Designing a Mobile Application for Identifying Strawberry Diseases with YOLOv8 Model Integration

Thuy Van Tran*, Quang - Huy Do Ba, Kim Thanh Tran, Dang Hai Nguyen, Dinh Chung Dang, Van - Luc Dinh
Faculty of Electrical Engineering, Hanoi University of Industry, Hanoi, Vietnam

***Abstract*—The progress in computer vision has led to the development of potential solutions, becoming a versatile technological key to addressing challenging issues in agriculture. These solutions aim to enhance the quality of agricultural products, boost the economy's competitiveness, and reduce labor and costs. Specifically, the detection of diseases in various fruits before harvest to avoid reducing product quality and quantity still relies on the experience of long-time farmers. This leads to difficulties in controlling disease sources over large cultivated areas, resulting in uneven quality control after harvest, which may lead to low prices or failure to meet export requirements to developed markets. Therefore, this stage has now been applied with modern technology to gradually replace humans. In this paper, we propose a mobile application to detect four common diseases in strawberry trees by using image processing technology that combines an artificial intelligence network in identification: based on size, color, and shape defects on the surface of the fruit. The proposed model consists of different versions of YOLOv8 with RGB input to accurately detect diseases in strawberries and provide assessments. Among these, the YOLOv8n model utilizes the fewest parameters with only 11M, but it produces more output parameters with higher accuracy compared to some other YOLOv8 models, achieving an average accuracy of approximately 87.9%. Therefore, the proposed method emerges as one of the possible solutions for strawberry disease detection.**

Keywords*—*Computer vision; YOLOv8; strawberry diseases

I. Introduction

Strawberries are among the high-value fruits widely consumed globally due to their nutritional value. In 2020, the global strawberry production was valued at $14 billion (FAO UN, 2021), with China being the largest producer accounting for $5 billion, more than three times the value of the second-largest producer, the United States [1]. In Vietnam, Son La strawberries reached a production of 320 tons and were distributed to 26 provinces and cities nationwide in 2020. Strawberries are a rich source of nutrients, including vitamin C, antioxidants such as quercetin and anthocyanins, as well as fiber, manganese, vitamin K, vitamin A, folic acid, vitamin B6, vitamin E, and potassium [2]. These components offer numerous health benefits, including immune system support, blood sugar balance, cell protection, and support for eye, skin, and bone health. Therefore, strawberries are a staple fruit consumed daily, providing not only delicious taste but also significant nutritional value [3].

Pests and diseases that damage crops are a major challenge in the agricultural sector, causing significant losses in food production. Nearly half of all crops grown globally are damaged by pests and diseases [4]. Strawberries are particularly susceptible to plant-pathogenic fungi, bacteria and viruses [5, 6, and 7]. Common pathogens in strawberries include Colletotrichum siamense, which causes anthracnose [8,9]; Botrytis cinereal, the causative agent of gray mold [10,11]; Neopestalotiopsis spp. [12], causing crown rot, fruit rot and leaf blight [8]; and other fungi cause powdery mildew, which typically affects petioles [13], leaves and fruits of strawberries [14]. These pathogens not only reduce photosynthetic efficiency but also negatively impact fruit quality, growth and production. Identifying strawberry diseases currently depends mainly on manual work, requiring a lot of effort and time. The shrinking of the workforce in agricultural areas increases the difficulty, as the ability to properly predict the severity of disease on a large scale becomes difficult. Therefore, there is a need to develop an automated, fast and accurate technique for early detection of strawberry diseases.

Therefore, many research articles have applied computer vision methods to assist people in classifying and detecting plant diseases [15, 16]. In published reports, convolutional neural networks (CNN) are one of the most popular ML techniques for plant disease detection. Jeon and Rhee [17] proposed a CNN technique for tree leaf recognition using the GoogLeNet model. The proposed technique can detect damaged leaves with an identification rate of >94%, even when only 30% of the leaves are damaged. Cervantes-Jilaja et al [18] proposed a computer vision-based method to detect and identify visual defects in chestnuts using external characteristics such as shape, color, size and structure. Mohanty et al. [19] used CNN to detect crop species and diseases based on public image datasets using training models of GoogleLeNet and AlexNet. Based on color, grayscale, and leaf segmentation, the proposed model has 99.35% accuracy.

The evidence of existing systems for automatic classification and detection based on machine vision for various agricultural products has inspired the authors' team to conduct this research. This study is aimed at meeting the practical demand for strawberry disease detection, and we have designed an app that can be used on both Android and iOS platforms to detect strawberry diseases, combining multi-dimensional features with the newly trained YOLOv8 model [28]. For the dataset, we collected a large number of strawberry disease images from laboratory and field settings using methods such as noise filtering and sharpness enhancement, thereby improving the model's generalization effectiveness. Additionally, we also experimented under low-light conditions to enhance the network's adaptability in natural environments and improve the efficiency of strawberry disease detection.

The proposed method of designing a mobile application to detect diseases in strawberries before harvest brings many significant benefits to the agriculture industry. Specifically:

- Early disease detection: This application helps farmers intervene in a timely manner to prevent the spread of diseases and minimize agricultural losses.
- Enhanced production efficiency: The ability to manage and monitor the health of crops is improved, leading to increased productivity and quality of agricultural products.
- Time and cost savings: The mobile application automates the disease detection process, saving time and labor costs.
- Increased income for farmers: Improving the quality and quantity of agricultural products through early disease detection and treatment helps increase income for farmers.

In conclusion, this method not only brings significant benefits to farmers in managing and protecting their crops but also holds the potential to improve productivity and income in the agricultural sector.

The rest of this paper is organized as follows. First, Section II presents a number of related works which motivate this study. Then, Section III presents the materials and methods for diseases of strawberry detection and recognition. Next, Section IV shows the evaluation results, while Section V provides the study's conclusions and future work.

II. Related Work

There have been several computer vision-based studies related to strawberry disease identification in recently published studies. Jia-Rong Xiao et al. [20] used a convolutional neural network (CNN) model – ResNet50 with two different datasets containing original images and feature images to detect diseases such as leaf fungus, gray mold and white mold. The scoring results have a 100% accuracy rate for leaf blight disease affecting roots, leaves and fruits; 98% for gray mold cases and 98% for white mold cases. In 20 epochs, the accuracy rate of 99.60% from the featured image dataset is higher than 1.53% from the original image dataset. However, this study only focuses on fungal diseases of strawberry plants without expanding on other diseases of strawberries.

In addition, methods for detecting strawberry diseases are based on leaf color. Dwi Esti Kusumandari et al. [21] proposed using digital image processing to analyze diseases of strawberry plants based on leaf color. Digital images of mulberry leaves will be processed to determine health status. Image processing includes image enhancement, color segmentation from RGB color space to HSV color space, and region segmentation to determine deformed and intact leaf areas. Image processing results show that 85% accuracy is achieved in detecting the health status of strawberry plants. Aldi Ramdani and Suyanto Suyanto [22] proposed using a CNN model to identify diseases on strawberries from leaves with four different types of strawberry leaves: healthy leaves, blighted leaves, spotted leaves and diseased leaves. Using ResNet-50 architecture for the model with 3600 images, the model achieved prediction accuracy of 100% for spotted leaves, 99% for diseased leaves, 99% for burned leaves and 100% for healthy leaves. However, these studies have not yet provided specific conclusions about the types of diseases of strawberry plants, but are still just generalizations about disease and non-disease.

In recent years, YOLO [23-28] is a developed model that allows the ability to detect objects from a distance perspective with small size and has won most of the attention of current researchers. with continuous improvements such as YOLOv1, YOLOv2, YOLOv3, YOLOv4, YOLOv5, YOLOv7 and most recently YOLOv8, a state of the art model. Along with this trend, we have applied YOLOv8 module versions to detect diseases in strawberry plants with a data set that we have built including four classes about specific diseases and one normal class. From there, we have addressed lingering issues from studies such as limitations on disease sources and the lack of specificity in identifying each type of disease in strawberry plants. Additionally, We also provide feedback to create the best version of the app that can be used on both Android and iOS.

III. Materials and Methods

A. YOLOv8

The proposed architecture of YOLOv8 aims to achieve optimal feature extraction. The backbone of the proposed architecture includes Convolutional Module, Module C2f, and Module SPPF, which are crucial for feature extraction.

The Convolutional Module in YOLOv8 is typically integrated into the backbone network, where its role is to transform the input image into feature representations using convolutional layers, batch normalization layers, and the SiLU activation function. These components play a vital role in extracting important information from the image, ranging from low-level features like edges to high-level features like object shapes and details. Additionally, the use of the SiLU activation function helps the model learn nonlinear representations efficiently, contributing to its ability to learn and accurately recognize objects in the image (see Fig. 1).

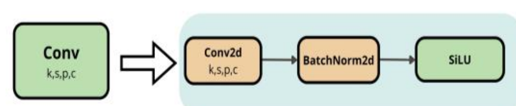


Fig. 1. Architecture of module convolutional.

Unlike YOLOv5, YOLOv8 does not bring many significant innovations, with the only notable change being the introduction of the Module C2f, replacing the Module C3 in YOLOv5. In YOLOv5, the Module C3 features three standard convolutional layers and multiple Bottleneck modules. Particularly, the Bottleneck module consists of two branches: one branch utilizes multiple stacked Bottlenecks and three standard convolutional layers, while the other branch passes through a basic convolutional layer before merging the two branches together. This not only helps reduce the number of training parameters and computations but also addresses issues of gradient explosion and disappearance in deep networks, enhancing the model's learning capabilities. While YOLOv7 improves gradient information by adding multiple parallel gradient streams and using the ELAN module to achieve higher accuracy and reasonable latency, YOLOv8 further develops this idea by designing the Module C2f. Inspired by the Module C3 and ELAN, the Module C2f helps gather diverse gradient streams while still maintaining the model's lightweight structure. This enhances the learning ability and performance of YOLOv8 while effectively reducing latency. Fig. 2 shows architecture of Module C2f.

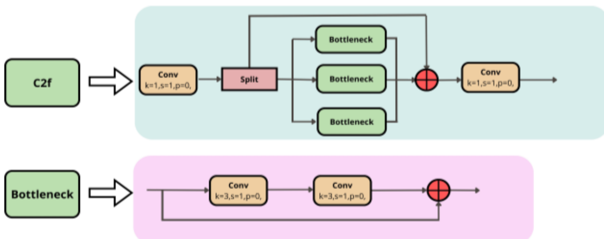


Fig. 2. Architecture of module C2f.

In YOLOv8, Module SPPF (Spatial Pyramid Pooling Fusion) module plays a crucial role in improving the model's accuracy, particularly in object detection tasks. This module is integrated to address the challenge of object detection at different positions and scales within the image. Module SPPF utilizes the Spatial Pyramid Pooling method to generate multi-level representations, enabling the model to accept and process information from regions of various sizes in the image. This enhances the model's recognition capabilities while helping to minimize accuracy issues at diverse positions across the image (see Fig. 3).

Fig. 4 provides an overview of the YOLOv8 model, integrating crucial components such as the Convolutional Module, Module C2f, and Module SPPF to efficiently extract features and address the challenge of varying input sizes in images. Particularly, the Module C2f plays a vital role in reducing the number of parameters and computations, addressing issues of gradient explosion and disappearance in deep learning networks, while enhancing the model's learning capabilities. Experimental results have affirmed the outstanding performance of YOLOv8, achieving significantly higher accuracy compared to previous versions of YOLO. This is why we selected YOLOv8 for our strawberry disease detection research.

B. Dataset for Strawberry Disease Detection

Faced with the complexity of the real environment, we developed machine learning models trained on real-world images using diverse data sources from Google Images, as well as photos taken at farms and from the Department of Agriculture. This process involved downloading images from the internet using both the scientific and common names of the five types of strawberries mentioned in our dataset. Additionally, we didn't solely rely on online data sources but also gathered additional images, especially during the large-scale strawberry disease research conducted on the field.

To create a quality dataset, we applied a meticulous filtering process. Selection criteria included metadata information on websites and principles outlined by the Department of Agriculture. Color, area, density of the infected area, and shape of each type were identified as the most important factors for categorizing images into groups. Furthermore, we discarded inaccurate images, such as those not depicting strawberries controlled in a laboratory setting and those outside the scope. Moreover, to ensure the accuracy of each type, we also removed duplicate images across classes through a search process.

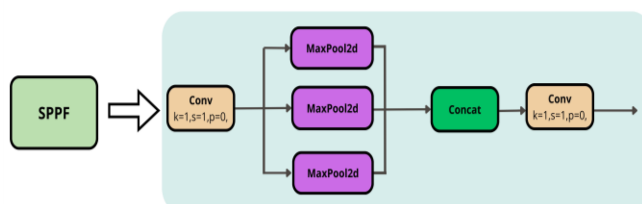


Fig. 3. Architecture of module SPPF.

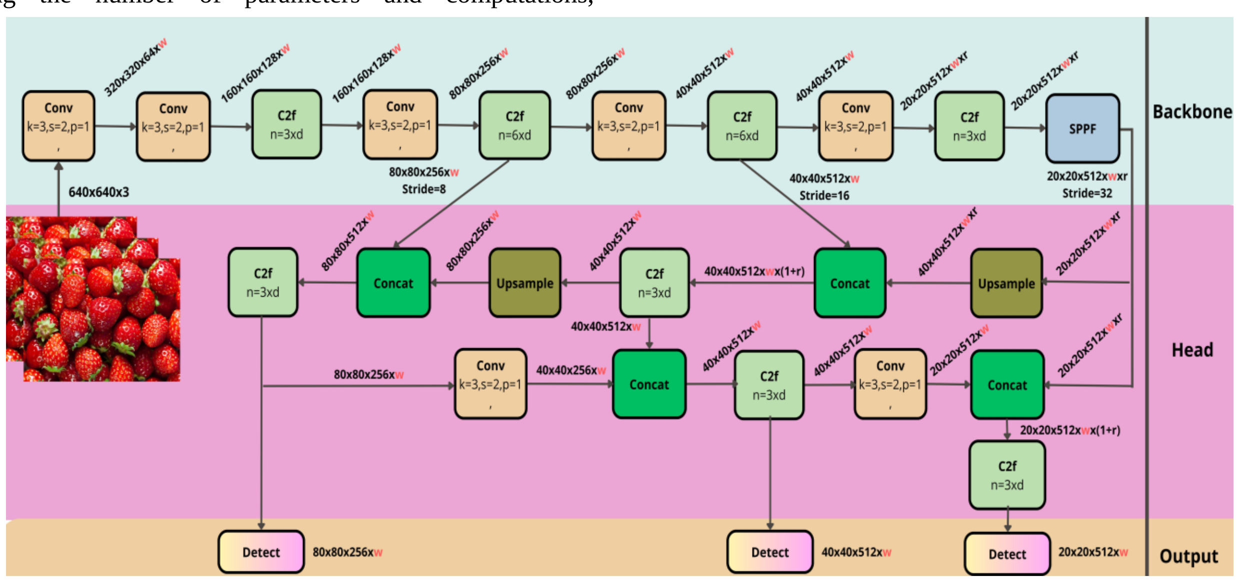


Fig. 4. Architecture of YOLOv8.

TABLE I. SYMPTOMS WITH SPECIMEN NUMBERS OF 5 STRAWBERRY TYPES

Type name	***Description***	***Number of samples***	***Image***
Normal	The strawberry has a bright red color, uniform throughout. It is free from large wounds or injuries, with a smooth surface and no signs of black spots or rot.	351	
Gray mold disease	The strawberry has areas of gray or white color covering the surface. These areas can expand and develop over time, forming a layer of gray mold.	100	
Black spot disease	The strawberry has areas of black color. Strawberries affected by black spot disease may also become softer and more prone to damage compared to healthy ones.	100	
Powdery mildew disease	The strawberry exhibits areas of pale white powdery patches on its surface. These white layers, resembling fine powder, cover the fruit, diminishing its natural glossy appearance.	100	
Rubber disease	The strawberry exhibits areas of brown, black, or possibly different colors compared to its normal hue. The surface of the strawberry becomes wrinkled and uneven, and it can be felt to be firmer and more water-retentive than a healthy fruit.	100	

Each image in our dataset was examined by two individuals following specific guidelines to minimize labeling errors and ensure the quality and accuracy of the data. As a result, we collected a dataset consisting of five classes, including four classes of strawberry diseases and one class of healthy strawberries, as described in Table I.

After constructing the dataset on strawberry diseases, precise bounding boxes containing strawberries in full images are needed. Therefore, we utilized Roboflow to create bounding boxes around the strawberries in all images. In real-world scenarios, images may contain multiple strawberries or a combination of diseased and healthy ones. We explicitly labeled all berries in the images with their respective classes. While labeling the boxes, we ensured that the entire strawberry was inside the box, and the area surrounding the box was not less than 1/8 (approximately) of the image size.

The result is a new dataset named STRAWBERRY dataset. It contains 751 images and 3910 instances, where 80% (600 images) were randomly selected for the training dataset, 10% (76 images) for the validation dataset, and the remaining 10% (75 images) for the test dataset. The test dataset is solely used to evaluate the model's performance after training, as shown in Table II.

TABLE II. NUMBER OF ANNOTATED IMAGES FOR EACH STRAWBERRY TYPE

STRAWBERRY dataset	**Normal**	**Gray mold disease**	**Black spot disease**	**Powdery mildew disease**	**Rubber disease**	**Number of samples**
Train	1414	420	364	287	252	600
Test	404	120	104	82	72	75
Valid	202	60	52	41	36	76

IV. RESULTS AND DISCUSSIONS

A. Experiment Enviroment

The proposed model was trained on our self-constructed dataset, as described above, using Google Colab with a High RAM Colab Runtime and Tesla V100 GPU configuration. After the training process was completed, we obtained corresponding sets of weights for each model. Next, we evaluated the effectiveness of each model based on the test dataset. Finally, we compared the results obtained among the YOLOv8l, YOLOv8m, YOLOv8n, and YOLOv8x versions.

B. Metrics for Performance Evaluation

To evaluate the effectiveness of the different versions of the YOLOv8 model for detecting strawberry diseases, the evaluation metrics used include GFLOPS (Giga Floating-point Operations Per Second), Precision, Recall, and Mean Average Precision (mAP).

GFLOPS (Giga Floating-point Operations Per Second) is the number of billion floating-point arithmetic operations per second, often used as a GPU performance parameter and can be observed through GFLOPs. The parameter size of the model can be used to determine the complexity of the model by examining the parameters. In model optimization, sometimes GFLOPs and parameters increase unavoidably. In general, we aim for smaller GFLOPs and parameters.

Precision is defined by the equation below. It is defined as the ratio of the number of true positive samples correctly predicted by the model to the total number of positive samples predicted:

$$precision = \frac{TP}{TP + FP} \tag{1}$$

Recall represents the number of true positive samples correctly predicted by the model as a percentage of all the targets. The formula for calculating the recall rate is shown in the equation:

$$recall = \frac{TP}{TP + FN} \tag{2}$$

The precision-recall curve is a curve displayed with precision on the y-axis and recall on the x-axis. It is defined as the area under the curve below as an average precision (AP) value. Precision values are shown through the precision-recall curve when the outermost boxes are accepted (i.e., higher recall values due to lower class probability thresholds). As recall increases, a strong model can maintain high precision. The CIoU (intersection over union) threshold is typically set at 0.5. The performance of the model is generally better when the AP value is higher. For each type of strawberry disease detected, the higher the AP value, the better the strawberry's ability to detect that disease, meaning the higher the detection accuracy.

$$AP = \int_0^1 P(R)dR \tag{3}$$

As seen below, mAP is the average precision across all classes. For the entire model, the higher the mAP value, the better the overall detection efficiency of the model and the higher the detection accuracy.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{4}$$

C. Experimental Results and Discussion

The experimental results based on Table III aim to compare the results and evaluate the performance of four models: YOLOv8l, YOLOv8m, YOLOv8n, and YOLOv8x. The table includes data on accuracy for five classes: Normal, Gray mold disease, Powdery mildew disease, Rubber disease.

TABLE III. RESULTS ON THE TEST DATASET

Model	Parameter	Precision	Recall	AP					mAP
				Normal	Gray mold disease	Black pot disease	Powdery mildew disease	Rubber disease	
YOLOv8l	43.7M	0.809	0.799	0.869	0.863	0.857	0.872	0.864	0.865
YOLOv8m	25.9M	0.768	0.828	0.879	0.866	0.859	0.867	0.869	0.868
YOLOv8n	**11M**	**0.850**	**0.845**	**0.890**	**0.872**	**0.874**	**0.879**	**0.880**	**0.879**
YOLOV8x	68.2M	0.819	0.825	0.872	0.857	0.845	0.864	0.862	0.860

Based on the data from Table III, the YOLOv8n model demonstrates the highest accuracy at 87.9%, outperforming the other three models: YOLOv8l (86.5%), YOLOv8m (86.8%), and YOLOv8x (86.0%). Furthermore, YOLOv8 versions tend to become more complex, slower, larger in size, and require more computations when combining models to improve accuracy. However, YOLOv8n still maintains an advantage with a very small parameter size, only 11 M compared to the other models.

Moreover, we can observe that most metrics for each class among the four models, particularly in the YOLOv8n model, maintain stability and achieve the highest accuracy compared to YOLOv8l, YOLOv8m, and YOLOv8x. In the "Normal" class, YOLOv8n achieves 89.0%, which is 2.1% higher than YOLOv8l (86.9%). For "Gray mold disease," YOLOv8n achieves 87.2%, surpassing YOLOv8x (85.7%) by 1.5%. In "Black pot disease," YOLOv8n achieves 87.4%, improving by 2.9% compared to YOLOv8x (84.5%). In "Powdery mildew disease," YOLOv8n achieves 87.9%, which is 1.5% higher than YOLOv8x (86.4%). Lastly, in "Rubber disease," YOLOv8n achieves 88.0%, surpassing YOLOv8x (86.2%) by 1.8%. This confirms that YOLOv8n has the highest accuracy performance among the 4 YOLOv8 models.

D. Results of the Application

After completing the training of the model, we observed that the YOLOv8n model has the highest performance compared to the remaining versions. Based on this result, our decision is to utilize the .yaml file of YOLOv8n to further develop the disease detection application for strawberries. This presents a new and significant opportunity in research and technology application to support agriculture and crop health monitoring. We believe that the combination of the accuracy of the YOLOv8n model and its practical applicability will make positive contributions to the farming community and researchers in this field.

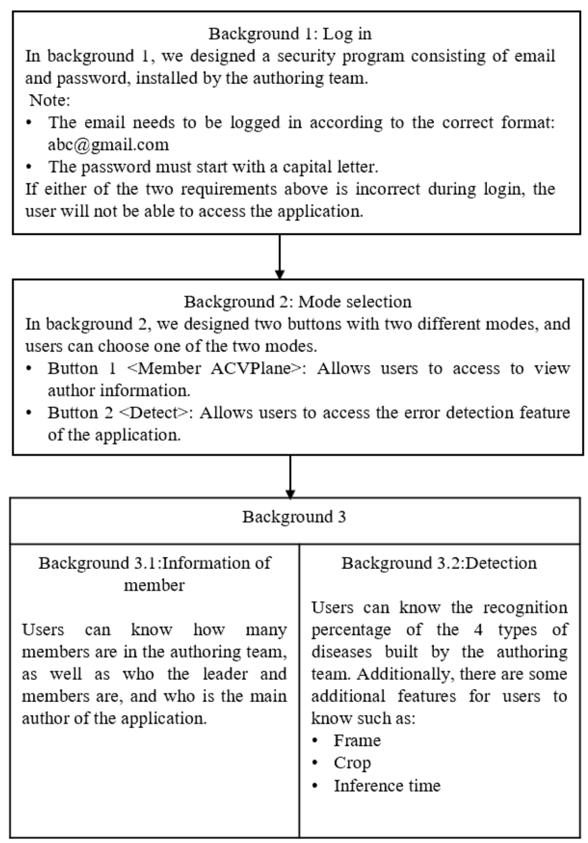
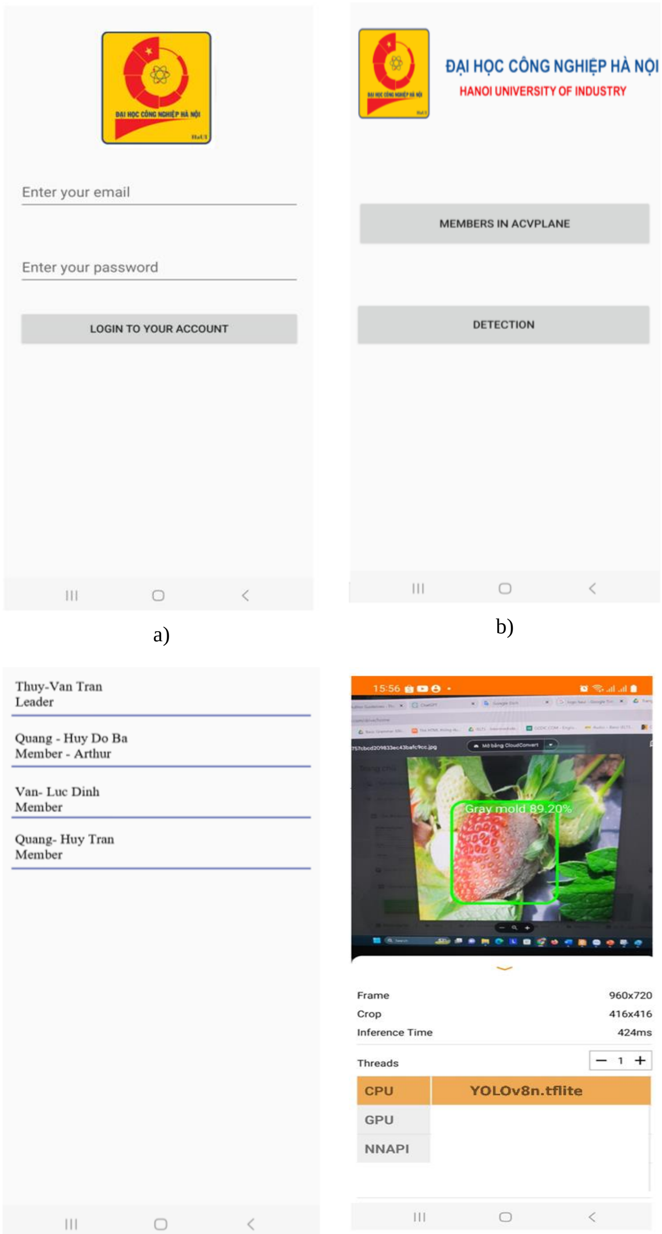


Fig. 5. Block diagram.

We have constructed according to the sequence of steps the structure of the application following the block diagram (see Fig. 5):



a) b) c) d)

Fig. 6. Image of application results a) Background 1; b) Background 2; c) Background 3.1; d) Background 3.2

V. Conclusion

In this article, the authors built and designed an integrated application with YOLOv8n to detect diseases in strawberries. Using a self-generated dataset of 751 RGB images of strawberries (including diseased and non-diseased fruits), combined with the YOLOv8n algorithm with an accuracy rate of up to 87.9% with 4 types of diseases popular. Fig. 6 shows image of application results. Through the observations mentioned previously, the outstanding accuracy of the YOLOv8n model in detecting strawberry defects can be demonstrated. However, the results still did not meet the authors' expectations of over 90% because when creating a data set of diseases such as "Gray mold disease" and "Powdery mildew disease" or "Black pot disease" and "Rubber disease" is not complete. When the disease first appears, the symptoms on their fruit are very similar, making identification difficult. Therefore, the authors will continue to research and expand their data set in the future. The results of this article can be further extended and developed for practical application with other fruits and nuts in agriculture.

Acknowledgment

This work was supported and financed by Hanoi University of Industry, Project Granted number 18-2023-RD/HĐ-ĐHCN.

References

[1] Nelda R. Hernández-Martínez, Caroline Blanchard, Daniel Wells, Melba R. Salazar-Gutiérrez. "Current state and future perspectives of commercial strawberry production: A review " Scientia Horticulturae,vol. 312, 15 March 2023, 111893.

[2] Skrovankova, Sona, et al. "Bioactive compounds and antioxidant activity in different types of berries." International journal of molecular sciences 16.10 (2015): 24673-24706.

[3] Tylewicz, Urszula, et al. "Chemical and physicochemical properties of semi-dried organic strawberries enriched with bilberry juice-based solution." Lwt 114 (2019): 108377.

[4] Li, Yanfen, et al. "Crop pest recognition in natural scenes using convolutional neural networks." Computers and Electronics in Agriculture 169 (2020): 105174.

[5] Pan, Leiqing, et al. "Early detection and classification of pathogenic fungal disease in post-harvest strawberry fruit by electronic nose and gas chromatography–mass spectrometry." Food Research International 62 (2014):162-168.

[6] Maas, J. L. "Strawberry diseases and pests-progress and problems." VII International Strawberry Symposium 1049. 2012.

[7] Paulus, Albert O. "Fungal diseases of strawberry." HortScience 25.8 (1990): 885-889.

[8] Chung, P-C., et al. "First report of anthracnose crown rot of strawberry caused by Colletotrichum siamense in Taiwan." Plant disease 103.7 (2019): 1775.

[9] Chen, X. Y., et al. "Genetic diversity of Colletotrichum spp. causing strawberry anthracnose in Zhejiang, China." Plant Disease 104.5 (2020): 1351-1357.

[10] Feliziani, Erica, and Gianfranco Romanazzi. "Postharvest decay of strawberry fruit: Etiology, epidemiology, and disease management." Journal of Berry Research 6.1 (2016): 47-63.

[11] Petrasch, Stefan, et al. "Grey mould of strawberry, a devastating disease caused by the ubiquitous necrotrophic fungal pathogen Botrytis cinerea." Molecular plant pathology 20.6 (2019): 877-892.

[12] Chamorro, M., A. Aguado, and B. De los Santos. "First report of root and crown rot caused by Pestalotiopsis clavispora (Neopestalotiopsis clavispora) on strawberry in Spain." Plant Dis 100.7 (2016): 1495.

[13] Amsalem, Liat, et al. "Effect of climatic factors on powdery mildew caused by Sphaerotheca macularis f. sp. fragariae on strawberry." European journal of plant pathology 114 (2006): 283-292.

[14] Rebollar-Alviter, Angel, et al. "An emerging strawberry fungal disease associated with root rot, crown rot and leaf spot caused by Neopestalotiopsis rosae in Mexico." Plant Disease 104.8 (2020): 2054-2059.

[15] Mahmud, Md Sultan, et al. "Development of an artificial cloud lighting condition system using machine vision for strawberry powdery mildew disease detection." Computers and electronics in agriculture 158 (2019): 219-225.

[16] Jayawardena, R. S., et al. "An account of Colletotrichum species associated with strawberry anthracnose in China based on morphology and molecular data." (2016).

[17] Ferentinos, Konstantinos P. "Deep learning models for plant disease detection and diagnosis." Computers and electronics in agriculture 145 (2018): 311-318.

[18] Cervantes-Jilaja, Claudia, et al. "Optimal Selection and Identification of Defects in Chestnuts Processing, through Computer Vision, Taking Advantage of its Inherent Characteristics." 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA). IEEE, 2019.

[19] Cheng, Xi, et al. "Pest identification via deep residual learning in complex background." Computers and Electronics in Agriculture 141 (2017): 351-356.

[20] Xiao, Jia-Rong, et al. "Detection of strawberry diseases using a convolutional neural network." Plants 10.1 (2020): 31.

[21] Kusumandari, Dwi Esti, et al. "Detection of strawberry plant disease based on leaf spot using color segmentation." Journal of Physics: Conference Series. Vol. 1230. No. 1. IOP Publishing, 2019.

[22] Ramdani, Aldi, and Suyanto Suyanto. "Strawberry diseases identification from its leaf images using convolutional neural network." 2021 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology (IAICT). IEEE, 2021.

[23] Bochkovskiy, Alexey, Chien-Yao Wang, and Hong-Yuan Mark Liao. "Yolov4: Optimal speed and accuracy of object detection." arXiv preprint arXiv:2004.10934 (2020).

[24] Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

[25] Redmon, Joseph, and Ali Farhadi. "Yolov3: An incremental improvement." arXiv preprint arXiv:1804.02767 (2018).

[26] Redmon, Joseph, and Ali Farhadi. "YOLO9000: better, faster, stronger." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

[27] Wang, Chien-Yao, Alexey Bochkovskiy, and Hong-Yuan Mark Liao. "YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2023.

[28] Diao, Zhihua, et al. "Navigation line extraction algorithm for corn spraying robot based on improved YOLOv8s network." Computers and Electronics in Agriculture 212 (2023): 108049.