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Detecting clustered fruits using a hybrid of convolutional neural networks and machine learning classifiers – Case study

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ABSTRACT

The last and most important procedure during fruit or vegetable cultivation is harvesting. One of the basic challenges during grape growing is the use of agriculture 4.0 machines (including robots) during harvesting which is associated with the need for quick identification of berries or grape clusters. In this work, a convolutional neural network (CNN) and a machine learning classifier were suggested for the identification (detection) of individual grapes. A free data set (Iceland) was used, which included two classes with different lighting conditions and berry sizes. The integrated method included two types of deep learning models, i.e. CNN (AlexNet and GoogleNet). CNN models were used to obtain discriminative deep features from different layers. The combination of two models AlexNet-Fc6 and SVM-Cubic yielded the highest accuracy, sensitivity and precision (mean ± standard deviation)% of 99.4 ± 0.13, 99.2 ± 0.14 and 99.49 ± 0.19, respectively. The developed grape detector can be used for practical applications requiring high accuracy, e.g. in the process of yield estimation or detection of grape diseases.

Keywords: CNN, grape detection, grape disease, single grape detection, SVM, yield estimation.

INTRODUCTION

A major problem in precision viticulture is the segmentation of individual grape berries or grape bunches in real-world RGB images. This is made even more challenging by differences in lighting conditions, size and shape of the berries, which requires the creation of sophisticated detection mechanisms. Previous approaches for grape detection are mainly based on single grape detectors or bunch detectors, which may not provide the required level of accuracy in various applications. To overcome these challenges, the agricultural sector has to adopt advanced technologies that can improve time effectiveness, precision, and productivity in vineyard operations. The use of robotic systems for automatic grape identification is a viable solution, which can enhance grape yield, enhance the accuracy of detection and assist in crop surveillance and control. Furthermore, such technologies could assist in reducing the increasing costs of labor and scarcity experienced in grape production globally [1, 2]. However, the detection of small fruits such as grapes still poses a challenge to many researchers even with the recent development. Accurate identification of individual grape berries is crucial for different purposes, including yield assessment, disease detection, and ripeness assessment. The accuracy of the detection directly determines the time of the harvest and the quality of the wine that is produced. Machines can be more effective than manual work in terms of observation and control of the vine condition and detection of the potential threats in the form of diseases or pests [3]. The current study proposes a new approach that employs Artificial intelligent (AI), machine learning (ML), and convolutional neural networks (CNNs) to address the challenges that come with conventional approaches. Although these technologies are used in other industries such as agriculture, health, and UAVs, their use in viticulture for single grape detection is relatively new [4–10].

Moreover, the scientific contribution of the study is to fill the gap of the development of highly accurate detection systems that can work in various vineyard environments, lighting conditions, and grape types. This research presents a more efficient solution by integrating deep learning-based feature extraction with optimized ML classifiers for practical applications such as automated grape berry detection and vineyard spraying systems [11–13] and grape detection for yield estimation. A review of the literature also reveals various studies focused on grape recognition [10, 14–22].

Moreover, Javidan and the team presented a novel system for diagnosing grape leaf disease using automatic k-means clustering and ML [23]. The results demonstrate the ability of clustering algorithms to detect dissimilarities among grape leaf images, leading to more accurate and timely disease classifications. The integration of clustering and ML offers a high degree of automation and scalability for disease detection in vineyards. Furthermore, [24] applied DL techniques to classify images from UAV imaging, achieving high success in identifying grapevine diseases. Additionally, [25] employed SVMs to automatically identify grape powdery mildew, suggesting that ML can be effective in addressing and detecting various plant ailments. In another study [26], a detector was developed to identify individual grapes in color images with a resolution of 1936 × 1288 × 3 pixels. This detector used histograms of oriented gradients (HOG) descriptors in combination with an SVM classifier employing a radial basis function (RBF) kernel. Given the limited computational capabilities of commonly used hardware, the detector's performance was evaluated on images resized to 0.75, 0.5, and 0.25 of their original dimensions [27]. At 0.25 of the original size, the performance was sufficient for applications like autonomous sprayers or combines but was inadequate for yield estimation purposes [27].

Bearing this in mind, our focus shifted towards developing a single grape detector specialized in identifying white wine grapes within full-color images sized at 484 × 322 × 3 pixels. The challenge lies in balancing detection accuracy with computational efficiency, focusing on specific grape varieties, and optimizing the system for a manageable image size. One of the methods employed is an automated technique for visual identification and counting of grapes and clusters from images taken under different lighting conditions and displaying various shades of grapes [28]. Image segmentation using k-means clustering was used to automatically identify the grapes.

The segmented image was then converted to binary using Otsu's automatic thresholding method, followed by the application of morphological opening techniques to remove image noise and create a mask. A fast radial symmetry transformation was subsequently applied to the mask to detect the grapes. The average accuracy of visible berry counting was 0.9 ± 0.0065. For pixel matching, the average accuracy of detecting visible berries and clusters was 0.94 ± 0.25 and 0.92 ± 0.179, respectively.

In a subsequent study, a deep convolutional neural network was proposed to identify individual white grape varieties in low-resolution color images [29]. Achieving accuracy, precision, and recall of 0.97, 0.965, and 0.98, respectively, this grape detector represents state-of-the-art technology. It is particularly suited for practical applications that require high precision, especially in yield estimation processes. These technologies provide grape growers and viticulturists with valuable information about vineyard health and productivity, enabling more informed decisions and sustainable vineyard management practices.

This paper focuses on the CNNs integrated with the ML algorithms for single grape detection since this method has been effective in different image classification areas [30–31]. Other works have investigated grape bunch detection using single grape berries [10, 32–34] and it has been shown that enhancements in single grape berry detection enhance grape bunch detection performance. The experiment was conducted by combining all the training and test set data into one set, which gave a total of 6880 samples, 4000 from the test set and 2880 from the training set with equal distribution of classes. The same approach is applied in the proposed method where 30% of the data is used for testing while the remaining is used for training. This will be done for 100 iterations, and in each iteration, the training and test data will be randomly chosen.

DATASET DESCRIPTIONS

In this study, the Iceland dataset [35] was employed, the dataset comprised a training set file named T-M, where M ϵ {1, 2, 3, 4, and 5}, encompassing resulting in 2880 samples. Each file set included 288 unique 'positive' and 288 unique 'negative' samples, evenly split between the two classes.

Each test set contains 50 and 200 examples positive and negative respectively. However, artificial positive examples are incorporated in the creation of test sets. These data augmentation involved rotating each image by angles (0º or 360º, 90º, 180º, and 270º), resulting in four images generated from one original image. Consequently, the test sets comprise 200 examples for each class. The inclusion of artificial examples introduces a form of distortion into the test sets. Furthermore, there were two types of test set data files: E-M for environment-type datasets and G-M for grape-type datasets. total 10 files 5 for each. Each file of test set data, included 400 samples, evenly split between the two classes, encompassing resulting in 4000 samples in test set data. All samples were captured in real scenes, devoid of artificial lighting, and taken at different times, specifically in the morning and afternoon. Full-color (RGB) images of 40 × 40 pixels were downloaded for further analysis. The positive examples exhibited grape berry diameters ranging from 30 to 40 pixels with a variance of ± 1. Regarding the test set creation, two distinct image sets were crafted. They varied in the selection of negative examples: in G-M sets, negative examples consisted solely of incomplete grapes, whereas in E-M sets, negative examples were derived solely from the environment, devoid of any grape elements. Fig. 1 shows (a) positive sample examples and (b) and (c) negative sample examples.

All the input images need to pre-processing stage to enhance the accuracy of single grape berry recognition, addressing key challenges in grape identification is essential. These challenges include variations in image size and quality, fluctuations in illumination levels, and the need to process a large number of images. Hence, employing pre-processing stages for image enhancement becomes crucial. This paper's pre-processing stage include image resizing techniques.

Image resizing

The dimensions of the cropped or dataset images play a crucial role in ensuring uniformity between the sizes of test and training images. Additionally, they need to match the input layer dimensions of the CNN being employed. In this experiment, we utilized image sizes of 40 × 40 × 3 pixels. However, we resized the images to align with the input size requirements of the CNN architectures. For instance, the input layer dimensions for AlexNet [36] were 227 × 227 × 3, and for GoogleNet [37], they were 224 × 224 × 3. The axis of the camera lens was approximately perpendicular to the vineyard rows, the distance between the lens and a row was 1.4 m; the altitude of the camera was 1.25 m and the focal length was 21 mm. All the photos were taken using a camera

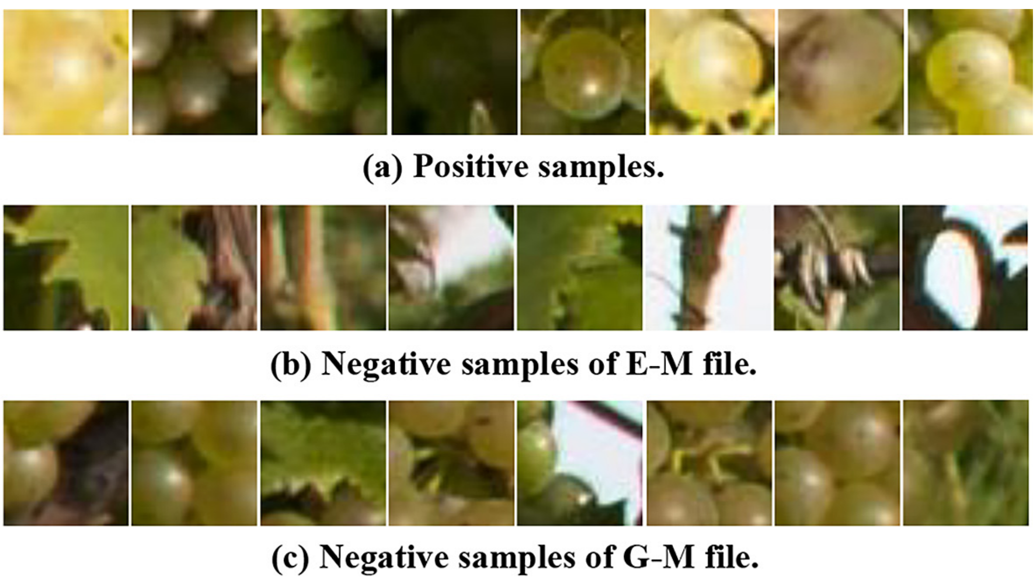

Figure 1. Examples of sampled samples: (a) positive, (b) negative E-M file, (c) negative G-M file

body CANON EOS 1000D and CANON ZOOM Lens EF-S 18-55 mm f/3.5-5.6 II. The settings for exposure are identical for all the photos, i.e. aperture was set to F6.7, shutter speed to 1/180 s and ISO to 100. The resolution of the RGB images is 1936 × 1288 px, 24-bit. The photos were taken in a vineyard in Cvetkovic, Czech Republic, in August 2014. All photos were taken in different places of the plant in two times: morning and afternoon on the grape variety: Welsch Riesling. The weather was stable and partly sunny throughout the day [33]. During the field experiment, no artificial lighting was used to reflect the real conditions during the work of intelligent machines for harvesting and assessing the health of grapes.

Convolution neural networks (CNNs)

Neural networks are widely acclaimed for their proficiency in pattern recognition and image classification tasks. Deep convolutional neural networks (DCNNs) possess the capability to automatically extract meaningful features from raw input images, enabling them to discern intricate patterns and classify images with remarkable accuracy [36]. The proposed method employs AlexNet [36], serves as a deep feature extractor in this study, and comprises three fully connected (Fc) layers denoted as Fc6 to Fc8. The networks have 25 layers in total. In our proposed method, the 6th Fc layer was empirically selected as the feature extractor, resulting in a feature-length of 4096 in Fc6 and Fc7 and 1000 in Fc8. Then, the input layer size of GoogleNet (224×224×3) [37], and the total number of layers 144 used in the study (loss3 classifier) fully connected provide features to the classifier with vector length 1000. Figure 2 shows the data flow diagram of the proposed new method.

Classification

The study used two classifiers which are described below:

- Support vector machine (SVM): utilize a discriminant hyperplane to classify data with enhanced speed, superior performance, and strong generalization capabilities by maximizing the margin and adjusting the kernel value. However, employing the kernel trick enables SVM to handle non-linear data classifications [39].
- Linear discriminant analysis (LDA): is a method that utilizes hyperplanes to classify a single grape dataset. This technique involves partitioning classes based on their respective mean values while striving to maximize the separation distance between them. However, LDA's efficacy diminishes when confronted with complex non-linear data and it may also be prone to overfitting issues [40].

RESULTS AND DISCUSSION

We have developed a hybrid architecture that integrates various transfer learning models and different classifiers, such as SVM (two kernels, i.e., linear and cubic) and LDA. With cross-validation 10-folds to avoid the over fitting risk.

This involves connecting the final Fc layer of used CNN models with an ML classifier such as SVM-(linear and cubic kernals), and LDA. Our experiment included four types of features generated by different Fc layers and CNN (e.g., AlexNet-Fc6, AlexNet-Fc7, AlexNet-Fc8, and GoogleNet) connected with two different classifiers (e.g., SVM-L, SVM-cubic, and LDA). To select

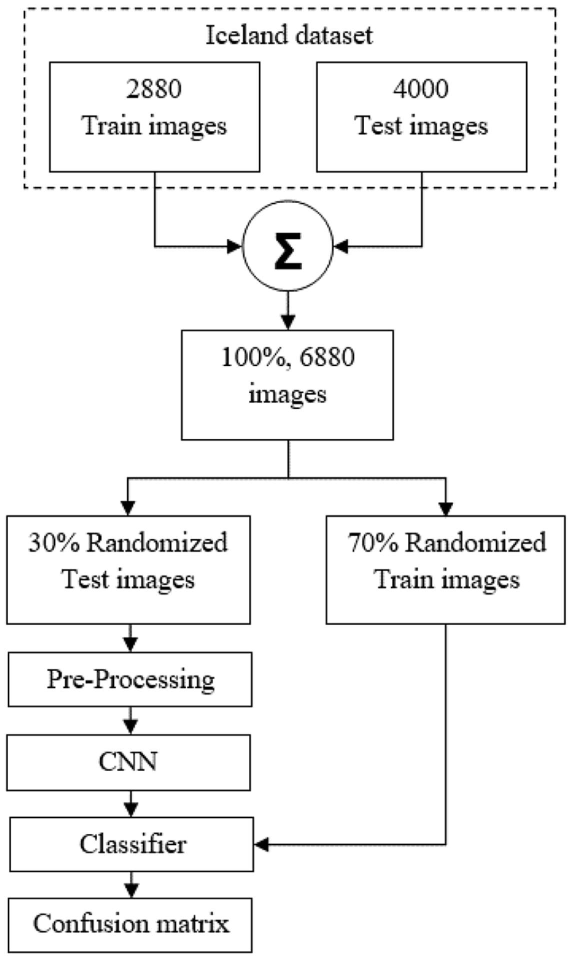

Figure 2. The workflow of the proposed method

the method that yielded the highest accuracy and lower standard deviation (SD). This approach is grounded in the no free lunch (NFL) theorem, which states that no single ML algorithm can universally excel in solving all problems [41]. An algorithm that performs effectively in one problem category might struggle to address others. Hence, it's crucial to assess the performance of different classifiers and transfer learning models to ascertain their efficacy.

The proposed method employed 60% samples for training and the remaining 30% samples for testing, ensuring a more precise evaluation of the model's performance. Results were recorded by 120 iterations. These samples were randomly selected for each iteration, which ensured a more accurate assessment and validation of the model, yielding resilient and reliable outcomes.

Consequently, this approach enhanced confidence levels in the results. The accuracy (Acc.), sensitivity (Sen.), and precision (Prec.) of the model were assessed using a confusion matrix [42] as displayed in Equation 1–3, Figures 4 to 6 and Table 1. The features generated by AlexNet-Fc6 combined with the SVM-Cubic classifier yielded the highest accuracy (mean ± SD)% 99.4 ± 0.13 as displayed in Tabel 2, Figure 3. The results of the current study were compared with those of [30], showing overall improvements of 12.1%, 5.2%, and 19.9% in accuracy, sensitivity, and precision, respectively. In comparison with [36], the overall improvements were 1.75%, 0.93%, and 2.3%, respectively.

The performance of a ML algorithm depends on input features, as well as the target class. As a result, it is crucial to investigate the different ML algorithms and the types of features to determine which approach provides the best accuracy. The effectiveness of our method is evaluated using the following confusion metrics. Figure 3 shows the confusion matrix of the results of the AlexNet-Fc6 features combined with SVM-Cubic kernel classifier.

Hence, it is essential to evaluate multiple ML algorithms to determine which one yields the best accuracy. The application of supervised ML algorithms is extensive and varies depending on the problem domain, as outlined by the "no free lunch" theorem [41]. Table 2 summarizes the generated Accuracy, Sensitivity and Precision values.

$$Accuracy\ (Acc.) = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

$$Sensitivity\ (Sen.) = \frac{TP}{TP + FN} \quad (2)$$

Table 1. An Example of a confusion matrix

Parameter		Predicted class	
		Non-grape	Grape
Actual class	Non-grape	TN	FP
	Grape	FN	TP

Note: TP: Sample with grapes correctly classified: green, TN: sample without grapes correctly classified: light green, FP: sample without grapes incorrectly classified: red, and FN: sample with grapes incorrectly classified: Orange.

Table 2. Results of proposed method – Mean ± SD

DL name	Feature layer	Feature length	Result	SVM-L	SVM-cubic	LDA
AlexNet	Fc6	4096	Acc.	98.5 ± 0.2	99.4 ± 0.13	99.15 ± 0.22
			Sen.	98.73 ± 0.41	99.2 ± 0.14	99.28 ±0.31
			Prec.	98.26 ± 0.21	99.49 ± 0.19	98.92 ±0.32
AlexNet	Fc7	4096	Acc.	99.0 ± 0.26	99.21 ± 0.2	98.73 ± 0.18
			Sen.	98.68 ± 0.43	99.0 ± 0.12	99.04 ± 0.29
			Prec.	99.32 ± 0.24	99.3 ± 0.13	98.42 ± 0.24
AlexNet	Fc8	1000	Acc.	98.84 ± 0.27	98.5 ± 0.28	98.25 ± 0.33
			Sen.	98.84 ± 0.44	98.2 ± 0.56	98.64 ± 0.38
			Prec.	99.42 ± 0.3	98.9 ± 0.27	97.86 ± 0.48
GoogleNet	loss3 classifier	1000	Acc.	97.7 ± 0.38	98.25 ± 0.14	97.54 ± 0.26
			Sen.	97.5 ± 0.57	98.3 ± 0.37	98.15 ± 0.33
			Prec.	98.05 ± 0.38	98.2 ± 0.18	96.96 ± 0.53

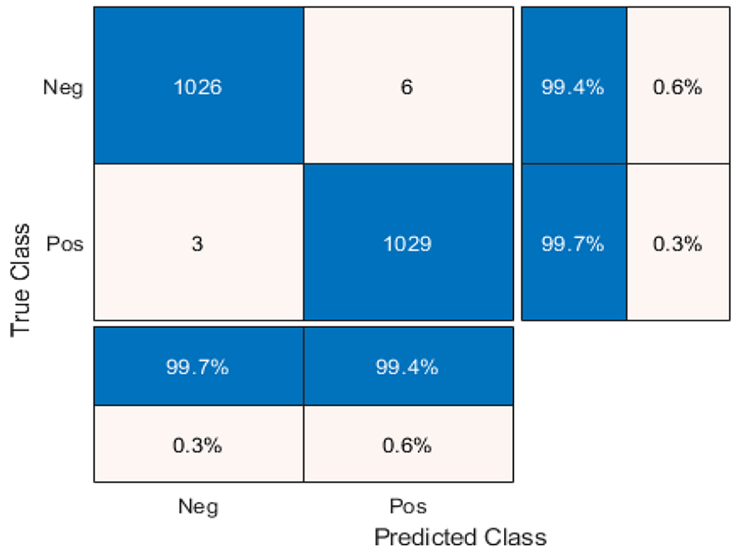

Figure 3. An example of confusion matrix of the results of SVM-cubic classifier combined with AlexNet-Fc6s

The current grape berry recognition approach has some challenges in terms of image quality, lighting and grape size which influences the detection. Although preprocessing is useful, it may not eliminate inaccuracy problems altogether, particularly in a complicated setting.

Further research will focus on enhancing the accuracy of the visual grape recognition by using different classifiers, adjusting the parameters and enhancing the CNN models. Moreover, classifiers from previous researches will be integrated to improve the performance of the system especially in robotic systems. The current study is also faced with some limitations such as the differences in the size, color and the natural lighting conditions which challenge the performance of the system.

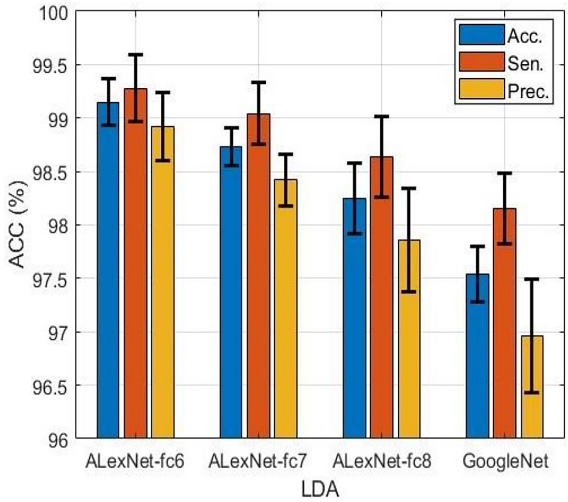

Figure 5. The results of the LDA classifier combined with CNNs

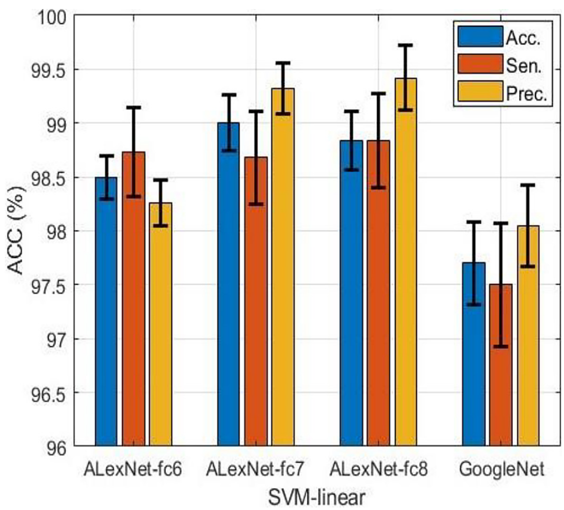

Figure 4. The results of the linear SVM classifier combined with CNNs

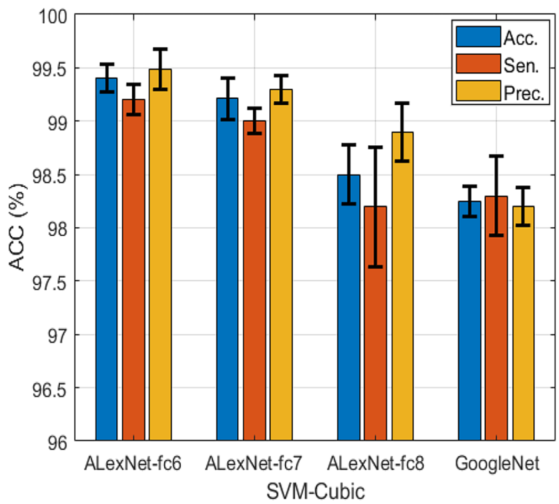

Figure 6. The results of SVM-polynomial (cubic) classifier + CNNs

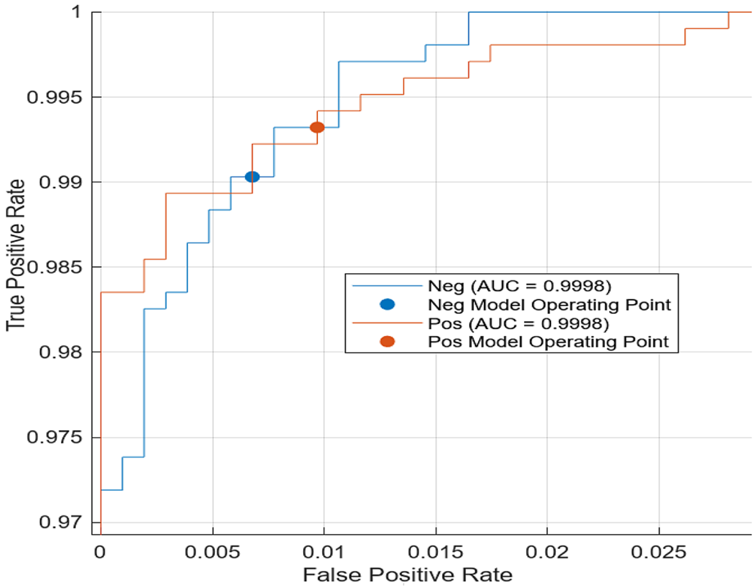

Figure 7. ROC of the results of SVM-cubic classifier combined with AlexNet-Fc6

$$Precision\ (Prec.) = \frac{TP}{TP + FN} \quad (3)$$

The summary of the results is displayed in Figures 4 to 6, where each figure illustrates the interconnection between a CNN architecture and various ML classifiers (e.g., SVM-L, SVM-Cubic, and LDA).

The study has used the receiver operating characteristics (ROC) curve to assess the performance. ROC curve is a graphical plot that depicts the performance of a binary classifier system by varying its discrimination threshold as shown in Figure 7. This curve, illustrating the relationship between the true positive rate (TPR) and the false positive rate (FPR) as the discrimination threshold varies, was generated using AlexNet-Fc6 features classified by the SVM-Cubic kernel. This combination achieved the highest accuracy and the lowest standard deviation, with a performance of 99.4% ± 0.13%.

The area under curve (AUC) stands, and it is the probability that a randomly chosen positive instance will be ranked higher than a randomly chosen negative one, as defined in Equation 4 [43].

$$\text{Area Under Curve} = \int_0^1 TPR(FPR)\ d(FPR) \quad (4)$$

CONCLUSIONS

This study employed a CNN, utilizing an automatic feature extractor such as AlexNet-Fc6, AlexNet-Fc7, AlexNet-Fc8 and GoogleNet, combined with classical ML classifiers such as LDA, and SVM (linear and cubic), which were implemented, tested, and trained. The Acc., Sen., and Prec. in the evaluation of the confusion matrix were involved, and their corresponding mathematical equations were explained in the results section. our experimental results showed that the AlexNet-Fc6 + SVM-Cubic classifier outperformed the using four features, namely AlexNet-Fc6, AlexNet-Fc7, AlexNet-Fc8, and GoogleNet plus LDA and SVM. Consequently, there is no single ML approach that universally performs well across all fields. Moreover, the accuracy of an ML algorithm depends on factors such as input features and the desired output class.

In this paper, we implemented, tested, and trained two different classifiers: LDA and two kernel of SVM. Additionally, we employed two CNN architectures (e.g., AlexNet, and GoogleNet) for feature extraction. The varying performance of CNN models stemmed from differences in their architecture design, including layer structure and convolution window size. Among the classifiers used, SVM-Cubic consistently yielded the best results across both CNNs. The results indicate that combining deep features extracted by AlexNet's 6th fully connected layer, with a feature-length of 4096 values, with the SVM-Cubic classifier produced the best outcomes in all scenarios. The error rate remained below 1% in Iceland datasets, demonstrating the success of the proposed method in single grape recognition.

The approach can also be used to detect grape diseases or to identify ripe grapes by changing the data set used.

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