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Resnet - Based Detection of Eggplant Leaf Diseases: A Machine Learning Approach

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Abstract: ***This study focuses on developing an eggplant leaf disease detection system using the ResNet algorithm. The system utilizes machine learning to analyze and classify leaf diseases based on image data, ensuring accurate and efficient disease identification. The study follows a developmental research approach, assessing system performance based on ISO 25010 characteristics, including functional suitability, reliability, and usability. Results indicate that participants strongly agree with the system's effectiveness, with high reliability and efficiency. The findings suggest that this detection system can serve as a valuable tool for farmers and agricultural professionals in disease management.***

Keywords: ResNet, eggplant leaf disease, deep learning, convolutional neural network (CNN), agricultural technology.

1. Introduction

This paper presents an eggplant leaf disease detection. The revolution of the modern technologies in the recent era has facilitated its application in agriculture to improve production. One such application is diagnosing eggplant leaf diseases using digital images, helping farmers monitor and manage disease outbreaks more effectively. The availability of cheap cameras and the explosive growth on the internet have made the diagnosis relatively less complex with the availability of tools and information about the disease online. But still, human diagnosis is prone to errors (Hassan, et. al, 2021).

Eggplant leaf disease detection highlights the importance of maintaining the health and productivity of eggplant plants. One such application is diagnosing eggplant leaf diseases using digital images, helping farmers monitor and manage disease outbreaks more effectively. The use of cameras for image capture and machine learning methods for disease identification are effective tools in this context (Zhang, et. al, 2022).

This study is significant as it offers an efficient, AI - powered tool to assist farmers in early disease detection, reducing crop losses and improving yield quality. The findings contribute to both agricultural innovation and machine learning applications in plant disease detection.

Objectives of the Study

The general objective of this study was to develop an Eggplant leaf disease detection.
Specific Objectives:
Specifically, this study aimed to:

1) To utilize color, texture, shape, and disorders as criterion variables in detecting diseases;
2) To test the efficiency using convolutional neural network (CNN algorithm; and
3) Test the quality of the characteristics of the developed system using ISO 25010 standards.

2. Methodology

Research Design

The researchers adopted the developmental type of research to achieve the purpose of the study. This method involves collecting a diverse dataset of healthy and diseased eggplant leaf images, preprocessing the images to enhance quality, extracting relevant features like color and texture characteristics, selecting appropriate algorithms such convolutional neural networks (CNNs).

Participants of the Study

This study was conducted at the farmlands at the Municipality of Tibiao, Antique with 30 respondents.

Data Gathering instruments and Techniques

The major instrument used in gathering data was conducting an interview. This was the main instrument used to gather information from the subject of the study. Guidelines questions are used to gather information regarding the Eggplant leaf disease detection.

Preparation of Instruments

Conducting an interview is the most important part in conducting the study. The researchers prepare some questions in order to come up with the idea and data needed in the study.

Validation of Instruments

An instrument is valid if it measures what it is intended to measure and accurately achieves the purpose for which it was designed. Declaration of information on the research must be reliable and certain in order to meet this standard. The validation for questionnaire is not needed due to the proponent uses ISO 25010 questionaries.

Data Gathering Procedure

In gathering the data, the researcher personally conducted interviews. First, the researcher prepared some questions, and all the questions were answered and through this procedure the researcher was able to get some important details and come up to the solution to that problem.

Statistical Tools

The questionnaires were retrieved and a table was prepared in an accordance to the characteristics of the system based on ISO 25010 characteristics analyzed using weighted mean and sorted ranking.

Weighted Mean

The weighted mean for each item was obtained by multiplying the scale value of responses by the total number of responses indicating it to get the total weighted points and dividing them by the total number or responses. The mean is the measure of central tendency. It points to where the majority of the participants' answers to a question cluster.

$$\bar{X} = \frac{\sum fx}{n}$$

Where:
X= Weighted Mean
F=Frequency
X =Scores
n = Total number of participants
∑ = Summation symbol

Likert Scale
In the interpretation of the Weighted Mean (WM), Likert's Scale method has been used by the researcher using the following intervals and verbal interpretations. the 5 - point scale was used in order to determine the rank or the adjectival description of the weighted mean of the responses for the proposed Prediction Model. The fields represent the rating, range, and the adjectival description for each rating.

Ranking
This will be used to get the rank average for each answers choice and determine which ever is the highest and lowest rank based on the results.

Software Model
This section gives a description of the methods used in developing the proposed system. The Eggplant Leaf Disease Detection was developed using the Rapid Application Development (RAD) model.

The researcher used this model because the application's requirement is very well documented, fixed, and clear.

Rapid application development (RAD) is a team - based technique that speeds up information systems development and produces a functioning information system. Like JAD, RAD uses a group approach, but goes much further. While the end product of JAD is a requirements model, the end product of RAD is the new information system. RAD is a complete methodology, with a four - phase life cycle that parallels the traditional SDLC phases. Companies use RAD to reduce cost and development time and increase the probability of success.

Listed below are the four phases for RAD model:

Requirements Planning. The requirements planning phase combines elements of the systems planning and systems analysis phases of the SDLC. This phase requires intense involvement from Users, managers, and IT staff members to discuss and agree on business needs, project scope, constraints, and system requirements. The requirement planning phase focus always remains on reaching the goals and end when the team agrees on the key issues and obtains management authorization to continue**.**

User Design: During the user design phase, users interact with systems analysts and develop models and prototypes that represent all system processes, outputs, and inputs. The RAD group or subgroups typically use a combination of JAD techniques and CASE tools to translate user needs into working models. User design phase is a continuous, interactive process that allows users to understand, modify, and eventually approve a working model of the system that meets their needs**.**

Construction: The construction phase focuses on program and application development tasks similar to the SDLC. In RAD, however, users continue to participate and still can suggest changes or improvements as actual screens, or reports are developed.

Cutover: The cutover phase resembles the final tasks in the SDLC implementation phase, including data conversion, testing, changeover to the new system, and user training. Compared with traditional methods, the entire process is compressed. As a result, the new system is built in precise manner, delivered, and placed in operation much sooner.

3. Results and Discussion

This chapter presents the analysis, presentation, and interpretation of data based on the appropriate statistical tools.

Table 3: Mean Distribution of Functional Suitability of the system

Functional	Rating					Mean	SD	Interpretation
Suitability	5	4	3	2	1			
Completeness	24	6				4.80	0.40	Strongly Agree
Correctness	26	4				4.87	0.34	Strongly Agree
Appropriateness	22	8				4.73	0.44	Strongly Agree

The data in table 3 present the results of the evaluation of the functional suitability of the system. The mean scores of 4.8, 4.87, and 4.73 for Completeness, Correctness, and Appropriateness indicate that the system is highly functional. This interpretation is further supported by the computed standard deviation results.

Table 4: Mean Distribution of Reliability of the System

Reliability	Rating					Mean	SD	Interpretation
	5	4	3	2	1			
Maturity	24	6				4.80	0.40	Strongly Agree
Availability	24	6				4.80	0.40	Strongly Agree
Fault Tolerance	20	10				4.67	0.47	Strongly Agree
Recoverability	24	5	1			4.77	0.50	Strongly Agree

Table 4 shows the results of the evaluation of the Reliability of the System. The mean scores of 4.8, 4.8, 4.67, and 4.77, for Maturity, Availability, Fault Tolerance, and Recoverability respectively, indicate that the system is really reliable which is interpreted as Strongly Agree, which is proven by the computed results of standard deviation.

Table 5: Mean Distribution of Portability of the System

Portability	Rating					Mean	SD	Interpretation
	5	4	3	2	1			
Adaptability	26	4				4.87	0.34	Strongly Agree
Durability	27	3				4.90	0.30	Strongly Agree
Installability	20	10				4.67	0.47	Strongly Agree
Replaceability	22	7	1			4.70	0.53	Strongly Agree
Affordability	23	7				4.77	0.42	Strongly Agree

Table 5 presents the results of the evaluation of portability of the system. The mean scores of 4.87, 4.9, 4.67, 4.7, and 4.77 for Adaptability, Durability, Installability, Replaceability, and Affordability respectively, indicate that the system is really portable which is interpreted as Strongly Agree, which is proven by the computed results of standard deviation.

Table 6: Mean Distribution of Usability of the System

Usability	Rating					Mean	SD	Interpretation
	5	4	3	2	1			
Appropriateness Recognizability	20	9	1			4.63	0.55	Strongly Agree
Learnability	25	4	1			4.80	0.48	Strongly Agree
Operability	25	5				4.83	0.37	Strongly Agree
User error protection	22	8				4.73	0.44	Strongly Agree
User Interaction aesthetics	21	9				4.70	0.46	Strongly Agree
Accessibility	28	2				4.93	0.25	Strongly Agree

The data in table 6 present the results of the evaluation of Usability of the system. The mean scores of 4.63, 4.8, 4.83, 4.73, 4.7 and 4.93 for Appropriateness, Recognizability, Learnability, Operability, User error protection, User Interaction aesthetics and Accessibility, that the system is really usable which is interpreted as Strongly Agree, which is proven by the computed results of standard deviation.

Table 7: Mean distribution of the performance Efficiency of the System

Performance Efficiency	Rating					Mean	SD	Interpretation
	5	4	3	2	1			
Confidentiality	23	7				4.77	0.42	Strongly Agree
Integrity	22	8				4.73	0.44	Strongly Agree
Non - Repudiation	22	8				4.70	0.53	Strongly Agree
Accountability	25	5				4.83	0.37	Strongly Agree

Presented in Table 7 are the mean scores and the Standard deviation of Performance Efficiency of the system. Results showed that the Accountability has the highest mean of 4.83 and the standard deviation 0.37 and followed by confidentiality mean score 4.77 and standard deviation of 0.42 and followed by Integrity mean score 4.73 and the standard deviation of 0.44, and Non- repudiation has the lowest mean scores of 4.7 with the standard deviation of 0.53 which interpreted as strongly agree.

Table 8: Mean distribution of Compatibility of the System

Maintainability	Rating					Mean	SD	Interpretation
	5	4	3	2	1			
Modularity	23	7				4.77	0.42	Strongly Agree
Reusability	24	6				4.80	0.40	Strongly Agree
Analyzability	26	4				4.87	0.34	Strongly Agree
Modifiability	23	7				4.77	0.42	Strongly Agree
Testability	25	5				4.83	0.37	Strongly Agree

Table 8 shows the results of the evaluation of Compatibility of the System. The mean scores of 4.7 and 4.8, simply state as the Co - Existence, Interoperability, and Appropriateness respectively, state that the system is really compatible which is interpreted as Strongly Agree, which is proven by the computed result of standard deviation.

Table 9: Mean distribution of Maintainability of the System

Compatibility	Rating					Mean	SD	Interpretation
	5	4	3	2	1			
Co - Existence	21	9				4.70	0.46	Strongly Agree
Interoperability	24	6				4.80	0.40	Strongly Agree

The data in Table 9 present the results of the evaluation of Maintainability of the System. The mean scores of 4.77, 4.8, 4.87, 4.77 and 4.83 simply as Modularity, Reusability, Analyzability, Modifiability, and Testability, that the system is really maintainable which is interpreted as Strongly Agree, which is proven by the computed results of standard deviation. The system demonstrates high maintainability based on the mean scores and interpretation of strongly agree.

4. Conclusion

After the thorough analysis and evaluation of the data gathered from the participants through the initial testing and their evaluation, the researcher came up with the following conclusions:

The Eggplant Leaf Disease Detection system is essential for improving agricultural practices by providing a reliable tool for detecting and managing diseases in eggplant leaves with the use of Resnet Algorithm. This system enhances efficiency in identifying diseases, supporting farmers in monitoring and maintaining healthy crops with ease and accuracy.

Weighted mean, Standard evaluation and Likert scale with verbal interpretation were used to analyzed and evaluate the system.

The respondents strongly agreed in all aspects of the developed system based on ISO 25010 characteristics which include Functional Suitability, Reliability, Portability, Usability, Performance Efficiency, Security, Compatibility and Maintainability.

This research successfully developed and validated an Eggplant Leaf Disease Detection system, proven effective and efficient in identifying eggplant leaf diseases, thus improving agricultural practices. Positive results across multiple evaluation methods support its efficacy and adherence to ISO 25010 standards.

5. Recommendation

Based on the conclusions of the study, the following recommendations are proposed:

The University of Antique – Hamtic Campus, College of Agriculture, Forestry and Food Science (CAFFS) is encouraged to implement and use the Eggplant Leaf Disease Detection system to aid farmers in identifying and managing diseases effectively.

Future researchers are recommended to enhance the system by incorporating additional features, such as advanced disease detection algorithms, real - time monitoring capabilities for more accurate and timely diagnosis.

References

[1] Abisha, et. al, (2023). Brinjal leaf diseases detection based on discrete Shearlet transform and Deep Convolutional Neural Network.

[2] Eunice, et. al, (2022). Deep learning - based leaf disease detection in crops using images for agricultural applications.

[3] Hassan, et. al, (2021). Identification of plant - leaf diseases using CNN and transfer - learning approach.

[4] Jung, M., Song, J. S., Shin, AY. et al. Construction of deep learning - based disease detection model in plants. Sci Rep 13, 7331 (2023).

[5] Li, et. al, (2021). Transfer learning for plant disease detection with deep convolutional neural networks. *Neurocomputing.*

[6] Maggay, J. G. (2020). Mobile - based eggplant diseases recognition system using image processing techniques.

[7] Nasution, et. al, (2022). Eggplant disease detection using yolo algorithm telegram notified. International Journal of Engineering, Science and Information Technology, 2 (4), 127 - 132.

[8] Rashwan, et. al, (2022). Plant leaf disease detection using deep learning on mobile devices: International journal of computational vision and robotics.

[9] Sabrol, et. al, (2020). Plant leaf disease detection using adaptive neuro - fuzzy classification. In Advances in Computer Vision: Proceedings of the 2019 Computer Vision Conference (CVC), Springer International Publishing.

[10] Suryavanshi, et. al, (2024, March). Smart Farming: Integrated Federated Learning CNNs for Brinjal Leaf Disease Detection. In 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation.

[11] Zhang, et. al, 2022). Deep convolutional neural networks for detection of eggplant leaf diseases: *Computers and Electronics in Agriculture.*

[12] Zhang, et. al, (2022). Automatic plant disease detection based on tranvolution detection network with GAN modules using leaf images. Frontiers in Plant Science.