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Spring Onion Disease Detection and Treatment Recommendations

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RESEARCH ARTICLE INFORMATION	ABSTRACT

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Spring onion is a delicate crop that demands much attention during its cultivation. Diseases such as purple blotch and leaf blight affect spring onion crops and, in any case, prevention of these diseases is rather complicated to detect. The study aimed to diagnose the diseases correctly and make suitable recommendations on the treatment needed. The researchers conducted a focused group discussion among spring onion farmers in Davao del Sur as a basis for the Android app that can identify spring onion disease and offer recommendations. In developing the app, the researcher used Google Colab for dataset training. The technique used in choosing the survey participants is simple purposive random sampling and a self-constructed checklist based on the ISO 9124 Likert scale was utilized to rate the app's functionality, reliability, and usability. The app is ideal for small and big farmlands, especially in regions without an internet connection, and during an experimental test, it gained an accuracy of 90% in the purple blotch and 93% in leaf blight-captured crop diseases within a three-inch distance capture. The significant results of this study include the application's ability to detect two types of diseases, namely purple blotch and leaf blight, and its ability to provide personalized treatments, such as recommendations, chemical treatments, and care tips, based on the specific disease detected. The app's contribution to the farming community is its ability to detect crop diseases early, simplify disease detection techniques, increase harvests, decrease chemical use, and prevent minor spring onion problems that could result in major outbreaks and damage large farmlands.

Keywords: *disease detection, Android-based, convolutional neural network, sequential model, functionality, reliability, usefulness*

Introduction

Machine vision has revolutionized agricultural disease management by enabling accurate disease recognition from captured images. This technology has replaced traditional methods and has become integral in identifying crop diseases, especially with the aid of deep learning algorithms (Gao et al., 2024). The synthetic neural network EfficientNet-B3, for instance, achieved an 80% success rate in plant identification, demonstrating the potential of advanced neural networks (Dawn et al., 2023).

Crop losses caused by fungi, viruses, and plant diseases can jeopardize up to 30% of agricultural production, making correct identification and disease diagnosis crucial. In regions like India, where many farmers lack proper agricultural consultation, automated disease identification systems can survey large crop areas and identify disease patterns. A mobile app serving as a diagnostic tool can provide quick, accurate, and inexpensive results through image processing techniques (Siddiqui et al., 2022), as a way to enhance agricultural practices and make disease management more accessible and efficient for farmers worldwide.

Farmers in different parts of Balutakay Bansalan and Kapatagan in Davao del Sur have long struggled with viral infection diseases in their spring onions. This is because the intricacies of viral infection among plants require technical knowledge, and to date, farmers in the area still practice indigenous ways of cultivating crops. Common diseases on their farm are purple blotch and leaf blight, and as a result, most of their spring onions are infected by these diseases. They claim that this incident caused a large loss in harvest season. Therefore, the researchers developed a mobile-based spring onion disease detection using a convolutional neural network- sequential model which aids in spring onion disease diagnosis. Additionally, the application provides treatment recommendations based on the diagnosis. Figure 1 outlines the app's process, from disease capture to treatment recommendations.

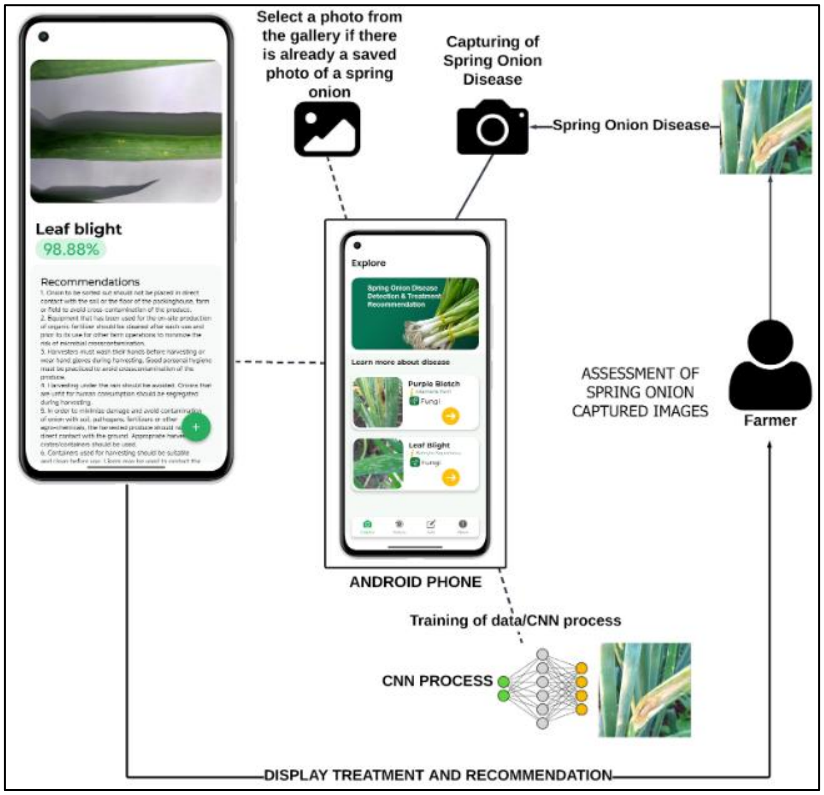

Figure 1. *Conceptual Framework of the Study*

Methods

System Requirements

To ensure the success of the development of the project, system requirements were identified by the researchers. These requirements are the minimum standard in order to ensure backward and forward compatibility of the application in the future. Table 1 highlights the software requirements in the development of the Android application. Google Colaboratory was the main engine used to develop and train the model. On the other hand, TensorFlow was used in order to convert the trained model to make it deployable on any Android device. This open-source software was used to develop and train the model as it offers more flexible and complete environment packages, it is also the widely used package among other researchers in the field, thus offering more extensive support and other pre-trained models. In this regard, the sequential model in CNN's deep learning was utilized. Sequential models utilize a series of layers to extract features from input to output that connect sequences, which typically include input layers, convolutional layers, pooling layers, fully connected layers, and output layers. This makes the CNN sequential model a powerful approach to analyzing ordered data which can effectively learn from complex sequences.

Table 1: Software Requirements of the Study

Software	Specification
Programming Software (*Mobile Development*)	Android Studio
Programming Language	Java
AI Toolkit Conversion	TensorFlow
AI Engine	Google Colaboratory

Distribution of Datasets

This capstone project used a total of 3000 labeled images to train the sequential model using Google Colaboratory. Purple blotch and leaf blight were the primary leaf diseases in onions involved in this project. Essential in model development in artificial intelligence is that a proper distribution of datasets must be followed; this ensures that any model developed is properly configured and tested. Table 2 shows the proper distribution of the datasets; it follows the general guide of dataset distribution of 80-10-10 distribution as highlighted in the study of Muriana et al. (2022). Figure 2 shows the sample actual dataset used to train the model. The images used to train the model were validated by a plant pathologist in the college who served as one of the technical experts of this project.

Table 2. Dataset Distribution

Disease Attributes	Number of Images	Training Data	Test Data	Validation Data
Purple Blotch	1000	80%	10%	10%
Leaf Blight	1000	80%	10%	10%
Healthy Leaf	1000	80%	10%	10%
Total	**3000**	**80%**	**10%**	**10%**

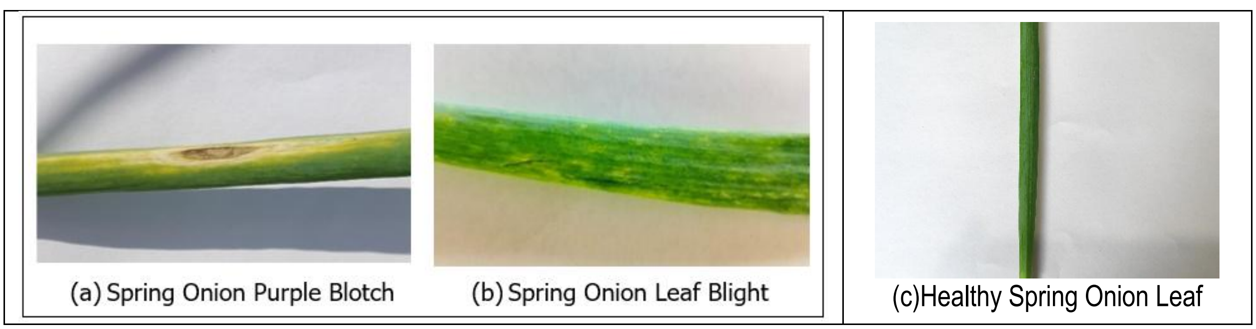

Figure 2. *Sample Dataset of the Study*

Data Flow Diagram of the Study

To visually represent the actual process that happens behind each output of the application, Figure 3 shows the data flow of the project. It entails the bird's-eye view of each process before the application provides usable output to each user. There are two major processes inside the application where the trained model was embedded, as the user captures an image in an onion with suspected disease infection using their smartphones (e.g., capture image), the model will take as input data which will be fed to the trained model (e.g., prediction and disease detection) and analyze whether or not it is infected with a disease. Once diagnosed as infected, the model will then provide a treatment recommendation to the user.

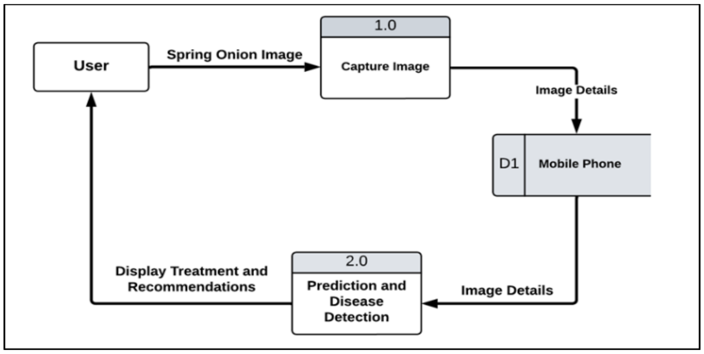

Figure 3. *Process Flow of the Study*

Testing and Evaluation Procedure

Rigorous testing following a standard evaluation was conducted in order to ensure that the application was working before it was deployed to the target users of this research project. Simple random sampling from a total of 22 respondents from diverse groups evaluated the application. Only farmers in the selected locale with one hectare onion farm are included as the participants to rate the application. Prior to the start of the project, the respondents, who were qualified in the inclusion and exclusion criteria, were given a consent form. A 5-point Likert Psychometric scale was used in the self-constructed survey questionnaire that follows the patterns of ISO/IEC 9126 metrics of selected variables (e.g., functionality, reliability, usefulness) to be measured in the study. Table 3 illustrates the Likert scale measurement of the aforementioned variables for this project study. Table 4 shows the distribution of the respondents.

Table 3. Likert Scale Measurement for Functionality, Reliability, and Usefulness

Mean Range	Descriptive Equivalent	Interpretation
4.51 – 5.00	Excellent (E)	The measure outlined in the item is exceptional and delivers all requirements.
3.51 – 4.50	Good (G)	The measure described in the item is satisfactory and fulfills most requirements, however there is potential for improvement.
2.51 – 3.50	Fair (F)	The measure described in the item is acceptable, but there is considerable potential for improvement.
1.51 – 2.50	Poor (P)	The measure described in the item required essential enhancement to fulfill requirements.
1.00 – 1.50	Very Poor (VP)	The measure described in the item requires major modifications in order to fulfill the requirements.

The evaluation scale ranges from one (1) to five (5), with five being the highest score and one as the lowest. The corresponding denotation of the scores are as follows: 4.51 to 5.00 as "Excellent (E)", 3.51 to 4.50 as "Good (G)", 2.51 to 3.50 as "Fair (F)", 1.51 – 2.50 as "Poor (P), and 1.00 to 1.50 as "Very Poor (VP)". As a result, the Likert scale will serve as a tool to assess the extent to which the product or service satisfies user requirements, as well as identify areas that require enhancement.

Table 3. Distribution of Respondents

Evaluators	**Sample Size**
Advisory Committee	4
Onion Farmers	10
IT Experts	6
Plant Pathologist	1
Total	**22**

Results and Discussion

Sequential Model Development and Training

Artificial intelligence involves the proper identification of a model to be used under the umbrella of machine learning. Keras models of a convolutional neural network, being one of the branches, have several supervised machine learning architectures which include the sequential model. This architecture was utilized by the researchers since it focused on learning from the raw pixel data of the images, without requiring any manual feature engineering or preprocessing. Furthermore, the algorithm carefully examines each image to categorize it according to any problems or diseases that may be present in the dataset that was labeled. Figure 5 shows the result of the training, it illustrates the AI's training accuracy which indicates its learning capability (e.g., model accuracy), and training loss (e.g., model loss) which indicates a level of error recognition. In other words, as the AI's ability to learn improves, the training loss should decrease, respectively.

The trend in the figure indicates that the model is effectively learning from the dataset and that the hyperparameter setup is appropriate. Thus, the model's confidence rate in recognizing nutrient deficiency and disease is expected to be high. The accuracy of a machine learning model during training increases over epochs (from 0 to 80), with values ranging from 0.75 to 0.99. The loss (error) of the model decreases over epochs, fluctuating but showing an overall downward trend (values range from 0 to 2.5). The learning curves highlighted in the figure help assess how well the model performs as it is being trained (Ibrahim, 2024).

The application in this study provides the user with detailed results when a diagnosis was carried out as shown in Figure 4.C. The application provides a confidence percentage for the type of disease it was able to recognize and a treatment recommendation. The recommendation is based on the established standard agricultural practices that were validated by the plant pathologist. Figure 4 also provides the other two modules in the application, particularly the application's Home Page, and the camera capture module which allows users to capture images using their smartphones.

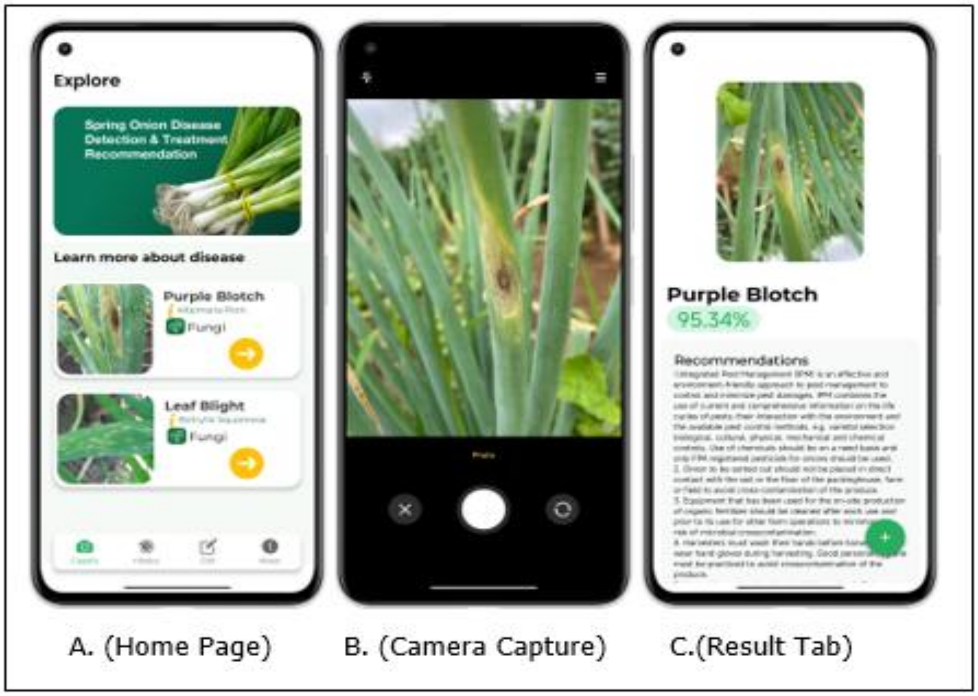

Figure 4. *Application Modules of the Project*

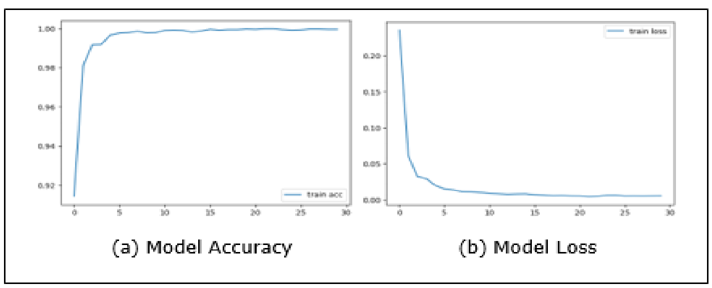

Figure 5. *Model Training Result*

To further investigate the model's performance, the researchers introduced an additional new set of images which contains a more complex environment setting of subjects for validation. This process was usually carried out in machine learning to ensure that the model can still accurately detect the diseases despite the intricacies of the new input data (Chi et al., 2022). The result of validation testing is shown in Figure 6. Similarly, the model was able to recognize disease with high accuracy.

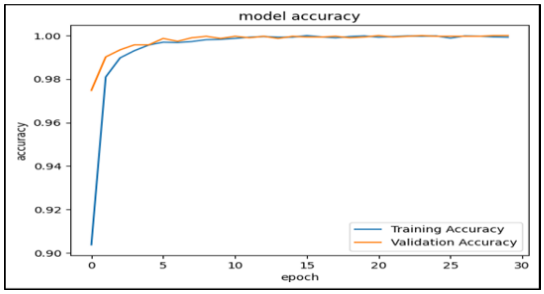

Figure 6. *Model Validation Training Result.*

The Confusion Matrix for the model trained to detect diseases in spring onions provides a detailed breakdown of its performance across four categories: healthy, leaf blight, purple blotch, and undefined as shown in Figure 7. The model correctly identified 290 healthy samples with no misclassifications. For leaf blight, out of 78 actual samples, the model correctly identified 25 but misclassified 1 as healthy, 3 as purple blotch, and 49 as undefined. For purple blotch, out of 75 actual samples, the model correctly identified 28 but misclassified 1 as healthy, 4 as leaf blight, and 42 as undefined. Lastly, the model correctly identified 64 undefined samples with no misclassifications. This Confusion Matrix highlights the model's strengths in identifying healthy samples and its challenges in distinguishing between leaf blight and undefined categories.

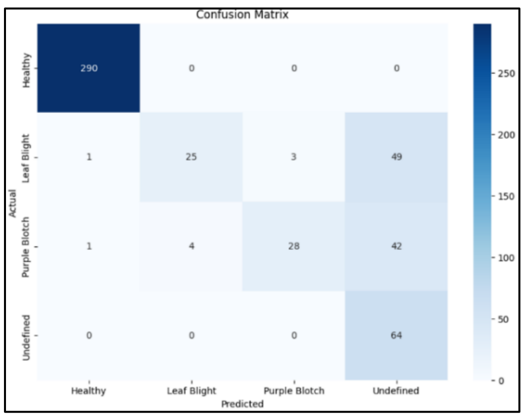

Figure 7. *Confusion Matrix*

Experimental Results for Identifying Disease Present in Spring Onion

After the trained model was embedded in the mobile application, it was put to actual use by the farmers where it was tasked to recognize diseases in three distinct conditions or levels of infection (i.e., semi-infected, severe infection). An experimental analysis was carried out, where six images with varying levels of infection were used. The level of infection was validated by the plant pathologist. Table 5 shows the result of the application, where it can be seen that varying levels of confidence rate of diagnosis by the application are provided, and the distance (e.g., inches) of capturing was also recorded in this experiment.

Table 5. Experimental Results for Spring Onion Diseases

Experiment No.	Disease Class	Confidence Rate	Distance
1	Purple Blotch	93.34%	1
2	Purple Blotch	91.21%	2
3	Purple Blotch	90.34%	3
1	Leaf Blight	95.33%	1
2	Leaf Blight	94.81%	2
3	Leaf Blight	93.15%	3

The table indicates that when closer images are taken, results would yield higher confidence rates. This underscores the importance of image quality in recognition systems. By ensuring that images are captured at an optimal distance to maintain clarity and detail, the effectiveness and reliability of this application can be significantly enhanced.

Descriptive Ratings of the Android Application

To assess the functionality, usefulness, and reliability of the project, a thorough testing process was conducted that involved administering a questionnaire to respondents to gauge their experience of using the application in line with its intended functionalities. Prior to the testing, the researchers provided an orientation and presentation of the project to the respondents to ensure that they understood its objectives and functions. The testing process was designed to ensure that the project was rigorously evaluated and could be relied upon to perform optimally in its intended context.

Table 6. Descriptive Ratings from the Respondents in Terms of Functionality

Particulars	Respondents				Mean	Remarks
	IT Experts	*Advisory Committee*	*Onion Farmers*	*Plant Patho-logist*		
The application can capture spring onion disease.	5.00	4.50	4.90	4.00	4.60	Excellent
The application can identify a type of disease that is present in spring onion.	4.50	4.00	4.90	4.00	4.35	Good
The application can provide treatment and recommendations based on the disease detected.	4.17	4.25	4.70	4.00	4.28	Good
The application buttons function as intended when clicked.	5.0	4.25	4.90	4.00	4.53	Excellent
Average	**4.67**	**4.25**	**4.85**	**4.00**	**4.44**	**Excellent**

Functionality refers to the essential feature of software, which enables it to perform specific tasks. For example, the first particular in the survey form indicates that the application can capture spring onion disease. In the survey, respondents gave a mean score of 4.60, indicating a high level of agreement that the application is able to deliver its intended functionality.

Table 7. Descriptive Ratings from the Respondents in Terms of Reliability

Particulars	Respondents		Mean	Remarks
	Onion Farmers	*Plant Pathologist*		
The module accurately identifies the disease on the spring onion.	4.20	4.00	4.10	Good
The treatment recommendations are clear and understandable.	3.80	2.50	3.15	Fair
The application provides convenient results.	3.70	3.00	3.35	Fair
The application did not crash while using.	4.10	4.00	4.05	Good
Average	**3.95**	**3.37**	**3.66**	**Good**

In terms of reliability, the strength of the application is the accurate disease detection which means that the application's disease detection capabilities are reliable and effective and its capabilities to handle tasks result in gaining a high score since the application did not crash while they use it. However, still one of the lowest to gain evaluators' approval is the treatment and recommendations and its suggested results which need some revisions. Thus, there is a need to make them clear and concise for the user to easily understand how the treatment will be implemented by non-technical users like novice small-scale farmers.

Table 8. Descriptive Ratings from the Respondents in Terms of Usefulness

Particulars	Respondents		Mean	Remarks
	Onion Farmers	*Plant Pathologist*		
The application was easy to use and understand.	4.00	4.00	4.00	Good
The application is usable without needing much effort.	4.10	4.00	4.05	Good
The disease identification	4.10	3.00	3.55	Good

process is effective				
The application is satisfying to use.	4.00	3.50	3.75	Good
Average	**4.05**	**3.63**	**3.84**	**Good**

It terms of usability, the strength of this application is its user experience since it is easy to use and can be understood easily by the one who uses it. On the other hand, improvements also needed to be made for the application to perform much better in disease identification since it had one of the lower scores in this section. Based on the result of the application, evaluation datasets need to be added to have a better disease identification result and although disease identification scored the lowest in this section of an application evaluation, it cannot be denied that the functions that are required to meet the target objectives have been achieved and the low score does not mean failure to provide the needs of the user, instead it shows a room for improvement for future development.

Table 9. Overall Descriptive Rating in Terms of Functionality, Reliability, and Usefulness

Particulars	Mean	Remarks
Functionality	4.44	Good
Reliability	3.66	Good
Usefulness	3.85	Good
Total	**3.98**	**Good**

Generally, results show that the application's functionality, reliability, and usefulness were determined to be good, which indicates that the majority of respondents agreed that the Android application can determine spring onion disease and can provide treatment recommendations. Moreover, in the survey of (Meshram et al., 2021), they show that deep learning technology is increasingly being used in agriculture, with CNNs showing significant improvements in accuracy and learning ability. However, challenges like dataset creation, testing time, hardware support, and deployment on small devices remain. In addition, it turns out that machine learning is starting to gain popularity in the field of agriculture because of its function, and projects like this can help reduce losses and give treatment recommendations to farmers which is a big help to maintain the health of the crops. Having an application that can provide recommendations, chemical treatments, and care tips can boost the planting journey, which can be one step to a good harvest.

Conclusion and Future Works

The application demonstrated its capability to detect spring onion diseases using a Convolutional Neural Network (CNN). It effectively identified diseases within a 1-inch range, achieving an average accuracy score of 93.34%. Additionally, it garnered an average user rating of 4.60, categorized as "Excellent." However, the application failed to detect diseases accurately beyond a 1-meter distance. Second, the application successfully identified specific diseases such as leaf blight and purple blotch, achieving a mean accuracy rate of 93.03% during experimental testing. It also received an average user rating of 4.35, classified as "Good." Nonetheless, its capability to provide treatment recommendations for other diseases remains limited. Third, the application offered recommendations, including chemical treatments and care tips, earning an average rating of 4.28, also marked as "Good." However, the recommendations provided were restricted in scope particularly that detections given are based on predictions that require expert validation. Additionally, the Confidence Matrix is relatively dependent on the range or distance of camera capture in the objects which could greatly affect the reliability of the prediction. Lastly, when compared to traditional assessment methods, the application achieved an overall accuracy of 89.37%, indicating its effectiveness in fulfilling its primary purpose. Despite this, further improvements are needed to raise its reliability, aiming for an accuracy level of 95% to meet higher standards.

With this in mind, the application can successfully capture spring onion disease using the sequential model of CNN, diagnose diseases, and provide treatment recommendations, and has been successfully compared to the traditional assessment indicating its effectiveness in combating spring onion diseases. However, improvements are needed to enhance its effectiveness. Additional datasets with varying image quality (e.g., pixels), range, or distance to capture the subject, and table of smartphones with different camera pixel capacity testing are also encouraged to have a baseline data as to what camera capacity the app would work best. The use of data augmentation for dataset preparation is also encouraged.

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Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.