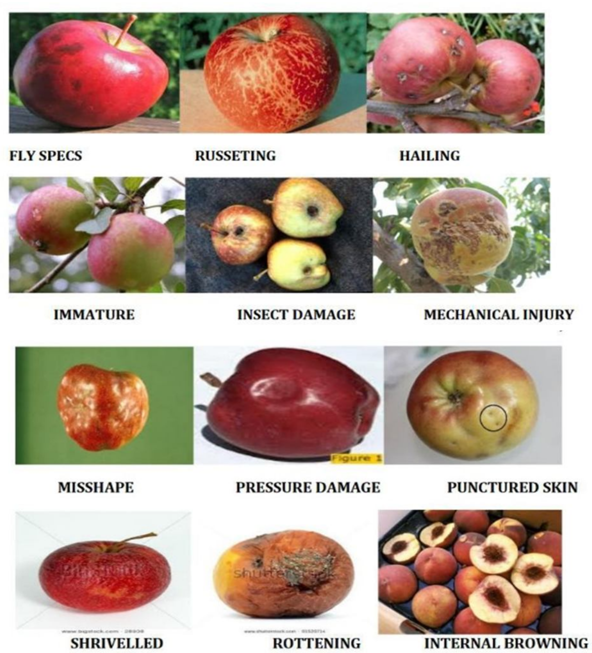

Fig6: Features Selection of Fruits

10) Step10: Intensity Based Feature Classification

In Fig. 6, we see a multilayer neural network being fed the accumulated data. It's made up of a network of interconnected neurons whose job it is to transform an input into an output. To identify flawed tomatoes, a feed-forward neural network with n inputs, h hidden neurons, and 1 output is utilised. The back propagation technique is used to fine-tune the weights of a supervised-learning-trained neural network.

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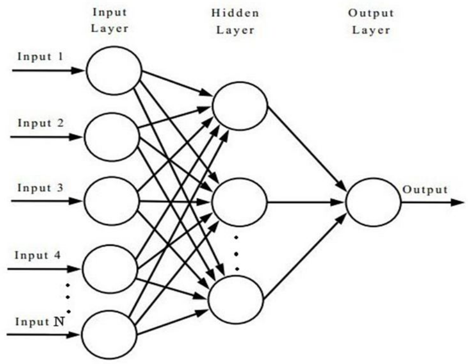

Fig7: Classification of fruits

11) Step 11: Determines whether fruit is Defective, Non-Defective, Ripe, Unripe.

Determine if the fruit is ripe, unripe, flawed, or not defective to choose the best and discard the worst.

TABLE II. Table of Classification whether the fruit is permitted or not

Defects	Premium	Regular
Fly Specs	Not permitted	Not permitted
Russeting	Not permitted	Permitted
Hailing	Not permitted	Permitted
Immature	Not permitted	Not permitted
.Insect Damage	Not permitted	Not permitted
Mechanical Injury	Not permitted	Not permitted
Misshape	Not permitted	Permitted
Pressure Damage	Not permitted	Permitted
Puntured Skin	Not permitted	Not permitted
Shrivelled	Not permitted	Permitted
Rottening	Not permitted	Not permitted

12) Step12: Grading Module

A grading module gives each piece of fruit a rating from "excellent" to "good" to "rejected." Customers place a premium on fruit quality, hence markets should only carry premium fruit. To accommodate the inspection needs of the fruit processing industry, fruit grading systems have developed during the last several years. Some of the various steps in processing fruit include grading, sorting, packaging, transportation, and storage. The importance of the grading process in producing a high-quality output cannot be overstated. Apples and mangoes have been the first targets of this programme. In this article, we take a look at the planning, building, and testing of a prototype automated fruit grading system that can spot cosmetic flaws in fruit. The technique captures an image of the fruit as it spins on a camera-equipped platform.

TABLE III. Table of Classification of fruits on the basis of statistics

Fruit Images	Fruits Name	Freshness	Means	Standard Deviation
	Apple	No	1.45	0.31
	Apple	No	2.34	0.34
	Apple	Yes	8.60	0.84
	Banana	No	2.75	0.25
	Banana	No	3.30	0.35
	Banana	Yes	8.90	0.96
	Mango	No	4.20	0.53
	Mango	Yes	9.21	0.94
	Mango	No	3.10	0.43
	Dragon Fruit	Yes	8.76	0.92
	Dragon Fruit	No	3.60	0.43
	Dragon Fruit	No	4.50	0.48
	Kiwi	No	5.50	0.44

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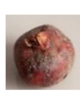
	Kiwi	No	3.20	0.23
	Kiwi	Yes	9.10	0.98
	Orange	Yes	9.20	0.89
	Orange	No	4.77	0.55
	Orange	No	5.10	0.47
	Pear	Yes	9.45	0.86
	Pear	No	4.50	0.38
	Pear	No	3.47	0.44
	Pomegranate	Yes	8.92	0.89
	Pomegranate	No	4.60	0.42
	Pomegranate	No	3.80	0.51

These results show that the proposed technique, which uses colour statistics and textural features to differentiate defective and nondefective items, works as intended. The image's other non-defective tomatoes' R, G, and B values may also be used by the algorithm to deduce whether or not the tomato is ripe. Color and texture have been the primary foci of research into using aesthetics to evaluate fruit quality. Take a look at Fig. 6 to evaluate the efficacy of these features in differentiating flawed from healthy tomatoes. Combining colour and texture was shown to improve the classifier's accuracy.

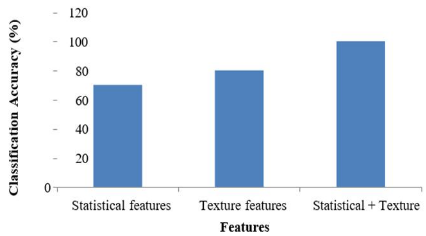


Fig.8. Comparison of the effectiveness of feature

IV. CONCLUSION

In this research, we show how to use computer vision techniques for automated tomato quality assessment. The hardware of the fruit grading system may then utilise the results from the image processing module to sort the fruit into the proper bins. All shots were correctly labelled as "defective" or "non-defective" by the algorithm, while 96.47 percent of fruit images were correctly labelled as "ripe" or "unripe." Growers and food processors may now effectively sort fruit thanks to a trustworthy system. Since the grading machine can only score 300 fruits per hour, high specular reflection in the fruit photos poses a challenge for the proposed image processing method. Since human grading takes so much time and may lead to contradicting conclusions when undertaken by different persons, there is an urgent demand for fruit grading using machine learning and computer vision. The training dataset cannot be created without first collecting example photographs with a wide variety of flaws. The proposed method may help make automated fruit grading systems more reliable in the long run. Before it can be used in the field, its speed and accuracy must be enhanced.

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