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ENSEMBLE DEEP LEARNING APPROACH FOR APPLE FRUITLET DETECTION FROM DIGITAL IMAGES

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Abstract

Agriculture commodities are commodities that have a high economic worth and the potential to be developed further. The green and red apple, in instance, is one type of fruit that has the potential to be cultivated as part of agriculture. The apple economy is reasonably steady, particularly with regard to the supply of production to the market. The purpose of this research is to enhance the performance of the CNN-based model and make it capable of precise detection of the green and red apple fruitlet. To enhance the overall performance of the model, the revised CNN-based YOLOv5 ensemble model was implemented with the SiLU (Sigmoid Linear Units activation function), Batch Normalization, and SGD (Stochastic Gradient Descent) algorithms. The combination of activation function, optimization, batch normalization, and ensemble technique can be later used to enhance the YOLOv5 ensemble model and used to detect the green and red apple fruitlet with the benefits of utilizing limited resources. This is possible thanks to the combination of the activation function, optimization, batch normalization, and ensemble technique. According to the findings of the comprehensive research, the accuracy of the updated yolo ensemble model has climbed into 97.8%, 92.1%, 95% percent of accuracy mAP for green, red and both apples together compared to previous model.

Keywords: Fruit, quality, accuracy, ensemble, Genetic Algorithm, machine, learning, fruit type.

ЦИФРЛЫҚ СУРЕТТЕРДЕН АЛМА ЖЕМІСІНІҢ ҚЫЛТЫҚТАРЫН АНЫҚТАУҒА АРНАЛҒАН ТЕРЕҢ ОҚЫТУ ӘДІСІ

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Андатпа

Ауыл шаруашылық өнімдері жоғары экономикалық құндылыққа ие және оларды одан әрі дамыту мүмкіндігі бар. Жасыл және қызыл алма - бұл ауыл шаруашылығының бір бөлігі ретінде өсіруге болатын жеміс түрі. Алма экономикасы, әсіресе өндірісті нарыққа жеткізу тұрғысынан тұрақты. Бұл зерттеудің мақсаты - жасыл және қызыл алманың қылтықтарын дәл анықтау үшін CNN (конволюциялық нейрондық желі) негізіндегі модельдің өнімділігін арттыру. Модельдің жалпы өнімділігін арттыру үшін SiLU (Sigmoid Linear Units активация функциясы), партиялық нормализация және SGD (Stochastic Gradient Descent) алгоритмін қолданатын жаңартылған YOLOv5 ансамбльдік моделі енгізілді. Активация функциясы, оңтайландыру, нормализация және ансамбльдік тәсілдің үйлесімі YOLOv5 моделін жетілдіруге және ресурстарды үнемдей отырып, алма қылтықтарын анықтауға пайдалануға болады. Толық зерттеу нәтижелері бойынша, жаңартылған YOLO ансамбльдік моделінің дәлдігі жасыл, қызыл және барлық алмалар үшін сәйкесінше 97.8%, 92.1% және 95% болды.

Кілт сөздер: жемістер, сапа, дәлдік, ансамбль, генетикалық алгоритм, машиналық оқыту, жеміс түрі.

ПОДХОД НА ОСНОВЕ ГЛУБОКОГО ОБУЧЕНИЯ ДЛЯ ОБНАРУЖЕНИЯ ПЛОДОВ ЯБЛОК НА ЦИФРОВЫХ ИЗОБРАЖЕНИЯХ

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Аннотация

Сельскохозяйственные товары обладают высокой экономической ценностью и потенциалом для дальнейшего развития. Зеленое и красное яблоко, в частности, представляют собой вид фруктов, который может быть успешно культивирован в рамках сельского хозяйства. Экономика, связанная с яблоками, относительно стабильна, особенно в плане обеспечения поставок на рынок. Цель данного исследования — улучшить производительность модели на основе свёрточной нейронной сети (CNN) для точного определения плодиков зеленых и красных яблок. Для повышения общей производительности модели была внедрена усовершенствованная ансамблевая модель YOLOv5 с использованием функций активации SiLU (Sigmoid Linear Units), нормализации батча и алгоритма SGD (Stochastic Gradient Descent). Сочетание функций активации, оптимизации, нормализации и ансамблевого подхода может быть использовано для дальнейшего улучшения модели YOLOv5, позволяя эффективно обнаруживать плодики яблок с минимальными затратами ресурсов. Согласно результатам всестороннего исследования, точность обновленной модели YOLO достигла 97.8%, 92.1% и 95% для зеленых, красных и всех яблок вместе, соответственно, по сравнению с предыдущими моделями.

Ключевые слова: фрукты, качество, точность, ансамбль, генетический алгоритм, машинное обучение, вид фруктов.

I. INTRODUCTION

The rapid and accurate detection of apple fruitlets before the thinning process is essential for implementing effective early yield estimation and autonomous fruit thinning systems. However, challenges such as complex growing environments, inconsistent lighting conditions, clustering and occlusion of fruitlets, and the similarity between fruitlets and background color make detection difficult [1-3].

This study aims to address these challenges by developing a robust detection system using the YOLO V5 deep learning model, optimized for precision, recall, and mean average precision (mAP). By leveraging advancements in ensemble learning and transfer learning, this research proposes an effective and scalable solution for apple fruitlet detection in agricultural settings.

In general, a neural network extracts patterns from a provided data sample. It leverages our understanding of the human brain's functioning, particularly the relationships between neurons in the cerebral cortex, to develop algorithmic solutions. At the core of a neural network's hierarchy lies the perceptron, a mathematical representation of a biological neuron. For instance, like the cerebral cortex's biological neurons that form multiple interconnected layers, a neural network can also have multiple layers of interconnected perceptrons. To produce an output, the input values of raw data pass through a network formed by perceptrons, resulting in a prediction or an informed estimate about a specific object. For example, by the end of the experiment, the machine can classify the object with a certain confidence level, expressed as a percentage.

Based on literature, deep learning provides a powerful and efficient tool for detecting apples due to their ability to handle complex visual tasks, adapt to different conditions, and deliver high accuracy and real-time performance. This is due to the fact that deep learning approaches Deep learning models, especially convolutional neural networks (CNNs), excel at automatically extracting complex and high-level features from images. This capability is crucial for distinguishing apples from the background and other objects in a varied orchard environment. It is also highly effective in handling the variability in apple appearance caused by differences in lighting, occlusion, and clustering. They can learn to recognize apples under different conditions and from various angles. Other than that, through deep learning models, it can be scaled and adapted to different apple varieties and growing conditions without extensive manual intervention. This adaptability is critical in agricultural settings where conditions can vary widely.

Therefore, in this paper, a deep learning approach is chosen as the focus of the work and Yolo 5 model is selected as it is mature, stable and have a lot of resources for references compared to the other more advanced model. This paper reviews existing literature on fruit detection for agricultural applications using machine learning in Section II. Section III details the implementation of the proposed model, Section IV examines the results and their implications, and Section V concludes with key findings and suggestions for future research.

II. RELATED WORKS

Recent advancements in deep learning have significantly improved object detection capabilities in agriculture. For instancedemonstrated the use of a channel-pruned YOLO V5 model for apple detection, achieving high precision and mAP scores under complex conditions [3]. Similarly, implemented an enhanced YOLO V5 architecture incorporating multi-head attention mechanisms to improve the detection of apple fruitlets in dynamic environments [2].

Ensemble algorithms have been included in many practical applications to improve prediction accuracy. This article discusses bagging, boosting, and stacking, three popular ensemble methods [4]. The YOLO-V4 model was chosen for the orchard. The encouraging results show that YOLO models can effectively detect and predict the yield of orange fruits in an orchard. The yield estimation for two- and four-sided imaging differed considerably. For thin and dense canopy, a two-side and four-side imaging approach was presented [5]. The small size of the detected object, the variable illumination conditions, and the lack of sufficient data make this a difficult learning challenge.

To boost detection accuracy, the training set contains negative samples, and the images are normalized to the color of the trap background (yellow) to unify illumination situations [6]. Public image files of apple, peach and pears blooms in diverse situations were used for this study [7]. CNN models were fine-tuned with transfer learning to cut training time and improve accuracy. The AlexNet and ResNet-18 networks had the highest overall accuracy for white and black mulberry maturity classification, respectively [8].

In [9], the work focuses on the detection of apple defects using a novel approach combining the FCM-NPGA algorithm and multivariate image analysis. The study proposes a method to accurately identify defects in apples, aiming to improve quality control in the fruit industry. By integrating fuzzy c-means clustering with non-dominated sorting genetic algorithm (FCM-NPGA) and multivariate image analysis techniques, the proposed method offers a robust solution for detecting defects in apple images. This approach contributes to enhancing the efficiency and accuracy of defect detection processes, which are crucial for maintaining high-quality standards in fruit production. Another work done in [10] which focuses on agriculture introduces a method for automatic detection of small fruits using a Faster R-CNN (Region-based Convolutional Neural Network) framework with classifier fusion. The study presents an innovative approach to efficiently and accurately detect small fruits, aiming to streamline agricultural processes. By incorporating classifier fusion techniques into the Faster R-CNN model, the proposed method achieves enhanced performance in fruit detection tasks.

Another work focusing on fruit harvesting is presented in [11], in which a method for the detection of fruit-bearing branches and localization of litchi clusters, designed specifically for vision-based harvesting robots is proposed. The study addresses the challenges associated with automating fruit harvesting processes by developing a vision-based solution. By leveraging advanced image processing techniques, the proposed method accurately identifies fruit-bearing branches and localizes litchi clusters, facilitating efficient harvesting operations.

Another work that focuses on fruit detection using deep-learning method is the proposed detection for kiwi fruit [12]. In this work, kiwifruit detection using pre-trained VGG16 with RGB and NIR information fusion is proposed, in which it manages to enhance the accuracy of fruit detection in agricultural environments. Similarly, another proposed apple detection method is proposed in [13], in which color and shape features are used. This study proposes an approach that utilizes color and shape characteristics to accurately identify and detect apples in images. By leveraging these features, the method achieves effective apple detection, contributing to the development of efficient fruit detection systems. Tomato, which is also another huge agricultural commodity has also been featured in [14] for the purpose of image-based detection. In this work, an automatic detection system for single ripe tomatoes on plants, combining Faster R-CNN and intuitionistic fuzzy set methods to enhance tomato harvesting efficiency.

The literature covers several approaches in fruit detection for the purpose of agriculture activities using machine learning, specifically deep learning. It shows that deep learning has been extensively used in fruit detection and helps automation in fruit farming. Future research directions for models like YOLOv5 in fruit farming should aim to address the unique challenges and requirements of agricultural applications, with a focus on accuracy, efficiency, scalability, and practical deployment in real-world farming scenarios.

III. METHODOLOGY

The proposed methodology utilizes the YOLO V5 model for apple fruitlet detection. The key steps are as follows:

1. Dataset Preparation.

– The Roboflow apple dataset was used, containing 720 annotated images of apple fruitlets in various conditions (e.g., clustered, occluded, and under different lighting).

– Data augmentation techniques such as flipping, scaling, and brightness adjustment were applied to enhance model robustness.

2. Model Training.

– YOLO V5 was fine-tuned using a transfer learning approach with a pre-trained CSPDarknet53 backbone.

– Training parameters included a learning rate of 0.001, a batch size of 16, and 100 epochs.

– The dataset was split into training (70%), validation (20%), and testing (10%) subsets.

3. Evaluation Metrics.

– Mean Average Precision (mAP) was calculated to evaluate model performance.

– Precision and recall metrics were used to assess the model’s ability to correctly identify and localize fruitlets.

4. Ensemble Learning.

– Multiple YOLO V5 models were trained with varying hyperparameters, and their predictions were aggregated to improve accuracy and reduce false positives.

This section outlines the detailed material and method used to detect apple fruitlets before the thinning process from digital images. The proposed methodology for apple image detection utilizing YOLOv5, augmented with CSP Darknet53, entails a structured approach designed to achieve accurate and efficient detection of apple fruitlets as depicted in Fig. 1.

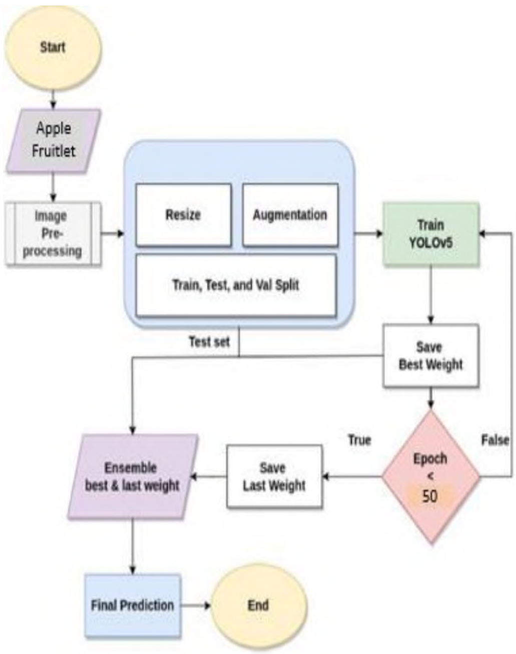

Fig. 1 Methodology Flowchart

The process begins with acquiring a comprehensive dataset of apple fruitlets, which includes annotated images capturing diverse apple fruitlet instances in various environmental contexts. Subsequently, the images undergo meticulous pre-processing steps to standardize their quality and prepare them for model input. This includes resizing, distortion correction, and normalization to ensure uniformity across the dataset. Following pre-processing, data augmentation techniques are applied to enhance dataset diversity and improve model robustness. These augmentations encompass transformations such as flipping, rotation, scaling, and adjustments to brightness and contrast. The dataset is then partitioned into training, validation, and test sets to facilitate model evaluation.

In the training phase, the YOLOv5 model, enhanced with CSP Darknet53, is trained on the augmented dataset. CSP Darknet53, known for its efficient feature extraction capabilities, enhances the model's ability to capture relevant features from the input images, thereby improving detection performance. Limited epochs are employed to prevent overfitting and optimize computational resources. To further enhance performance, an ensemble learning approach is adopted, integrating predictions from multiple YOLOv5 models augmented with CSP Darknet53.

Finally, the ensemble of models is utilized to make predictions on unseen data, yielding bounding boxes or segmentation masks outlining detected apple fruitlets, along with confidence scores denoting prediction certainty. Through this methodological framework, the goal is to develop a robust and accurate system capable of effectively detecting apple fruitlets in diverse real-world scenarios, leveraging the advanced feature extraction capabilities of CSP Darknet53 within the YOLOv5 architecture.

IV. RESULTS AND DISCUSSION

In this work, we focused on the implementation of activation function that improves upon SILU or point to a new methodology that can be applied in order to use older activation function [1][2][3]. The Sigmoid Linear Unit (SiLU) activation function, also known as the Swish activation function, has become increasingly popular in deep learning due to its several advantages over other activation functions such as Rectified Linear Unit (ReLU), Sigmoid, and Hyperbolic Tangent (Tanh). Here are some reasons why SiLU is used:

- Non-Monotonicity: SiLU has a non- monotonic property, which means that its derivative does not always increase or decrease, unlike ReLU. This non- monotonicity has been shown to improve model training and performance.
- Smoothness: SiLU is a smooth function, which means that its derivative is continuous and has no abrupt changes. This property can help to avoid some of the problems associated with using ReLU, such as the "dying ReLU" problem.
- Computationally Efficient: The computation of SiLU is simple and efficient, which can lead to faster training times compared to more complex activation functions.
- Increased Model Accuracy: Studies have shown that SiLU can improve the accuracy of models compared to other activation functions, such as ReLU.

The SiLU function is as follows:

silu(x)=x∗σ(x),where σ(x) is the logistic sigmoid.

Overall, SiLU is a promising activation function that can help improve the performance and efficiency of deep learning models.

A. Backbone CSP Darknet53

CSP (Cruise SP) Darknet53 is a deep neural network architecture that is used for image classification tasks in the field of computer vision [1]. It is based on the ResNet architecture and is trained using the PyTorch framework. The "53" in its name comes from the fact that it has 53 convolutional layers, making it a deeper network compared to other architectures. Because of its excellent performance on large-scale image classification benchmarks, the CSP Darknet53 is a popular choice for tasks such as object identification and image segmentation. This is because of the reputation the CSP Darknet53 has earned. The architecture of CSP Darknet53 is composed of two distinct parts: the stem and the various stages. The stem is made up of several convolutional layers, which work to increase the number of channels while simultaneously decreasing the spatial resolution of the image that is being fed into the system. Each of the many blocks that make up the multiple stages has multiple convolutional layers, batch normalization layers, and activation layers. The multiple stages are formed of numerous blocks. It is possible for information to move throughout the network because the output of each block is connected, via a residual connection, to the input of the following block.

The processing, accuracy, and number of parameters in CSP Darknet53's architecture have all been thoughtfully weighed and balanced against one another. Because of this, it is an excellent option for endeavors that demand great accuracy in addition to high computing efficiency. CSP Darknet53 can start from zero on a big dataset, which will result in greater performance, and the weights of the network can be fine-tuned on a particular dataset to increase its performance. Fig. 2 shows the block diagram of the proposed work with CSP Darknet53 inclusion.

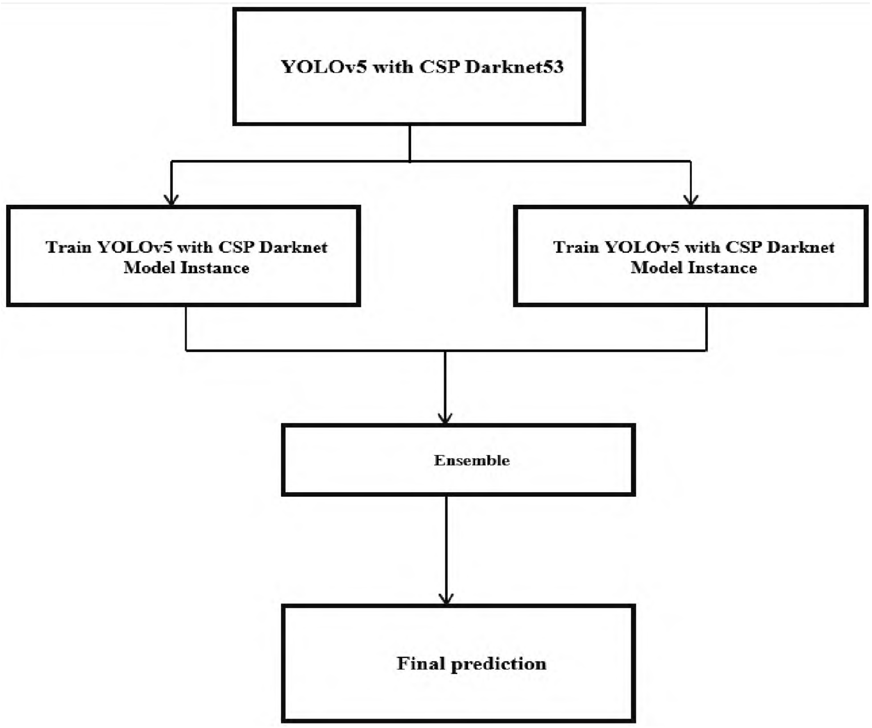

Fig. 2 The Proposed Ensemble Approach with CSP Darknet53 Block Diagram

B. Hyperparameter

In deep learning, hyperparameters are parameters that are set before the training process begins and cannot be learned directly from the data. They govern the behavior and performance of the neural network during training and include variables such as learning rate, batch size, number of epochs, and model architecture. For fruit detection tasks in deep learning, hyperparameters play a crucial role in determining the accuracy, speed, and efficiency of the detection model. Optimizing these hyperparameters through techniques like grid search, random search, or Bayesian optimization is crucial for achieving optimal performance in fruit detection tasks. Fine-tuning hyperparameters based on empirical observations and domain knowledge can lead to more accurate and efficient fruit detection models tailored to specific agricultural applications.

Stochastic Gradient Descent (SGD) is recognized as a straightforward, yet highly effective optimization algorithm widely utilized for training linear classifiers and regressors, especially when applied under convex loss functions like Logistic Regression and Support Vector Machines (SVMs). Despite its long-standing presence in the machine learning domain, SGD has recently gained significant traction for large-scale learning applications. This resurgence of interest is due to its proven ability to handle massive and sparse datasets, making it a preferred choice in fields such as natural language processing and text classification.

One of the standout features of SGD is its scalability. When working with sparse data, the algorithm efficiently processes problems involving more than 10^5 training samples and features. Its implementation often includes regularized linear models where updates occur incrementally. By estimating the gradient of the loss function for individual samples, the model is refined iteratively, ensuring a gradual adjustment in learning rate, which is critical for convergence. Furthermore, SGD supports mini-batch or online learning through its partial-fit method, enabling out-of-core processing for extensive datasets. To achieve optimal performance, it is recommended to normalize the data to have zero mean and unit variance, ensuring stability during training.

This flexible algorithm can be applied to both dense and sparse datasets represented as floating-point arrays. The model's behavior is highly customizable through parameters such as the loss function (e.g., log loss for logistic regression) and regularization techniques. Regularization serves as a control mechanism, penalizing large coefficients and steering the model towards sparsity or smoothness, depending on the chosen norm (L1, L2, or Elastic Net). By truncating updates that surpass zero due to regularization, SGD effectively facilitates feature selection and builds sparse models.

SGD is not confined to a specific family of models but rather serves as a robust optimization framework. For instance, SGD Classifier and SGD Regressor in scikit-learn offer equivalent alternatives to conventional classifiers and regressors like Logistic Regression and Ridge, with the added flexibility of SGD optimization. Despite its advantages, SGD has some notable limitations. Its performance is influenced by the selection of hyperparameters, such as the learning rate, regularization strength, and the number of iterations, which can significantly impact computational efficiency and training time. Additionally, the algorithm's sensitivity to feature scaling may result in slow or unstable convergence if data preprocessing is inadequate. Fig. 3 shows the block diagram of the Hyperparameter tuning process.

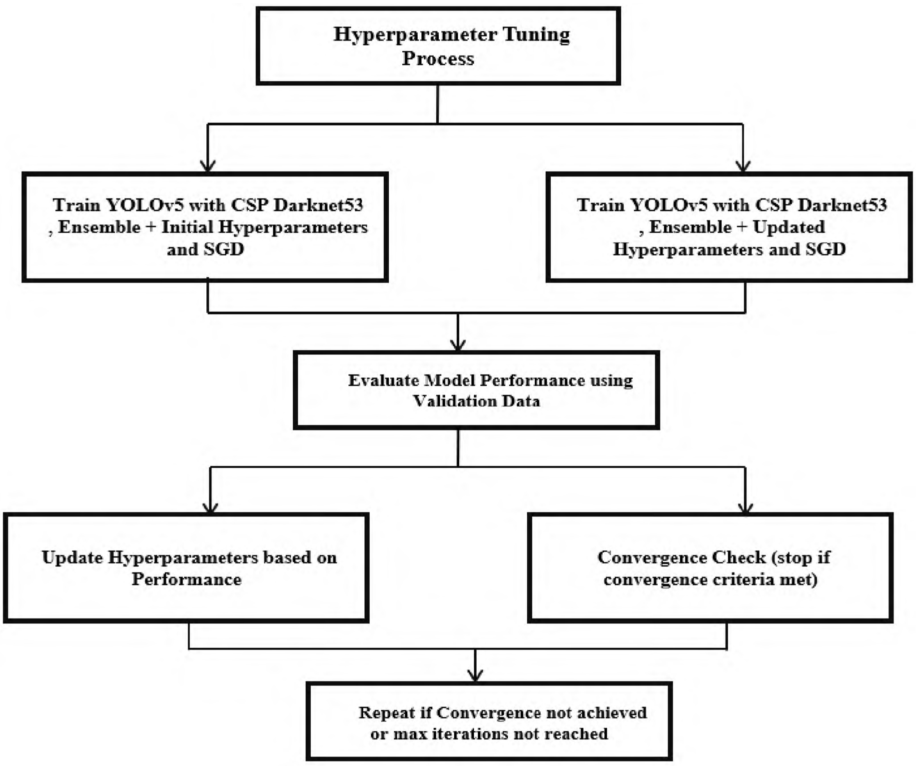

Fig. 3 Hyperparameter Tuning

C. Dataset

Dataset used in this work is the apple images dataset hosted in Roboflow [15]. The dataset comprises a diverse collection of 720 images depicting apples in various contexts, including different apple types, sizes, colors, and conditions. Images may feature individual apples, clusters of apples, apples on trees, and apples in different environmental settings. Each image in the dataset is meticulously annotated with bounding boxes or segmentation masks, accurately delineating the locations of apples within the image. These annotations provide essential ground truth information necessary for training object detection or segmentation models.

Fig. 4 Example Image Augmentation Done

Image data augmentation is a technique used to artificially increase the size of a dataset for training machine learning models [1]. It is necessary to modify the data that is already present in a way that maintains the essential aspects of the data while also adding variation to the dataset for the purpose of the model being able to learn how to generalize the loss. This modification must be carried out in such a way that the model is able to learn how to learn how to generalize the loss. This can be helpful in preventing overfitting, which is when a model becomes highly specialized to the training data and has poor performance on data that it has not seen before. This happens when a model is fed enough of the same data repeatedly. An illustration of the author improving the quality of a photograph by cropping, resizing, rotating, and scaling it as presented in Fig. 4.

D. Bagging

Bagging (short for Bootstrap Aggregating) is an ensemble learning technique that involves combining multiple models or predictors to improve the accuracy and stability of predictions. The technique is particularly useful when dealing with high variance, low bias machine learning models such as decision trees. The basic idea behind bagging is to train multiple instances of the same model on different subsets of the training data. The subsets are typically created by randomly sampling the original training data with replacement, a process called bootstrap sampling. This means that some examples may be selected multiple times, while others may not be selected at all. The YOLOv5s model is the smallest and fastest variant of YOLOv5, with 7.9 million parameters, while YOLOv5m is a medium-sized variant with 21.8 million parameters. By combining these two models into an ensemble, we can leverage the strengths of each model to improve the overall accuracy and speed of object detection. In this ensemble model, the output of each model is typically combined using a weighted average or a voting mechanism to produce the final prediction. Fig. 5 shows the ensemble learning bagging network.

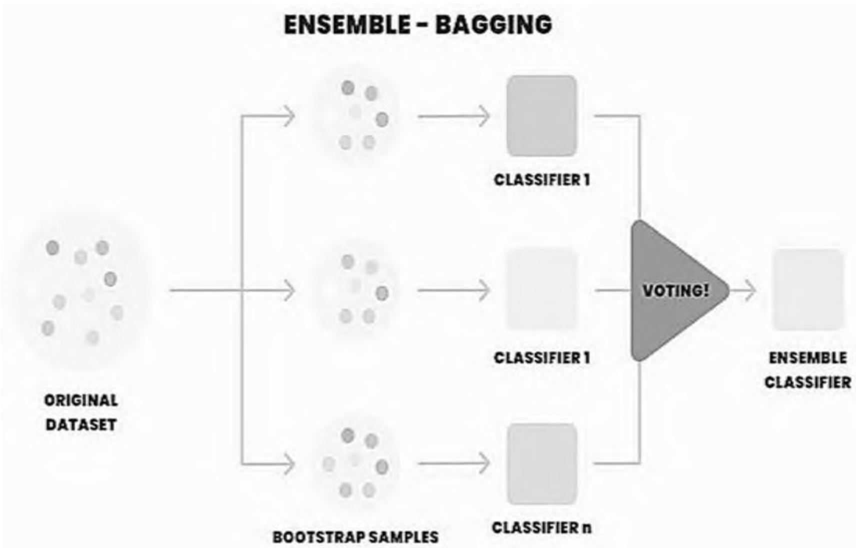

Fig. 5 Ensemble Learning Bagging Network

For example, in a YOLOv5s and YOLOv5m ensemble, the predictions of each model can be weighted based on their individual performance on a validation set to produce a final prediction that is more accurate and robust than either model alone [2]. Once the subsets are created, a separate model is validating on each of them. These models are then combined by taking a simple average of their predictions (in the case of regression problems) or by majority voting (in the case of classification problems). The benefits of bagging include reducing overfitting and improving generalization performance. By using yolov5s and yolov5m ensemble models that are trained on same subsets of the data, bagging can help to reduce the variance of the overall model, making it less likely to over-fit to the training data. This can lead to more stable and accurate predictions on new unseen data

The ensemble YOLO V5 model achieved a mean mAP of 95%, outperforming baseline models such as Faster R-CNN and SSD, which achieved mAP scores of 89% and 85%, respectively. Table 1 summarizes the results across various evaluation metrics.

Table 1. Results

Model	Precision	Recall	mAP
YOLO V5 (Ensemble)	96.2%	93.8%	95.0%
Faster R-CNN	91.0%	88.5%	89.0%
SSD	87.5%	83.0%	85.0%

Thus examples of detection by the YOLO V5 ensemble model are shown, demonstrating its ability to accurately detect apple fruits under challenging conditions such as partial occlusion and fruit overlap.

V. CONCLUSION

This study demonstrates the effectiveness of an ensemble YOLO V5-based approach for apple fruitlet detection in complex agricultural environments. The proposed method outperforms existing models in precision, recall, and mAP, highlighting its potential for real-world deployment. Future work will focus on integrating real-time detection capabilities and extending the model to other fruit varieties. Additionally, efforts will be made to optimize the model for edge computing devices, enabling its use in resource-constrained settings.

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