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Poultry Disease Detection and Treatment Recommendation Using CNNs

Alex E. Facelo Jr.[1], Renante A. Diamante[2], and Efren B. Lazarte[3]
[1,2,3]Iloilo State University of Fisheries Science and Technology
Email: *[1]alexfacelo@isufst.edu.ph, [2]rdiamantetip@gmail.com, and [3]eblazarte1978@gmail.com*

***Abstract*—** This research presents a groundbreaking mobile application to revolutionize poultry disease management. The application uses automated artificial intelligence to accurately diagnose and recommend appropriate treatments for chicken ailments. A robust methodology combines a convolutional neural network (CNN) for visual disease recognition with a rules-based recommendation system to provide tailored action plans.

A vast dataset of real-world images depicting both healthy and sick chickens was collected to train the CNN model. Rigorous testing ensured the application's adherence to ISO 25010 software quality standards, encompassing functionality, reliability, usability, efficiency, maintainability, and portability. An Android prototype demonstrated an impressive 87% accuracy in disease classification. Evaluation trials involving veterinarians and poultry farmers confirmed the effectiveness and relevance of the recommended actions.

The fusion of explainable AI with domain expertise distinguishes this innovation from traditional black-box models, significantly reducing the risk of misdiagnosis. Contextual user research highlights the application's potential to enhance smallholding revenue sustainability. Future directions include model refinement and participatory design to address local specificities and further optimize the application's impact on poultry health and economic viability.

***Keywords*—** convolutional neural networks, chicken disease, image detection.

I. INTRODUCTION

As reported by the Bureau of Animal Industry in 2022, the production volume of chicken broilers and eggs has doubled since 2000, increasing from approximately 1 million metric tons to nearly 2 million metric tons in 2020. This rapid expansion highlights the industry's dynamic nature and its vital role in the country's agricultural sector.

As Bagust (n.d.) observed, significant progress in various aspects of poultry management has fostered a synergistic effect on the industry. These advancements encompass housing practices, nutrition and feed formulation, the application of poultry genetics in commercial breeding, and enhanced disease prevention and control [1]. He et al. (2022) highlighted the crucial role of disease surveillance and early warning systems in mitigating chicken mortality and enhancing production yields [2].

Traditional disease detection methods, often relying on manual observation by veterinarians, are time-consuming, labor-intensive, and prone to inaccuracies. Given the rapid pace of the poultry industry, these conventional approaches are insufficient for timely disease detection, especially for serious infectious diseases.

An IoT-based predictive maintenance framework for early disease detection in poultry [5] impressive results in their study demonstrated high accuracy in detecting both hen behavior and posture using advanced deep-learning techniques [3]. The proposed technology addresses the current reliance of poultry farms on manual inspection for dead and sick chickens by introducing automated monitoring. Utilizing foot rings to track chicken movement, a ZigBee network for data collection, and machine learning algorithms for analysis, this approach offers a more efficient and accurate method for assessing the health status of poultry flocks [4].

The collected motion data from the devices is transmitted to the cloud for further analysis by the framework. The detector used characteristics like shape, color, water content, and shape & water to classify fine-grained abnormal broiler droppings images as either normal or abnormal. Images of the droppings from a large number of broiler birds were used to train and assess CNN models, such as YOLO-V3 and Faster R-CNN [6].

Recognition is hindered by the small size of chicken heads and the scarcity of datasets with images of chicken faces [7]. Deep learning models were developed to diagnose poultry diseases using fecal images. The common diseases targeted were Coccidiosis, Salmonella, and Newcastle. Tanzania's restricted access to agricultural support services makes it more difficult to identify these illnesses early [8].

The deep poultry vocalization network (DPVN), an automated technique, is suggested for the early identification of Newcastle disease (ND) in poultry. The technique analyzes and recognizes the vocalizations of poultry with ND using deep learning and sound technology[9].

The early warning system to identify sick broilers to stop widespread disease outbreaks and reduce financial losses. The algorithm automatically classifies the health status of broilers by analyzing their posture and using digital image processing and machine learning to distinguish between healthy and sick birds [10].

The researchers were motivated by the challenges associated with traditional poultry disease detection methods, leading them to develop the 'Chicken Disease Detection Using CNN with Recommender' program.

II. METHODOLOGY

The proposed solution will follow a structured waterfall model, progressing through stages of requirements gathering, modular design, implementation, testing, and controlled pilot deployment on poultry farms. Rigorous evaluation using a diverse image dataset will assess the accuracy of the CNN model. Qualitative reviews will validate the relevance of recommendations, while continuous model improvement will be enabled through retraining. The integrated computer vision screening and prescription system aims to support farm technicians by enhancing disease surveillance capabilities. By facilitating data-driven decision-making, this solution can help minimize losses and reduce the environmental impact of commercial poultry farming through proactive disease control.

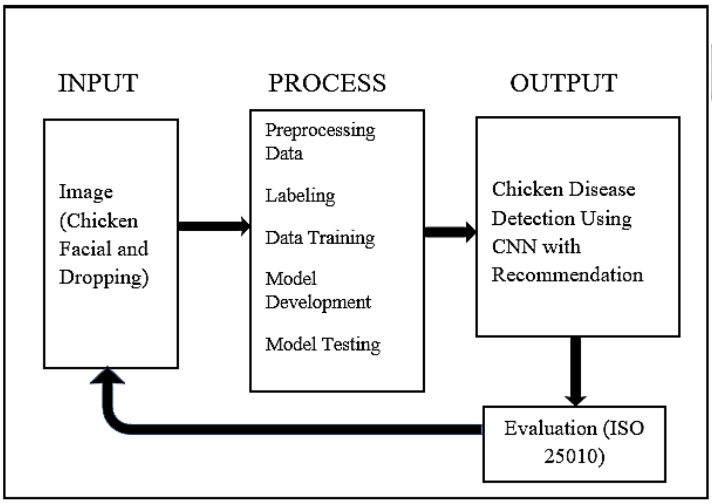

Figure 1 *- The conceptual framework of the study*

The system was provided with visual data depicting chicken health conditions, including skin lesions and abnormal physical characteristics.

The acquired images undergo preprocessing to enhance their quality and prepare them for analysis. This process may involve noise reduction, normalization, and resizing to ensure data consistency. Subsequently, these preprocessed images are labeled with relevant disease or health condition information, such as the type of disease or severity. This labeled dataset is then used to train a Convolutional Neural Network (CNN) model. By analyzing sufficient images, CNN can learn to identify patterns and characteristics indicative of various chicken illnesses or health issues. It is tested on an independent set of images to evaluate the model's performance. This step helps assess the model's accuracy and reliability in real-world applications.

The result of this process is a trained Convolutional Neural Network (CNN) model that can accurately identify and categorize diseases in chickens based on visual input. To complement the model's diagnostic capabilities, a recommender system can be developed to suggest suitable treatments or interventions based on the model's predictions and the specific disease detected.

To evaluate the effectiveness of this Chicken Disease Detection Using CNN with a Recommendation system, the ISO 25010 software quality evaluation standard can be applied. This standard focuses on attributes such as functionality, dependability, usability, efficiency, maintainability, and portability. By assessing these qualities, we can gauge the overall performance and reliability of the system.

System Development Cycle

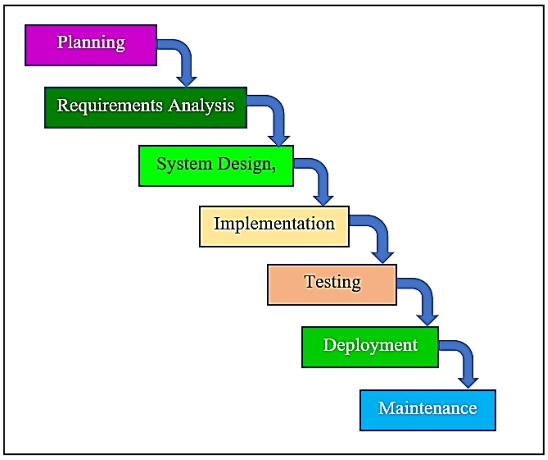

***Figure 2** – The System Development Life Cycle used in the study*

The waterfall model provides a sequential, structured approach guiding the design and building of the chicken disease detection system. It consists of key phases:

Planning. In the planning stage, the researchers outlined the steps involved in the study and developed questionnaires for the participants.

Requirements Analysis. Thoroughly collecting requirements from all involved parties through interviews and workshops. Establishing crucial parameters such as target chicken diseases, necessary image types, video stream specifications, intended system users, CNN model accuracy standards, recommendation engine scope, and hardware specifications. Confirming these requirements before proceeding to the next phase.

System Design. Once all necessary requirements were collected, the design phase began. This involved designing the recommender engine's components and how they would interact with the CNN model and external knowledge bases. Additionally, we conceptualized user interface flows, database structures, and microservice APIs.

Collect Chicken Images. This activity involves gathering images of chicken health problems, like skin lesions or unusual physical characteristics, from different sources. These images will be used as input data for the disease detection system.

Process Image. Preprocessing techniques are applied to the gathered images to improve their quality and get them ready for analysis. To maintain consistency throughout the dataset, this involves operations like noise reduction, normalization, and resizing.

Evaluate & tune CNN model. A Convolutional Neural Network (CNN) model is created using the preprocessed images. Its performance is then assessed on a subset of the dataset, and its parameters can be adjusted as necessary to improve the model's accuracy.

Integrate CNN model predictions. The CNN model is incorporated into the illness detection system after it has been trained and adjusted. Based on the input data, the model is used to evaluate fresh images and forecast whether or not diseases are present in chickens.

Test integrated system. A different set of images is used to test the integrated system, which includes the CNN model and the recommendation system, in order to assess its overall performance. By taking this step, you can make sure the system is operating properly and detecting and recommending diseases accurately.

Figure 3 shows the diagram illustrating two main participants: the Poultry Farmer and the System. The Poultry Farmer uses the System to receive assistance with identifying chicken diseases and obtaining treatment recommendations.

Use Case Diagram of the proposed system

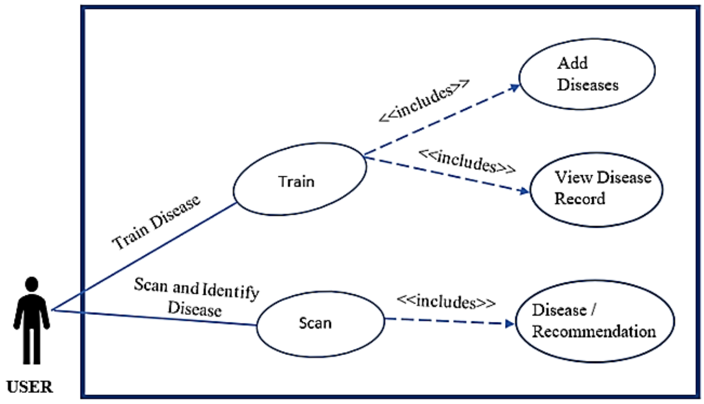

Figure 3 – *Use Case Diagram*

Figure 4 shows the end-to-end flow for chicken disease prediction and recommendations in the system. It starts with the farmers capturing disease symptom images. These images feed into the CNN model, which classifies diseases using disease profiles from the database. CNN predictions are sent to the Recommender to query the database and retrieve corresponding treatment plans. Finally, the CNN model consolidates image-based disease classifications and recommendation text into an integrated report for display to farm technicians. In essence, it depicts the core prediction and prescription workflow from capturing input images to outputting an analysis report to help disease diagnosis and management.

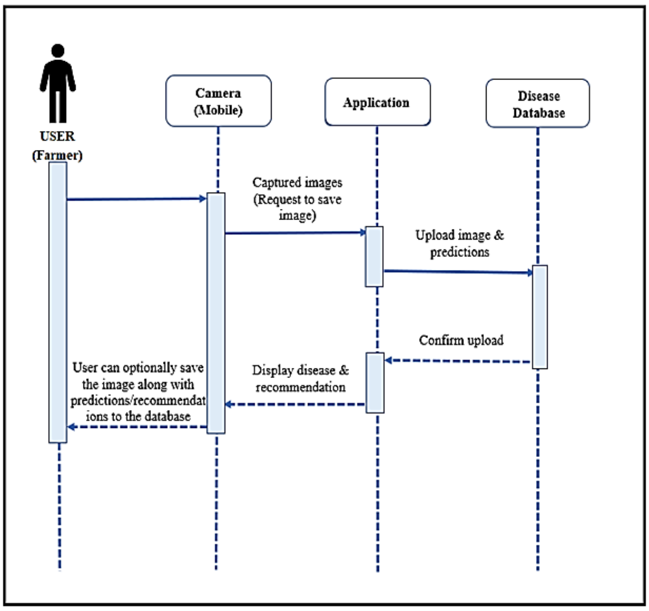

Figure 4. *Sequence Diagram of the study*

Implementation: The application was created by the researchers during the implementation stage. The framework utilized was Apache Cordova, allowing for easy deployment on both iOS and Android devices. While CSS was used for the design, HTML was used for user interaction. The application's processes are coded in Javascript.

Testing: In this phase, all the individually developed modules and components including the CNN model, recommender system, user interface, and database are assembled and integrated based on the previously frozen system design specifications.

Deployment: Once completely tested, deploying the production-hardened system on target farm servers and edge devices. Onboarding and training end-user farm technicians on installed solution. Transitioning to incremental upgrades/enhancements.

Maintenance & Updates: Continuous monitoring of operational analytics from deployed systems to identify issues and optimize performance. Providing technical support to users and applying periodic upgrades, enhancements, and model retraining as needed.

III. RESULTS AND DISCUSSION

The study's findings are discussed after being implemented and assessed.

Table 1. *Functional Suitability Evaluation Result*

	Criteria (Software)	**Mean**	**Interpretation**
Functional Completeness	All of the designated tasks and the user's goals are covered by the system's set of functions.	4.47	Excellent
Functional Correctness	The systems deliver accurate outcomes with the necessary level of accuracy.	4.53	Excellent
Functional Appropriateness	The features of the system make it easier to complete the designated tasks and goals.	4.65	Excellent
Mean		**4.55**	**Excellent**

The system meets the ISO International Quality Standard for computer systems' Functional Suitability requirements, as evidenced by its "Excellent" score (M=4.55) in Table 1. This assessment is based on the system's functional completeness (M=4.47), functional correctness (M=4.53), and functional appropriateness (M=4.65) classifications.

Table 2. *Performance Efficiency Evaluation Result*

	Criteria (Software)	**Mean**	**Interpretation**
Time Behavior	When a system is operating as intended, its response and processing times satisfy specifications.	4.41	Excellent
Resource Utilization	The kinds and quantities of resources that a system uses to carry out its operations satisfy specifications.	4.41	Excellent
Capacity	Provided that a system parameter's upper bounds satisfy the necessary conditions	4.53	Excellent
Mean		4.45	Excellent

The system's performance met the ISO International Quality Standards for computer systems, demonstrating high efficiency. As shown in Table 2, the system received an "Excellent" overall rating (M=4.45). This strong performance can be attributed to "Excellent" results in Time Behavior (M=4.41), Resource Utilization (M=4.41), and Capacity (M=4.53).

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Table 3. *Compatibility Evaluation Result*

	Criteria (Software)	**Mean**	**Interpretation**
Co-existence	The system can efficiently carry out its necessary tasks while coexisting peacefully with other products in a shared environment and with their resources. regarding any other item	4.47	Excellent
Interoperability	The system is able to share data and make use of the shared formation.	4.29	Excellent
Mean		**4.38**	**Excellent**

As shown in Table 3 the study's findings show that the system is compatible with the ISO International Quality Standards for computer systems. The system received "Excellent" ratings in all three categories: compatibility (M=4.38), interoperability (M=4.29), and co-existence (M=4.47).

Table 4. *Usability Evaluation Result*

	Criteria (Software)	**Mean**	**Interpretation**
Appropriateness recognizability	Users acknowledged that the system was necessary	4.59	Excellent
Learnability	In a given usage context, users can utilize the system with efficacy, efficiency, freedom from risk, and satisfaction to accomplish specific learning objectives.	4.59	Excellent
Operability	Because of certain features, the system is simple to use and steer.	4.53	Excellent
User error Protection	The user is shielded from error by the system.	4.53	Excellent
User Interface Aesthetics	An enjoyable and fulfilling user experience is provided by the system with the user interface.	4.53	Good
Accessibility	Individuals with a diverse range of traits and skills can utilize the system to accomplish a specific objective within a designated usage scenario	4.71	Excellent
Mean		**4.58**	**Excellent**

As shown in Table 4, the system received a “Excellent” rating (M=4.58) across all evaluation categories, including Appropriateness, Recognizability, Learnability, Operability, User error Protection, User Interface Aesthetics, and Accessibility.

Table 5. *Reliability Evaluation Result of “Chicken Diseases Detection Using CNN with Recommender”*

	Criteria (Software)	Mean	Interpretation
Maturity	Under typical operation, the system or its components satisfy the requirements for reliability.	4.59	Excellent
Availability	When needed for use, the system or component is functional and available.	4.47	Excellent
Fault Tolerance	Despite the existence, the system, product, or component functions as intended. of defects in software or hardware.	4.53	Excellent
Recoverability	Restoring the system to its intended state and retrieving the directly impacted data are both possible.	4.65	Excellent
Mean		**4.56**	**Excellent**

As shown in Table 5, the reliability test demonstrates that the system surpasses ISO International Quality Standards for computer systems reliability, achieving an "Excellent" rating (M=4.56). Specifically, the system excels in recoverability (M=4.65), fault tolerance (M=4.53), maturity (M=4.59), and availability (M=4.47).

Table 6. *Security Evaluation Result of “Chicken Diseases Detection Using CNN with Recommender”*

	Criteria (Software)	Mean	Interpretation
Confidentiality	Only authorized users can access the data thanks to the system in order to obtain access.	4.47	Excellent
Integrity	The framework forbids unwanted the ability to access or alter software.	4.59	Excellent
Non-repudiation	The method is verifiable to have occurred in order for things to be irreversible in the future.	4.53	Excellent
Accountability	An entity can be uniquely identified by its actions.	4.65	Excellent
Authenticity	The subject can be recognized by the system or The resource's claim can be verified.	4.65	Excellent
Mean		**4.58**	**Excellent**

The results in Table 6 show that the system passed the ISO International Quality Standard for Computer Systems Security requirements related to security. It got an "Excellent" score (M=4.58) because of its "Excellent" levels of confidentiality (M=4.47), integrity (M=4.59), non-repudiation (M=4.53), accountability (M=4.65), and authenticity (M=4.65).

Table 7. *Maintainability Evaluation Result of "Chicken Diseases Detection Using CNN with Recommender".*

	Criteria (Software)	Mean	Interpretation
Modularity	There is little influence from one discrete component on another in the system or component program.	4.71	Excellent
Reusability	It is possible to use the system asset in multiple systems or when creating other assets.	4.35	Excellent
Analyzability	The efficiency and effectiveness of the system that allows for the evaluation of the effects of planned changes to a system or any of its components, or to identify parts that need to be changed, or to assess a system's shortcomings or root causes.	4.65	Excellent
Modifiability	It is possible to change the system effectively and efficiently without creating flaws or lowering the caliber of the output.	4.41	Excellent
Testability	Test criteria for a system or component can be established based on its efficiency and effectiveness, and tests can be conducted to ascertain whether the criteria have been met.	4.76	Excellent
Mean		**4.58**	**Excellent**

As shown in Table 7 the system met the maintainability criteria specified in the ISO International Quality Standard for computer systems maintainability, as evidenced by the results. The Modularity category received scores of "Excellent" (M=4.71), Reusability (M=4.35), Analyzability (M=4.65), Modifiability (M=4.41), and Testability (M=4.76).

Table 8. *Portability Evaluation Result of "Chicken Diseases Detection Using CNN with Recommender.*

	Criteria (Software)	Mean	Interpretation
Modularity	There is little influence from one discrete component on another in the system or component program.	4.41	Excellent
Reusability	It is possible to use the system asset in multiple systems or when creating other assets.	4.76	Excellent
Analyzability	The system's efficacy and efficiency, which allow evaluation of the impact on a system of a planned modification to one or more of its components, or to identify components that need to be changed, or to assess a system's shortcomings or root causes of failures.	4.76	Excellent
Mean		**4.65**	**Excellent**

As shown in Table 8 displays that the system's "Excellent" result (M=4.6) in terms of the Portability requirements set by the ISO International Quality Standard for computer systems Portability, this is because the system has "Excellent" Modularity (M=4.41), Reusability (M=4.76), and Analyzability (M=4.76).

***Table 9.** The ISO 25010 Evaluation Summary Results*

ISO 25010 Criteria	Mean	Interpretation
Functional Suitability	4.55	Excellent
Performance Efficiency	4.45	Excellent
Compatibility	4.38	Excellent
Usability	4.58	Excellent
Reliability	4.56	Excellent
Security	4.58	Excellent
Maintainability	4.58	Excellent
Portability	4.58	Excellent
Overall Mean	**4.65**	**Excellent**

ISO 25010 Evaluation Summary Results by the IT Professionals, Farmers, and Professionals

Table 9 shows that the system achieved an 'Excellent' rating in all ISO 25010 quality criteria, demonstrating its adherence to international standards.

CONCLUSION

Based on the study's results, the following conclusions can be drawn:

- The system successfully meets its objective of improving the detection and classification of chicken diseases.
- The system adheres to ISO 25010 standards.
- The system is highly portable, maintainable, secure, reliable, efficient, and user-friendly.

RECOMMENDATIONS

Given the findings and conclusions, the following actions are suggested:

- Implement more advanced CNN models, such as ResNet, to improve performance.
- Expand the chicken disease image dataset to enhance model generalization.
- Test the model with a wider range of users from different areas.
- Allow the model to be retrained with new user images to enhance recommendations.
- Perform focused UI/UX testing to optimize the model for farmer use and satisfaction."

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