



UNIVERSITY of
RWANDA



COLLEGE OF SCIENCE AND TECHNOLOGY

**AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS
(ACEIoT)**

***Designing and Implementation of a TinyML and IoT-based
Chicken Egg Quality Analysis and Monitoring System***

*A dissertation submitted in partial fulfilment of the requirements for the award of Master of
Science degree in Internet of Things: Embedded Computing System (ECS)*

Submitted By:

OMOY KOMBE Hélène (Ref.No: 221031195)

December 2023



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Dr. Louis SIBOMANA

Dr. Martin KURADUSENGE

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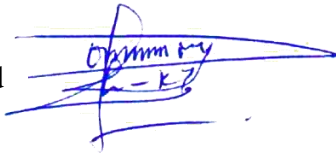
Declaration

I, **OMOY KOMBE Hélène**, Master student in Internet of Things – Embedded Computing System from African Center of Excellence in Internet of Things, at University of Rwanda, declare that this research thesis entitled “**Design and Implementation of a TinyML and IoT Based Chicken Egg Quality Analysis and Monitoring System**” is my own original work and it has never been presented before anywhere in the world for the similar title.

OMOY KOMBE Hélène

221031195

Signed

A handwritten signature in blue ink, appearing to read 'OMOY KOMBE Hélène', written over a horizontal line.

Date: Monday, 11th December 2023

Bonafide Certificate

This is to certify that this submitted Research Thesis work report is a record of the original work done by **OMOY KOMBE Hélène (Ref. No: 221031195)**, at the University of Rwanda / College of Science and Technology / African Center of Excellence in Internet of Things: Embedded Computing System (ECS) program, the Academic year 2021 - 2023.

This work has been submitted under the supervision of:

Main Supervisor: **Dr. Louis SIBOMANA**

Co-Supervisor: **Dr. Martin KURADUSENGE**

Date: 13/12/2023

Date:

Signature:



Signature:

The Head of master's and Training

Dr. James RWIGEMA

Date :

Signature.....

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Abstract

The poultry industry has experienced significant development in recent years due to the rising demand for high-quality protein sources. However, it is crucial to maintain the quality of chicken eggs during the incubation process in order to ensure the generation of healthy chicks and optimal production results. At present, the conventional method of manually inspecting eggs and using artificial candling leads to a time-consuming, labor-intensive, and error-prone process of evaluating and monitoring the quality of poultry eggs. The quality of eggs is influenced by a range of environmental conditions, including temperature, humidity, and lighting, which can be challenging to control through manual means. Furthermore, the absence of immediate feedback results in delays in identifying possible issues during the incubation process. In addition, current technologies lack guidance on automating the egg mirage process and enhancing the incubation process. This study aims to address these challenges by developing a comprehensive solution that combines artificial intelligence (AI) and Internet of Things (IoT) technologies. The solution automates the egg mirage process and the environmental aspect of egg quality analysis and monitoring. This automation reduces the reliance on manual labor and enhances the accuracy of data collection. Consequently, it improves the efficiency and quality of the egg production process while also reducing costs. The web-based program will display real-time feedback on the quality of eggs, allowing the farmer to easily assess the condition and maturity of the eggs in the incubator. A Convolutional Neural Network was employed as the classifier algorithm for discerning between viable, non-fertile, and deceased eggs. The suggested system achieves a TinyML classification F1-Score of 97.4% when deployed on the Arduino Nano 33 BLE Sense. This deployment demonstrates notable enhancements in efficiency, leading to an accuracy rate of 95.79%. The system possesses the capacity to revolutionize the poultry industry by offering a more effective and precise method to monitor the quality of eggs. This enables poultry farmers to enhance and mechanize the process, reduce errors, and offer immediate feedback, leading to accelerated incubation and increased production rates.

Key terms: IoT, AI, Sensors, CNN, classification, quality assessment, candling, egg, TinyML.

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List of Acronyms

AI: Artificial Intelligence
AP: Average Precision
API: Application Programming Interface
APN: Access Point Name
ARM: Advanced RISC Machine
BLE: Bluetooth Low Energy
CNN: Convolutional Neural Network
CPU: Central Processing Unit
CSS: Cascading Style Sheets
D: Digital pin
DHT: Digital Humidity Temperature
DL: Deep Learning
FAO: Food Association Organization
IDE: Integrated Development Environment
GND: Ground
GPU: Graphical Processing Unit
HTML: Hypertext Markup Language
HTTPS: Hypertext Transfer Protocol
IoT: Internet of Things
IoU: Intersection over Union
LCD: Liquid Crystal Display
LED: Light Emitting Diode
MB: Megabyte
MHz: Megahertz
ML: Machine Learning
NFC: Near Field Communication
OEM: Original Equipment Manufacturer
OLED: Organic Light Emitting Diode
PDL: Process Design Language

PPG: PhotoPlethysmoGraphy

RAM: Random Access Memory

R-CNN: Region-based Convolutional Neural Network

ReLu: Rectified Linear Unit

SCL: Serial Clock Line

SDA: Serial Data line

TFLITE: TensorFlow Lite

TinyML: Tiny Machine Learning

VCC: Common Collector Voltage

CHAPTER 1: GENERAL INTRODUCTION

1.1 Introduction

Poultry farming is a vital sector of the agriculture industry, providing an essential source of protein for human consumption worldwide. Eggs are an essential food source and have a big impact on world nutrition. It is crucial to ensure the production of high-quality eggs to satisfy consumer demand, maintain the poultry industry's profitability, and uphold the standards of public health. Artificial incubators have been used all over the world for a long time, both now and in the past[1]. Normally, eggs are incubated under ideal conditions so that they can develop properly[2], but as modern technology advances, artificial incubators are developed to maintain an environment for eggs that is more effective[1].

Artificial Intelligence (AI) and the Internet of Things (IoT) have emerged as powerful technologies with transformative potential across various industries. One such area where these technologies are making significant advancements is in the mirage process for chicken egg incubation[3]. Mirage, also known as candling, involves the examination of eggs to assess their quality, fertility, and development stage using a bright light source[2][4]. The eggs were exposed to a strong light during this operation[2], [5] to see the shadow formed by the embryo inside the egg. To accurately categorize the eggs, they were candled one by one. The only issue is that this candling procedure takes too long, which can lead to errors and be labor-intensive.

Incubation promotes embryonic development, which is required for egg hatching. Several factors must be considered in the process for eggs to hatch properly and without dying. Several studies have shown that the following elements influence the incubation process: temperature, humidity, ventilation, and egg turning[1], [2], [6]. An artificial incubator should be capable of stimulating and maintaining optimal environmental conditions. Overheating and underheating are two reasons why eggs do not hatch, as temperature is crucial for the speed of their metabolic rate.

Moreover, inconsistencies in grading and sorting eggs due to human judgment further add to the challenges. An infertile egg has an increased danger of rupturing or spoiling if left in the incubator for too long. Recent advancements[1] in AI and the IoT present new opportunities to revolutionize the mirage process, enabling automated, accurate, and data-driven solutions for eggs. The integration of AI and IoT in this process offers promising opportunities to overcome the limitations

of traditional manual inspection methods and improve efficiency, accuracy, and decision-making[7].

1.2 Background and Motivation

Egg hatching and the general profitability of egg production facilities relate directly to the number of eggs that survive the production process. However, research indicates that the current chances of survival are only 80% and 70% respectively[7]. One of the critical aspects of poultry farming is the production[8] of high-quality eggs. According to poultry learning event 2019[9], Rwanda's commercial poultry industry is still in its early stages of development. It is distinguished by larger flock sizes than village poultry and sales of farm-raised chicken flesh and eggs. In Rwanda, the demand for day-old chicks continues to be higher than the supply, despite the presence of local hatcheries. If they have hatching facilities, commercial farms frequently import day-old chicks or fertilized eggs rather than hatching their own. A large percentage of Rwanda's commercial poultry producers obtain their day-old chicks from either Uganda, the Netherlands, or Belgium[9], [10]. In Rwanda, most broiler poultry farms are small (meaning their capacity is less than 1000 chickens) and medium, with a capacity of 1000–5000 chickens. According to the Poultry Sector Analysis Rwanda based on the Poultry Learning Event 2019[9], there are approximately 26 small, 11 medium-size and 5 large-scale broiler poultry farms in Rwanda. And approximately 210 small farms, 108 medium-size farms and 27 large-scale layer poultry farms are active in the country. In Rwanda, there are two types of chicken farming systems: extensive (traditional) and intensive (commercial)[8].

Traditional methods of egg quality assessment and monitoring have limitations that can be addressed through the integration of AI and IoT technologies to improve efficiency and accuracy in egg quality assessment. The swift progress of AI and IoT technologies have opened new possibilities for transforming various industries, including agriculture. These technologies can be harnessed to develop innovative solutions for quality monitoring and evaluation. The integration of AI and IoT allows for real-time data collection, analysis, and decision-making. This capability can lead to prompt interventions, minimizing risks and optimizing egg production processes. While there might be some existing egg quality monitoring systems, integrating AI and IoT to create a comprehensive solution is relatively new and innovative.

This research aims to bridge the gap between traditional methods and cutting-edge technologies, enhancing egg quality assessment in a holistic manner. By combining the power of AI and IoT, a chicken egg quality analysis and monitoring system can revolutionize how the poultry industry manages egg production, ensuring consistent quality, reducing waste, and enhancing food safety. The motivation behind this research lies in the potential to make a significant positive impact on both the poultry industry and consumers by providing reliable and efficient egg quality evaluation methods.

1.3 Problem Statement

With the world's population steadily increasing, the demand for high-quality and safe food products is on the rise. Eggs are a valuable protein source, and consumers expect consistent quality and safety standards. However, the inefficiency and inconsistency in the incubation process led to inaccuracies in determining egg quality, low hatching rates, poor chick health, and low production efficiency. Conventional incubation methods rely on manual mirage process to inspect eggs, monitoring, and adjustment of incubator conditions, which is labor-intensive and subject to individual variations in judgment. Its limitations are time-consuming, costly, error prone, and unsanitary, that may cause diseases such as avian flu to eggs and employees. Moreover, eggs with compromised quality may pose food safety risks if consumed. Poor-quality eggs not only affect consumer satisfaction but also lead to economic losses for poultry farmers. Moreover, it is very challenging to detect issues early in the hatching process, if infertile eggs are not removed from the hatchers, an egg explosion may occur. Which result in high mortality rates and decreased production efficiency.

The AI and IoT-based egg quality analysis and monitoring system aims to overcome these challenges by providing real-time monitoring of egg quality factors such as temperature, humidity, and egg turning, using sensors connected to the internet. The system used CNN to analyze the data and optimize the incubation process for better candling and hatching rates, chick health, and production efficiency. The system also will monitor the hatching eggs process and post-hatching growth for early detection of any issues, enabling prompt intervention to minimize losses by classifying fertile and infertile eggs.

1.4 Study Objectives

1.4.1 General Objectives

The general objective of this proposed solution is to develop an AI and IoT comprehensive solution to automate the egg mirage process and environmental aspect of egg quality analysis and monitoring, reducing the need for manual labor and improving the accuracy of data collected to improve the efficiency and quality of the egg production process while reducing costs.

1.4.2 Specific Objectives

In order to accomplish the general objective, our purpose is to:

- ✓ Design an IoT device to continuously monitor environmental factors of egg within the incubator.
- ✓ Collect data of fertile, infertile and death eggs images on the field for CNN training and learning model for accurate and automatic candling, classification of fertile, non-fertile and death eggs.
- ✓ Integrate IoT sensors and CNN model for egg turning within the incubator and for good quality analysis and monitoring of incubation.
- ✓ Develop a web application that is easy for users to navigate in real-time assessment and visualization of environmental condition and egg development stage.

1.5 Research Questions

The aforementioned precise objectives aim to address the following inquiries:

- A. What environmental factors have the most significant impact on egg development, and what sensors are appropriate for monitoring them?
- B. What are the key challenges in manual candling, and how can these challenges be addressed through automated image classification?
- C. What is the optimal frequency and duration for egg turning to enhance embryo development, and how can this be controlled using IoT devices?
- D. In what ways can the CNN model contribute to the quality analysis and monitoring of incubating eggs beyond traditional methods?

- E. What are the key features and functionalities that users would find essential in a web application for monitoring egg incubation?
- F. What are the security and privacy considerations in the development of a web application for real-time monitoring of sensitive data?

1.6 Hypothesis

The adoption of an AI and IoT-based system for monitoring and analyzing the quality of chicken eggs can greatly increase the effectiveness and accuracy of egg quality evaluation, resulting in increased production and profitability in the poultry industry.

The efficiency and accuracy of this cutting-edge system would surpass those of traditional manual techniques of evaluating egg quality. It asserts that compared to human inspection, AI-powered analysis would yield quicker and more reliable conclusions, requiring less time and effort for evaluation. Additionally, the system may recognize and handle elements that may have an impact on egg quality by using IoT devices to monitor environmental variables, leading to better production methods.

1.7 Study Scope

This study integrates the AI model with the IoT devices to develop a comprehensive egg quality analysis and monitoring system and web-based application for data visualization and remote control of the incubator. The primary focus of this study is to develop an AI model that will accurately assess egg quality based on the development stage of embryo and different attributes, such as shell integrity, yolk color, albumen consistency, and egg weight. This study includes the implementation of IoT devices to collect real-time data from the incubator, such as temperature, humidity, air quality, egg turning, and picture of eggs for better candling process and monitoring. This project involves data preprocessing techniques to clean and prepare the collected data for AI model training and analysis. It will explore two different algorithms for egg quality analysis: CNN. The developed system will be tested and validated in a real-world poultry farm setting to assess its practical effectiveness.

By using this system, farmers will improve egg quality, increase productivity, reduce costs, and improve animal welfare.

1.8 Significance of the Study

This research study is essential since it addresses critical issues in the poultry sector. First, the research aims to improve food safety, increase resource efficiency, and promote sustainable agriculture by adopting novel technology. Second, farmers may make decisions based on information about egg quality in real-time, minimizing waste, improving productivity, and contributing to global food security. Third, the study's potential for broader applications encourages technological adoption and advancements in precision agriculture. Finally, this system has the potential to transform the poultry business by providing a more efficient and accurate means to monitor egg quality. That allows poultry producers to optimize and automate the process, decrease errors, and provide real-time feedback, which results in faster incubation and higher production rates.

1.9 Organization of the Study

This project is divided into six chapters and organizes as follows: First chapter introduces the research topic, problem statement, objectives, and significance of the study. The second chapter presents a review of existing related studies on egg quality analysis. The third chapter explains the methodology used. The fourth chapter discusses the AI and IoT-based egg quality system model, describes the integration of AI and IoT components and discusses data preprocessing. Fifth chapter presents findings and results from AI model and evaluation, showcases real-world data collected through IoT devices and analyzes the performance and accuracy of the system. The last chapter summarizes the research outcomes and achievements, highlights the significance of the study's contributions, and provides recommendations for future enhancements.

1.10 Conclusion

This chapter presented an introduction of the study, provides background information on traditional manual and artificial techniques of evaluating egg quality in Rwanda. It defines the problem statement and research objectives with precision, emphasizing the need for AI and IoT-based chicken egg analysis and monitoring system. The chapter highlights the importance of the study in addressing these critical aspects of poultry farming and its potential to have a significant impact on reducing cost, improving productivity, and contributing to global food security. It

provides the context, motivation, and justification for the developing an innovative solution to enhance poultry farming especially egg assessment in Rwanda.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Eggs are a major source of animal protein, making poultry production a global industry. Maintaining proper hatchery incubation conditions ensures high-quality egg production. However, controlling incubation conditions can be difficult, and traditional methods lack consistency and precision in evaluating and identifying viable and infertile eggs. Thus, AI and IoT in egg incubation and production attract attention. In this chapter, a comprehensive literature review is presented, surveying traditional methods of environmental parameters, existing studies and research works related to egg quality analysis, and IoT-based monitoring systems, providing the foundation for the development and significance of the AI and IoT-based chicken egg quality analysis and monitoring system.

2.2 Related works

Machine learning (ML) plays a crucial role in the agricultural sector, serving as a pivotal facilitator in the transition towards farming 5.0. ML technology holds the potential to enhance farm productivity and reduce resource requirements necessary for sustaining the farming cycle[11]. An instance of TinyML[12] implemented on the edge showcases a grape leaf disease detector that exhibits reduced complexity. This detector utilizes a compressed CNN architecture. Remarkably, it achieves an accuracy exceeding 98% while maintaining a remarkably small memory footprint of less than 13Kb of ROM. This accomplishment is made possible by employing a low-rank CNN architecture.

A comprehensive survey in [13] presented a detailed overview of the field of TinyML, exploring its diverse uses and the potential it holds for enabling sustainable development. The article examined the impact of TinyML on latency reduction and its ability to facilitate the deployment of real-time applications at the data source. Nevertheless, there is a deficiency in conducting a comprehensive examination of the implementation of TinyML in the domain of poultry farming, resulting in a lack of comprehension about the particular obstacles and potential advantages associated with its use in this unique setting.

A study in [14] developed an IoT-based automated poultry farm for layer chicken system for monitoring eggshell temperature, egg weight, and humidity during incubation. Machine learning techniques were utilized to discover trends in the data and predict chick hatchability. The method predicted hatchability with an accuracy of 87%. Lack of candling management which refers us to the traditional method which consumes a lot of time and cannot be used in large-scale industry. Farmers also cannot monitor the incubator remotely.

Casanovas et al. [15] implemented a fuzzy controller applied to temperature adjustment in incubation of free-range eggs. In this study, authors mentioned how temperature variation in egg incubation can negatively affect the hatching time and weight gain of chicks, hence improving the incubator temperature accuracy can improve hatching rates. They developed four incubators were two with fuzzy controller and two with a conventional controller. They focused on hatchability and power consumption. The study found that when compared with the convolutional controller, the fuzzy logic-based controller maintained uniform internal temperature and saving on power usage of 10.68%. The lack of precise regulation of the incubator's conditions is a significant caveat of this work. The authors focused solely on temperature regulation, ignoring all other relevant variables. And the management of fertility was not mentioned.

The study in [16] developed an IoT-based egg incubation monitoring system that used wireless sensor networks to collect temperature, humidity, and egg weight data. The data was displayed on the LCD screen. The study showed that the eggs were well fertilized with little or no infected eggs. The use of this solution is limited to small scale farming and egg embryo research and laboratory work. Other limitations include the manual classification of infertile eggs, lack of egg quality monitoring approach and incubation monitoring by farmers.

A study conducted by Z. Zhong et al. [7] compared several studies on computer-based methods to distinguish fertilized eggs from infertile ones. He found that generally, computers distinguish live and fertile eggs based on the difference in temperature, shape and size, electric property and acoustic, and the candling image. This study showed that the computer-based methods involve acoustic, bioelectrical, image test and other methods. It has the advantages of high efficiency, speed, and accuracy. However, research on computer-based methods for detecting fertilized eggs

is still limited, and more robust methods with high accuracy and cheap cost should be developed and implemented in the actual production line.

Another study in [1] developed an AI-based method using image processing for predicting egg fertility and hatchability using data from IoT sensors such as egg weight and shell thickness. The system is accurately and autonomously reads and maintains temperature and humidity, controls egg turning and reduces time and effort in the eggs as it hastens candling process using image processing and effortlessly monitor egg development due to ingenious design of built-in candling apparatus inside the incubator. This study has a gap of heating and ventilation system that can affect the hatching rate of the egg during the incubation process.

M. Hashemzadeh and N. Farajzadeh[17] developed a fertility detection machine vision system for detecting eggs in the incubation industry. Utilized a mechatronic device to capture precise digital photos of eggs, employing a low light source to enhance visibility. This allowed a CCD camera to get high-quality and instructive images from the interior of the eggs. This study devised a machine vision system to analyze the acquired photos and differentiate between viable and sterile eggs. An Artificial Neural Network (ANN) method was utilized to train a model for fertility detection. The average rates of fertility throughout the first five days of incubation were as follows: 47.13%, 81.41%, 93.08%, 97.73%, and 98.25%. However, the machine can only hold 6 eggs, which is very limited. This method of candling takes a long time to do, so it can't be used on a big scale. Also, the study doesn't separate the infertile from the fertile eggs. If this isn't done, the infertile eggs may rot while the fertile eggs are being grown.

For more precise and efficient identification of the hatch rate and detecting fertility in hatching eggs using CNN, Lei et al. [18] developed a new method that blends a CNN with the heartbeat signal of the hatching eggs. To identify the variation in blood volume in living tissues by photoelectric means, the researchers used the PhotoPlethysmoGraphy (PPG) technique to record the signals of the eggs' heartbeats. They developed the E-CNN network to examine the timing of embryonic heartbeats. They said that using E-CNN and SR-CNN, they could figure out what percentage of eggs would be fertile enough to hatch. The detection accuracy of the two network topologies proposed is up to 99.50% and 99.62%, respectively, making them useful for identifying

hatching eggs that have survived. However, they did not achieve the classification of fertile eggs, dead eggs, and weak embryos.

Similarly, in Deep Learning (DL) based egg fertility detection, Çevik[19] employed a Mask R-CNN technique along with the transfer learning model to accurately detect fertile and infertile eggs. This novel study uses a single DL model to carry out detection, classification and segmentation of fertile and infertile eggs based on incubator images. Based on incubator images, this study developed a DL approach to the fertile egg detection problem. The study used a Mask R-CNN-based technique to categorize chicken eggs based on segmentation and growing status. Images can thus be processed by a single DL model to successfully detect, classify, and segment viable and infertile eggs. This study employed two distinct testing procedures. A data collection including 5 viable eggs was employed in the first test application. The second test was performed on a data set including 18 fertile eggs. To evaluate the work, they employed AP, one of the most essential metrics for evaluating object recognition and segmentation models in computer vision. When the findings were evaluated, the optimal threshold value (IoU) was determined to be 0.7. On the third day of both test periods, all viable eggs in the incubator were accurately determined, according to the IoU of 0.7.

However, when the test data is analyzed, the segmentation performance has a significant impact on the proper detection of the viable egg since the AP values acquired during segmentation and the number of correct detections of fertile eggs were parallel to each other. Improving segmentation performance is thus far more critical than recognizing viable eggs. As the segmentation performance is limited, it is required to improve the camera assembly and lighting installation for image capture to develop the image acquisition mechanism. In addition, to create a commercial product that will assist farmers.

All this above research shows the use of AI and IoT-based systems in chicken farming, including egg incubation and production. AI and IoT advancements have the potential to improve egg incubation methods. However, most of the previous research used historical dataset and existing AI models, others didn't implement their researches in the real world and all of them are not addressed in Rwanda. Ignoring that power system is more important to maintain the incubator running to provide real time data, there is lack of power management on all this research. Due to

these limitations, there is a growing need for innovative approaches that leverage AI and IoT technologies to address the challenges posed by traditional methods and enhance egg quality analysis and monitoring systems in the poultry industry.

CHAPTER 3: RESEARCH METHODOLOGY

In this chapter, we outline the comprehensive research methodology employed to develop and implement the AI and IoT-based chicken egg quality analysis and monitoring system, encompassing data collection, AI model creation, tools, and software used.

3.1 Research process

The research process began with an idea that prompted further interrogation by undertaking a comprehensive literature review, system level design, data collection and preprocessing, model training, and finally analysis and performance of the proposed AI and IoT system.

3.2 Data sources

For this study, we selected eight well established poultry farms from different location, different size and different management practices in Rwanda and one incubator farm in Bukavu/DRC. Two broiler chicken farms (Poultry East Africa Ltd from Bugesera and Bishenyi Chicken Farm from Kamonyi), two-layer chicken farms (Isimbi Farm Ltd from Rwamagana and Abusol Ltd from Bugesera), two hatcheries' farms (Uzima Chicken from Nyagatare and Kigali and Easyhatch from Musanze) and three home-based incubators (Gatunda, Ntarama and Bukavu/DRC). In addition, we had a productive discussion with students in veterinary medicine and animal production from the University of Rwanda/Nyagatare Campus.

Data was collected from five among nine selected poultry farms through field visits. During these visits, we interacted with five farmers' owners and managers to obtain permission for data collection and explain the research objectives. The data gathered during these visits included observations and measurements of egg quality attributes, such as shell quality, yolk color, and albumen consistency, environmental factors like temperature and humidity. To ensure accurate and organized data collection, we prepared a questionnaire interview. Below are figures depicting several graphs illustrating the responses obtained from farmers during in-person visits. It has come to our attention that many farmers are encountering difficulties in accurately evaluating the quality of eggs. Some farmers continue to rely on traditional methods to estimate fertility, temperature, and humidity to analyze and monitor egg quality. The following figures depict the farmers' response in accordance with the mirage process. They are abstaining from doing the candling

procedure. The involvement of veterinary medicine students was crucial in obtaining precise and pertinent data for the study.

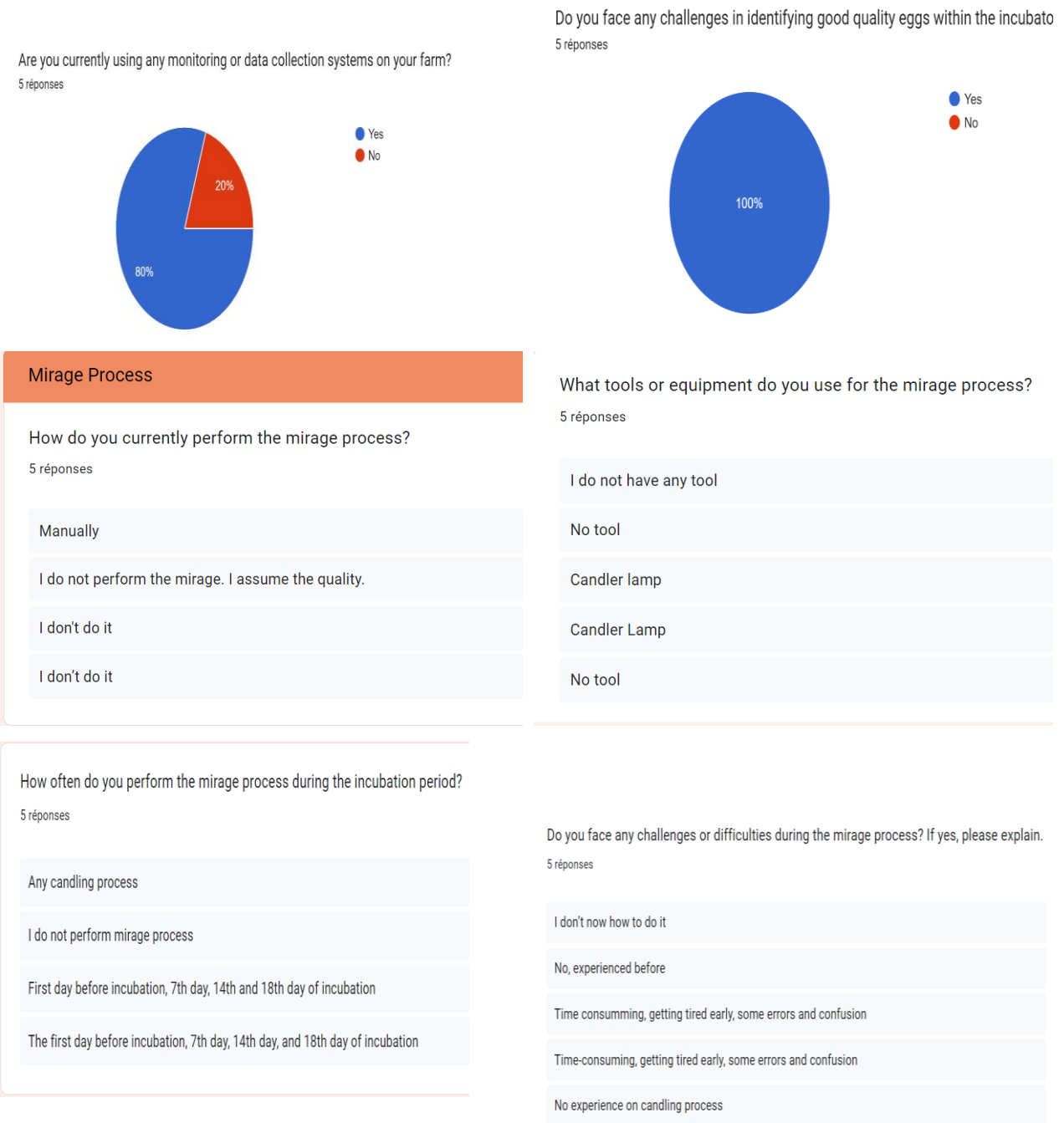


Figure 1: Questionnaire interview and responses [20], [21]

3.3 Data variables

The data variables in this study represent essential characteristics of the eggs and their surroundings. Egg quality attributes, such as shell integrity and thickness, albumen consistency, and embryo assessment were measured to assess overall quality. Additionally, environmental factors, including temperature and humidity, egg turning frequency were recorded to understand their influence on egg quality. Chicken eggs take 21 days to incubate[22]–[24]. The optimal temperature[22] within the incubator for chicken egg incubation typically ranges between 99.5°F to 100°F (37.5°C to 37.8°C). This temperature range is considered ideal for the development of chicken embryos and successful hatching. The optimal humidity[25] within the incubator for chicken egg incubation ranges between 55% to 60%. Figure 2 below shows the optimal temperature (38°C) and humidity (60%) in green and current temperatures (37.6°C) and humidity (56%) in red.

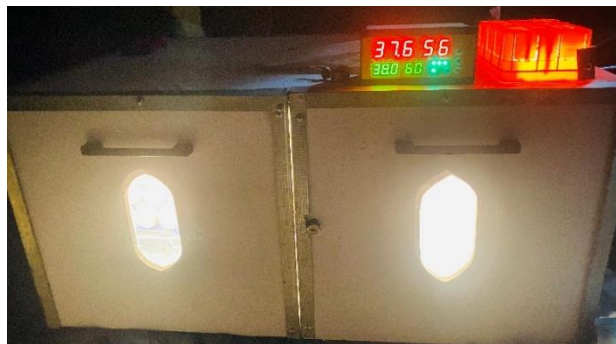


Figure 2: Incubator of Gatunda / Nyagatare

It is essential to maintain a stable and consistent temperature throughout the incubation period to ensure proper embryo growth and minimize the risk of developmental abnormalities.

3.4 Machine Learning Process

The ML steps followed the normal steps undertaken in any ML algorithm. The figure below shows the steps of ML.



Figure 3: Machine Learning Process

1. Data Collection

The machine learning process began with data collection. The quality and quantity of data determined how accurate the model would be. Our own dataset was collected from the data sources identified and used as inputs for the training.

Table 1: Dataset details

Label	Class Name	Number of images	Images Format
0	Death	1000	JPG File (.jpg)
1	Fertile	1000	JPG File (.jpg)
2	Infertile	1000	JPG File (.jpg)

2. Dataset size

A dataset of 3000 images with varying backgrounds and different sizes was collected on the field. 1000 images for each class: fertile egg, infertile egg, and death egg. Figure 4 below and Table 1 above shows a sample dataset of each class of egg.

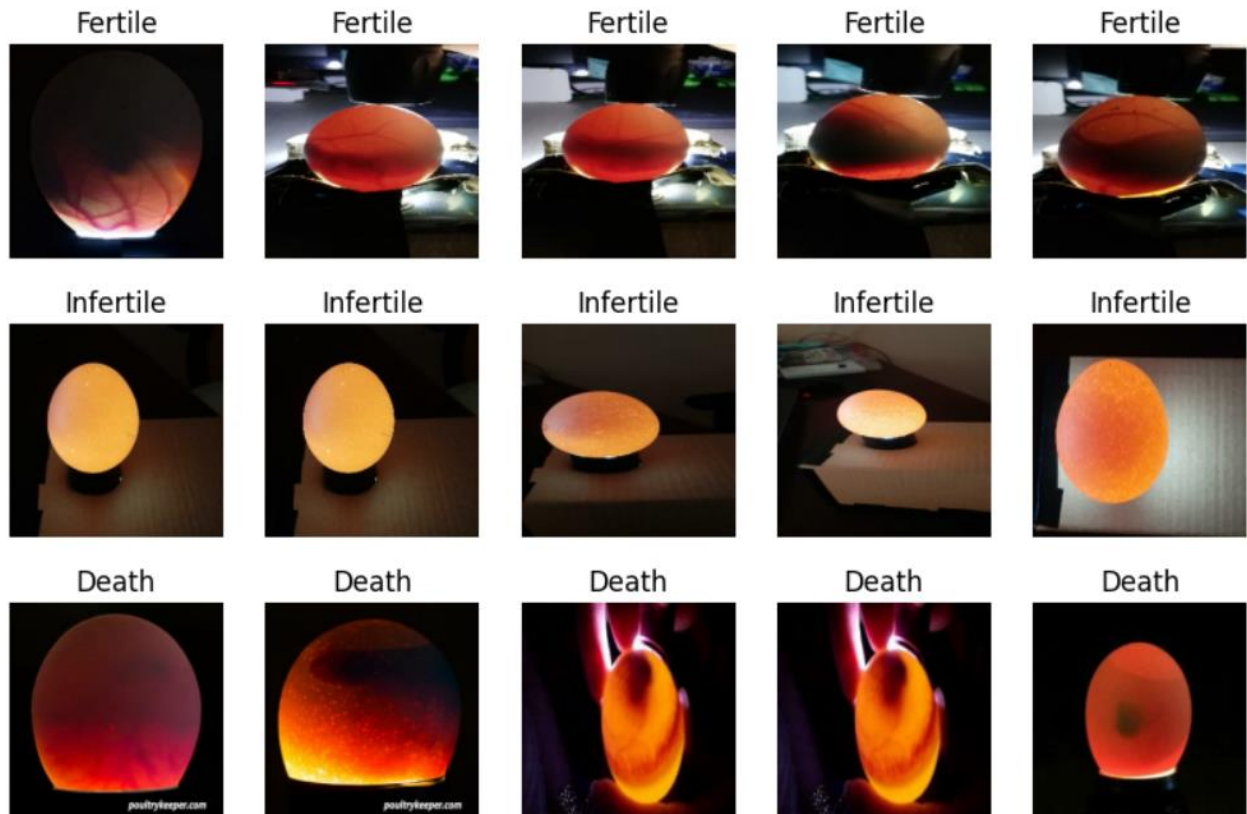


Figure 4: Sample Dataset of fertile, infertile and death eggs

3. Data pre-processing

The gathered images underwent preprocessing to ensure their suitability for the model. Normalization, label encoding, resizing, and equalization were performed to guarantee that the photos adhere to the required specifications for optimal learning of the model. Figure 5 below describes the python code used for image resizing and normalization.

```
image = cv2.imread(image_path)
image = cv2.resize(image, (224, 224)) # Resize image if needed
image = image / 255.0 # Normalize the pixels values(0 à 1)

images.append(image)
labels.append(class_label)
```

Figure 5: Data Resizing and Normalization python code in Colab

1) Resizing Image

In order to ensure compatibility with the CNN architecture, all images in the dataset were resized to a resolution of 224x224 pixels using the PIL library, as depicted in Figure 4 above. This resizing technique guaranteed that the model was provided with uniform input sizes.

2) Data Normalization

Normalization is a vital aspect of model training as it ensures consistency, numerical stability, and enhances the performance and stability of the model during training [26]. By normalizing pixel values to a standardized range of [0, 1], we minimized the potential for discrepancies in photos with varying pixel value scales. We also employed the '*ImageDataGenerator*' class utilizing the 'rescale' argument set to '1./255', which effectively transformed the pixel values from the original range of [0, 255] to the normalized range of [0, 1]. By employing this preprocessing strategy, we significantly improved the reliability and resilience of our Convolutional Neural Network (CNN) model for accurately detecting the fertility of eggs.

3) Encoding categorical variables using label encoding.

A binary label was assigned to each egg picture to indicate its overall interior quality. More precisely, eggs categorized as 'Death' were assigned the label 0, eggs categorized as 'Fertile' were assigned the label 1, and eggs categorized as 'Infertile' were assigned the label 2.

The utilization of this binary labeling technique aimed to streamline the categorization of eggs according to their quality state, hence enabling effective analysis and training of the detection model.

4) Data Augmentation

In order to improve the accuracy of the model, we utilized image enhancing techniques including flipping, random rotation, brightness adjustment, scaling, and cropping on the collected images. By employing these methodologies, the model was exposed to a wider variety of instances, enabling it to extrapolate more efficiently to novel data. After using data augmentation techniques, the dataset now contains 4,275 photos of eggs, divided into three (3) classes.

1. Flipping in both vertical and horizontal directions

Images underwent both vertical and horizontal rotational modifications. This modification incorporated mirrored images of eggs to replicate potential differences in egg orientation in real-world scenarios[27].

2. Random Rotation

Images underwent a random rotation process to mimic the appearance of egg images taken from different perspectives. This modification took into consideration possible angle disparities between the egg and the camera while capturing the image.

3. Cropping

Images were subjected to a cropping procedure to extract specific regions of interest. The preprocessing phase enhanced the diversity of the dataset by highlighting different egg parts and changes in image composition.

4. Model Design

After pre-processing the machine learning model was designed, the inputs to the model training were the eggs image dataset and a Keras Neural Network selected for training the model with the expected output being a classification as to whether the egg is fertile, infertile or death.

5. Data splitting

Following the preprocessing stage, the egg picture dataset was partitioned into three separate subsets to enable the training, validation, and testing of our CNN model for egg fertility identification. Out of all the preprocessed images, 70% were allocated to the training dataset, 15% to the validation dataset, and the remaining 15% to the testing dataset..

```
train_df, temp_df = train_test_split(df, test_size=0.3, random_state=42)
valid_df, test_df = train_test_split(temp_df, test_size=0.5, random_state=42)
```

Figure 6: Splitting dataset in Colab

The training set was utilized to train the model, the validation set was employed to optimize hyperparameters and monitor training progress, and the testing set was utilized to assess the model's performance on data that it had not been exposed to previously.

6. Model Training

In Google Colab, the CNN model was trained using TensorFlow, a Python machine learning framework. The CNN model was constructed using the Keras library, a Python-based high-level neural networks API. Keras utilized the TensorFlow machine learning framework as a backend to optimize computation. The CNN model was subsequently trained on the preprocessed picture dataset to precisely categorize eggs as either viable, infertile, or dead. Data augmentation and regularization approaches were employed throughout the training phase to enhance the model's performance and capacity to generalize. The model's accuracy was assessed by employing metrics like as precision, recall, and F1 score to verify if they achieved the acceptable performance threshold. Subsequently, the model was saved in a *'joblib'* file and subsequently transformed into a TensorFlow Lite *'tflite'* file, which is now prepared for exportation and deployment in our embedded system.

7. CNN architecture

In this research, a Convolutional Neural Network (CNN) model was constructed using the Keras library for image classification. The model involves convolutional layers for detecting patterns, followed by max pooling layers to reduce spatial dimensions.

Fully connected layers are incorporated for classification, with Rectified Linear Unit (ReLU) activation functions for non-linearity. The final layer employs a softmax activation function to categorize input images into one of three classes (fertile, infertile and death). Training the model was conducted over 20 epochs using an Adam optimizer and categorical crossentropy loss function. Data generators were employed to facilitate efficient loading and processing of training data.

Regularization techniques, such as dropout, were applied to prevent overfitting during training. The Adam optimizer efficiently updated model weights based on the training data.

8. Evaluation and Optimization

The test data was used to evaluate the performance of the model on unseen data. This unseen data is meant to be somewhat representative of model performance in the real world, but still helps tune the model (as opposed to test data, which does not). The model was also optimized for performance in an embedded device.

9. Model Conversion

After evaluation the model was converted into a tiny machine learning model that can run on an embedded device in readiness for deployment.

10. Make Inferences

Using further (test set) data which had, until this point, been withheld from the model (and for which class labels are known), were used to test the model in both the cloud environment (edge impulse) and on the embedded device(microcontroller); a better approximation of how the model perform in the real world.

3.5 Data Collection Methods

For this study, a multi-faceted approach was adopted to comprehensively capture the nuances of chicken egg quality attributes and environmental factors.

1. Camera-Based Image Acquisition:

The internal aspect of egg quality was captured through the use of two distinct cameras: High-resolution Canon and iPhone 11. Manual candling procedures were meticulously photographed to create an extensive image dataset. This dual-camera strategy aimed to introduce diversity in image conditions and perspectives, enhancing the robustness of the dataset for subsequent machine learning endeavors. Figure 7 and Figure 8 below show the sample and difference of images took from high-resolution camera and iPhone camera.



Figure 7: Images sample took from High-resolution Canon Camera

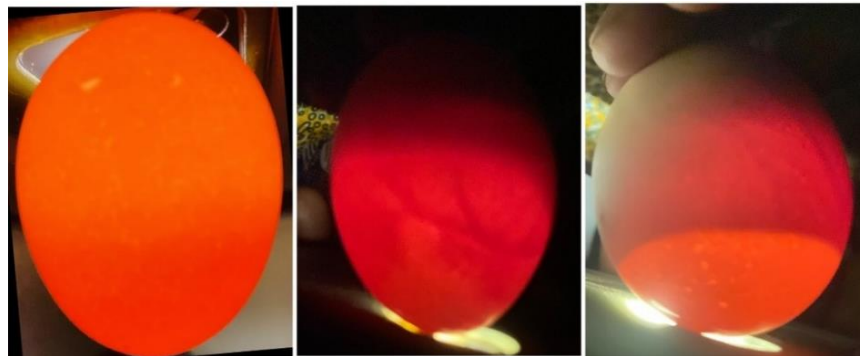


Figure 8: Images sample from with iPhone Camera

2. Manual Measurements:

Rigorous manual measurements were conducted, involving meticulous assessments of shell integrity, yolk color, albumen consistency, and other vital quality attributes. This hands-on approach ensured a detailed and reliable dataset foundation.



Figure 9: Manual assessment of egg from Uzima Chicken at Nyagatare

3. IoT Devices for Real-time Monitoring:

Internet of Things devices played a pivotal role in real-time data acquisition. These devices, strategically integrated into the incubator setup, facilitated continuous monitoring and logging of environmental parameters. The real-time nature of this data not only contributed to immediate insights but also served as a valuable resource for ongoing system optimization. Figure 10 below shows how environmental parameters like temperature and humidity and egg turning tool are monitored within the incubator of Jean-Marie from Gatunda/Nyagatare.



Figure 10: DHT22 Waterproof sensor integrated in the incubator.

3.6 Hardware Setup

This part describes the IoT devices used for data acquisition and monitoring.

i) *Arduino Nano 33 BLE Sense:*

The Arduino Nano 33 BLE Sense is an evolution of the traditional Arduino Nano, but featuring a lot more powerful processor, the nRF52840 from Nordic Semiconductors, a 32-bit ARM® Cortex®-M4 CPU running at 64 MHz. It has 1MB of program memory, 32 times bigger.

The main processor includes other amazing features like Bluetooth® pairing via NFC and ultra-low power consumption modes[28]. The main feature of this board, besides the impressive selection of sensors, is the possibility of running Edge Computing applications (AI) on it using TinyML.



Figure 11: Arduino Nano 33 BLE Sense

The Arduino Nano 33 BLE Sense is a compact, yet powerful microcontroller board equipped with Bluetooth Low Energy (BLE) capabilities and a variety of onboard sensors. The Arduino Nano 33 BLE Sense serves as the core microcontroller in this project. Its integration with the OV7675 camera facilitates the automated capturing of egg images for candling. Additionally, it hosts the TinyML model responsible for on-device machine learning tasks such as candling, egg fertility prediction, and classification. This allows for real-time decision-making within the incubator environment, reducing the need for external processing. Below is Table 2 that describes the technique specification of this board.

Table 2: Technique Specifications of Arduino Nano 33 BLE Sense

Microcontroller	nRF52840
Operating Voltage	3.3V
Input Voltage (limit)	21V
DC Current per I/O Pin	15 mA
Clock Speed	64MHz
CPU Flash Memory	1MB (nRF52840)
SRAM	256KB (nRF52840)
EEPROM	none
Digital Input / Output Pins	14
PWM Pins	all digital pins

UART	1
SPI	1
I2C	1
Analog Input Pins	8 (ADC 12 bit 200 ksamples)
Analog Output Pins	Only through PWM (no DAC)
External Interrupts	all digital pins
LED_BUILTIN	13
USB	Native in the nRF52840 Processor
IMU	LSM9DS1
Microphone	MP34DT05
Gesture, light, proximity	APDS9960
Barometric pressure	LPS22HB
Temperature, humidity	HTS221
Length	45 mm
Width	18 mm
Weight	gr (with headers)

ii) Camera OV7675

The 0.3MP Arduino camera OV7675 provides support for resolutions of up to 640x480 pixels, ensuring the capture of clear and sharp images.

The OV7675 camera is employed to capture high-resolution images of chicken eggs during the candling process. These images are crucial for both real-time analysis through the TinyML model on the Arduino Nano and potential future data collection. Below is table 3 that describes the specifications of the camera OV7675.



Figure 12: Camera OV7675

Table 3: Tech Specification of ov7675 camera

Image Sensor	OV7675
Active Array Pixels	640x480
Pixel Size	2.5µmx2.5µm
S/N Ratio	38 dB
Dynamic Range	71 dB
Interface	20-pin DVP
Shutter Type	Electronic Rolling Shutter
Color Filter Array	Quad-Bayer RGB
Output Format	RAW/YUV/RGB
Resolution & Frame Rate	640x480/320x240/160x120@15fps
Lens Optical Size	1/9 Inch
EFL	1.75mm
F.NO	2.8
Field of View Angle	63.9°(D)
Lens Distortion	<1.0%
Focus Distance	0.12M - ∞(AT=0.23M)
Power Supply	AVDD: 2.7VA ~ 3.0V DOVDD: 1.7V ~ 3.0V DVDD: 1.5V
Operation Temp.	-30° C to 70° C
Board Size	30.5mm x 30.5mm

iii) ESP32

Created by Espressif Systems, ESP32 is a low-cost, low-power system on a chip (SoC) series with Wi-Fi & dual-mode Bluetooth capabilities! The ESP32 family includes the chips ESP32-D0WDQ6 (and ESP32-D0WD), ESP32-D2WD, ESP32-S0WD, and the system in package (SiP) ESP32-PICO-D4. At its heart, there's a dual-core or single-core Tensilica Xtensa LX6 microprocessor with a clock rate of up to 240MHz. ESP32 is highly integrated with built-in antenna switches, RF balun, power amplifier, low noise receives amplifier, filters, and power management modules. Engineered for mobile devices, wearable electronics, and IoT

applications, ESP32 achieves ultra-low power consumption through power saving features including fine resolution clock gating, multiple power modes, and dynamic power scaling[29], [30].



Figure 13: ESP32 board

The ESP32 is utilized for environmental control within the incubator. It manages various components such as the DHT22 sensor for temperature and humidity monitoring, LEDs for lighting during candling process, an LCD for display purposes, a fan for ventilation, and a heater for temperature regulation. The ESP32 plays a central role in creating and maintaining the optimal conditions required for successful egg incubation.

iv) DHT22

DHT22 Digital Temperature & Humidity is a digital signal output with a calibrated temperature and humidity combined sensor. It uses a dedicated digital module and acquisition of temperature and humidity sensor technology.

Specifications:

Weight:4g, Temperature:-40-80 °C-/+0.50C, Humidity:20-90%RH-/+2%RH, Power supply:3.3-6V DC, Dimension:40*23mm, Port: Digital two way single bus.



Figure 14: DHT22 Sensor

The DHT22 sensor is responsible for measuring temperature and humidity within the incubator. This data is crucial for maintaining the ideal environment for egg incubation. The ESP32 communicates with the DHT22 sensor to obtain real-time readings.

v) ***OLED***

The OLED display has a diagonal measurement of 1.12 inches and consists of 96x96 grayscale pixels. Due to the utilisation of OLEDs, the absence of a backlight in the display results in a remarkably high contrast. The display is managed by the SSD1327 driver chip in this OLED. The driver chip can be interfaced via the 4-wire I2C protocol, which involves connecting the clock, data, power, and GND pins[31], [32].

Specifications:

Communication Protocol: I2C

Monochrome Screen: 16 levels of grey.

Enables both regular and inverted color display.

Enables uninterrupted horizontal scrolling.

Interface compatible with Grove

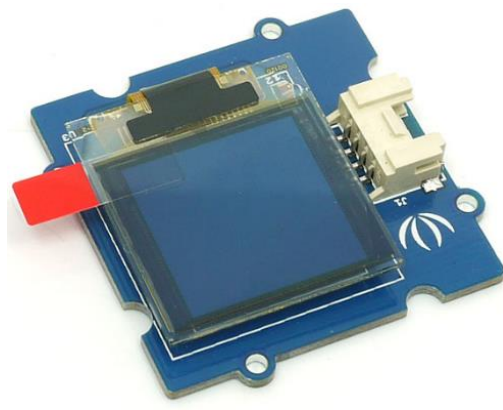


Figure 15: OLED display 1.12-inch v2.0

vi) ***LCD display***

16x2LCD Display with I2C/IIC great blue backlight LCD display. It is fantastic for Arduino based project.

Specifications: I2C adapter allows flexibility in connections, I2C Reduces the overall wirings. 16 characters wide, 2 rows, White text on the Blue background, Single LED backlight included can

be dimmed easily with a resistor or PWM. Interface: I2C, Interface Address: 0x27, Character Color: White, Backlight: Blue, Supply voltage: 5V



Figure 16: 16x2 LCD Display

Is used to display the environmental parameters collected by temperature and humidity sensors in the incubation.

vii) White LEDs

Placed strategically under each egg, the white LED serves as an illuminating source for candling. It ensures uniform and controlled lighting conditions, allowing the OV7675 camera to capture clear images for detailed analysis of egg contents.



Figure 17: Ultra Bright 5mm Clear Lens LED Light Emitting Diode

viii) Heater

The 100W heater lamp serves as a crucial component for maintaining the optimal temperature inside the incubator. It emits radiant heat, contributing to the regulation of the incubator's internal environment.

The heater is controlled by the ESP32, which adjusts its operation based on real-time temperature readings from the DHT22 sensor.



Figure 18: 100Watt heater lamp

This ensures that the temperature remains within the desired range for the healthy development of chicken embryos during incubation. The use of a heater lamp provides an efficient and controlled heat source, promoting a stable and conducive atmosphere for the incubation process

ix) Fan

YD8010 5V cooling fan is a small but powerful fan, it maintains the temperature of the extruder, which results in good heat dispersion and wonderful performance. The cooling fan operates on a 5V DC power supply which can be easily powered from the RPI board. It has a 2 pin just connect easily connect to the printer controller system and provide hassle free operation. The fan is made of plastic and is light weight.



Figure 19: YD8010 5V cooling fan.

Features: Cooling fan, Long connecting wire, Perfectly fit on the extruder, Noiseless performance, Good airflow, Operating voltage:5V DC, Dimension (LxWxH):80 x 80 x 10mm, Power:1.0W, Current:0.20A. It ensures proper air circulation within the incubator. It helps distribute heat evenly, prevent temperature variations, and maintain consistent humidity levels.

x) Relays

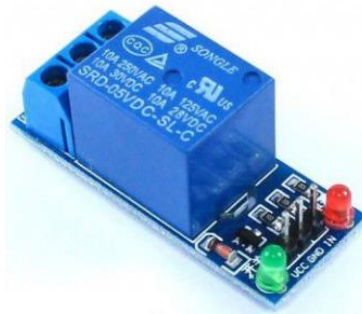


Figure 20: Relay

The relay acts as a switch, controlled by the Arduino ESP32. It controls various electrical components, including heater, fan, and egg turner. It is responsible for activating the stepper motor at predefined intervals. The relay serves as an interface between the microcontroller and the high-power stepper motor, allowing for precise control over the egg-turning mechanism.

xi) Stepper motor

The stepper motor is connected to a turning mechanism within the incubator. Its design enables precise and incremental rotations, ensuring gentle and effective egg turning. The stepper motor receives commands from the ESP32 board via the relay, determining the turning frequency and duration.

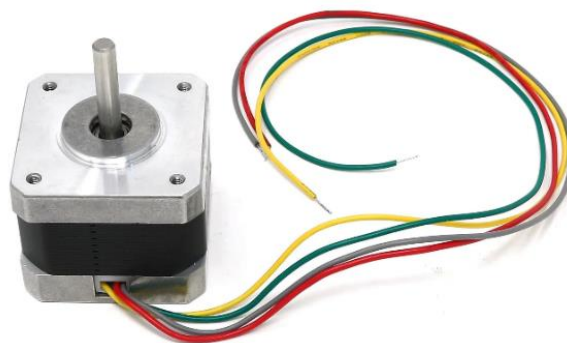


Figure 21: Stepper Motor

xii) Egg turner

It is a mechanical device that gently tilts or rolls the eggs at regular intervals during incubation to prevent the embryo from sticking to the inner shell membrane.

xiii) Connecting wires and breadboard

Connecting wires and a breadboard are fundamental elements in the hardware setup, facilitating the interconnection of various electronic components within the system.



Figure 22: Connecting Wires and Breadboard

3.7 Data Analytics Tool and Software

TinyML refers to the practice of running machine learning algorithms on microcontrollers or other low-power devices[33], [34]. Here are some tools that were used for analyzing data from egg incubation using TinyML:

- ***Google Colab***

Google Colab is a cloud-based platform that provides free access to GPU resources. It is commonly used for machine learning tasks and collaborative coding. Google Colab likely played a key role in training machine learning models related to egg fertility prediction using TensorFlow.

- ***TensorFlow***

TensorFlow is an open-source ML library. It is extensively used for developing and training machine learning models, including those deployed on edge devices like the Arduino Nano 33 BLE Sense using Tensorflow Lite.

TensorFlow Lite[33] is a framework developed by Google that enhance development, and deployment of lightweight (TinyML) models to the resource constrained devices[30] such as microcontrollers to help them manage running of ML inferences in real-time.

- ***Edge Impulse***

Edge Impulse[35], [36] is an end-to-end development platform that supports TinyML. It provides an easy-to-use platform for developing and deploying TinyML applications. It offers a range of pre-built signal processing blocks and ML models that will be utilized for egg incubation analytics. Edge Impulse is a platform for developing machine learning models for edge devices. It's likely used for deploying TinyML models on the Arduino Nano 33 BLE Sense, especially for tasks like candling and egg fertility prediction.

- ***Arduino IDE***

The Arduino IDE (Integrated Development Environment) is a popular platform for programming microcontrollers, and it also has support for TinyML. Arduino provides libraries and tools that integrate with the Arduino Nano 33 BLE Sense Lite's hardware capabilities, that allow to interface with sensors, collect data, and perform analytics tasks specific to egg incubation.

- ***Python***

Python is a versatile programming language widely used in data science, machine learning, and IoT. Used for various tasks, including data analysis, script development, and possibly backend development for the web app. Python, within the Google Colab environment, serves as the primary coding language for developing and training TinyML model.

- ***Photoshop***

Adobe Photoshop is an image editing software used for image preprocessing (data cropping) and enhancing visuals for documentation and presentation.

- ***Serial Monitor***

It is a tool in the Arduino IDE that allows you to communicate with your Arduino board. It's useful for debugging and monitoring the data being sent or received through the serial port.

- ***Windows Terminal***

Windows Terminal provides a command-line interface.

It might be used for running scripts, managing project files, or interacting with various tools and environments.

- ***Google Drive***

Google Drive serves as a reliable cloud storage solution for housing the image datasets, and model weights. Its integration with Google Colab facilitates seamless data access. Colab notebooks can directly read and write data from/to Google Drive, streamlining the data workflow.

3.8 Web Application Development

The frontend and backend of the web-based application were constructed utilizing HTML, CSS, PHP, and MySQL. It functions as a platform for offering immediate monitoring and visualization of environmental parameters within the incubator. The web application functions as a centralized platform that allows users to retrieve up-to-date information, display detection outcomes visually, interact with the platform, and get warnings or notifications. The program is designed to be user-friendly and straightforward, enabling users to effortlessly traverse the system and retrieve the needed information. The web app encompasses essential characteristics and capabilities such as:

1. **Authentication and Security:** The web app incorporates authentication methods to safeguard user data and ensure the integrity of the system. Prior to accessing the system, users are required to provide authentication information.
2. **Dashboard:** The web application provides up-to-the-minute information on sensor measurements and graphic representations, such as temperature, humidity, and egg turning status.
3. **Detection Results:** The web application also presents the findings of egg fertility detection.
4. **Historical Data analysis:** The web application allows farmers to get and analyze previous data. As time proceeds, farmers have the ability to examine trends, patterns, and variations in the sensor data and detection outcomes. Users can analyze certain time periods by utilizing interactive charts and graphs.

3.9 Data Transmission

The ESP Wi-Fi module is employed to transmit sensor data wirelessly to a web-based platform for visualization. Users can monitor the egg incubator environment in real time via the web portal. Additionally, it enables farmers to create alerts or notifications in case of any modifications in the system's performance or environmental parameters. Additionally, the system may be utilized for precise data analysis and visualization, making it easier to identify trends and patterns in the information collected by the sensors.

3.10 Model Integration

The Arduino nano 33 BLE Sense will incorporate the trained CNN to enable on-device computation and analysis, facilitating prompt actions. The camera will take photos of an egg for real-time study. The model will analyze the photos, identifying and forecasting the fertility of the eggs.

CHAPTER 4: SYSTEM ANALYSIS AND DESIGN

This Chapter articulates the systematic analysis and design of the proposed AI and IoT-based Chicken Egg Quality Analysis and Monitoring System. This chapter serves as the cornerstone for the development phase, delineating the logical and physical structure of the system, software components, and hardware architecture. It meticulously outlines the planned functionalities, interfaces, and interactions, providing a scholarly roadmap for subsequent phases of implementation and testing. By adhering to rigorous system analysis and design principles, this chapter ensures the scholarly rigor and viability of the proposed solution, aligning it with the identified research objectives and industry requirements.

4.1 System requirements

The functional requirements include the device features that must be included to enable the system to meet its objectives while the non-functional requirements include quality attributes that affect the behavior of the system. Table 4 gives the functional and non-functional requirements for the system.

Table 4: Functional and non-functional requirements

Functional requirement	Non-functional requirements
<ol style="list-style-type: none">1. The system should be capable of automatically capturing images of eggs using the OV7675 camera for candling purposes.2. The system must collect data on temperature and humidity from the DHT22 sensor.3. Images collected through candling should be stored in a database for further analysis.	<ul style="list-style-type: none">❖ Availability: the system's functionality and services should be available for use with all operations 99.99% of the time.❖ Reliability: The system should be highly reliable, ensuring consistent and accurate data collection and analysis.❖ Scalability: The system should be scalable to accommodate different sizes of incubators and varying numbers of eggs.❖ Power Efficiency: The system should be designed to minimize power

<ol style="list-style-type: none"> 4. The AI model for egg fertility prediction and classification should be deployed on the Arduino Nano 33 BLE Sense. 5. The ESP32 should regulate environmental conditions, controlling the fan, heater (100W lamp), and providing real-time feedback on the temperature and humidity. 6. A relay and stepper motor system should be implemented for automating egg turning within the incubator. 7. The ESP32 should communicate with a web application to relay real-time temperature and humidity data. 8. A user-friendly interface should be provided, displaying the status of the incubator and allowing users to set preferences. 	<p>consumption, especially for prolonged incubation periods.</p> <ul style="list-style-type: none"> ❖ Usability: The user interface should be intuitive and easy to use. ❖ Performance: The AI model should provide fast and efficient predictions. ❖ Security: Data storage and transmission should adhere to best practices for security and privacy. ❖ Maintainability: The system should be designed for ease of maintenance, allowing for updates and improvements. ❖ Compatibility: The system should be compatible with common browsers for the web interface and should support integration with future IoT devices. ❖ Accuracy: The AI model should achieve a high level of accuracy in predicting egg fertility.
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4.2 System Architecture

The system architecture is made up of:

- ❖ Perception Layer: is the first layer of IoT architecture. In this layer, a number of sensors and actuators are used to gather useful information like temperature, humidity, and images.
- ❖ Network Layer: it is the connecting layer between perception and middleware layer. It gets data from perception layer and passes data to middleware layer using networking technologies like 3G, 4G, UTMS, WiFi, infrared, etc.
- ❖ Middel Layer: has some advanced features like computation, processing, action taking capabilities[37]. For this system, we developed an ML model capable of extracting insights from data.

- ❖ **Application Layer:** manages all application processes based on information obtained from middleware layer. It interfaces the system to the user.

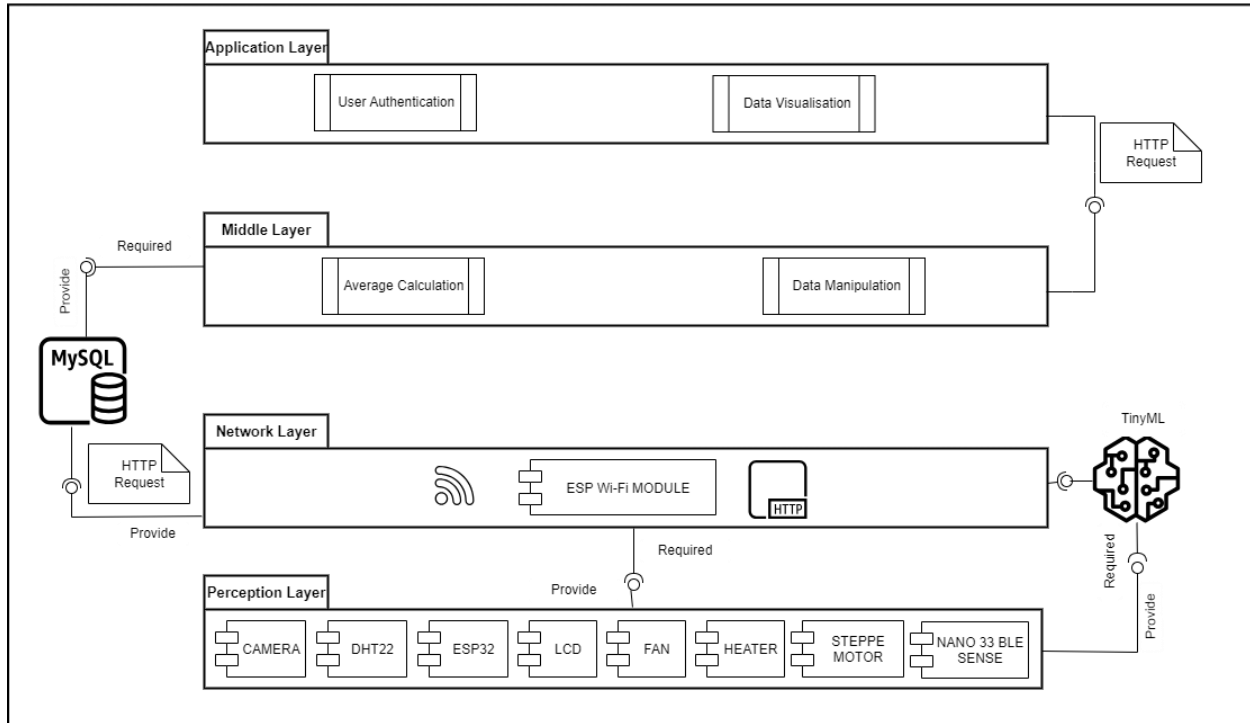


Figure 23: System Architecture

4.3 Embedded System-Level Design

The embedded system for Chicken Egg Quality Analysis and Monitoring is a sophisticated integration of hardware and software components. It leverages AI algorithms and IoT technologies to automate and optimize the egg incubation process. This section provides an overview of the system's architecture and how its various components work cohesively.

4.3.1 System Block Diagram

Below is the block diagram of the system:

1. **Sensing Unit:** is vital for gathering key data from incubators on environmental parameters and egg characteristics. The following sensors are employed:
 - 1) **DHT22 Sensor:** Collects temperature and humidity data within the incubator.
 - 2) **OV7675 Camera:** Captures images of eggs for candling.
2. **Processing Unit:** After data is gathered, it is subjected to processing within this component. The detection of eggs is carried out by the utilization of a CNN algorithm. This algorithm

analyzes images from camera to identify the internal quality of the egg. Additionally, environmental data such as temperature and humidity are processed into the device to determine if the incubator is in optimal condition. The following sensors are employed:

- 1) Arduino Nano 33 BLE Sense: Responsible for capturing egg images using the OV7675 camera and deploying the TinyML model for egg fertility prediction and classification.
- 2) ESP32: Manages environmental conditions within the incubator, controls the fan and heater based on real-time data from sensors, and sends temperature and humidity data to the web application.

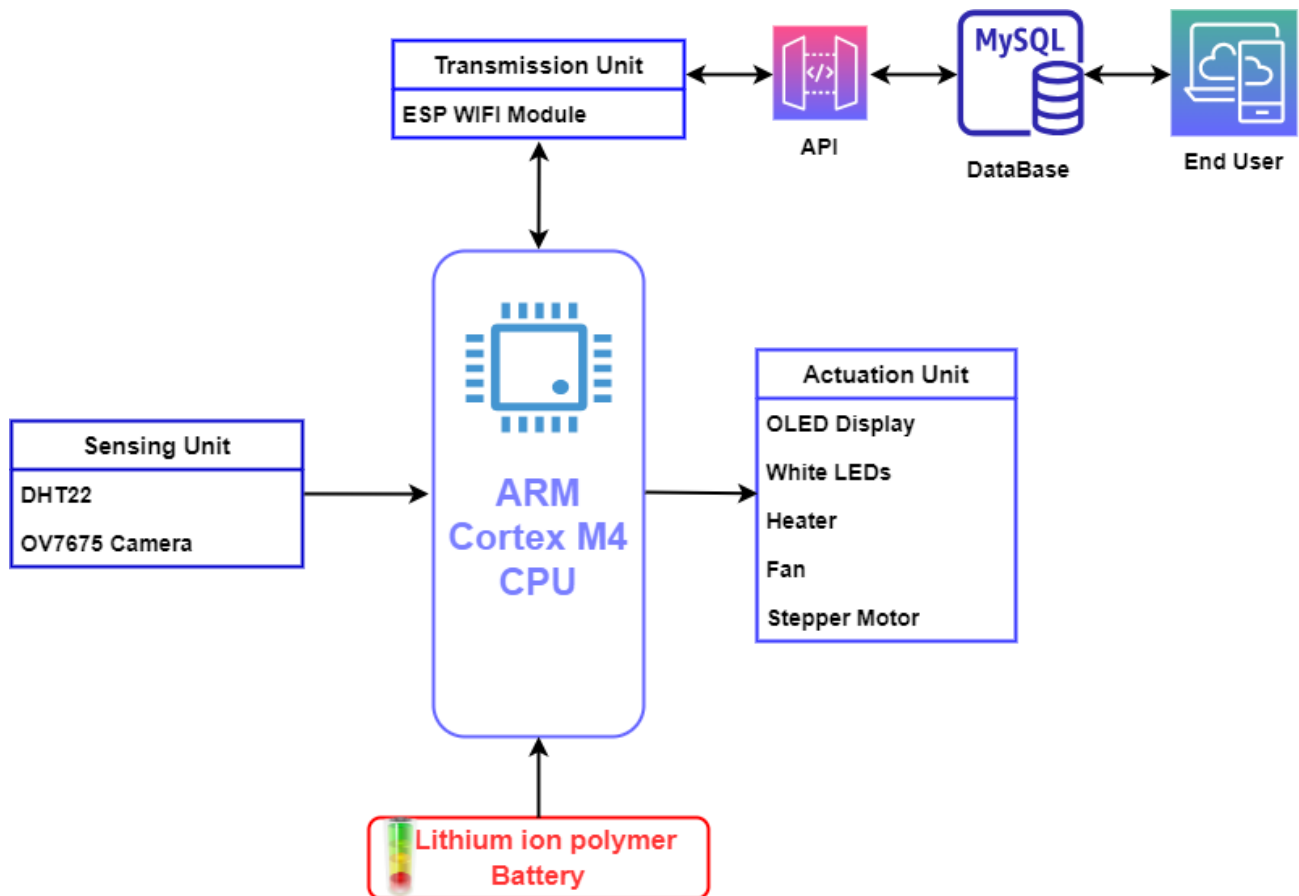


Figure 24: Block Diagram of the system

3. **Actuation Unit:** refers to the components within the system that are responsible for taking actions based on the processed data and decisions made by the control system[38]. The actuation unit includes devices or mechanisms that actively influence the environment within the egg incubator. The following components are responsible for "actuating" changes based on the system's internal logic and external conditions:

- 1) OLED Display: Displays the egg fertility prediction and provides real-time information on temperature and humidity.
 - 2) Relay and Stepper Motor: Automates the egg turning process.
 - 3) Fan: Regulates air circulation within the incubator and ensures uniform conditions.
 - 4) Heater: Maintains optimal temperature conditions for egg incubation.
 - 5) White LEDs for candling light facilitate candling lighting for egg quality assessment.
 - 6) Stepper Motor for Egg Turning ensures uniform development by periodically turning egg.
4. Data Transmission Unit: the processed data, consisting of egg fertility detection findings, environmental factors, and images, is transmitted in real-time and stored in MYSQL cloud database through WiFi communication protocol.
- 1) The Hypertext Transfer Protocol (HTTP) is an application-layer protocol that facilitates the transfer of hypermedia documents[39]. The primary purpose of its development was to enhance the exchange of information between web browsers and web servers; however, it possesses the potential for utilization in various additional capacities. The HTTP protocol adheres to the conventional client-server architecture, wherein a client establishes a connection to send a request and subsequently awaits a response. To facilitate efficient data sharing between a sensor model and a cloud server, we have implemented the HTTP protocol. This protocol enables the initialization of an API request to retrieve data from the sensor model and subsequently transmit it to our MySQL cloud database. This database serves as a centralized repository, allowing end users to access the data. The HTTP protocol has been utilized to facilitate the initiation of communication between the user and the server via a web browser running on the user's end device.
 - 2) An application programming interface (API) refers to a set of regulations that facilitate communication between different applications[40]. The function of this component is to act as an intermediary layer that facilitates the movement of data between different systems. The research conducted in this study has implemented an API to facilitate the transmission of data from the sensor model to the cloud server. This data transfer is achieved using the HTTP protocol. The process of data

exchange and storage after data collection by sensors encompasses the following sequential processes.

- ❖ Initially, the ESP32 module initiates a Wi-Fi connection by utilizing the Access Point Name (APN) to facilitate internet connectivity for the sensor model.
- ❖ Secondly, the API initiates an HTTP request and transmits it to the control system.
- ❖ Thirdly, the sensor model subsequently returns the response including data to the API by utilizing the WiFi and HTTP protocols.

3) MySQL is an RDBMS that operates on Structured Query Language (SQL). According to the cited source[41], this language is widely recognized as the predominant choice for both accessing and administering database records. MySQL is software that is given under the GNU General Public Licence, making it free and open source. Considering our decision to utilize PHP as backend language for our web application, it was logical for us to choose a MySQL database. MySQL follows a Client-Server architecture that is specifically designed to allow end users to access server resources. This architectural approach provides an additional benefit by facilitating seamless interaction between our server and the target users when they need to request information[41].

4.3.2 System Flow Charts

- **Control of Temperature and Humidity**

Figure 25 below depicts the automated regulation of the temperature and humidity. At the beginning of the incubation process, heaters are activated until the temperature reaches 38°C. Subsequently, the temperature will be maintained within the range of 35-38°C. The sensors will measure the temperature to regulate it. If the temperature reading exceeds 38°C, indicating that it is excessively hot for the eggs, the heater will be deactivated and the exhaust fan will be activated to eliminate the surplus heat. However, if the temperature reading is lower than 37°C, the heater will be activated while the exhaust fan will be deactivated. Each reading will be showcased on the web application, enabling the user to monitor if the incubator is effectively maintaining the optimal temperature and humidity.

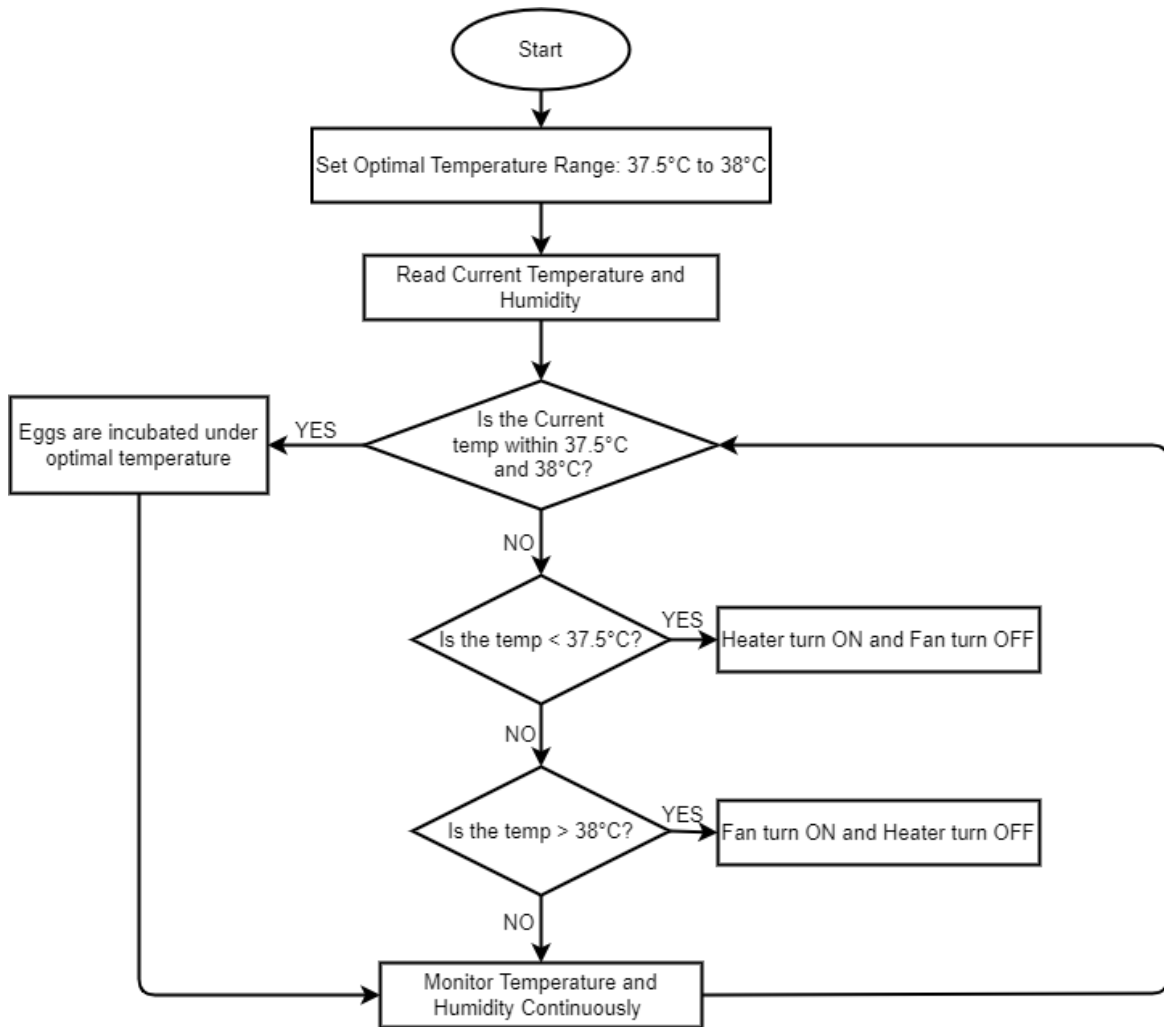


Figure 25: Temperature and Humidity control Flowchart

- **Egg Rotation Control**

The egg must be turned regularly and carefully so that the embryo passes through fresh nutrients in the egg white while forming in the correct position for hatching[6], [22], [23], [42]. Mother hen sits on her nest and uses her feet and wing butts to move around and turn her eggs regularly, so they all retain a constant warmth, and most importantly, the growing peeps inside the eggs get regular turning so they stay fit and healthy and do not stick to the inside of the shell. All of this is critical for the developing folks.

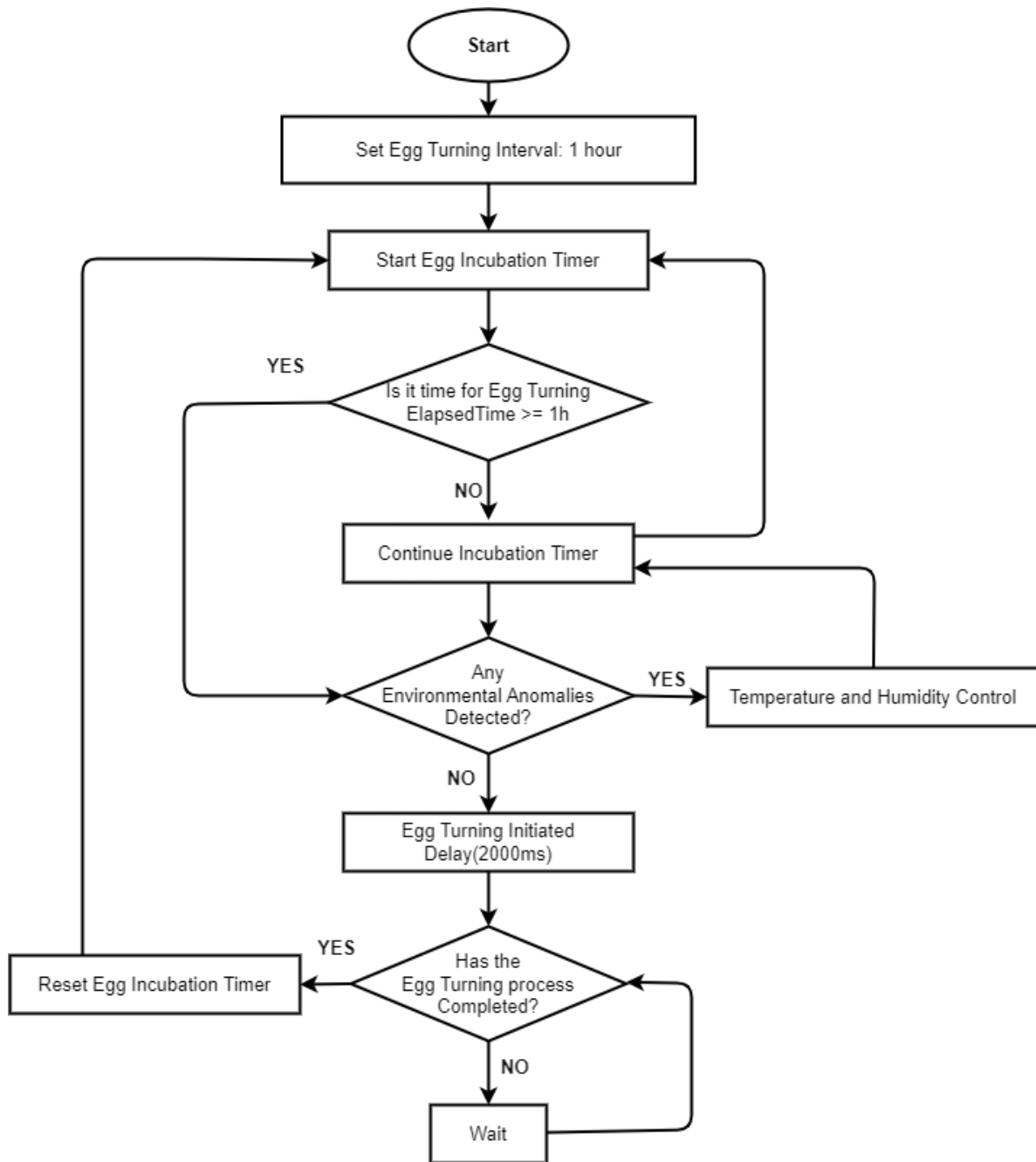


Figure 26: Egg Turning Flowchart

The egg turning control flowchart shown in Figure 26 explains how egg turning for chicken eggs is automatically regulated. The rollers will commence, initiating a 2-minute duration of egg rotation.

The turning process will stop after 2 minutes, and the machine will wait 1 hour before repeating the cycle. The technique will be repeated until the 18th day of the incubation[22], [23].

- **Candling and egg fertility detection**

Candling is the act of simply shining a light through an egg[5]. Figure 27 below represents the flowchart of the automatic egg candling process within the incubator on specific days (Day 7, 14 and 18) during the incubation period. When the incubation timer reaches the set candling days, the camera takes pictures of candling. During the candling process, the eggs are illuminated with white LEDs to observe the embryo development.

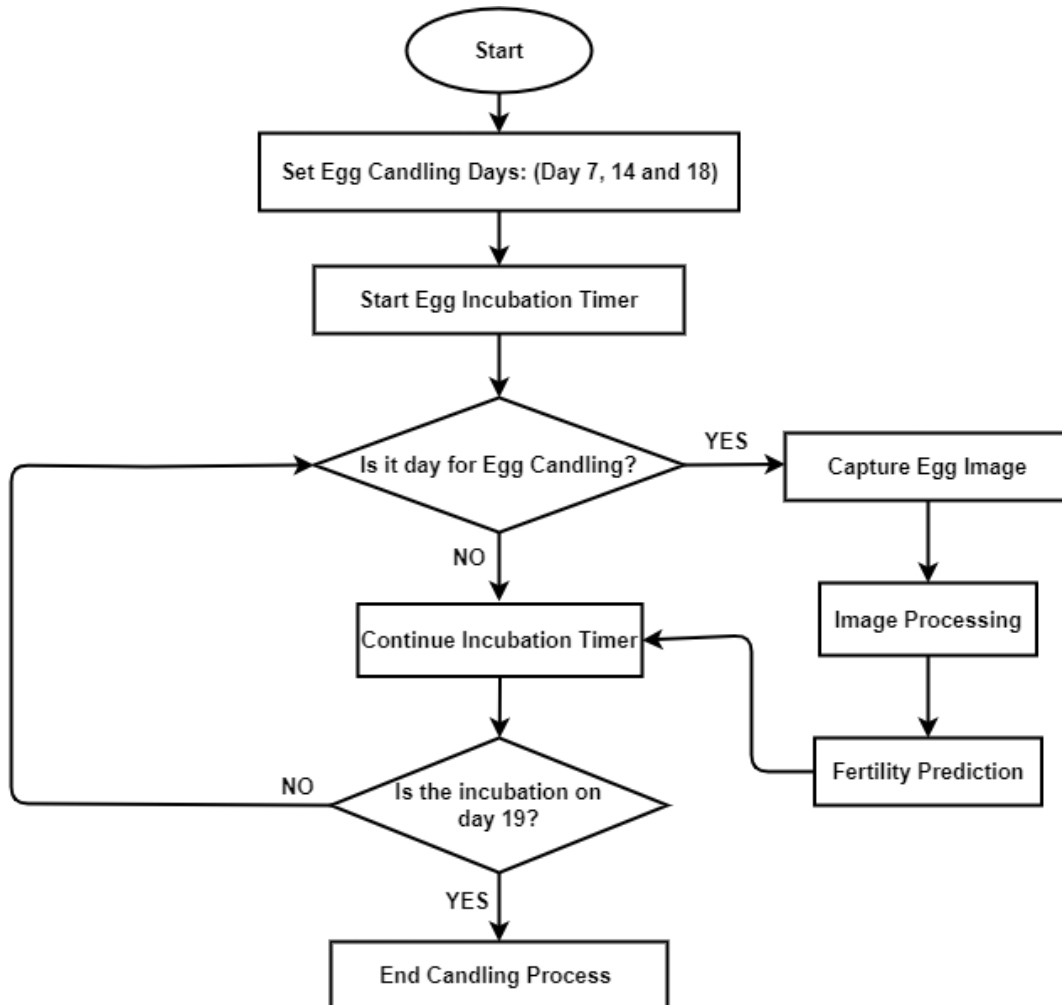


Figure 27: Flowchart of Egg Candling Process

Based on the visible embryo development, the eggs are classified as either fertile (containing an embryo) or non-fertile (without an embryo) or death (death embryo). The prediction results are displayed on OLED and sent on web app for further monitoring. The incubation process continues until the last candling day (Day 18), after which the eggs are allowed to continue incubation until hatching[6], [23].

4.4 ML Model Design

The deployment of a TinyML model on the Arduino Nano 33 BLE Sense empowers the microcontroller to perform on-device machine learning tasks. This includes candling, egg fertility prediction, and classification without the need for continuous connection to external resources.

This capability significantly reduces the dependency on external processing, making the system more efficient and responsive. The integration of TinyML enhances the autonomy of the Arduino Nano, allowing it to execute complex tasks within the incubator environment. It's a key feature in achieving real-time and on-the-edge intelligence for the chicken egg quality analysis and monitoring system.

4.5 Embedded Device Set-Up

We employed two microcontrollers: the Arduino Nano 33 BLE Sense for image processing, which was connected to the OV7675 camera for making inferences, and an OLED display for presenting the results. On the other hand, we employed an ESP32 to establish a connection with the LEDs, which were utilized for illumination. Additionally, we utilized a DHT22 sensor, a fan, and a heater to regulate temperature and humidity. Furthermore, a motor and a relay were employed for the purpose of egg rotating. The outcome is transmitted to the cloud with the ESP WiFi module integrated into the ESP32 board. The objective was to utilize a single board; however, the camera consumed a significant number of pins on the Arduino Nano 33 BLE Sense. The camera is interfaced with the Arduino nano 33 BLE Sense using a 20-pin connection. The pins used are VCC, GND, SCL, SDA, IIS, VS, PCLK, XCLK, D7, D6, D5, D4, D3, D2, D1, D0, NC, NC, PEN, and PDN. The OLED display is attached to the GND, 3V3, SDA, and SCL pins of the Arduino Nano 33 BLE Sense. Figures 28 and 29 below depict the connecting of boards and sensors.



Figure 28: OLED and camera connected to Arduino nano 33 ble sense

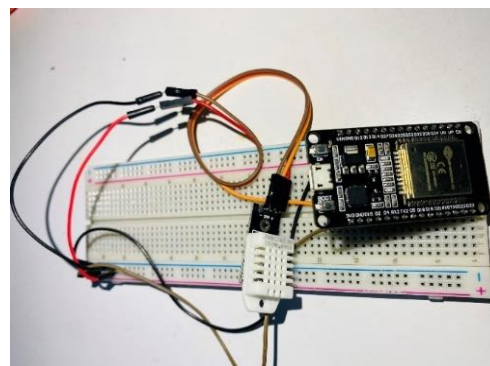


Figure 29: Other sensors connected to esp32

CHAPTER 5: RESULTS AND DISCUSSION

The chapter provides an overview of the findings and outcomes obtained from each Machine Learning technique employed in this study. The process of model development involved two distinct approaches. The first approach involved the building of a Python-based model on Google Colab, while the second approach involved utilizing Edge Impulse. Same datasets were employed in these methodologies, yielding disparate outcomes. The average performance outcomes of the Colab Notebook are provided and may be accessed at[43]. Similarly, the average performance results obtained by Edge Impulse can be found at[44].

5.1 ML Performance Metrics

1. CNN using Python.

The model underwent training using a dataset consisting of 4275 images from three (3) classes that are Fertile, Unfertile and Dead. Datasets were split into the ratio of 70% training, 15% for testing and 15% for validation, whereas the training dataset contains 2993 images, validation dataset contains 641 images and testing dataset contains 641 images. The model constructed inside this framework was configured with various parameters and underwent multiple training iterations, ultimately achieving an F1-Score of 96% accuracy as shown in the figure 30 and each class has its own average F1-Score as depicted in the same figure.

```
367/367 [=====] - 178s 477ms/step
      precision    recall  f1-score   support

 death          0.95     0.99     0.97         975
 fertile         0.98     0.92     0.95         974
 infertile       0.96     0.98     0.97         985

 accuracy                   0.96         2934
 macro avg          0.96     0.96     0.96         2934
 weighted avg       0.96     0.96     0.96         2934
```

Figure 30: Average F1-Score of each class

In addition, although the training had positive results, the size of the model surpassed the RAM limit of a microcontroller. After conversion and quantization, the CNN model had a size of 26 megabytes.

The model deployment appears unattainable due to the Arduino Nano 33 BLE Sense's limited random-access memory (RAM) capacity of 256 kilobytes (kb), which serves as the maximum limit for data storage and access during operation.

❖ Confusion Matrix

A confusion matrix is a technique used in machine learning to evaluate the effectiveness of a classification model by measuring its accuracy. The output includes the count of correctly identified positive cases, correctly identified negative cases, incorrectly identified positive cases, and incorrectly identified negative cases. The matrix facilitates the analysis of model performance, the identification of mis-classifications, and the enhancement of predicted accuracy[45].

Figures 31 and 32 provide a comprehensive overview of the confusion matrix for the CNN model. They illustrate how the model effectively identifies each class as either true positive, true negative, false positive, or false negative.

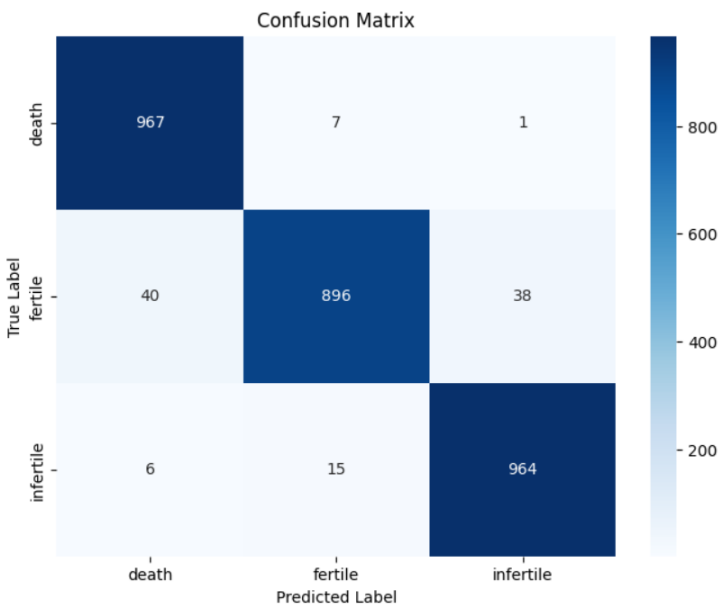


Figure 31: Confusion Matrix graph of CNN model

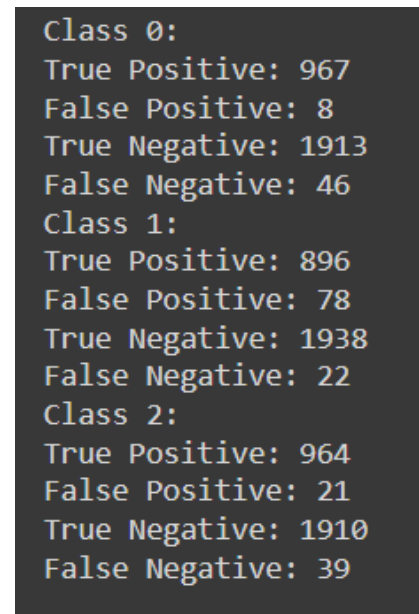


Figure 32: Confusion Matrix details

2. Transfer Learning on Edge Impulse

This approach involved the utilization of the Edge Impulse framework. The methodology used in Edge Impulse consists of four (4) distinct classes, containing a total of 5,700 samples as shown on

the figure 33 where the training set had 4,560 images and testing set with 1,140 images. Different Neural Network settings such as Training Cycle, Learning Rate, Batch size, Argumentation with various pre-built models, namely MobileNetV2 and MobileNetV1. This study demonstrates disparities in accuracy between MobileNetV1 models and MobileNetV2 models, specifically in relation to Training Accuracy when comparing optimized and unquantized models. Consequently, these discrepancies also extend to the accuracies seen during deployment.

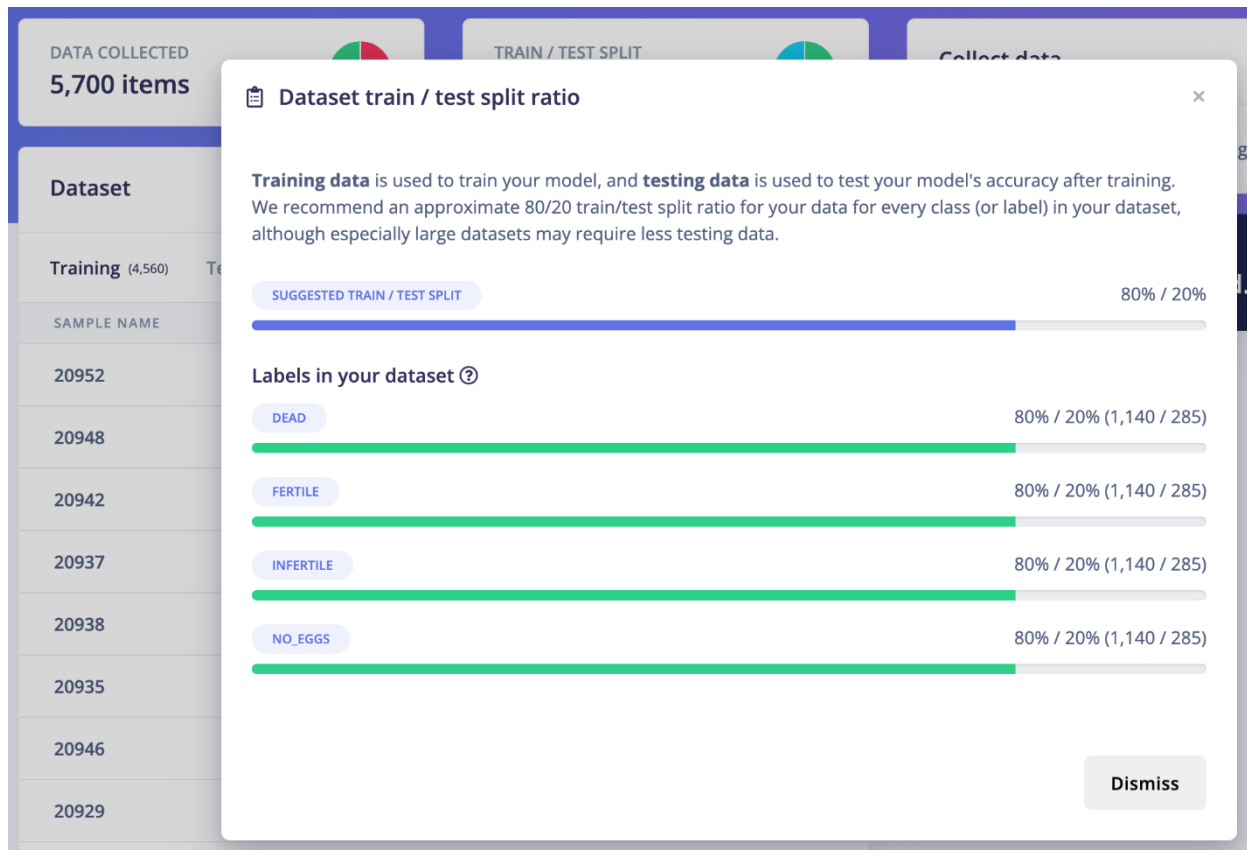


Figure 33: Showing data acquisition and dataset splits in Edge impulse.

i) MobileNetV2

The MobileNetV2 model demonstrated superior performance in both training (quantized and unoptimized versions) and testing stages. However, on several model training a notable issue arose about the Latency and RAM requirements for on-device performance after deploying the model. These requirements exceeded the capacity of the microcontroller, as depicted in figures 34, 35 and 36. The model testing result accuracy of 99,12% is shown in figure 37.



Figure 34: Best model training results in unoptimized version using MobileNetV2.

Quantized (int8)		IMAGE	TRANSFER LEARNING	TOTAL
LATENCY	Selected ✓	1 ms.	98 ms.	99 ms.
RAM		4.0K	334.6K	334.6K
FLASH		-	575.0K	-
ACCURACY				77.11%

Unoptimized (float32)		IMAGE	TRANSFER LEARNING	TOTAL
LATENCY	Select	1 ms.	251 ms.	252 ms.
RAM		4.0K	893.6K	893.6K
FLASH		-	1.6M	-
ACCURACY				99.12%

Figure 35: Expected RAM and Latency consumption for on-device performance



Figure 36: Model training results in quantized version using MobileNetV2.

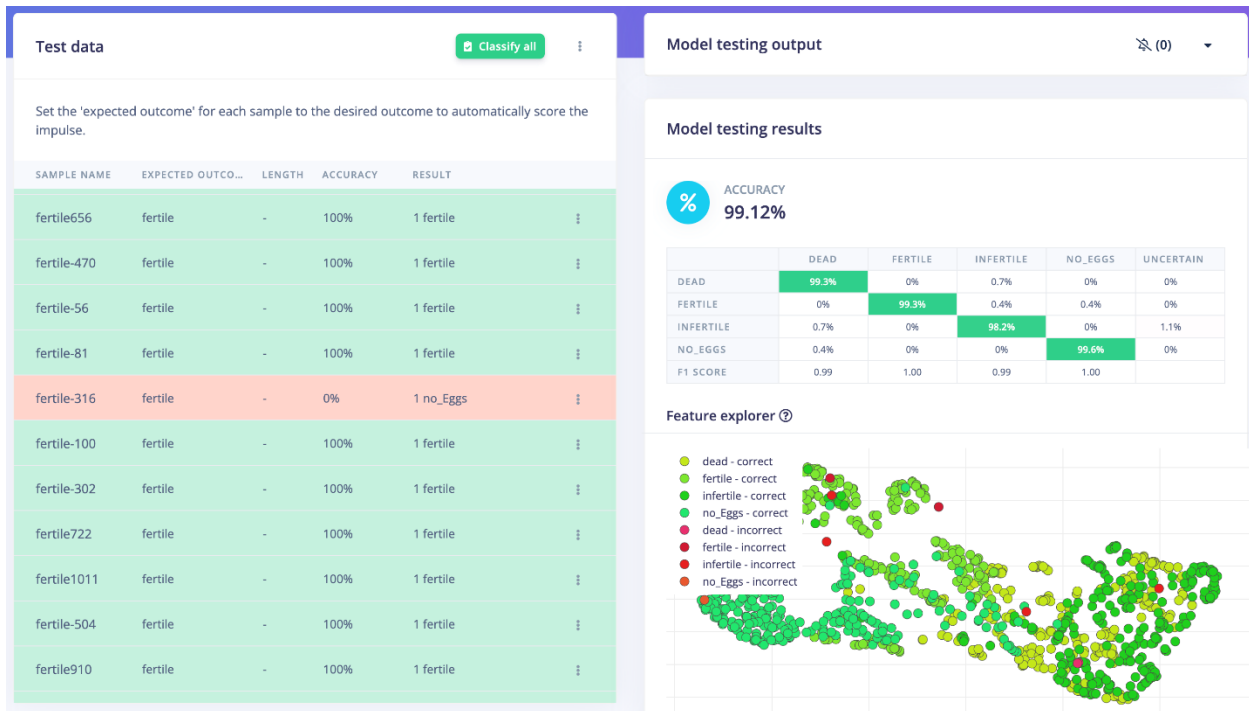


Figure 37: Model testing result using MobileNetV2.

Despite the favorable outcomes of the training, and validation, the dimensions of the model exceeded the RAM capacity that a microcontroller could accommodate. This model was failing to allocate enough memory for the Neural Network to run on the device since there was no allocated tensor arena for running inferences.

ii) MobileNetV1

Several model trainings were being performed but changing different parameters during setting the Neural Network and different results were obtained. The preferable results obtained from this method showed excellent performance in both training and testing accuracies. The training accuracy in unoptimized (float32) version was 99.1% F1-Score, as shown in figure 38 and in a quantized (int8) version was 97.4% F1-Score, as shown in figure 39, while the testing accuracy was 98.86% F1-Score, as indicated in figure 40. These results were achieved due to the superior precision and performance measures of the models, which can be attributed to the differences in the datasets used and the neural networks employed for training.



Figure 38: Model training results in unoptimized version using MobileNetV1.



Figure 39: Training result in quantized(int8) version using MobileNetV1.

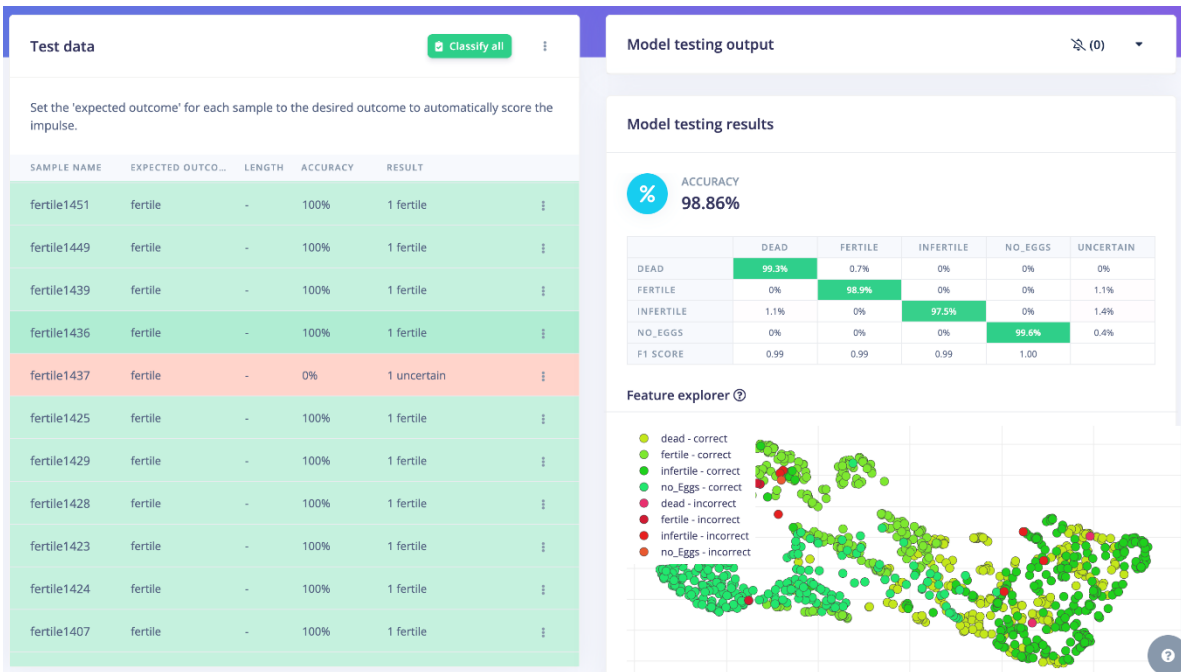


Figure 40: Model Testing results

Figure 41 clearly depicts an image that is categorized as uncertain. Despite belonging to the fertile class, the model is unable to accurately categorize the data as fertile, infertile, or death.

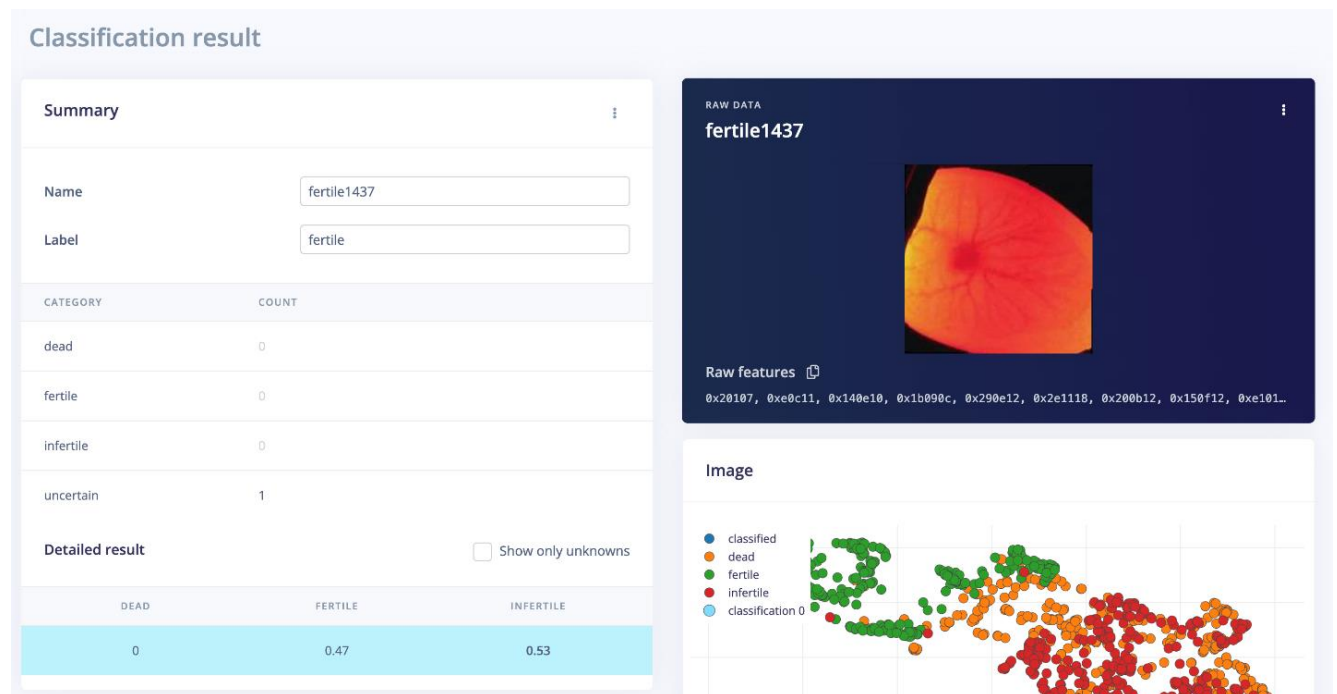


Figure 41: Fertile egg classified as uncertain.

The deployment of the model after fine-tuning it using EON Tuner yielded good outcomes in terms of latency and RAM needs, as illustrated in Figures 42 and 43. The Model was effectively deployed on a microcontroller to perform real-time inferences, exhibiting high accuracy as demonstrated in figure 43.



Figure 42: On-device performance metrics

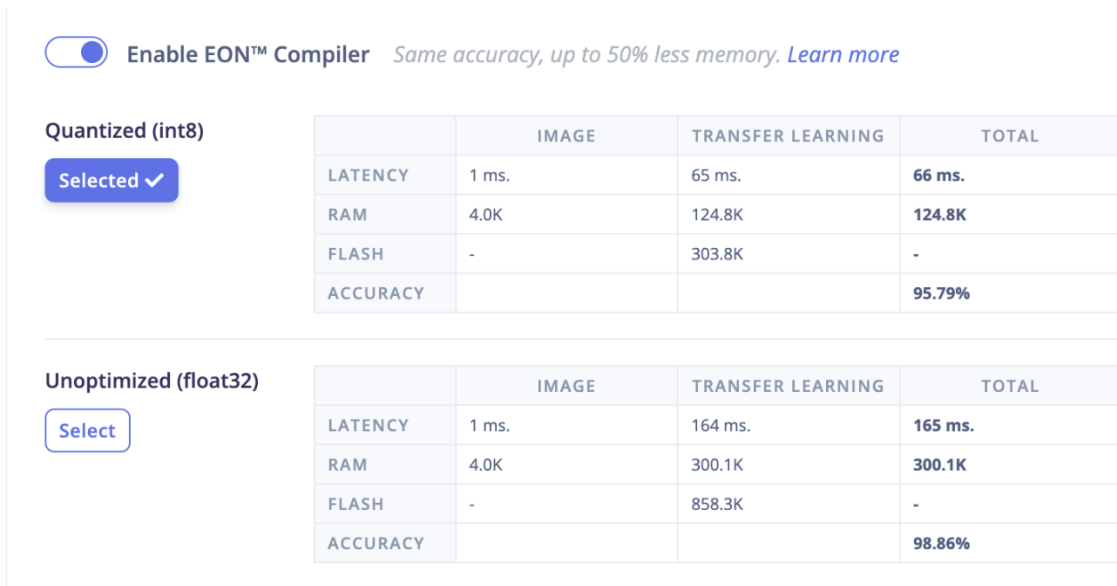


Figure 43: On device performance metrics after deployment.

Figures 44, 45, and 46 depict the performance of the MobileNetV1 model in real-time classification, even after it has been deployed on the device via Edge Impulse Studio.

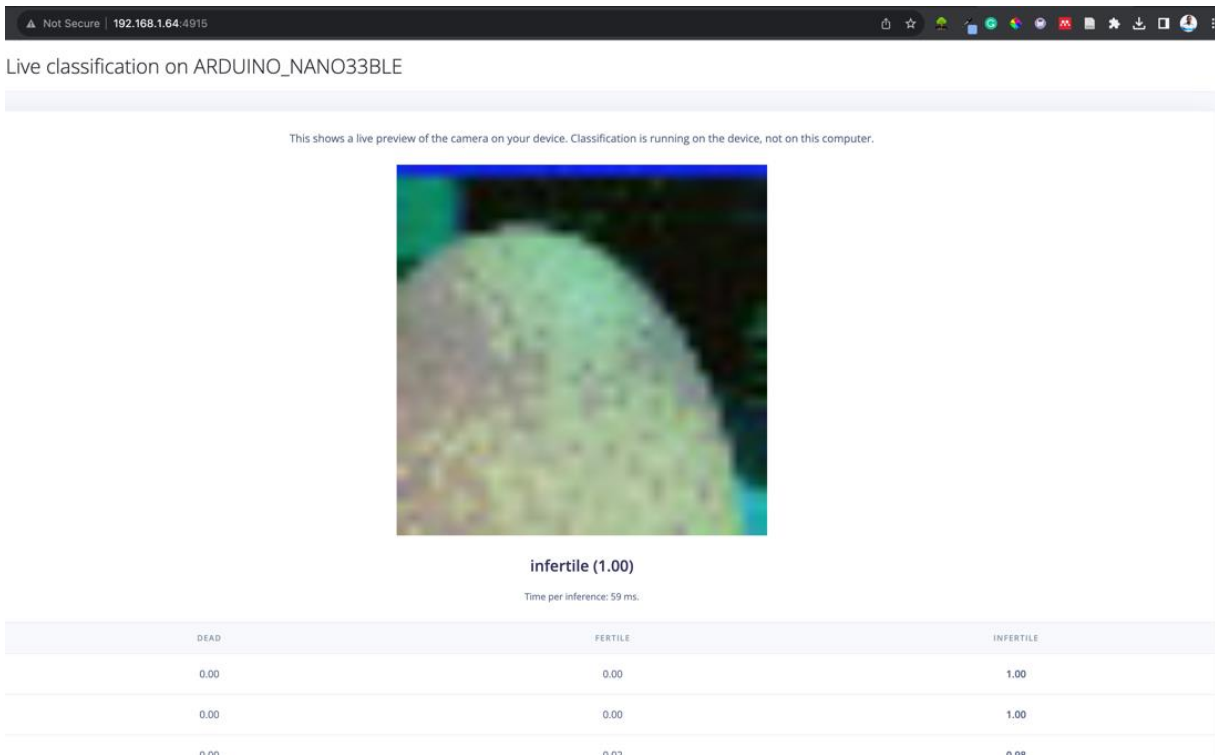


Figure 46: Live classification on the device on web using the API.

The findings indicate that MobileNetV1 demonstrates favorable outcomes when implemented for doing inferences on the device. The model exhibits a high level of accuracy in accurately classifying eggs classes, as depicted in Figures above. Despite the increased accuracies, MobilNetV2 has faced issues in terms of adaptation. In contrast, MobileNetV1 has demonstrated good performance in both training and testing. Furthermore, even after the deployment of the model, the inferences remain accurate as shown on table 5.

Table 5: Comparison of the resource use from the pretrained models used.

Model	Version	Accuracy (%)	Latency (ms)	RAM (kb)	ROM (kb)
MobileNetV1	Quantized(int8)	97.4	65	124.8	303.8
MobileNetV1	Unoptimized (float32)	99.1	173	300.1	858.3
MobileNetV2	Quantized(int8)	79.7	98	334.6	576
MobileNetV2	Unoptimized (float32)	99.8	251	893.6	1600

5.2 IoT Performance and Web Application Results

5.2.1 Automatic candling result

The automated egg candling process is a crucial element of the chicken egg quality analysis system that utilizes artificial intelligence (AI) and the Internet of Things (IoT). The system utilizes an OV7675 camera and Arduino Nano 33 BLE Sense to integrate and execute a TinyML model for immediate evaluation of egg quality. The candling procedure entails obtaining an image of the egg, utilizing the onboard TinyML model to process it, and presenting the detection outcomes on an OLED display.

Each candling cycle is initiated after a fixed interval, capturing an image of the egg after precisely 6 seconds. This timeframe is optimized to ensure adequate illumination and image clarity for accurate model inference. The execution of the TinyML model for egg quality classification takes approximately 6 seconds. During this time, the model processes the captured image and provides a detailed analysis of the egg's viability. The results are then promptly displayed on the connected OLED display as shown on figures 47.

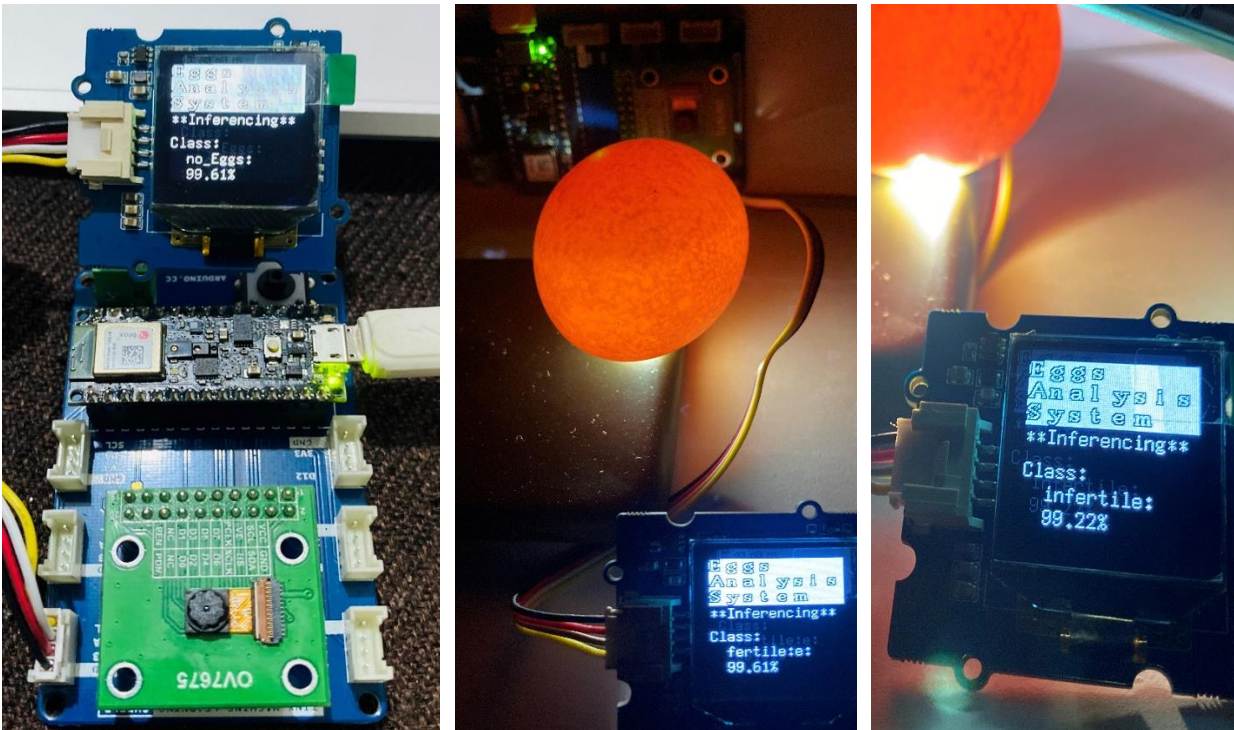


Figure 47: Egg classification results

The TinyML model exhibits commendable performance in accurately classifying eggs as fertile, infertile, death, or no-egg. The model's accuracy is a result of the training data collected during the

manual candling process, ensuring that it can effectively generalize across diverse egg samples. The OLED display serves as the immediate output interface for the detection results. The display showcases the classification outcome, allowing users to swiftly interpret and respond to the status of each egg. This real-time feedback is invaluable for timely decision-making in the incubation process.

The utilization of the OV7675 camera and TinyML model to automate egg candling signifies a notable progress in enhancing the efficiency and precision of evaluating egg quality. The synchronized 6-second intervals for image collection and model inference optimize the procedure, guaranteeing prompt and dependable information for each egg in the incubator.

The OLED display functions as a highly efficient interface, delivering immediate feedback and promoting user involvement. The effectiveness of the model, based on a carefully selected dataset, highlights the significance of thorough data gathering in the creation of AI models for poultry-related tasks.

5.2.2 Temperature and Humidity monitoring

The prototype we have demonstrates exceptional performance in live monitoring of temperature and humidity, which are crucial elements that significantly impact the growth of egg embryos in an incubator. Figure 48 depicts the serial monitor displaying the temperature and humidity readings from the DHT22 sensor, as well as the successful response code (200) indicating the data has been successfully delivered to the web application.

```
httpRequestData: api_key=tPmAT5Ab3j7F9&dev_id=101&temperature=25.60&humidity=79.70
HTTP Response code: 200
Temperature level:25.60 *C
Humidity level:79.80 %
httpRequestData: api_key=tPmAT5Ab3j7F9&dev_id=101&temperature=25.60&humidity=79.80
HTTP Response code: 200
Temperature level:25.60 *C
Humidity level:79.80 %
```

Figure 48: Environmental factors monitoring on serial monitor.

The system verifies the status of the Wi-Fi network and the HTTP connection between the ESP Wi-Fi module and the system API. After the network and connection have been established, the API initiates an HTTP request to the device in order to commence the process of transferring data to the cloud, where the web application is hosted.

Server: 127.0.0.1:3306 » Database: u191905341_egg » Table: device

Options: Show all | Number of rows: 20 | Filter rows: Search this table

				id	dev_id	temperature	humidity	r_date
<input type="checkbox"/>	Edit	Copy	Delete	1	100	20	30	2023-10-26 20:27:34
<input type="checkbox"/>	Edit	Copy	Delete	2	100	25	40	2023-10-26 20:27:34
<input type="checkbox"/>	Edit	Copy	Delete	3	101	18	27	2023-10-26 20:28:36
<input type="checkbox"/>	Edit	Copy	Delete	4	101	26	61	2023-10-26 20:28:36
<input type="checkbox"/>	Edit	Copy	Delete	5	101	24.8	82.9	2023-12-04 20:44:28
<input type="checkbox"/>	Edit	Copy	Delete	6	101	25.5	79.4	2023-12-04 20:45:04
<input type="checkbox"/>	Edit	Copy	Delete	7	101	25.5	79.3	2023-12-04 20:45:39
<input type="checkbox"/>	Edit	Copy	Delete	8	101	25.6	79.5	2023-12-04 20:46:16
<input type="checkbox"/>	Edit	Copy	Delete	9	101	25.6	79.5	2023-12-04 20:46:51
<input type="checkbox"/>	Edit	Copy	Delete	10	101	25.5	79.5	2023-12-04 20:47:27
<input type="checkbox"/>	Edit	Copy	Delete	11	101	25.5	79.5	2023-12-04 20:48:04
<input type="checkbox"/>	Edit	Copy	Delete	12	101	25.6	79.6	2023-12-04 20:48:39
<input type="checkbox"/>	Edit	Copy	Delete	13	101	25.5	79.6	2023-12-04 20:49:16
<input type="checkbox"/>	Edit	Copy	Delete	14	101	25.6	79.7	2023-12-04 20:49:51
<input type="checkbox"/>	Edit	Copy	Delete	15	101	25.6	79.8	2023-12-04 20:50:26
<input type="checkbox"/>	Edit	Copy	Delete	16	101	25.6	79.8	2023-12-04 20:51:01
<input type="checkbox"/>	Edit	Copy	Delete	17	101	25.5	79.6	2023-12-04 20:51:37
<input type="checkbox"/>	Edit	Copy	Delete	18	101	25.8	87.7	2023-12-05 13:02:13
<input type="checkbox"/>	Edit	Copy	Delete	19	101	25.7	87.2	2023-12-05 13:02:49
<input type="checkbox"/>	Edit	Copy	Delete	20	101	25.9	81.6	2023-12-05 13:03:24

Figure 49: MYSQL sensor data table

5.2.3 User Interface

Once the data is transmitted to the cloud server, it is retrieved and presented on the end user dashboard through a PHP backend script. The web application features a resilient authentication system to guarantee secure entry into the system.

The management of user credentials ensures robust protection against unauthorized access and safeguards critical data.

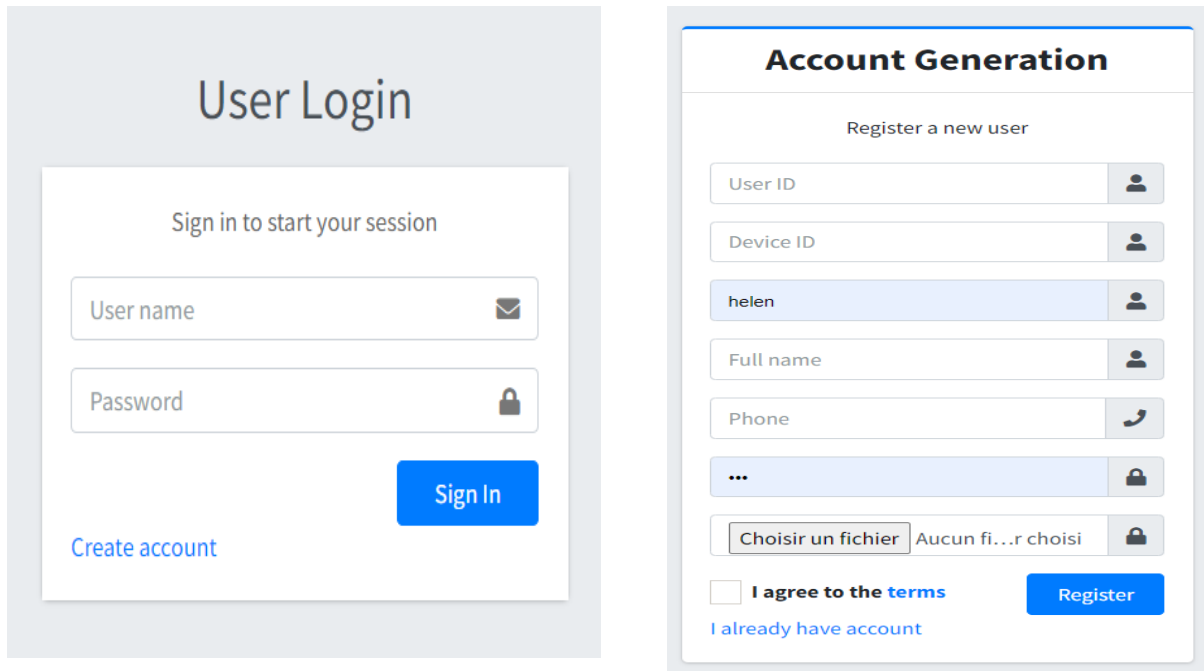


Figure 50: Farmer(user) authentication page

Figures 50 depict the authentication pages, specifically the login and registration pages. Once the farmer has logged into the system, they can access, visualize, and alter various activities on the dashboard page shown in figure 51 below. The dashboard functions as a centralized hub for users, providing a concise summary of essential information. The incubator's latest temperature and humidity values are dynamically displayed. Furthermore, the device has live visualizations of temperature and humidity, allowing users to easily understand the current environmental conditions. The present date and status of incubation are conspicuously showcased for rapid evaluation.

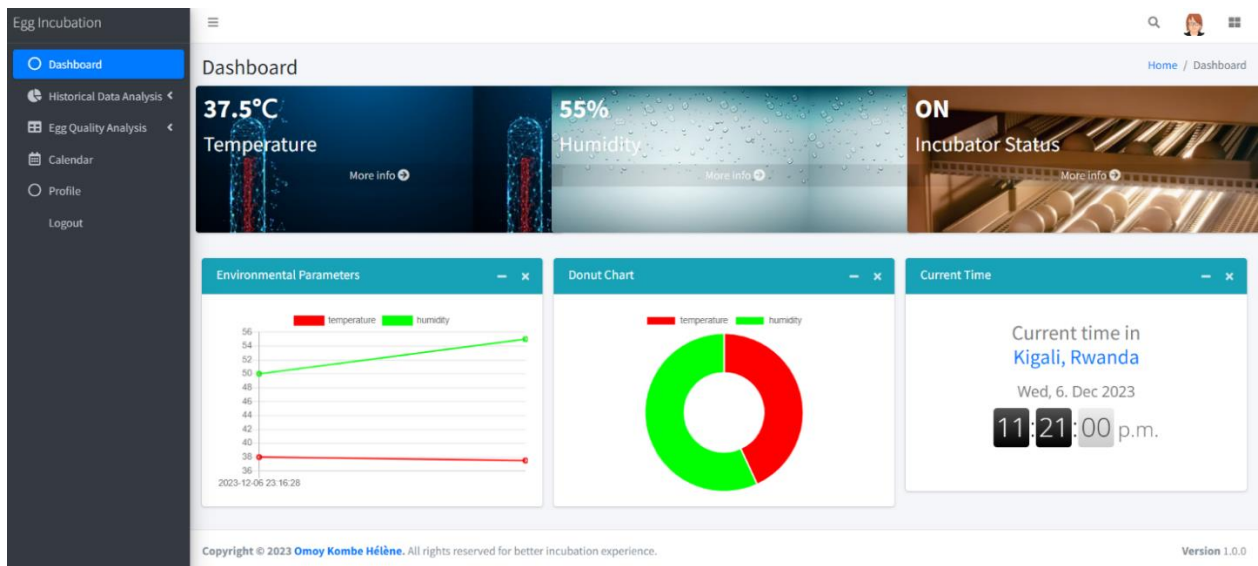


Figure 51: Dashboard page of egg incubation web app

By clicking the "more info" option, users or farmers will have access to all readings on the historical data analysis page depicted in the figure 52 below. Users can access a specialized webpage that provides comprehensive historical data on temperature and humidity. The historical data is presented in a tabular style, which allows for a full perspective and facilitates trend analysis and long-term monitoring. Provide the option to download data in various formats for the purpose of doing feature analysis.

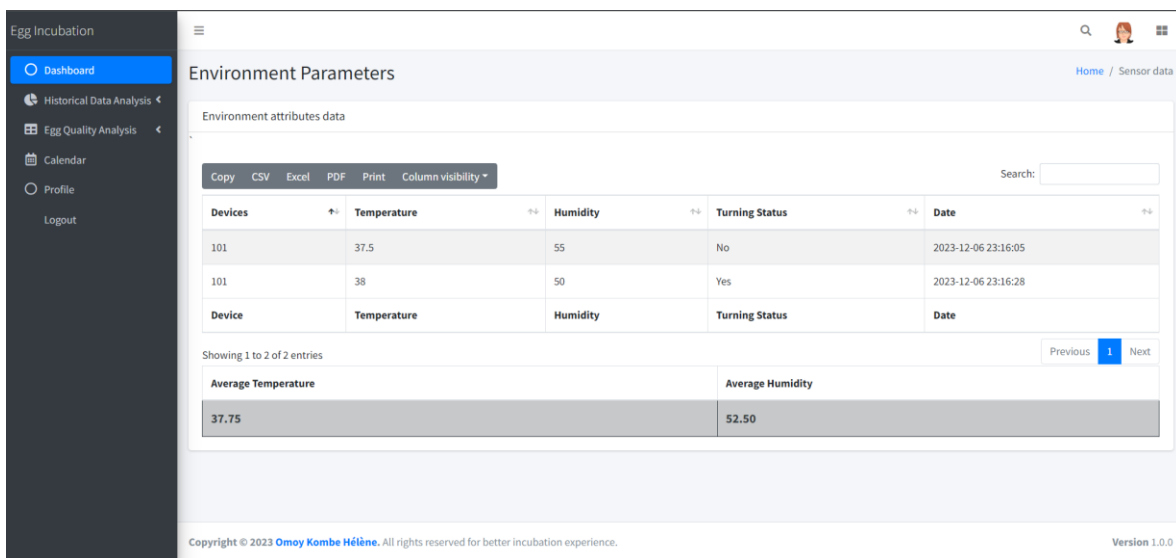


Figure 52: Environmental parameters readings

The user interface incorporates features for analyzing the quality of eggs, which offers users valuable information about the well-being and growth progress of eggs inside the incubator. This feature utilizes an AI model that has been trained using a dataset of photos to classify eggs into three categories: fertile, infertile, or non-viable as shown in figure 53 below. This helps in achieving efficient and precise assessment of eggs.

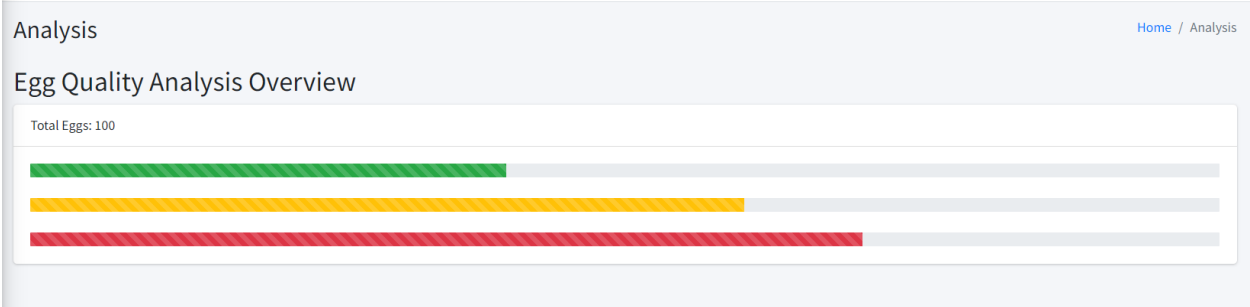


Figure 53: Egg quality analysis page

A calendar page is introduced to improve user organization and incubator planning. This functionality enables users to plan and monitor significant occurrences associated with the incubation procedure. It offers a graphical depiction of important milestones, enabling efficient administration of the incubation timeline. The user can create an event with an incubation period of 21 days, as depicted in Figure 54, and then schedule the event on the calendar page, as shown in Figure 55.

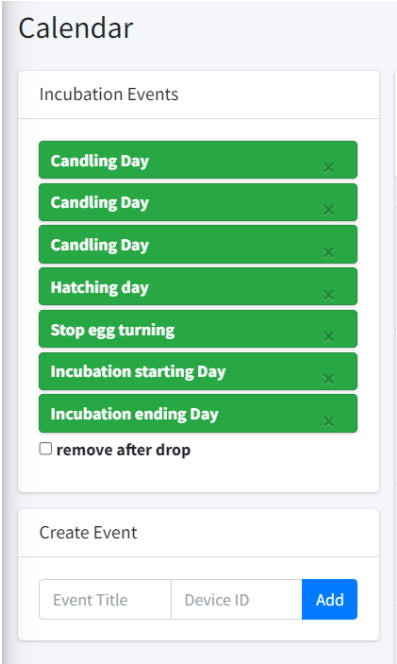


Figure 54: Incubation events creation

The farmer has the ability to determine the first day of the incubator, the day of egg candling, the day when to stop turning the eggs, the day of hatching, and the final day of the incubation process. The web application interacts with the device and performs actions such as initiating the candling process and terminating the egg-turning process, based on the incubation date and event.

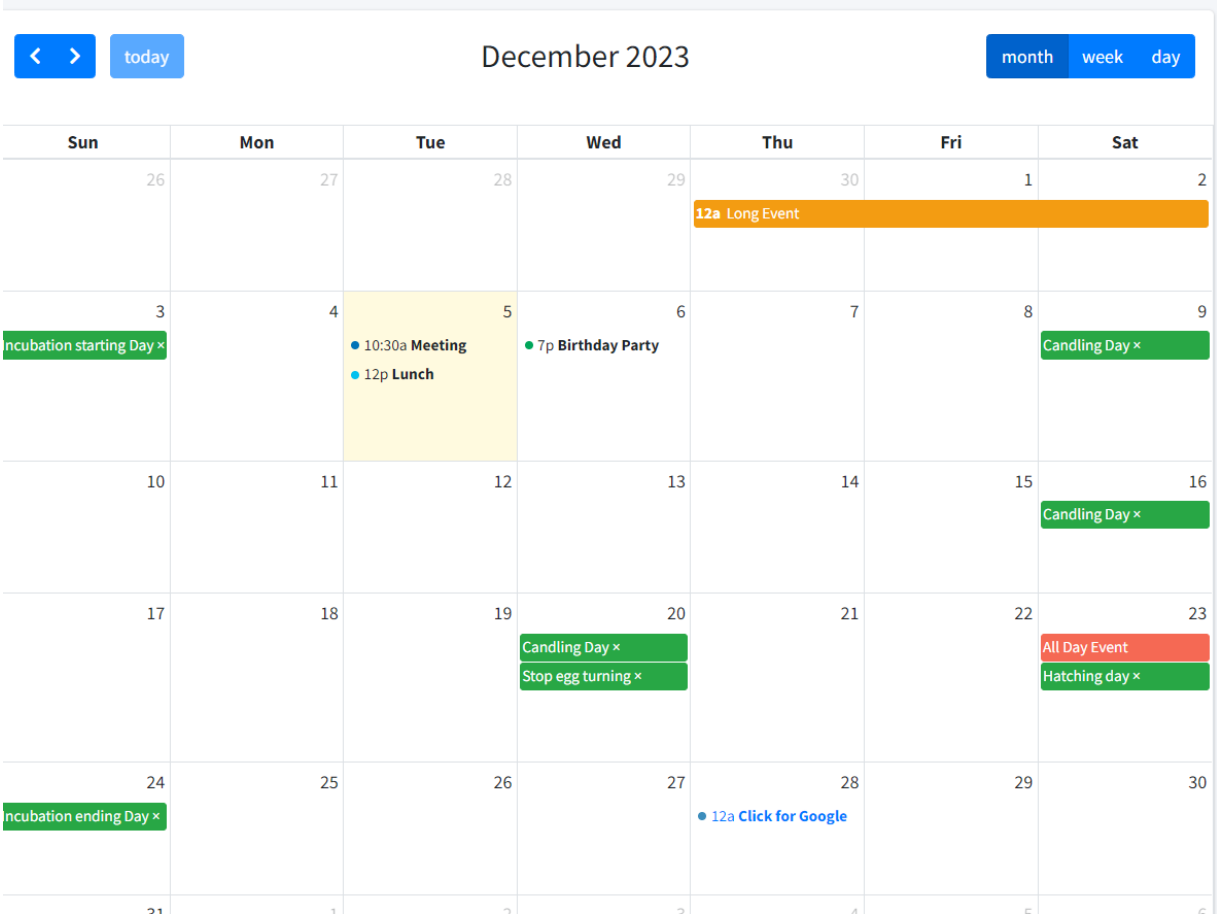


Figure 55: Incubation schedule

The User Profile Page provides a customized area for users to oversee and control their account information. Users have the ability to update their personal information, make changes to account settings, and customize information, which allows for a personalized experience within the system as shown in figure 56 below. The web application guarantees secure sessions by including a logout feature. Users have the option to log out of their accounts, which enhances security and privacy.

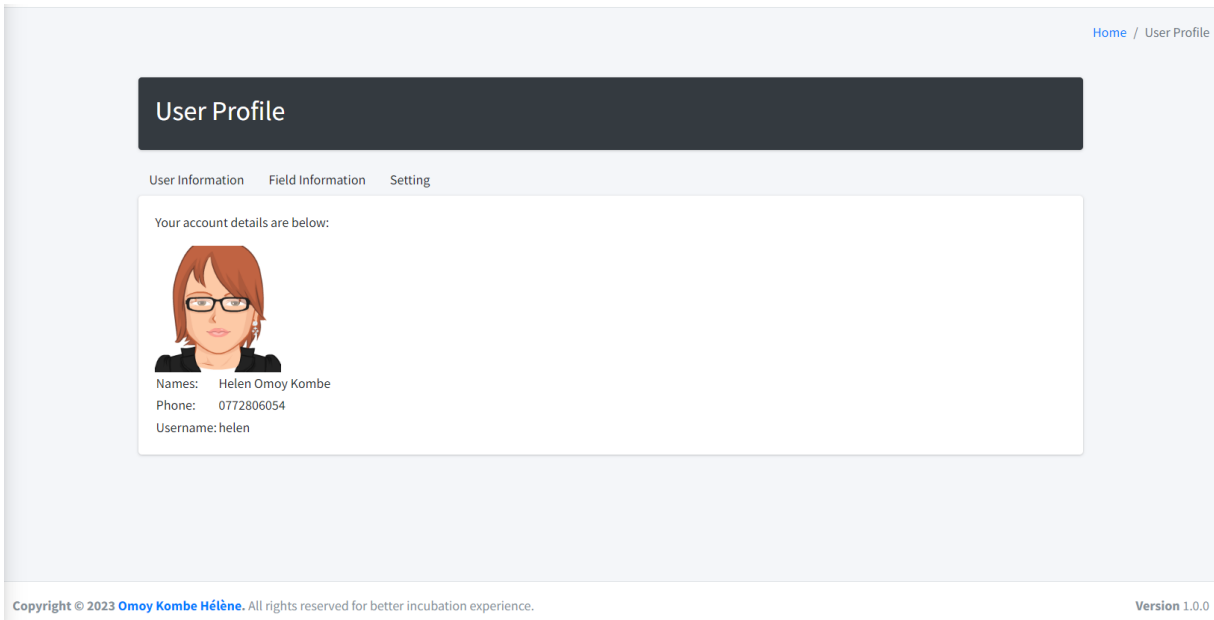


Figure 56: User profile page

The web application plays a vital role in enhancing the functionality and accessibility of the chicken-egg quality analysis and monitoring system, which is based on AI and IoT technology. The interface, designed to be easily understood and used by users, along with real-time and historical data visualization capabilities, empowers users to make informed decision regarding the optimal conditions for incubation and the quality of eggs.

Implementing an authentication system guarantees the security of sensitive data, effectively addressing issues regarding unauthorized access. The addition of the egg quality analysis tool enhances the system's functionality beyond simple monitoring, offering practical insights for enhanced hatchery management.

The calendar page functions as a utilitarian instrument for organizing and synchronizing, therefore optimizing the incubation process. The User Profile Page improves the user experience by enabling individuals to personalize their interactions with the system, promoting a design that is more focused on the needs and preferences of the user. In general, the web application improves the user experience and enables the smooth functioning of the entire system.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

a. General Conclusion

In summary, the successful deployment of TinyML in the poultry farming system has demonstrated its efficacy in automating tasks such as egg quality analysis and monitoring. The results obtained from the training approach employed by Edge Impulse, specifically focusing on the utilization of the MobileNetV1 model, represent a notable progression in the field of Convolutional Neural Networks for Tiny Machine Learning, particularly in relation to the classification and analysis of eggs. The approach demonstrates its effectiveness in accurately categorizing various egg classes, as evidenced by the notable achievement of a 97.4% F1 Score, highlighting its robustness and accuracy. The utilization of the EON Tuner for the Arduino Nano 33 BLE Sense in subsequent optimization shows significant improvements in efficiency, resulting in an accuracy rate of 95.79%. Significantly, the model demonstrated a maximum utilization of RAM up to 124.8 Kb, ROM storage capacity of 303.8 Kb, and latency of 53 ms. The combination of these measurements provides evidence for the feasibility and efficiency of implementing these models on embedded devices with limited resources. The findings not only confirm the viability of utilizing TinyML for poultry farming purposes but also emphasize the possibility of economical, energy-efficient, and reliable solutions, specifically in the domain of chick rearing. The integration of powerful machine learning techniques with tiny, edge-based hardware presents a potential opportunity to improve productivity, accuracy, and sustainability in chicken farming practices. The evolving research landscape is enriched by these findings, which offer useful insights and lay the foundation for future breakthroughs in the utilization of TinyML in the wider domains of agriculture and animal husbandry.

b. Recommendations

Based on the extensive findings obtained from this research, it is strongly advised that the poultry farming industry proactively adopts technological improvements, particularly the incorporation of TinyML. To minimize losses caused by many factors that can impact the incubation process, it is crucial to provide researchers and farmers with efficient technologies for monitoring, analyzing, and categorizing eggs in real-time. In order to enhance the implementation of sustainable practices in poultry farming, it is recommended that stakeholders in the sector consider investing in the

integration of TinyML applications. This would contribute to the continuing global initiatives aimed at promoting the durability and lifetime of poultry resources. The adoption of this collaborative strategy would not only bolster the technical resilience of the business but also make significant contributions towards the establishment of a sustainable and technologically proficient poultry farming environment.

c. Future Work

In the future, our continuing project aims to enhance the capabilities of TinyML models by investigating Real-Time Operating Systems (RTOS) for embedded devices with limited resources. Our objective is to improve the system by implementing an automated process for identifying and sorting faulty, infertile, and deceased eggs within the incubator. Transmitting the outcome of detection and categorization via the web application for further analysis. The goal is to provide embedded solutions that are both cost-effective and energy-efficient, while also being capable of being easily adjusted and integrated into various ecosystems. The proposed implementation of these solutions in the field has the potential to completely transform the chicken farming industry. Our goal is to significantly increase poultry farming production and improve farmers' income by effectively using available resources.

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