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GRAPE QUALITY PREDICTION IN PRE - POST HARVESTING WITH IMPLEMENTATION OF FUSION DEEP LEARNING

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ABSTRACT

The act of tilling and nurturing the land, engaging in the growth and harvest of various crops, and managing the rearing of domesticated animals is commonly denoted as the agricultural enterprise of farming. The significance of agriculture is indispensable in enhancing a nation's economic growth and development. Fruit is considered a type of perishable agricultural commodity. The Vitis genus, consisting of approximately 60 to 80 species of climbing plants within the Vitaceae family, is indigenous to the northern temperate region. This genus encompasses cultivars that can be consumed as fresh produce, sun-dried for the production of raisins, or extracted for the manufacturing of grape juice or wine. The utilization of Artificial Intelligence (AI) has become prevalent within the realm of precision agriculture as a means of assessing the food quality. This notion is particularly pertinent when evaluating crops during different stages of harvest and postharvest. It is imperative that fruits are harvested at an appropriate stage of maturity to ensure optimal quality and enhanced storability. Convolutional neural networks (CNNs), which belong to the category of feedforward artificial neural networks, have demonstrated efficacious implementation in the field of agriculture for the purpose of image segmentation and object classification. The application of these techniques possesses the potential to facilitate the identification of objects of significant relevance, such as fruits or leaves, in agricultural imagery. Consequently, it presents itself as a viable and efficacious approach towards addressing the inherent obstacles encountered in large-scale agricultural operations. The present investigation puts forth a novel grape quality forecast model utilizing machine learning methods and image processing techniques to ascertain the ripeness and size of grapes. The corpus was generated through the acquisition of photographic representations of diverse grape cultivars at varying growth phases, harvested from assorted vineyards. The utilization of convolutional neural networks (CNNs) in modelling has resulted in the attainment of remarkable accuracy levels in grape size and ripeness prediction. The investigation resulted in a noteworthy model that attained an optimal precision level of 100% in anticipate grape dimensions and maturity. Prospective research endeavours could centre on enhancing the performance of the model, augmenting the scope of the dataset, and creating an instantaneous prognostication system for the management of vineyards.

Keywords - Grape quality, grape maturity, ripeness, machine learning, CNN

[1] INTRODUCTION

Agriculture, also referred to as farming in the vernacular, encompasses the systematic cultivation of crops and livestock husbandry. This phenomenon significantly contributes to the economic development of a nation. Numerous agricultural commodities, both in the form of raw materials and consumables, are generated by farming practices. Agriculture plays a pivotal role not only in providing sustenance to the growing population but also in generating the required resources for the development of commercial products. The agricultural industry employed conventional methodologies for the cultivation of crops. Conventional or traditional farming is a predominant practice pursued worldwide. The methodology includes approaches recommended by proficient farmers with extensive expertise in the field. The imprecision of these techniques leads to increased laboriousness and time consumption. Precision Agriculture is often associated with the utilization of advanced digital technologies such as robots, electronic devices, as well as sensor and automation technologies. The objective of this technology is to mitigate workloads, augment profitability, and optimize decision management.

The utilization of machine learning techniques in agriculture has been a subject of increasing interest in recent years. In prior research, a limited number of algorithms, such as SVM and decision tree classifier, were applied. However, in this study, a more comprehensive array of machine learning algorithms was employed to recommend crops to users. Specifically, the algorithms utilized included Decision Tree, K Nearest Neighbour, Linear Regression model, Neural Network, Naïve Bayes and Support Vector Machine. This approach provides a more nuanced and robust framework for crop recommendation, thereby enhancing agricultural productivity and efficiency. The augment in food consumption, anxieties pertinent to climate change in the agricultural sector, and economic exigencies have cumulatively fostered the expansion of the precision farming enterprise. In vinification procedures, machine learning algorithms have the potential to be utilized in conjunction with computer vision technologies in order to provide grape quality monitoring. The study makes use of a specialized database containing images of various grape cultivars, which have been classified based on their distinct improvement stages. Subsequently, the ground truth information obtained from the ongoing investigation is compared against this database in order to assess the accuracy and reliability of the findings. Machine learning endeavors to execute data processing in practical scenarios for the advancement of intelligent vineyards [2].

Multiple aspects can affect the quality of fruits, including size, color, and other readily observable characteristics. Nevertheless, fruit imaging primarily emphasizes the coloration of the fruit, whereas morphological analysis predominantly emphasizes the fruit's size. The chromatic attribute commonly serves as a distinguishing factor for the degree of maturation in various fruits, such as grapes, tomatoes, bananas, and apples. The determination of ripeness in fruits involves considering various visible aspects such as texture, shape, size, and color [3] [4]. These factors hold significant importance in the overall assessment of fruit ripeness. A method for the detection of grape harvesting was devised, wherein the use of Machine learning was employed to effectively identify grape bunches in vineyards at multiple phases of growth, including the initial stage following the bloom and a middle stage where the grape bunches demonstrate an intermediate level of development [5].

Determining grape yield can prove to be a particularly arduous task due to the clustering of grapes. The expertise of human resources proves to be inadequate in the evaluation of grape quality as their assessment lacks precision, thus rendering it less effective. Conversely, deep learning techniques exhibit better accuracy in this regard, thereby holding greater potential as a more precise means of evaluating grape quality. In the field of grape crop assessment, the utilization of deep learning techniques has been noted for its heightened efficiency in the estimation of several key variables such as size, count, and texture of clustered grape bunches. These techniques have been observed to produce an accuracy level exceeding 90%, thereby facilitating the attainment of more precise and reliable estimates of grape yield in agricultural settings. The accurate forecasting of grape growth phases is imperative in upholding the standard of grape cultivation. The conventional approaches employed for these purposes are characterized by their protracted duration, cost-intensiveness, and lack of absolute precision. Through the progression of machine learning (ML) algorithms, it has become possible to automate and enhance the precision of predicting grape developmental stages.

Machine learning (ML) algorithms are formulated to acquire knowledge from provided data and subsequently form predictions that are grounded upon the acquired understanding. The employment of machine learning algorithms has exhibited noteworthy potential in various domains, encompassing the agricultural domain as well. The implementation of machine learning (ML) algorithms within the agricultural sector has the potential to facilitate the projection of crop yields, detect occurrences of pests and diseases, and optimize the effectiveness of irrigation and fertilizer utilization. Numerous research endeavours have been undertaken in the previous year's employing machine learning (ML) algorithms to forecast grape maturation phases.

The conventional method for determining grape yield involves the physical enumeration of grapes on a representative subset of vines and subsequent extrapolation to encompass the entire vineyard. Nonetheless, it should be noted that this approach may prove to be a time-intensive endeavour and may not result in precise outcomes. A novel method utilizing machine-learning techniques has been proposed to estimate grape yield through the analysis of images of grapevines. These images are acquired through the deployment of unmanned aerial vehicles (UAVs) [2]. The presently disclosed research endeavours to utilize a sophisticated deep learning approach that involves the implementation of a Faster R-CNN (Region-based Convolutional Neural Network) algorithm. The primary objective of this approach is to identify and enumerate the grapes within the input images. Additionally, the grape count information extrapolated from the aforementioned methodology is utilized to accurately predict the overall grape yield. Moreover, the researchers conducted an exploratory study on the applicability of deep learning methodologies to forecast the ripening state of grape vines. The spectral information of grapes at distinct points of maturation was gathered, subsequently, a deep-learning model was instructed to anticipate grape ripeness by utilizing the aforementioned spectral data. The enhancement of grape yield assessment and ripeness prognostication can potentially facilitate judicious decision-making and resource optimization for grape cultivators.

A considerable amount of research has been conducted utilizing Python libraries for the purpose of implementing machine learning (ML) algorithms, which offer manifold features for both the implementation and evaluation of said algorithms. In evaluating the performance of machine learning algorithms, the accuracy metric is frequently employed. The metric of accuracy computes the proportion of accurate predictions generated by the model. In summary, the prompt and precise anticipation of grape growth phases holds significant importance in safeguarding the excellence of grapes. The integration of machine learning algorithms into the prediction of grape development stages presents a promising solution to mitigate the inherent subjectivity observed in conventional methodologies, while also yielding predictions that are more precise and unbiased. The assessment of the efficiency of a machine learning-based forecasting model for grapes involves the use of diverse machine learning techniques such as Random Forest, Decision Tree, KNN, SVM, and Gradient Boosting.

[2] RELATED WORK

As previously discussed, modern deep learning models have demonstrated notable efficacy in the context of computer vision techniques and the estimation of fruit quality. The majority of Deep Learning (DL) techniques utilized for Computer Vision (CV) entail the utilization of Convolutional Neural Networks (CNNs) [6]. The present study employed a Linear Regression model to forecast the production value based on the influential climatic variables, including rainfall, temperature, and humidity. According to reference [7], the algorithms tested yielded scores that were below 90%.

The quality and quantity of input data, the best choice of machine learning algorithms, including the precise adjusting of model parameters are all important considerations in determining how well machine learning models anticipate expected outcomes [8]. To determine grape prediction, a variety of machine learning methods have been used, including random forests, choice trees, support vector AI, neural networks with algorithms, and deep learning models. The complexity and size of the dataset, the particulars of the prediction target, the resources obtainable for computing analysis, and other considerations all play a role in choosing the best method for a given predicting assignment.

The study postulates a machine vision approach towards the evaluation of dates, as proposed by [9]. The technique employed in ascertaining the caliber of dates involves an assessment of their visual attributes through the examination of two-dimensional pictorial representations. Near-infrared reflected imaging is utilized for gauging fruit size and skin delamination. The findings of this approach evince an enhancement in grading precision relative to human grading, alongside a curtailment in operational expenditures and grading duration linked to labor. Nonetheless, the principal limitation of the system is its mechanical subsystem, whose upkeep presents significant challenges. Furthermore, it is worth noting that the aforementioned methodology exclusively evaluates a singular, designated variety of date fruit. Moreover, discrepancies in the positioning of the fruit may have an impact on the precision of the measurements taken.

The method of classification-based segmentation has gained considerable popularity, particularly in the context of RGB color images. The approach utilized is a pixel-based methodology, whereby each individual pixel is assigned a classification as either an object or background component. Linear discriminant analysis is widely regarded as the preeminent classification-based segmentation technique employed in color imaging, as attested by its popularity within the literature [10]. The presented methodology endeavors to produce a linear separation (or classification) hyperplane within a multi-dimensional space through the application of statistical analyses to distinct regions (i. eobject or background). This is accomplished by the selection of a limited number of representative pixels from the aforementioned regions. The task of generating hyperplanes, which is commonly referred to as training, is typically executed offline, prior to the execution of online image processing. The support vector machine (SVM) has gained increasing popularity as a means of determining the separation hyperplane in agricultural settings, as has been evidenced in recent research [11].
The endeavor of ascertaining vine yield in viticulture continues to pose a considerable challenge. The pivotal factors that substantiate this challenge include the appraisal of blooming and fruit set, which carry notable influence on grapevine output. In order to obtain precise measurements of fruit sets, it is imperative to employ flower counts. The present study outlines a novel methodology for the automated segmentation of flowers within inflorescence images captured under field conditions. This methodology makes use of morphological image processing techniques coupled with pyramidal decomposition. These techniques have been previously reported in literature [12]. The principal aim of the study, as indicated in the source [13], is to optimize the diminution of pesticide usage. In pursuit of the aforementioned goal, the algorithm underwent optimization through the specification of the curtailment of pesticide utilization as the predominant parameter. In order to achieve the intended grape detection rates, the algorithm underwent optimization procedures with the primary objective of minimizing pesticide levels.
A limited-scale conceptual demonstration has been undertaken to showcase accurate yield estimation in vineyards through the utilization of image processing methodologies. Due to the fact that only a minor portion of the images featuring vineyards requires enlargement to achieve the desired efficacy, this process of scaling up necessitates a considerable degree of computational resources. Through a process of isolating and quantifying clusters captured in photographic images, the authors referenced in [14] introduce an image processing methodology that effectively integrates both color and texture information utilizing a support vector machine for expediting fruit identification.
In the realm of winemaking, determining the key attributes that exert an influence on the quality of wine remains a crucial quest. In this regard, a study conducted by [15] has opted for a diverse set of machine learning techniques with the aim of identifying the aforementioned attributes. This investigation focused on utilizing 11 physiochemical traits to develop machine learning models that predict the quality of red wine, involving a total of 24 different variables. Kumar et al. acquired data pertaining to the quality of red wine from the machine learning library of UCL. In this study, data mining techniques were employed by the researchers. In this study, an uncomplicated approach for identifying and pinpointing clusters of grapes in photographs

captured in natural settings is presented, entailing rudimentary image processing techniques. The proposed methodology has been previously outlined by [17]. Moreover, the system has the ability to operate during nocturnal hours with minimal alterations in illumination and differentiate between grapes of white and red coloration. It is possible to guide a harvesting robot based on the system's capacity to detect the precise position of the bunch stem.

[3] Methodology

1.1 CNN

Over the recent years, significant advancements in the domain of perception and computer vision algorithms have been attributed to the noteworthy influence of Deep Learning (DL) techniques [154]. The aforementioned concept has the potential to be utilized for the purpose of detecting objects in images. In particular, this technique can prove to be advantageous for the detection of fruits in agricultural applications. Convolutional Neural Networks (CNNs) have been extensively employed to execute the aforementioned undertaking. According to recent studies, the aforementioned individuals have demonstrated exceptional levels of proficiency in various competitions related to the fields of machine learning and pattern recognition [155]. CNNs have been progressively integrated into the realm of plant phenotyping in recent years. Due to their aptitude for discerning patterns and extracting regularities from data, they have achieved significant success in the modelling of intricate systems. Examples can be further extended to the identification of various seeds and intact plants by examining their leaves. The implementation of aforementioned techniques in practical scenarios has propelled the development of more efficient computational models and dedicated hardware, thereby advancing the current state-of-the-art. Convolutional Neural Networks (CNNs) are a computational architecture utilized for purposes such as image categorization, recognition of objects, and segmentation. Convolutional neural networks (CNNs) employ a hierarchical methodology to extract top-tier components from unprocessed image data, thus rendering them a highly suitable tool for tasks involving image analysis.

In conclusion, Convolutional Neural Networks (CNNs) have demonstrated remarkably high efficacy in predicting the quality of agricultural produce, specifically grapefruit. Through the utilization of fruit images and the training of a model on annotated datasets, Convolutional Neural Networks (CNNs) can acquire the ability to discern discernible patterns and distinguishing characteristics that distinguish fruits of high quality from those of substandard quality. The mathematical formulations dictating the functionalities of a Convolutional Neural Network (CNN) can be intricate, yet they are imperative in comprehending the modus operandi of the model for computing the input images, culminating in the eventual outcome.

The accurate forecasting of fruit growth constitutes a critical activity in the field of precision agriculture, as it equips farmers with the ability to ascertain the optimal moment for harvesting crops, estimate the projected yield, and design efficacious strategies for managing their crops. Over the past few years, several academic studies have recommended the utilization of Convolutional Neural Networks (CNNs) for the prediction of fruit growth through the analysis of images of fruits at diverse developmental stages. Grapefruit, a well-liked type of citrus fruit, is appreciated for its sharp and rejuvenating flavour profile. The assessment of grapefruit's quality is contingent upon a multitude of factors, including but not limited to texture, color, and flavour. In the grapefruit industry, accurate prediction of grapefruit quality is paramount to its market value. As such, the quality of grapefruit is a crucial determinant in the industry's success.

The application of deep learning methodologies has brought forth novel opportunities in the realm of quality assessment for agricultural yields, notably those for grapefruit. Convolutional Neural Networks (CNNs) have demonstrated significant efficacy in the recognition and analysis of images. Convolutional neural networks (CNNs) have been employed in the prediction of the quality of diverse types of fruits and vegetables, such as apples, oranges, and tomatoes, among other produce.

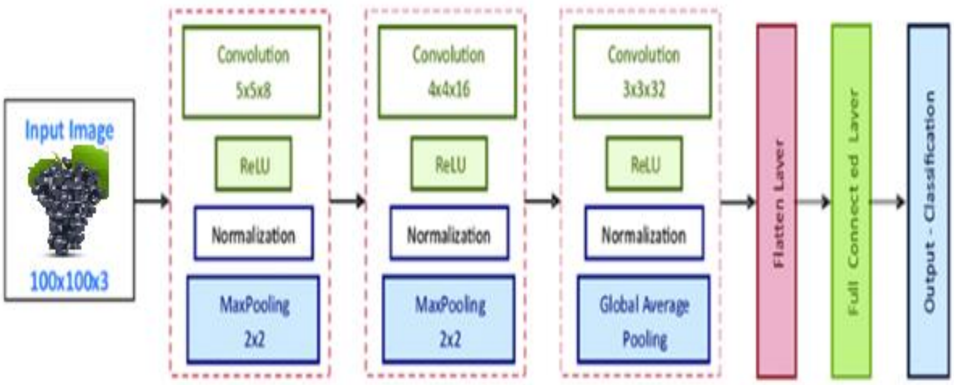

Figure 1: CNN architecture used for grapefruit quality prediction [18]

The pre-processed images were subsequently introduced to the Convolutional Neural Network (CNN) architecture, which comprised multiple convolutional layers, pool layers, and fully connected layers. The model underwent training with a labelled dataset consisting of images, in which label assignments were made according to the degree of quality exhibited by the grapefruit. The convolutional neural network (CNN) model underwent a training process to discern the discriminative patterns and characteristics that delineate grapefruits exhibiting superior quality from those manifesting inferior quality.

CNNs have demonstrated considerable potential in catalysing a transformative shift in the domain of agriculture through the provision of precise and effective approaches for forecasting the quality of various fruits and vegetables. Through extensive research and development, convolutional neural networks (CNNs) have the potential to enhance the calibre of agricultural goods and augment their economic value, thus yielding advantageous outcomes for both producers and consumers.

I. Image segmentation

The task of image segmentation is considered a fundamental aspect in the field of image processing. This involves the methodical partitioning of a given image into multiple segments or regions, considering specific criteria like color, texture, or intensity. The primary objective of image segmentation is to simplify and partition the raw image data into distinct and meaningful elements, with the explicit aim of enhancing the effectiveness of analytical, interpretive, and visualization processes. The segmentation of images can be executed through a diverse range of techniques that encompass thresholding, edge detection, region growing, clustering, as well as deep learning-based methodologies. The aforementioned methodologies are adaptable in their implementation, providing the ability to apply them uniformly across a singular channel or across several channels within an image. This flexibility is dependent upon the specific underlying objective and the inherent characteristics of the data at hand.

Here are some equations related to image segmentation:

- **Thresholding:**

Binary thresholding:

$$I(x,y) = 1 \; if \; I(x,y) > T, 0 \quad otherwise \tag{1}$$

Adaptive thresholding:

$$T(x,y) = k^{*}mean(I) - C \tag{2}$$

$$I(x,y) = 1 \; if \; I(x,y) > T(x,y), 0 \quad otherwise \tag{3}$$

- **Edge detection:**

Sobel operator for gradient magnitude:

$$G(x,y) = sqrt(Gx(x,y)^2 + Gy(x,y)^2) \tag{4}$$

Loss function for semantic segmentation:

$$L(y,y') = \frac{-1}{N^*}\sum i\,, \sum j\,, \sum c\,, y_{ijc} * \log\,(y'_{ijc}) \tag{5}$$

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The given statement pertains to the determination of ground truth label for a pixel (i,j) in a given class c, indicated by yijc, and the corresponding predicted probability for this class at the same pixel, represented by y'ijc. This information is of substantial significance in academic writing while discussing topics such as image classification, computer vision, and related domains.

Image segmentation is a widely utilized method in the field of computer vision, with numerous practical applications such as object detection, image recognition, and scene understanding. The utilization of image processing techniques facilitates the extraction of significant visual attributes, such as contours, borders, and textures that can be effectively leveraged in sophisticated applications such as object classification and recognition. In various image processing applications, image segmentation represents a crucial phase as it streamlines data embedded in an image and leads the way for a more effective analysis and interpretation of informative elements.

The process of detecting grape clusters emulates the hierarchical structure of Convolutional Neural Networks (CNNs). In the initialization stage, the images are segregated into diminutive patches, which are progressively amalgamated with their contiguous neighbours in the more profound detection strata.

The diagram depicted in Figure 2b illustrates the overarching framework for the identification of clusters in a given dataset, whereby each cluster is represented by a feature space of 4x4x3 dimensions. Moreover, it is noteworthy that the envisaged characteristic dimension is transmitted through a linear embedding stratum with the aim of deriving a dimension of choice. In order to produce hierarchical feature representations, a series of batch detection blocks are applied to the altered patch tokens. In the scope of grape bunch detection, it is pertinent to note that every block dedicated to this task serves to learn feature representations. In conjunction, the layer responsible for group merging manoeuvres to augment the dimensionality of the output. The grape cluster inhibitions may be delineated in a consistent manner as indicated below:

$$f^{\wedge L=} W - MSA\left(LN(f^{L-1})\right) + f^{L-1} \qquad (6)$$

$$f_L = MLP(LN(f^{\wedge L})) + f^{\wedge L} \qquad (7)$$

$$f^{\wedge L}+1 = SW - MSA\left(LN(fL)\right) + f^{L} \qquad (8)$$

$$f^{L+1} = MLP\left(LN\left(f^{\wedge L}+1\right)\right) + f^{\wedge L}+1 \qquad (9)$$

One segment is assigned to Window Multi-Head Self-Attention (W-MSA), while the remainder is devoted to Shifted-Window Multi-Head Self-Attention. The number of segments in the Self-Attention for Transformer Language prototype (STL) is typically a multiple of two. The supplied notation is used to signify Layer Normalization (LN(:)) and a multilayer perceptron (MLP) with two entirely linked layers and a Gaussian Error Linear Unit (GELU) activation function [19]. The current example serves as a demonstration of how Mask R-CNN may be used to identify and delineate grape items within a picture.

(a) Object Detection **(b) Image Segmentation**

Figure 2: General architecture for grape bunch detection

[4] Conclusion

The prediction of grape quality involves the utilization of machine learning algorithms to determine the maturation level of grapes. The process encompasses a comprehensive assessment of multiple factors, including grape size, color, and sugar concentration, to ascertain the degree of ripeness. Machine learning models, particularly Convolutional Neural Networks (CNN), have the potential to achieve high accuracy in predicting grape maturity by means of training on datasets that encompass various aspects of grape development stages, including but not limited to, identification of grapes in images, measurement of grape size, and classification of grape colors. The present study advances a model for predicting grape quality utilizing a sophisticated machine-learning algorithm. The grape maturity levels are monitored to make a prediction about the optimal time for harvesting.

We conducted an investigation into several convolutional neural networks (CNNs) for the purpose of identifying grapes within images and subsequently inferring their quality. The application of Convolutional Neural Networks (CNNs) is characterized by an approach that involves feature extraction and the design of architectures custom-tailored to the demands of the given task, which entails a thorough exploration of diverse feature spaces relevant to grape processing. The present study concludes that the remarkable accuracy demonstrated by the pre-trained model substantiates the notion that the training of architecture using distinct algorithms yields differential outcomes in the prediction of grape yields.

The proposed methodologies serve as an initial measure towards the creation of feasible intelligent agricultural technology systems that have potential applications in intelligent vineyards, in brief. The introduction of the grape quality prediction model holds significant potential to bring about a transformative change in the wine industry by enhancing the management of supply chain processes. The prognostications of the model have the potential to provide valuable insights, enabling winemakers to make well-informed determinations regarding the ideal time for grape harvesting, optimization of the production processes, and enhancement of the ultimate quality of the end product.

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