Machine Learning for Automated Quality Control in Industry 4.0

Bachelor Thesis

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This is to certify that:

(i) the thesis comprises only my original work towards the Bachelor Degree

(ii) due acknowledgement has been made in the text to all other material used

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Abstract

Quality control has always been an important and challenging process for all industry areas as they seek to have a constant and accurate quality control process. The industrial revolution 4.0 had a positive effect on quality control as the usage of machine learning techniques for automated quality control evolved and increased, improving the whole quality control process. This research paper discusses an application of automated quality control which is using machine learning in the classification and grading of different fruits and vegetables. The suggested technique is using k-nearest neighbour (knn) classifier to grade Orange images into 3 grades: Grade 1, Grade 2 or Grade 3 (Rotten). This technique yielded a high accuracy of approximately 99.06% which is high compared to other papers that also implemented the k-nearest algorithm.

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List of Abbreviations

KNN	K-nearest Neighbour
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
SVM	Support Vector Machine
DNN	Deep Neural Network
FFNN	Feed Forward Neural Network
MLP	Multilayer perceptron
RBP-NN	Radial Basis Probabilistic Neural Network
FSCABC	(Fitness-scaled Chaotic) Artificial Bee Colony
BP-NN	Back Propagation Neural Networks
MLP-BPNN	Multilayer perceptron
RBF-NN	Radial basis function neural network
CMCM	Color- Mapping Co-occurrence Matrix
GLCM	Gray- Level Co-occurrence Matrix
HOG	Histogram of Oriented Gradient
IoT	Internet of Things
CPS	Cyber-physical Systems
HMI	Human Machine Interaction
RGB	Red, Green, Blue
HSI	Hue, Saturation, Intensity
HSV	Hue, Saturation, Value

Contents

Chapter 1
Introduction

The phrase "Industry 4.0" was established by the German government to stimulate the use of innovative technology approaches. The present shift in the industrial paradigm demands a deep integration of digital communication technologies into the production process (Godina & Matias, 2018). The goal of Industry 4.0, according to Lu (2017), is to increase operational efficiency and production while also improving automation. The goal of Industry 4.0, according to Vaidya et al. (2018), is to turn regular machines into self-aware, self-learning machines that can improve overall performance and maintenance management by interacting with their environment. Industry 4.0's objective is to provide an open, smart manufacturing platform for industrial-networked data applications. In addition to improving quality control directly, Industry 4.0's tools could improve quality at all stages of the manufacturing process, including the quality of information needed for optimization, planning, and operation, the quality of forecasting, simulations, and prototyping, and even better employee participation and engagement (Godina & Matias, 2018). One of the applications of automated quality control is in the agriculture industry which is the main topic of this thesis. The development of automated quality control, specifically in the agriculture industry is being driven by increased customer awareness of their health and a reaction by manufacturers to the necessity to offer quality-guaranteed products with consistency (Njoroge et al., 2002).According to Kondo (2010), applying automated quality control in the agriculture industry can produce higher-quality, higher yielding crops with less input.

1.1 Motivation

Agricultural products, unlike most industrial items, have unique quality inspection challenges because of aspects such as appearance, which is important, cannot be exactly defined, and consumers may sometimes accept minor abnormalities. In this context, automated quality inspection and machine vision play a key role in agricultural product quality control (Njoroge et al., 2002).

So, as the demand for automated quality control increases, including in automated quality control for the agricultural products such as fruits and vegetables, the demand for high accuracy and easy to implement machine learning algorithms that grades fruits and vegetables has also increased.

1.2 Aim of the thesis

This thesis discusses different machine learning and image processing techniques that are used in different studies in the process of classifying and grading different agriculture products. It also includes a comparison between different machine learning algorithms used in different papers in terms of their accuracy. The aim of the thesis is to create a machine learning model that grades fruits, specifically oranges by analyzing features of these images. This model can assure the quality of the oranges, in other words it will serve the quality control purpose.

1.3 Structure of the work

- Chapter One includes an introduction to industry 4.0, quality control, motivation, and the aim of this thesis.
- Chapter Two is a background knowledge on industry 4.0, automation of quality control in the agriculture industry and different machine learning algorithms.
- Chapter Three is a review on different literatures that have implemented image processing and machine learning techniques for the classification and grading of different fruits.
- Chapter Four discusses the methodology of the suggested model.
- Chapter Five presents the results of the suggested model and also includes the conclusion.

Chapter 2
Background Knowledge

2.1 Industry 4.0

Industrial 4.0 is a comparatively recent industry concept that incorporates the significant technical advancements in the areas of automation, control, and information technology as they apply to production processes. This industrial revolution toward automation and artificial intelligence (AI) is the new trend. It encompasses concepts such as Cyber-Physical Systems, the Internet of Things (IoT), and Internet Services. Manufacturing processes are becoming more efficient, autonomous, and customizable (Lasi et al., 2014). The term "Industry 4.0" comes from a German government initiative to encourage innovative technology methods. The current industrial paradigm change necessitates a thorough integration of digital communication systems with the manufacturing process. Industry 4.0 promotes communication between physical objects, such as machines and devices, sensors, and company's assets, as well as connectivity to the cloud. This allows stakeholders to have real-time access to whatever information they need. Image and pattern recognition, as well as sensor technology, have advanced at a breakneck pace, allowing for innovative solutions. The existing transformation necessitates a deep integration of digital communication technologies (digital media) into industrial processes, as well as the redesign of products, services, and production methods. At its core is a technological disruption marked by the merging of the physical world of industrial plants and the virtual world of digital information, a "merge" that results in the systemic integration of processes, information, people, machines, places, and products. Industry 4.0 combines automation with a model that embraces the hallmarks of digital culture: knowledge-based systems, pervasive sensor technology (from network connectivity to total connectivity within IOT systems), process flexibility and adaptability, and the shift from specialization (vertical) to process (horizontal). All of this adds to the complexity of the issue. As a result, the concept of the future factory is closely linked to the concept of a factory that is both digital and flexible, or rather, flexible because it is digital (Lasi et al., 2014; Godina & Matias, 2018; Mazali, 2018).

As shown in Figure 1, a wide range of technologies and elements essential to Industry 4.0 are represented. Cyber-physical systems (CPS), Internet of Things (IoT), Smart Factory, and Big Data are some of these aspects. The primary goal of the Industry 4.0 concept is to further satisfy client expectations, thereby impacting the most different aspects of production, beginning with R&D, management, commissioning, logistics, and ending with product usage and recycling.

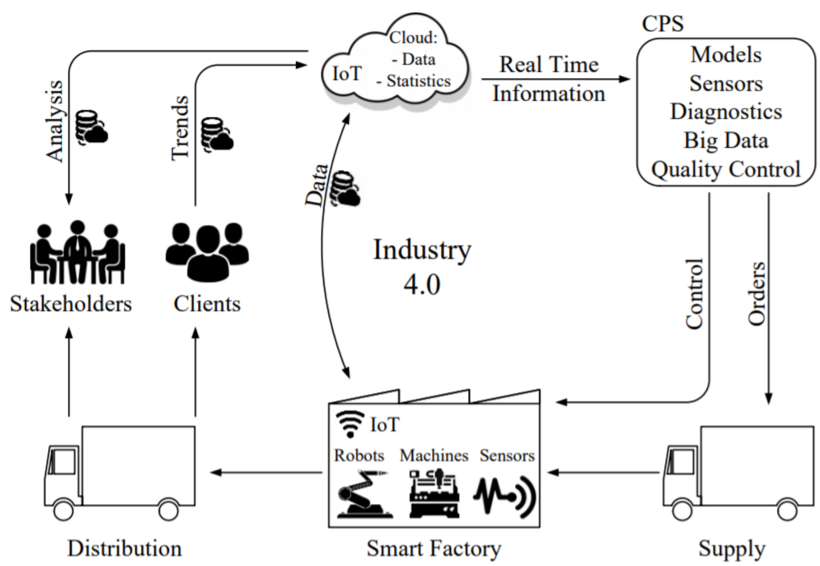


Figure 1: The main elements of Industry 4.0 (Ahuett-Garza & Kurfess, 2018).

Lu (2017) stated in their study that the objective of Industry 4.0 is to achieve more operational efficiency and productivity, as well as improved automation. According to Roblek et al. (2016) and Posada et al. (2015) digitization, optimization, and customization of manufacturing; automation and adaptability; human machine interaction (HMI); value-added services and enterprises; and automatic data interchange and communication are the five key aspects of Industry 4.0. Vaidya et al. (2018) stated that the aim of Industry 4.0 is to transform ordinary machines into self-aware, self-learning machines that can enhance overall performance and maintenance management by interacting with their surroundings. The goal of Industry 4.0 is to provide an open, smart manufacturing platform for industrial-networked information applications. The key requirements of Industry 4.0 include real-time data monitoring, tracking product status and locations, and storing instructions to regulate manufacturing operations.

2.1.1 Automated Quality Control.

One of the big challenges of any industry is ensuring the highest quality standards at a reasonable price. The automation of the quality inspection process can reduce its cost and ensure a high quality standard (Villalba-Diez et al., 2019). In a research paper conducted by Villalba-Diez et al. (2019), they used deep learning in order to automate the quality inspection process. They combined a high-resolution optical quality control camera and a Deep Learning soft sensor application to improve the accuracy and lower the cost of an industrial visual inspection process in the Printing Industry 4.0. Mineo et al. (2020) also discussed how the automation of the quality control process through the usage of robotic arms with server computers, sensors and actuators can improve the accuracy of the inspection process in the manufacturing industry.

Aside from improving quality control directly, Industry 4.0's tools could improve quality at all stages of the manufacturing process, including the quality of information needed for optimization, planning, and operation, the quality of forecasting, simulations, and prototyping, and also improve employee participation and engagement (Godina & Matias, 2018).

2.1.1.1 Automated Quality Control in Agriculture

Another application of automated quality control that can yield many benefits is its application in the agricultural industry. Automation in the agricultural industry can have multiple benefits. According to Pandey et al. (2013) it is essential for boosting the country's production and economic growth, therefore an automated system for accurate, quick, and high-quality determination of fruits is required. Numerous algorithms for grading and categorizing fruit quality have been developed by different researchers. Njoroge et al. (2002) stated that because of the rising demand for high-quality food in a short amount of time, several farmer organizations are promoting automated grading of agricultural goods. Increased customer awareness of their health well-being, as well as a response by manufacturers to the requirement to deliver quality-guaranteed products with consistency, are the driving forces behind this trend.

Agricultural products, unlike most industrial products, present distinctive problems in terms of quality inspection due to factors such as appearance which is crucial, cannot be precisely defined, and sometimes little irregularities may be acceptable to customers. The field of automated inspection and machine vision plays a significant role in quality control for agricultural products in this context.

Another benefit of the automated technologies that have been used in many grading facilities is that they can record a lot of grading information on agricultural product characteristics, which ensures food safety and security. Color, size, shape, exterior defect, sugar content, acidity, and other interior characteristics may all be measured. Furthermore, records of producer operations (for example, when, where, and what sort of pesticides were sprayed, and what kind of fertilizers were used) can be stored in a database. This information is shared with customers for risk management and food traceability, as well as with farmers for precision agriculture, which aims to produce higher-quality, higher yielding crops with less input (Njoroge et al., 2002; Kondo, 2010).

2.2 Machine Learning Algorithms

Machine learning algorithms play a vital role as classifiers and decision makers in the fruit classification and grading process as the classification is the final phase of the process which is all about knowledge-based comparison and decision making. In the classification process, images are converted into usable data. (Naik & Patel, 2014; Bhargava & Bansal, 2020). Bhargava & Bansal (2018) described classification as the most important aspect for evaluating food quality as it provides a structure in which computer simulations of human thinking are used to help humans in making complex judgements quickly, properly, and consistently. In other words, the classification process utilizes machine learning algorithms in order to classify objects such as fruits and vegetables. After acquiring a set of features such as color, size, shape and texture using image processing techniques, these features are utilized to create a training set, after which a classification algorithm is employed to extract a knowledge base from which a decision for an unknown case is made. For image classification in food quality evaluation, a variety of methods such as KNN, SVM, Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) have been developed.

2.2.1 K-nearest Neighbour (KNN)

K-Nearest neighbor (K-NN) is a statistical classifier that measures the distance between points in input data and trained data using Euclidean distance. Within its closest k-neighbors, it allocates data to the closest k-neighbors. Figure 1 illustrates how k-NN works (Bhargava & Bansal, 2020).

Fruit recognition systems can utilize the knn algorithm as a classifier to classify fruit based on mean color values, shape roundness value, area and perimeter values of the fruit (represent size). The value of k is chosen and mostly euclidean distance is used (Naik & Patel, 2014).

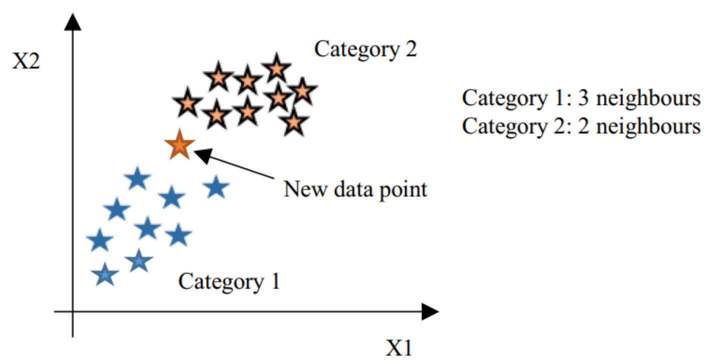


Figure 2: KNN institution for k = 5 (Bhargava & Bansal, 2020)

2.2.2 K-means Clustering

According to Dubey et al. (2013), clustering is an effective way for processing food images. Clustering divides items into separate groups, or more precisely, partitions a data set into clusters (subsets), with the data in each cluster sharing some common attribute which is based on some distance measurement. Data partitioning is a common statistical data analysis technique that is utilized in a variety of fields such as machine learning, image analysis, pattern recognition, bioinformatics, and data mining. Unsupervised learning refers to the computational job of splitting a data set into k subsets. Clustering can be done in a variety of ways and for a variety of objectives. A common clustering algorithm is K-means. The K-means algorithm is commonly used to detect the natural groups of pixels in an image. In practice, it is appealing since it is straightforward and generally quick. The input dataset is divided into k clusters. Each cluster is represented by an adaptively moving center that starts with some seed-point values. The distances between the inputs and the centers are calculated using K-means clustering, and the inputs are assigned to the center that is closest to them. The K-means clustering method is an unsupervised clustering method that divides input data objects into various classes based on their inherent distance from one another. The clustering algorithm assumes that the data characteristics constitute a vector space and attempts to find natural clustering in it (Dubey et al., 2013).

Sreekanth et al. (2020) stated in their study that using an improved k-means algorithm will improve the identification of fruits. They suggested that k-means rule is employed to classify the fruits from other objects such as leaves and branches. The rule can categorize the things by means of similarity. To calculate that similarity, the geometrical distance is used as measuring.

2.2.3 Artificial Neural Networks (ANN)

ANN stands for artificial neural networks, which are computer programs that are biologically inspired and designed to mimic the way the human brain processes information. An artificial neural network (ANN) is a type of computer program that works in a similar way to our brains. Artificial neural networks are a type of classification technique that extends several other techniques. ANNs are capable of dealing with ambiguous data and challenges that necessitate the interpolation of enormous amounts of information. The input, hidden, and output layers are all incorporated within the ANN. Each layer contains nodes, also known as neurons. Each link contains weights that connect the nodes and the feature vectors are referred to as neurons. The weighted total of the inputs plus a bias determines the output of neurons. The entire neural network's function is just to compute the outputs of all the neurons. Figures 2 and 3 show sample ANN structure and layers connections. A mathematical structure that processes information through connected neurons using a configurable threshold, weights, and transfer function is another definition for artificial neural networks. ANN has the best decision-making skill, which may be employed in the categorization of biological products when no mathematical function is able to classify size and shape. It also produces reliable results when it comes to classifying agricultural products. The hidden layer and output layer both have an activation function. Hand activation functions are determined based on the application. Rectifier, sigmoid, and hyperbolic tangent are some of the activation functions. The sigmoid function is the mostly used activation function which is mathematically represented as shown in equation (1) (Bhargava & Bansal, 2020; Naik & Patel, 2014).

$$f(net) = tanh(x.net-y)+z \qquad (1)$$

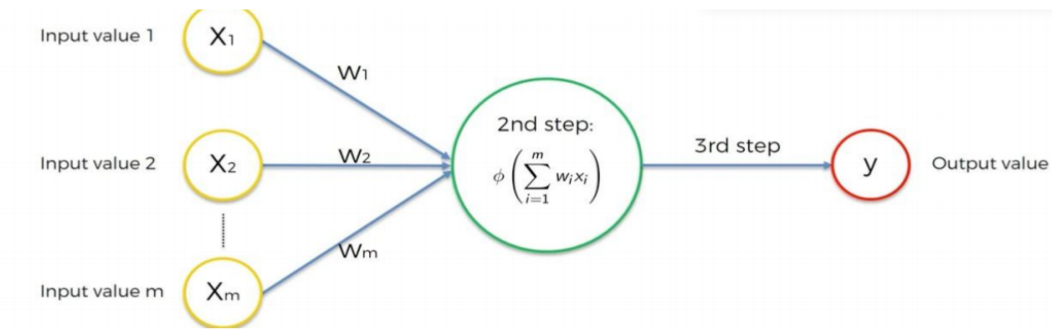


Figure 3: Basic structure of ANN (Naik & Patel, 2014)

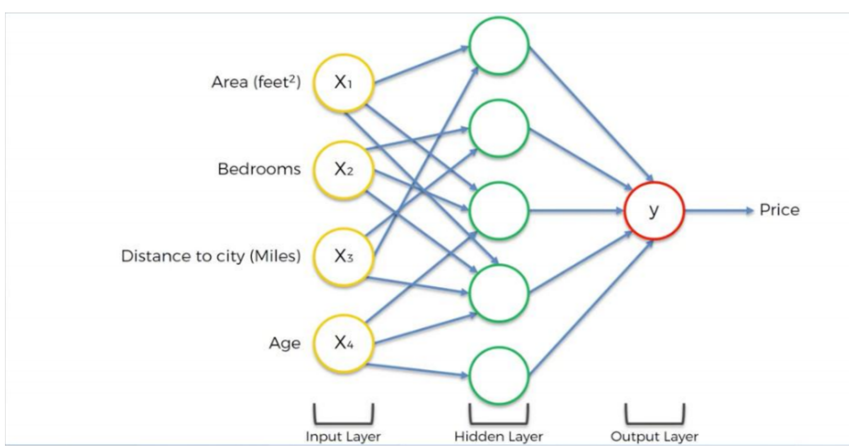


Figure 4: ANN layers and neurons intuition (Naik & Patel, 2014).

2.2.4 Deep Learning

Machine Learning has a sub-field called Deep Learning. It's a set of techniques for modeling high-level abstractions in data. To conduct analysis, a computer-based statistical model interprets and learns from images, sounds, or text. These models can achieve cutting-edge accuracy, sometimes even outperforming humans. In terms of accuracy, models are trained utilizing a huge quantity of labeled data and neural network architectures with multiple layers. Deep learning became popular due to two factors: it requires a large amount of labeled data and a lot of computational power. In the recent decade, the number of deep learning applications is increasing, including natural language processing, image classification, and information retrieval, among others.

2.2.4.1 Convolutional Neural Networks (CNN)

Convolutional neural networks (CNN), a DNN-class neural network, is commonly used for visual analysis. CNNs are feed-forward neural networks (FFNN) that can instantly recognize, classify, and identify any features in an image. The network input in CNNs consists of image pixel values with varying weights depending on the feature to be extracted as defined in the hidden layer. Despite the pooling and convolution layers, CNNs are made up of completely linked layers to recognize various elements in an input image. A CNN classifier performs the convolution process over pixels in an image. It is made up of four of the most common layers. The convolution layer is the first layer, and its job is to convolve the pixels in an image with a specified kernel (Harris) in order to extract or remove various features. The second layer is the ReLU layer which defines an activation function, which might be a sigmoid or any nonlinear function. The image is run through the convolution and ReLU layers numerous times, where all negative pixels are transformed to zero and image trends and properties are analyzed. The Pooling layer is the third layer, and its primary function is to turn the image into the desired dimension without blurring it. The pooling layer has several kernels to recognize sharp edges and detect different shapes in a picture for this purpose. After that, the image is converted into a 1-D linear matrix. The last layer, which is fully connected, is utilized to identify and classify images based on the accuracy (confidence value) acquired. Figure 4 illustrates a typical CNN architecture (Chung & Van Tai, 2019).

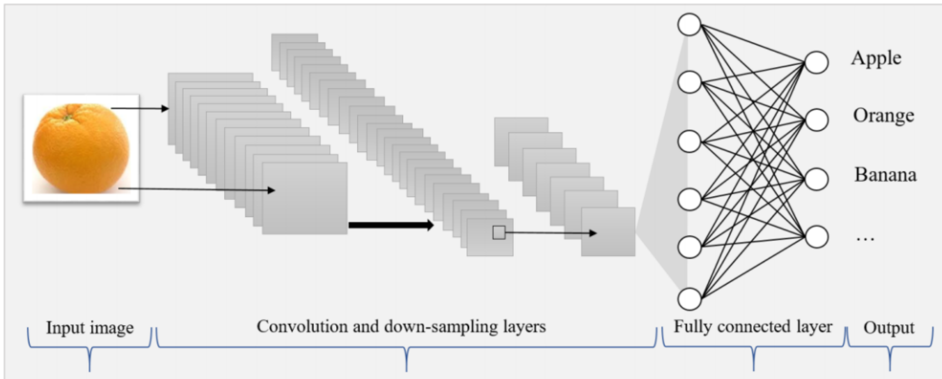


Figure 5: A convolutional neural network (Chung & Van Tai, 2019).

Chapter 3
Literature Review

In this chapter, several research papers and theses that have investigated the application of image processing and different machine learning algorithms on fruit classification and grading are reviewed. The literature review discusses different image pre-processing, image segmentation, feature extraction and image classification techniques used by different authors in the classification or grading of fruits.

3.1 Image Preprocessing

After the acquisition of the image, comes image preprocessing which eliminates noise from images, smoothes them out, and resizes them. Many noises are present in images captured using different techniques, degrading the image's quality. As a result, it will be unable to provide relevant data for image processing. Preprocessing improves image data by removing reluctant distortions and enlarging image features that are essential for processing, resulting in a more relevant image than the original for a specific application. Pixel preprocessing and local preprocessing are two methods used for image pre-processing. Pixel preprocessing is the process of converting an input image into an output image in which each output pixel is linked to the input pixel with the same coordinates. Color space transformation (CST) is the most widely used pixel pre-processing method for evaluating food quality like the grading of fruits. The majority of CST applications use the hue, saturation, and intensity (HSI) color space, where saturation results in a monochromatic image that vividly conveys the image texture. On the other hand, Local preprocessing, which is also known as filtration, produces a new brightness value in the output image by using a small neighborhood of a pixel in the input image. It employs a simple filter to reduce noise, median filter to reduce peak noise, and modified unsharpened filter (Raja Sekar et al., 2018; Bansal & Bhargava, 2018).

According to the processing goal, local preprocessing methods can be divided into two groups: smoothing suppressed noise or other minor fluctuations in the image; equivalent to suppressing high frequencies in the frequency range. Unfortunately, the sharp edges also smoothed important details in the picture. Gradient operators are built on the image function's local derivatives. At the parts of the image where the picture function changes quickly, derivatives are larger. The gradient operators' aim is to draw attention to such areas in the picture. In the frequency domain, gradient operators inhibit low frequencies, in other words they act as a high-pass filter (Naik & Patel, 2017).

Capizzi et al. (2016) and Arakeri (2016) used median filtering in the preprocessing step in order to remove noise and suppress the reflection by normalizing the unequal distribution of light which will improve the quality of the image which will make the processing easier. The median is less sensitive to extreme values, also known as outliers than the mean. As a result, median filtering is better at removing outliers without losing picture sharpness. While filtering out the peak noise, the median filter technique allowed the edges to be maintained which is important as the edges might be a distinctive feature in classifying the fruit. Bhargava & Bansal (2020) proposed using the gaussian filter to remove noise. It is usually applied by convolving an image with a kernel of Gaussian values.

Bhargava & Bansal (2020) also proposed the conversion of color space into one that is suitable for detecting defects quickly. Usually , images captured by digital cameras are of RGB color model and since the RGB color space is non-linear and difficult to distinguish between color and brightness, it cannot be used to evaluate fruit properties. To solve this problem, they converted RGB images to grayscale images to speed up processing time. Sidehabi et al. (2018) also remodeled the color space in order to improve the color quality by reducing the lighting effect as they transformed the color space from RGB to CIE Lab. They also, as a preprocessing step, resized the size of the video data frame measuring 1280x720 pixels to 384x216 pixels in order to save memory and decrease the execution time.

3.2 Image Segmentation

Image segmentation is an important stage in which a digital image is partitioned into various parts. The main purpose is to isolate the background so that the significant area can be processed during the object evaluation. A proper segmentation is essential for further image analysis progress. Poor segmentation will degrade the classifier's efficiency (Bansal & Bhargava, 2018).

As mentioned before , image segmentation involves the separation or division of the image into areas of similar attributes. In another way, image segmentation is nothing more than pixel classification. The degree of complexity in which the image segmentation process must be carried out is largely determined by the problem at hand. It is viewed as a crucial operation for interpreting and analyzing the acquired images in a meaningful manner. It's one of the most important aspects of image analysis and pattern recognition, and it's also one of the most difficult tasks in image processing and analysis (Dubey et al., 2013).

Image segmentation techniques are typically based on one of two fundamental properties of image pixel intensity values: similarity or discontinuity. Methods based on methods similarity are called region-based methods, and the methods based on discontinuities are called boundary-based methods. In the similarity-based method, the idea is to divide the image into many regions, each of which has image pixels that are identical based on a set of predetermined criteria. The method of partitioning an image on the basis of sudden shifts in intensity values is used in the discontinuities- based methods. The edge detection technique, which is similar to boundary extraction, is an example of this category (Naik & Patel, 2017; Dubey et al., 2013) .

Many segmentation methods have been developed based on the discontinuity or similarity criterion, and they can be divided into six methods: Histogram based method, Edge Detection, Neural Network based segmentation methods, Physical Model based approach, Region based methods such as Region splitting, Region growing & merging and Clustering Methods such as Fuzzy C-means clustering and K-means clustering (Dubey et al., 2013).

Arakeri (2016) and Azarmdel et al. (2020) applied the Otsu’s thresholding method, which is one of the most common image segmentation methods in order to partition the image into two parts, the fruit and the background by converting the image to binary. If the defects on the fruit are close in intensity to the background, the fruit area will contain holes. The hole will be then filled with pixels of value 1 (1 corresponds to fruit and 0 to background) in order to extract the entire region of the fruit.

Azarmadel et al. (2020) also applied the erosion operator which is used to separate the stems from the fruit in order to accurately classify the fruit while minimizing classification errors. It is applied by taking into account a structural factor indicating the number of pixels in the neighbourhood in order to filter the image by destroying the edges of the objects. After that, the image was dilated to get the fruit region back to its original size with the least amount of erosion possible.

Bhargava & Bansal (2020) and Sidehabi et al. (2018) both used clustering methods for segmenting the image into background and fruit region as they used the fuzzy c-means clustering method and the k-means clustering method, respectively. The goal is to reduce the dissimilarity function for cluster centroids to the smallest possible value. Capizzi et al. (2016) used the HSV histogram in order to segment the fruit region from the background which is a fast and efficient image segmentation method.

Moallem et al. (2017) used two different image segmentation methods, they first used the heuristic thresholding method to segment the fruit from the background. Secondly , in order to segment the defects in the fruit from the healthy parts they used a pixel based artificial neural network. Based on corresponding R, G, B, and H values, each apple image pixel is classified into two classes: healthy and defected. To classify each input pixel into one of two healthy or defected groups, they used an MLP neural network with two layers, four inputs (R, G, B, and H values of pixels), 15 neurons in the hidden layer, and two neurons in the output layer.

3.3 Feature Extraction

After image segmentation, the next step in image processing is to extract image features useful in describing fruits. In an image, the feature is the "interest" part. Before classifying an image, this step is used to obtain features such as color, texture, and shape that reduce the amount of resources required to describe a large set of data. Various features can be extracted from the image: color, shape, size and texture (Naik & Patel, 2017; Raja Sekar et al., 2018).

3.3.1 Color Features

Color is one of the factors that influences a consumer's decision to deny or choose fruits and vegetables. Throughout the ripeness, growth, and postharvest processing and handling stages, it is the indirect measurement of quality characteristics such as freshness, desirability and variety, maturity, and safety. In image retrieval and indexing, the color feature is the first and most commonly used visual feature. High efficiency, ease of extracting color information from images, size and orientation independence, powerful in representing visual content of images, robust to background complications, and powerful in separating images from each other are just a few of the benefits of the color feature. For color inspection of fruit and vegetable quality, the RGB color space, HSI color space, and CIELab color space are widely used (Bansal & Bhargava, 2018).

CIELab color space is an international standard for perceptual uniformity. The goal of this color model is that color variations that a human perceives as equal conform to equal Euclidean distances in CIELAB space. L*, a*, b* are the coordinates of this model, where L* is the measure of lightness, a* is the red/green balance, and b* is the changes in the green/blue balance. HSI color space means hue which refers to tint, saturation which represents shade and intensity. HSI is very similar to HSV, but it focuses on the color palette. HSI is the best method for developing color-based image processing algorithms that are natural and perceptible to humans. Color features can be extracted from images once the color spaces have been specified. Many researchers have proposed various color features, such as the color correlogram, color coherence vector, color moments, and color histogram. Color moments are simple and effective among them. The mean, standard deviation, and skewness are the most common moments. (Kumar & Gill, 2015; Bansal & Bhargava, 2018).

Moallem et al. (2017) used color features computed from a defected region's histogram of pixel intensities. The statistical features employed in this article include color features, such as the mean and standard deviation of the defected region's red (R), green (G), blue (B), and hue (H) components. While Capizi et al. (2017) converted the RGB color space into HSI and for all the converted color space values (hue, saturation and intensity), the mean and standard deviation were calculated. Each fruit image has a distinct mean and standard deviation value, which facilitates classification.

The frame was extracted into four features of RGB value and a* value in a study by Sidehabi et al. (2018). The RGB value of the RGB segmented frame is extracted. The frame is then transformed to L*a*b* color space, which allows the a* value to be obtained. The three L*a*b* coordinates represent the color's brightness, with L*=0 indicating black and L*= 100 indicating white. Then, between red and green, a* is placed, with negative values indicating green and positive values indicating red. Blue's position between yellow, with negative values denoting blue and positive values denoting yellow. The a* value was utilized as one of the features in this study since the ripeness of passion fruit can be distinguished by their red or green color.

RGB color space is converted into another color space such as HSV and for all the converted color space values, the mean and standard deviation are calculated. Each fruit image gives different values of mean and standard deviation, therefore assisting its classification.

3.3.2 Morphological Features

Morphological features, such as shape and size, are the most widely used features for fruit classification. Size features are physical dimensional measurements that provide information about an object's appearance. Morphological features include area, perimeter, major and minor axis lengths, and aspect ratio (Kumar & Gill, 2015).

In a study conducted by Capizzi et al. (2016), an RGB image is transformed to a grayscale image for the purpose of determining shape features. The image displays a brightness intensity scale after it has been converted to grayscale. Because the intensity levels of the object to be identified and the background differ, a threshold value is employed to distinguish the object from the background. A gray scale image is then converted into a binary image using this threshold value, with the value greater than the threshold equaling 1 and the value less than the threshold equaling 0. Different shape features are computed with the help of this binary image. The image area, perimeter, major axis length, and minor axis length are used to calculate the most common shape features.

The geometric features employed by Moallem et al. (2017) were defect ratio, defect perimeter, and defect medial axes length. The defect ratio is the number of pixels in defective regions divided by the number of pixels in the fruit region. The length of the defective region boundary is used to calculate the perimeter. Bhargava & Bansal (2020) used geometric features such as solidity, area, and a maximum length of the area, eccentricity, and perimeter. Those geometric features were used in their study to detect the type of fruit and a mix of statistical, textural, and geometrical features were used for grading (Rank 1/ Rank 2 / Defected) of fruits.

3.3.3 Textural Features

The surface appearance and distribution of elements are represented by texture features. It's a crucial feature of machine vision because it predicts surface properties. Textural features predict surface properties such as contrast, correlation, energy, homogeneity, and entropy. The textural properties of geometric moments are often used in pattern recognition. The texture feature of an image can be calculated using one of two approaches. The first is statistical texture analysis, and the second is structure of texture analysis. Statistical texture analysis is the most conventional. It includes spatial autocorrelation method, Fourier power spectrum method, Co-occurrence matrix method, gray level difference statistics method and trip length statistics method. There are two types of co-occurrence metrics, Color mapping co-occurrence matrix (CMCM) which is used to extract the texture information from a skin image and Gray level co-occurrence matrix (GLCM) which is used to extract texture features in an image (Kumar & Gill, 2015; Bhargava & Bansal, 2020; Capizzi et al., 2016).

Gray level co-occurrence matrix (GLCM) is a type of tabulation that contains various combinations of pixel brightness values (gray levels) that can be found in an image and displays the number of occurrences for gray-level pairs as a square matrix. Given that a total number of gray levels n is known, GLCM (G[i,j]) is constructed by specifying a displacement vector d = (dx,dy) and counting pixel pairs at angle θ with gray levels i and j separated by distance d. G[i,j] is added with its transpose as the GLCM is not symmetric due to the number of pixel pairs being unequal. GLCM can be computed in four different directions, horizontal (0°), vertical (90°), left-diagonal (45°), and right-diagonal (135°). A gray level co-occurrence matrix is created in order to calculate several texture features such as contrast, correlation, entropy, energy, homogeneity, variance and skewness. The power of a pixel and its neighbor over the image is measured by contrast. Correlation is a measure of pixel pairings' joint chance of occurrence. The degree of pixel match repetition is measured in energy. Homogeneity refers to how close the distribution of elements in the GLCM is to the GLCM diagonal. The texture of an image is described by entropy. The mean of the reference and neighbor pixels is measured by variance. The degree of asymmetry in which a bend appears skewed left or right is measured by skewness (Bhargava & Bansal, 2020; Capizzi et al., 2016).

Arakeri (2016) used the gray level co-occurrence matrix (GLCM) in order to extract four texture features. The features they extracted using GLCM are contrast, homogeneity, energy and correlation. While Capizzi et al. (2016) used GLCM to extract texture features from the image by using some of the standard statistical descriptors which are, Angular Second Moment, Contrast, Correlation, Gradient Module and Intensity symmetry. Due to the reason that defective areas have no spatial orientation, Moallem et al. (2017) utilized the average of GLCM with d= 1 in four directions: 45, 90, 135, and 180 degrees. Then the textural features including, contrast, correlation, energy, homogeneity, and entropy were extracted from GLCM.

3.4 Image Classification

The next step would be applying a classification algorithm. There are multiple classification algorithms that can be used for the classification or grading of fruits, some of them are briefly explained in the background knowledge chapter. In this section we will compare the accuracy of different classification algorithms that are used to classify or grade multiple different fruits. The algorithms compared are K-nearest neighbor, Artificial Neural Networks, K-means Clustering and Convolutional Neural Networks. Table 1 contains each study's reference, the fruit whether classified or graded, the algorithm used and the corresponding accuracy percentage.

3.4.1 Comparison of different machine learning and deep learning algorithms

Table 1: Comparison of different classification algorithms

Reference	Fruit	Classification	Accuracy
Arakeri (2016)	Tomatoes	ANN	Defective/ Non-Defective - 100% Ripe/ Unripe - 96.47%
Azarmadel et al. (2020)	Mulberry	ANN	Using CFS method - 99.13% Using CONS method-98.26%
Bhargava & Bansal (2020)	Multiple Fruits	ANN	Detection - 91.03% Grading - 88.27%
		KNN	Detection - 80% Grading - 77.24%
Sidehabi et al. (2018)	Passion fruit	ANN	Ripeness level - 90%
Capizzi et al. (2016)	Oranges	CNN (RBPNN)	97.25%
Moallem et al. (2017)	Apples	ANN (MLP)	90%
		KNN	87.5%
Chung & Van Tai (2019)	Multiple fruits	CNN (EfficientNet)	95.67%
Zhang et al. (2014)	Multiple fruits	FSCABC-FNN	89.1%
Choi et al. (2018)	Pears	ANN	97.4%
Oo et al. (2018)	Strawberry	3-layer NN	97%
Arlimatti (2012)	Apples	KNN	92%
Nosseir & Ahmed (2019)	Multiple Fruits	KNN	96.3%
Nasir et al. (2021)	Multiple fruits	KNN	87.1% - 97.3%
Chithra & Henila (2017)	Apples	K-means clustering	91.67%
Al Ohali (2011)	Dates	BP-NN	80%
Alrajeh & Alzohairy (2012)	Dates	MLP-BP (NN)	87.5%
		RBF-NN	91.1%
Haidar et al. (2012)	Dates	KNN	Manhattan - 89% Euclidean - 90%
		ANN	96.7%
Sakib et al. (2019)	Multiple Fruits	CNN	100%
Alipasandi et al. (2013)	Peaches	ANN	99.3%

3.5 Conclusion

Based on the literature reviewed in this paper, it is concluded that deep learning (Convolutional neural networks) yields the best accuracy when it comes to classification and grading of fruits as it is a hierarchical model that constructs a network, it develops a fully connected layer in which all neurons are connected to one another and the output is processed. In some of the research papers included in this literature review, the CNN algorithm reached a 100% accuracy. However, CNN can be a complex algorithm to implement. In terms of accuracy, the ANN classification comes in second place as it also has high accuracy rates, but not as high as the CNN algorithm. According to the reviewed paper the accuracy of ANN ranges between 80% and 99%. And then comes KNN with accuracy ranging 77.2% - 97.3%.

Although KNN has the lowest range in terms of accuracy, it is a straightforward and generally quick algorithm to implement as new data can be added seamlessly without the need of training (Dubey et al., 2013). Implementing the KNN algorithm using the right image preprocessing, segmentation and feature set can yield a high accuracy.

Chapter 4

Methodology

In this chapter we will discuss the implementation of a knn algorithm on an Oranges dataset in order to grade them into grade 1, 2 or 3. The chapter includes details about the dataset used, the python libraries imported in the algorithm, the preprocessing phase, the features used in classification and the flowchart of the algorithm implemented.

4.1 Dataset

The Oranges dataset used in this research paper is “Orange grading dataset” which was acquired through kaggle. It contains labeled data and is divided into Training data (1545 images) and Testing data (964 images). The data consists of three types of Oranges; Grade 1, Grade 2 and Grade 3 (Rotten).

4.2 Python libraries

- Numpy

  It was used for manipulating the data and labels arrays.

- OpenCV

  It was used for loading and manipulating images. It was also used in the extraction of the Histogram of Oriented Gradients (HOG).

- Matplotlib

  Used for plotting figures and orange images.

- Scikit-image

  It is an image processing library that was used in this implementation in order to transform image color and size and in feature extraction also.

- Scikit-learn

  Used for training the training dataset with knn and obtaining an accuracy score.

4.3 Preprocessing

The images data need to be preprocessed in order to be able train the knn classifier with them and to achieve the highest possible accuracy. There are plenty of preprocessing methods such as those mentioned in the literature review chapter. In order to prepare the dataset for classification, the images were transformed from RGB to Grayscale in order to be able to apply the Histogram of oriented gradient as it only takes gray images as an input. The images were also resized as they were of different sizes. A median filter was also applied to remove noise by normalizing the unequal distribution of light which will improve the quality of the image.

4.4 Features

As mentioned in the literature review there are plenty of features that could be used in the classification of fruit, whether classifying fruits in a dataset with different types of fruits or grading the fruits. Previous studies used a mix of different features like shape , size, texture and colors, some of the studies used all of the features and some used one or two of them. In this study we will two features, which are:

- Color Feature (RGB)

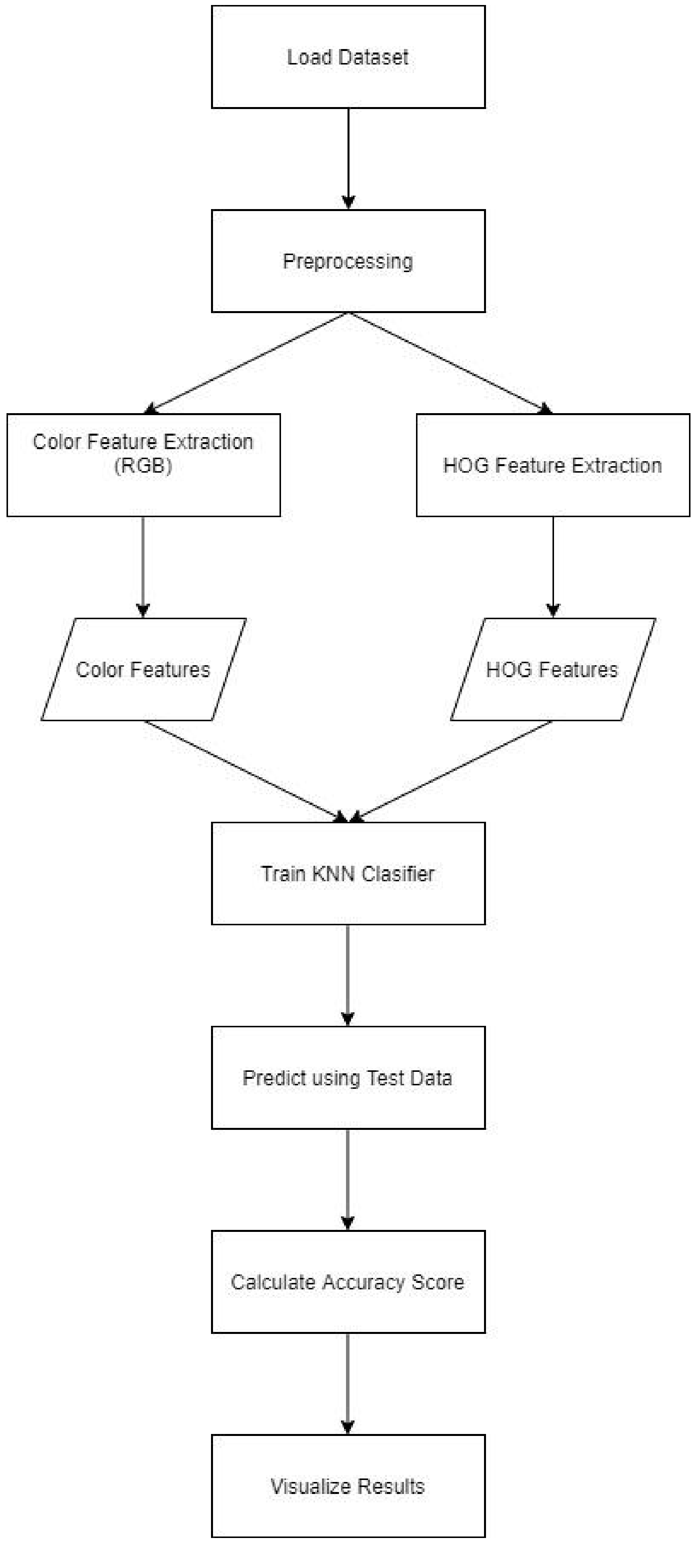
  Color in this case is the most important feature as we are grading oranges only so there are no major differences in their shape and size. The color feature can help us detect the maturity and the defects of the fruit. Other studies like the ones mentioned in the literature review use size,shape and texture also as they were classifying different fruits which will most probably have different shapes and sizes.

- Histogram of oriented gradient (HOG)

  HOG is a feature descriptor used in computer vision for object classification that counts the frequency of oriented gradients in a confined area of an image (Naik & Patel, 2017). In order to extract the HOG features, the first filter is performed in both the horizontal and vertical directions. Then, using formulae, determine the magnitude and direction of the gradient. After that, the picture is divided into cells, the gradient Histogram is computed, and lastly the HOG feature vector is created. In this research paper the images were divided into 8x8 cells, dividing the images into 16x16 cells yielded at the end lower accuracy that why the 8x8 was chosen.

  Although as mentioned above in this case the color features are the most important and are almost enough to grade the oranges with high accuracy, using the HOG features with the color features increased the accuracy of the classifier and improved predictions, even if the difference in accuracy was not that great.

4.4.1 Algorithm flowchart



Chapter 5

Results & Conclusion

This chapter discusses the result of the proposed method, comparing the accuracy corresponding to each k value from 1 to 10 and also it concludes the thesis and the findings of this research paper.

5.1 Results

The testing dataset used contains a total of 964 images:

- 169 Grade 1 oranges
- 713 Grade 2 oranges
- 82 Grade 3 oranges (Rotten).

The following table shows the accuracy score using each K value from 1 to 10 after applying the knn predictor on the testing data.

K Value	Accuracy
k=1	98.96265560165975 %
k=2	98.96265560165975 %
k=3	99.06639004149378 %
k=4	98.96265560165975 %
k=5	98.7551867219917 %
k=6	98.85892116182573 %
k=7	98.7551867219917 %
k=8	98.7551867219917 %
k=9	98.7551867219917 %
k=10	98.7551867219917 %

Table 2: Accuracy corresponding to each k value

Using the k=3 yields the highest accuracy (99.066%) among the other k values which makes it the best choice. It is also an odd number which is another reason why it is the most suitable as assigning the k parameter to an even number can cause a tie between 2 classes.

5.2 Conclusion

The application of k-nearest neighbour (knn) algorithm for the grading of oranges is proposed and evaluated in this paper. Training the knn algorithm with the color gestures and the HOG features and applying the previously mentioned preprocessing techniques yielded a high accuracy of approximately 99.066% which is the highest among the previous studies mentioned in the literature review that implemented knn, as the highest accuracy in the comparison table (Table 1) is 97.3% which was the result of Nasir et al. (2021) study.

As shown in this study, using the K-nearest neighbour algorithm can yield a high accuracy that is similar to the accuracies of Artificial neural networks (ANN) classification algorithms, as according to Table 1 the range of the accuracy of the ANN algorithm is 80% - 99.3%. Also as mentioned before the Knn algorithm is simpler, generally quick to implement and new data can be added seamlessly without the need of training (Dubey et al., 2013).

In conclusion, using the machine learning technique of grading the orange fruit using the k-nearest neighbour classifier as an automated quality control application has shown high accuracy of predicting the grade of fruit, proving that the automation of the quality control process improves it and yields accurate results.

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