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Effectiveness of Deep Feature Extraction Algorithm in Determining the Maturity of Fruits: A Review

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Abstract—Intelligent farming technology helps farmers overcome tough obstacles in the farming process, such as increased sup-plier costs, a lack of labour, customer satisfaction, and more. Artificial Intelligence (AI) is a remarkable technology in smart farming because it deeply understands the issue and can help farmers make decisions. This article's main objective is to identify and examine the concepts and techniques of Convolutional Neural Networks (CNN) technology that could aid in classifying the ripeness stages of fruit in intelligent farming. This paper systematically reviews 18 previous works for classifying the ripeness stages of fruit. This review outlines the most commonly used algorithms, activation functions, optimisation functions, and platforms for algorithm implementation. In addition, found that not all algorithms are suitable for even near-equivalent processes. Therefore, this study suggests the intensity of the CNN algorithms concerning various metrics to find the suitability for the operations/applications. Finally, this paper offers some future research directions in the ripeness classification of fruits.

Keywords- Deep Learning, Convolutional Neural Networks, Ripeness Classification, Smart farming, Transfer Learning.

I. INTRODUCTION

Agriculture is one of the most traditional industries yet to adapt digital technology. Agriculture plays a vital role in the economy of any country. It is very much required for the agriculture industry to have many technological advancements to improve the economy and meet the food demand. In order to improve the quality and quantity of farm products through smart and precision farming researchers investigated every aspect of traditional farming, that includes moisture levels, seed quality, soil conditions, yield mapping, harvesting, and grading. The John Deere team introduced the first precision farming system, "GreenStar", in 1993. This system supports yield mapping and demonstrates the process from planning to harvest [1]. In 1977, Parrish and Goskel presented an image processing technique that recognize apples and guides the robot to harvest the apples. In 1996, Rockwell introduced a crop management and analysis model that integrates a "Vision System" for precision farming; the components of the system include a vision receiver, a computer display, and vision software. It is observed to be the pioneer of modern precision farming technology [2]. In general, Artificial intelligence and Machine vision are primarily used in harvesting robots and are extended to every process of intelligent farming.

Pre-harvesting, harvesting, and post-harvesting are the three main tasks involved in traditional farming. In an intelligent farming system, all these stages are implemented with innovative technologies. Artificial Intelligence techniques such as Ex-pert Systems (ES), Fuzzy Logic (FL), Machine Learning (ML), Deep Learning (DL), Neural Networks (NN), Swarm Intelligence, and Computer Vision (CV) are used to simplify the process of farming through innovations. The stages that are in the lifecycle of intelligent farming is depicted Figure 1.

It would be beneficial for farmers, the food industry, and small retail stores to predict the maturity of fruits. Fruit maturity classification is the process of categorizing the fruits according to their ripeness level [3]. A Systematic Literature Review (SLR) of fruit ripeness level classification using CNN is presented in this paper. This study mainly focused on the effects of Convolutional Neural Networks (CNN) technologies in smart agriculture's fruit ripeness level classification process, intending to identify the present limitations and suggest future research areas to focus in order to overcome the restrictions. The remaining sections of this article are structured as follows; section 2 provides an overview of the existing work. In Section 3, the fundamental concept of CNN architecture is presented. Section 4 discusses the methodology used to generate the SLR. Section 5 presents the results and discusses the importance of CNN in classifying the ripeness stages. The next is the penultimate section which summarizes the research findings and discusses future work, and the last section presents the conclusion of this study.

Table 1 lists the acronyms used in this manuscript. The next section discusses related works in the innovative farming process as well as the uniqueness of the current study.

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II. RELATED WORK STYLE

Ripeness or maturity level has a significant impact on the prices of agricultural product. Therefore, the automation of find-ing the level of ripeness would be very helpful for the farmers and the research towards this automation gained lots of at-tention among researchers. For any research, the literature review is crucial and this part of the article covered some prelim-inary analysis of fruit categorization in intelligent farming. The articles published after 2017 are considered for the literary analysis, and are given in Table 2. Sapan Naik and Bankim Patel examined the publications on fruit grading and categoriza-tion techniques in 2017 [4]. A critical evaluation of various cutting-edge computer vision techniques provided by researchers for categorizing fruit and vegetable was presented in 2018 [5] (Hameed et al., 2018) and in the same year, Raja Sekar L et al. reviewed image processing in fruit disease detection methods. Also they highlighted the benefits and drawbacks of detec-tion methods [6]. Another critical study by K. Muthukannan et al. investigated the techniques that include morphological, color intensity and area algorithms, LDA, GCLM, HSV, HSI color space, etc. utilized for fruit ripeness analysis [7].

In 2019, M. Surya Kiran and G. Niranjana presented a survey on fruit maturity categorization methods in 2019 [8]. In their study, Mayuri Wankhade and U. W. Hore discussed the proper segmentation, feature extraction, selection, and classification approaches for ripeness classification based on image processing and ML [9]. Usha Mittal and Nagnath Aherwadi investi-gated and presented an article on ML and DL fruit identification, classification, and quality detection techniques [3]. Charan G et al. studied real-time fruit detection and classification methods using image processing and CNN [10]. In 2023, Jeisson Enrique Cueva Caro and Jorge Isaac Necochea-Chamorro conducted a systematic review on fruit identification using ML and DL in 2023 [11].

This study presents an extensive study on CNN algorithms, which may help classifying the fruits based on ripeness level. The main objective of this study is to analyze the most recent publications that focuses mainly on CNN methods. The primary concerns of this study is to identify the novelty used by researchers to improve the performance of classification algorithms. This study considers the datasets, implementation frameworks, and the number of ripeness stages that are used by the researchers in the existing works.

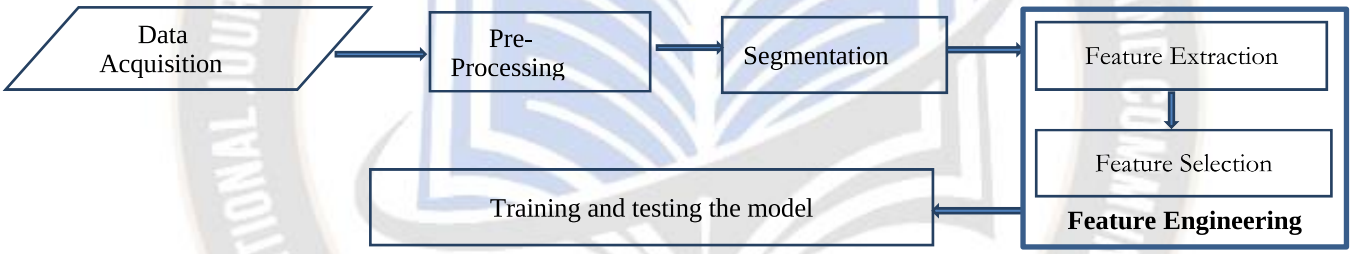

Figure 1. Process distribution of precision farming

TABLE 1. NOMENCLATURE

ANN	Artificial Neural Networks	MAE	Mean Absolute Error	RMSProp	Root Mean Squared Propagation
CNN	Convolutional Neural Networks	MD	Multi-model	RQ	Research Question
DL	Deep Learning	ML	Machine Learning	SE	Squeeze-and-Excitation
ELU	Exponential Linear Unit	MLP	Multi-Layer Perceptron	SGD	Stochastic Gradient Descent
GCLM	Gray-Level Co-Occurrence Matrix	MSE	Mean Square Error	SLR	Systematic Literature Review
HSI	Hue, Saturation, Intensity	NASNet	Neural Architecture Search Network	TL	Transfer Learning
HSV	Hue, Saturation, Value	ReLU	Rectified Linear Unit	VGG	Visual Geometry Group
KNN	K-Nearest Neighbors	ResNet	Residual Network	YOLO	You Only Look Once
KSVM	Kernel Support Vector Machine	RF	Random Forest		
LDA	Linear Discriminant Analysis	RMSE	Root Mean Square Error		

TABLE 2. LITERATURE REVIEW

S.No.	Reference	Year	Primary focus
1	[11]	2023	Machine Learning and Deep Learning for Fruit Identification
2	[10]	2022	Real-Time Fruit Detection and Classification Using Image Processing and Convolution Neural Network
3	[3]	2022	Fruit Quality Identification Using Image Processing, Machine Learning, And Deep Learning
4	[9]	2021	Fruit Ripeness Classification Based on Image Processing with Machine Learning
5	[8]	2019	Fruit Maturity Detection Techniques
6	[6]	2028	Fruit Classification System Using Computer Vision
7	[7]	2018	An Image-Based Analysis on Fruit Maturity
8	[5]	2018	Fruit And Vegetable Classification Techniques
9	[4]	2017	Machine Vision-Based Fruit Classification and Grading

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III. BACKGROUND

This section provides an overview of CNN and TL techniques; also the section analyzes the strategies applied to the classification of fruits based on ripeness level.

A. *Convolutional Neural Networks*

The basic component in a Neural Network is called a node or unit that takes input and process to exhibit itself as a neuron. The node takes input from other nodes or an external source and uses one or more hidden layers to compute an output. CNN is the name for how these (convolutional) layers are combined to produce the desired output. In general, CNN outperforms ordinary neural networks with respect to scalability, high computing cost, and overfitting. Being a subset of ML, CNN gains knowledge through sharing of parameters. CNN is essential for analyzing, detecting, predicting, and classifying spatial data. This architecture's main element is feed-forward neural networks with convolutional, pooling, and fully connected layers. The convolutional layer, which serves as the CNN's entry point, employs linear algebra to perform feature engineering tasks. The structure of this layer is made up of filter, stride, and padding. The filters extract visual features and boost the model's efficiency. The stride parameter specifies the number of rows and columns that the kernel will skip as it moves over the image matrix. The number of strides is inversely proportional to the size of the output matrix. Padding is primarily used to add zeros around the matrix to maintain the size of the input image. It helps to obtain the image's low-level features. Pooling layers are then used to compress the image and extract the features regardless of the iimage's position. In addition to these layers, dropout and batch normalization layers are optional in CNN. Before the output layer, one or more fully connected layers are added. It is made up of bias and weights and combines two different layers.

Nonlinearity in hidden layers boosts the model's learning rate, which can be accomplished through activation functions. The activation function transfers the computed values to other/output nodes. Table 3 shows the characteristics of various activation functions.

A computer vision model is trained using massive data sets in order to classify, predict, identify, and detect. Deep learning algorithms are used to train and test the datasets to meet the demands of intelligent farming that uses neural networks. These algorithms take raw data and recognize an underlying governing pattern before they are applied to new situations. In other words, computers learn to uncover hidden truths within data. CNN turns input data into feature maps in order to improve the machine's learning capabilities. Figure 2 depicts the tomato's feature maps.

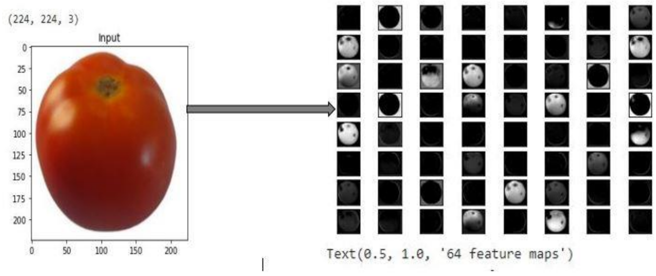

Figure 2. Feature maps of a tomato image

B. *Transfer Learning*

CNN was launched in the mid-1980 and found it was unable to recognize handwritten digits. Currently, CNN has the abil-ity to recognize patterns that human eyes cannot. At the same time, it demands a large amount of computation power, computation time, and specialized hardware. The researchers are developing a pre-trained architecture know as Transfer Learning in order to overcome these challenges. In 1998, the history of Transfer Learning began with the implementation of LeNet [12]. LeNet is one of the most known and notable pre-trained CNN architectures. After the popularity of LeNet model, the other models with CNN architecture came into existence and are, (i) AlexNet [13], (ii) VGG [14], (iii) Goog-LeNet/Inception [15], and (iv) ResNet [16]. Recently, plenty of methods are introduced by researchers that incorporate strategies to (i) reduce the burden of training from scratch, (ii) increase the effective utilization of time, and (iii) limit the re-quirements towards hardware. Figure 3 shows some of the pre-trained architectures used in intelligent farming include AlexNet, VGG, ResNet, NASNet [17], Inception etc. are listed in the Keras documentation [18]. Among these architec-tures, ResNet is trained with 224 x 224 x 3 size images and can extract 25 million parameters from the input images. This method ensures high efficiency and accuracy while it classifies the objects from small sized datasets. It is found that ResNet gained its popularity among researchers in the recent times.

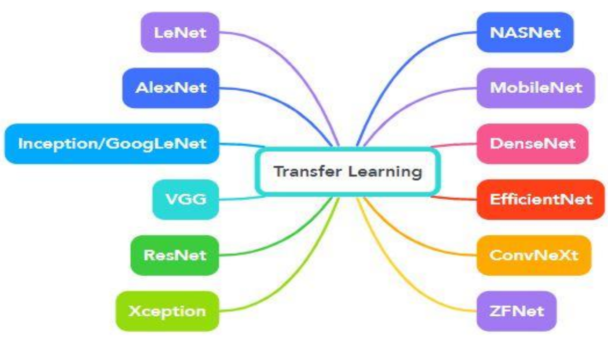

Figure 3. Transfer learning techniques

IV. METHODOLOGY

This section describes the procedures to thoroughly review and assess prior research on innovative farming practices using

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CNN methodologies. Kitchenham et al. provide seven steps for doing a SLR in software engineering [19]. This SLR study is centered on the first six steps guided by Kitchenham et al., shown in figure 4.

A. Research Questions

The following research questions serve as the framework for this work:

RQ1: What CNN architectures are employed to classify the ripeness/maturity of the agricultural product in intelligent farming?

RQ2: Which platform is used to implement and test the ripeness classification algorithms?

RQ3: Which optimization algorithms are employed? Why?

RQ4: Which activation function dominates feature extraction and classification?

B. Critical Terms For Article Search

Search terms such as "deep learning in smart farming", "precision farming", "intelligent farming", "harvesting robot", "transfer learning", "CNN in smart farming", "fruits and vegetable ripeness classification", "fruits and vegetable maturity classification", "fruits detection in the tree image", "ripeness classification using CNN", "maturity classification using CNN", and "computer vision in agriculture" are used to find the relevant research articles.

C. Inclusion And Exclusion Criteria

The following explicit inclusion criteria are used to assess the papers for review, (i) articles on smart farming using CNN techniques; (ii) published in a journal; and (iii) published after 2019. Based on these criteria, 120 papers are collected from the major publishers' sites. After collecting the papers, the exclusion criteria for this study includes (i) duplicate articles, (ii) papers relevant to intelligent farming but not computer vision, (iii) articles published in special issues, (iv) papers published in conferences, (v) published in non-Scopus indexed journals (compared with January 2023 Scopus list) and (vi) articles did not meet the quality assessment. After all these criteria are executed, it is found that 18 are found valid and are selected for further examination as illustrated in figure 5.

D. Articles Quality Assessment

The brilliance of the review paper is determined by the SLR, which is dependent on the conclusions of other researchers and results in the quality of the selected articles. Therefore, it is crucial to evaluate the chosen article's quality. In this study, the following questions are used to assess the quality of the papers.

- Is the primary study design reliable?
- Was the research approach sound?
- What are the outcomes?
- Will the findings be advantageous to the newcomer?

E. Data Gathering

After article collection, data was gathered for analysis. The notable parameters extracted for this study are the datasets used for processing, the application area of the research and approaches used by the researchers to resolve the problems, the performance of the model, and the reference details.

TABLE 3. ACTIVATION FUNCTIONS: OVERVIEW

Activation function	Equation	Nature	Layer	Application	Drawbacks
ELU	$f(x) = \begin{cases} x, & x > 0 \\ \propto (e^x - 1), & x \le 0 \end{cases}$	Non-Linear	Hidden	Classification	Exploding gradients
Linear	$Y = ax$	Linear	Output	Regression	Constant derivation
ReLU	$f(x) = \max(0, x)$	Non-Linear	Hidden	Classification	Dying ReLU
Sigmoid	$f(x) = \frac{1}{1 + e^{-x}}$	Non-Linear	Hidden and Output	Binary and multilabel classification	Vanishing gradients
SoftMax	$f_i(x) = \frac{e^{x}i}{\sum_{j=1}^{n} e^{x_j}}$ for $i = 1, \dots, n$	Non-Linear	Output	Multi-class classification	Uncertainty
Tanh	$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	Non-Linear	Hidden	Classification	Vanishing gradients

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Figure 4. Steps in the Systematic Literature Review

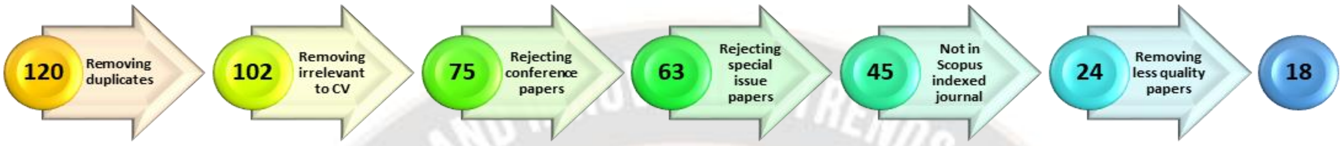

Figure 5. Process of fine-tuned article selection

F. Data Examination

The data tabulated to demonstrate:

- The object used to determine ripeness
- For classification, the CNN architecture is used (Addressing RQ1)
- The paper's novelty (Addressing RQ1)
- Parameters fine-tuned to achieve acceptable performance (Addressing RQ1 & RQ3)
- The activation functions that are used in the layers (Addressing RQ4)

Development platforms are shown using a diagram. (Addressing RQ2)

V. RESULTS

The primary objective of this section is to examine, synthesize, and discuss the works filtered by the SLR methodologies. Furthermore, the goal is to summarize existing information, recognize new contributions, and explore alternate implementations of top CNN techniques in ripeness classification in intelligent farming.

RQ1: What CNN architectures are employed to classify the ripeness/maturity of the agricultural product in intelligent farming?

Identifying the ripeness stages of the fruits is the first and pivotal step for robot harvesting. The main objective of the ripeness level classification is to enhance the vision of the machine to identify the matured fruits. In general, 18 relevant CNN architecture-based articles are identified for analysis. Furthermore, about 26 CNN architectures used by researchers are identified. Most are based on transfer learning methods, with only a few being custom models. In particular, the most commonly used transfer learning methods areAlexNet, DenseNet, DenseNet121, EfficientNetB0, InceptionV1, InceptionV2, InceptionV3, InceptionV4, MobileNetV1, MobileNetV2, NASNet, ResNet, ResNet18, ResNet50, ResNet101, ResNeXt50, VGG16, and VGG19, as shown in figure 6. In addition to pre-trained models, shallow CNN architectures are used to classify maturity stages [20], [21], [22], [23], as shown in Table 4.

Brahim Benmouna et al. proposed a personalized, shallow, and optimal CNN architecture to classify Fuji apples from hyperspectral images based on their ripeness stages. The one-hot-encoder is used to encode the four ripeness levels in this model. This novel CNN architecture consists of six layers, and ReLU has presented as an activation function in the dense layers. Compared to ANN, SVM, and KNN, this petty CNN architecture has outperformed them with 96.5% accuracy [21]. Nirmala Gururaj et al. proposed another customized CNN architecture to categorize the stages of mango ripening. This model comprised one input layer, four convolutional layers, four pooling layers, and two fully connected layers. Over-fitting is reduced by introducing the 10% dropout after the convolutional modules. This model took 65 minutes for 50 epochs in the Google cloud platform and accurately classified the four stages of ripeness level with around 95.11% accuracy [22].

Nagnath Aherwadi et al. proposed a model for predicting banana maturity and quality. The proposed CNN model and AlexNet are tested against three types of datasets: original, augmented, and Fruits360. Based on the performance of the three other datasets, the authors concluded that the proposed CNN model is the best for banana maturity classification and quality detection [20]. N. Saranya et al. proposed another shallow model for banana maturity status classification. This model was tested with the original and augmented datasets and

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compared its performance with VGG16 and ResNet50. The proposed method produced the best results in all test cases with a high validation accuracy of 96.1436% [23].

Researchers use transfer learning methods to classify the ripeness of palm family fruits. Table 5 shows some of the analyses of these classification articles. Suharjito et al. created a mobile application to locate ripened oil palm bunches using four lightweight ImageNet transfer learning CNN architectures: EfficientNetB0, MobileNetV1, MobileNetV2, and NASNet Mobile. In this application, they improved the model's performance using the novel data augmentation method "9-angle crop". This model has also been further optimized using the float16 quantization technique. EfficientNetB0 has classified the ripeness level in Android mobile with 89.9% accuracy among the four algorithms [24].

Mohammed Faisal et al. proposed a real-time system for maturity level classification, type identification, and weight estimation of dates fruit in the orchard. They used four transfer learning models: ResNet, VGG19, InceptionV3, and NASNet. To fine-tune the model, the authors froze a few layers and added a few layers using transfer learning models. This tech-nique improved the performance of the models, with ResNet achieving the highest accuracy of the four models [25]. In the same year, Mohammed Faisal et al. proposed an intelligent decision-making system for determining the maturity of dates fruits. This innovative harvesting decision-making system can identify seven stages of maturity: immature stage1, immature stage2, pre-khalal, Khalal, khalal with rutab, pre-tamar, and tamar. The effectiveness of the maturity level detection method evaluated in comparison to various maturity levels and CNN architectures. According to the authors, VGG19 outperformed VGG16, AlexNet, NASNet, and InceptionV3 [26]. These studies are done on the same dataset, "DATE FRUIT DATASET FOR AUTOMATED HARVESTING AND VISUAL YIELD ESTIMATION," created by the Center of Smart Robotics Research [27].

Amin Nasiri et al. introduced the innovative CNN from VGG16 and classifier block. Dense layers, batch normalization, dropout, and max pooling are used to redesign the classifier block. Date fruit's four levels of maturity can be categorized using this methodology. The improved model performed on average from 96% to 99% in classification accuracy, precision, specificity, sensitivity, and AUC for each class [28].

Using CNN architecture, scientists extended their research to categorize the phases of ripeness for tomatoes, strawberries, plums, papayas, muskmelon, mulberries, and jujube fruits. Table 6 includes a summary of their research methods and findings. The following paragraphs contain some concise descriptions of recent studies.

Santi Kumari Behera et al. proposed a non-destructive maturity status classification of papaya fruits based on machine learning and transfer learning techniques. Transfer learning techniques like ResNet101, ResNet50, ResNet18, VGG19,

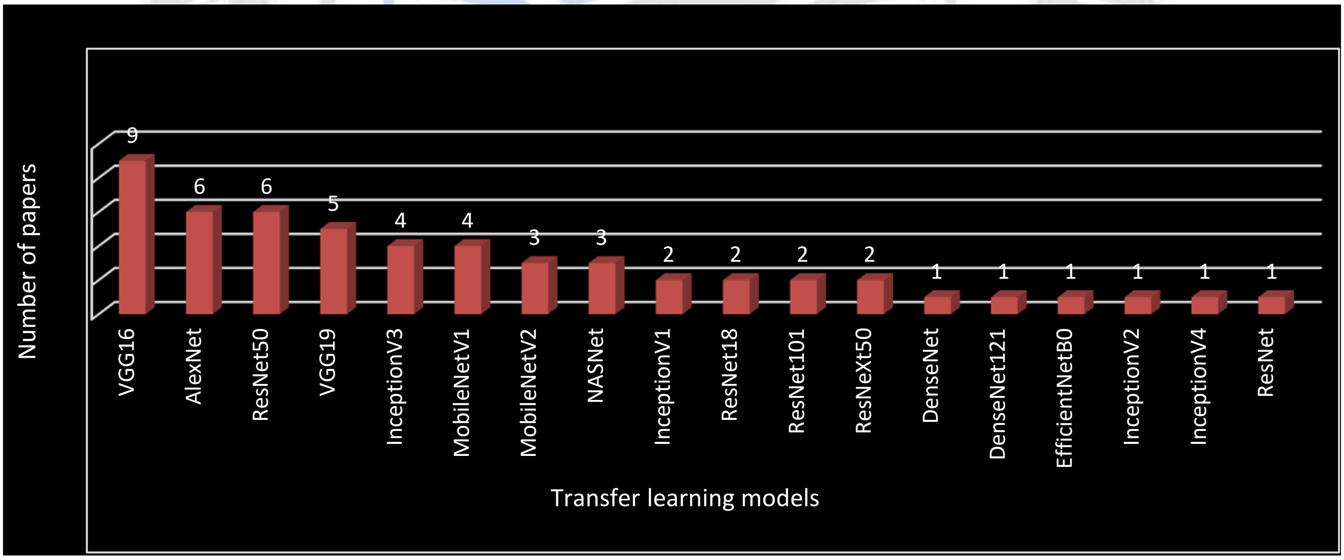

Figure 6: Commonly used transfer learning algorithms in ripeness classification

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TABLE 4. OPTIMAL CNN ARCHITECTURE FOR RIPENESS CLASSIFICATION

Object	CNN architecture	Novelty	Fine-tuned		Maturity Classes	Accuracy	Reference
			Parameters	*Values*			
Fuji apple	2 convolutional layers 1 max pooling layer 1 flatten layer 2 dense layers	Shallow and optimal CNN architecture	Batch Size Epoch	30 35	• Unripe • Half-ripe • Ripe • Over-ripe	96.5%	[21]
Mango	1 input layer 4 convolutional layers 4 max pooling layers 2 dense layers	Personalized CNN architecture	LR Momentum Optimizer Batch Size Epoch	0.0001 0.9 Adam 10 50	• Raw • Early ripe • Partial ripe • Ripe	95.11%	[22]
Banana	3 convolutional layers 2 max pooling layers 1 dropout 1 flatten layer 2 dense layers & AlexNet	Optimal CNN architecture	Optimizer Epoch	Adam 10	• Unripe • Ripe • Overripe	Proposed CNN – around 99%	[20]
Banana	5 convolutional layers 2 max pooling layers 1 dropout 1 flatten layer 2 dense layers VGG16 & ResNet50	Shallow CNN architecture and One hot encoding	Optimizer Epoch	Adam 50	• Unripe • Partially ripe • Ripe • Overripe	Proposed CNN – 96.14	[23]

VGG16, GoogLeNet, and AlexNet used to classify the papaya maturity level. According to the comparative findings, VGG19 surpassed the remaining methods in execution and convergence speed. VGG19 classified the papaya based on their maturity with an accuracy of 100% [29]. The second noteworthy paper, by Cinmayii A et al., suggested a multimodal framework for estimating papaya fruit maturity. The initial and most crucial stage in this architecture was to combine visible light and hyperspectral pictures to create feature cubes. The seven transfer learning models AlexNet, VGG16, VGG19, ResNet50, ResNeXt50, MobileNet, and MobileNetV2 are fed with these multimodal feature cubes. These models are also known as MD-AlexNet, MD-VGG16, MD-VGG19, MD-TesNet50, MD-ResNeXt50, and MD-MobileNetV2. This influ-ential concept divides the maturity phases into six tiers. MD-VGG16 achieved the best performance out of these seven models, whereas MD-AlexNet and MD-VGG19 displayed comparable results [30].

Seetha Ram Nagesh Appe et al. proposed a model for categorizing tomato maturity stages as ripe or unripe. This model is constructed using VGG16, and MLP was used instead of the CNN's fully connected layers for classification. This model is tested both with and without fine-tuning. The results showed that the fine-tuned model outperformed the other by around 8%. For the development of real-time applications, a categorization based on just two stages of maturity is insufficient. More research is carried out to categorize tomato ripeness into four stages [31]. In one study, Fei Su et al. suggested a mod-el for categorizing the four maturity stages of tomatoes named SE-YOLOv3-MobileNetV1. The YOLOv3's backbone DenseNet was replaced with MobileNetV1 in this model. The depth-wise separable convolution method helped the model run more quickly. When comparing YOLOv3, YOLOv3-MobileNetV1, and YOLOv5, the SE-YOLOv3-MobileNetV1 performance accuracy is found to get enhanced using Mosaic data augmentation, the K-means clustering technique, and the

TABLE 5.CLASSIFICATION OF RIPENESS OF PALM FAMILY FRUITS

Ref.	Dataset	CNN architecture	Novelty	Fine-tuned		Maturity Classes	Accuracy
				Parameters	*Values*		
[24]	653 Oil palm images collected from an oil mill in central Kalimantan, Indonesia	EfficientNetB0 MobileNetV1 MobileNetV2 NASNet Mobile	9-angle crop	LR Momentum Optimizer Batch Size Epoch	0.0001 0.9 SGD 8 150	• Unripe • Under-ripe • Ripe • Over-ripe • Abnormal	EfficientNetB0 – 89.9%
[25]	Dates images from the dataset created by the Center of Smart Robotics Research [27]	ResNet VGG-19 InceptionV3 NASNet	Additional layers: Global average pooling, Dropout, Dense, Batch normalization and Softmax (5 classes)	LR Optimizer Batch Size Epoch	0.0001 Adam 16 50	• Immature • Khalal • Khalal with Rutab • Pre-Tamar • Tamar	ResNet - 99.058%

[26]		VGG19 VGG16 AlexNet NASNet InceptionV3	Model tested with different number of maturity levels and compared with the two other studies	LR Optimizer Batch Size Epoch	0.0001 Adam 16 30	• Immature stage 1 • Immature stage 2 • Pre-Khalal • Khalal • Khalal with Rutab • Pre-Tamar • Tamar	VGG19 – 99.4%
[28]	Dates images collected from Jahrom, Iran	VGG16	Modified classifier layers	Optimizer Batch Size Epoch	RMSProp 32 15	• Khalal • Rutab • Tamar • Defective	96% to 99%

TABLE 6. SUMMARY OF CNN-BASED RECENT RESEARCH IN FRUITS MATURITY CLASSIFICATION

Object	**CNN architecture**	**Novelty**	**Fine-tuned**		**Maturity Classes**	**Accuracy**	**Reference**
			Parameters	Values			
Strawberry **Tomato**	VGG16, VGG19, InceptionV1, InceptionV2, InceptionV3, ResNet50, ResNet101, & MobileNetV2	ML algorithms used to classify the fruits	Not Stated		• Unripe • Partially ripe • Ripe • Overripe	Strawberry: VGG16 + SVM– 90% Tomato: VGG16 + KSVM-83%	[33]
Papaya	VGG16, VGG19, ResNet18, ResNet50, ResNet101 GoogleNet, &AlexNet	The output layer is modified to classify three maturity levels.	LR Optimizer Batch Size Epoch	0.001 SGD 32 10	• Immature • Partially mature • Mature	VGG19 – 100%	[29]
Papaya	AlexNet, VGG16, VGG19, ResNet50, ResNeXt50, MobileNet, & MobileNetV2	Visible light + hyperspectral image feature concatenation (multi-model)	LR Optimizer Batch Size Epoch	0.0001 Adam 100 300	• MS1 to • MS6	MD-VGG16 - 100%	[30]
Muskmelon	ResNet29, ResNet18, ResNet50, VGG16, MobileNetV2, ResNeXt50, DenseNet121, & InceptionV4	Two augmentation methods and ResNet with 29 layers	LR Momentum Optimizer Epoch	$1*10^{-2}$ 0.9 SGD 50	• Green • White • Yellow	ResNet29 – 99%	[36]
Plums	Modified AlexNet	Classification of interclass and their various ripeness stages	LR Optimizer Epoch	$1*10^{-2}$ SGD 300 & 500	• 10 weeks • 3 weeks • 11 weeks	89.4%	[38]
Mulberry	DenseNet, InceptionV3, ResNet18 ResNet-50, &AlexNet	Conceptual Design of mulberry sorting system	The model has varied the number of epochs. The other parameters are not specified.		• Unripe • Semi-ripe • Ripe • Overripe	ResNet18 - 98.03%	[35]
Jujube	AlexNet& VGG16	Modified output layer	LR Optimizer Batch Size Epoch	0.003 Adam 32 50	• Unripe • Ripe • Overripe	VGG16 – 99.17%	[37]
Tomato	VGG16	Custom fully connected layers with MLP	LR Optimizer Batch Size Epoch	0.001 SGD 16 100	• Unripe • Ripe	96.66%	[31]
Tomato	SE-YOLOv3-MobileNetV1, YOLOv3,YOLOv5, & YOLOv3-MobileNetV1	Mosaic data augmentation and the Squeeze-and-Excitation attention mechanism	LR Momentum Epoch	0.001 0.937 200	• < 60% • 61%_70% • 71%_80% • 81%_100%	SE-YOLOv3-MobileNetV1 - 97.5%	[32]
Strawberry	AlexNet	Features extracted from HSI images	Not stated		• Early ripe • Ripe	98.6%	[34]

Squeeze-and-Excitation attention mechanism. The matured tomato categorization performance of the suggested model was 97.5% accurate [32].

Wan Hyun Cho et al. claim that combining the features of the transfer learning algorithm with the classification of the machine learning algorithm can address the issue of the classification problem with insufficient data. Furthermore, when com-pared to ResNet, VGG16 extracts the desirable attributes from tomatoes and strawberries. According to their study, VGG16 with MLP generated the highest accuracy, 90%, when

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determining the ripeness stages of strawberries, and VGG16 with KSVM performed admirably, 83%, when determining tomato maturity level [33]. Zongmei Gao et al. demonstrated that CNN's AlexNet could provide remarkable accuracy in hyperspectral pictures. According to their study, this model successfully distinguishes between ripe and unripe strawberries in the test dataset with a classification accuracy of 98.6% [34].

Seyed-Hassan Miraei Ashtiani et al. used transfer learning methods such as DenseNet, InceptionV3, ResNet18, ResNet50, and AlexNet to investigate the classification of mulberry ripeness levels. The AlexNet and ResNet18 networks among these models classify the ripeness phases with 98.32% and 98.65% accuracy, respectively. ResNet18 takes less time to classify data than AlexNet. The authors claim that these excellent results enable exact classification and create an automated sorting system. Based on these findings, the authors have presented a conceptual framework for an automatic mulberry sorting system [35]. Based on data augmentation, Huamin Zhao et al. suggested two approaches for classifying the maturity stage of muskmelon. They created the dataset in indoor and outdoor environments, and one more dataset is generated by combining the two environment's datasets. Datasets augmented with two types of data augmentation, such as code and image, are tested with the novel CNN architecture ResNet29. According to the authors, image-based augmentation improves performance over code-based augmentation [36].

Atif Mahmood et al. investigated AlexNet and VGG16 to classify the jujube maturity stage. The performance of these models is evaluated using the original and augmented datasets. The models' performance improved by 4% and 2% in AlexNet and VGG16, respectively. VGG16 had less variance than AlexNet. The authors discovered that VGG16 is the best choice for their dataset due to its high classification accuracy of 99.17% [37]. Rolando Miragaia et al. proposed a tool to analyse the plums variety and their ripeness status. This DL-based tool can classify the three different varieties of plums, Red Beaut, Black Diamond and Angeleno with 92.83% accuracy and ripeness stages with 94%.

RQ2: Which platform is used to implement and test the ripeness classification algorithms?

The testbed is generally necessary to demonstrate the results of the research. Most research concepts about categorizing fruit maturity levels are built and tested using the frameworks Keras [20],[21],[22], [24] [25][26][28][30][36][37], and Pytorch [31] with a backend TensorFlow. Because of their open-source nature and easily approachable APIs, Keras and Tensor-Flow have gained popularity among researchers. When the application is implemented in a mobile context, researchers also use TensorFlow Lite [24][36]. The mathematical processing capability, interactive interface, and visualization capabilities of MATLAB [29][35] make it a unique development platform. The prominent implementation environments that the researchers used are shown in figure 7.

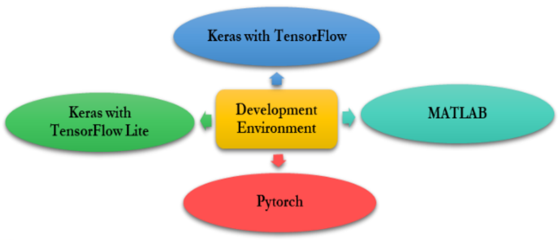

Figure 7: Implementation platform for ripeness classification

RQ3: Which optimization algorithms are employed? Why?

Mathematical techniques referred to as optimization algorithms are used to optimize weight. They minimize the value of the loss functions and allow the neural networks to produce the best predictions. The loss function primarily compares predicted output values to the target values. There are two categories for the loss function, one for regression, and the other for classification. The classification loss function chooses the input category based on the pre-set categories with the highest probability. Optimization and loss functions boost the model's prediction ability and avoid overfitting. Categorical cross entropy [20][28] [36] and sparse categorical entropy [22] are used to classify the ripeness level of fruit because there are typically more than two classes in the fruit maturity level classifications. SGD [24][29][31][36][38], RMSProp [28], and Adam [20], [22][25][26][30][37] are well-known optimization techniques that are utilized in the classification of ripeness levels because they just require a small amount of memory and computing resources and are easy to implement.

RQ4: Which activation function dominates feature extraction and classification?

In neural networks, a node's activation status is determined using the activation function. The function's primary goal is to add nonlinearity to the node's output. Activation functions are used in the dense layer to identify and categorize output like-lihood. LeakyReLU and ReLU are utilized in the convolution layers, and ReLU and SoftMax functions are used in the dense layer to classify fruit ripeness. Table 7 lists the activation mechanism employed in the chosen articles. This table con-cludes that SoftMax is used for classification while researchers throughout the feature engineering phase mostly employ ReLU.

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TABLE 7. MOST COMMONLY USED ACTIVATION FUNCTIONS IN RIPENESS CLASSIFICATION

Convolutional Layer		Dense/Output Layer	
Activation Function	*Reference*	*Activation Function*	*Reference*
Leaky ReLU	[21]	ReLU	[21]
ReLU	[22][23][25][28][29][31][32][33][34][35][36][37][38]	SoftMax	[22][23][24][25][28][29][31][33][36][37][38] [20]

VI. DISCUSSION

The outcomes and findings of the systematic review would help future maturity classification research to improve accuracy and design autonomous harvesting robots. As can be observed, several different CNN architectures have been used to varying degrees by researchers, demonstrating CNN's usefulness and suitability for ripeness classification. This work evalu-ated and compared the model accuracy of various maturity classification techniques found in the literature. This section de-scribes the main findings of this analysis.

As shown in Figure 6, this SLR identified approximately 18 TL techniques, four shallow CNN architectures, and two modi-fied TL architectures used by researchers in the selected primary studies. More precisely, Cho et al., 2021, have proposed fusion methods (VGG16 with SVM and KSVM) to improve classification accuracy [33]. The proposed shallow CNN ar-chitecture competes with TL techniques with nearly equal accuracy. 18 TL are used by the researchers, among which Res-Net, VGG16, VGG19, AlexNet, and EfficientNetB0 provided the best acceptable performance. The high accuracy-producing TL architectures for ripeness classification from this literature review are depicted in figure 8. It is evident from Figures 6 and 8 that VGG16 outperforms other models in the classification of fruit ripeness issues. This analysis will make it easier for newbies to test their datasets without too much time selecting suitable CNN approaches.

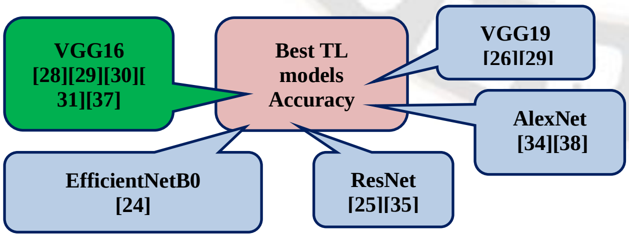

Figure 8. Top five ripeness classification algorithms based on the accuracy

The optimizer algorithms are applied to lower the error rate and increase the model's learning rate. There are ten optimizer functions in the Keras package (SGD, RMSprop, Adam, AdamW, Adadelta, Adagrad, Adamax, Adafactor, Nadam, and Ftrl) [39]. Still, only three (SGD, Adam, and RMSprop) have been discovered in the chosen publications. The advantages of each of these three have led the majority of researchers to select one of them. For some particular problems, however, the remaining functions are equally appropriate. Unfamiliar optimizer functions also have the potential to increase the algorithm's accuracy. Researchers can also propose their innovative optimizer methods.

Based on their state of maturity, fruits and vegetables can be divided into two categories: mature and immature. The agricultural industry demands that researchers categorize the maturity level in smart farming into multiple classes. As a result, researchers expand their research to classify the maturity status. This study discovered that the maximum number of maturity classes is seven. The most common number of maturity classes is two (2 times), three (5 times), four (7 times), five (1 time), six (2 times), and seven (1 time). The research may be extended to several stages of ripeness classification based on the object and requirement.

The researchers primarily use TensorFlow and Keras to build the models. TensorFlow light, Pytorch, and MATLAB are used to build the models for classifying ripeness stages. There are currently numerous low-code and no-code APIs available for testing the models. Such tools allow beginners to create a model through experimentation.

The examined publications include Fuji apples [21], oil palm [24], dates fruit [25][26][28], tomato [31][32][33], plums [38], strawberry [33][34], mulberry [35], papaya [29][30], muskmelon [36], banana [20][23], mango [22], and jujube [37] are used to classify the ripeness of the various stages. Images of all these immature and adult fruits are displayed in table 8. These images taken from the corresponding papers. According to the table, the color of these fruits differs between their immature and mature stages. As a result, practically all classifications are made just using colors. We discovered that there is a study gap in the classification of fruit and vegetable maturity. Existing research cannot categorize the phases of fruit and vegetable maturity if the fruit and vegetable maturity level cannot be categorized based on color.

TABLE 8. FRUIT'S TWO RIPENESS CLASSIFICATION STAGES

Fruit	Immature	Matured	Image sources
Dates			[25]
Papaya			[30]
Muskmelon			[36]

Fuji apple			[21]
Oil palm			[24]
Mango			[22]
Tomato			[31]
Plums			[38]
Strawberry			[34]
Mulberry			[35]
Jujube			[37]
Banana			[20]

To summarize, there is a need to introduce novel TL methods, shape-based maturity classification, flexible platforms for developing algorithms, experimenting with different types of optimizer algorithms and introducing the optimum function, and a more significant number of classes for determining the maturity level.

VII. CONCLUSION

Using CNN techniques and modern agricultural technologies, this systematic review summarizes the categorization of ripe-ness levels. The articles for this review are chosen with the utmost care, and reliable analysis parameters are selected. As a consequence of this investigation, we can point out that the VGG16 technique is the most widely employed, along with the tools Keras and TensorFlow, Adam and SGD for optimising, and ReLU, LeakyReLU, and Softmax for activation. Fruits are categorised according to their ripeness degree into two to seven classes. The most often employed performance metric is accuracy.Following all of this investigation, we discovered the following areas of unmet need: i) categorising ripeness phases according to form, size, and texture; ii) analysing the dataset using a variety of optimizer functions; and iii) creating low- or no-code APIs for rapid categorization. We hope that these gaps will be the basis for future study.

The categorization of fruit ripeness levels is the main emphasis of this study; however, in the future, the evaluation may be broadened to cover the classification of fruits and vegetables as well as intra-class classification.

REFERENCES

[1] Nelson, F., Pickett, T., Smith, W., & Ott, L. (2002). The GreenStar precision farming system. 1996 IEEE Position, Location and Navigation Symposium, PLANS '96 – Proceedings, 6–9. https://doi.org/10.1109/plans.1996.509048

[2] Bloom, K. V., Smith, L. C., Elliott, C. A., & Boerhave, S. J. (2002). Precision Farming From Rockwell. 1996 IEEE Position, Location and Navigation Symposium, PLANS '96 - Proceedings. https://doi.org/10.1109/PLANS.1996.509047

[3] Aherwadi, N., & Mittal, U. (2022). FRUIT QUALITY IDENTIFICATION USING IMAGE PROCESSING, MACHINE LEARNING, AND DEEP LEARNING: A REVIEW. Advances and Applications in Mathematical Sciences, 21(5), 2645–2660.

[4] Naik, S., & Patel, B. (2017). Machine Vision based Fruit Classification and Grading - A Review. International Journal of Computer Applications, 170(9), 22–34. https://doi.org/10.5120/ijca2017914937

[5] Hameed, K., Chai, D., & Rassau, A. (2018). A comprehensive review of fruit and vegetable classification techniques. Image and Vision Computing, 80, 24–44. https://doi.org/10.1016/j.imavis.2018.09.016

[6] Gaikwad, R. S. ., & Gandage, S. . C. (2023). MCNN: Visual Sentiment Analysis using Various Deep Learning Framework with Deep CNN. International Journal of Intelligent Systems and Applications in Engineering, 11(2s), 265 –. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2625

[7] Sekar, R. L., N.Ambika, V.Divya, & T.Kowsalya. (2018). Fruit Classification System Using Computer Vision: A Review. International Journal of Trend in Research and Development, 5(1), 2394–9333. www.ijtrd.com

[8] K.Muthukannan, J.Petchiammal, S.Muthuveni, & A.Rajeshwari. (2018). An Image based analysis on fruit maturity-Review. International Journal of Scientific Development and Research, 3(4), 53–57. www.ijsdr.org

[9] Kiran, M. S., & Niranjana, G. (2019). A Review on Fruit Maturity Detection Techniques. International Journal of Innovative Technology and Exploring Engineering, 8(6S). https://doi.org/10.11648/j.ajai.20170101.12

[10] Wankhade, M., & Hore, U. W. (2021). A Survey on Fruit Ripeness Classification Based On Image Processing with Machine Learning. International Journal of Advanced Research in Science, Communication and Technology, 5(1), 73–78. https://doi.org/10.48175/ijarsct-1097

[11] Charan.G, Ganesh.P, Dheeraj.MS, & N, S. . (2022). Survey on Real Time Fruit Detection and Classification using Image Processing and Convolution Neural Network. INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH IN TECHNOLOGY, 8(11), 617–622.

[12] Enrique Cueva Caro, J., & Isaac Necochea-chamorro, J. (2023). MACHINE LEARNING AND DEEP LEARNING FOR FRUIT IDENTIFICATION: SYSTEMATIC REVIEW. Journal of Theoretical and Applied Information Technology, 15(1). www.jatit.org

[13] Lecun, Y., Bottou, E., Bengio, Y., & Haffner, P. (1998). Gradient-Based Learning Applied to Document Recognition. Proceedings of the IEEE, 86(11), 2278–2323. https://doi.org/10.1109/5.726791

[14] Dr. M. Varadharaj. (2019). Density Based Traffic Control System with Smart Sensing Of Emergency Vehicles. International Journal of New Practices in Management and Engineering, 8(02), 01 - 07. https://doi.org/10.17762/ijnpme.v8i02.75

[15] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. International Conference on Neu- Ral Information Processing Systems, 1097–1105. https://doi.org/10.1145/3065386

[16] Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. http://arxiv.org/abs/1409.1556

[17] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1–9. https://doi.org/10.1109/CVPR.2015.7298594

[18] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2016-December, 770–778. https://doi.org/10.1109/CVPR.2016.90

[19] Zoph, B., Vasudevan, V., Shlens, J., & Le, Q. V. (2018). Learning Transferable Architectures for Scalable Image Recognition. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 8697–8710. https://doi.org/10.1109/CVPR.2018.00907

[20] Team, K. (n.d.-a). Keras Documentation: Keras applications. Keras. https://keras.io/api/applications/

[21] Kitchenham, B., Pearl Brereton, O., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering - A systematic literature review. Information and Software Technology, 51(1), 7–15. https://doi.org/10.1016/j.infsof.2008.09.009

[22] Aherwadi, N., Mittal, U., Singla, J., Jhanjhi, N. Z., Yassine, A., & Hossain, M. S. (2022). Prediction of Fruit Maturity, Quality, and Its Life Using Deep Learning Algorithms. Electronics (Switzerland), 11(24). https://doi.org/10.3390/electronics11244100

[23] Benmouna, B., García-Mateos, G., Sabzi, S., Fernandez-Beltran, R., Parras-Burgos, D., & Molina-Martínez, J. M. (2022). Convolutional Neural Networks for Estimating the Ripening State of Fuji Apples Using Visible and Near-Infrared Spectroscopy. Food and Bioprocess Technology, 15(10), 2226–2236. https://doi.org/10.1007/s11947-022-02880-7

[24] Gururaj, N., Vinod, V., & Vijayakumar, K. (2022). Deep grading of mangoes using Convolutional Neural Network and Computer Vision. Multimedia Tools and Applications. https://doi.org/10.1007/s11042-021-11616-2

[25] Saranya, N., Srinivasan, K., & Kumar, S. K. P. (2022). Banana ripeness stage identification: a deep learning approach. Journal of Ambient Intelligence and Humanized Computing, 13(8), 4033–4039. https://doi.org/10.1007/s12652-021-03267-w

[26] Jackson, B., Lewis, M., González, M., Gonzalez, L., & González, M. Improving Natural Language Understanding with Transformer Models. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/152

[27] Suharjito, Elwirehardja, G. N., & Prayoga, J. S. (2021). Oil palm fresh fruit bunch ripeness classification on mobile devices using deep learning approaches. Computers and Electronics in Agriculture, 188. https://doi.org/10.1016/j.compag.2021.106359

[28] Faisal, M., Albogamy, F., Elgibreen, H., Algabri, M., & Alqershi, F. A. (2020). Deep Learning and Computer Vision for Estimating Date Fruits Type, Maturity Level, and Weight. IEEE Access, 8, 206770–206782. https://doi.org/10.1109/ACCESS.2020.3037948

[29] Faisal, M., Alsulaiman, M., Arafah, M., & Mekhtiche, M. A. (2020). IHDS: Intelligent harvesting decision system for date fruit based on maturity stage using deep learning and computer vision. IEEE Access, 8, 167985–167997. https://doi.org/10.1109/ACCESS.2020.3023894

[30] Altaheri, H., Alsulaiman, M., & Muhammad, G. (2019). Date Fruit Classification for Robotic Harvesting in a Natural Environment Using Deep Learning. IEEE Access, 7, 117115–117133. https://doi.org/10.1109/ACCESS.2019.2936536

[31] Nasiri, A., Taheri-Garavand, A., & Zhang, Y. D. (2019). Image-based deep learning automated sorting of date fruit. Postharvest Biology and Technology, 153, 133–141. https://doi.org/10.1016/j.postharvbio.2019.04.003

[32] Behera, S. K., Rath, A. K., & Sethy, P. K. (2021). Maturity status classification of papaya fruits based on machine learning and transfer learning approach. Information Processing in Agriculture, 8(2), 244–250. https://doi.org/10.1016/j.inpa.2020.05.003

[33] Garillos-Manliguez, C. A., & Chiang, J. Y. (2021). Multimodal deep learning and visible-light and hyperspectral imaging for fruit maturity estimation. Sensors (Switzerland), 21(4), 1–18. https://doi.org/10.3390/s21041288

[34] Dr. S.A. Sivakumar. (2019). Hybrid Design and RF Planning for 4G networks using Cell Prioritization Scheme. International Journal of New Practices in Management and Engineering, 8(02), 08 - 15. https://doi.org/10.17762/ijnpme.v8i02.76

[35] Appe, S. R. N., Arulselvi, G., & Balaji, G. N. (2023). Tomato Ripeness Detection and Classification using VGG based CNN Models. Journal of Intelligent Systems and Applications in Engineering, 11(1), 296–302. www.ijisae.org

[36] Su, F., Zhao, Y., Wang, G., Liu, P., Yan, Y., & Zu, L. (2022). Tomato Maturity Classification Based on SE-YOLOv3-MobileNetV1 Network under Nature Greenhouse Environment. Agronomy, 12(7). https://doi.org/10.3390/agronomy12071638

[37] Cho, W. H., Kim, S. K., Na, M. H., & Na, I. S. (2021). Fruit Ripeness Prediction Based on DNN Feature Induction from Sparse Dataset. Computers, Materials and Continua, 69(3), 4003–4024. https://doi.org/10.32604/cmc.2021.018758

[38] Gao, Z., Shao, Y., Xuan, G., Wang, Y., Liu, Y., & Han, X. (2020). Real-time hyperspectral imaging for the in-field estimation of strawberry ripeness with deep learning. Artificial Intelligence in Agriculture, 4, 31–38. https://doi.org/10.1016/j.aiia.2020.04.003

[39] Miraei Ashtiani, S. H., Javanmardi, S., Jahanbanifard, M., Martynenko, A., & Verbeek, F. J. (2021). Detection of mulberry ripeness stages using deep learning models. IEEE Access, 9, 100380–100394. https://doi.org/10.1109/ACCESS.2021.3096550

[40] Zhao, H., Xu, D., Lawal, O., & Zhang, S. (2021). Muskmelon Maturity Stage Classification Model Based on CNN. Journal of Robotics, 2021. https://doi.org/10.1155/2021/8828340

[41] Mahmood, A., Singh, S. K., & Tiwari, A. K. (2022). Pre-trained deep learning-based classification of jujube fruits according to their maturity level. Neural Computing and Applications, 34(16), 13925–13935. https://doi.org/10.1007/s00521-022-07213-5

[42] Thompson, A., Walker, A., Rodriguez, C., Silva, D., & Castro, J. Machine Learning Approaches for Sentiment Analysis in Social Media. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/153

[43] Miragaia, R., Chávez, F., Díaz, J., Vivas, A., Prieto, M. H., & Moñino, M. J. (2021). Plum Ripeness Analysis in Real Environments Using Deep Learning with Convolutional Neural Networks. Agronomy, 11(11). https://doi.org/10.3390/agronomy

[44] Team, K. (n.d.-b). Keras documentation: Optimizers. Keras. https://keras.io/api/optimizers/