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A Mixed-Model Approach to Ripeness Classification using Convolutional Neural Networks and Support Vector Machines in the Mango Industry

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Abstract—

This study proposes a hybrid method that uses a convolutional neural network (CNN) and a support vector machine (SVM) to determine when mangoes are ripe. A crucial agricultural activity that boosts production productivity and decreases overages during storage is sorting mangoes according to maturity. Current approaches for mango ripeness classification might be made more efficient and accurate with the help of the proposed hybrid model. A dataset consisting of around one thousand photographs of ripe, unripe, and overripe mangoes was used to train and evaluate the hybrid CNN-SVM model. The suggested hybrid approach combines SVM classification precision with CNN's capacity to extract features from visual input. The hybrid model outperforms both deep learning and conventional machine learning in trials, with an impressive accuracy rate of 98.53%. These findings show that hybrid models may be used to determine when mangoes are ripe, which might help farmers make better decisions.
Hybrid model, convolutional neural networks, support vector machines, agricultural image analysis, mango ripeness categorization

I. INTRODUCTION

The food and agriculture industries rely on maturity classifications for fruits since it affects harvesting, transportation, storage, and customer happiness. Ripeness has a significant impact on many aspects of fruit, including taste, texture, nutritional value, and shelf life. Optimizing the supply chain, reducing food waste, and satisfying consumers all depend on accurately labeling fruits as "unripe," "ripe," or "overripe" [1]. As a species, we have depended on our senses of sight, touch, smell, and taste to determine whether food is safe to consume for countless generations. Because it is individual and subjective, this process is laborious. Thanks to developments in computer vision and machine learning, automated systems that recognize when fruit is ripe are becoming more popular. A. Approaches to Determining When Fruit Is Getting Ripe The use of ML and DL has caused a sea change in the fruit processing business. Technological advancements in the last several years have made determining when fruit is ripe for consumption more simpler and more precise. These techniques use computer vision to scour fruit images for characteristics that could suggest freshness. Some of the most common ways that ML and DL determine whether fruit is ripe are as follows: (1) Conventional ML Methods: • Support vector machines (SVMs): SVMs often use binary and multiclass data for classification. For example, Random Forest is well-known for being both very accurate and very adaptable [2]. The Second Step: Extracting and Choosing Features • Color-based features: As fruit ripens, its look changes, and these changes are commonly represented by color-based features. Histograms and moments of color are two examples of such features. • Texture Analysis: Data retrieved from the fruit's surface attributes using texture characteristics using techniques such as Local Binary Patterns (LBP) or Gabor filters might indicate when the fruit will be ripe. • Formal Characteristics: Some characteristics of the fruit's shape, such its contours, may help in determining whether it is ripe. CNNs have been extensively utilized for ripeness classification of fruits because they can automatically learn hierarchical properties directly from raw photos. Convolutional layers, pooling layers, and fully connected layers are the many layers that make up a convolutional neural network (CNN)[3, 4]. 4) Transfer Learning: • Using pre-trained deep learning models, one may modify them using transfer learning to categorize the fruit's ripeness. Because it makes use of features learnt from a large dataset, transfer learning usually improves classification performance with less training data, which speeds up training (like ImageNet) from [5] to [7]. 5) RNNs and LSTM networks: • RNNs and LSTM networks are useful for instances of sequential or time-series data related to fruit maturations, such changes in texture or color over time. [8, 9]. • These models look at the ripening process from every angle, taking into account how different fruit qualities are dependent on each other. 6. Data Augmentation: • Images may be rotated, cropped, and brightened as part of data augmentation to improve model generalization and increase diversity in the training sample. In this study, we look at how convolutional neural networks (CNNs) may be used to automate the process of determining whether fruit is ripe. CNNs excel in picture categorization because to their ability to extract several properties from photos. In order to efficiently and accurately classify fruit ripeness, this study introduces a hybrid approach using CNNs and SVMs. This model integrates convolutional neural networks' (CNNs') feature extraction efficacy with support vector machines' (SVMs') classification scalability. This study's overarching goal is to improve methods for determining when fruit is ripe. B. The Paper's Outline The following is the structure of the remaining portions of this work: With an eye on the development of automated methods and machine learning systems, Section II reviews the literature on fruit ripeness classification. Part III goes into detail about the dataset, convolutional neural network architecture, support vector machine integration, and training process. Section IV details the experimental setup and findings, as well as compares the performance of the proposed hybrid model to that of comparable tactics. The findings and recommendations for further studies on fruit ripeness classification are reviewed in Section V.

II. LITERATURE REVIEW

The use of ML and DL has greatly improved the efficiency and accuracy of fruit ripeness classification. Classifying fruit ripeness generally makes use of classic ML methods, such as SVM, which can detect patterns in the feature space. Early research found

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that support vector machines (SVMs) could distinguish between ripeness phases using visual cues such color, texture, and shape [10], [11]. Because of its capacity to automatically learn and extract hierarchical characteristics from raw photos, deep learning approaches—and CNNs in particular—have recently been popular in fruit maturity assessment [12], [13]. CNNs excel in picture classification due to their ability to discern nuanced patterns and textures that indicate various degrees of ripeness [14]. Researchers have using CNNs to determine the optimal time to consume fruit based on its color and texture. [15]. The capacity to categorize fruits according to their ripeness has also been enhanced via transfer learning. This approach makes use of pre-trained deep learning models. To classify fruits according to their ripeness level, researchers have used pre-trained convolutional neural network (CNN) models such as VGG and ResNet [17] based on data from large datasets like ImageNet [16]. Combining neural networks with more conventional machine-learning techniques may provide better results, according to recent research. These models integrate convolutional neural networks' (CNNs) ability to extract features with traditional machine learning techniques' (ML) classification capabilities. Because of this, it is easier and more accurate to determine when fruit is ripe [18]. The use of visible light imaging to ascertain when fruit is ripe for picking has been the subject of much study. The use of near-infrared (NIR) and hyperspectral imaging, which are part of the non-visible spectrum, has been shown to enhance classification accuracy [19]. Because they are able to detect the metabolic changes that occur during ripening, non-visible ranges may provide a more comprehensive view of when fruit is ripe. Classifying fruits according to their ripeness has become simpler and more precise with the use of ML and DL methods, including CNNs. To further enhance the categorization process, future studies may investigate hybrid models that combine more spectrum data with robust machine-learning techniques.

III. MATERIALS AND METHODS

A. Data Set

The dataset [20] that was used for this study is classified as either unripe, ripe, or overripe. There are three distinct kinds of 975 pictures. In the end, as one moves down the hierarchy, each set has 911, 43, and 21 photos, respectively. There are 800 pixels per inch on the longest edge of a picture. The dataset is shown in Fig. 1 using sample photographs.

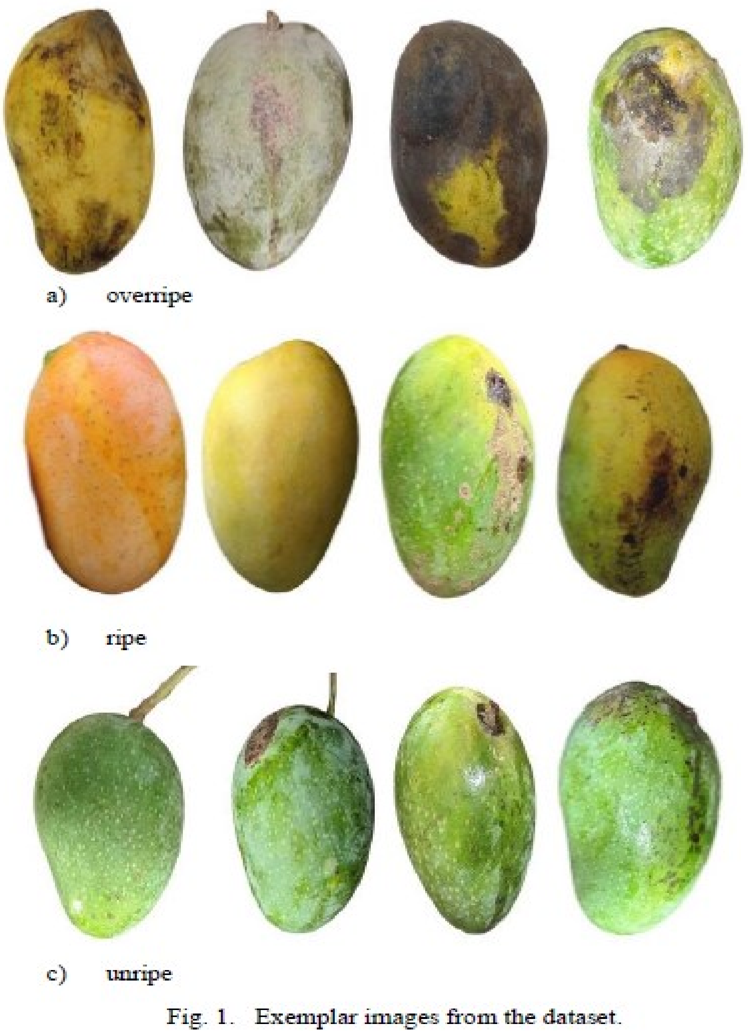

Fig. 1. Exemplar images from the dataset.

Section B: Suggested Approach This CNN-SVM hybrid takes the greatest features of both models and uses them to classify mangoes as either ripe, overripe, or unripe. One common deep learning model in computer vision and image processing is the convolutional neural network (CNN) [21]. Due to its convolutional and pooling layers, CNNs are able to successfully extract hierarchical information from pictures. They are therefore well-suited for the task of picture classification. Extracting Features:

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CNN extracts features using the hybrid technique. To begin, we utilize a pre-trained CNN model to extract detailed information from mango pictures. Everything from intricate patterns and textures to visual clues that indicate when something is ripe is part of this. These characteristics are obtained using the CNN's convolutional and pooling layers. The feature vector for each mango picture is created by flattening the CNN-retrieved features. The CNN incorporates some abstract characteristics into this feature vector, which is sent into the SVM. A well-liked machine-learning technique for categorization issues is the support vector machine (SVM). This technique uses the feature space to find the best inter-class discriminating hyperplane. The convolutional neural network (CNN) feature vectors are used to train a support vector machine (SVM) classifier. The SVM is trained to differentiate between ripe items. To determine a decision boundary, the SVM optimizes the variation in feature vectors over the various ripeness stages. Classification: Following training, the SVM might be used as the hybrid method's classification component. Using CNN's feature extraction capabilities, the SVM can now determine if a mango is ripe, overripe, or unripe based on images taken over the last several days. 3) Hybrid Integration: Here, convolutional neural networks (CNNs) serve as the feature extractor, enabling the discovery of intricate structures in mango photos. After that, it utilizes these characteristics to train a support vector machine (SVM) to classify mangoes into one of many age categories. In this hybrid model, SVM's classification capabilities are paired with CNN's robust feature extraction capabilities, which are particularly well-suited to comprehending visual information. When taken as a whole, these parameters provide a strong model that distinguishes different mangoes of comparable ripeness. This hybrid approach combines deep learning with more conventional machine learning techniques to classify mango ripeness in a short amount of time. Thanks to CNN's feature extraction capabilities and SVM's speed in mango grouping, we have a trustworthy and precise maturity assessment. Figure 2 shows the whole procedure.

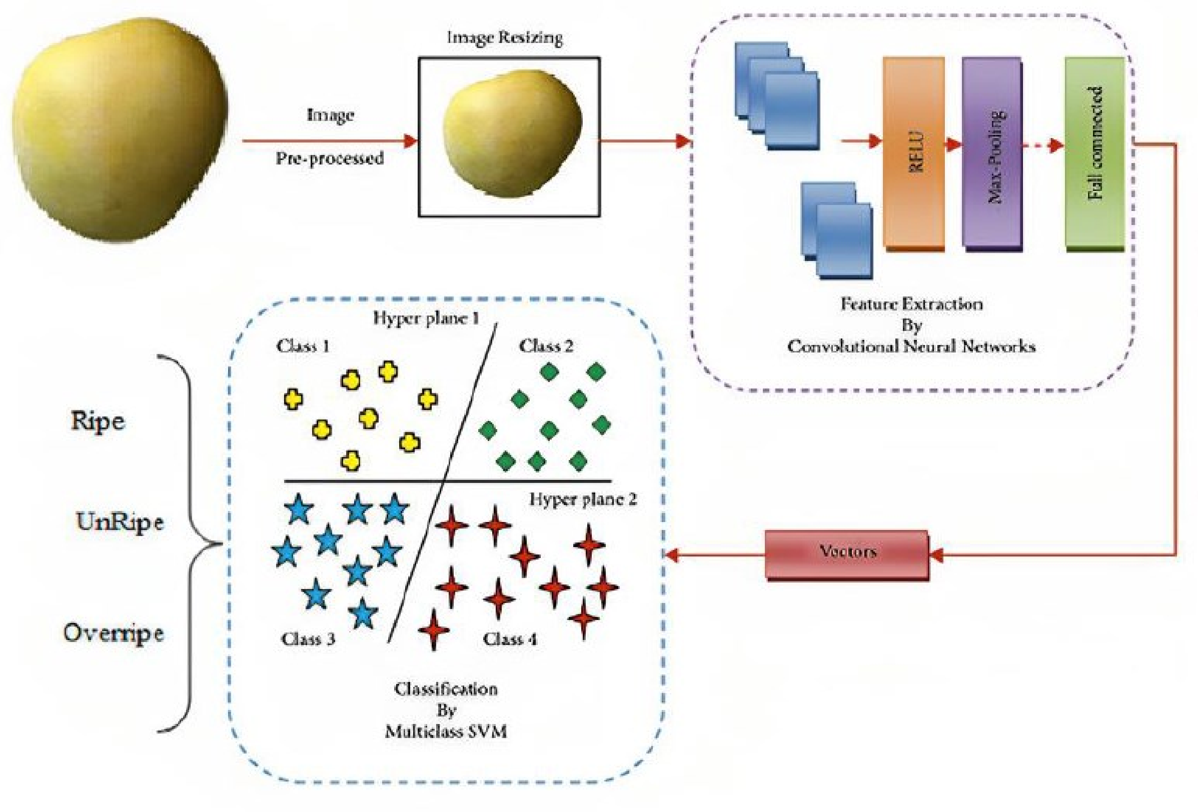

Fig. 2. The process of putting the suggested model into action.

Below is a simplified pseudocode of the proposed hybrid approach in algorithmic language:

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Pseudocode: Hybrid CNN-SVM Approach for Mango Ripeness Classification

Data Preparation
1. Load the mango dataset with images and corresponding ripeness labels
2. Split the dataset into training and testing sets

Convolutional Neural Network (CNN) Training
3. Initialize CNN model [Let f(x) represent the CNN model, where x is the input image.]
4. Train the CNN model on the training set
   a. Forward pass: Extract features from mango images

   features=f(x)

   b. Compute loss using the extracted features and ground truth labels
   c. Backward pass: Update model weights using gradient descent
5. Save the trained CNN model

Support Vector Machine (SVM) Training
6. Extract features from the training set using the trained CNN model. $\phi(x)$ denotes the feature vector extracted by the CNN, and y represents the ground truth ripeness label.

7. Initialize SVM classifier
8. Train SVM on the extracted features and corresponding ripeness labels

SVM Model: $h(x)=\text{sign}(w\cdot\phi(x)+b)$

Here, w represents the weight vector, · denotes the dot product, and b is the bias term.

Hybrid Classification
9. Load the testing set
10. For each mango image in the testing set:
   a. Use the trained CNN to extract features
   b. Use the trained SVM to classify the mango based on the extracted features
   c. Record the predicted ripeness label

Predicted Label: $\hat{y}=\text{sign}(w\cdot\phi(f(x))+b)$

Evaluation (optional)
11. Compare predicted labels with ground truth labels to evaluate accuracy

End of Hybrid Approach

IV.RRESULTS AND ANALYSIS

C. Experimental Setup

The study was carried out using a 64-bit Ubuntu system that has the most recent version of Ubuntu, 20.04.4 LTS, an Intel Xeon W-2223 CPU operating at 2.60 GHz, and an NVIDIA TU104GL QuadroRTX 5000 graphics card. Colab, a Python-based environment, was used to conduct the whole experiment, and the Python library was used to construct the suggested hybrid model. D. Analyzing Deep Learning Model Results Lots of hyperparameters, including learning rate, batch size, and epoch, were used in the experiment. Figure 3 shows that the results of the training and validation were correct when the learning rate was 0.01 and the batch size was 50.

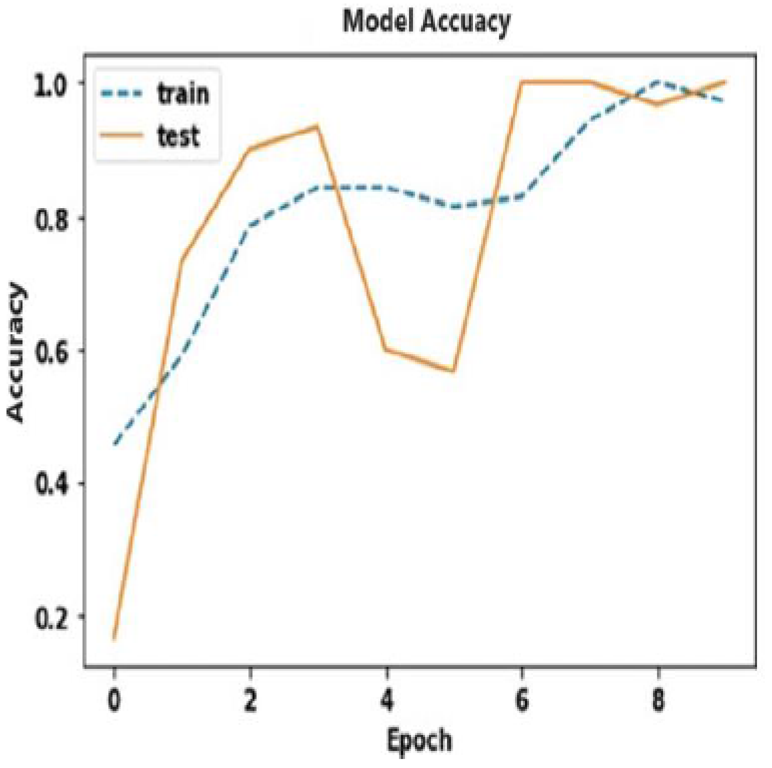

Fig. 3. Epochwise Accuracy and Precision of Proposed Model

The performance of the proposed model was compared to that of classic ML and DL techniques. The results of evaluating performance using ML models in terms of classification accuracy (CA), F1 score, Precision (P), Recall (R), and Matthews correlation coefficients (MCC) are shown in Table I and Fig. 4 in reference [18].

TABLE I. COMPARISION WITH ML APPROACHES

Model	CA	F1	P	R	MCC
Hybrid Model	0.9853	0.9834	0.9829	0.9822	0.734
Random Forest	0.952	0.939	0.95	0.952	0.512
SVM	0.961	0.949	0.939	0.961	0.628
Naive Bayes	0.512	0.636	0.946	0.512	0.252

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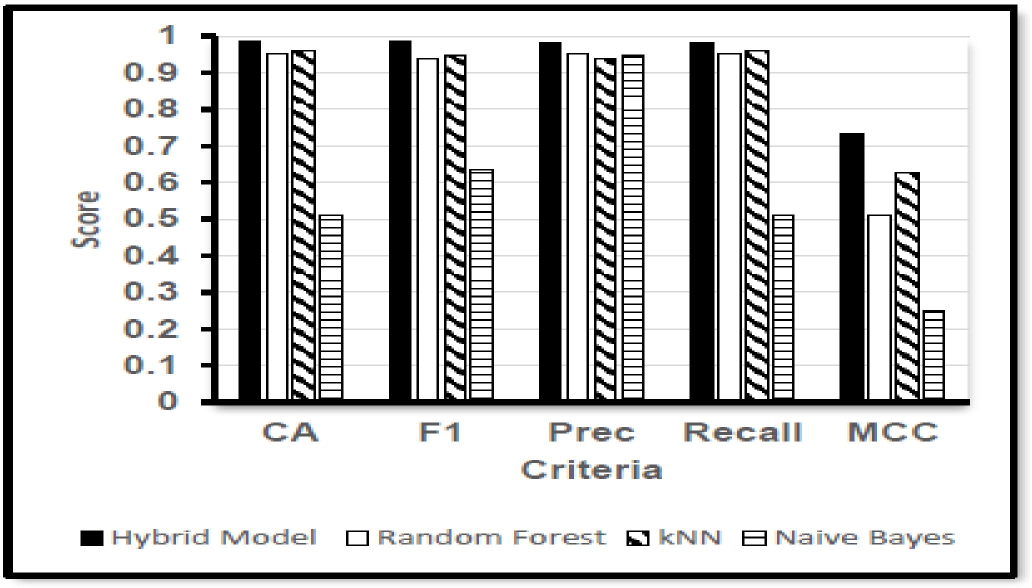

Fig. 4. Comparison with ML Models

The results of a comparison between the proposed model and several DL models are shown in table II and fig. 5.

TABLE II. MODEL COMPARISON WITH DL MODELS

Model	CA	F1	P	R	MCC
Hybrid Model	0.9853	0.9834	0.9829	0.9822	0.734
VGG16	0.912	0.919	0.95	0.952	0.552
Inception	0.921	0.929	0.939	0.961	0.678
Exception	0.798	0.699	0.946	0.512	0.212
MobileNet	0.823	0.824	0.844	0.87	0.325
AlexNet	0.90125	0.9024	0.8911	0.9	0.45

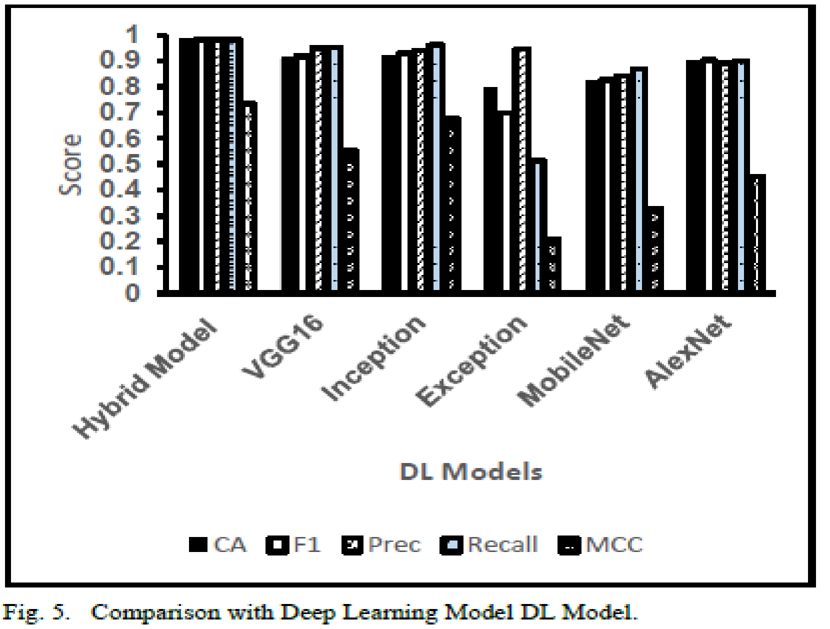

Fig. 5. Comparison with Deep Learning Model DL Model.

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The confusion matrix for the proposed model is depicted in fig 6.

		Predicted			
		OverRipe	Ripe	UnRipe	∑
Actual	OverRipe	98.53%	0.35%	1.12%	21
	Ripe	0.33%	98.50%	1.17%	43
	UnRipe	0.80%	0.50%	98.70%	911
	∑	14	40	921	975

Fig. 6. Confusion Matrix for Proposed Hybrid Model.

V. CONCLUSION

This study suggests a CNN-SVM hybrid method for precise mango ripening phase classification. Using a carefully selected dataset that includes pictures of mangoes at three distinct ripeness stages, experimental experiments are conducted to evaluate the performance of many machine learning models. Based on the results of this study, SVM obtained a remarkable 96.1% correct classification rate when trained using traditional machine learning methods. This shows how effective SVM is at determining ripeness levels from data-retrieved attributes. But the optimal approach was to combine CNN with SVM, which achieved a correct classification accuracy of 98.53%. Strongholds in standalone deep architecture such as VGG16, Inception, Exception, MobileNet, and AlexNet were beaten by this multi-deep architecture approach. The accuracy of mango ripeness assessment was significantly improved by combining CNN's feature extraction abilities with SVM's excellent classification capacity. Combining deep learning with traditional machine learning techniques yielded a 98.53% accuracy rate in fruit ripeness classification, demonstrating the efficacy and potential of this method. By enhancing classification accuracy, this strategy emphasizes the importance of hybrid models in solving complex agricultural issues. The successful implementation of the hybrid CNN-SVM model opens the way for further research and use of advanced machine learning techniques in agriculture, which will ultimately benefit customers, distributors, and farmers via better decision-making and more efficient supply chains. Possible next directions for the research include refining the hybrid model, learning more about different kinds of fruit, and using real-time data to assess ripeness more precisely and faster.

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