Use of Machine Learning and IoT for Monitoring and Tracking of Livestock.

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A thesis submitted to the Department of Computer Science and Engineering in partial fulfillment of the requirements for the degree of B.Sc. in Computer Science

> Department of Computer Science and Engineering BRAC University September 2022

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Declaration

It is hereby declared that

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- 2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
- 3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
- 4. We have acknowledged all main sources of help.

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Ethics Statement

We the individuals, therefore and truly pronounce that this thesis report has been done based on the findings of our extensive research. This report correctly notes and cites all of the materials that were utilized. This research work, not one or the other in full nor any portion has never been submitted by any other individual to another university or any institution for the grant of any degree or for any other reason.

Abstract

Given the present era's expanding population and rising necessity of dairy products, livestock supervision is one of the issues that is becoming progressively more of a priority. Moreover, periodic cattle health monitoring is crucial for extending the lifetime and maintaining the quality of livestock. Numerous ailments can be conveyed from animals to people, thus it is important to determine the condition and health status of livestock early on. This research analyzes the elements provided by various innovation systems and associated equipment, as well as their advantages and disadvantages. Additionally, we have suggested a real-time interval system for monitoring cattle health that is based on the Internet of Things (IoT). The suggested system would include a multi-sensor board that has been specially built to track various physiological indicators, such as skin temperature, heart rate, and the Temperature Humidity Index (THI) of the environment's temperature and humidity. Wi-Fi technology will be used to transfer the observed data to the server, where data analytics will be carried out using machine learning (ML) models such as Decision Tree Classifier and Support Vector Machine (SVM) to identify sick animals and forecast cattle health over time so that prompt medical attention may be given.

 ${\bf Keywords:}$ Livestock Monitoring, IoT, THI, Wi-Fi
 Module, Decision Tree Classifier, SVM

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Chapter 1

Introduction

1.1 Background and Motivation

Livestock is vital to rural life and the economics of emerging countries. Bangladesh is no exception because it is a developing country. It has a crucial role in agricultural output. Bangladesh's livestock population today numbers 25.7 million cattle, 0.54 million buffaloes, 16.3 million goats, 1.29 million sheep, 97.8 million poultry, and 39.43 million ducks [27]. The average number of these livestock per square kilometer in 2017 was 19.7 to 361.7, 0.39 to 15.4, 12.4 to 359, 0.3 to 43.0, 105 to 1212, 6 to 746, and 1.5 to 190 [27]. The livestock sector accounts for around 2.6% of national GDP in 1990s [18]. Draught power for tilling the ground, cow dung as manure and fuel, and animal power for transportation are all substantial contributors to GDP. According to Rahman et al. (2014) [18], the livestock sub-sector employs 20% of the overall population full-time and another 50% part-time. Poultry meat accounts for almost a third of Bangladesh's total meat production.Furthermore, livestock husbandry products such as leather, hides, and skins are important key export items, accounting for roughly 13% of total foreign exchange in the 1970s and 1980s. Cattle's uncounted sectoral contribution is worth three times the amount of official GDP allocated to it, according to one estimate (FAO 1990). The cattle sector has suffered considerable damage as a result of poor maintenance and oversight, and has seen repeated downturns that have harmed the economy. For example, the GDP contribution of 1990s was lower than 1970s (5%) and 1980s (10%) [18].

Because livestock are so important to the country's economy, continuous monitoring is essential. People who are financially insecure are more committed to this sector of the economy. Without effective monitoring and a strategy for implementing and monitoring all measures, our economy faces a bleak future. Veterinary well being administrations, conveyance frameworks for veterinary organic items, quality generation inputs, veterinary expansion administrations, and participation between the private and open divisions managing with different animals well being issues, such as illness determination, hospitalization, anticipation, and control, are all critical variables within the improvement of animals assets [25].

The fact that a large number of people in Bangladesh are dependent on livestock for their livelihood, it is very important to ensure good livestock monitoring. In Bangladesh livestock monitoring is quite a new concept. There are not many implementations or usage of livestock monitoring devices [46]. This is a concept which is still under research and yet to be implemented. But it is very important for the farmers to be aware of their livestock and get alerts about any kind of irregularities in their cattle's health. It is important because if one of the cattle of the livestock farm becomes sick and the disease is infectious, all the cattle of the farm might get infected and that will be a great concern and also economical loss for the farmer [35]. Another thing is many of the livestock farmers in Bangladesh are from rural areas. It is not easy for them to monitor their cattle all at once. Keeping that in our mind we found motivation to work vastly in this sector especially focusing on the farmers and industries that support and maintain large scale livestock farm. Our main focus will be to create a cost efficient system that will be easily accessible for the livestock farm owners even who are living in rural areas [14]. The system will not focus only on cost efficiency, our target will be also making it simple and easy to use, so that the end users can use the system with some basic knowledge and training. This will be our primary goal since maintaining a number of livestock and keeping track of their every action sometimes become tedious, furthermore many of the farmers living in the under developed areas face an educational barrier, so they would prefer a device which gives a simple output easy to understand. Keeping that in our mind we will try to focus on making a system as simple as possible as well as cost efficient. So the livestock farm owners can easily afford the system provided by us and also can use it without any complacency. Since livestock plays a vital role in the economy of Bangladesh, it is quite important to ensure a system that can monitor the livestock and help the farmers to take necessary steps whenever it is needed. The farmers work very hard regularly, a system like this might be a solution for their economical loss and it can even help them in their economical growth [50].

1.2 Problem Statement

We all know animals are incapable of communicating or expressing their difficulties. Thus, it gives a farmer full responsibility for all the livestock under his control. Since these cattle are unable to go scavenging for food, habitat, breeding, wellness, development, trading, shipping; all of these fall under the purview of the farmer. Despite the fact that these obligations seem to stem more from morality, the farmer's financial interests are nevertheless quite important in this situation. The primary goal of the majority of livestock and poultry businesses is to fulfill consumer needs by offering a merchandise that satisfies those needs at a cost that allows the provider to generate a profit.

Modern livestock operations rely heavily on animal health management and early detection of problems. Temperature, movement patterns, feeding habits, and animal stress levels may all be tracked using wearable electronics and infrared cameras [38]. It not only assists farmers in better understanding their livestock's status, but it also makes it easier to manage them and provide extra attention when necessary. The term "IoT" describes a collection of interlinked sensors and/or devices which transfer and reroute localized data across a hermetically sealed or semi-open wireless connection. Sensor innovations are utilized in animal well being observing frameworks to track heart rate, body temperature, breathing rate, rumination, blood pressure, and substantial gestures, among other things. The area checking framework employs an assortment of strategies to track the cattle's current area, counting GPRS, Wireless Sensor Systems (WSN), and RFID labels [20]. A smart feeding system for cattle employs ultrasonic sensor technology. Rural Bangladeshis do not have access to high-speed bandwidth such as 3G/4G, which is readily available in urban regions [29]. Our primary focus will be on providing customers with a reliable and easy to

use service. The Cloud IoT-based LMS (Livestock Monitoring System) proposed in (K., S. 2018) has three features: a convenient collar for recording and checking animal well being status utilizing IoT sensors, animals distinguishing proof employing a one of a kind identifier (UID), and remote show of the points of interest by means of QR code perusing and handling. Progressed animals observing gadgets identify physiological variables like body temperature and heart rate, as well as physical movements like sitting, standing, bolstering, and beating, as well as surrounding circumstances like temperature and stickiness. Their approach is significantly more technologically advanced and technologically minded. Our target audience is local rural residents who are unfamiliar with technology. It is easily accessible, and the convenience of usage could be advantageous to them. That is what we are attempting to accomplish. Our main focus will be creating a device that can easily monitor some physiological factors of livestock such as temperature, pulse rate, etc.

1.3 Research Objectives

The goal of this research study is to develop a cost-effective and efficient livestock monitoring system allowing farmers to monitor their farm animals remotely. The main objectives of this research is:

- 1. How IoT can be used to monitor cattle. To create a device using IoT based sensors which will be utilized to continuously monitor each animal, detecting any irregularities in their body and alerting the owner to any observable situations.
- 2. To develop an idea that would assist farmers in remote areas in keeping track of their cattle. To create a cost efficient, easy to use device for all the farmers even in rural areas. So that they can use this device on their own to monitor the livestock and take necessary actions if any irregularity is detected.
- 3. To create a database to ensure easy management. There will be central database which will be accessible by veterinary hospitals, veterinary doctors, farmers, husbandry management units. Which will make the system easily accessible for the users and ensure high quality service.
- 4. Constructing the use of algorithms of Machine Learning. Using Decision Tree Classifier and SVM algorithms in order to compare data and predict cattle health.
- 5. Offer a recent and new dataset. Using our device to get accurate livestock data from various cattle ranches. In order to provide a free dataset source for public study, there are not many datasets available online.

1.4 Our Contribution

Our main focus of this research was to build a system which will be easy to use and cost friendly so that all the livestock farm owners in every area of Bangladesh including rural areas can use it with some basic knowledge. There have been few works on this topic since livestock is a very important part of the economy of a country. Food products such as milk, eggs, and meat are produced by these animals. They are also used to make fibers like fur, leather, and wool. All of these are extremely economical. We tried to build a system that will help to monitor overall health of livestock in livestock farms of Bangladesh. After reviewing the existing works we tried to build a system that :

- 1. Our system can detect body temperature, environmental temperature and humidity and heart beat of the cattles.
- 2. We used our device to create an original and recent dataset and worked practically on field to have a practical and real life idea about cattle's health.
- 3. We used two machine learning algorithms (Decision Tree Classifier and SVM) on our dataset which give the output of Milk Fever of the cattles.
- 4. We used DHT11, ESP8266 WiFi Module, DS18B20 sensor, Heart Rate and Oxygen monitoring sensor to create the device and tried to keep it cost friendly as much as possible to meet our target audiences.

With this device it is quite easy to monitor basic health of cattle in the livestock farms. We tried not to make the device much complicated as our primary goal was to make an easy to use device for the users.

1.5 Overview of Thesis

This thesis paper is based on livestock monitoring system and the research focuses on Bangladesh and the target audience is all the owners of livestock farms including rural areas.

In Chapter 2, we describe our findings and knowledge about the theories related to our research. In the Chapter 3 we reviewed some research works related to our work. This section covers review on paper works on livestock monitoring system using IoT, Networking, Cloud Computing. This section also covers reviews of research papers related to our device and Machine Learning algorithms. In Chapter 4 is where we tried to describe our workings, the dataset, the device configuration and algorithms used for our research. Chapter 5 is about our findings from the work. This section thoroughly explains the results of our research. In the Chapter 6 we tried to overview the limitations of our research works, device and algorithms. Chapter 7 overviews our research works and our ideas of future work.

Chapter 2

Background

We tried to overview as much as paper we could and also took help from various websites and youtube to learn about livestock, livestock monitoring, systems used in livestock monitoring.

2.1 Sensors For Device

Various types of sensors can be used to measure body temperature, environmental temperature and moisture level and heart rate. MLX90615, KG011, MAX30100, DS18B20, infrared thermometer etc. are used as body temperature sensor and heart rate sensor. DHT11 is used as an environmental temperature and humidity measurement sensor. ESP8266, ESP8266-12, Zigbee, etc.are some Wi-Fi modules which is another crucial part of our device as we learned from our findings.

2.1.1 DS18B20



Figure 2.1: DS18B20 Wi-Fi Module [48]

We found the DS18B20 sensor suitable for our system. It is used for measuring the body temperature of cattle. The 1-wire connector and 64-Bit serial information contained in the on-board ROM, which are sophisticated characteristics of the employed temperature probe, are not dependent on an outsourced service. Power source 3.0v-5.5v is used to energize it. It can measure temperature from -55° C to $+125^{\circ}$ C with $\pm 0.5^{\circ}$ C accuracy. It does not require any external components. The single-bus interface which is used to connect the microprocessor, is cost friendly and has strong anti-interference ability [48].

2.1.2 DHT11



Figure 2.2: DHT11 [36]

This module is used for measuring environmental temperature and humidity. This sensor includes a 4-pin single row device and features an 8-bit microprocessor with an integrated resistive type humidity measurement component and an NTC type temperature measurement component. This sensor is widely known for giving very precise value. This sensor is quite easy to use and the main advantage of this sensor is unlike other sensors, it's portable and cheap [36].

2.1.3 ESP8266

ESP8266 is a Wi-Fi module which we need in order to send and receive data. The ESP8266 needs a 3.3v and up to 250mA power supply. This module is created quite self sufficient thus it does not require much external circuitry and it operates in different modes which makes it power efficient. This Wi-Fi Module is extremely cheap compared to the others. This module is also very easy in terms of interface [19].

2.2 Machine Learning Algorithms

2.2.1 Decision Tree Algorithm

The decision tree algorithm belongs to the family of algorithms for supervised learning. The decision tree methodology, unlike other supervised learning systems, can solve regression and classification problems [2]. A Choice Tree is used to train a model that can predict the class or value of a target variable based on basic choice rules learnt from previous data (training data). A record's class label is predicted using decision trees, which start at the root of the tree [7]. The root and record attributes' values are compared. Based on the comparison, we move to the node that follows the branch that corresponds to that value. A variety of applications have successfully used decision tree classifiers [5]. The capacity to extract descriptive decision making information from data is its key characteristic. Training sets may be used to create decision trees [44].

2.2.2 Support vector Machine

For situations requiring regression and classification, supervised learning techniques like Support Vector Machines (SVM) are frequently used. However, it is frequently used in machine learning to address categorization issues [8]. In order to categorize the n-dimensional space, the SVM technique seeks the ideal decision boundary or line, which enables the speedy addition of new data points to the relevant category. It is best to have a hyperplane as a border [22]. The extreme vectors and SVM-selected locations are used to build the hyperplane [12]. The Support Vector Machine method is used in these severe situations, also known as support vectors.By transforming data points into a high-dimensional feature space, SVM may discriminate between data points that are otherwise indistinguishable linearly [11]. The data is analyzed and a separator between the categories is chosen, allowing the separator to be shown as a hyperplane. The next step is to decide which category a new record should be placed in using the new data properties [9].

2.2.3 Multi-Layer Perceptron

Multi Layer Perceptron is a supplement of feed forward neural network. The multilayer perceptron contains an input layer through which the data is sent [21]. The input layer are to be processed and then the task of prediction and classification is done by the output layer. Multi-layer perceptron consists of another type of layer known as the hidden layer in between the input and output layer. The hidden layer is where the model computes its data, and it can have an arbitrary number of layers [1]. The flow of data in MLP is from the input layer to the output layer. The neuron in MLP is trained with a back propagation learning algorithm, and the prediction can be achieved for continuous function. The major use cases of MLP are pattern classification, recognition, prediction and approximation [37].

2.3 Livestock Diseases

Every living being can face different types of health issues. Cattle are no exception. Cattle can also suffer from different types of health issues and diseases. Our system focuses on monitoring the basic health meters to find out any irregularities in the cattle's health. Livestock may suffer from various diseases and as they cannot express themselves, it can be detected by measuring a few parameters like change in body temperature, heart rate, stiffness, weight loss, etc.

2.3.1 Milk Fever

It is also known as acute hypocalcemia. This is a metabolic disorder caused by lack of calcium in blood. The major symptoms of milk fever are subnormal body temperature, increased heart rate, muscular weakness, etc. It usually occurs within the first 24 hours of post-calving. It can increase the risk of ketosis and metritis. Early detection of milk fever can be treated by calcium gluconate [3].

2.3.2 Hypomagnesemic Tetany

Also known as grass tetany or winter tetany this disease is caused by low levels of magnesium. Nervousness, paralysis, stiff gait, etc. are common symptoms. This disease must be treated within hours by injecting calcium and magnesium [13].

2.3.3 Pregnancy Toxaemia

This disease is commonly faced by the cattle during pregnancy because of low blood sugar or glucose. Weight loss, losing appetite are some symptoms. Usually cattle carrying multiple fetuses and having protein deficiency might face this issue. It can be treated by propylene glycol [4].

Chapter 3 Related Work

This section aims to critically review previous relevant work of cloud computing and IoT for monitoring and tracking livestock with cellular network systems. We analyze the different techniques used for the main results achieved, and we show how cellular network services have its specific challenges due to the lack of precision and accuracy.

The proposal was accomplished in (Maphane et al. 2017) [28], which offers a livestock monitoring and identification system employing an electrical control circuit and a Wireless Sensor Network (WSN) and GSM. The circuit models in this system are simulated using Proteus 8, a software application. The proteus 8 software is used for simulation since it can generate third-party modules such the Arduino Microcontroller MCU, XBee module, XBee shield, GPS receiver, and SIM900 GSM/GPRS shield. An Arduino microcontroller is in charge of this project. The XBee is used to broadcast and receive wireless signals, while GPS is used to pinpoint the location of the cattle. In this example, the XBee shield is utilized as a framework for developing the Arduino MCU to the XBee module.

In another research, Seokkyun Jeong et al (2013) [15], for their cloud computingbased livestock monitoring employed the Apache Hadoop cloud. The open-source framework of Google's distributed file system and MapReduce was employed in this research. The system creates an HDFS cluster based on Hadoop core, combining multiple nodes into a single cloud, and then installs HBase to store sensor data from cattle as well as facility status data. This study's livestock management data is stored in HBase, an HDFS-based distributed column-oriented database. Data saved in HBase within the cloud is processed in parallel using the MapReduce architecture to deliver services such as livestock monitoring, environmental monitoring, and facility control. The system suggested in this thesis creates an application for the current iOS 7.0.x update by utilizing the Xcode 4.6.x IDE, which runs on MAC OS 10.8.x.

Three components make up the proposed cloud-based IoT-based LMS (Livestock Monitoring System): an IoT-enabled wearable collar for monitoring and recording animal health parameters; a unique identifier (UID) for identifying livestock; and wireless information display via QR code reading and processing (K., S. 2018). Physiological signals including body temperature, heart rate, physical activity like sitting, standing, eating, and pounding, as well as environmental indicators like air temperature and relative humidity, may all be picked up by established animal monitoring systems. The MLX90614 sensor monitors the cattle's body temperature, the KG011 cardiac pulse sensor counts the animal's heartbeats per minute, and the 3

axis accelerometer sensor tracks its movements. The ambient temperature and humidity are measured via the DHT11 sensor. An Arduino UNO, which is connected to a Bluetooth HC-05 module and an ESP8266 Wi-Fi module, is used to control this system. The sensors gather data, which is then stored in the cloud. One element of this system that will enhance communication between farmers, veterinarians, and animal hospitals is a web-based animal husbandry system [49].

In 2019, Y. P. Pratama et al. [41] developed a collar device that connected to a base station and viewed and evaluated health concerns via a web application. It tracked cattle's pulse rate, body temperature, and action. Sensor data is captured and processed using ML to produce wellness classification outcomes such as normal, less common, and irregular states. The Wemos D1 microcontroller, the MLX90615 body temperature sensor, the MAX30100 heart rate sensor, the GY-25 accelerometer and spinner sensor, the TP4056 charging module, and the Baterai 18650 battery are all used in this approach. A seven-layer IoT paradigm was incorporated in the framework.

(P. Khatate et al. 2018) [32] conducted research on the development of a wearable smart wellbeing checking framework employing IOT. The owner wears wearable animal well-being monitoring technology wisely, and the data is forwarded to a veterinary specialist for necessary medical care. Among the criteria are temperature, heart rate, and respiratory rate. Sensors such the DS18B20 for temperature detection, the flex sensor for breathing rate detection, and the Oscillometric technique for blood weight detection are all consolidated into the Arduino UNO, and the results are shown on the LCD.

Saravanan K (2017) [30], an coordinated engineering presents a creature cultivation animal administration framework with the objective of observing the animal's wellbeing, warm push, and recognizing the fitting time for counterfeit insemination. The innovation is planning to help ranchers by giving way better observation and care for their cattle through the utilization of real-time information. The sensor in this case is an infrared thermometer sensor, which screens the animal's body temperature. The arduino computer program is required to program an Arduino board, and it was utilized to arrange the wifi module. The information from the temperature sensor is utilized to analyze temperature-related infection, to expect the animal's warm push and categorize it as ordinary, low stretch, mellow push, or unsafe stretch, and to decide when fake insemination ought to be performed. This strategy interfaces the sensor to the arrangement through wifi and utilizes ThinkSpeak, an Internet of Things (IoT) based expository program, to store the information obtained from the sensor [33].

Notably an architecture was introduced where continuous monitoring of livestock was achieved with LoRa LPWAN technology proposed by Germani, L., et al. (2019) [39]. This architecture focuses on automatic transfer of data over a greater coverage and also at a low power consumption. In this architecture, each and every end device (EDs) collect raw data from the one or more sensors attached to the livestocks. The data that are received is preprocessed with benefits in reducing the data rate. The preprocessed dataset is then transmitted through the wireless channel using the LoRa PHY technology through one or more gateways [40]. The APIs can maintain long-term and scalable storage for the incoming datas. This architecture uses a decentralized server and the users have a GUI where they can visualize the analytics sent by the sensors [43].

Likewise we can look in another paper Mayer, K., et al 2004 [6] conducted three experiments using wireless sensor networks for monitoring cattle health. The first experiment was carried out on a steer using a cannula that allowed access to his rumen. The purpose of the first experiment, internal health monitoring. Although there was no assurance of continuous coverage, every ten minutes, it would send a report of the temperature to the Canberra database. The second one was radio transmission through a cow. The goal of this one was to see if Berkeley Motes could be used as internal sensing devices that wirelessly send data to the exterior of the animal. This experiment was carried out on the spur of the moment utilizing qualitative analysis. This program sends the signal with a consistently increasing integer on a regular basis. The "RfmToLeds" application was used to program the second mote, which uses the LEDs to display a binary counter that shows the value of the number in the previous radio message received [47].

Mariana University (Pasto, Nario, Colombia) created a prototype of a livestock surveillance system in 2014 to prevent cattle rustling. The model collects information from organic factors and GPS and sends it to a central computer. The model utilizes Xbee transmission innovation. Since of its costly fetched, confined transmission capacity, and generally high control utilization, we feel Xbee innovation is unsuited for this sort of extent. Since the model has not however been promoted, it cannot fathom the issue of dairy animals estrus discovery [42]. Furthermore a Colombian company named Extreme technologies with ten years of experience designing, creating, and implementing technologically challenging corporate solutions, mostly for commercial, industrial, logistical, and domestic government agencies [16].

Extreme Technologies gives data innovation administrations based on modern mechanical frameworks that join cutting-edge data and communication innovations. The company's trade zones incorporate inaccessible information transmission, locationbased administrations, portable resource following, and online and portable computing program arrangements. Serves a diverse spectrum of Latin American industries, providing high-quality services and enhancing client value via process improvement [17].

The animals have contracted a number of diseases. With the use of inexpensive, non-invasive sensor technologies, many illnesses can be found. The most important sensors for identifying these diseases have been connected to certain animal behavior features that have been linked to these ailments. If sensor data changes, farmers may monitor cow behavior to determine whether illness has an impact. Delivering sick cattle to veterinarians is difficult for farmers. In hospitals, doctors are not always on call. In these circumstances, the ESP8266 Wi-Fi module might be utilized to gather various health data, like body temperature and heart rate, and send a graph to doctors. Using this graph, the veterinarian can discover more about the health of the animal. The health of cows may be significantly impacted by changes in the seasons and surroundings. High temperatures reduced cow feed intake and output rates. To maintain the health of the cattle, the environment's humidity and temperature must be adjusted [24].

In (2017) Swain depicted an Arduino-based calves' wellbeing checking framework that captures information such as heart rate, body temperature, digestion, and

body mugginess. The Arduino serves as an interface, whereas the Xbee is utilized for remote communication. The DHT11 sensor detects calf heart rate, the kg011 detects calf temperature and humidity, and the three-axis gyro-accelerometer evaluates cow rumination. The heart rate is calculated and shown in LabView using an Arduino microcontroller. The XCTU protocol is used to exchange data between Xbee software. Cattle health monitoring systems provide accurate health metrics that aid in cattle health monitoring and detection of any changes in health problems or behavior. As a result, it might be a very useful tool for farmers to examine every condition without relying on vets. Using sensor technology, (Shinde) proposed a technique for automatically detecting a range of health parameters such as temperature, pulse, and animal movement. The animal's body has this sensor attached to it. The temperature is detected using an LM35, the heartbeat is detected using a stethoscope, and the cow's every movement is recorded using an electronic accelerometer. Data is collected by sensors for early disease identification, lower treatment costs, and cow health monitoring. The Internet of Things allowed this to happen. The sensor is connected to an Arduino UNO (Controller), and the Controller's signals are sent through the Wifi module to the wellbeing checking app [10].

Some study has been done on this [31], in which one of the papers mentioned theft prevention in passing. CelMax was created to curb cattle rustling in South Africa. One sheep out of 500 had a collar placed around its neck. Sheep imitate each other's behavior, so if one sheep does anything strange, the others will follow suit. When the collar sensors detect movement in the dark, they suspect that they are being pursued, maybe by a sheep thief. The gadget then sends the farmer an SMS message telling him that the sheep have disappeared and are most likely being chased. This gadget is inexpensive and has a battery life of 6 to 8 weeks. In 2009, the Pro-TagTor system [26] was developed, which operates similarly to the CelMax system but transmits SMS to farmers via base stations rather than onboard GSM modules. Base stations receive signals and process them. On a single charge, these tags last 4 to 7 years and cost 10% less than GSM collars.

To transport environmental sensing data to a server for processing, the ESP8266 (WIFI module) was used as the system's IoT device, and an environmental control system for a farming operation was constructed on the Arduino platform. The ESP8266 and the sensors are both connected to the server via Zigbee technology. After that, it is agreed, the irrigation system for the cultivation house will be managed. In and, these systems were on show. It is a widespread assertion that zigbee modules consume less power than WIFI modules. Its protocol is more complex than WIFI, though. The ESP8266 is a suitable option for use with the WIFI module since, when configured properly, it requires a respectably low amount of power. The most effective method for using the ESP8266 as an IoT device on an environmental management system will be the subject of our research. With little runtime programming and loading, this module has sufficient processing power and storage to connect to sensors and other application-specific devices through its GPIOs. Only a few external circuits are required because of its superb on-chip integration, such as the front-end module, which is made to take up the least amount of PCB space feasible. Without the need for additional RF components, VoIP apps and Bluetooth coexistence interfaces may be used with the ESP8266's self-calibrated RF [34].

Machine learning played a vital role in livestock farming. Well there are different approaches applied depending on the users. For example for measuring cattle's weight,

there are two methods for calculating an animal's BW (direct and indirect). One direct means of determining animal weight, either passively or actively, on big farms is the installation of full-weight or partial-weight industrial scales in key places. Despite the high level of accuracy of these instruments, small and medium-sized farms and commercial operators cannot afford the high costs associated with their acquisition, intended use, and operational size, as well as the repeated calibration and maintenance costs related to their placement in high-temperature variability and corrosive environments. Indirect techniques based on actual or potential relationships between the biometric and morphometric characteristics of cattle and their body weight have been developed as a less expensive alternative to direct weighing procedures [23]. By combining computer vision and machine learning algorithms we can achieve the result we want. Automatic feature selection is made possible by machine learning (ML) technology when paired with the CV methodology outlined in the CV approach (Tasdemir and Ozkan, 2019; de Moraes Weber et al., 2020; Rudenko, 2020). The image and feature selection, image segmentation, and extraction of morphometric measurements are all methods used by the CV and CV+ML systems that are human-based. Since manual procedures will prevent such technologies from being used in high-throughput systems capable of processing thousands of animals, commercial solutions must be totally automated [45].

Chapter 4

Methodology

4.1 Design Principle

We have designed this model with a purpose such that it will work precisely and it will be easy to use for the end users. The IoT-based sensors that make up the model are used to track changes in a number of aspects of the animals. The sensors are used to measure a variety of variables. This contains internal factors like heart rate and body temperature, including external factors which include the environmental temperature and humidity. Due to their ongoing activity and operation, the sensors may also monitor cattle for subliminal actions. Different measures during various acts carried out by the cattle are noted. This data is processed inside the processor and a detection for various conditions are presented. For simplicity of the end users, the results would be detected through the device itself with the help of LED light, during specific intervals.

4.2 Livestock Dataset Generation

For our processing we have collected sample data from various cattle farms. The sensors were connected to the livestock and some factors were taken into reading by the IoT device. The arduino used in the IoT device is programmed to run at some specific intervals to activate the sensors and take the current readings. Once the readings are taken they are sent to the database where we stored the previous values. The database consists of the reading for body temperature, outside temperature, outside humidity, Temperature-Humidity Index flag and milk fever flag. Since the data was collected from different locations we have given an Id number to distinguish between the farms. Every individual livestock has their own unique id which has a prefix of the farm id followed by its unique number. Multiple readings of a single livestock is taken at different intervals recording its body temperature, pulse rate of the livestock and the record for environmental temperature and humidity is also taken into account. The temperature humidity index column is not directly achieved from the sensors, instead the temperature humidity index is derived from the outside temperature and outside humidity. For the milk fever column, initially we determined the condition by measuring the temperature manually but later on the results will be predicted by the machine learning algorithm used. The machine learning algorithm used with the collected dataset to predict any abnormalities and return a milk fever flag. Since every individual livestock has an unique set of raw values, we used machine learning to predict the condition instead of attaining the result from a hard coated condition.

4.3 Dataset Preprocessing

4.3.1 Normalizing Dataset

Initially the dataset contained a mixture of values, including both string boolean and floating numbers. Initially all the different data types were normalized to a single data type float. This makes the data more readable for the machine learning algorithm and easier to computate. Then we checked for any null values in the dataset and filtered them out. When the dataset is free from all the null values, the dataset has to get rid of all unnecessary information. The columns that we do not need for the algorithm include FarmId, Species, LivestockId. These columns hold information about the livestock details only and therefore are redundant for the machine learning algorithm to be included for processing.

4.3.2 Scaling Dataset

Normalizing the data is followed by Scaling it. When we use a raw dataset the columns have a specific range of values, and they can deviate by a huge margin. Such deviation can result in unprecedented training and prediction. So in this dataset we are scaling the dataset using the minimax scaler. Minmax scaler takes the minimum and maximum value of each individual column and then finds the corresponding value of the row data with the help of the formula,

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{4.1}$$

Here, x = value of data of the column

 $\min(x) = \min(x)$ are the column

 $\max(x) = \max(x)$ are a maximum value of the column

This formula converts the specific value of the column to a new value ranging between 0 and 1, since all of the columns have a similar value it is much easier for the algorithm to process.

scaler = MinMaxScaler()scaler.fit(X)

 X_{train} scaled = scaler.transform(X_{train})

 $X_{test_scaled} = scaler.transform(X_{test})$



Figure 4.1: Architecture of IoT-based cow health monitoring system

4.4 Animal Monitoring System

The animal monitoring system consists of IoT based sensors which has the purpose of detecting changes in various factors of the livestock. Various factors are measured through the sensors. Which includes physiological parameters such as skin temperature, heart rate. The sensors being constantly active and working can check for subconscious behaviors performed by the livestock also. Different measurements of different actions performed by the livestocks are taken into record. Records of time it stands, the time it passes sitting is recorded at different intervals in the database. A reading of surrounding temperature and humidity index is used to calculate realtime Temperature Humidity index [26]:

 $\text{THI} = T_{db} - [0.55 - (0.55 \text{ X RH} / 100)] \text{ X} (T_{db} - 58)$

 T_{db} : Bulb Temperature (°F)

RH : Relative humidity (%)

The sensors detect their respective values and send them to a processing module which is also fitted inside the device. The analog to digital converter in the processing module converts the signals into digital values and they are sent through the wireless communication module after processing. The monitoring IoT device monitors the data for temperature of the livestock, humidity and temperature in the environment, heart rate along with the physical performances of the livestock at an interval.



Figure 4.2: Internal chip management for the livestock EarTag

4.5 Proposed Non-invasive Medical Hardware

Wherein size is one of the key constraints, Biomedical sensors utilize underlying technology for healthcare systems. Moderate dimensions and weight are ideal for

the sensor system. Nevertheless, the sensors employed in these devices ought to be capable of detecting skin temperature, heart beat, and Oxygen saturation, as well as the ambient temperature and moisture level, which are vital for both clinical and diagnostic purposes. The need for controllers and remote access to these systems and devices is another restriction.



Figure 4.3: Our proposed prototype implementation using several sensors

The hardware non-invasive project is divided into the following areas :

4.5.1 Embedded System

Various types of sensors have been used in this device to collect basic information in order to ensure proper livestock monitoring. The sensors are connected to the ESP32 microcontroller. The data the device collects is compared with a regular database and whenever the system sees an irregularity it then sends a signal.

- 1. Body Temperature Sensor: DS18B20 sensor has been used to measure body temperature. Diseases such as lactation fever, indigestion and poisoning, may cause an animal's body temperature to be lower than its normal body temperature, which is 37.8 to 39.2°Celsius on an average. If an animal's body temperature is irregular it can be caused by diseases such as anthrax, influenza and foot-and-mouth disease 2. The sensor will immediately notify if the temperature is higher or lower than normal.
- 2. Heart Rate & SpO2 Sensor: Cattle typically have a heart rate between 48 and 84 beats per minute. The cattle's distress and panic are both detected by this sensor, since it increases or decreases the heart rate in such situations. It has an IR pair that can find the pulse and oxygen saturation levels in the blood.
- 3. **Temperature and Humidity Sensor:** The DHT11 is a popular temperature and humidity sensor. This has been used in this device as well since it is known that environmental changes have effects on cattle's health. The sensor

has a dedicated NTC for temperature sensing as well as an 8-bit CPU for serial temperature and humidity output. The sensor is also factory calibrated, making it simple to connect to other microcontrollers.

4.5.2 Communication Protocol

The ESP8266 WiFi Module is a stand-alone SOC with an integrated TCP/IP protocol stack that lets any microcontroller connect to the WiFi network. The ESP8266 may execute applications or outsource all WiFi networking functionality to a different application processor. Each ESP8266 module comes pre-programmed with AT command set firmware, allowing to connect it to the Arduino device and have almost the same WiFi capabilities as a WiFi Shield (right out of the box) The ESP8266 module is a low-cost board with a large and rapidly expanding user base. This is a system that allows the users to see data from different things in the form of a graph which helps farmers and doctors to monitor the cattle from anywhere outside the farm.



Figure 4.4: Flowchart of Proposed System

4.5.3 Software Integration

The local host records normalized values of health parameters and compares them to what is considered normal. If there are any changes, it creates a graph to show the owner. The owner will look at the value and do something about it right away and take them to the nearest livestock health centers. If the number of cattle is increased, then the amount of data stored about them also increases.



Figure 4.5: Local Host Server

4.6 Training and Testing

To essentially send the data for training and testing, the columns of the dataset particularly are split into two sections, one section consists of the columns that generally are used as an input and the very other contains the output columns, which specifically is quite significant. Finally, we used the train_test_split method from the sklearn module to split the data into a training set and testing set in the ratio of 0.8 : 0.2. This provides the algorithm to definitely have generally more data for training and achieving a much more accurate prediction. The algorithm uses the training data provided to determine all of the conditions and the relation between the input and output datas. The more data we specify for training the better understanding the machine learning algorithm will have about the provided datas. During testing the machine learning algorithm runs its model on the given test data. When it determines a milk fever output, the value of the output is compared with the corresponding raw data of the output. Which is necessary to justify the predicted value. Based on the ratio of current predictions the algorithm provides us with an accuracy value from which we can understand the performance or the limitations of the machine learning algorithm.

4.6.1 Data split

To send the data for training and testing, the columns of the dataset are split into two sections, one section consists of the columns that are used as an input and the other contains the output columns. Finally we used the train_test_split method from the sklearn module to split the data into a training set and testing set in the ratio of 0.8 : 0.2. This provides the algorithm to have more data for training and achieving a more accurate prediction.

4.7 Machine Learning

The machine learning algorithm predicts the suitable range for each and every individual livestock and checks whether the current data is inside or outside the range. The algorithm uses X_train and Y_train sets to train the model. The more data we provide to the training sets, a better accuracy is to be expected. After running the algorithm the datas in the X_test set is used to predict an output and then it is matched with its corresponding Y_test results. The prediction set and the Y_test result set is matched to give us an accuracy of the running model.

4.7.1 Decision Tree Classifier

Since this is a classification problem with the outcome being a boolean, decision tree classifier algorithm is used, the decision nodes represents whether the body temperature value satisfies the condition and based on the result a next node is created which ends up in a leaf node that gives us the predicted boolean for Milk Fever.



Figure 4.6: Partial Fever Detect Decision Tree

4.7.2 Support Vector Machine

This is also a Supervised Learning Algorithm, which splits the data in two distinct groups. One includes the data that returns a false fever condition and the other consists of conditions that are considered when the livestock has a fever condition during training the model. The SVM algorithm's objective is to establish the best line or decision boundary also known as the hyperplane. The best line is determined in a way such that the line has the maximum margin from both groups. During prediction, the body temperature is checked to determine how close it is to the hyperbole and which side of the hyperbole it falls into. The result is determined by whether the temperature has a value which is similar or dissimilar to other values that have a fever condition.

4.7.3 Multi-Layer Perceptron Classifier

The input data is sent to the neurons of the input layer in the multi-layer perceptron classifier. The model uses a back propagation algorithm in which the neurons of the hidden layers compute and analyze the data into distinct classes. The final output layer can predict the milk fever output.

Chapter 5

Performance Evaluation

- 5.1 Experimental Settings
- 5.1.1 Dataset Generation



Figure 5.1: Our authors are collecting data from a Livestock Farm

The dataset used here are created from the different values taken by the sensors at different time intervals. This dataset will later be used to run our Machine learning algorithms and determine a prediction of future values. We categorized the different columns with respect to the Device Id, Farm Id, the species of the livestock furthermore we have also taken readings from the sensors which includes environmental temperature, environmental humidity, and for the livestock the data for their body temperature and pulse rate were taken. From all the data taken the machine learning algorithm used can determine the Temperature Humidity index from the farm temperature and humidity and it can determine the Milk Fever boolean from the internal temperature.

	FarmId	Species	LivestockId	OutTemp	OutHum	BodyTemp	PulseRate	THI	Fever
0	2	1	212	81.0	0.65	100.4	80	0	0
1	10	1	1009	93.0	0.73	100.7	81	1	0
2	3	1	308	87.3	0.71	101.2	85	1	0
3	8	1	802	81.9	0.65	100.4	85	1	0
4	8	1	807	89.0	0.61	102.4	85	0	0
5	5	1	505	91.4	0.75	100.9	60	1	0
6	5	1	509	78.5	0.63	102.6	65	1	0
7	3	1	310	92.4	0.74	102.3	71	0	0
8	5	1	510	90.7	0.68	99.7	70	1	0
9	6	1	606	87.8	0.71	101.4	72	1	0

Figure 5.2: Dataset Preview

Joint Plot

In ?? the Joint Plot of body temperature of the livestock against the corresponding environmental temperature is shown. From this plottin we can assume that the temperature of the environment does not directly affect the body temperature of the livestock as the distribution of the body temperature is uniform throughout the range of outside temperatures.

Frequency Distribution

Figure 5.4 provides us a chart for distribution of body temperature from the overall livestock. This plotting makes it easier for us to understand the variation of temperature of individual livestock. From here we see that most of the livestock has a body temperature ranging from 100F to 102.5F. Thus we can assume the average temperature of a healthy livestock.

5.1.2 Training Configuration

The machine learning algorithm predicts the suitable range for each and every individual livestock and checks whether the current data is inside or outside the range. The algorithm uses X_train and Y_train sets to train the model. The more data we provide to the training sets, a better accuracy is to be expected. After running the algorithm the datas in the X_test set is used to predict an output and then it is matched with its corresponding Y_test results. The prediction set and the Y_test result set is matched to give us an accuracy of the running model.

5.1.3 Testing Configuration

The machine learning algorithms used for testing are:



Figure 5.3: JointPlot of Outside Temperature with Body Temperature

Decision Tree Classifier

Since this is a classification problem with the outcome being a boolean, decision tree classifier algorithm is used, the decision nodes represents whether the body temperature value satisfies the condition and based on the result a next node is created which ends up in a leaf node that gives us the predicted boolean for Milk Fever.

Support Vector Machine

This is also a Supervised Learning Algorithm, which splits the data in two distinct groups. One includes the data that returns a false fever condition and the other consists of conditions that are considered when the livestock has a fever condition during training the model. The SVM algorithm's objective is to establish the best line or decision boundary also known as the hyperplane. The best line is determined in a way such that the line has the maximum margin from both groups. During prediction, the body temperature is checked to determine how close it is to the hyperbole and which side of the hyperbole it falls into. The result is determined by whether the temperature has a value which is similar or dissimilar to other values that have a fever condition.

Multi Layer Perceptron

Since we are using the back propagation algorithm for multi layer perceptron, it will predict the data with the help of neural network. During the testing session, this algorithm takes body temperature of the livestock as an input and apply a predicted range on the testing data, as it moves forward it will check how much accuracy the multi layer perceptron can get. If the accuracy percentage is too low, the back



Figure 5.4: Frequency distribution of Body Temperatures

propagation algorithm has the ability to return to the previous testing data with a new prediction range. This algorithm is satisfied when it finds a suitable accuracy percentage. The output which is the milk fever boolean is shown in the output layer.

5.2 Experimental Results

5.2.1 Decision Tree Classifier Result

After running the model on body temperature to predict milk fever on the livestock, we get a result of 90% accuracy during training and an accuracy of 78% during testing. So we can determine that the decision tree classifier can predict whether the livestock suffers from a milk fever condition and it can predict the result correctly most of the time.



Figure 5.5: Heatmap of DTC Test Predictions

Figure 5.5 gives us a heatmap of the predicted result from the decision tree classifier. This heatmap gives us a visual representation of data for four sections. Actual Positive and Predicted Positive segments show us the 1500+ of livestock have a positive fever, and the algorithm also predicts their true condition. Actual Positive and Predicted Negative 250+ livestock has a positive fever but the algorithm could not determine their actual condition. Actual Negative and Predicted Positive segment

displays that 190+ of the livestock does not actually have a positive fever but the algorithm has a positive fever prediction on them. Actual Negative and Predicted Negative segment predicts 37 livestock does not have any fever condition which is also true for their raw fever condition.

5.2.2 Support Vector Machine Result

We obtain a result of 95% accuracy during training and an accuracy of 89% during testing after running the model on body temperature to forecast milk fever on the animals. We may infer from this that the support vector machine can predict if the cattle has a disease known as milk fever and that it generally predicts the outcome accurately.



Figure 5.6: Heatmap of SVM Test Predictions

Figure 5.6 gives us a visualization of the predicted results by running the dataset through the Support Vector Machine model. From this visual representation we can see, the algorithm predicted 1800+ values which were actually what the data provided, thus predicting them correctly. On the other hand 220+ values of the test input was predicted to have a fever condition but in reality the condition was negative. This algorithm did not provide us with any fever condition that is negative in nature.

5.2.3 Neural Networks Result

The model on body temperature is run to predict milk fever in the animals, and the results show 95% accuracy during training and 89% accuracy during testing. This suggests that the neuron network can anticipate whether the cattle would contract the milk fever sickness and that it can forecast the outcome rather well in general. By processing the dataset via the Neuron Network model, this Heatmap in figure 5.7 provides us with a visual representation of the anticipated outcomes. We can see from this visual depiction that the algorithm properly anticipated 1800+ values since these were what the data really delivered. The test input's 220+ values, on the other hand, were anticipated to have a fever condition, but the condition was actually negative. We received no negative-natured fever conditions from this method.



Figure 5.7: Heatmap of NNC Test Predictions

5.3 Experimental Findings

From the dataset and machine learning algorithm we were able to determine the Milk Fever output and whether any livestock suffers from this condition or not. We trained and tested the dataset through 3 different algorithm models. All three of them provided us with a similar accuracy. But among them Support Vector Machine gave us the best predicted results.



Figure 5.8: Test accuracy comparison

In figure 5.8 we compare the accuracy scores of predictions given by three different models. We can determine Support Vector Machines give us an accuracy of 86%, Neural Network gives us an accuracy of 90% and Decision Tree Classifier has an accuracy of 76%. If we consider this bar graph alone we have to say the Neural Network model gives us the optimum prediction result.

In figure 5.9, we not only compare the three different models for the test accuracy but also the train accuracy is included. In this comparison, Support Vector Machine has the highest training accuracy of all models followed by Neural Networks and Decision Tree Classifiers have a similar accuracy. When comparing both train and test accuracy, the Neural Network model has an equal accuracy for both test and



Figure 5.9: Test and Train accuracy comparison

Attribute	Decision Tree	Support Vector	Neural Network
	Classifier	Machine	
Accuracy	Moderate Accu-	High Accuracy	Has a better
	racy		accuracy than
			DTC
Training Speed	Fast	Slow	Slow
Irrelevant at-	Takes more	Can detect the	Take most at-
tributes	irrelevant at-	relevance of the	tributes into
	tributes into	attribute in a	consideration
	consideration	better manner	

Table 5.1: Comparison table between different machine learning model approaches

train whereas Support Vector Machine has a better training accuracy. With which we can conclude Support Vector Machine will provide us with a better prediction as it is more accurately trained than the others.

Name	MLX90615	KG011	DHT11	DS18B20	ESP8266	Decision	Support
						Tree	Vector
						Classi-	Ma-
						fier	chine
Y.P.	Yes	-	-	-	-	-	-
Pratama							
(2019) [41]							
Swain	-	Yes	Yes	-	-	-	-
(2017) [10]							
Vigneswari	-	-	Yes	-	Yes	-	-
(2021) [49]							
P.Khatate	-	-	-	Yes	-	-	-
(2018) [32]							
Mahmud	-	-	-	-	Yes	-	-
(2018) [34]							
Ani(2017)	-	-	-	Yes	-	Yes	-
[23]							
Our	-	-	Yes	Yes	Yes	Yes	Yes
method							

Table 5.2: Device and Algorithm Comparison Between Previous Works and Our Method

Chapter 6

Discussion

6.1 Discussion

In this research paper we tried to specifically make a user friendly device using the definitely less complicated and cost friendly sensors like DS18B20, DHT11, ESP8266 Wi-Fi module, sort of contrary to popular belief. These sensors are easily accessible, not basically much complicated, purposeful and most importantly cost efficient which generally helped us in our very primary goal of making the device not pretty costly in a really big way. As we wanted to actually build a system for livestock farm owners of every aspect in Bangladesh, which is really easy to use and definitely cheap. We used two different Machine Learning algorithms on our dataset to get precise and as really much as possible accurate values. While working on this research work we faced some limitations as well, contrary to popular belief.

6.2 Limitation

1. Ethical Concerns:

Trusting an algorithm has vast benefits. Using computer algorithms to automate tasks, check big amounts of data and make difficult results have helped humanity. Again, trusting algorithms does have some demerits. Sometimes exceptional can exist in any stage of development. Exceptional rates can not be reduced as they are trained by humans. Many ethical issues are still not solved.

If something goes wrong, there is nobody to take responsibilities. ML will take the most certain case in point. For autonomous vehicles, in the event of a road collision, who should be considered as responsible? Who is more responsible—the driver, the automobile company, or the software creator? These questions remain unanswered. One thing is certain. ML cannot decide on challenging moral or ethical issues or any crucial moment on its own. For that, we have to develop a framework in the early future to address ethical issues with ML technology.

2. Deterministic problems:

There are many applications in ML such as weather forecast, studies on environment and nature. To help calibrate and adjust the sensors for measuring the environmental indicators like pressure, temperature and humidity sensors. Models can be developed to simulate weather and simulate atmospheric emissions to forecast pollution. ML can be used to predict the future weather by the training done by humans by reading the data and complexity data of weather. Experts can train ML by simple forecasting algorithm data from various and different weather stations. They can give the information required to train a neural network to predict tomorrow's weather, such as air pressure in a particular area, air humidity, wind speed, etc. Nevertheless, neural networks are unable to calculate the real criteria of the weather. Whereas, ML is capable of making predictions, computations of intermediate fields like density may result in negative values that defy the laws of physics. AI is unable to comprehend cause-and-effect relationships. The neural network can link input and output data, but it cannot tell why the data are connected.

3. Lack of Data:

To work well, neural networks need vast amounts of data for training. The lack of data is another issue. A neural network's requirement for data grows as it gets bigger. In these cases, some might decide to reuse the data, but this will never result in a good way. This happens only for the scarcity of data. Consider a scenario in which your neural network needs additional data and you provide it with a sufficient amount of low-quality input.

4. Lack of interpretability:

From the problem of interpretability, deep learning algorithms suffer greatly. If you consider the case where you are developing a model for a financial company to detect fraudulent transactions, your model ought to be able to defend the way it verifies transactions. A deep learning system may perform admirably for this task in terms of accuracy, but it may struggle to confirm its findings. It is possible that someone working for an AI consulting firm. They would want to work for a client who only uses traditional statistical methods. AI models that cannot be comprehended may end up being ineffective since human interpretation involves complexities that go way beyond technical proficiency. If they are unable to convince their client that they fully understand how an algorithm makes decisions, tehy will fail. It is essential that ML approaches become interpretable if they are to be employed in practice.

5. Lack of reproducibility:

Lack of model testing processes and open source code enhances lack of reproducibility which is a complicated and growing issue in machine learning (ML). In research labs, new models are developed and swiftly used in real-world settings. But even if the models are developed to take into account the most recent scientific discoveries, they might not work in actual circumstances. Reproducibility allows different businesses and professions to use the same model and solve problems more quickly. A lack of reproducibility can have an influence on reliability, bias detection, and safety.

6. Having One Analog Pin:

The ESP8266 Wi-Fi Module has only one analog pin, so it is not possible to use it for two or more analog inputs and also while it allows analog pins as digital pins but not the other way around.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

Ensuring the health and preservation of cattle is essential, especially in rural areas, given the significance of cattle towards both the economy and our food supply. The major objective of this project is to provide a practical and affordable method for Bangladeshi farmers to monitor their cattle. The objective is to create a sensor that is simultaneously inexpensive and is able to send data over a cellular network with limited capacity. Our study primarily focuses on rural farmers in regions who, due to the high cost of regular livestock monitoring devices, are unable to purchase them. This study will help create a device that is less costly and has all the capabilities of typical livestock monitoring equipment. Farmers will not require smartphones or high bandwidth to keep an eye on their livestock, making it simpler for them to manage herds and give them special care as necessary. Therefore, by mixing different IoT With Cloud Computing sensors, we can develop a workable method to help Bangladeshi farmers care after their animals well and make contributions to the economic well-being of the nation.

7.2 Future Work

The data will be transferred in the form of radio waves with a bandwidth of 900Mhz and 868MHz, a lower frequency can ensure a greater coverage. The signals generated will pass through a mesh topology, where the relayed signals will be transmitted through numerous radios at a receiver connected to the cloud. A mesh topology ensures a longer travel distance because the radio passes the signals from one radio to the other reducing signal loss. The mesh network using zigbee technology also ensures that there is always an alternative route for the signals to be transmitted. From the cloud an application to person (A2P) message will be generated. The message generated will contain the health monitoring record of the specific livestock. The message will also alert the user about the conditions of the livestock. The cloud will send the A2P message to the mobile service provider which then will be relayed to the specific user maintaining a cellular data transfer from the cloud to the end user.



Figure 7.1: Transmission of signals from IoT devices to the cloud and GSM network

The central unit for livestock monitoring will be the web based database. It can be accessed by various stakeholders such as, veterinary hospitals, veterinary doctors, farmers, husbandry management units. The database will be accessible from anywhere around the globe, everyone signed up to the web application can have their livestock monitored and recorded. The server will have its own security system, a method to handle data loss, and scalability maintained for millions of various datas and a region free access. The database will collect records of many different values from the initial form to be filled up by the farmers. The values will contain, UID of the tags, age, type of species, name of the owner and the address of the husbandry. UID will be different for every tag, so it is recommended to keep a permanent tag attached to every individual livestock. A web page can be created where data about cattle will be stored using cloud computation. This web page can be accessed from anywhere.

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