DESIGN AND DEVELOPMENT OF POULTRY PATROLLING AND HEALTH MONITORING ROBOT WITH AID OF IMAGE PROCESSING AND DEEP LEARNING TECHNIQUES

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Introduction:

The demand for poultry farming has been rapidly increasing, as reflected by the rise in global chicken meat production from an average of 45.93 million tons between 1961 and 2018 to an expected 139.19 million tons in 2025 (Uzundumlu & Dilli, 2023) [10]. The rapid growth of poultry production causes challenges for keeping chickens healthy and safe. As a result, infectious diseases spread quickly among chickens. It causes the high mortality rates and huge economic losses [7]. Early detection of disease can help reduce the transmission of the infection's disease in poultry. Traditional disease detection methods depend on manual inspection, which is labor intensive, time consuming, and inaccurate [3-8]. The most Common infectious diseases in poultry include Salmonella, Coccidiosis, and Newcastle disease. Salmonella infections are caused by bacterial pathogens of the genus Salmonella. Coccidiosis is induced by parasites of the genus Eimeria that affect the intestinal tract of chicken. Newcastle disease is caused by the avian paramyxovirus type 1 virus. it affects the chickens respiratory, nervous, and digestive system [4-6]. Recently, there has been remarkable promise for image processing in animal health and welfare. This progress is solely due to the increasing demand for more sophisticated methods to observe, analyse, and manage their health, behaviour, and overall development [9]. Image processing has generally been employed to enhance the features of an image, extract information of interest, or to prepare it for further analysis. Pre-processing operations such as enhancement, noise removal, segmentation, edge detection, and colour transformation are commonly performed on images [5- 2]. Deep learning primarily provides a way for computers to learn from large datasets to make intelligent decisions on their own. It is widely applied for classification, detection, prediction, and pattern recognition tasks [1]. This project focuses on integrating robotics, artificial intelligence, and automation into traditional poultry farming to reduce human effort and improve accuracy in monitoring Poultry chicken health.

Objectives:

1. To design and develop a poultry patrolling robot for efficient health monitoring of the chickens.
2. To separate and monitor the diseased chickens using Image processing and deep learning techniques.
3. To enable early health monitoring, reducing reliance on manual checks and reducing the labour cost and save time.

Methodology:

1. Design Methodology

The Poultry Patrol Robot was designed through a number of systematic stages. Its 3D model was developed from scratch using SolidWorks and Blender, starting with some research into the specific demands to be met by the robot in terms of poultry requirements, including dimensions, weight, movement, detection, colour spraying, and other functionalities. Then, a detailed 3D model was created in SolidWorks and Blender, including compartments in the model for sensors, sprayers, and control systems.

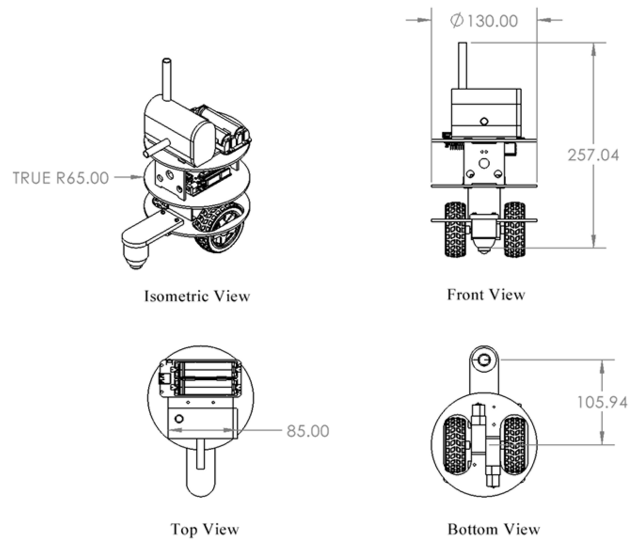

Figure 1: Base of the model

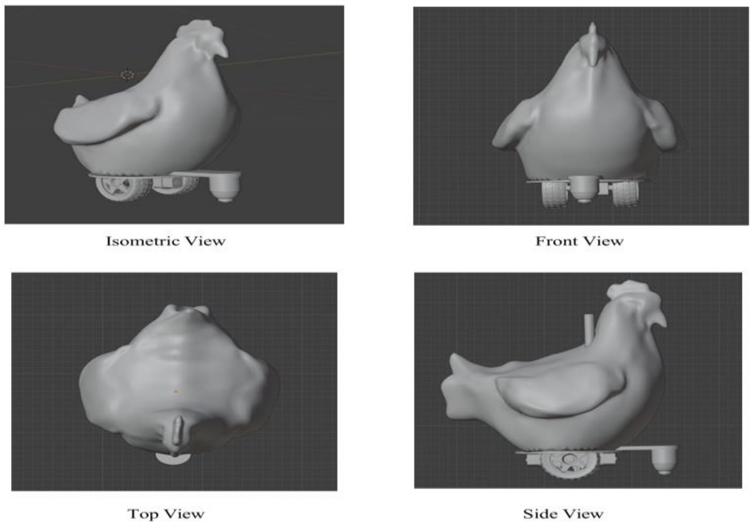

Figure 2: 3D Model

2. Collection of Data

The next step would be to gather datasets that can train the efficient net model for the classification of healthy and diseased chickens. Images were gathered from the sources, including taking photos in the farm, Kaggle, with a variety of conditions like lighting, angles, and many others that can improve robustness. Proper labelling of datasets was performed with regard to maintaining balance across categories, and data augmentation techniques involving rotation, flipping, and scaling were used in order to improve dataset diversity. A total of 8067 poultry fecal images were collected from Zenodo open database. The dataset was taken in Arusha and Kili manjaro regions in Tanzania between September 2020 and February 2021. Each image represents a poultry sample affected by one of the diseases or showing normal, disease-free conditions. The dataset contains four classifications Healthy, Salmonella, Coccidiosis, and New Castle disease.

Class	**Images**
Salmonella	2625
Coccidiosis	2476
New Castle Disease	1953
Healthy	2404
Total	**9458**

Table 1: Data set

3. Collection of Components

After collecting all the required components and completing the 3D-printed parts, the assembly of the model was Started. The process started with the integrating of a 3D-printed body structure to an acrylic sheet, used as the first layer for placing all other parts. The motors, wheels, Raspberry Pi and Arduino UNO were mounted on to an acrylic plate. The camera module was attached to the 3D printed body chicken body. The battery and tank were added on top of the acrylic plate. Finally, all wiring and connections were neatly organized.

4. 3D Printing of the Model

The robot was 3D printed using approximately 3kg of PLA filament. PLA was chosen because it was lightweight, easy to print, and cost effective. The PLA material used print the parts like complete body of the robot, tank, and support brackets. The PLA helps for stability and reduces the overall weight of the robot.

5. Assembly of Model

After collecting all the required components and completing the 3D-printed parts, the assembly of the model was Started. After gathering all the components and finishing the 3D-printed parts, the work on model assembly began. This started by attaching a 3D-printed body onto an acrylic sheet, acting as the base on which other components would be mounted. Next, motors and wheels were attached to an acrylic sheet, followed by the installation of the motor driver, Tyre and Arduino UNO. Further, the mounting of the Raspberry Pi and camera module was completed carefully so that stable processing and optimal field of view for capturing images could be achieved. The battery was located in a position where it could supply power consistently to all parts, while the water pump allowed for the efficient spraying of the nontoxic chemical. Lastly, all wiring and connections were laced neatly so they could not interfere with the working of the robot.

Figure 3: Working Prototype

6. Testing

The Poultry Patrol Robot is a critical component in the development phase as it tests each component and subsystem to assure that it works together in order to achieve the project objectives. The prime functionality of the robot is to detect sick chickens through their movement behaviour and define potential health problems through faecal matter analysis.

Working Principle:

The poultry patrolling robot is designed to move autonomously around the poultry farm to observe the health condition of chickens. Its main objective is to detect diseased chickens by analysing their movements. The chickens affected by illness usually show slow or abnormal motion. During patrolling, the robot continuously observes and detects any chicken showing such unusual movement patterns. Once the robot detects a diseased chicken in the poultry farm, it sprays non- toxic chemical on it to make it recognizable. Then, it immediately sends an alert message to the farm owner. The owner then collects the suspected chicken and takes a sample from its fecal (poop) for further disease analysis. This sample is uploaded to a web application that uses a trained deep learning model, developed using a dataset of various chicken diseases. The model analyzes the uploaded sample and identifies the specific disease affecting the chicken. Based on the result, the farmer can then take appropriate treatment measures to protect the chicken.

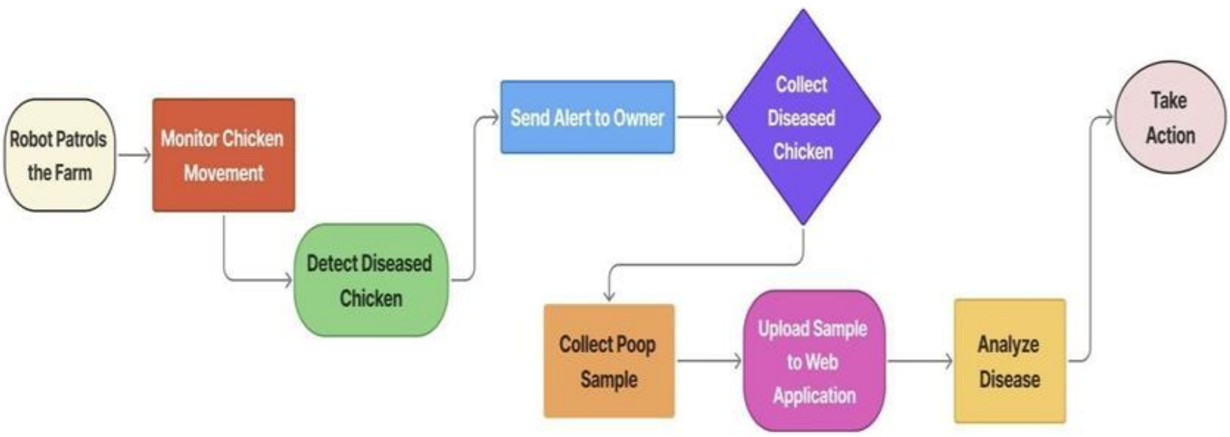

Figure 4: Process Flow of Poultry Disease Detection System

Process Explanation:

1. Start Screen

- The user begins at the start screen (Figure a), which introduces the tool called Poultry Disease Detection.
- Here, the user can see options to upload an image of a poultry fecal sample using a camera or by selecting a file.
- The screen also lists the detectable conditions (such as Coccidiosis, Healthy, Newcastle Disease, and Salmonella) the AI can identify.

2. Picture uploading

- Next, the user proceeds to the picture acquiring screen (Figure b).
- The user is given two main options: Take Photo (using a camera) or Upload Image (from device storage).
- This provides flexibility in sourcing poultry sample images, making the tool accessible in various situations.

3. Result and Analysis

- After providing the image, the application processes the sample and displays the results (Figure c).
- The result screen shows:
  1. The uploaded image for reference.
  2. The diagnosis result

Result:

The project successfully achieved two key objectives: the development of a Poultry Health Monitoring Robot and a Disease Detection app that identifies diseases through fecal image analysis.

1. Poultry Patrolling Robot

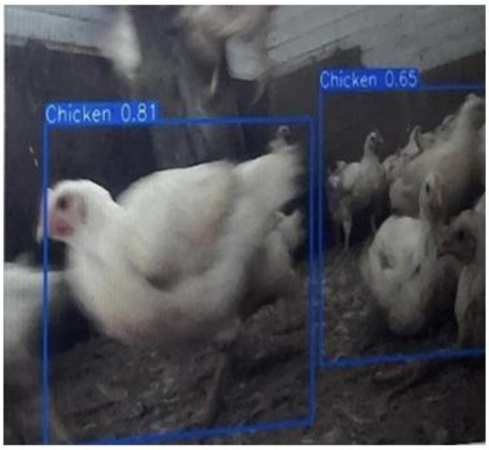

Figure 6: Robot deployment

A fully functional robot was developed that autonomously patrols the poultry shed to detect diseased chickens based on their movement and behaviour. Once a diseased chicken is identified, the robot automatically activates a spraying mechanism that releases a non-toxic marking chemical, allowing farmers to easily locate and isolate the affected bird within the poultry area. During the testing phase, this functionality was successfully demonstrated by the developed robot, proving its effectiveness in real-time farm conditions.

2. Disease Detection System

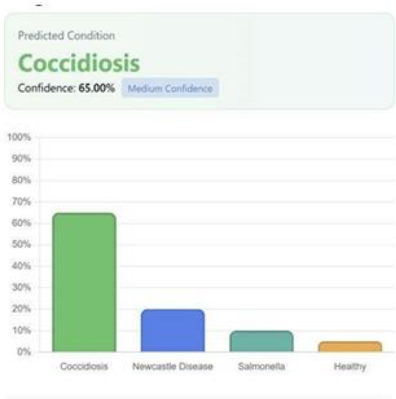

Figure 8: Result Obtained

A website was designed and developed to analyse the fecal images of chickens. Using image processing and machine learning techniques, the system could identify specific diseases based on colour, texture, and pattern features of the fecal matter. The website provides an easy-to-use platform for farmers to upload images and receive instant results. The first image shows the fecal sample of a chicken captured and uploaded to the disease detection website. The system uses image processing and deep learning algorithms to analyse the texture, colour, and pattern of the fecal image to identify possible diseases. The second image displays the output generated by the trained model. The system predicts the most probable disease condition as Coccidiosis with a confidence level of 65%. It confirms that chicken is affected with the Coccidiosis disease.

Conclusion:

The present project work demonstrates the design and development of an autonomous Poultry Patrolling and Health Monitoring Robot. It is capable of improving disease detection, reducing human effort and enhancing poultry farming management. The integration of robotics with image processing and deep learning provides a practical solution to solve the challenges faced in the poultry industry. The robot developed in this project is able to autonomously patrol the poultry shed, monitor chicken behaviour and identify chickens showing abnormal or slow movement patterns, which are common early indicators of illness. Upon detection the robot accurately marks the suspected Chicken using a non-toxic chemical spray and simultaneously alerts the farm owner. This automated marking mechanism was successfully validated during testing and proved effective in real-time farm conditions. Meanwhile, the fecal based diagnosis system was developed using EfficientNetB0 deep learning model, trained with a large dataset of fecal images. The model achieved a mean accuracy of 92.93%, indicating a very strong capability in distinguishing between the Healthy, Salmonella, Coccidiosis, and Newcastle disease classes. The website interface allows users to upload fecal images and receive instant disease predictions supported by probability-based visual results. Based on this two-stage approach, first behavioural detection and then classification using fecal images, the system provides both early-stage screening and confirmation diagnosis, further making the diagnosis more reliable than traditional manual inspection methods. The successful implementation of this prototype gives way to further enhancements in the form of multi-robot coordination, IoT-based environmental monitoring, integration with mobile apps, and higher versions of real-time disease prediction models. This system will revolutionize traditional poultry farming in terms of efficiency, safety, and intelligence at a future date with further development and field-level deployment.

Project Outcome & Industry Relevance:

1. This project focuses on solving a major challenge in large-scale poultry operations, which is manual disease detection. Conventional methods rely on workers to inspect large numbers of chickens every day, making the process slow, inconsistent, and often ineffective in preventing the early spread of diseases. This system enables early detection of diseases in chickens by monitoring their movement and analyzing fecal samples, allowing timely intervention, reducing mortality rates, and improving overall productivity, while also minimizing manual monitoring to save time and labor costs and providing accurate and reliable health assessment to enhance the overall welfare of chickens.
2. The robot provides a two-stage automated solution in which it first performs behavioural screening by patrolling and identifying chickens with slow or abnormal movement, and then carries out fecal confirmation by uploading samples to a web application powered by an EfficientNetB0 deep learning model, which classifies diseases such as Salmonella, Coccidiosis, Newcastle Disease, or identifies healthy cases with a mean accuracy of 92.93%.
3. Large-Scale Commercial Poultry Farms: Farms managing thousands of broiler chickens face enormous challenges in early disease identification. Deploying this robot would reduce the need for constant human monitoring, allow faster isolation of sick birds, and significantly cut disease-related mortality and economic losses.
4. Veterinary & Agricultural Diagnostics: The disease-detection website could be used independently by farm owners or veterinarians anyone can photograph a fecal sample and get an instant AI-powered diagnosis. This is particularly valuable in rural areas with limited access to veterinary services.

Working Model vs. Simulation/Study:

This project involved the development of a physical working model. A functional prototype robot was designed and built, capable of patrolling within a poultry farm environment.

Project Outcomes and Learnings:

Through this project, significant learning was achieved in multiple areas. It provided hands-on experience in designing using SolidWorks and Blender. It also helped in gaining knowledge in the field of 3D printing. Additionally, it improved understanding of assembling the model with components such as motors, cameras, and Raspberry Pi. The project also helped in understanding how to develop and train models for disease classification. Furthermore, it enhanced skills in programming, system integration, and the integration of hardware with software components. Problem-solving and troubleshooting abilities were improved while working under real-world constraints. The project also strengthened teamwork, time management, project planning, and presentation skills. Overall, this project provided valuable exposure to poultry farming and offered practical insights into implementing robotics and AI-based solutions in real-world farming scenarios.

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Future Scope:

The future scope of this project includes:

1. **Advanced Intelligence & Automation:** Enhancement of AI models for accurate disease detection, behavior analysis, and development of data-driven decision support systems.
2. **Autonomous & Scalable Operations:** Implementation of autonomous navigation, expansion to large-scale farms, and incorporation of swarm robotics for efficient coverage.
3. **Enhanced Monitoring Capabilities:** Addition of environmental sensors, alert systems for early disease detection, and adaptation for multiple livestock applications.
4. **Efficiency, Durability & Commercialization:** Improvement in battery life, energy efficiency, durability in harsh environments, and cost optimization for practical and commercial use.
5. **Smart Connectivity & Data Management:** Integration of IoT, cloud computing, and farm management software for real-time monitoring, remote access, and predictive analytics.