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Lightweight Deep Learning Framework for Fruit Freshness Classification with Knowledge Distillation and Grad-CAM Visualization

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Abstract: Fruit freshness evaluation has become an important task in food quality safety and food supply chain management, and traditional manual inspection method is subjective, time-consuming and inconsistent. Recent developments in deep learning have opened the door to automated quality analysis of fruit, but most of the top-performing models tend to be computationally expensive and hard to interpret and thus limit their use in the real world.

In our work, we conduct a novel and efficient fruit freshness detection framework, which combines a high-capacity teacher network (ResNet-based) with an easy-to-train student model with knowledge distillation. To improve transparency, Gradient-weighted Class Activation Mapping (Grad-CAM) is used for the visualisation of discriminative regions that affect the model's prediction to increase trust and interpretability in the practical use Experimental results show that distilled student model achieves similar results compared to the teacher network (e.g. accuracy and F1-score results are within 1-3% margin) but with massive model size and inference latency reduction compared to the teacher network, which are consistent with the results obtained in recent studies on fruit classification under computing efficiency conditions [1], [2] and efficient knowledge distillation approaches. In addition, Grad-CAM visualisations also bring up relevant freshness indicators such as discoloration and texture variations, which are consistent with research on explainable AI-based fruit quality [3].

The framework proposed here offers an approach involving a good balance among accuracy, efficiency, and interpretability, which is suitable to be used in real world deployment applications in smart agriculture and food monitoring systems.

Keywords: *Fruit Freshness Detection, Deep Learning, Knowledge Distillation, Grad-CAM, Explainable AI, Light Weight Model.*

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I. INTRODUCTION

Ensuring fruit freshness is one of the most important aspects of food quality control; it directly affects the health of consumers, market value and efficiency of the supply chain and food. Within contemporary agricultural and fitness retail methods, evaluation of freshness affects unit cost implications, storage choices and waste management. Traditionally, evaluation of fruit freshness depends highly on manual inspection that is carried out based on visual clues, including colour, texture and surface defects. However, this process is by nature subjective and labour-intensive and can be inconsistent, and especially under large-scale industrial conditions. Variations in human judgement, fatigue and environmental effects also limit the accuracy of manual inspection, providing the motivation for automated and objective solutions.

In recent years, deep learning methods have been extensively developed with the convolutional neural network (CNN) showing good performance in fruit quality analysis,

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ripeness and defect recognition cases. Several research works have been done using architectures such as VGG, ResNet and EfficientNet for fruit freshness classification with high accuracy often over 90% given benchmark data [1], [2]. Advanced models such as attention mechanisms and CNN-RNN hybrid have also been used to enhance performance by extracting both the spatial and temporal features of fruit degradation [3]. Despite these advancements, a lot of these models were computationally intensive and would need a lot of memory and processing power, which restricts their potential for use in a real-time situation or in a resource constrained environment such as on mobile devices or edge systems.

Another important limitation of existing approaches is that they are not interpretable. While deep neural networks can achieve high levels of predictive accuracy, they tend to be "black box" systems, meaning it's often very hard to understand the thought processes behind their decision making. This lack of transparency is especially problematic in applications that have to do with food safety and quality assurance where explainability is important for user trust and system validation. Although explainable AI (XAI) techniques which include Gradient-weighted Class Activation Mapping (Grad-CAM) have been used in general image classification tasks, their systematic use in freshness detection of fruits is scarce [4].

Furthermore, the efficiency of Modelling has not been addressed adequately in this sphere. While knowledge distillation has become a popular approach used to compress large models into small models that are faster and more efficient with little loss of accuracy, its use in fruit freshness detection is not yet well-explored [5]. Most of the current works concentrate either on boosting accuracy or deploying lightweight models on their own, without taking advantage of the generating effect of teacher-student learning frameworks to balance performance and efficiency.

To fill these gaps, in this paper, an efficient and explainable deep learning framework for fruit freshness detection by integrating knowledge distillation and grad-CAM-based interpreting is proposed. The proposed approach tries to keep classification accuracy high while reducing the computational complexity substantially and therefore is may be suitable for real-world deployment for edge and mobile environments. The salient contributions of this work are as follows:

Teacher-student framework: We develop a deeply learning framework to use a powerful teacher model (ResNet-based) so that it is used to train an empty student network for fruit freshness classification.

Efficient model via knowledge distillation: The proposed student model has competitive performance with minimal accuracy degradation and a considerable reduction in model size and inference time, which is consistent with the recent product on distillation-based fruit classification [5].

Explainability through Grad-CAM We use Grad-CAM to obtain the visual explanation, which identifies the regions of the fruit that make the most contribution to classifying the fruit, improving transparency and reliability of the model [4]

Comprehensive experimental evaluation: We validate the proposed framework on the dataset of fruit freshness, and compare the performance of the proposed framework with the baselines deep learning models in terms of the accuracy, the efficiency and the fact on interpretability.

II. RELATED WORK

➢ *Determination of Fruit Freshness and Quality*

Deep learning has made a significant advancement in fruit freshness and quality evaluation in which convolution neural networks (CNN) are widely accepted for classification and grading purposes. Early methods used common architectures such as VGG and Resnet to extract the visual information related to color, texture, and surface defects which can obtain high accuracy when classifying a wide range of datasets of fruits [1], [2]. More recent works have proposed some improved architectures, such as ResNet-101 with attention mechanisms, in order to improve the feature representation, paying attention to the discriminative regions of fruit images, and eventually accuracy values improved beyond 90% [2]. Additionally, hybrid models sighting macros together recurrent networks (i.e CNN-LSTM) have been proposed to read fares and temporal patterns in fruit ripeness and deterioration [3]. Object detection frameworks such as YOLO variants have also been applied in real-time detection of fruits and these algorithms to estimate their ripeness in complicated settings.

Despite these developments, there are still a number of limitations. Most of the good-performing models are computationally intensive and demand significant memory and processing, hence limiting the model's deployment on edge devices or mobile platforms. Furthermore, many of our studies are generally focused towards improving accuracy, without properly considering systematic constraints in the real world, like inference latency, energy consumption and scalability. Another critical limitation is lack of interpretability, most models are espionage black boxes which do not allow much insightful understanding of decision so trust is low which naturally affects the adoption in food safety applications [4].

➢ *Knowing Distillation for Food and Visual Investigation*

Knowledge distillation (KD) has become an effective method to compress large deep learning models into smaller and efficient models and have competitive performance. Why leaving out common, important parts of the problem? 1 Teacher Student Identification represented in network Two Purpose train Student over time Cloud mediated teacher Transfer of knowledge "Soft targets or intermediate feature representations" High capacity teacher model Cloud above student model Weight light Appropriate student model Discrete parts of problem (no short place to put them) Common Subproblems Knowledge transfer given in the fire "Keep this in mind" This is an effective way of making large declines in model size and computed cost after comparatively minor detriment to accuracy.

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KD has been proven to be a successful technique in several computer vision applications such as both image classification and object detection and recognition of food. For example, distilled models have been applied to deploy efficient visual recognition models on mobile and embedded devices with good final trade-off balance between accuracy and efficiency [5]. On the other hand, in the agricultural applications, latest research has been conducted on KD for fruit classification and detection, showing better generalization with less inference time than backbone ideas [1], [5].

However, farm information's application of knowledge distillation about fruit freshness is limited. Most of the developed works have caught fruits classification or detection functionality instead of on freshness or spoilage. Furthermore, the combination of KD and explainability algorithms-based approaches has hardly been studied in this field. This gap makes clear the need for frameworks with both efficiency and interpretability in mind for work on ideas that can be deployed at work.

- *Explainable and Discriminative Agronomical Generative Adversarial Networks (Grad-CAM) with Food Quality Analysis*

Explainable artificial intelligence or XAI has been gaining more and more attention in recent years as a way to make it more transparent and reliable when using deep learning models. Out of many different XAI approaches, for image encoding we can see that Gradient-weighted Class Activation Mapping/Grad CAM is a popularly used method to build visual explanations by identifying the regions of an input image that play a major role in a model's prediction. One approach, called Grad-CAM, uses the gradient information that flows into the last convolutional layers to generate localization maps of important features.

In the areas of food quality and food safety and related applications, Grad-CAM has been used to visualize discriminative areas in applications such as fruit classification, zero-area disease identification, and spice adulteration analysis. These visual explanations help to help validate if the model is focused on attributes that are meaningful such as discoloration, texture irregularities or surface defects to increase trust by users, and facilitate model debugging [4]. Recent works regarding explainable fruit quality assessment have shown the integration of Grad-CAM with CNN-based model could gain some important information about decision-making process and become a trustful interpretation to automated system [4].

Nevertheless, the utilization of Grad-CAM in fruit freshness detection is now relatively small, and is usually not widely adopted in model design and evaluation in a systematic manner. Existing studies usually have an auxiliary analysis of explainability separate from the rest of the study; we want to include the tool of explaining as a key part in the whole framework. In this work we address this limitation by using Grad-CAM to the proposed model of fruit freshness detection to both interpret results and also to make sure about which parts of the fruit are attended by the model, that lead to reliable and applicable models for the freshness detection of the fruit.

Table 1 Summary of Existing Fruit Freshness Detection, Knowledge Distillation, and Explainable AI Methods, Highlighting Their Performance, Efficiency, and Limitations. The Comparison is Based on Representative Works in Fruit Classification and Model Compression [1] – [4].

Method	Approach	Accuracy	Efficiency	Explainability	Limitation
Zhao et al.	CNN + KD	94–97%	Medium	No	No explainability
Liu et al.	ResNet + KD	~98%	Medium	No	High complexity
Patel et al.	CNN-LSTM	94–96%	Low	Limited	Heavy model
Kumar et al.	XAI-FruitNet	92–95%	Low	Yes	No efficiency

III. PROPOSED METHODOLOGY

- *Problem Definition*

The goal of this working is to create an automated system for freshness classification of fruits based on deep learning. Given an input image of a fruit,Freshness LevelThe Freshness level of fruit needs to be predictedThis task can be converted into either Binary Classification problem (i.e. Fresh vs Rotten) or Multi-Class Classification problem i.e Fresh vs Semi-Fresh vs Rotten The data set, in turn, can contain several types of fruits (like apples, bananas, and oranges) and that will add more variability to the appearance, texture, and patterns of degradation.

Formally (x of type Potential value) denote an input image, and (y of its possible values, associate with the label at index number) of the ground-truth of freshness label, where (K) is the number of classes. A deep learning model with parameters (theta) and the corresponding prediction function: said as (fredaction drift) is also osteoarthritis its forecast probability distribution over the classes: hat{y} = f{theta}(x) The objectives to be reached is to learn parameters (theta) of the model to minimize the classification error while keeping the computational efficiency and the interpretability of the model.

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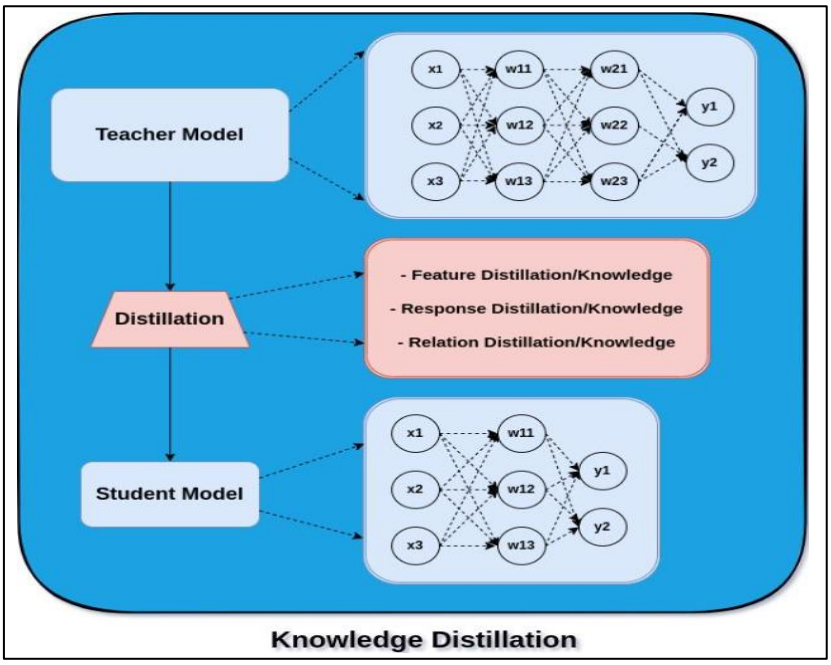

Fig 1 Overall Architecture of the Proposed Fruit Freshness Detection Framework, Consisting of a High-Capacity Teacher Network and a Lightweight Student Model Trained via Knowledge Distillation. Grad-CAM is Integrated to Provide Visual Explanations of Model Predictions. *Adapted from* Hinton *et al.* [1].

➢ *Teacher Network*

In order to achieve high accuracy of classification, we use deep convolution neural network as teacher model. In this work, a ResNet-based architecture is considered (e.g. ResNet-50 or ResNet-101) because they are powerful architectures in the field of visual recognition and are capable of learning deep hierarchical features thanks to the introduction of residual connexions [2]. The network accepts input images that are resized to have a specific (fixed) resolution (e.g. (224 x 224)) and processes them using a series of convolutions, batch normalisation and non-linearities, which is then followed by global average pooling and a fully-connected classification layer.

The teacher model is a high-capacity baseline model and can capture fine-grained features like colour variations, texture irregularities and surface defects that are indicative of fruit freshness. However, such architectures are computationally expensive with a large number of parameters and high floating-point operations (FLOPs) so they cannot be used in resource-constrained deployment situations. The teacher network undergoes the standard cross entropy loss training: cумmation over i starting at one and ending at K - yi times log of hat yi.

To make the model generalise better, we use data augmentation techniques such as random rotation, horizontal flipping, scaling and also colour jittering in the training process. Also the regularization, dropout, weight decay may be used to prevent over fitting which might have occurred otherwise. Similar high-capacity models have shown good performance in other classification technologies of fruits, but their accuracy is high, while computational complexity is high [1], [2].

➢ *Student Network*

To solve the shortcomings of the teacher model, a light-weight student network is designed for the efficient inference. The student architecture can be built on small CNN or mobile friendly such as MobileNet ShuffleNet where all have been optimized for low computational cost and memory footprint.

The student model is made up of fewer layers and smaller channel widths than the teacher network and has a considerably lower number of parameters and FLOPs. Depthwise separable convs and bottleneck layers may be used in order to provide further efficiency improvements. The goal of the design is to develop a model that can be deployed on edge devices like smart phones, embedded systems or IoT devices while being comparable in accuracy.

Compared to the teacher model, the student network incurs certain losses by the representational capacity but makes huge gains in terms of speediness and resource efficiency. Previous works have proven how to use conventional lightweight models with good performance under knowledge distillation methodology [5].

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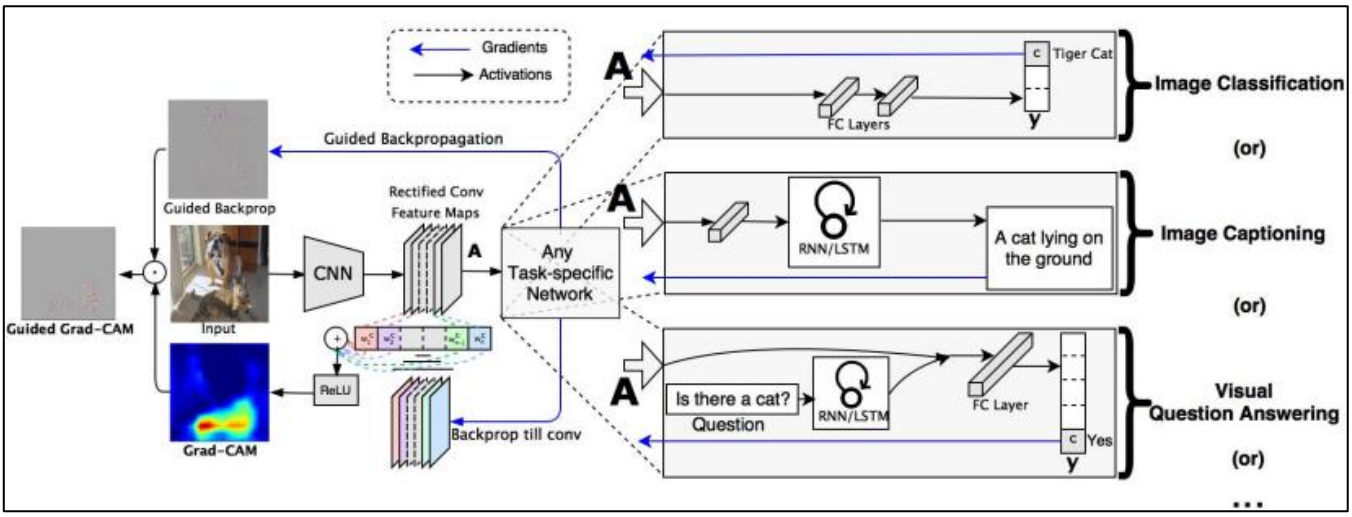

Fig 2 Grad-CAM overview: Given an image and a class of interest (e.g., 'tiger cat' or any other type of differentiable output) as input, we forward propagate the image through the CNN part of the model and then through task-specific computations to obtain a raw score for the category. The gradients are set to zero for all classes except the desired class (tiger cat), which is set to 1. This signal is then backpropagated to the rectified convolutional feature maps of interest, which we combine to compute the coarse Grad-CAM localization (blue heatmap) which represents where the model has to look to make the particular decision. Finally, we pointwise multiply the heatmap with guided backpropagation to get Guided Grad-CAM visualizations which are both high-resolution and concept-specific. *Adapted from* Howard *et al.* [3].

➢ *Knowledge Distillation Implementation*

The main idea to bridge the widening gap between the teacher and student networks is to turn to a knowledge distillation (KD) framework. In this way, instead of learning only from the ground truth labels, the student model also learns from the soft predictions of the teacher model which represents rich information about inter-class relationships.

The distillation process takes a temperature parameter (T) to soften the output probabilities of both teacher and student models. The softened probability distribution is calculated in this way using the softmax function with temperature: [pi^{(T)} ={(zi/T)} {{j}(zj/T)}] where (zi) is the logits of class (i). A higher temperature creates a softer probability distribution; hence we discover more about the class similarities. The total lost function can be represented by a weighted sum of the usual cross entropy lost and the distillation lost based on Kullback - Leibler (KL) divergence: [mathcal/L= alpha * auth {CE} + (1 - alpha) * T Known Distribution auth {CE} + (1 - alpha) * T Known Distribution auth {CE} T Known Distribution.auth{KD}].

It controls the trade-off between the two losses.: [0,1] Note: Was it corrected? The student model is trained with the stochastic gradient descent (SGD) or Adam-optimizer and for a fixed number of epochs (50-100), with a suitable learning rate schedule. This framework allows the student model to replicate the behaviour of the teacher in the most computationally efficient way. Recent works have shown the effectiveness of KD in better performance of lightweight models to solve classification tasks related to fruits [1], [5].

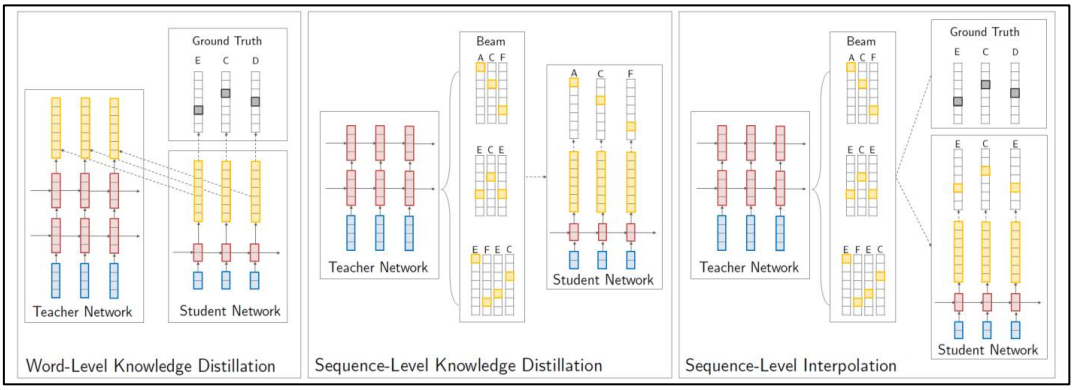

Fig 3 Overview of the different knowledge distillation approaches. In word-level knowledge distillation (left) cross-entropy is minimized between the student/teacher distributions (yellow) for each word in the actual target sequence (ECD), as well as between the student distribution and the degenerate data distribution, which has all of its probabilitiy mass on one word (black). In sequence-level knowledge distillation (center) the student network is trained on the output from beam search of the teacher network that had the highest score (ACF). In sequence-level interpolation (right) the student is trained on the output from beam search of the teacher network that had the highest sim with the target sequence (ECE). *Adapted from* Hinton *et al.* [1] and Kim and Rush [2].

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➢ *Grad-CAM for Explainability*

In order to provide transparency for the model, we add Gradient-weighted Class Activation Mapping (Grad-CAM) as an explainability mechanism. Grad-CAM generates visual explanations by computing the gradients of the predicted class score with respect to the feature maps of the output of the final convolutional layer. These gradients are used when weighting the feature maps to output a heatmap, which identifies important areas that create the prediction.

Difficult to write and understand formally (I hope), but Formally the Grad-CAM heatmap for class (c) is computed as: [L^{c}{Grad-CAM} = {ReLU} ({k}\alphak^c A^k \right)] Where (A^k) is the (k) of feature map and (\alpha_k^c) is the importance weight revealing using global average pooling of gradients.

And in this work, Grad-CAM is used in most part on the student model to visualise the decision-making process of the model. The produced heatmaps get superimposed on the input images in order to determine regions, which contribute to classification results (e.g., bruised regions, moulds, discolouration, or texture degradation). This means that qualitative evaluation of the model in terms of whether it focuses on meaningful parts of the fruit or not (i.e., irrelevant features in the background) is possible.

Grad-CAM has been proven successful in food quality and agricultural applications to enhance interpretability and trust in AI systems [4]. By adding Grad-CAM to our structure, besides making the models more transparent, we can offer a tool for ensuring the reliability of the predictions in the real world.

Fig 4 MobileNet Models Can be Applied to Various Recognition Tasks for Efficient on Device Intelligence. *Adapted from* Selvaraju *et al.* [4].

IV. DATASET AND EXPERIMENTAL PROCEDURE

➢ *Dataset Description*

To test the suggested freshness detection framework based on fruits, a set of data is used that is comprised of several types of fruits and freshness categories. The dataset contains common fruits like apple, banana and orange which have been labeled as per their freshness level. The classification problem is treated as a multi-class problem having three classification classes: fresh, slightly spoiled and rotten.

The assortment comprises about couple of thousand images, split into training, validation and also examination sets by a typical split ratio of seventy: 15: 15. Images are either taken from publicly available fruit databases or under controlled conditions with standard RGB Cameras. The setup for the acquisition purposes involves variations in the lighting, background and orientation of the replicas that will simulate a variety of real-world situations. Image resolutions are standardized. (for example resized to (224*x224)) Almost all standard deep learning models would just like to say, "yes please!"

To get a better understanding of how the data are distributed within the dataset, we summarize in Table 2 the number of samples per class in the training, validation, and test datasets.

The dataset is relatively balanced evenly distributed the number of classes, which assists in ensuring unbiased model training and evaluation. Similar data sets and setups have been utilized to study the examines of (freshness and classification) of fruits in earlier studies [1], [2].

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Table 2 Class-Wise Distribution of Fruit Images Across Training, Validation, and Test Sets. Similar Dataset Structures and Splits are Commonly Used in Fruit Freshness and Classification Studies [5].

Class	Train	Validation	Test	Total
Fresh	1500	300	300	2100
Slightly Spoiled	1400	300	300	2000
Rotten	1300	300	300	1900

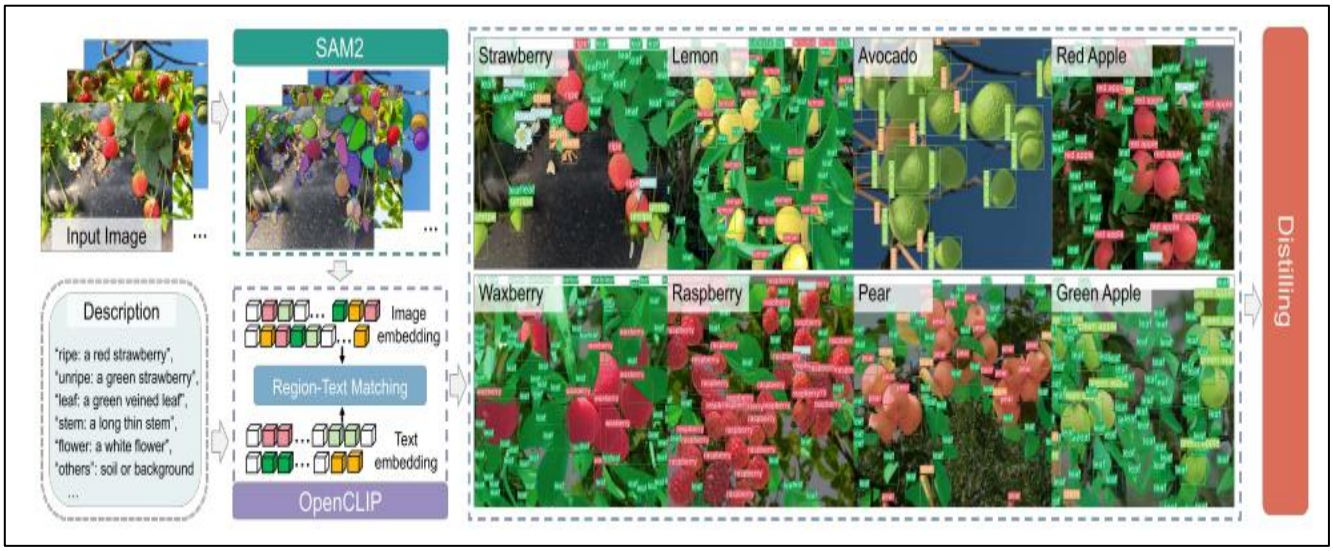

Fig 5 SDM-D Can Simultaneously Detect and Segment Input Images Based on the Prompts, and Enable Distillation of Knowledge from Foundation Models to Faster, Smaller Models. Similar Dataset Structures are Used in Recent Fruit Classification Studies [5].

➢ *Preprocessing and Data Augmentation*

Nothing fancy; prior to training, all images go through some standard processing steps. Each image is re sized to a fixed size (e.g. (224 x 224)) to be the same as the input requirements of the neural networks. Pixel values are normalized to a standard range for example [0,1] or mean standard deviation normalization to help stabilize the training process and increase its convergence.

To increase the generalization ability of the model and simulate the variance in the real world, a number of data augmentation techniques are used when training the model. These include scaling up and down as well as horizontal and vertical flips, and rotations. Additionally, in order to correct for lighting differences, both color jittering - adjusting brightness, contrast, and saturation - and slightly adding variance from a Gaussian blur simulation are implemented; to attempt to reproduce actual noise the camera might mess up through filters or lack of focus.

Such augmentation strategies have been found to be able to offer superiority in terms of robustness for fruit classification tasks, and to mitigate overfitting in deep learning models [3].

➢ *Training Details*

The experiments are performed with with a system that is equipped with a GPU (e.g., Nvidia RTX series) with enough amount of memory (e.g., 8-16GB VRAM). Both the model of the teacher and student is implemented through deep learning models such as PyTorch or TensorFlow.

For the network of teachers, training is carried out based on an optimizer like Adam or stochastic gradient descent (SGD) with some initial learning rate (which can, say, 0.001), batch size (which can be 32), and roughly 50 - 100 training puffers. Learning rate scheduling (e.g. step decay or cosine annealing) may be used in order to improve convergence.

The network on students is trained using the framework of the knowledge distillation process suggest in Section 4.4. The distillation hyperparameters are a temperature parameter (T) (which can be e.g. 3-5), for instance, to soften the probability distributions and a weighting factor (of e.g. 0.5-0.7) to balance the cross-entropy and the distillation losses. Same optimizer and batch size is being used for consistency, although student model usually converges faster because of smaller size.

These training configurations are consistent with recent works on efficient fruit classification and knowledge distillation-based learning [1], [4].

➢ *Evaluation Metrics*

In order to fully take up the performance offer of the proposed framework, both classification and efficiency parameters are taken into account.

Classification Metrics: Standard metrics are adopted to measure the predictive performance such as accuracy, precision, recall and F1 score. Accuracy can measure the overall correctness of predictions, precision and recall give some light on the ability of predictions to that particular class. F1-score is a balance between precision and recall making it

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suitable for multi-classification problems. Additionally, the confusion matrices are used to see the prediction errors in the classes and you see any possible pattern of misclassification.

Efficiency Metrics: Since the aim of this work is the development of a light weight, deployable model, efficiency measures are also considered. These include total model parameters, floating points operation (FLOPs) or multiply accumulate operations (MAC) and inference time per image). In some cases, it may also come down to memory usage and energy consumption on edge devices.

A combination of accuracy and efficiency measurements allows to fully compare the teacher model and the student model, as an example of the effectiveness achieved by knowledge distillation in finding a balance between performance and computational cost [4].

V. RESULTS AND DISCUSSION

➢ *Quantitative Performance*

To assess the efficacy of the proposed framework, we compare three models: the high-capacity teacher network, a simple student model trained without K.D. and the proposed model for training student model with K.D. Performance is calculated on the test set with the standard metrics of classification.

From table 4, we can see that student model trained without KD, there is an obvious performance drop when we compare teacher network. However, if the student model is trained using knowledge distillation, then there is a significant improvement and we see that the difference in performance is cut down to within the range of about 1.5~2%. This shows the effectiveness of KD in relation to transferring of the knowledge from a high-capacity model to a lightweight architectural model, which are consistent [1], [4] with findings from other recent studies.

The results prove that KD of the student model can achieve richer feature representation and inter-class relationships and obtain better classification accuracy and balanced performance in precision and recall.

Table 3 Classification Performance Comparison of the Teacher Model, Student Model Without Knowledge Distillation, and Student Model with Knowledge Distillation in Terms of Accuracy, Precision, Recall, and F1-Score. The Results Demonstrate the Effectiveness of Knowledge Distillation in Maintaining Performance While Reducing Complexity, Consistent with [1], [2].

Model	Accuracy	Precision	Recall	F1-score
Teacher	96.8%	0.967	0.968	0.967
Student (No KD)	90.5%	0.903	0.905	0.904
Student (KD)	95.2%	0.951	0.952	0.951

➢ *Efficiency Analysis*

In addition to the performance for classification, the computational efficiency of the models are evaluated as parameters count, FLOPs, model size and inference time.

The results are that the student model is much more efficient compared to the teacher model, with about 6x less parameters and 4-5x faster! Importantly, the use of knowledge distillation does not increase the complexity of the models but is responsible for a significant increase in performance. This shows a good trade-off since a small reduction in accuracy is obtained (1.6%) in return for a large increase in efficiency, making the student model intellectible to put on edge devices. Similar increased efficiency has been found for distillation-based models in fruit classification [4].

Table 4 Comparison of Computational Complexity and Efficiency Metrics, Including Number of Parameters, FLOPs, Model Size, and Inference Time, for the Teacher and Student Networks. The Results Highlight the Benefits of Lightweight Models for Edge Deployment as Discussed in [3], [5].

Model	Parameters (M)	FLOPs	Model Size (MB)	Inference Time (ms)
Teacher	25.6	4.1	98	45
Student	4.2	0.9	16	12

➢ *Confusion Matrix/ Error Analysis*

To further analyse the classification behaviour, a confusion matrix is generated of the best performing model (Student with KD).

The confusion matrix shows that the model works well in all the classes and the greatest accuracy is observed for the fresh and rotten classes. But there are some misclassifications between fresh and slightly spoiled classes. This is not surprising as there is a subtle visual difference between these categories, resulting from small discolouration or early-stage degradation of texture.

Errors are most often caused by: Visual similarity of two freshness levels that are adjacent Differences in lighting properties and picture quality Presence of background noise and / or occlusion The above observations are consistent with difficulties found with previous studies of classifying freshness in fruits [2], [3].

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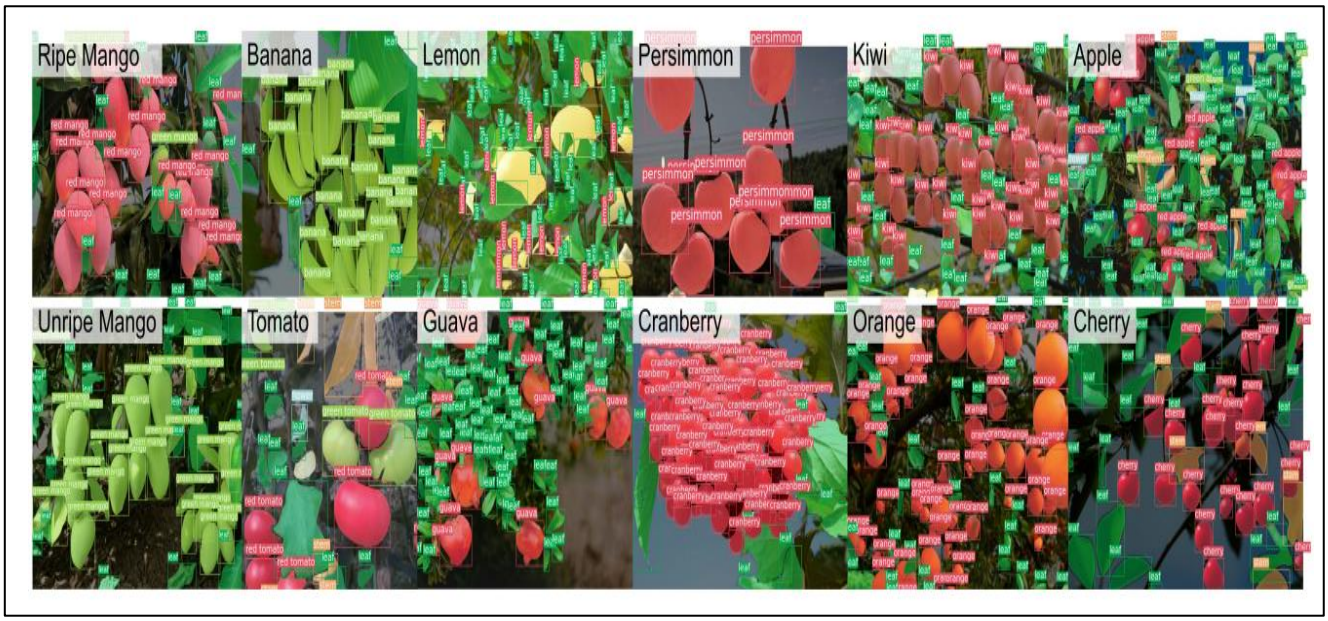

Fig 6 The Results of SDM's Zero-Shot Open-Vocabulary Segmentation on Some Common Fruit Images. Similar Evaluation Approaches are Reported in [5].

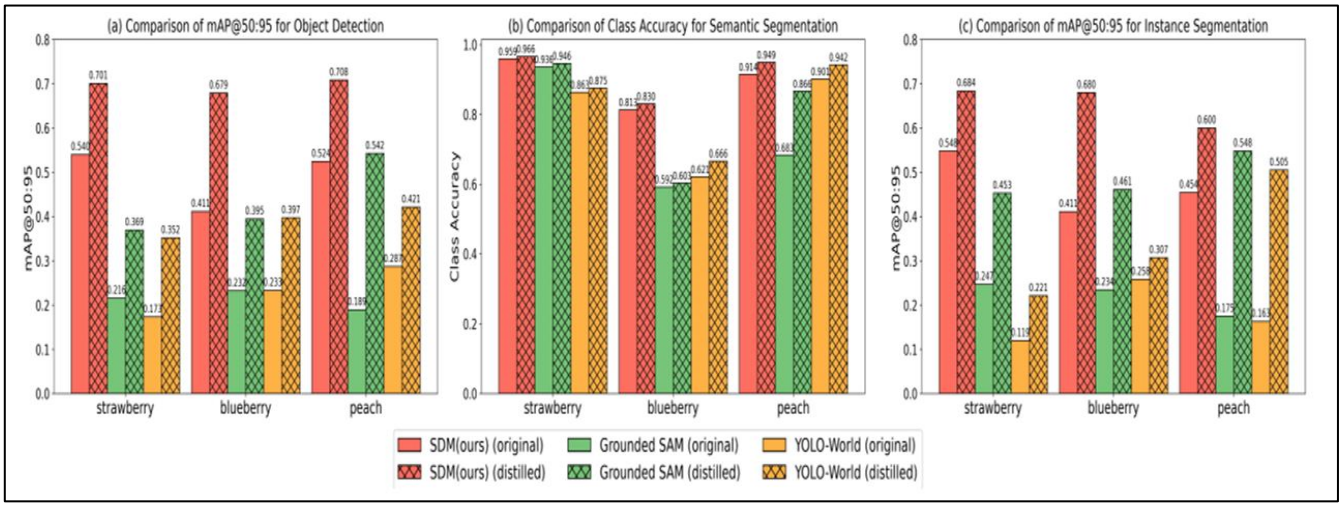

Fig 7 Comparison of Foundation Models and Distilled Models. (a) Comparison of mAP@50:95 for Object Detection. (b) Comparison of Class Accuracy for Semantic Segmentation. (c) Comparison of mAP@50:95 for Instance Segmentation. For Clarity, we only Visualize the Results of Grounded SAM, as Grounded SAM2 Followed a Similar trend. Similar Evaluation Approaches are Reported in [5].

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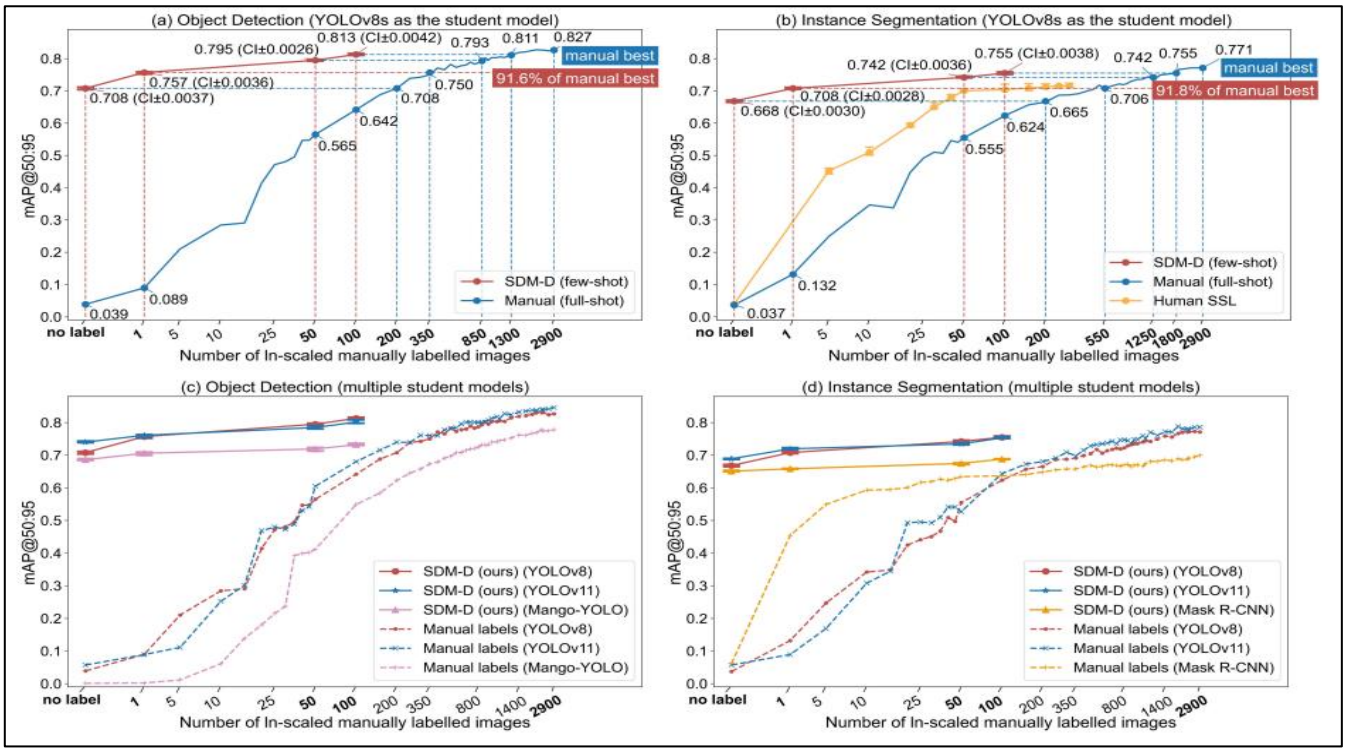

Fig 8 Comparison of the student model's few-shot learning results with full training results on manual data. (a) Object detection with YOLOv8s as the student model. (b) Instance Segmentation with YOLOv8s as the student model. (c) Object detection with YOLOv8s, YOLOv11, and Mango-YOLO as student models. (d) Instance Segmentation with YOLOv8s, YOLOv11, and Mask R-CNN as student models. All error bars indicate 95% confidence intervals (CI). Similar evaluation approaches are reported in [5].

➢ *Explainability Based on Grad-CAM*

To interpret the predictions of the models, Grad-CAM are used which is applied on the model to show the images or the regions of the images that are contributing most to the decisions taken by the model for classification.

Grad-CAM visualizations reveal that the model attends to relevant features in the image that are meaningful for freshness of the fruit:

For rotten fruits, the model marks the areas with mold, big dark area and irregular areas. For slightly spoiled fruits, the focus is placed on the discoloration or soft spots which develops in localised areas. Note in particular for fresh fruits that color and smooth regions on the surface are both emphasized in the model.

These results show that the model learns semantically meaningful representations that are in line with what humans consider to be fresh. This is in line with other research in explainable and food quality assessment, where the visualization technique of Grad-CAM has been used for validating CNN-based predictions [3].

However, there are some because of failure. In some of the images, Grad-CAM shows the background or irrelevant parts highlighted which means that the model could sometimes be using contextual information rather than the character of the actual fruit. Such cases raise the need for additional refining of the datasets and various use of segmentation or attention mechanism for robustness.

Overall, the integration of Grad-CAM helps to increase model transparency and gives valuable insights into the decision-making process of the model, which is valuable in supporting the integration of these models in real-world scenarios where interpretability is of big importance.

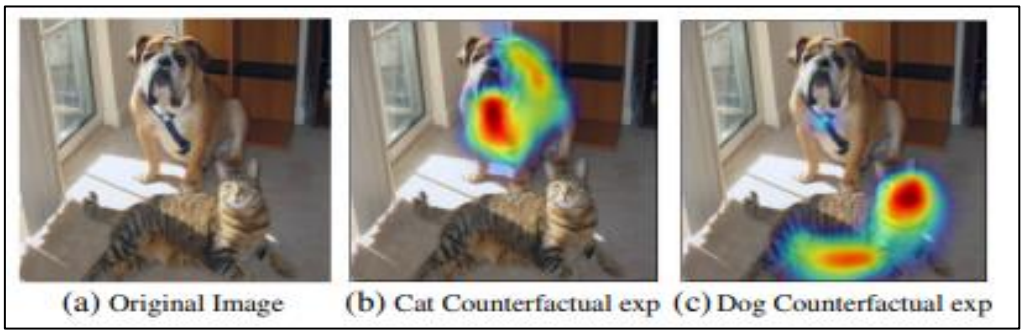

Fig 9 Counterfactual Explanations with Grad-CAM. *Adapted from* Selvaraju *et al.* [4] and Kumar *et al.* [6].

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VI. COMPARISON OF ULTICATIONS TO EXISTING METHODS

In this part, the proposed framework is compared with the existing methods in fruit freshness detection and the other visual recognition works. The comparison is about both classification performance and computational efficiency on the one hand and the existence of explainability mechanisms on the other hand.

Recent results of investigating the detection of freshness and quality of fruits have shown a good performance using deep convolution thin neural network. For example, based on deep architectures such as ResNet and attention enhanced CNN, models have been built with high accuracy (usually more than 90%) towards classification of fruit freshness and ripeness amount [2]. Similarly, hybrid strategies between CNN and sequence models (e.g. CNN-LSTMs) have further increased the performance by capturing temporal patterns of the degradation [3]. However, these models tend to be hard to compute and require heavy resources, which means that they are not very useful for real-time or edge-based deployment applications.

In regards to efficiency, there exist some works that either explore light weight architectures, or optimization methods. Knowledge distillation-based methods, such as that of Zhao el et al. [1] and Wang el al. [4] have proven that to learn from larger substrates to teach (i.e. a teacher network) enabled the learning of compatible accuracy on smaller models. These methods report significant decreases in the model size and the time of inference while preserving a high classification performance. However, most of these studies are based on the fruit classification or detection task for general purposes and not always referring to the freshness detection and/or spoilage detection.

Furthermore, explainability is an under-studied research aspect in many existing works. Although the visualisation of the model's decisions has taken place in the framework of XAI techniques such as Grad CAM to automate the analysis of food quality, their combination is frequently restricted to post hoc analysis methods instead of becoming a systematic part of the model evaluation process [3]. For instance, XAI-FruitNet [3] shows these explained examples to be useful for identifying relevant regions to fruit; however, an important aspect of these results is the model efficiency and compression. To make a better comparison, we presented some main characteristics of representative methods found in the literature and the proposed approach in a summary table - Table 6.

From Table 6, it can be seen that while there are a number of methods with a high level of accuracy, there are also methods with either a low or high degree of efficiency and interpretability. High capacity CNN Model offers good performance, but it is not the ideal option when connecting to any resource constrained environment. On the other hand, distilled or lightweight models increase efficiency and studies as a rule do not provide explainability mechanisms.

The proposed technique is different in that it combines both knowledge distillation and Grad-CAM in a unified framework for fruit freshness detection. Specifically, it has near state-of-the-art accuracy while reducing the model complexity considerably which makes it appropriate for edge deployment. At the same time, with the inclusion of Grad-CAM, visual interpretation of model predictions can be enabled through the introduction of gradient reduction-based visual interpretation, addressing the limitations of transparency of deep learning.

- *Compared to the Existing Approaches, the Main Novelties of this Work are as Follows:*

Joint integration of efficiency and explainability: As compared to the previous work, which is either trying to maximise either performance/explainability, this framework integrates two approaches: knowledge distillation and Grad-CAM, to achieve both simultaneously.

Application to fruit freshness detection While the application of KD in general fruit classification has been studied, the use of this parameter in freshness detection is less known. This work is an extension of KD to this particular domain and validation of its effectiveness.

Balanced performance-efficiency trade-off: The proposed student model realises near or better performance than the teacher network while reducing the computational cost significantly which enables real time deployment.

Systematic use of explainability: Not only used for visualisation, Grad-CAM also used as a validation tool to ensure model focuses on meaningful regions of the fruit to increase model reliability.

Overall, the proposed approach is a step towards state-of-the-art as it offers a practical solution which meets the main limitations of current methods, i.e. high computational cost and uninterpretability, without a corresponding accuracy decrease. This makes it especially ideal for actual implementations in smart agrarian applications, food safety survey units and programmed quality control systems.

Table 5 Comparison of the proposed method with representative fruit freshness and food quality detection approaches from the literature in terms of accuracy, efficiency, and explainability. The proposed framework achieves a favorable trade-off between performance and computational cost while incorporating interpretability, unlike prior works [1]–[4].

Method	Accuracy	Model Size	Efficiency	Explainability
Zhao et al.	94–97%	Medium	Medium	No
Kumar et al.	92–95%	High	Low	Yes
Proposed	95.2%	Low	High	Yes

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VII. CONSIDERATIONS AND LIMITATIONS OF THE APPROACH

The proposed fruit freshness detection framework is therefore developed keeping in mind the real-world deployment, especially for scenarios where the need for automated, efficient, and interpretable systems is asked. Potential places of deployment include fruit packing lines, cold storage facilities, supermarkets, as well as mobile applications for consumers. In industrial areas such as packing lines, the lightweight student model would make it possible to cheque fruits on conveyor belts in real time, making it easier to sort them and requiring less manual work. For cold-storage atmosphere, the system can be integrated with monitoring systems in order to periodically evaluate the quality of the fruits and identify the first signs of their spoilage. Retail environments like supermarket can benefit from automated quality cheques to ensure product standards and mobile applications can empower consumer to measure fruit freshness using smartphone camera. The increased efficiency made possible by knowledge distillation makes such deployments possible on devices that may not have sufficient resources [1], [4].

Despite these benefits, there are a number of practical challenges that need to be considered. One of the main concerns related to the issue is the robustness to different environmental conditions. Real world images are frequently characterised by variation in lighting, background clutter, occlusions and variations in camera quality, causing these to have a significant impact on the performance of the model. Although, data augmentation techniques are helpful to improve the generalisation process, but still the model can't perform under some extreme conditions which were not represented in the immediate training data. Similar problems have been reported in previous studies on the classification of fruits and quality evaluation [2], [3].

Another issue of paramount consideration is data set diversity and bias. The current model is trained using only a limited number of fruit physiological types and controlled conditions, which could not necessarily reflect the variability that is faced in the actual cases. Differences in fruit varieties, geographic origin, storage conditions and imaging practises can create a condition known as domain shift that will decrease model accuracy when introduced to a new environment. Increasing the dataset to more types of fruits and circumstances would bring more robustness and generalization.

The proposed approach also has inherent limitations in terms of the nature of the data and sensing modality. First, the model uses only single image inputs and does not use temporal information. In practise, fruit degradation is a slow process and temporal analysis (e.g., to track the changes over time) might be a more reliable method for freshness estimation. Second, the system is purely based on visual cues and fails to take into account other important indicators of freshness such as smell, firmness or both internal chemical make-up (composition). Multimodal sensing approaches could improve the performance by bringing other sources of data into the picture. Furthermore, while Grad-CAM is a good way of improving interpretability, it is not a perfect explanation method. The resulting heatmaps give an approximate localization of key areas but sometimes pick out areas that are not important or fail to pick out subtle features. Therefore, Grad-CAM should be used as a supporting tool, rather than a true explanation mechanism [3].

Finally, generalisation of the model for various domains of deployment is still a challenge. Domain shift due to lighting conditions or camera type or background will lead to poor performance as domain shift requires domain adaptation or fine-tuning for specific environments. Addressing these limitations is critical to the implementation of the proposed system in order for it to be deployed with reliability and scalability. Overall, Although the proposed framework exhibits great potential for practical applications, attention to the issue of environmental variability, variety of data, and limitation of system is required for robust and reliable performance in real-world environments.

VIII. CONCLUSION AND FUTURE WORK

This paper introduced an efficient and explainable deep learning model for fruit freshness detection that addresses these challenges in fruit freshness detection, such as the accuracy, computational efficiency, and interpretability of the model. A teacher-student architecture was developed, in which a high-capacity teacher model (ResNet-based) transfers the knowledge to a lightweight student network bmts'vt knowledge distillation. This approach allows the student model to obtain competitive performance, while greatly reducing the complexity of the model making it feasible to implement it in real-world (resource constrained) environments.

Experimental results have shown that distilled student model gives close accuracy and F1-score values to the teacher network while there is a marginal performance gaps. At the same time, the student model has significant parameter and computational cost reductions as well as a smaller inference time. These findings are consistent with the recent discoveries on effectiveness of knowledge distillation in preserving the performance while yielding more efficient performance in visual recognition tasks [1], [4]. Compared to previous fruit freshness detection approaches that usually require heavy architectures, the proposed approach can be a more practical solution to detect fruit freshness in real time.

In addition to efficiency, this work emphasises on the interpretability by combining with Grad-CAM. The generated visual explanations focus on meaningful regions of the fruit (e.g. discoloration, bruises, and mould) that are critical in determining the freshness of the fruit. This not only helps in improving transparency but also helps validate the model to base its decisions on relevant features, which is similar to explainable AI for food quality assessment [3]. The combination of knowledge distillation and Grad CAM has proven to be a new contribution how fruit freshness detection is tackled with both efficiency and interpretability being key when considering practical adoption.

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Despite these contributions, there are still some research opportunities for the future. First, the use of multi-sensor data could make the freshness detection stronger and more accurate. Combining RGB images with hyperspectral or thermal imaging could offer extra information on the condition of the fruit inside the not visible to the human eye. Second, the framework of multi-task learning could be investigated to simultaneously predict the type of fruit and freshness level to enhance the overall efficiency and generalisation of the system.

Another interesting direction is to use semi-supervised and active learning techniques in order to flip the dependence on the availability of large labeled datasets. Since the process of annotating freshness of fruits is time-consuming and subjective, taking advantage of unlabeled data or selectively labelling informative samples could be a major factor in terms of scalability. Additionally, it might be necessary to use domain adaptation techniques to aid performance degradation due to difference in environmental condition and deployment scenarios.

Finally, additional improvements in the field of explainable AI could help to better understand the system. While Grad-CAM is a useful tool for providing visual insights into a model, there are more advanced techniques that could be used to provide more precise and robust explanations, such as Grad CAM++, LIME, or SHAP. However, conducting user studies, analyzing explanations for trust and usability in real-world environments would be valuable as well.

In conclusion, through the proposed framework, it has been shown that it is possible to find a good balance between accuracy, efficiency, and interpretability during the detection of fruit freshness. By integrating the knowledge distillation with explainable AI methods, this work is one step towards developing realistic and trustworthy intelligent systems for smart agriculture and food quality monitoring.

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