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RESEARCH ARTICLE

Fusion deep learning with pre-post harvest quality management of grapes within the realm of supply chain management

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Abstract

It is becoming increasingly vital in supply chain management to use different algorithms, particularly when it comes to pre and post-harvesting of grapes. This is especially true in the wine industry. Grapes must be processed both before and after harvesting as part of the management process for supply chains in the food industry. The grape bunch identification in vineyards was performed using machine learning at various stages of growth, including early stages immediately after flowering and intermediate stages when the grape bunch reached intermediate developmental stages. The machine learning method can predict annual grape output and also identify grape harvesting. The impressive performance of the pre-trained model shows that architecture training using different algorithms differs in the performance of grape predictions. We achieved 100% accuracy in grape prediction using LR, DT, RF, NUSVC, Adaboost and gradient algorithms, while KNN and SVC lag behind with an accuracy of 83.33% each. Our model includes the color and size of the grapes to differ in grape quality using a variety of grape images as a reference. It is capable of predicting the maturity stage of grapes by predicting Brix, TA and pH values (ranging between 18.20–25.70, 5.67–9.83 and 2.93–3.77) according to the size and color of grapes.We compared different algorithms and their performances by evaluating grape quality prediction accuracy, processing time and memory consumption.

Keywords: Pre-post harvesting, Machine learning, Convolutional neural network, Computer vision, Supply chain management, Deep learning.

Introduction

Our culture cannot exist without the agriculture sector. Therefore, promoting and implementing innovation, research, and development across a wide range of agriculture-related disciplines is important. In this context, automation of agricultural activities is becoming important since it may boost output and product quality while lowering production costs and environmental effects (Aguiar *et al.*, 2021). The quality of fruits depends on different aspects such as size, color and other visible aspects, while a fruit image highlights the color of the fruit and morphologic highlights the size of the fruit. The color commonly distinguishes the feature of ripeness for various fruits, including grapes, tomatoes, bananas, and apples. However, the visible aspects of the fruit are important in the determination of ripeness, which needs to consider texture, shape, size and color (Kangune, Kulkarni, & Kosamkar, 2019; Patil, Tiwari, & Kumar, 2022).

Increased food consumption, agriculture-related worries about climate change, and economic pressure have all contributed to the growth of the precision farming industry. Machine learning algorithms can be associated with computer vision in vinification procedures to monitor grapes' quality. It uses a database with pictures of grape breeds, including different improvement stages and compares ground truth information acquired from this investigation. Machine learning aims to implement real-world data processing for development in smart vineyards (Seng, Ang, Schmidtke, & Rogiers, 2018). The machine learning (ML) method can predict annual grape output and also identify grape harvesting. In recent years, ML has substantially aided the advancement of algorithms for computer vision and perception (Sozzi, Cantalamessa, Cogato, Kayad, &

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Marinello, 2022). The grape bunch identification in vineyards was performed using machine learning at various stages of growth, including early stages immediately after flowering and intermediate stages when the grape bunch reached intermediate developmental stages.

The initial stage in this procedure is to use artificial vision to find grapes in a vine area. In agriculture, image processing has a wide range of uses. Several efforts have been made to use artificial vision to check the quality of fruits and vegetables (Lu, Gouton, Guillemin, My, & Shell, 2001). These innovations improve product throughput, selection uniformity and reliability, and worker efficiency. Humans have difficulty identifying grapes, especially when the leaves and grapes are the same color. The setting for such an application makes it challenging to identify grapes. Climate change also affects grape ripening in addition to late leaf removal under different watering regimes (Buesa *et al*., 2019).

The economic and social impact of the grape industry on society is substantial. One of the most important aspects of winemaking is grape yield estimation. It depends on managing agricultural resources with plant health guarantee while satisfying the conditions of preserving equilibrium and long-term economic viability. One approach employed at the moment to estimate productivity is manually sampling grape bundles to measure characteristics like bundle weight and fruit size. An average number of bunches per vine and average bunch weight are calculated relative to the number of vines per acre. Then the results are extrapolated across the vineyard. Due to the fact the yield distribution may not be uniform over the vineyard, it's far inherently untrustworthy. Second, since the sample of bunches is plucked off the vine and thrown away, it takes a lot of time and money. Furthermore, seeing that sample processing and yield forecasts aren't usually completed on time, harvest logistical delays greatly impact fruit quality (Cecotti, Rivera, Farhadloo, & Pedroza, 2020).

Deep learning allows us to discriminate between two major strategies: Building a model with trained input photographs for the first stage. The second is the transfer learning model, with knowledge from one previously solved issue to another related problem. A pre-trained system that gives a somewhat comparable task, such as a computer vision task, can be utilized to extract knowledge that is then used to enhance a new classifier (Comba, Biglia, Aimonino, Gay, & agriculture, 2018).

Literature Review

This experiment demonstrated that since a second class includes smaller grape bunches, the models were more accurate in categorizing grape bunches at the medium development stage than those observed in the vineyard after bloom as shown in Table 1. Grape bunches that are more like the surrounding flora in terms of color and texture complicate things in their heir discovery.

Autonomous machines for automated site-specific crop management are essential in advanced crop monitoring systems and not-too-distant future to managing precision viticulture processes. In this context, it would be crucial, for instance, to accurately identify grape vineyards from 3D cloud maps made on multispectral imagery taken by unmanned aerial vehicles in order to improve the data that is sensed remotely and control the movement along with the operations of unmanned vehicles (Comba *et al*., 2018).

Numerous studies have used grape blossom detectors to tackle the issue of yield estimation for grapes in their early phases of development. In order to locate the visible grape blooms, (Liu *et al*., 2018) suggested a technique of detection method was proposed by extracting texture information from photographs. The goal of (Diago *et al*., 2014) was to evaluate the grapevine's bloom density per inflorescence. The grape bunches in this piece were arranged over flat backdrops and kept apart from one another by the use of a threshold.

In the DL-based methodology published by (Palacios *et al*., 2020), a semantic segmentation architecture is used to extract regions of interest containing floral clusters. (Pérez-

Table 1: Various methods with applications based on their performances

References	*Application*	*Performance*
(Liu *et al*., 2018)	Automated vine flower counting to identify potential early harvest.	Accuracy of 84.3% for flower estimation
(Palacios *et al*., 2020)	Estimation of flowers in bruise.	F1 score 73.0% for individual
(Pérez-Zavala *et al*., 2018)	Grape bunch detection to automate vine growth monitoring, spraying, thinning and harvesting.	AP of 88.6% and average recall (AR) of 80.3%
(Cecotti *et al*., 2020)	Study of the best CNN architecture to detect grapes in images	Accuracy of 99.0% for both red along with white images
(Santos, de Souza, dos Santos, Avila, & Agriculture, 2020)	Gain insight into crop health for yield forecasting, precision farming and automated harvesting	F1 score 91.0% for instant grape bunches
(Xiong *et al*., 2018)	Night-time fruit picking using artificial illumination.	Accuracy of 91.7% for green grape identification
(Kangune *et al*., 2019)	Estimation of grape ripeness	Classification accuracy with 79.5% between grapes ripened and grapes unripened.

Table 2: Various methods and grape harvesting accuracies

Method	*Accuracy of grape harvesting (R^2 (avg)) (%)*
Machine learning	95–97
Adaboost	60–70
ARD	80–90
SVM	65–70
Deep learning	90–92

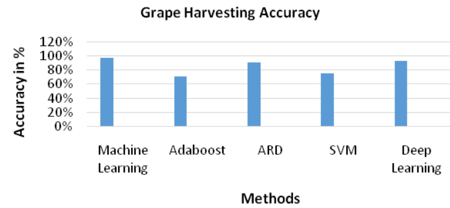

Figure 1: Graph of the various methods and accuracy of grape harvesting

Zavala, Torres-Torriti, Cheein, Troni, & Agriculture, 2018) grouped pixels with grape bunches utilizing shape along with texture data from photos to recognize grape bunches in advanced development stages. (Cecotti *et al*., 2020), who were more interested in DL, researched the ideal CNN architecture to apply in agricultural settings. The authors evaluated several designs for the recognition of two different varieties of grapes in photographs in this context. With a 99.0% accuracy rate, the findings demonstrated that Resnet (K. He, Zhang, Ren, & Sun, 2016) was the optimal design.

To execute the best cropping techniques in viniculture, which is essential to envisage the production levels of various vineyard zones. The results showed that it is necessary to distinguish between canopy and soil using computer vision techniques to obtain accurate results in precision viticulture (Sozzi, Cantalamessa, Cogato, Kayad, & Marinello, 2021). However, existing vegetation production models are frequently too imprecise to take into account agricultural heterogeneity and are based on global satellite observations. Increased understanding and many of the limitations of individual sensors can be achieved by the integration of data from numerous sensors (Ballesteros *et al*., 2020).

A method for making intelligent harvesting decisions depending on the ripeness of the date fruit. The system identified seven distinct date fruit development phases using computer vision and deep learning algorithms (Bhatnagar, Gohain, & Technology, 2020). The collection includes images of date fruit bunches in various pre-maturity and maturity phases from a variety of date cultivars (M. He *et al*., 2018).

In order to identify leaf photos, Lee *et al*. (Lee, Chan, Wilkin, & Remagnino, 2015) suggested a CNN technique with an average accuracy of 99.7% on a dataset that included 44 species. According to Zhang *et al* (Zhang, Zhang, Wu, & Systems, 2019), transfer learning can improve a deep learning model's effectiveness in identifying agricultural diseases. Mohanty *et al*. (Mohanty, Hughes, & Salathé, 2016) improved deep-learning models that were previously trained on ImageNet for crop species. According to Liu *et al*. (2018), a robust grapevine flower estimation system enhances the flower counting performance and it uses single images of inflorescences. The detection algorithm uses segmentation, and an unsupervised learning method is used for classification as shown in Table 2.

Pre and post-harvesting of grapes are critical aspects of the supply chain management process in the food industry. As grapes are a perishable commodity, efficient management of the pre and post-harvesting processes can significantly impact the product's quality (Boiko, Shendryk, & Boiko, 2019). With the help of machine learning techniques, every task is finished quickly and accurately. To control the quality of grapes with soluble solids content (SSC) into two categories, i.e., unripe and overripe, with HSI technique, "a deep learning classifier, RNN, can train a machine or system. Analysing the extracted features to determine the quality of the fruit" (Dhiman, Kumar, & Hu, 2021). The categorization with visual segmentation of grape bunches can be done more accurately by utilizing deep learning methods like AlexNet, GoogLeNet, and VGG16 (Arab, Noguchi, Matsushita, Ahamed, & Environment, 2021).

Deep learning methodology is used to train the system. The grapes from the recognized grape varieties can be automatically identified (La Porte, Branger, Chapon, Martinaud, & Derache, 2020). The weight of grapes can be determined by shooting pictures from different vineyards with smartphones using CNN and transfer learning (Silver & Monga, 2019). Predict fruit position in 2D and 3D using a color camera and a single shot multibox (SSD) detector. It also performs faster and more accurate predictions for different fruit scales (Onishi *et al*., 2019). Performing reliable aerial object recognition using convolutional neural networks and its multilayer features is a viable method for localizing the region of interest (ROIs) in image classification-based approaches (Gulve, 2020).

The Figure 1 shows that the machine learning method achieves very good accuracy in grape harvesting and deep learning in addition to ARD shows significant performance. However, SVM obtains lower accuracy but higher than the Adaboost method.

Methodology

The datasets of grapes are important for training the ML model for grape quality prediction. The variety of grape development stages improves the quality of prediction thus, we created our own grapes dataset. A database consists of images taken from Nashik District vineyards. The database of pre and post-harvesting Grape images is collected in 3 different stages of grape development, including the

Table 3: Image distribution in each dataset

Dataset name	*Images*							*Size of dataset (MB)*
	#1	*#2*	*#3*	*#4*	*#5*	*#6*	*Total*	
Flowering stage	14	13	6	6	4	27	70	30
Growing stage	19	23	3	6	2	5	58	45
Harvesting stage	18	2	11	6	3	7	47	38
Total	51	38	20	18	9	39	175	113

flowering stage [A], growing stage [B] and harvesting stage [C]. These images are classified and added to three datasets as shown in Figure 2, including each stage. A flowering stage of grapes is incorporated with 70 photographs in the early stage. Another group of 58 images of the grapes' growing stage are added to the second dataset. Furthermore, harvesting stage images, including 47 photographs, are collected and added to the third dataset. These images are collected from 6 different grape vineyards to obtain varieties of grape quality at different development stages of grapes. It differs in size and color and is used for references in grape quality prediction (Patil, 2023). Table 3 shows the distribution of the number of images in each dataset.

Table 3 shows the image distribution in each dataset. The images are categorized into 6 varieties of grapes images indicated as #1,#2, #3, #4, #5 and #6. The last column presents a total number of images in each dataset. The dataset includes total of 175 images for training and testing the model.

Then the classifier is trained with a fixed batch size and a number of iterations. RGM and binary images are processed to resize the images and then a masking of the images outlines the border of grape bunches in the image. Using the feature extraction technique, a training set of images analyses the size and shape for the prediction of grape development.

However, each image is also screened for grape components, where 98% of image pixels represent grapes. Similarly, 98% of image pixels containing components not relevant to grapes are non-grape components. Figure 3 shows the grape segmentation process.

Architecture

The architecture is built on three different input kinds. The input for the first kind corresponds to RGB color pictures. The input for the second kind comprises grayscale pictures, while the third one contains 3 histograms considering information related to the color blocks. We include the histograms in RGB colors displayed inside the block. We used 157 layers and selected 7015519 parameters for this model, while the prediction of grape maturity is based on the size of grapes, pH value and percentage of colors of grapes such as greenish, yellow, greenish-yellow, screaming green, forest green etc. The quality parameters and color distribution is mentioned in Tables 4 and 5.

Figure 2: Grape images from the dataset: Flowering stage, growing stage and harvesting stage

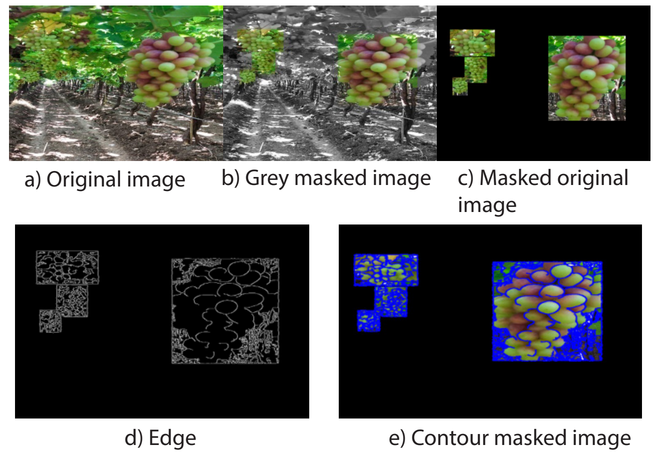

Figure 3: Grape segmentation process

Table 4: Quality parameters of grapes

S. No.	*Average size*	*Brix*	*pH*	*TA*
1	2.74	18.20	2.93	5.67
2	24.79	25.70	3.77	9.83
3	10.22	18.20	2.93	5.67
4	4.24	18.20	2.93	5.67

Table 5: Color distribution of grapes

S. No.	*Average size*	*Color%*				
		Greenish	*Yellow*	*Greenish yellow*	*Screaming green*	*Forest green*
1	2.74	24.04	21.33	26.87	23.91	3.86
2	24.79	1.45	12.72	49.19	34.08	2.56
3	10.22	20.35	23.72	28.91	20.65	6.37
4	4.24	13.12	24.31	37.25	23.91	1.41

Table 6: Distribution of the images into three datasets

Type	*Stage*	*Size*	*Train*	*Validation*	*Test*
A	Flowering stage	30	56	7	7
B	Growing stage	45	46	6	6
C	Harvesting stage	38	37	5	5

Table 6 defines the three architectures. The progresses are set to 2 in both dimensions for the second convolutional layer of the two initial CNNs. We consider a multilayer perceptron, a traditional feed-forward artificial neural network with one hidden layer for a transfer learning strategy using a

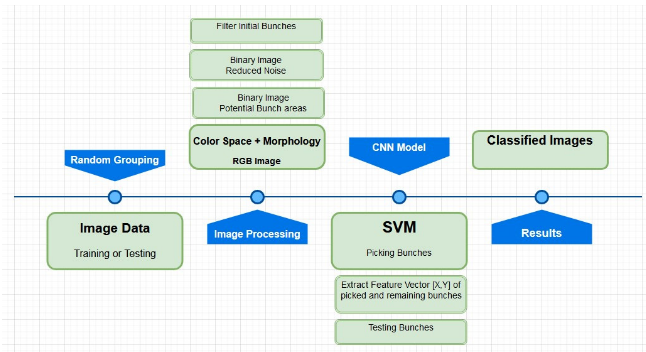

Figure 4: Proposed model architecture

pre-trained network. The inputs are entirely coupled to the 157 layers, which are fully coupled to the 2-unit output layer. Our dataset of a total of 175 images is distributed in three types, including the growing stages of grapes. Table 6 includes the dataset's A, B and C types, including the flowering, growing and harvesting stages of grapes. The dataset is further divided into 80% images for the training set, 10% for validation and 10% for the testing set.

Proposed Model

The bunch segmentation approach suggested in this work involves a multi-stage methodology. Some of the procedures involved are image preprocessing, training with the test set on a sample set of segmentation images, and splitting the initial set of hypotheses using morphological operations in the HSV color space. Figure 4 illustrates how the entire procedure is well structured for cluster data processing and segmentation. The algorithm was developed using 11 photographs as the training set.

The process begins with preprocessing the images in an effort to reduce noise and enhance image quality. In the second stage, a form filter is applied to remove spurious bundles or clusters. This filtering process is crucial to eliminating FPs and increasing segmentation accuracy. The next step involves bunch segmentation in the test set using an SVM. SVM is a well-liked machine learning technique for tasks involving regression and classification. Finding the hyperplane that best splits data points into different classes is how it operates.

In this study, a total of 80 photos from block 11 were preprocessed to identify bunches of grapes. During the preprocessing step, some false positive areas were discovered in some of the images. To solve this problem, every found site was manually classified as either right or incorrect.

Data Augmentation

The most popular technique for improving the data collection of photographs is to apply geometric modifications without altering the object's class. The grapes in this image can be arranged in various locations and directions. The images can be increased with different rotations and mirroring of the grape images. It gives several distinct images using a single original image and can significantly expand the training dataset.

Results and Discussion

We selected a subset of bunches from the available photos such that they are equal numbers of bunches that correspond to grapes and non-grape bunches from available images for the valuation. A similar evaluation enables classrooms to remain balanced. Assessing the area of ROC curve (AUC) with accuracy allows for the 5-fold cross-validation's overall performance to be determined (Fawcett, 2006). The stated measurements are defined as follows:

True Positive Rate

The true positive rate (TPR) is the probability of actual positive, also known as sensitivity. It is calculated as

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{1}$$

True Negative Rate

The true negative rate (TNR) or specificity gives the probability of an actual negative.

$$\mathrm{TNR} = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \tag{2}$$

False Negative Rate

The false negative rate (FNR) is given by the following equation to evaluate the false negative by the testing.

$$\mathrm{FNR} = \frac{\mathrm{FN}}{\mathrm{FN+TP}} \tag{3}$$

False Positive Rate

The false positive rate (FPR) is given by the following equation.

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{TN+FP}} \tag{4}$$

Accuracy

$$\mathrm{Accuracy} = \frac{\mathrm{TP+TN}}{\mathrm{TP+FP+TN+FN}} \tag{5}$$

Where TP, FP, FN, and TN denote the numbers of true positives (bunches that match grapes with recognition as grapes), false positives (bunches that were recognized as grapes with non-grapes bunches), false negatives (bunches that weren't grapes but were detected as grapes), and true negatives (number of non-grape bunches recognized as non-grapes). Positive (P) and negative (N) in the tests denote the total number of bunches representing grapes and non-grapes, respectively.

Grape Quality Prediction

The following results in Table 7 calculates the average size of grapes in the image, predicting values of Brix, pH and Titratable Acidity (TA) in the grapes (Table 4). Furthermore, the color of the grapes is evaluated as shown in Table 5 to determine the maturity of the grapes.

We evaluated the next set of images for the prediction of days required for the ripeness of grapes centered on the size of grapes, with predicted values of Brix, pH and TA in grapes.

Discussion

We evaluated and compared our model with other models, as shown in Table 8. The table compares accuracies obtained by different models and algorithms used for the prediction of grapes.

We plotted a graph of the maximum accuracy obtained in various models as compared to the maximum accuracy obtained by our model. The Figure 5 shows the graph of accuracy performance by various models.

Furthermore, we compared the performance of some algorithms with other models. LR, DT, RF KNN and Adaboost algorithms are compared with other models for accuracy, as shown in Table 9 and Figure 6.

The graph shows the better performance of our model in terms of all algorithms. Moreover, other valuation parameters like precision, recall and f1 score were compared with other grape prediction models (Onishi *et al.*, 2019) using KNN, RF, DT and AdaBoost algorithms. The Table 10 shows the significant performance of our model and we achieved enhanced values for each parameter.

Supply Chain Management

Supply Chain Management (SCM) is a complicated process that entails coordinating a number of different entities and activities related to the production, delivery, and distribution of goods and services to consumers. The application of AI and ML approaches in the field of supply chain management has grown in popularity in recent years. CNNs are one such method that has demonstrated significant promise in SCM system optimization. The fresh fruit supply chain is characterized by long lead times for suppliers, significant supply and demand unpredictability, and narrow profit margins. Modern decision-making methods and efficient management are required to solve these issues.

Grapes, as indicated by the Food and Agriculture Organization (FAO), hold a prominent position among the most extensively cultivated fruits worldwide (S. F. Khyber). Effective management of the grape supply chain is crucial,

Table 7: Grape maturity prediction

S. No.	*Average size*	*Days required to mature*	*Brix*	*pH*	*TA*
1	1.61	84	20.60	3.20	7.00
2	2.32	27	21.80	3.33	7.67
3	1.12	124	21.50	3.30	7.50

Table 8: Comparison of various models

S. No.	*References*	*Accuracy in %*					
		Max	*DT*	*RF*	*KNN*	*AdaBoost*	*LR*
1	(Onishi *et al.*, 2019)	100	90	100	62	100	-
2	(Cecotti *et al.*, 2020)	94.0	-	90.8	80.7	-	-
3	(Santos *et al.*, 2020)	88.4	-	-	-	-	88.4
4	(Xiong *et al.*, 2018)	95.5	-	-	-	-	-
5		100	100	100	83.33	100	100

Table 9: Accuracy obtained in various algorithms

Sr. No.	Algorithm	Accuracy in %	
		Our	Others
1	Logistic regression	100	88.4 (Santos *et al.*, 2020)
2	Decision tree	100	90 (Onishi *et al.*, 2019)
3	Random forest	100	90.8 (Cecotti *et al.*, 2020)
4	KNN	83.33	80.7 (Cecotti *et al.*, 2020)
5	AdaBoost	100	100 (Onishi *et al.*, 2019)

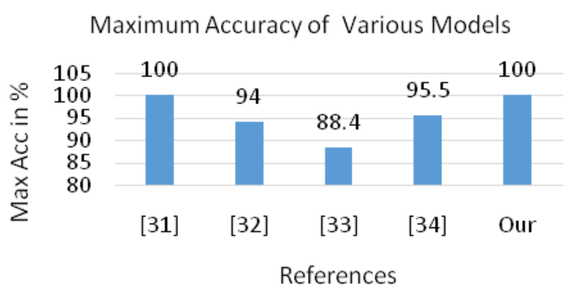

Figure 5: Maximum accuracy of various models

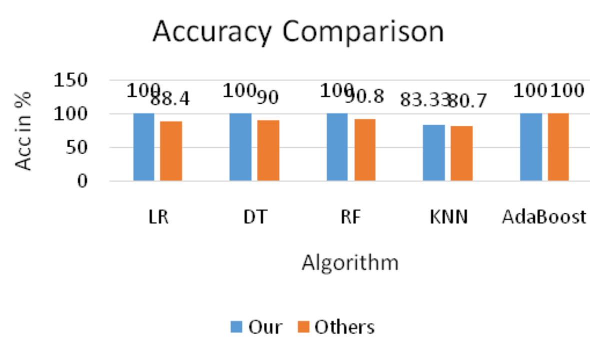

Figure 6: Accuracy obtained in various algorithms

Table 10: Performance parameters

S. No.	*Algorithm*	*(Onishi et al., 2019)*				*Our Values*			
		Precision	*Recall*	*F1 score*	*Acc%*	*Precision*	*Recall*	*F1 score*	*Acc%*
1	KNN	0.62	0.62	0.62	62	1.00	0.67	0.80	83.33
2	RF	1.00	1.00	1.00	100	1.00	1.00	1.00	100
3	DT	0.90	0.75	0.78	90	1.00	1.00	1.00	100
4	Adaboost	1.00	1.00	1.00	100	1.00	1.00	1.00	100

Table 11: Findings from various research on SCM

S. No.	*Year*	*Authors*	*Findings of the research*
1	(2015)	(Nadal-Roig, 2015)	A linear programming model for planning daily transport of fruit from warehouses to processing plants is presented, aiming to minimize transport costs.
2	(2015)	(González-Araya, 2015)	A mixed integer linear programming model to support planning decisions in an orchard, aiming to minimize the amount of resources used and ensure the highest-quality fruit production.
3	(2014)	(Lambert, 2014)	Impact on the Persian lime supply chain of orchard yield and fruit quality predictions.
4	(2014)	(VELYchKO, 2014)	The development of integrated methods and a model of preparing decisions in the fruit and vegetable servicing cooperative logistics is presented. Possible alternatives and existing limitations in separate technological, logistical and marketing business processes are explored.

encompassing various aspects such as procurement, transportation, storage, and delivery, to ensure the timely and cost-effective delivery of products to customers.

The application of AI and ML approaches has been the subject of various studies aimed at enhancing the grape supply chain. CNNs, a type of DL algorithm, have shown great potential among these methods. CNNs have been successfully used in the grape SCM to automate the critical tasks of grading and sorting grapes according to size and quality. By using AI and ML to leverage historical data, predict consumer demand, optimize inventory levels, and guarantee on-time delivery, SCM specialists can improve customer happiness and cut costs.

The study referenced as (F. Jianying, 2021) provides valuable insights into mitigating risks and enhancing the sustainability of the fresh grape industry's supply chain. The analysis finds that the links between the chain's different participants present the greatest risk, based on thorough risk assessments. In order to mitigate risks in the grape supply chain, the study recommends that cultivating a cooperative culture among chain participants and actively campaigning for sustainable development principles are critical.

Conclusion

We examined numerous CNN approaches for the identification of grapes in pictures in order to estimate the quality of grapes. Research enumerates the following conclusive factors:

- The impressive performance of the pre-trained model shows that architecture training using different algorithms differs in the performance of grape predictions.
- We achieved 100% accuracy in grape prediction using LR, DT, RF, NUSVC, Adaboost and gradient algorithms while KNN and SVC were behind with an accuracy of 83.33% each.
- On the other hand, our model achieved better performance than other grape prediction models, with higher precision and recall value, in addition to the f1 score and accuracy. The highest values of these parameters reached 1.00, except for KNN and SVC algorithms.
- Our model includes the color and size of the grapes to differ in grape quality using a variety of grape images as a reference. It is capable of predicting the maturity stage of grapes by predicting Brix, TA and pH values (ranging between 18.20 to 25.70, 5.67 to 9.83 and 2.93 to 3.77) according to the size and color of grapes.

As part of ongoing research, a review was conducted to better understand the current state and possible future directions for implementing a supply chain management information system in a multi-component manufacturing company. Table 11 shows findings from various research on supply chain management. The study results also highlight the necessity of continuing to monitor and periodically evaluate the hazards in the grape supply chain.

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