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INTEGRATION OF MACHINE LEARNING TECHNIQUES IN DETERMINING TOMATO RIPENESS: A LITERATURE REVIEW

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Abstract—**The maturity of tomatoes is an important factor in determining crop quality and marketability. This article emphasizes the transformative potential of machine learning algorithms in determining the ripeness of tomatoes. The present paper builds upon a previous publication, to identify the most significant methods for enhancing the assessment of tomato ripeness. These developments have shown significant increases in both accuracy and speed, providing the framework for more significant growth in the future. By fully harnessing machine learning approaches, this review can facilitate future research endeavors in the field, addressing the challenges posed by agricultural sustainability and food security.**

Keywords—**Algorithm, Speed and Accuracy, Image Classifier, ML Techniques**

I. INTRODUCTION

The Philippines predominantly functions as an agrarian society, where a significant proportion of the Filipino population resides in rural regions and sustains their livelihood through agricultural pursuits. Tomato cultivation holds considerable significance within the nation, boasting a substantial yield. The evaluation of tomato ripeness serves as a crucial element in assessing the overall quality, as consumers rely on ripeness as a determining factor for the freshness and quality of the fruit [1].

The measurement of tomato maturity is critical in determining the crop's quality and marketability [2]. Now, machine learning algorithms may be used to estimate the amount of tomato maturity by taking into consideration parameters such as color, size, and surface flaws [3]. Researchers have successfully constructed algorithms that can automatically identify tomatoes based on their freshness, color, size, and surface flaws using machine vision. These systems, which depend on machine learning and neural networks, can evaluate camera pictures and properly identify tomatoes into several maturity categories [4].

The utilization of machine learning techniques in determining the ripeness of tomatoes gives a reliable and efficient approach for farmers, distributors, and consumers to appraise the quality of tomatoes before harvesting, during the sorting and packaging process, and when making purchasing decisions. Several research studies have demonstrated that the implementation of machine learning methods in commercial settings for assessing tomato ripeness has been supported by empirical evidence, resulting in significant levels of accuracy in ripeness detection. By accurately identifying and classifying the ripeness of tomatoes, machine learning methodologies offer valuable insights for the tomato industry, enabling the optimization of harvesting procedures, the reduction of waste, and the assurance that only fully ripe tomatoes are provided to consumers [4].

II.FUNDAMENTALS OF TOMATO RIPENESS DETERMINATION

A. Traditional Methods –

1. Visual inspection

The assessment of tomato ripeness holds significant importance within the agricultural industry, as it allows farmers and retailers to determine the optimal time for harvesting and selling tomatoes to consumers [6]. Ensuring precise evaluation of tomato ripeness guarantees that tomatoes are collected at their prime state in terms of both flavor and nutritional value, resulting in heightened customer satisfaction and increased market demand. Several techniques and methods have been proposed and utilized to achieve an accurate assessment of tomato ripeness [5]. One commonly utilized technique involves the manual evaluation of tomato ripeness by human operators, who rely on visual indicators such as color, firmness, and overall appearance [6]. This approach heavily depends on the expertise and knowledge of human operators in determining the level of ripeness and has been extensively employed for many years due to its cost-effectiveness and absence of specialized equipment requirements.

2. Colorimetric approach

The conventional approach of evaluating the ripeness of tomatoes by employing color charts and a colorimeter presents certain limitations due to its reliance on lighting conditions. This reliance on lighting conditions can result in fluctuations in the assessment of tomato ripeness. For instance, if the lighting conditions are not uniform or standardized, it can impact the perception and quantification of color, thereby making it challenging to precisely determine the ripeness of tomatoes. Moreover, disparities in lighting can also influence the functionality of colorimeters and their capacity to accurately measure color [7].

B. **Introduction to Machine Learning –**

Machine learning is a potent subfield within the realm of artificial intelligence that is dedicated to the creation of algorithms and models with the ability to scrutinize data, detect patterns, and generate predictions or decisions based on said analysis [8]. This field possesses the potential to profoundly transform numerous industries, including agriculture. In particular, machine learning can automate the assessment of tomato ripeness. Traditional methods of gauging tomato ripeness rely on manual inspection, which can be time-consuming and susceptible to human error. Machine learning algorithms can be trained to identify ripe tomatoes by thoroughly examining attributes such as color, shape, texture, and size. Through the utilization of sophisticated techniques like deep learning and neural networks, it becomes feasible to accurately pinpoint individual tomatoes and automatically assess their ripeness. This not only simplifies the harvesting process but also enhances recognition accuracy, thereby enhancing efficiency and productivity within the agricultural sector [9]. Moreover, machine learning can be further harnessed for tomato classification, paving the way for its integration into commercial applications and bolstering overall crop management. By employing machine learning algorithms, tomato ripeness can be automatically ascertained through the analysis of various factors, including color, shape, texture, and size [10]

III. MACHINE LEARNING TECHNIQUES FOR TOMATO RIPENESS DETECTION

A. **Image Processing and Computer Vision**

Image processing and computer vision algorithms have been utilized in several studies to analyze the visual characteristics of tomatoes for ripeness assessment. These studies aim to provide accurate, precise, and fast methods for determining tomato ripeness levels.

Table 1 - Related studies for image processing and computer vision

Lead Author and Year	Title	Databases searched	Total studies included	Image processing and computer vision algorithm	Findings
Madhavi, K 2023	Review on Tomato Ripe Detection and Segmentation Using Deep Learning Models for Sustainable Agricultural Development[11]	E3S Web of Conferences	22	EfficientNet B3 model	This examination discovered that the EfficientNet B3 architecture exhibited superior performance compared to frequently employed architectures such as VGG and ResNet [11].

Zuo, H 2022	Analysis and Detection of Tomatoes Quality UsingMachine Learning Algorithm and Image Processing[12]	Research Square	48	MATH LAB software algorithm	The present study employs the MATH LAB software algorithm to carry out the process of classification and shows that deep learning has the potential to be more efficient in real-time processing [12].
Appe, S 2023	CAM-YOLO: tomato detection and classification based on improved YOLOv5 using combining attention mechanism[13]	PeerJ Computer Science	26	YOLOv5	The CAM-YOLO algorithm, as suggested, attained an average precision of 88.1% when employed to detect tomatoes that are both overlapped and small [13].
Garcia, M 2019	Tomayto, Tomahto: A Machine Learning Approach for Tomato Ripening Stage Identification Using Pixel-Based Color Image Classification[14]	IEEE Xplore	44	Support Vector Machine (SVM) classifier and CIELab color space via a machine learning approach.	The average accuracy of 83.39% was attained by using a machine learning strategy that used SVM and the L*a*b color space to identify the ripeness maturity of tomatoes based on pixel color [14].
Siddiquee, K 2020	Detection, quantification, and classification of ripened tomatoes: a comparative analysis of image processing and machine learning[16]	IET Image Processing	29	Cascaded Object Detector(COD)	Comparing machine learning and traditional methods. The machine learning method was found to be much more accurate as it uses HOG methods of detection and mean RGB values are calculated [16].
Appe, S 2023	Tomato Ripeness Detection and Classification using VGG-based CNN Models[17]	International Journal of Intelligent Systems and Applications in Engineering	30	VGG-based CNN Models	Tomatoes are detected and classified using VGG-based Convolutional Neural Network (CNN) models. Fine-tuning is used to improve the efficacy of tomato ripeness detection and categorization using the transfer learning approach [17].

Wang, C 2023	A Lightweight Cherry Tomato Maturity Real-Time Detection Algorithm Based on Improved YOLOV5n[18]	Agronomy	49	YOLO V5n	The revised model outperformed the prior version after strengthening the current YOLOv5n model for recognizing and classifying the ripeness of cherry tomatoes. The suggested I-YOLOv5n model outperformed in terms of accuracy, precision, recall, and F1 score. It also outperformed the prior model in terms of detection speed [18].
Wu, J 2019	Automatic Recognition of Ripening Tomatoes by Combining Multi-Feature Fusion with a Bi-Layer Classification Strategy for Harvesting Robots[19]	Sensors	55	relevance vector machine (RVM) classifier	The authors advocated using numerous tomato fruit properties to improve the accuracy of the proposed model. They suggest combining different feature fusion approaches and using a bi-layer classification algorithm designed specifically for harvesting robots [19].
Wan, P 2018	A methodology for fresh tomato maturity detection using computer vision[20]	Computers and Electronics in Agriculture	48	back propagation neural network (BPNN) classification technique	Based on color signals indicative of ripeness, the back propagation neural network (BPNN) correctly recognized and sorted Roma and Pear tomato kinds. This approach yielded an excellent 99.31% accuracy rate [20].
Lawal, O 2021	Development of a tomato detection model for the robotic platform using deep learning[21]	Multimedia Tools and Applications	48	YOLOv3	The incorporation of spatial pyramid pooling, feature pyramid network, CIoU loss, and Mish activation function within a DenseNet backbone for the YOLODenseNet model, as well as the inclusion of DarkNet for the YOLOMixNet model, resulted in significant performance improvements. The later suggested model displayed remarkable accuracy, speed, and the ability to be used in real-time harvesting robots [21].
Su, F 2022	Tomato Maturity Classification Based on SE-YOLOv3-MobileNetV1 Network under Nature Greenhouse Environment[22]	Agronomy	35	YOLOv3 model detection algorithm with a supporting backbone from MobileNetV1	The proposed model, which combines the YOLOv3 recognition algorithm with MobileNetV1 as its backbone, was trained using 460 photos of tomatoes at various stages of maturity. The results demonstrate the model's ability to accurately recognize and classify tomatoes [22].

Li, R 2023	Tomato Maturity Recognition Model Based on Improved YOLOv5 in Greenhouse[23]	Agronomy	48	YOLOv5	The model achieved an amazing accuracy rate of 97.42% after applying the YOLOv5 model and training it on a dataset including 6000 photos depicting various maturity stages of tomatoes. This precision outperforms that of other models such as YOLOv3 and RCNN. Furthermore, the model is faster, taking just 9.2 milliseconds to assess each picture [23].
Liu, G 2019	A Mature-Tomato Detection Algorithm Using Machine Learning and Color Analysis[24]	Sensors	30	Machine (SVM) classifier	A Support Vector Machine (SVM) classifier is trained using a method for identifying tomato ripeness using histograms of gradient (HOG) information. This technique was tested on a large dataset that included photos of tomatoes with different backgrounds, including ones with leaves and stems. The algorithm achieved a 90% recall rate and a 94.41% accuracy rate [24].
Hernandez, G 2023	Detection of Tomato Ripening Stages using YOLOv3-tiny[25]	arXiv	25	YOLOv3	The system prioritizes accurate tomato ripening evaluation by utilizing YOLOv3-tiny's simplified deep learning framework. The system got a stunning 90% F1 score through thorough parameter tuning, indicating its efficiency in both pinpoint localization and stage categorization of tomatoes in the bespoke dataset [25].

de Luna R 2020	Tomato Growth Stage Monitoring for Smart Farm Using Deep Transfer Learning with Machine Learning-based Maturity Grading[26]	AGRIVITA Journal of Agricultural Sciences	24	Artificial Neural Network (ANN), K-Nearest Neighbors (KNN) and Support Vector Machines (SVM)	Tomato fruit maturity was predicted using SVM, ANN, and KNN. Testing accuracy rates for SVM, KNN, and ANN were found to vary from 93.78% to 99.32%, 91.33% to 99.9981%, and 93.78% to 99.9981%, respectively [26].
Ruparelia R. 2022	Real-Time Tomato Detection, Classification, and Counting System Using Deep Learning and Embedded Systems[27]	Springer Link	22	Yolo V3, V2, NVIDIA Jetson TX1, for real-time testing	YOLOv4 achieved high mean average precision, indicating accurate detection and classification of tomatoes. Revealed the effectiveness of the proposed system in real-time tomato detection and classification [27].

Kumar D. 2020	The design of disease prediction method based on whale optimization employed an artificial neural network in tomato fruits[33]	Science Direct	25	Whale Optimization Based Artificial Neural Network (WOANN)	Compared to conventional methods, the proposed method was shown in this paper to accurately predict tomato disease more effectively than Probabilistic Neural Networks (PNNs), K-Nearest Neighbour Networks (K-NNs), and Back-Propagation Artificial Neural Networks (BPANN) [33].
Hu C. 2019	Automatic Detection of Single Ripe Tomato on Plant Combining Faster R-CNN and Intuitionistic Fuzzy Set [37]	IEEE	41	Faster R-CNN detector	The proposed method achieves high accuracy in detecting ripe tomatoes on plants, replacing manual labor with a robotic vision-based harvesting system [37].
Mutha S. 2021	Maturity Detection of Tomatoes Using Deep Learning [38]	Springer Link	17	Yolo V3	The results show that artificial intelligence and robotics can be effectively used in agriculture to automate the detection of diseases and estimate the ripening status of fruits and vegetables [38].

Moreira G. 2022	Benchmark of Deep Learning and a Proposed HSV Colour Space Models for the Detection and Classification of Greenhouse Tomato [39]	Agronomy	66	DL models (SSD MobileNet v2 and YOLOv4)	The YOLOv4 and SSD MobileNet v2 models shown potential in recognizing tomatoes, with the YOLOv4 model earning an F1 Score of 85.81% [39].
Tsironis V. 2020	Tomatod: Evaluation of Object Detection Algorithms on a New Real-World Tomato Dataset[40]	ISPRS	20	RetinaNet, Faster RCNN detector, YoLo v3, and PPN	With a mean average accuracy (mAP) of 74.51, RetinaNet outperformed YoLo v3, PPN, Faster RCNN, and YoLo v3 [40].
Widiyanto S. 2021	Image-Based Tomato Maturity Classification and Detection Using Faster R-CNN Method [41]	IEEE Xplore	9	Faster R-CNN	Tomato maturity levels were classified and detected based on color using the Faster R-CNN approach in the study. During the validation stage, the average classification accuracy was around 98.70% [41].

Pardede J. 2021	Implementation of Transfer Learning Using VGG16 on Fruit Ripeness Detection[42]	MECS Press Journal	39	VGG16	The suggested transfer learning architecture, which combined VGG16 with a Multilayer Perceptron (MLP) block, performed better in the field of fruit ripeness identification than traditional machine learning methods that made use of feature extraction techniques. Compared to the best accuracy of 76% recorded in prior studies, this design demonstrated notable increases in accuracy, reporting gains of 18.42% with Dropout, 10.52% with Batch Normalization, and 2.63% with Regularized kernels [42].
Dineshkumar N. 2023	Design of IoT and Machine Learning based Model for Crop Prediction and Fruit Ripeness Detection[43]	IEEE Xplore	11	Artificial neural network	The paper proposes a system that utilizes information analytics methods and an artificial neural network to predict the most profitable crops based on current environmental conditions, providing a service for wise farming and increasing farmers' productivity [43].
Phan Q. 2023	Classification of Tomato Fruit Using Yolov5 and Convolutional Neural Network Models[44]	Plants	49	YOLOV5m and Yolov5m combined with ResNet50, ResNet-101, and EfficientNet-B0,	Yolov5m and ResNet 101 together produced an astounding 100% prediction accuracy for young tomatoes, demonstrating their synergistic capabilities. Furthermore, Yolov5m and the Efficient B0 model combined to produce a powerful prediction accuracy of 94% for tomatoes with damage. Impressive testing accuracies, ranging from 97% to 98%, were seen for different combinations of the ResNet 50 Efficient Net B0, Yolov5m, and ResNet 101 networks. Notably, high accuracy values of 99.7% and 99.3% were demonstrated by Yolov5m and ResNet 101, respectively [44].

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Pangilinan J. 2022	InceptionV3, ResNet50, and VGG19 Performance Comparison on Tomato Ripeness Classification[36]	IEEE Xplore	21	InceptionV3, ResNet50, VGG19	The VGG19 algorithm outperformed the other tomato categorization algorithms tested, with an accuracy score of 95%. This beat the accuracy of the ResNet50 algorithm (93.33%) and the InceptionV3 approach (91.67%). VGG19 demonstrated its ability to accurately categorize tomatoes, beating its competitors in this specific classification task [36].
Denih A. 2023	Analysis of Tomato Ripeness by Color and Texture Using Cielab and K-Means Clustering[57]	Komputasi	20	Cielab and K-Means Clustering	This paper revealed the accuracy rate of tomato ripeness has an average value of 92.70%. The benefit of this research is that it can save time in classifying tomato ripeness and make it easier to determine tomato ripeness based on color [57].

B. **Spectroscopy and Hyperspectral Imaging**

Spectroscopic techniques and hyperspectral imaging have been used in several studies to capture and analyze tomato ripeness-related spectral data. Fernandez-Rosales et al. investigated the possibility of non-destructive pesticide residue detection on tomatoes using hyperspectral and low-cost imaging technology. They developed classification models based on hyperspectral images acquired by a commercial camera and achieved high accuracy.

Table 2 - Related studies for spectroscopy and hyperspectral imaging

Lead Author and Year	Title	Databases searched	Total studies included	Image processing and computer vision algorithm	Findings
Rosales C. 2022	Tomato pesticide residue detection method based on hyper spectral imaging[28]	IEEE Xplore	19	720 ROIs: support vector classifier (SVC), K nearest neighbor, decision trees and multilayer perceptron (MLP).	With an accuracy of 0.9, the MLP model performed the best for the identification of chlorantraniliprole [28].
Huang Y. 2020	Assessment of Tomato Maturity in Different Layers by Spatially Resolved Spectroscopy[29]	Sensors	20	Support vector machine discriminant analysis (SVMDA) models	With recognition rates for green, breaker, turning, pink, pale red, and red phases of 100%, 94.6%, 97.5%, 100%, and 97.1%, the mean_SR 15 had the best categorization results for tomato maturity

					[29].
Varga L. 2021	Measuring the Ripeness of Fruit with Hyper spectral Imaging and Deep Learning[30]	IEEE Xplore	30	Deep learning and hyper spectral imaging	The system using hyper spectral imaging and deep learning outperformed competitive baseline models in predicting fruit ripeness [30].
Alksnis R. 2023	Non-Destructive Quality Evaluation of 80 Tomato Varieties Using Vis-NIR Spectroscopy[31]	Sensors	46	Vis-NIR reflectance spectra	PLS models demonstrated high prediction accuracy, with a determination coefficient of 0.90 for intact tomato dry matter and lycopene concentration [31].
Fatchurrahman D. 2020	Early discrimination of mature and immature green tomatoes (Solanum lycopersicum L.) using fluorescence imaging method[32]	Science Direct	29	Hyper spectral fluorescence imaging technique with excitation wavelength at 365 nm and UV–vis CCD camera	With a non-error rate of 96% in calibration and 100% in external prediction, a univariate classification algorithm was utilized to differentiate between mature-green and immature-green tomatoes based on the grey scale values derived from fluorescence imaging [32].
Abdulridha J. 2020	Laboratory and UAV-Based Identification and Classification of Tomato Yellow Leaf Curl, Bacterial Spot, and Target Spot Diseases in Tomato Utilizing Hyper spectral Imaging and Machine Learning[34]	Sensors	52	RDVI and MTVI 1	In both laboratory and field circumstances, the renormalized difference vegetation index (RDVI) and the modified triangular vegetation index 1 (MTVI 1) were determined to be the most efficient VIs for diagnosing illnesses [34].
Skolik P. 2019	Determination of developmental and ripening stages of whole tomato fruit using portable infrared spectroscopy and Chemo metrics[45]	Research Gate	54	ATR-FTIR spectroscopy coupled with chemo metrics	Using support vector machine (SVM) chemo metrics, changes in the spectral fingerprint area (1800-900 cm 1) were adequate to detect nine developmental and six ripening phases with good accuracy [45].

Cen Y. 2021	Early Detection of Bacterial Wilt in Tomato with Portable Hyper spectral Spectrometer[46]	Remote sensing	58	(SVM) classifier	The GA-SVM tomato stem model obtained an F1 score of 0.80 and an overall accuracy (OA) of 88.6%, confirming the model's dependability [46].
Borba K. 2021	Portable near Infrared Spectroscopy as a Tool for Fresh Tomato Quality Control Analysis in the Field[47]	Applied Sciences	45	handheld near-infrared spectrometer	Model performance was improved by using a handheld spectrometer equipped with a MEMS-based interferometer and InGaAs detector arrays that take advantage of the unique spectral information in the long-wave NIR (LWNIR) region, outperforming other commercial handheld devices that use the SWNIR region [47].
Abdelhamid M. 2020	Technological Methods of Assessing the Maturity of Tomatoes[48]	eLibrary,ru	12	Spectral, hyper spectral imaging, luminescent, laser, technical vision, and other methods were used for non-destructive assessment of tomato fruit quality.	The luminescent method offers a more comprehensive and reliable approach to assessing tomato maturity, allowing for better optimization of storage conditions, forecasting storage periods, and improving the quality and sorting of tomato fruits [48].
Ramos-Infante S. 2019	Assessment Of Tomato Quality Characteristics Using Vis/Nir Hyper spectral Imaging And Chemo metrics[49]	IEEE Xplore	22	VIS/NIR hyper spectral imaging	The best models for predicting tomato quality attributes were those based on NIR spectra; these models had reasonable predictions for color (RPD > 2.0) and outstanding predictions for SSC, firmness, and pH (RPD > 3.0) [49].
Logan R. 2020	Hyper spectral imaging and machine learning for monitoring produce ripeness[50]	SPIE.DIGITAL LIBRARY	40	visible near-infrared (VNIR) hyper spectral imager from Resonon, Inc.	Results showed that the genetic algorithm-based feature selection method outperforms RGB images [50].

Zhao M. 2023	Determination of quality and maturity of processing tomatoes using near-infrared hyper spectral imaging with interpretable machine learning methods[64]	Science Direct	44	Near-infrared hyperspectral imaging with interpretable machine learning	With a maturity classification accuracy of 96.6%, which was 17% higher than PLS and 40% higher than RF, the RNN performed the best. All quality characteristics were accurately predicted by the regression models, with an R2 of prediction greater than 0.75 [64].
Rosales C. 2022	Tomato pesticide residue detection method based on hyper spectral imaging[28]	IEEE Xplore	19	720 ROIs: support vector classifier (SVC), K nearest neighbor, decision trees and multilayer perceptron (MLP).	The MLP model showed the best performance for chlorantraniliprole detection with an accuracy of 0.9 [28].
Huang Y. 2020	Assessment of Tomato Maturity in Different Layers by Spatially Resolved Spectroscopy[29]	Sensors	20	Support vector machine discriminant analysis (SVMDA) models	The mean SR 15 acquired the optimal classification results for tomato maturity with recognition rates of 100%, 94.6%, 97.5%, 100%, 100%, and 97.1% for green, breaker, turning pink, light red, and red stages [29].

Varga L. 2021	Measuring the Ripeness of Fruit with Hyper spectral Imaging and Deep Learning[30]	IEEE Xplore	30	hyper spectral imaging and deep learning	The system using hyper spectral imaging and deep learning outperformed competitive baseline models in predicting fruit ripeness [30].
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Ramos-Infante S. 2019	Assessment Of Tomato Quality Characteristics Using Vis/Nir Hyper spectral Imagitheng And Chemo metrics [49]	IEEE Xplore	22	VIS/NIR hyper spectral imaging	NIR spectra; these models had reasonable predictions for color (RPD > 2.0) and outstanding predictions for SSC, firmness, and pH (RPD > 3.0) [49].
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IV. PERFORMANCE EVALUATION AND COMPARATIVE ANALYSIS

A. Accuracy and Reliability –

In the context of determining the ripeness of tomatoes, several machine learning models are utilized as exhibited in previous studies.

Three categories include some of the most widely used machine learning models today: semi-supervised, unsupervised, and supervised [35]. In supervised learning, the algorithm learns to attempt to predict the outcome given a set of labeled input data. This method is used by most machine learning algorithms as they develop over time and reach a high degree of performance and accuracy. Classification is one general use case for supervised machine learning; in this case, inferences are made from observed values to identify the category to which subsequent incoming observations belong.

A research conducted by Yamamoto et al. used RGB digital camera photos to train a neural network based on image color, shape, texture, and size classification models to reliably recognize individual tomato fruits, even immature ones [3]. With a high detection accuracy of 96%, Zhao et al. conducted a second research that concentrated on color analysis and used machine learning techniques to identify ripe tomato fruits. Arefi and colleagues also created a novel algorithm that employs a machine vision system to identify tomato maturity, indicating the accuracy and dependability of this method [4]. Additionally, El-Bendary et al conducted research on tomato ripeness and utilized various machine learning techniques to evaluate different stages of tomato ripeness automatically [5]. Furthermore, El-Bendary et al. studied tomato maturity and used a variety of machine learning approaches to automatically assess the various phases of tomato ripeness [5]. These experiments demonstrate how well machine learning models work to reliably identify and categorize tomatoes according to a range of characteristics, including size, color, texture, and shape. These results imply that machine learning algorithms have potential for reliably and precisely assessing tomato maturity based on attributes including size, color, texture, and shape.

B. Comparison with Traditional Methods –

Machine learning over traditional methods offers several advantages in detecting the ripeness of tomatoes. Firstly, such algorithms used in machine learning (i.e., Convolutional Neural Networks (CNNs)) have the ability to accurately classify tomatoes on the basis of its ripeness, even when there is a constraint on the similarity of the images used during the ripening cycle of fruit. Secondly, machine learning can handle the challenges of occlusion, manifested by by the leaves and branches as well as the color similarity between tomatoes and the surrounding foliage of the whole plant system, this was made possible by taking advantage of the advanced techniques like convolutional transformer architectures [51]. In addition to that, machine learning can be subjected to training and testing using carefully labeled images, allowing a robust and reliable means of detection and grading of tomatoes [52]. However, as noted by Pangilinan, Legaspi and Linsangan [36] the methodologies applied in machine learning require an immense amount of labeled data for training, and its performance varies depending on the algorithm utilized.

V. APPLICATIONS AND IMPACT

A. Precision Agriculture

Machine learning-based tomato ripeness detection plays a crucial role in optimizing resource allocation in agriculture. By accurately detecting the ripeness stages of tomatoes, farmers can efficiently allocate resources such as labor, time, and storage facilities. These detection methods utilize advanced techniques such as convolutional neural networks (ConvNets) [8], improved YOLOv5 tomato detection algorithm [16], deep learning with edge contour detection [36], and improved YOLOv3 models [21]. The utilization of machine learning-based methodologies for the categorization and evaluation of tomato ripeness signifies a notable progression in agricultural technology. By incorporating intricate algorithms and data analysis, this approach provides various noteworthy benefits within the domain of quality control and yield optimization in tomato cultivation[33]. Initially, through the utilization of machine learning algorithms, the automated evaluation of tomato ripeness becomes viable. These algorithms are trained on extensive datasets that encompass different stages of tomato ripening, enabling them to discern subtle disparities in color, texture, size, and other significant characteristics indicative of ripeness45]. This meticulous and automated categorization process ensures that only ripe tomatoes are chosen for further processing or distribution, thus augmenting the overall quality of the product. Additionally, the integration of machine learning in ripeness detection reduces the reliance on labor-intensive manual sorting procedures. Historically, human labor was extensively employed to visually inspect and sort tomatoes based on their ripeness. However, this method is not only time-consuming but also prone to errors and inconsistencies. By automating this process, the necessity for labor-intensive sorting diminishes significantly, resulting in heightened operational efficiency and cost-effectiveness for farmers and producers. Moreover, the ramifications of this technological shift extend beyond immediate enhancements in efficiency. The consistent and accurate sorting of ripe tomatoes contributes to diminished waste within the supply chain. By ensuring that only ripe tomatoes are harvested and distributed, the unnecessary discarding of unripe or overripe produce is minimized, thereby optimizing yield and reducing economic losses [19].

B. Supply Chain Management

Accurate ripeness assessment of tomatoes has several implications in streamlining the logistics of the tomato supply chain. One of its implications is that it enables automation of sorting tomatoes through a grading system based on its maturity level, thus reducing processing time and reduction of possible errors [53]. This can lead to a better income to suppliers as it ensures a consistent delivery of quality goods to consumers. Moreover, another implication it provides is its ability to aid in automatic segmentation of tomatoes in systems utilizing conveyor belts and robots for harvesting, which can significantly impact the reduction of food waste generated by certain maturity factors observed during harvest time [54]. Furthermore, tomato ripeness may be precisely classified using machine learning techniques like Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) based on color characteristics, offering a more objective evaluation of the crop [55][14][8]. This has significant implications for improving tomato production efficiency and yield, which will help the agriculture sector.

As a means for reducing food waste, utilizing machine learning has enabled the detection of potential disease damage present in tomatoes, reducing imminent crop loss, further helping in decision-making in picking optimal harvesting time [38]. In addition to that, estimation of tomato ripeness is done through automated means, saving tomatoes from damage and reducing the likelihood of subjective visual assessment errors [13]. Combining different approaches in machine learning such as deep learning and integrating hyperspectral imaging technology can accurately predict certain desirable attributes and maturity levels of tomatoes facilitating a standard for precise grading and quality control of the crop in the agricultural sector [64]. Overall, machine learning-based assessment methods of determining the ripeness of tomatoes offer the potential to further improve in streamlining the supply for the crop through quality control, thereby enhancing the profitability of the crop in the process.

C. Quality Control in Food Industry

Integrating machine learning in tomato ripeness determination has the potential to significantly impact the food sector by maintaining consistent product quality and meeting industry standards. By automating the ripeness evaluation process, machine learning algorithms can ensure optimal production of high-quality tomatoes, increasing profitability [13]. Deep learning algorithms, such as YOLOv5 and YOLOv3, have been proposed for tomato quality analysis, achieving high precision and accuracy in identifying good and rotten tomatoes [56]. Additionally, deep learning frameworks like Yolov5m combined with ResNet-101 have shown promise in classifying tomatoes into ripe, immature, and damaged categories, with high prediction accuracy. Moreover, tomato ripeness has been successfully identified by Convolutional Neural Network algorithms such as InceptionV3, ResNet50, and VGG19, with VGG19 obtaining the best accuracy score of 95%. These developments in machine learning-based tomato ripeness assessment have the potential to improve quality assurance procedures, boost output effectiveness, and eventually satisfy the needs of the food sector [44].

CASE STUDIES AND REAL-WORLD IMPLEMENTATIONS

D. Successful Applications

There are several effective implementations of machine learning-based tomato ripeness detection where different machine learning algorithms are used in conjunction with other ripeness detection techniques. Garcia [14] identified tomato ripeness with an accuracy of 83.99% using a Support Vector Machine (SVM) classifier and CIELab color space. Three Convolutional Neural Network algorithms—InceptionV3, ResNet50, and VGG19—are evaluated against one another in a different study to see which is more accurate in determining the tomato maturity classification. According to the same study, the VGG19 algorithm scored 95% accuracy, which was higher than ResNet50's 93.33% and InceptionV3's 91.67% [36]. In a different study, it was suggested to categorize tomatoes into three categories utilizing four deep learning frameworks, such as YOLOv5m in combination with ResNet-101, ripe, immature, and damaged. For both ripe and immature tomatoes, this framework produced forecast accuracy scores of 100%, while for damaged tomatoes, it obtained 94%. Furthermore, a deep learning-based tomato maturity grading system outperformed previous approaches, achieving an average of 99.8% in tomato maturity level classification [44].

In the context of CNN-based models, a Transformer-based mask R-CNN model using Swin Transformer as the backbone network was presented in order to precisely identify and classify tomato cultivars and their maturity. The model achieved 89.4% mean average precision (mAP) for detection and 89.2% for segmentation [70]. Analogously, a tomato-detection model was created utilizing faster R-CNN in conjunction with Resnet-101, and it attained an impressive 87.83% benchmark precision [71]. However, a better YOLOv4-tiny model with a mAP of 82.8% and a precision of 96.3% was suggested for tomato identification [71]. Similarly, to recognize tomatoes, the YOLOv4 basic model was coupled with MobileNet v2, using a suggested histogram-based HSV color space mode. The suggested combined model obtained a macro F1-Score of 74.16% for classification and an F1 score of 85.81% for detection [39].

E. Lessons Learned

Deploying machine learning in detecting the ripeness of tomatoes is also marred with challenges. Such challenges include occlusion caused by leaves and branches, as well as the similarity in color between the tomato itself and the surrounding foliage of the whole plant system during the tomato's developmental stages [51]. In addition to that, complications in the environmental conditions of the whole plant system such as uneven illumination, overlapping between the tomato fruits, and clustering are also noted as challenges in implementing machine learning in the detection of the ripeness of tomatoes [8][70][79]. Such conditions make it difficult to deploy machine learning into the commercial application of training robots for the manual labor of detecting and classifying the ripeness of tomatoes [21]. To address the issues that arise while utilizing machine learning, scholars have suggested many enhancements to current models. These enhancements include the use of improved backbone networks to enhance feature extraction and lessen the laborious work of complex computations, the application of spatial pyramid pooling and feature pyramid networks to improve detection accuracy, the implementation of attention mechanisms to further enhance feature expression ability, and the introduction of circle representation to optimize the tomato detector [18][21][79].

Improving machine learning algorithms' capacity to discern various phases of a crop's maturity has been investigated in other crops where color is the primary foundation for its stage of ripeness. Because of its capacity to handle multimodal data such as RGB and hyperspectral imaging systems, deep convolutional neural networks (CNNs) are one of several techniques to further enhancing current machine learning models [80]. Alternatively, the random forest technique may be used, which is ideal for the highly changeable domain of agricultural applications because to its robustness and efficiency in calculations [81]. In order to further enhance the performance of current machine learning models, support vector machines (SVMs) and multiple linear regression (MLR) models are also recommended for use. These models demonstrate promising results in determining the crop's maturity stage by capturing multiple wavelengths and texture features [82]. In order to achieve high accuracy in maturity classification, transfer learning strategy employing pre-trained models like VGG19 has been proven beneficial [83]. Additionally, tomato ripeness detection by machine learning may be further enhanced by combining methods used for other crops.

VI. FUTURE DIRECTIONS

A. Advancements in Machine Learning Techniques

The recent strides in machine learning algorithms have demonstrated significant potential in transforming the evaluation of tomato ripeness. These developments have presented noteworthy enhancements in both accuracy and speed, paving the way for even more substantial improvements in the years to come.

In the year 2023, Li et al. introduced YOLOv5s-tomato, a model for identifying tomato maturity based on an upgraded version of YOLOv5. This model achieved a precision rate of 95.58% and a mean Average Precision (mAP) of 97.42% [23].

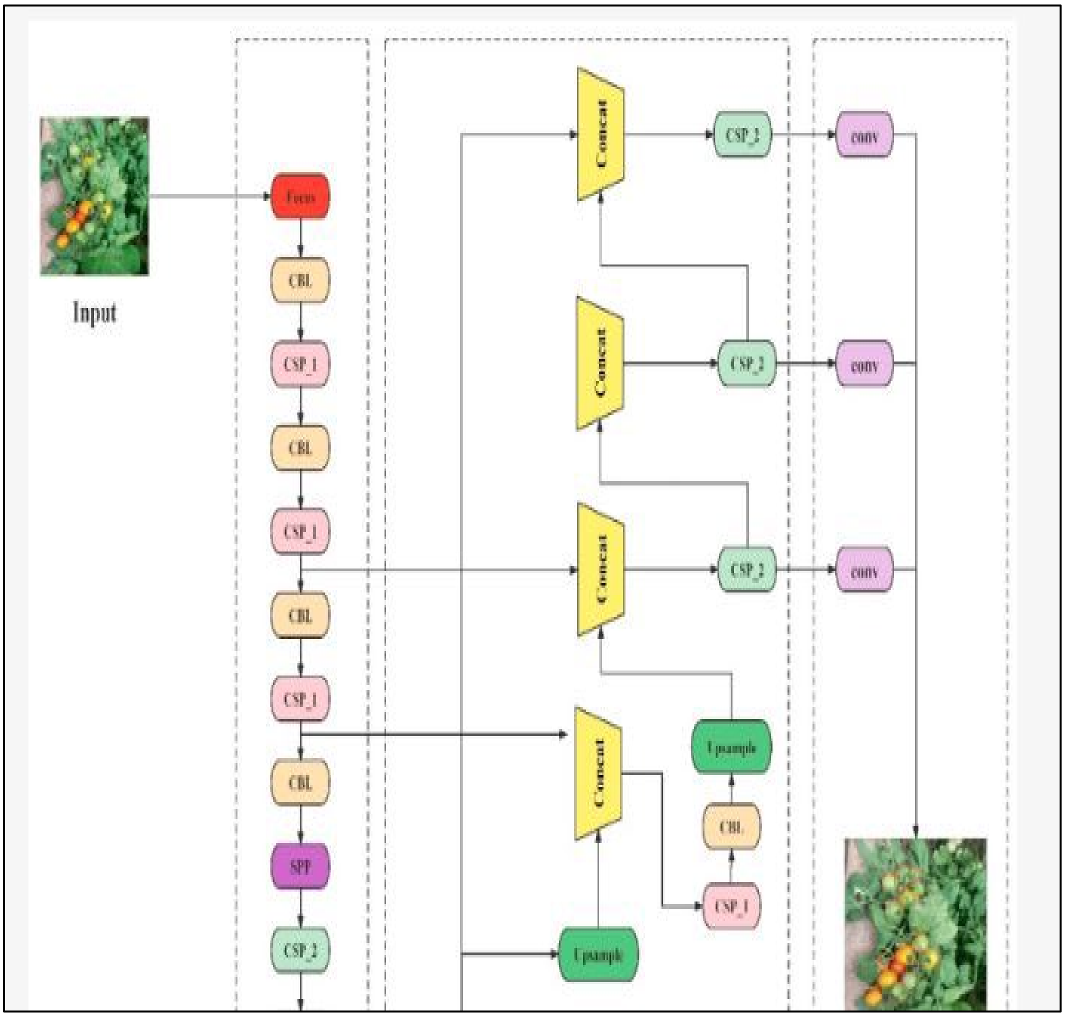

Figure 1. Li et al. YOLOv5 network model structure diagram

In this present document, the Yolov5 algorithm inhibits the network structure and training procedures of the Yolov3 algorithm. Remarkably, it attains a detection performance that is equivalent to Yolov4 while significantly reducing the model size by approximately 90%. The Yolov5 is made up of four different network structures, specifically Yolov5s, YoloV5m, YoloV5l, and Yolov5x. Among these, Yolov5s possesses the smallest network structure, highest speed, and least accuracy. In contrast, the other three networks delve deeper and expand the network, resulting in higher accuracy but slower speed. The complete network structure of the Yolov5s target detection algorithm is visually depicted in Figure 1. Yolov5s encompasses four fundamental components: input, backbone, neck, and prediction [23].

In the year 2023, Ifmalinda et al. developed an Android-based application using image processing methods to accurately determine the ripeness level of tomatoes, with validation coefficients of determination and correlation values ranging from 0.9978 to 0.9999 [5].

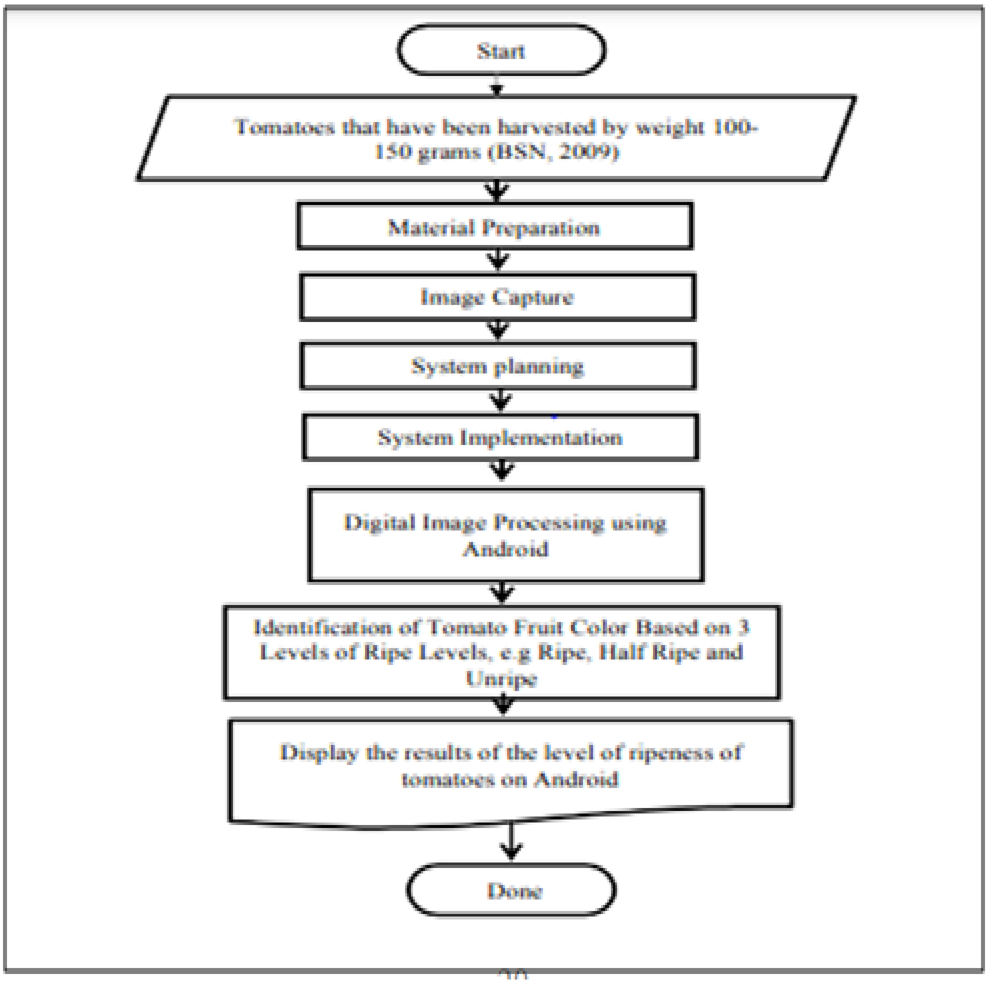

Figure 2. Ifmalinda et al. Flowchart of Determination of Ripeness in Tomato Fruit

The investigation utilizes digital image processing techniques to ascertain the tomato's maturity stages by analyzing the skin color. With Unity 3D software and the C# programming language, tomato maturity levels were detected. Ifmalinda together with others. To specify the range of values for various tomato maturity groups, the HSV (Hue, Saturation, Value) color system was utilized. Based on the tomatoes' skin color, the range of HSV values for ripe, semi-ripe, and unripe Ko et al. present SDF-ConvNets, a method for determining tomato freshness that uses their stochastic decision fusion (SDF) methodology in conjunction with multiple streams of convolutional neural networks (ConvNets). The method starts with a deep learning-based tomato ripeness detection stage and generates the final classification result by fusing the original results with stochastic decision making. Furthermore, a tomatoes was determined. Coefficient of determination (Lab) values and correlation values were obtained from the experiment using a chromameter and digital photos to assess the accuracy of the identification process [5].

In the year 2021, Ko et al. proposed the SDF-ConvNets method, which utilized multiple streams of ConvNet and stochastic decision fusion to detect tomato ripeness with an average accuracy of 96% [8].

comprehensive image dataset of 2712 tomato samples was assembled to validate and hone the suggested methodology, with five-fold cross-validation being utilized for evaluation. The classifier's algorithm is shown in Figure 3. The findings showed that 96% of tomato samples could be correctly identified as belonging to one of the five ripeness phases.

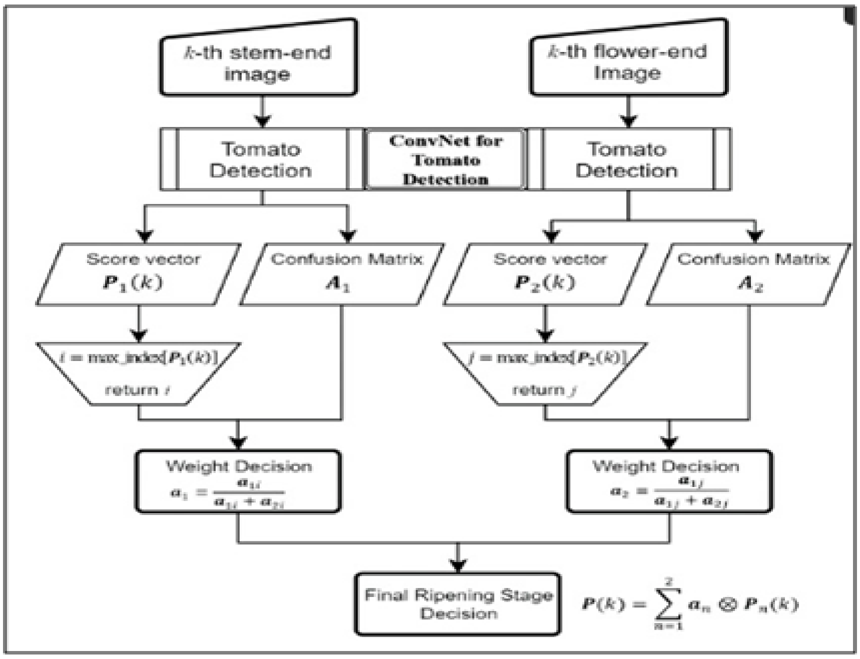

Figure 3. Ko et al. Flowchart of the proposed stochastic decision fusion algorithm

In the year 2019, Wu et al. deploy a relevance vector machine (RVM) classifier and a bi-layer classification strategy method to recognize ripening tomatoes. This innovative approach exhibited 94.90% detection accuracy [19].

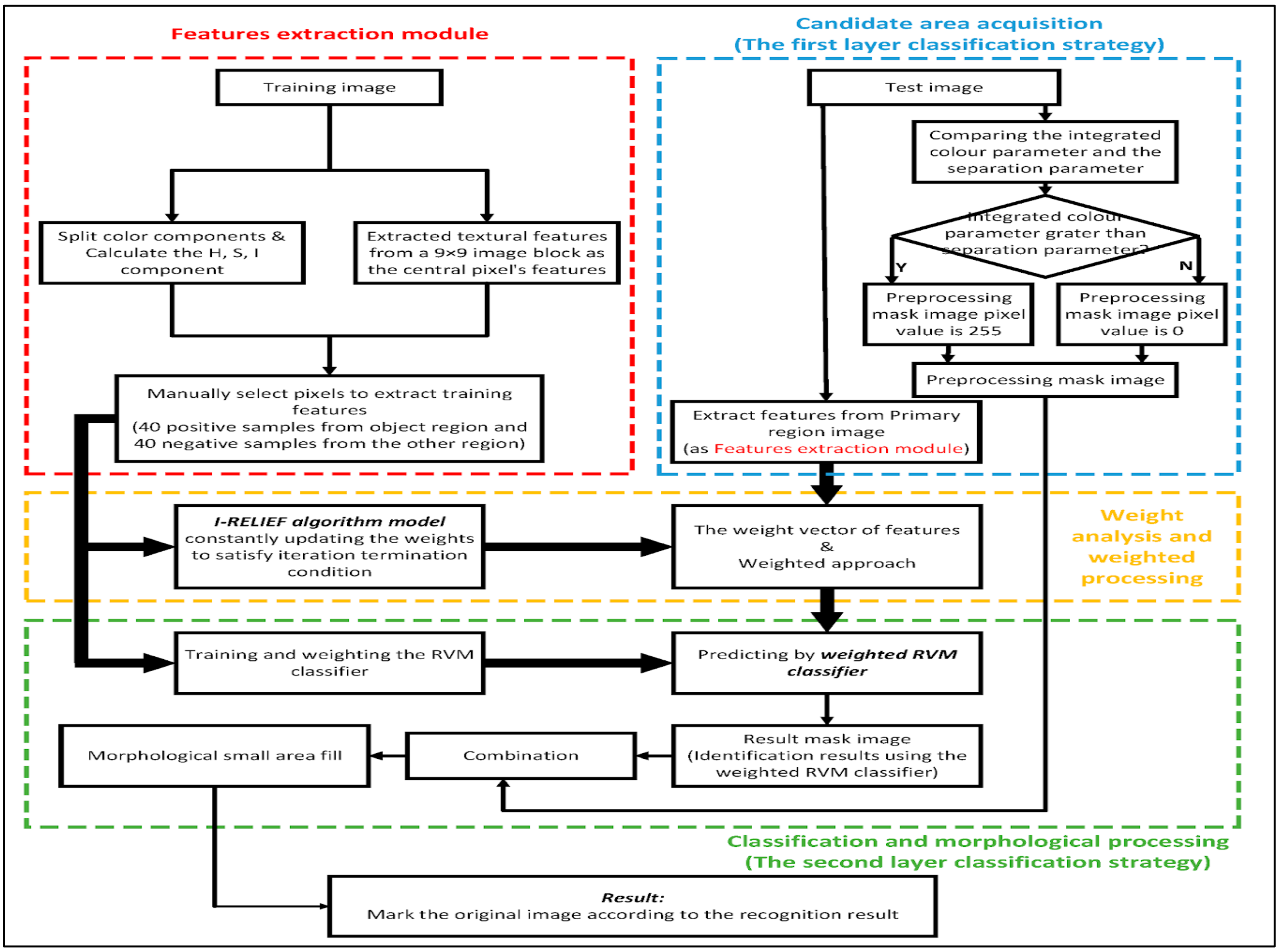

Figure 2. Wu et al. Flowchart of the algorithm for automatic recognition of ripening tomatoes

A weighted RVM classifier was used in this experiment to identify picture areas containing tomatoes based on attributes collected from target regions in training set images. Using the iterative RELIEF technique, the features were allocated real-valued weights, and these weighted features were then employed in the RVM classifiers to increase the accuracy of the findings. The system employs a two-layer technique, with the first layer attempting to detect tomato-containing patches in pictures using color difference information and the second layer relying on a classifier trained on multi-medium characteristics, as illustrated in Figure 4. The photos are subsequently processed by the second layer, which separates them into 9x9 pixel blocks, which are the fundamental units in the classification job, boosting computation simplicity and recognition performance. To increase classification accuracy, six color-related characteristics (Red, Green, Blue, Hue, Saturation, and Intensity components) and five textural features (entropy, energy, correlation, inertial moment, and local smoothing) were extracted from pixel blocks.

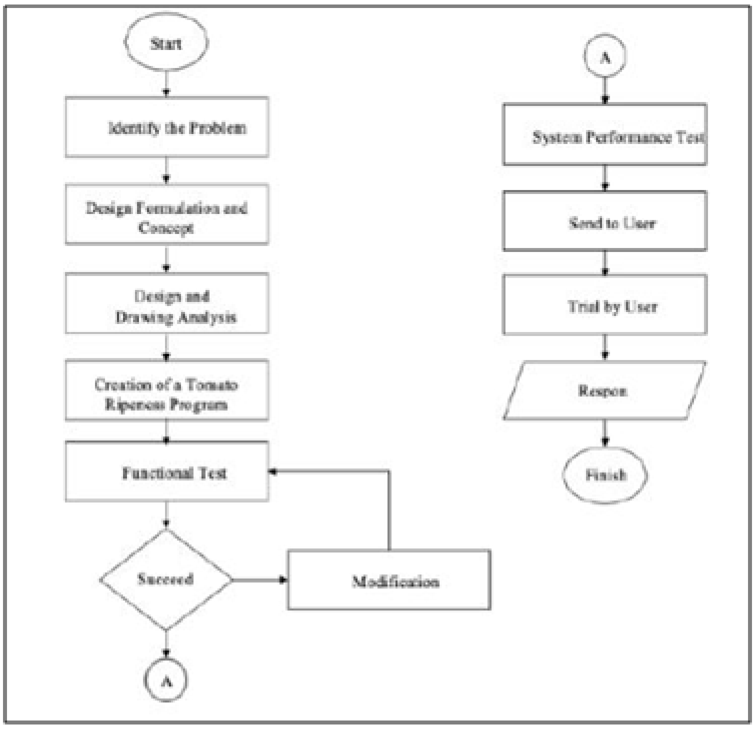

Figure 5. Denih et al, Algorithm flow chart

In the year 2023, Denih et al. created a tomato maturity level analysis system based on color and texture, employing CIELAB and K-Means clustering to accurately and properly evaluate tomato maturity. This method provided a tomato maturity value accuracy rate of 92.70% [57].

An analysis of tomato ripeness will be performed using MATLAB with light intensity using a 5-WATT LED lamp so that the light results are not too bright or dim when photographing a tomato, the accuracy of the level of tomato ripeness can reach above 90%, and 5 RGB images will be used. The framework's five key steps are depicted in Figure 4 in the following order: issue identification, design formulation and concept, design and drawing analysis, tomato maturity program creation, and functional test. In the system performance test, which is known as training data, a maturity test of tomatoes known to be unripe and ripe as much as 3 each was done. Then, 6 tomatoes were evaluated for ripeness, which was not known to be ripe or ripe, and this is referred to as the test data. The accuracy calculation is used to assess the system's validity. CIELAB images, binary images, grayscale images, and segmented images are all available.

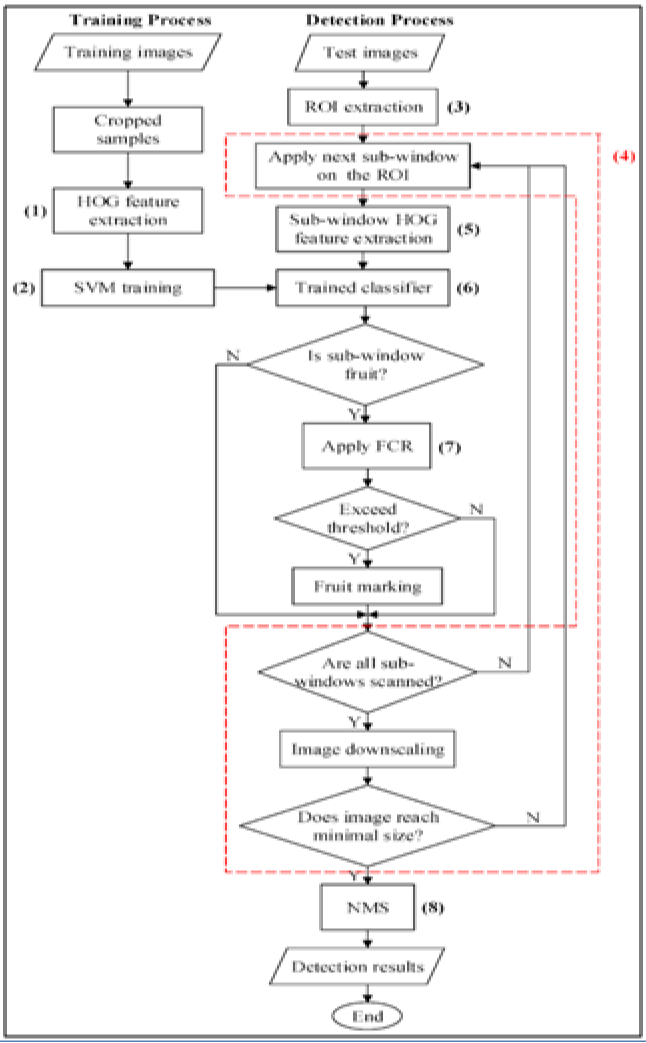

Figure 3. Liu et al. Algorithm flow chart

Liu et al. trained a Support Vector Machine (SVM) classifier in 2019 with a Histograms of Oriented Gradients (HOG) descriptor. To identify tomatoes, a coarse-to-fine scanning strategy was developed, and False Color Removal (FCR) was proposed as a means of removing false-positive detections. Non-Maximum Suppression was used to combine the results (NMS). Using this strategy, the classifier's accuracy was 90.00%, 94.41, and 92.15% [24].

In order to lessen the effects of lighting and occlusion, Liu et al. provide an automated tomato detection method in normal color photographs in this experiment. The strategy uses the Histograms of Oriented Gradients (HOG) descriptor to train a Support Vector Machine (SVM) classifier. A coarse-to-fine scanning strategy is developed for tomato identification, and then False Color Removal (FCR) is applied to remove false-positive detections. The recommended methodology greatly enhances tomato identification as compared to current methods. Using test pictures, the proposed method achieves 90.00% recall, 94.41% accuracy, and 92.15% F1 score in tomato detection.

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Phan et al. (2023) presented four deep learning frameworks for tomato fruit classification, namely Yolov5m and Yolov5m in combination with ResNet-50, ResNet-101, and EfficientNet-B0, respectively.

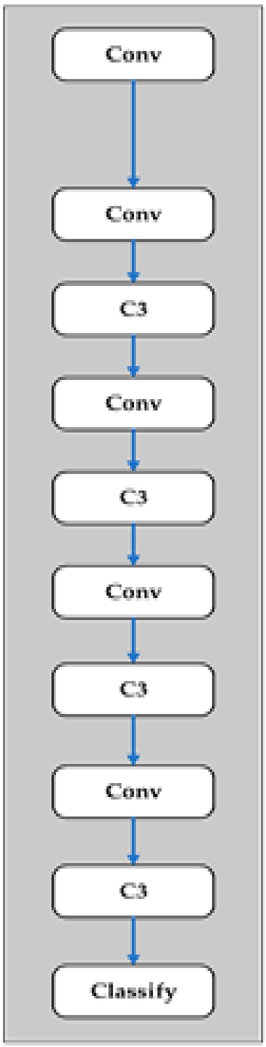

Figure 4. Figure 7. Phan et al. Backbone structure of Yolov5m model

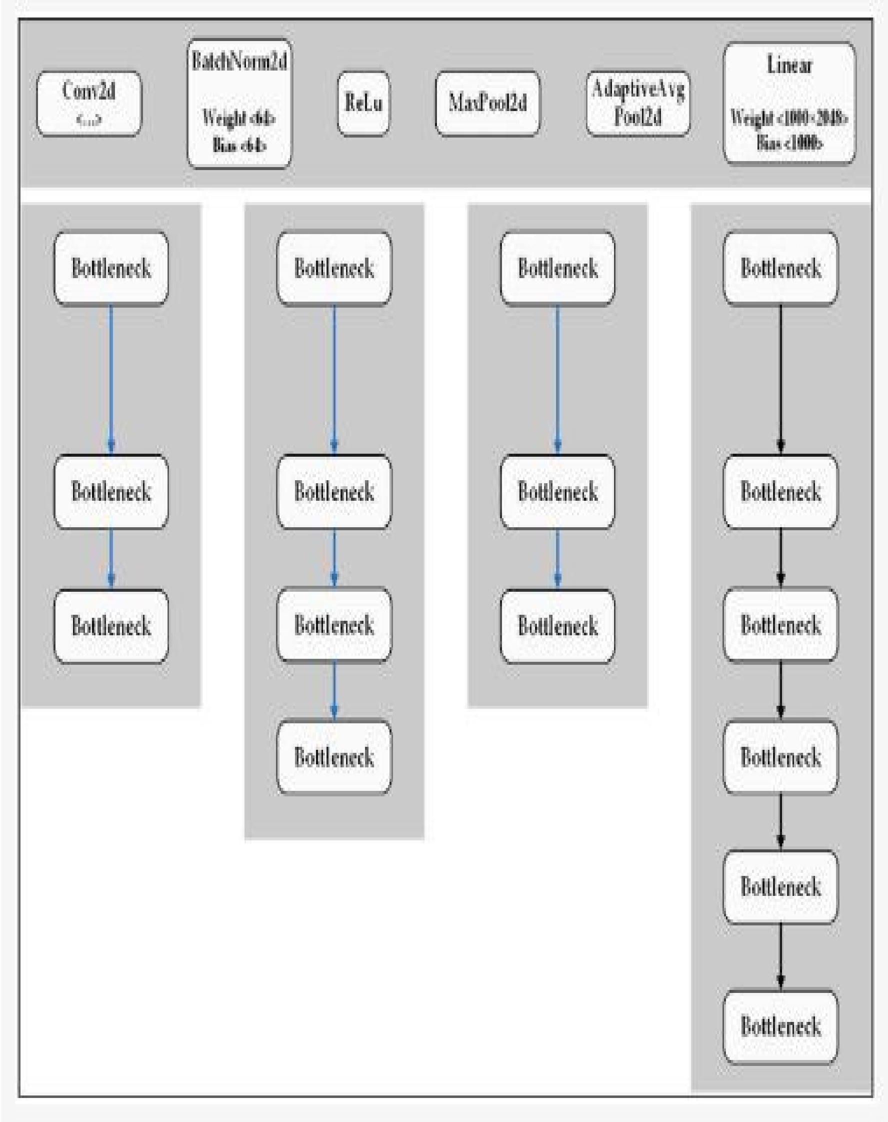

Figure 5. Phan et al. Structure of ResNet-50 model.

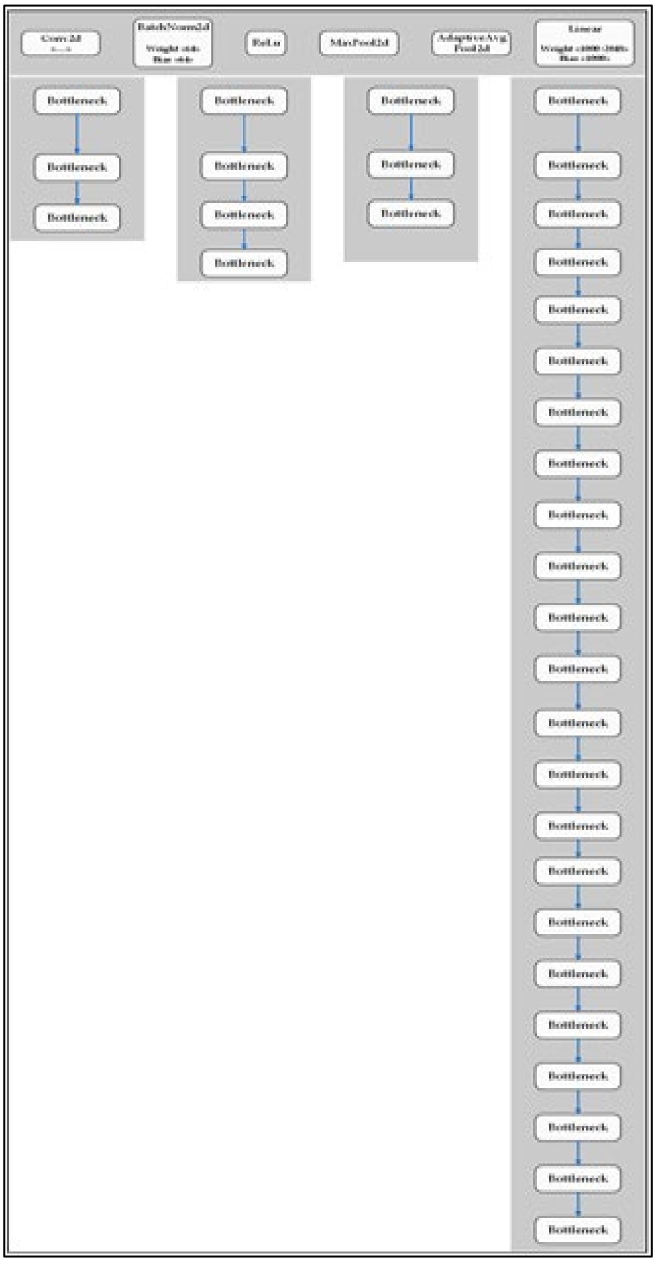

Figure 7. Phan et al. Structure of ResNet-101 model

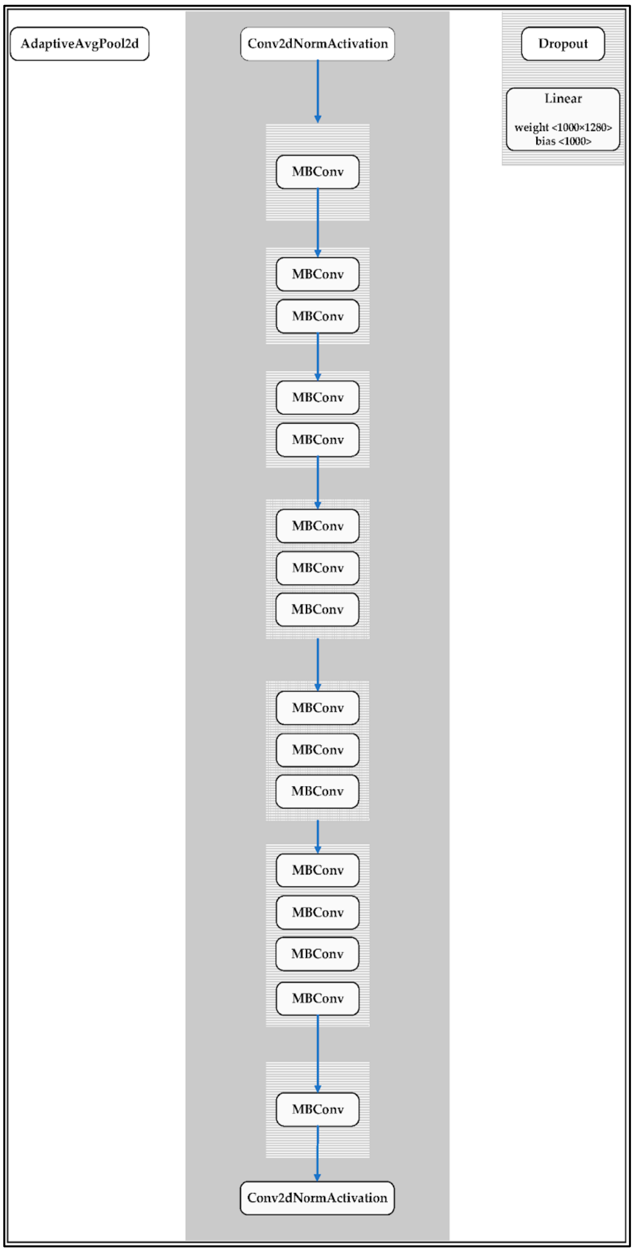

Figure 6. Phan et al. Structure of EfficientNet-B0.

In this experiment, the Yolov5m and ResNet-101 combo was able to predict ripe and immature tomatoes with 100% accuracy. Yolov5m and the Efficient-B0 model together provide a 94% prediction accuracy for damaged tomatoes. It was discovered that the accuracy of the ResNet-50, EfficientNet-B0, Yolov5m, and ResNet-101 networks was 98%, 98%, 97%, and 97%, respectively.

B. Integration with IoT and Smart Farming

Real-time monitoring and automated crop management may be made possible by fusing machine learning-based ripeness detection with IoT and smart farming techniques. Farmers may improve crop output and minimize waste by using machine learning algorithms and Internet of Things (IoT) sensors to make well-informed decisions on crop planting, watering, and harvesting [58]. By boosting crop yields and reducing waste, the combination of these technologies has the potential to completely change current agriculture [43]. Kumar et al. and as well as Pareek et al. Both stress the relevance of IoT in delivering real-time data for environmental monitoring and illness detection [59][60], whereas Maduranga et al. and as well as Vitali et al. et al. emphasize the potential of machine learning in data analysis and processing to boost productivity [61][62]. Tahir et al.present a unique framework called Intelli-farm that combines IoT and ML to identify the demand for water in a specific farm with an average accuracy of 93.87%, indicating a greater possibility of integrating ML and IoT for detecting tomato ripening in a real-time setting [63]. By combining machine learning-based ripeness detection with IoT and smart farming methods, agriculture may be revolutionized by enabling real-time monitoring, automated crop management, and efficient resource allocation.

C. Industry Collaboration and Adoption

Collaboration among researchers, technology developers, and agricultural sector stakeholders is critical for accelerating the deployment of enhanced ripeness-detecting methods. This partnership enables the creation of innovations that address the genuine requirements of the agricultural industry and the area, therefore making their influence evident and producing a spillover effect among laggard adopters [65]. Armenta-Medina et. al emphasizes the increase in publications on sophisticated information and communication technology in agriculture, emphasizing the importance of collaboration in driving this expansion [69]. Researchers may give essential insights and experience in establishing accurate and reliable ripeness detection methods by collaborating, while technology developers can provide user-friendly and practical solutions for farmers [66]. Collaboration with agricultural sector stakeholders, such as farmers and industry groups, ensures that innovations are matched with the aims and priorities of the industry, boosting the possibility of adoption [67]. This collaborative approach also allows for the exchange of information, experiences, and best practices, allowing the widespread use of ripeness detecting devices in agriculture [68]. Therefore, the synergy between researchers, technology developers, and agricultural industry stakeholders is vital for driving the successful adoption of advanced ripeness detection technologies in agriculture.

VII. CONCLUSION

A. Summary of Key Findings

Machine learning approaches for evaluating tomato maturity have evolved, highlighting intriguing areas. **Phan et al., (2023)** used deep learning frameworks to incorporate Yolov5m, ResNet-50, ResNet-101, and EfficientNet-B0, accurately predicting ripe, immature, and damaged tomatoes [44]. **Madhavi et al., (2023**) discovered that the EfficientNet B3 architecture exhibited superior performance compared to frequently employed architectures such as VGG and ResNet [11]. **Zuo et al., (2022)** employ the MATH LAB software algorithm to carry out the process of classification and show that deep learning has the potential to be more efficient in real-time processing [12]. **Appe et al., (2023)** used the CAM-YOLO algorithm, as suggested, and attained an average precision of 88.1% when employed to detect tomatoes that are both overlapped and small [13].**Garcia et al., (2019)** revealed an average accuracy of 83.39% was attained by using a machine learning strategy that used SVM and the L*a*b color space to identify the ripeness maturity of tomatoes based on pixel color [14], while **Siddiquee et al., (2020)** compared machine learning and traditional methods. The machine learning method was found to be much more accurate as it uses HOG methods of detection and mean RGB values are calculated [16].**Appe et al., (2023)** used VGG-based Convolutional Neural Network (CNN) models. Fine-tuning is used to improve the efficacy of tomato ripeness detection and categorization using the transfer learning approach [17].**Wang et al, (2023)** improved the new model surpassed the prior model in terms of accuracy, precision, recall, and F1 score, and it enhanced the current YOLOv5n model for the detection and maturity categorization of cherry tomatoes. The new I-YOLOv5n model outperformed the prior model in terms of detection time [18]. **Wu et al., (2019)** recommended leveraging several aspects of the tomato fruit to increase the accuracy of the proposed model by combining multiple feature fusion with a bi-layer classification technique for harvesting robots [19]. **Wan et al, (2018)** show color cues indicating the maturity of the Roma and Pear tomato types were recognized and categorized using the backpropagation neural network (BPNN). Using similar approaches, an accuracy of 99.31% was achieved [20].**Lawal et al., (2021)** improved the existing YOLOv3 model by incorporating Spatial pyramid pooling, feature pyramid network, CIoU loss, Mish activation function under a DenseNet backbone for the YOLODenseNet model and DarkNet for the YOLOMixNet model, and discovered that the latter proposed model has good accuracy, speed, and real-time potential when applied to harvesting robots [21]. **Su et al., (2022)** used the YOLOv3 model detection algorithm with a supporting backbone from MobileNetV1, the proposed model was trained using 460 data set images of tomatoes under different stages of maturity. Results show that the model can accurately detect and classify tomatoes [22]. **Li et al, (2023)** used the YOLOv5 model and trained it using 6000 images of tomatoes under different maturity stages, the model achieved an accuracy of 97.42%. Higher than other models such as YOLOv3 and RCNN. The model is also relatively fast, taking only 9.2 milliseconds to process an image [23]. **Liu et al., (2019)** used histograms of gradient (HOG) features are used to train a Support Vector Machine (SVM) classifier. Such an algorithm was evaluated on a data set of photos with varied circumstances, including but not limited to numerous tomatoes, and tomatoes included by leaves and stem. The algorithm attained a recall rate of 90% and an accuracy rate of 94.41% [24]. **Hernandez et al., (2023)** proposed utilizing the YOLOv3-tiny model as it is a lightweight deep neural network model known for its efficient processing. Hyperparameter optimization is done to achieve optimal performance. The system achieved an F1 score of 90%, showing that it has an accurate localization and classification of the ripening stages of the custom data set of tomatoes [25]. According to **De Luna et al., (2020),** the tomato fruit's ripeness was determined using Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), and Support Vector Machines (SVM). The training-testing accuracy rate for SVM was 97.78%–99.81%, the accuracy rate for KNN was 93.78%–99.32%, and the accuracy rate for ANN was 91.33%–99.32% [26]. **Ruparelia et al., (2022)** revealed a YOLOv4 that achieved high mean average precision, indicating accurate detection and classification of tomatoes. Revealed the effectiveness of the proposed system in real-time tomato detection and classification [27]. Compared the other established techniques like Probabilistic Neural Networks (PNN), K-Nearest Neighbor (K-NN), and Back Propagation Artificial Neural Networks (BPANN), it is demonstrated by **Kumar et al., (2020)** that the suggested method is successful in predicting tomato diseases [33]. **Hu et al., (2019)** proposed methods to achieve high accuracy in detecting ripe tomatoes on plants, replacing manual labor with a robotic vision-based harvesting system [37]. **Mutha et al., (2021)** demonstrated how robots and artificial intelligence may be deployed to agriculture to automatically identify illness and gauge the ripening state of fruits and vegetables [38]. It was discovered by **Moreira et al, (2022)** that the YOLOv4 and SSD MobileNet v2 models both produced encouraging results for tomato identification, with the F1-Score of 85.81% for the YOLOv4 model standing out [39]. RetinaNet, with a mean average accuracy (mAP) of 74.51, outperformed YoLo v3, PPN, Faster RCNN, and other networks, according to **Tsironis et al., (2020)** [40]. Tomato maturity stages were classified and detected based on color using the Faster R-CNN approach by **Widiyanto et al, (2021).** During the validation stage, the average classification accuracy was about 98.70% [41]. When it comes to fruit ripeness identification, the suggested transfer learning architecture by **Pardede et al., (2021)** with VGG16 and a Multilayer Perceptron (MLP) block performed better than conventional machine learning with feature extraction techniques. While the suggested design yielded an accuracy gain of 18.42% with Dropout, 10.52% with Batch Normalization, and 2.63% with Regularized kernels, the greatest accuracy reached in earlier experiments was 76% [42]. **Dineshku et al., (2023)** suggest a system that makes use of artificial neural networks and information analytics techniques to forecast the most lucrative crops depending on the state of the environment, offering a service for prudent farming and boosting farmers' production [43]. When Yolov5m and ResNet-101 were combined, it was discovered by **Phan et al., (2023)** that the prediction accuracy for both ripe and immature tomatoes was 100%. When Yolov5m was used in conjunction with the Efficient-B0 model, the prediction accuracy for tomatoes with damage was 94%. Testing accuracies for the ResNet-50, EfficientNet-B0, Yolov5m, and ResNet-101 networks were 98%, 98%, 97%, and 97%, in that order. Top 1 accuracies were highest for Yolov5m and ResNet-101 at 99.7%, and lowest for EfficientNet-B0 and ResNet-50 at 99.3% [44]. According to **Pangilinan et al., (2022),**the VGG19 algorithm had the greatest accuracy score of 95%, followed by the ResNet50 method at 93.33% and the InceptionV3 algorithm at 91.67% [36]. The accuracy rate of tomato maturity was found by **Denih et al., (2023)**, to be 92.70% on average usingCielab and K-Means Clustering. This study has the potential to reduce time in defining tomato maturity and make it easier to assess tomato ripeness based on color [57]. The MLP of **Rosales et al., (2022)** model performed the best for chlorantraniliprole identification, with an accuracy of 0.9 [28]. According to **Huang et al., (2020),** the mean SR 15 had the best classification results for tomato maturity, with recognition rates of 100%, 94.6%, 97.5%, 100%, 100%, and 97.1% for green, breaker, changing, pink, pale red, and red stages [29]. **Varga et al., (2021)**, discovered that utilizing hyperspectral imagery and deep learning beat rival baseline models in predicting fruit ripeness [30]. PLS models by **Alksnis et al., (2023)**, demonstrated high prediction accuracy, with a determination coefficient of 0.90 for the lycopene and dry matter content of intact tomatoes [31]. **Fatchurrahman et al., (2020)**, used grey scale values collected from fluorescence imaging, al employed the univariate classification approach to discriminate mature-green and immature-green tomatoes, with a non-error rate of 96% in calibration and 100% in external prediction [32]. **Abdulridha et al., (2020)**, renormalized the difference vegetation index (RDVI) and the modified triangular vegetation index 1 (MTVI 1) were discovered to be the most efficient VIs for disease identification in both laboratory and field situations [34]. **Skolik et al., (2019),** used support vector machine (SVM) chemometrics, to demonstrate that changes in the spectral fingerprint area (1800-900 cm 1) were adequate to detect nine developmental and six ripening phases with good accuracy [45].**Cen et al., (2021)**found that the GA-SVM tomato stem model obtained an overall accuracy (OA) of 88.6% and an F1 score of 0.80, confirming the model's dependability [46]. **Borba et al., (2021)** demonstrated how using a portable spectrometer with a MEMS-based interferometer enhanced model performances. Comparing detector arrays to other commercial portable devices that use the SWNIR area, they perform better because they utilize the unique spectral information found in the long-wave NIR (LWNIR) region [47]. **Abdelhamid et al., (2020)** show that the luminescent method offers a more comprehensive and reliable approach to assessing tomato maturity, allowing for better optimization of storage conditions, forecasting storage periods, and improving the quality and sorting of tomato fruits [48]. **Ramos-Infante et al., (20219)** revealed that the NIR spectra-based models outperformed the others in predicting the quality attributes of tomatoes, exhibiting good prediction for color (RPD > 2.0) and outstanding prediction for SSC, firmness, and pH (RPD > 3.0) [49]. **Logan et al., (2020)** show that the feature selection technique based on genetic algorithms works better than RGB photos [50]. **Zhao et al., (2023)** demonstrate that the RNN outperformed RF and PLS in maturity classification, with a classification accuracy of 96.6%, which was 40% greater than the latter two. With an R2 of prediction above 0.75, the regression models demonstrated strong performance in predicting all quality aspects [64]. These studies highlight the effectiveness of machine learning techniques in automating tomato ripeness determination, which can contribute to improving tomato quality inspection and sorting in the industry.

B. Implications for Agriculture and Food Industry

The use of machine learning in tomato ripeness monitoring has important consequences for agricultural practices, food business operations, and consumer welfare. In terms of agricultural operations, automated machine learning-based technologies can increase the efficiency and accuracy of tomato maturity categorization, allowing farmers to make educated harvesting and storage decisions. In the agricultural landscape, the integration of machine learning algorithms for tomato maturity assessment revolutionizes crop management practices. These algorithms, embedded within image processing and classification systems, serve as a sophisticated tool to meticulously evaluate and segregate tomatoes based on their ripeness. By accurately identifying ripe tomatoes, these systems streamline the harvesting process, ensuring that only produce at its peak maturity is selected. This not only enhances the overall quality of harvested goods but also bolsters the efficiency of crop yields. The precision offered by machine learning algorithms significantly minimizes errors that could arise from human judgment, contributing to more consistent and reliable food production cycles. Therefore, the use of machine learning in tomato ripeness detection has the potential to change agricultural methods, optimize food sector operations, and improve customer welfare [36] [73].

C. Call to Action for Future Research

Efforts to overcome the issues and optimize the impact of machine learning-based ripeness detection on agricultural sustainability and food security should be promoted. Machine learning (ML) and deep learning (DL) techniques for sustainable production prediction and fruit counting have been developed, delivering dependable accuracy but being constrained by the necessity for huge databases [74]. Soil parameter prediction, crop yield prediction, disease and weed identification, and species discovery are all examples of ML applications in agriculture [75]. Advanced deep-learning technology and domain-specific annotated datasets are needed for various agricultural tasks [76]. Artificial intelligence algorithms can evaluate complex interactions and increase crop yield variability, accelerating agricultural research and identifying sustainable practices [77]. Machine learning approaches can investigate the determinants of almond yield variation, improving understanding of climate-crop interactions and benefiting data-driven climate adaptation and orchard management [78].

Moreover, expanding the avenues for further research in the field helps address the challenges brought about by agricultural sustainability and food security, harnessing its full potential. Applications of machine learning (ML) in precision agriculture can enhance overall crop yield prediction, disease and weed detection, and livestock production, leading to an improved sense of productivity and quality [84]. Such advancements in research in the field ensure that farmers can make informed decisions, optimize the utilization of available resources, improve food quality, and reduce food wastage, further contributing to maintaining food security and agricultural sustainability.

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