MACHINE LEARNING BASED SMART BEEHIVE MONITORING SYSTEM WITHOUT INTERNET NETWORK

(İNTERNET AĞI OLMADAN MAKİNE ÖĞRENİMİ TABANLI AKILLI ARI KOVANI İZLEME SİSTEMİ)

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TABLE OF CONTENTS

LIST OF SYMBOLS

Wi-Fi : Wireless Fidelity
RFID : Radio Frequency Identification
IoT : Internet of Things
GSM : Global System for Mobile communications
POMDP : Partially Observed Markov Decision Process
LoRaWAN : Low Power Wide Area Networking
MQTT : Message Queuing Telemetry Transport
GPRS : General Packet Radio Service
WSN : Wireless Sensor Network
SMS : Short Message Service
RF : Radio Frequency
LTE : Long Term Evolution
PAS : Precision Apiculture System
SVM : Support Vector Machines
ANN : Artificial Neural Network
SVR : Support Vector Regression
BBN : Bayesian Belief Networks
RF : Random Forest
NLP : Natural Language Processing
DT : Decision Tree
LSTM : Long Short-Term Memory
MLP : Multilayer Perceptron
CNN : Convolutional Neural Network
FCN : Fully Convolutional Network
SMOTE : Synthetic Minority Oversampling Technique
ENN : Edited Nearest Neighbors
SD Card : Secure Digital Card
PVC : Polyvinyl Chloride
AT : Apparent Temperature
T : Temperature
RH : Relative Humidity
WS : Wind Speed
Q : Radiation
FFT : Fast Fourier Transform
EDA : Exploratory Data Analysis
RNN : Recurrent Neural Network
MEA : Mean Absolute Error

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Beekeeping plays essential role both in terms of agricultural yields and agricultural economy; they produce honey, wax, royal jelly, apitoxin, pollen, and propolis. Nowadays, these natural products become more importantly suitable and preferable for nutrition, food supplement, medicine, and industry. However, to produce organic honey, majority of the apiaries are located in remote or distant rural areas where utilities such as electricity and Internet network are not available. Additionally, due to colony failures, world honey production decreases year by year despite the increase in the number of beehives. The objective of this master's thesis is to develop a smart beehive monitoring system for apiaries including those that do not have access to Internet network. In this context, temperature and relative humidity inside the beehive, and ambient temperature were measured with RFID sensors. Control center, where all sensor data was sent and stored at, has a GSM module used to warn the beekeeper via SMS when an anomaly is detected. Simultaneously, using the collected data, an unsupervised machine learning algorithm is used for detecting anomalies and calibrating the warning system. The results show that the smart beehive monitoring system can detect fatal anomalies up to 4 weeks prior to colony loss.

Keywords: Beekeeping, Smart systems, Machine learning, Anomaly detection

ÖZET

Arıcılık, hem tarımsal verim hem de tarım ekonomisi açısından önemli bir rol oynamaktadır; arılar bal, balmumu, arı sütü, apitoksin, polen ve propolis üretirler. Günümüzde bu doğal ürünler beslenme, gıda takviyesi, ilaç ve sanayi için daha da uygun ve tercih edilir hale gelmektedir. Bununla birlikte, organik bal üretmek için arılıkların çoğu, elektrik ve internet ağı gibi hizmetlerin bulunmadığı uzak veya uzak kırsal alanlarda bulunmaktadır. Ayrıca koloni başarısızlıkları nedeniyle kovan sayısındaki artışa rağmen dünya bal üretimi yıldan yıla azalmaktadır. Bu yüksek lisans tezinin amacı, İnternet ağına erişimi olmayanlar da dahil olmak üzere arılıklar için akıllı bir kovan izleme sistemi geliştirmektir. Bu kapsamda RFID sensörler ile kovan içindeki sıcaklık ve bağıl nem ile ortam sıcaklığı ölçülmüştür. Tüm sensör verilerinin gönderildiği ve saklandığı kontrol merkezinde, bir anomali tespit edildiğinde arıcıyı SMS ile uyarmak için kullanılan bir GSM modülü bulunmaktadır. Eş zamanlı olarak, toplanan veriler kullanılarak, anomalileri tespit etmek ve uyarı sistemini kalibre etmek için denetimsiz bir makine öğrenmesi algoritması kullanılmıştır. Sonuçlar, akıllı arı kovanı izleme sisteminin koloni kaybından 4 hafta öncesine kadar ölümcül anomalileri tespit edebildiğini göstermektedir.

Anahtar kelimeler: Arıcılık, Akıllı sistemler, Makine öğrenmesi, Anomali tespiti

1. INTRODUCTION

Honeybees (apis melifiera) have had an important role in human life from the beginning of civilization. Honeybees cannot just be defined as only a vital part of our ecosystems since they are at the same time to lead a sustainable future for agriculture by pollinating. In this day and age, the honeybee plays a big role in a range of human activities, including nutrition, medicine, and agriculture (Edwards-Murphy et al., 2016). Beekeeping plays essential role both in terms of agricultural yields and agricultural economy; they produce honey, wax, royal jelly, apitoxin, pollen, and propolis. The production of 75% of global fruits, vegetables and seed crops rely on animal pollination, which represents 35% of global food production (Tosi et al., 2018). In addition to the information about pollination, honeybees are the most active contributor among all animals (Brown et al., 2016). Crops, including fruits like strawberries are dependent on pollination from bees (Klatt et al., 2013) where honey consists of secretions of bees and extracts of plant nectar (Naila et al., 2018).

The United Nation’s Food and Agriculture Organization (FAO) affirmed that the bees pollinate 71 of the 100 crop species that provide 90% of the world’s food and the bee population has fallen year by year. On the other hand, in June 2021, upon the call of the European Commissioner for Health and Food Safety of the European Commission, the farming ministers of member states of European Council came together and agreed on a realistic approach; to protect honeybees from external interventions and to decrease the loss of honey production.

Burucu (2020) thoroughly reviewed that world honey production decreased by 1.5% in 2018 compared to the previous year. According to a survey was conducted by the Bee Informed Partnership, from April 2020 to April 2021, 45.5% of the honeybee colonies were lost across the United States (Steinhauer et al., 2021). In addition, Data of Food and Agriculture Organization of the United Nations (2020) showed that despite the increase in the number of beehives in the world, the total amount of honey production did not increase accordingly (Figure 1.1). Due to the pandemic, data for 2020 and the following years have not been disclosed yet.

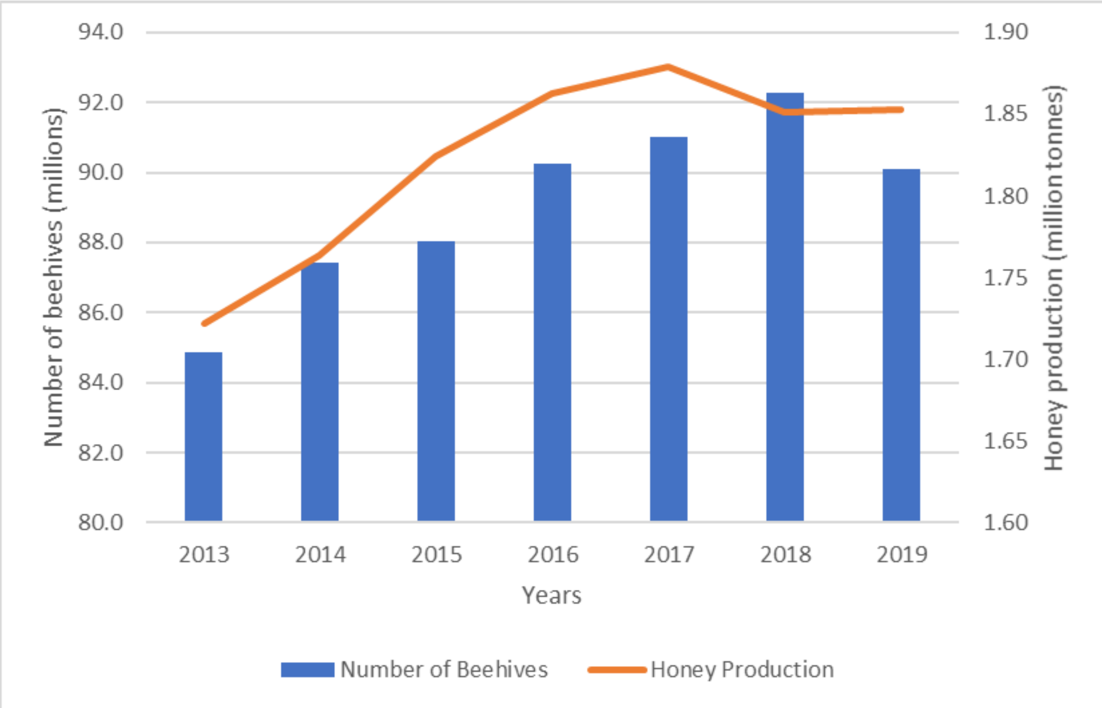

Figure 1.1: Number of hives and honey production in the world between 2013 and 2019

Main reason of decrease in the amount of honey produced per beehive is colony failures. Honeybee colony failure may occur at any time of the year, but winter is a drastic challenge for colonies due to starvation, ceased brood production and the colony need to survive for months instead of weeks in summer (Brodschneider et al., 2019). A honeybee society usually contains within it autoregulatory mechanisms that operate to maintain the functions of the society against external stressors: fully understanding colony failure requires understanding how these social systems have failed (Barron, 2015).

To detect honeybee colonies' abnormal states like low adult bee population, spotty brood pattern, and queen loss, it is usually necessary to do inspections by opening the beehives, removing the frames and checking on them. A careful inspection can cause additional stress to colonies (Braga et al., 2020), which can negatively affect the pollination services and also honey production.

Since the first beekeeping activity in the world, beekeeping has been based on individual observations and periodic inspections of beekeepers. However, this method was not sufficient, practical, and cheap. The biggest problem of beekeeping is the loss of the hive and the decrease in production. In order to solve this problem, different-based research has been done in different countries and research is still ongoing. The aim is to maximize production and production quality by reducing bee loss.

Currently, there is various intelligent beekeeping monitoring systems had been on hand in the world. Some of the systems are designed on the wireless node and cloud database server or local data server and some other systems use Bluetooth or Wi-Fi to get data which includes different variables: temperature, relative humidity, sound, colony activity, and weight.

Monitoring internal and external temperature of the beehive provides essential information about honey production, swarming state, and beehive health. To exemplify, it is known that the honeybees keep the internal temperature around 35°C and before the swarming occurs, there is a reduction of the internal temperature of the hive from 35°C to 32°C is obtained.

During the honey production period, the internal relative humidity of a beehive remains constant at around 70% (Yusof et al., 2019). On the other hand, relative humidity inside the hive decreases by 10% before swarming period (Catania et al., 2019).

In a healthy beehive, there are two main frequency ranges are clearly visible in the spectrum: the typical buzz sound of the hive (100-150 Hz) and the rise and decline in the proportions of the wing beat frequency (200-250 Hz) (Zacepins et al., 2016). Therefore, the health status and swarming period can be monitored using information from the sound of the beehive.

Zacepins et al. (2016) monitored beehive entrance to monitor honeybee activity. By counting the number of bees entering and leaving the beehive during the day, he was able to observe and analyze the general activity patterns.

Collecting continuous data on weight variations of the beehive can be used for monitoring: honey production, food consumption, mass of nectar and pollen collected, swarming and start of the hibernation season.

To produce organic honey, majority of the apiaries are located in remote or distant rural areas where utilities such as electricity and Internet network are not available. In this sense, remote monitoring of apiaries via wireless sensors is the key element of precision beekeeping. In order to transfer the collected data, the options are limited with Internet of Things, RFID and Bluetooth technologies.

The aim of this study is to develop a remote monitoring system for apiaries that does not have access to Internet network. The system is designed to warn the beekeeper only when an anomaly occurs. To achieve this goal, a combination of RFID (to collect sensor data) and GSM (to communicate with the beekeeper) technologies are used. For this study, temperature and relative humidity data of the beehives, and ambient temperature were logged between August 2021 and May 2022. Using logged data, an unsupervised machine learning algorithm is chosen and implemented the system.

This study is structured as follows: Section 2 reviews existing smart beekeeping systems and various applications of machine learning. Section 3 explains the proposed methodology with subtopics of tool and model development, data collection, and solution deployment. Section 4 and 5 describes obtained results and discussion, respectively. Finally, Section 6 presents the conclusions.

2. LITERATURE REVIEW

2.1 Smart Beekeeping

The literature review on smart beekeeping has been completed for the last decade, taking into account the measured parameters, the technology used for data transfer and the methodology used for data evaluation. It is shown in Table 2.1 that most of the studies were solely developed for continuous beehive monitoring since these studies included neither data evaluation nor system calibration methods.

Chen et al. (2012) developed an imaging system to monitor and analyze the beehive entrance activity. The system automatically recorded the honeybees with an infrared CCD camera, and then these acquired images transferred to a personal computer via wired connection and processed. Character encoding tags and Hough transform were used to identify and locate honeybees in a video frame. Then, the authors segmented the extracted character symbols and used the Support Vector Machine (SVM) algorithm for identifying the individual honeybees.

Fitzgerald et al. (2015) presented a load cell platform to determine the productivity and condition of the colony. The system solely measured the weight of the beehives. However, ambient temperature and relative humidity were measured to perform adjustments on the load cells for accurate weight measurement. Zigbee, a low power RF technology, was used for transferring data to the base station of network. The authors concluded that the system needed improvements before any integration to beehives.

Kviesis et al. (2016) implemented a smart apiary concept to monitor and manage honeybee colonies. The system measured temperature, sound, weight, and recorded video of beehive entrance. Wi-Fi was used for transmitting data to cloud server. The authors mentioned that future studies should include a decision support system based on predefined algorithms or neural networks.

Rybin et al. (2017) proposed a wireless data acquisition system for automated beehive monitoring. The system measured temperature, relative humidity, weight, and sound. nRF24L01 radio frequency modules were used for collecting sensor data. The data was used for training the artificial neural network in MATLAB to detect swarming periods. 2000 audio samples were selected for training the three-layered network.

Zacepins et al. (2017) presented an Internet of Things (IoT) system prototype to monitor honeybee colony. The system solely measured temperature every 10 minutes. GPRS module was used for transferring the collected temperature data to cloud server. The data stored was available to the beekeeper in web application. Based on defined rules and algorithms, the application makes conclusions and informs the beekeeper.

Debauche et al. (2018) developed an Internet of Things (IoT) based technical solution to accurately monitor and follow honeybees' behavior. The system measured temperature, relative humidity, air and acceleration inside the beehive. Low Power Wide Area Networking (LoRaWAN) was used for forwarding data to cloud architecture. The data was collected in order to be used in scientific research.

Catania et al. (2019) developed a Precision Apiculture System (PAS) for recording, monitoring, and controlling both inside and outside the beehive. The system measured temperature, relative humidity, and weight. Bluetooth module was used for transferring data to a smartphone. The accuracy of the data was analyzed by the authors to provide decisional support in future studies.

Komasilovs et al. (2019) described a hardware system to remotely monitor colonies, recognize their states, and minimize the necessity for on-site visits. The system measured temperature, relative humidity, weight, and sound. Wi-Fi was used for transferring data to data warehouse cloud service. An integrated module of the data warehouse analyzed the data and helped beekeeper in decision making.

Kontogiannis (2019) proposed an integration of an Internet of Things (IoT) management and alert system to focus on livestock monitoring of the beehive. The system measured temperature and relative humidity, and adjusted the conditions when necessary with thermo-pad, Peltier cells and fan actuators to provide thermal comfort, cool comfort, and moisture comfort, respectively. Every 48-72 minutes, data transferred by low power RF over a central hive and by LoRaWAN transceivers to a cloud-based system.

Mahamud et al. (2019) described a microcontroller-based system to monitor bee colony using IoT. The system measured the total load, temperature, relative humidity, noise, and gas status inside the beehive. The Message Queuing Telemetry Transport (MQTT) protocol was used for data transfer to the hardware system with local server and mobile application. All the sensor data can be viewed by a mobile application.

Ochoa et al. (2019) proposed an IoT based real-time monitoring system to observe behavior patterns and states of the colony. The system measured temperature, relative humidity, and weight of the beehives. Wi-Fi protocol was used for transferring data to cloud server to be displayed as charts, tables and graphs. In addition to this, the system used preset temperature values to warn the beekeeper via voice call, email and SMS.

Zabasta et al. (2019) proposed an example of Internet of Things (IoT) technologies to control the apiary without interfering neither beehives nor honeybees. The system recorded video and measured temperature, relative humidity, and weight. LTE was used for collecting data from the beehives. The data evaluation and decision making were up to the users.

Zabasta et al. (2019) applied an Internet of Things (IoT) solution to monitor and control the bee colony activities. The system recorded beehive entrance activity, and measured temperature, relative humidity, and weight of the beehive. GPRS and Wi-Fi modules were used for transmitting the data to cloud of autonomous beekeeping system. The cloud data displayed on multi-chart views to be evaluated by the users.

Cecchi et al. (2020) proposed a complete system to monitor and discriminate events such as swarming, theft, honey production, food consumption, illness and its effects. The system measured temperature, relative humidity, weight, sound, and CO2 levels inside the beehive. Wi-Fi module was used for transferring measured data to remote server. The authors analyzed the data and labeled the events to implement an automatic tool for determining beehive status in future works.

Fiedler et al. (2020) developed a honeybee colony monitoring solution which implemented in Ethiopia and Indonesia. The system measured temperature, relative humidity, weight, and sound inside the beehive. A mobile GSM Wi-Fi router was used for transferring the data to web server. The authors noted that frequent interruptions during data transfer challenged the study. A web application was developed for data display and graphical interface.

Yusof et al. (2020) implemented a real-time WSN system to monitor the colonies. The system measured temperature, relative humidity, smoke, and weight. Microcontroller with built in Wi-Fi was used for transferring data to cloud server. The cloud data was displayed on charts and graphs at a webpage for monitoring purposes.

Johannsen et al. (2021) implemented a do-it-yourself sensor kit aiming to create a digital twin of the beehive. The kit measured relative humidity, barometric pressure, temperature, and weight. The authors collected sensor readings every 5-10 seconds and used Internet of things for transferring sensor data to server. A partially observed Markov decision process (POMDP) model was designed in order to estimate current state and chose actions to achieve or maintain desirable states.

Table 2.1: Summary of the related works on smart beekeeping

Author	Measured Parameters	Hardware (excl. sensors)	Data Transfer	Study Method
Chen et al. (2012)	Video record	Personal Computer, electricity	Wired connection	Support Vector Machine
Fitzgerald et al. (2015)	Weight, ambient temperature and RH	ATmega1281, battery	Zigbee	Data monitoring
Kviesis et al. (2016)	Temperature, sound, weight, video record	Raspberry Pi, electricity	Wi-Fi	Data monitoring
Rybin et al. (2017)	Temperature, RH, weight and sound	Arduino with ATmega328, electricity	RF	Artificial Neural Network
Zacepins et al. (2017)	Temperature	PIC16LF1554, battery	RF	Data monitoring
Debauche et al. (2018)	Temperature, RH, air, acceleration, and ambient temperature, RH and pressure	LoPy, battery	LoRaWAN	Data monitoring
Catania et al. (2019)	Temperature, RH, weight, and ambient temperature and RH	Arduino with ATmega2560, electricity	Bluetooth	Data monitoring
Komasilovs et al. (2019)	Temperature, RH, weight and sound	Raspberry Pi, battery	Wi-Fi	Exploratory Data Analysis
Kontogiannis (2019)	Temperature and RH	ATmega328, battery	LoRaWAN	Data monitoring
Mahamud et al. (2019)	Temperature, RH, gas, sound and weight	ESP8266, battery	MQTT	Data monitoring
Ochoa et al. (2019)	Temperature, RH and weight	ESP8266, battery	Wi-Fi	Data monitoring

Zabasta et al. (2019)	Temperature, RH, weight, video record	ESP8266, battery	LTE	Data monitoring
Zabasta et al. (2019)	Temperature, RH, weight, video record	ESP8266, battery	Wi-Fi	Exploratory Data Analysis
Cecchi et al. (2020)	Temperature, RH, weight, sound, CO2	Raspberry Pi, electricity	Wi-Fi	Exploratory Data Analysis
Fiedler et al. (2020)	Temperature, RH, sound and weight	Raspberry Pi, battery	Wi-Fi	Data monitoring
Yusof et al. (2020)	Temperature, RH, smoke and weight	CC3200, battery	Wi-Fi	Data monitoring
Johannsen et al. (2021)	Temperature, RH, pressure and weight	ESP32, battery	Wi-Fi	Markov decision process

2.2 Applications of Machine Learning

The literature review on applications of machine learning has been completed for the last decade, considering the application areas and algorithms used for data evaluation. It is shown in Table 2.2 that despite the increasing food crisis around the world, there are not enough machine learning applications in agriculture.

Najafi et al. (2012) proposed diagnostic algorithms to recognize component failures and malfunctions of air handling units. These failures may not cause occupant complaints but can significantly increase the air handling unit’s energy use. Based on analyzing the observed behavior of the system, the authors used the Bayesian probabilistic model to detect various faulty conditions.

Wang et al. (2012) described a solution to model energy consumption for coal-fired power plants to consume less coal. Since coal-fired power generation is a nonlinear complex process, it is difficult to accurately calculate energy consumption, and optimize the operation parameters and boundary conditions. In the study, the energy consumption of the plant was reduced by Support Vector Regression and Genetic Algorithm.

Candelieri et al. (2013) presented a framework to simulate and improve reliability of aircraft fuselage panels. Based on finite elements analysis simulation, the training dataset was created, and then the Support Vector Machines (SVM) classification and Artificial Neural Network (ANN) were performed.

Mercer et al. (2013) used a machine learning model to predict warm-season rainfall events. As current weather forecast simulations provide only modest skill, the authors used Support Vector Machine (SVM) classifications to more accurately observe and predict warm season precipitation days.

Yu et al. (2013) built a model to forecast newspaper and magazine sales. The authors applied Support Vector Regression (SVR) model to sample data to avoid overfitting. Achieving minimal structural risk is the reason for the success of SVR.

Francis et al. (2014) developed a model to predict water pipe breaks in the United States. Due to difficulties in data collection, current prediction models were either statistical physical or hypothesis generating until this study. The authors used Bayesian Belief Networks (BBN) that learned from pipe breaks and covariate data.

Sharif et al. (2015) used machine learning to determine the water quality and identify the pollution sources. For this purpose, data was collected from 30 monitoring stations and classified into 6 clusters. K-means algorithm was applied to determine the origins of pollution in the Klang River Basin.

Tixier et al. (2016) presented a model to predict whether the injuries in construction are random or not. First, training data was developed with Natural Language Processing to extract information from the textual structure of injury reports. Then, Random Forest and Stochastic Gradient Tree Boosting were applied to predict injury and energy types, and body parts. It was aimed to study construction safety empirically and quantitatively rather than a subjective data. The results showed that the injuries were mostly random and extra layers of information needed to be used before making predictions.

Raith et al. (2017) presented a model to classify dental cusps from three-dimensional surface scan data. The study aimed to develop an automated model for the classification of teeth to be used for automated computer-aided planning of prosthetic treatments. To do so Artificial Neural Networks was used for the classification of dental cups.

Bhattacharya et al. (2018) predicted the presence of different facies and fractures in sedimentary rocks using machine learning. The authors used Bayesian Network Theory and Random Forest for classifying facies and fractures in unconventional shale and conventional sandstone, and carbonate reservoirs.

Ip et al. (2018) presented some big data applications for managing plant diseases and controlling crop yield losses caused by weeds and pests. The study and data collection completed in Australia. Markov Random Fields were used for herbicide resistance modeling of ryegrass.

Wang et al. (2018) used machine learning for optimizing therapeutic regimens for gastro-esophageal reflux disease. In order to simulate a treatment system, Artificial Neural Networks were used. The results of the study were feasible and worthy of further study.

Benson et al. (2019) proposed a tool to create a drone classifier. The authors aimed to standardize different classifiers into a single form and execute them in parallel. For this purpose, without labeling the training data, Drone Neural Network was used in the study.

Shaikhina et al. (2019) presented a machine learning model to predict high-risk kidney transplants. The aim of the study was to determine the key risk factors associated with acute rejection of the kidney. Decision Tree and Random Forest algorithms were used for this purpose. The results showed that the model predicted the transplant rejection with an accuracy of 85%.

Li et al. (2020) proposed a model to predict individual mobility. Location predictions were determined by focusing mainly on short-term dependencies between next location and locations traveled. On the other hand, long-term location predictions are important for traffic planning. In this study, the authors applied LSTM model to predict the sequence of individual locations. The LSTM algorithm captured both long- and short-term dependencies and revealed frequent and periodic mobility patterns.

Moorthy et al. (2020) proposed a machine learning model to detect phishing attacks. Phishing is a cyber-crime aimed to steal personal information by sending spoofed emails. The authors applied K-Nearest Neighbor to create an optimal phishing attack predictor. The results showed that K-Nearest Neighbor had better accuracy than Decision Trees and Naïve Bayes algorithms.

Mostafiz et al. (2020) proposed a model for detecting COVID-19 from chest X-ray images. During the COVID-19 pandemic, it is important to make a prompt and accurate diagnosis. For this purpose, deep Convolutional Neural Network and discrete wavelet transform were used in this study to extract features from the X-ray images. Then, a Random Forest based bagging approach was used to detect whether the patient was positive for COVID-19 or not. The model performed with an overall accuracy of 99%.

Nomm et al. (2020) presented a machine learning model to distinguish between the Archimedean spiral drawing tests produced by the Parkinson's patients. Combination of both geometric and kinematic features were trained with Convolution Neural Network. The results exceeded the accuracy of classifier algorithms.

Soares et al. (2020) presented a model for simulating the adsorption of methylene blue dye in residual agricultural biomass. For this purpose, Random Forest and Artificial Neural Network were used in the model and a total of 202 experiments were conducted to validate the accuracy of the model. The results showed that it was possible to satisfactorily predict all response variables.

Zhang et al. (2020) proposed a model to identify the mechanical responses of caisson foundations in marine soils. Long Short-Term Memory (LSTM), a deep learning algorithm, was used in the study. As a result of the study, the LSTM based model showed a great potential for further engineering applications.

Elhag et al. (2021) presented a model to evaluate the potential for more waves of COVID-19 to occur. Since 2020, COVID-19 has caused human deaths and economic damage worldwide. This study aimed to assess the potential for further waves to occur and for this purpose Artificial Neural Networks and logistic regression were applied on the data collected from 32 European countries between January and May 2020.

Goyal et al. (2021) developed a model to automatically diagnose wheat diseases before crop spoilage. Wheat is the top three most harvested and consumed grain in the world, but most of it is spoiled due to diseases. The authors applied the Convolutional Neural Network architecture of VGG16 and ResNet to diagnose and classify diseases. The study was able to classify 10 different diseases with an accuracy of 98%.

Grimstad et al. (2021) presented a machine learning model to predict flow rates in oil and gas wells. Data-driven flow meters are important because they allow inexpensive evaluation and ease of calibration of new data. The aim of this study was to contribute to previous works on predicting the flow rates of oil and gas wells with a probabilistic virtual flow meter based on the Bayesian Neural Networks. For this purpose, data consisting of 60 wells across five different oil and gas assets was used. The results provided more robust estimates than the reference approach.

Ravnik et al. (2021) developed three different models to forecast natural gas consumption in the Energy sector. These models were: the sigmodal function regression, the feed-forward neural network, and the recurrent neural network. The training and validation data were gathered from 115 different stations in Slovenia and Croatia. The performance of the models was measured with mean absolute percentage error and the results showed that all three models performed similarly.

Withington et al. (2021) aimed to classify the pressure sensor data produced by medical detection dogs with machine learning. A detection dog is trained to recognize the odor emitted by one of wide variety of diseases. Pressure sensors were attached to the samples to generate data on the dog's foraging behavior. Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Fully Convolutional Network (FCN) and ResNet were used to classify the pressure data generated in the study.

Han et al. (2022) designed a classification model to detect crop lodging. Remote sensing image is a popular tool for this purpose but designing a robust model in an imbalanced distribution dataset is difficult. The authors used a combination of Synthetic Minority Oversampling Technique (SMOTE) and Edited Nearest Neighbors (ENN) method to treat imbalanced datasets. Then, employed a XGBoost model to identify the maize lodging at the plot scale. The results of the study were encouraging for further machine learning applications.

Sarpal et al. (2022) proposed an Android application for the agricultural workforce to yield better crop production. The study took place in India, where agriculture is the primary source of income for millions of people. The authors collected real-time data and used the Random Forest algorithm to predict suitable crops, taking into account the varying weather parameters. The study reduced water usage by more than 60%.

Table 2.2: Summary of the related works on machine learning applications

Author	Application Area	Algorithm
Najafi et al. (2012)	Fault diagnostics of air handling units	Bayesian
Wang et al. (2012)	Optimization of coal-fired power plants	Support Vector Regression, Genetic Algorithm
Candelieri et al. (2013)	Improving reliability of aircraft fuselage panels	Support Vector Machines, Artificial Neural Network
Mercer et al. (2013)	Warm weather rainfall prediction	Support Vector Machines
Yu et al. (2013)	Newspaper sales prediction	Support Vector Regression
Francis et al. (2014)	Predicting water pipe breaks	Bayesian Belief Networks
Sharif et al. (2015)	Determining the water quality and identifying the pollution sources	K-Means Algorithm
Tixier et al. (2016)	Predicting whether the injuries in construction are random or not	Natural Language Processing, Random Forest, Stochastic Gradient Tree Boosting
Raith et al. (2017)	Classification of dental cups from 3D scans	Artificial Neural Networks
Bhattacharya et al. (2018)	Predicting the presence of different facies and fractures in rocks	Bayesian Network Theory, Random Forest
Ip et al. (2018)	Managing plant diseases and crop yield losses	Markov Random Fields
Wang et al. (2018)	Optimizing therapeutic regimens for gastro-esophageal reflux	Artificial Neural Networks
Benson et al. (2019)	Creating a drone classifier	Drone Neural Network
Shaikhina et al. (2019)	Predict high-risk kidney transplants	Decision Tree, Random Forest

Li et al. (2020)	Predicting individual mobility	Long Short-Term Memory
Moorthy et al. (2020)	Detecting phishing attacks	K-Nearest Neighbor
Mostafiz et al. (2020)	Detecting COVID-19 from chest X-ray images	Convolutional Neural Network, Random Forest
Nomm et al. (2020)	Distinguishing between the Archimedean spiral drawing tests produced by Parkinson's patients	Convolution Neural Network
Soares et al. (2020)	Predicting the adsorption of methylene blue dye in residual agricultural biomass	Random Forest, Artificial Neural Network
Zhang et al. (2020)	Identification of the mechanical responses of caisson foundations in marine soils	Long Short-Term Memory
Elhag et al. (2021)	Predicting the potential for more waves of COVID-19 to occur	Artificial Neural Networks, Logistic Regression
Goyal et al. (2021)	Diagnosing wheat diseases automatically	Convolutional Neural Network, ResNet
Grimstad et al. (2021)	Predicting flow rates in oil and gas wells	Bayesian Neural Networks
Ravnik et al. (2021)	Forecasting natural gas consumption in the Energy sector	Sigmodal Function Regression, Feed-Forward Neural Network, Recurrent Neural Network
Withington et al. (2021)	Classifying the pressure sensor data produced by medical detection dogs	Multilayer Perceptron, Convolutional Neural Network, Fully Convolutional Network, ResNet
Han et al. (2022)	Crop lodging detection	Edited Nearest Neighbors, XGBoost
Sarpal et al. (2022)	Increasing crop production	Random Forest

2.3 Motive of the Study

While the global hunger crisis has begun to be felt all over the world, it is seen that there is not enough research on this subject and current technologies are not applied. Agriculture and livestock applications of today's technologies, especially machine learning, have not become popular enough. For example, the increase in hive losses worldwide is not a coincidence, it is an issue that requires immediate investigation and action for scientists.

There are 3 steps to consider in the application of technology in both agriculture and animal husbandry: data collection, data transfer and data analysis. In this study, these 3 fundamental steps have been followed and a solution has been developed that enables the tracking of hive losses under all conditions.

First of all, most of the apiaries are located in areas with poor or non-existent Internet network, which makes any application depending on Wi-Fi impractical. Even if cloud systems are to be used, the solution should be a hybrid combination of offline and online data transfer systems. With the offline system, data should be transferred to the beekeeper and then the data should be uploaded to the cloud when the Internet access is provided.

Secondly, instead of expecting a full-time beekeeper to analyze data, it would be a more feasible and realistic approach to guide the beekeeper through automatic analysis and/or setting alarm values to perform an inspection. Since it is not possible to define an exact value for the hive parameters, it would be appropriate to use machine learning for analyzing the data and creating a decision support system for beekeepers.

The motive of this study was to restrain Colony Collapse Disorder by developing a simple but reliable remote monitoring system that can be applied anywhere in the world. For that purpose, an offline system was designed to warn the beekeeper only when an anomaly occurs.

3. PROPOSED METHODOLOGY

The developed tool and its methodology are explained in 5 steps. First, the problem is defined, then the tool and model development and data collection methods are explained. Finally, the created solution is implemented to the developed tool. The implementation steps of the proposed methodology are shown in Figure 3.1.

Figure 3.1: Flow chart of the study

3.1 Problem Definition

The objective of the study is to develop a smart beehive monitoring system to prevent honeybee colony failures for apiaries including those that do not have access to utilities and Internet network. In this context, a tool developed to collect and transfer beehive data wirelessly and alert the beekeeper in case of anomalies (Figure 3.2).

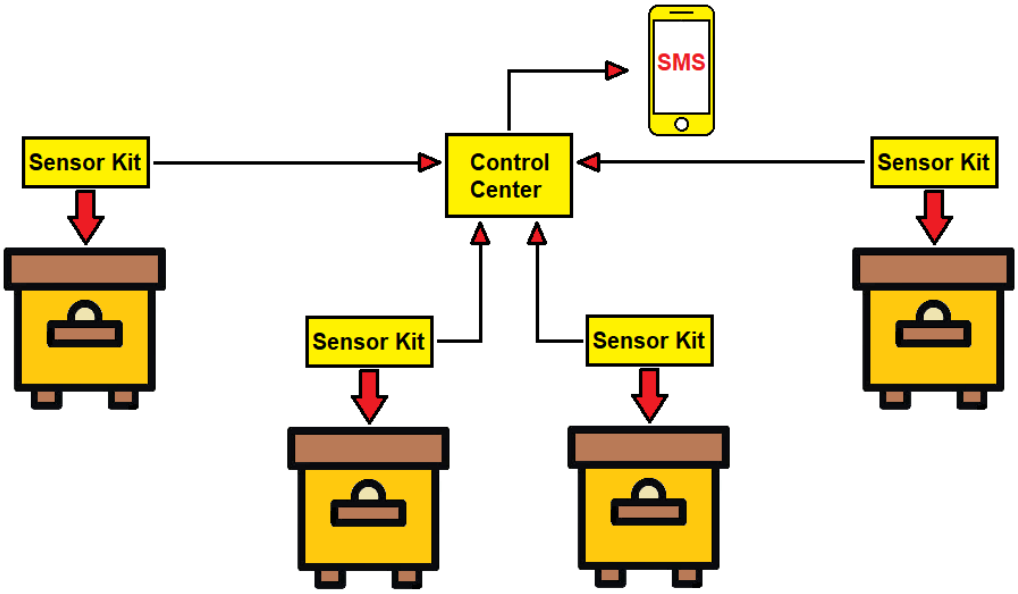

Figure 3.2: Tool to collect and transfer beehive data

3.2 Tool Development

3.2.1 Location and Duration of the Study

All experiments related to this study were performed at an apiary located in the village of Çanakkale in Turkey (40° 19’ 37” N & 26° 28’ 47” E) at an altitude of 110 meters. The city of Çanakkale has more than 80 thousand beehives and produced more than 1900 tons of honey in 2020. The study completed between August 2021 and May 2022, out of the honey harvesting season, in order to prevent interference on the sensors. The region has an annual mean temperature of 15.1°C. The coldest month is January, with minimum and mean temperatures of 3.1°C and 6.2°C, respectively; the warmest month is July, with maximum and mean temperatures of 30.7°C and 25.1°C, respectively.

The annual production of the apiary where this study was conducted is approximately 2 tons. Beekeeper Servet Yavuz is a retired accountant, and it has been observed that his habit of keeping records is better than other beekeepers contacted for the study. Produced honey is sold under the brand name of Ilgardere Bal (Instagram: ilgarderebal).

The apiary where the study took place has an average of 100 beehives with an average loss of 20 beehives per year, and only standard 10 framed Langstroth size beehives were used in the apiary.

The 2021-2022 winter season was much longer and harsher than previous years. The coldest month was still January, with significantly lower minimum and average temperatures of -6.3°C and 4.8°C, respectively. On the other hand, the hottest month was August, with remarkably higher maximum and mean temperatures of 40.8°C and 26.4°C, respectively. The monthly minimum, maximum and average values of temperature during the study shown in Table 3.1.

Table 3.1: Temperature values at the apiary during the study

Year	**Month**	**Temperature Average**	**Maximum Temperature**	**Minimum Temperature**
2021	August	26.4°C	40.8°C	17.0°C
2021	September	20.6°C	32.1°C	9.9°C
2021	October	14.4°C	24.1°C	7.1°C
2021	November	12.5°C	25.7°C	4.6°C
2021	December	8.2°C	16.6°C	-2.7°C
2022	January	4.8°C	17.3°C	-6.3°C
2022	February	7.1°C	17.3°C	-1.2°C
2022	March	5.2°C	20.0°C	-3.5°C
2022	April	13.4°C	26.7°C	3.9°C
2022	May	18.2°C	33.5°C	5.5°C

3.2.2 System Preparation with Arduino

The beehive monitoring system consists of two different modules: a control center (Figure 3.3) and sensor kits/RFID tags (Figure 3.4) that put inside the beehives. The control center has following characteristics: Arduino UNO board with ATmega328 processor, DHT21 temperature and relative humidity sensor, nRF24L01 2.4 GHz wireless transceiver module, GSM module and SD card module. All the sensor data are transmitted to the control center with radio frequency and saved on a removable SD card. The beekeeper is warned via SMS when an anomaly is detected. And the RFID tags have following characteristics: Arduino Nano board with ATmega328 processor, DHT21 temperature and relative humidity sensor, and nRF24L01 2.4 GHz wireless transceiver module were used.

Among the many technological options for wireless data transfer, the most ideal technological combination was chosen, considering energy consumption, data transfer distance, ease of prototyping in terms of cost and use, and module dimensions. The cost of prototype components given in Table 3.2.

Table 3.2: Cost of prototype components

Component	Cost
Control Center	
Arduino UNO (ATmega328)	29.98 €
DHT21 temperature and relative humidity sensor	9.84 €
nRF24L01 2.4 GHz wireless transceiver module	2.69 €
GSM module	21.99 €
SD card module	3.29 €
Sensor Kit	
Arduino Nano (ATmega328)	17.98 €
DHT21 temperature and relative humidity sensor	9.84 €
nRF24L01 2.4 GHz wireless transceiver module	2.69 €
Other	
Jumper wires	8.98 €
Breadboards	8.95 €
Batteries	2.00 €
Consumables	4.00 €

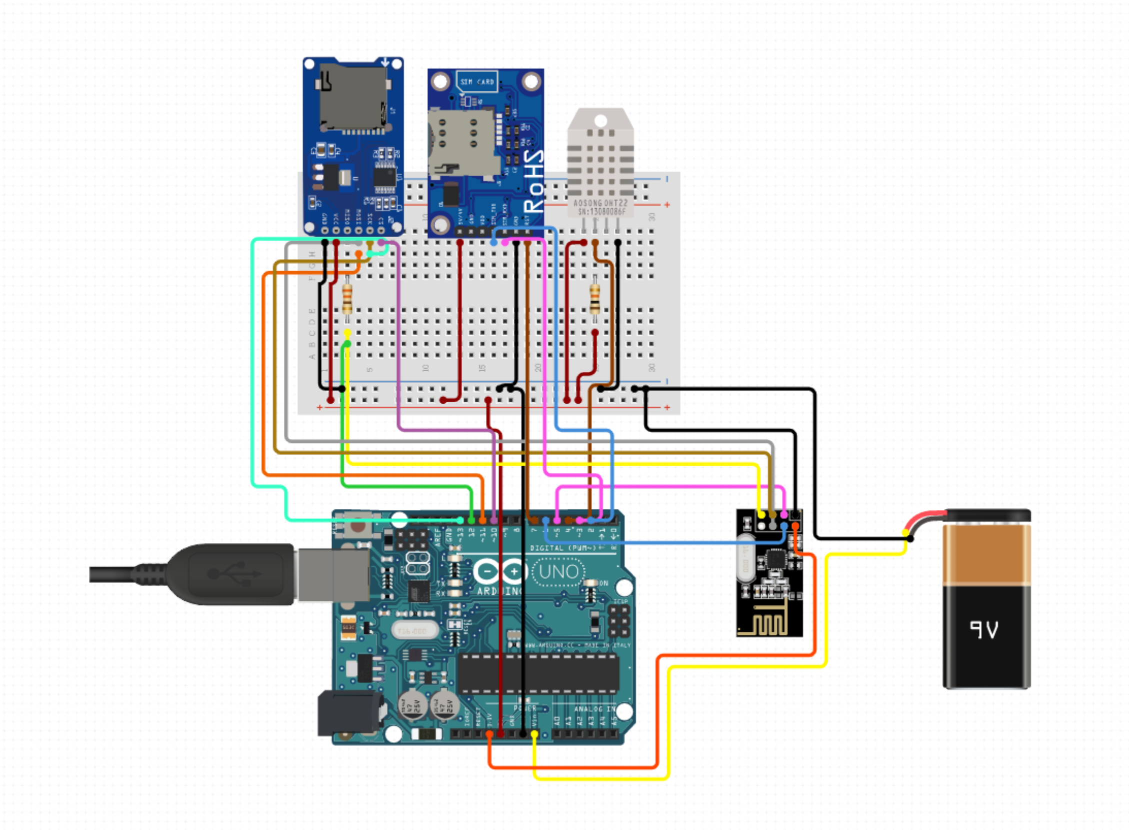

Figure 3.3: Simulation diagram of the control center

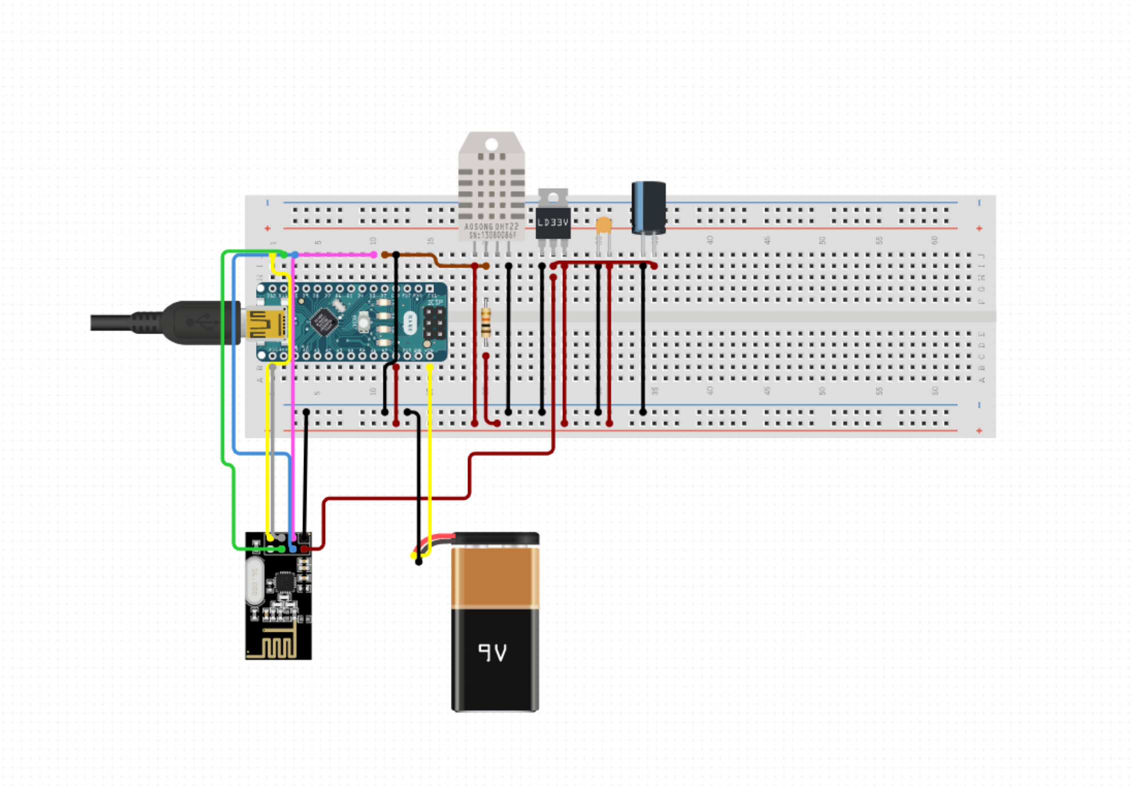

Figure 3.4: Simulation diagram of the sensor kits/RFID tags

DHT21 sensor has a measuring range between -40°C and 80°C (with an accuracy of 0.5°C), 0% and 100% (with an accuracy of 3%) for temperature and relative humidity, respectively. The nRF24L01 single chip wireless transceiver was chosen because of its low power operation (around 12 mA during transmission), adequate data rate (up to 2 Mbps) and high communication range (over 50 meters). Moreover, up to 256 nRF24L01 modules can be connected to a single transmitting module. Since an average apiary has 100 beehives, the system can be managed by only one control center.

Honeybees maintain the inside temperature and relative humidity of the beehive around 35°C and 70%, respectively. Temperature values change between 10°C and 36°C. Relative humidity values vary between 40% and 100%. The selection of equipment that can operate continuously in these challenging temperature and relative humidity values is of great importance for the sustainability and accuracy of the study.

All the components of the monitoring system are resistant to the harsh conditions of a beehive interior by having operating temperature range between -40°C and 80°C, and relative humidity between 20% and 90%. Also, each module of the system is powered by 9V batteries to generate continuous energy supply.

In addition to above information, it is known that honeybees seal all kinds of holes and foreign material with propolis to keep the hive clean and sterile. Removing frame, cutting out some part of the frame and/or drilling holes on the beehive were improbable since that would negatively affect the processes of harvesting, inspection, and honey production. For this reason, beehive monitoring tools should be designed according to these conditions.

Housing of the system was designed both to fit between the frames, and easy to put on and take off. Additionally, as a precaution to prevent system damage can be caused by honeybees, different housing variations were tested with data loggers. The tested housing variations were made of PVC, wood, cotton, and nylon. During the study, regular inspections were made to check the condition of the data loggers, the system components, and the honeybees.

3.3 Data Collection

The apiary where this study was performed uses only standard 10 framed Langstroth size beehives. Two beehives, hive 17 and 85, were randomly chosen for the study. Later, due to the loss of hive 17, hive 36 was included the study. Temperature and relative humidity data loggers were located at the center of the beehives since it is the core of each hive. The data loggers have a measuring range between -30°C and 60°C (with an accuracy of 0.5°C), 0% and 100% (with an accuracy of 3%) for temperature and relative humidity, respectively. The core is the place where queen bee is found and where the formation of honey takes place (Catania et al., 2019). The ambient and beehives’ internal temperature and relative humidity data were recorded every 60 minutes during the study.

It was mentioned in the previous section that honeybees cover all foreign material with propolis. For the study to continue without any problems in both hardware development and data collection phases, the possibility of damage to the equipment by the contact of propolis and honey should be considered. In addition, it should be noted that the beehives cannot be inspected during the winter season, and therefore it will not be possible to diagnose and correct any malfunctions.

Due to the above reasons, RFID sensor kits and control center weren’t used until the end of the winter to prevent any damage to the system that can be caused by environmental and meteorological conditions. During this time, beehive data were measured with data loggers, and ambient data were obtained from Meteoblue.

Apiaries often located in the areas where utilities such as electricity and internet network does not exist. These factors considerably impair the possibility of continuous monitoring, data transferring and applying any smart system. Therefore, to design and test a system that fits for real life scenarios, only temperature and relative humidity data were recorded.

3.4 Model Development

The objective of the study was to create a monitoring system that warns the beekeeper when only an anomaly occurs. Abou-Shaara et al. (2012) suggested that the best condition for honeybees is the beehive's interior temperature and relative humidity values constant (or around) at 35°C and 75%, respectively. However, that is not the case in actual fact, and a methodology is required to calibrate the warning system. Therefore, an unsupervised machine learning algorithm needed to be used.

First, a dataset consisting of daytime, beehive temperature, beehive relative humidity, beehive apparent temperature, ambient temperature, ambient relative humidity, ambient apparent temperature, temperature difference between beehive and ambient, and apparent temperature difference between beehive and ambient were prepared to be used for calibration.

Apparent Temperature (AT) is the perceived temperature invented by Robert Steadman to define thermal comfort. The definition of the Apparent Temperature is given in Equation (1).

$$AT = T + 0.348 * \left(\frac{RH*6.105}{100}\right) * \left(e^{\frac{17.27*T}{237.7+T}}\right) - 0.70 * WS + 0.70\left(\frac{Q}{WS+10}\right) - 4.25 \quad (1)$$

Where T is temperature (°C), RH is relative humidity (%), WS is wind speed (m/s) and Q is radiation (W/m2). The effect of solar radiation was neglected since the beehives used in this study were in the same place. Also, there is no direct measurement of the wind originating from wing flaps of honeybees inside the beehive. Therefore, while calculating the Apparent Temperature inside the beehive, wind speed and radiation were taken as 0.

In order to understand the data, Exploratory Data Analysis (EDA) was performed using statistical methods. Mean, standard deviation, quartiles and skewness were calculated. Later, outlier data was removed from the dataset using the interquartile range (difference between quartiles 1 and 3). Then, the data was normalized and set by the min-max method to be used in the unsupervised machine learning algorithm.

The dataset shows a cyclical time series characteristic since it is comprised of hourly temperature and relative humidity values. However, time series needs decomposing from seasonal components to improve forecasting accuracy. For this reason, Fast Fourier Transform is used for decomposing functions depending on time into functions depending on frequency. The Fast Fourier Transform can show the frequencies by detecting the day/night and summer/winter variations in the data.

A Recurrent Neural Network (RNN) is a special class of Artificial Neural Networks adapted to work for data that consisting of sequences such as time series. Ordinary feedforward neural networks are only for independent data points. However, if there is data in a sequence such that one data point is dependent on the previous data point, it is necessary to modify the neural network to combine the dependencies between these data points. RNNs have the concept of "memory" which helps them store the states or information of previous inputs to generate the next output of the sequence.

A simple RNN has a feedback loop as shown in the Figure 3.5. The feedback loop shown in the red box can be unrolled in 3-time steps to create the second network of the figure. The architecture can be changed to unroll the network k-time steps. Variables used in the Figure 3.5 are listed below.

- x_t : Input at time step t.
- y_t : Output of the network at time step t.
- h_t : Values vector of the hidden units/states at time t.
- w_x : Weights related to inputs in recurrent layer.
- w_h : Weights related to hidden units in recurrent layer.
- w_y : Weights related to hidden to output units.
- b_h : Bias related to the recurrent layer.
- b_y : Bias related to the feedforward layer.

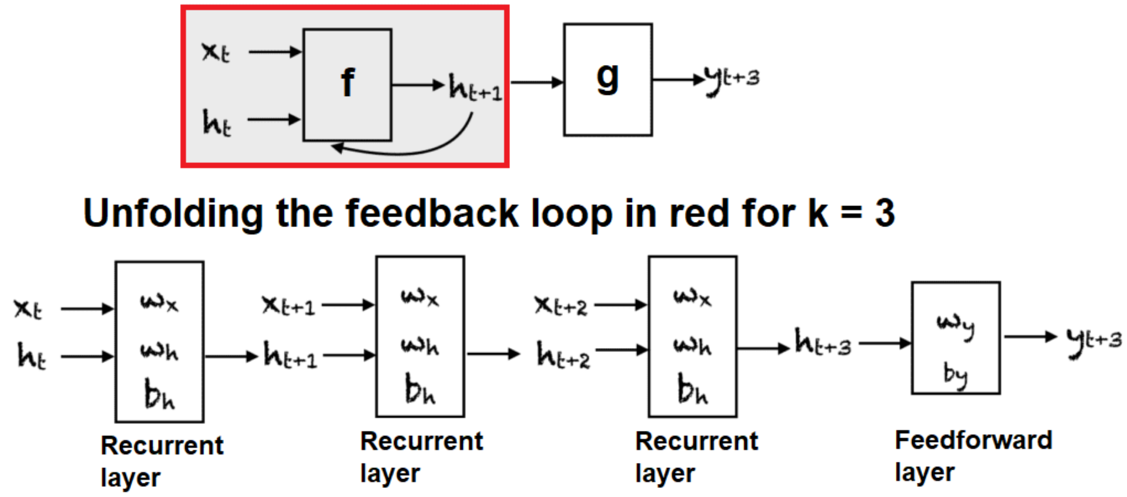

Figure 3.5: Compressing and unfolding RNN

At each time step, the network can be unfolded for k-time steps to get the output at time step k+1. The unfolded network is quite similar to the feedforward neural network. The box in the unfolded network shows an operation taking place. An activation function f is shown as an example in Equation (2).

$$h_{t+1} = f(x_t, h_t, w_x, w_h, b_h) = f(w_x x_t + w_h h_t + b_h) \tag{2}$$

Computation of the output y at time t is shown in Equation (3).

$$y_t = f\left(h_t, w_y\right) = f(w_y \cdot h_t + b_y) \tag{3}$$

In the feedforward pass of a RNN, the network computes the values of the hidden units and the output after k-time steps. Each recurrent layer has set of input and hidden unit weights. The last feedforward layer that computes the final output for the kth time step is similar to a regular layer of a traditional feedforward network.

Various advantages of the RNNs are listed below.

- Ability to run sequence data.
- Ability to process inputs of different lengths.
- Ability to store and memorize historical information.

On the other hand, the disadvantages of the RNNs are listed below.

- Model run may be very slow.
- Future inputs are not considered for decision making.
- Gradients approach zero and prevent the network from learning new weights as the network gets deeper.

Long Short-Term Memory (LSTM) is a specific Recurrent Neural Network (RNN) architecture that was designed to recognize patterns and model temporal sequences and their dependencies. RNN has neurons and their connections, the weight of every connection is calculated through Back Propagation. Back Propagation moves backward from the final error through the outputs, weights and inputs of each hidden layer assigning those weights responsibility for a portion of the error and recalculating the different weights until the composition that minimizes the error is found (Braga et al., 2019).

A single LSTM unit, shown in Figure 3.6, consists of 4 different components: a forget gate, an input gate, an output gate, and a cell. The gates regulate the information flow in and out of the cell and the cell remembers values over arbitrary time intervals.

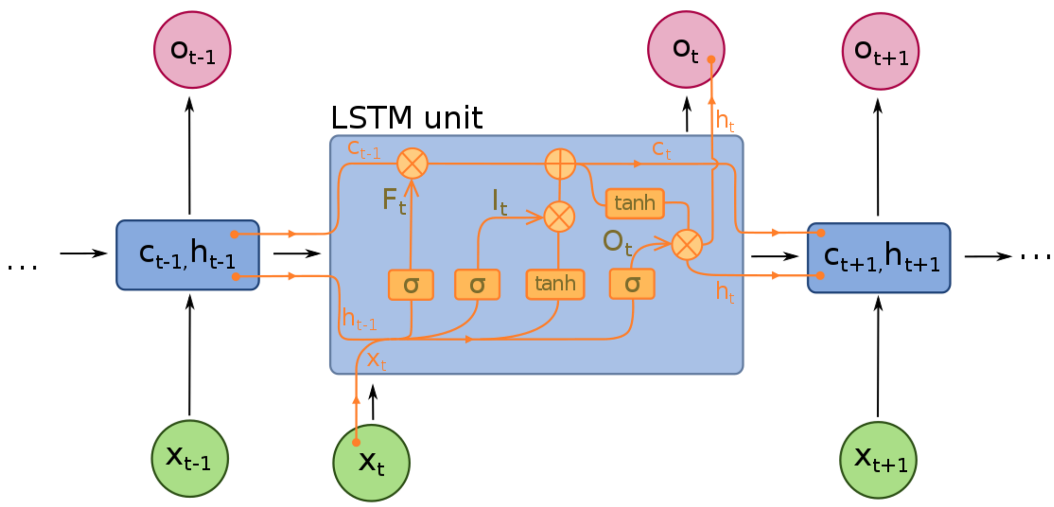

Figure 3.6: Long Short-Term Memory unit

The forget gate is responsible for deciding what information to discard or hide from the final step. This part is done by the first sigmoid layer. The forget gate decides a value between 0 and 1 for each value in cell state (c_{t-1}) based on the previous hidden state (h_{t-1}) and current input at time step t (x_t). For each value of 1, all the information is kept intact. And for each 0 value, all the information is discarded, and it is decided how much information from previous states are to be carried to next state by evaluating other values.

The input gate decides what new information is to be stored in the cell state. First, input gate layer decides which values are to be updated. Next, a vector of new candidate values is created by a tanh layer.

The cell state serves as the memory of an LSTM unit. At each time step, the previous cell state (c_{t-1}) combines with the forget gate to decide what information to carry forward, which in turn combines with the input gate (i_t and c_t) to create the new cell state or the new memory of the cell.

The LSTM unit gives outputs through the output gate. The obtained cell state is passed through a hyperbolic function called tanh to filter the cell state values between -1 and 1.

Before deploying the LSTM model, the number of epochs and batches, and the data used for training/testing shall be determined. An epoch is the number of passes of the entire training data the model will complete. A small epoch number would cause a model not predicting values with high precision (underfitting). On the other hand, a big epoch number would cause a model to learn the details and noise in the data which also negatively affect the performance of the model (overfitting). An epoch consists of one or more batches. Popular number of epochs are 10, 50, 100, 500 and 1000.

Learning curves often used to determine whether the model is overfitting, underfitting or a good fit. A representative image of each 3 fit condition is given in Figure 3.7. A learning curve is a line plot that shows epochs along the x-axis as time and the skill or error of the model on the y-axis.

On the other side, a batch is a hyperparameter that defines the number of samples to work through before updating the internal model parameters. A batch can be described as a for loop iterating over samples and making predictions. At the end of the batch, the predictions are compared to the expected output variables and an error is calculated. Using the calculated error, the algorithm is updated to improve the model.

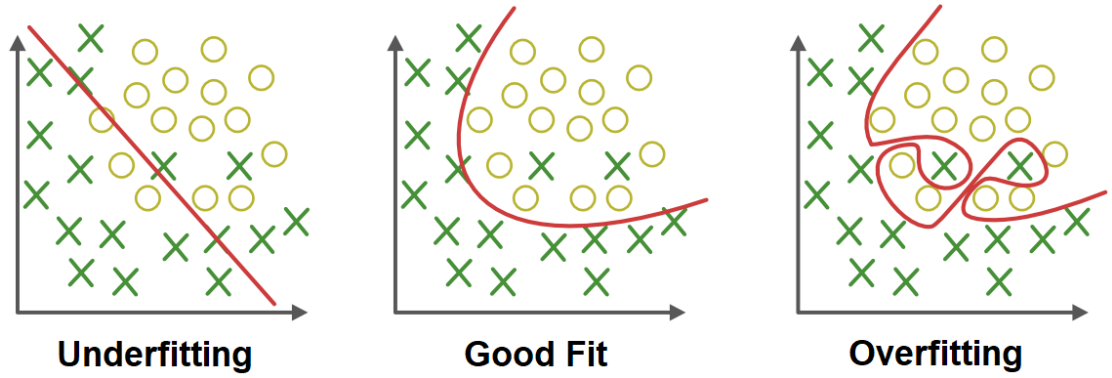

Figure 3.7: Representative image of underfitting, overfitting and a good fit

As listed below, a training dataset can be divided into one or more batches.

1. Batch gradient descent:
   Batch size = Size of training dataset
2. Stochastic gradient descent:
   Batch size = 1
3. Mini-batch gradient descent:
   1 < Batch size < Size of training dataset
   Popular batch sizes are 10, 32, 64 and 128.

Both hyperparameters (batch and epoch) must be determined for an LSTM model to run. There are no strict rules or shortcuts on how to configure these hyperparameters. As a start, different combinations of popular epoch and batch values should be tried and the best ones for the model should be selected.

In this study, considering the runtime and accuracy of the model, the optimum hyperparameters were determined as 100 epochs and 10 batches. Beehive 85 was used for training since it was stronger and more stable than others, and beehive 17 and 36 was used for testing the model.

3.5 Solution Deployment

After training the model with continuous data between August 2021 and May 2022, the final steps of determining the threshold value and transferring codes to Arduino were completed to deploy the solution.

The accuracy of the model was summarized and evaluated with Mean Absolute Error (MAE) and a suitable threshold value was determined for identifying anomalies. The threshold value shall be set above noise level so that false positives are not triggered. Based on the loss distribution shown in Figure 3.8, threshold value of 0.06 was used.

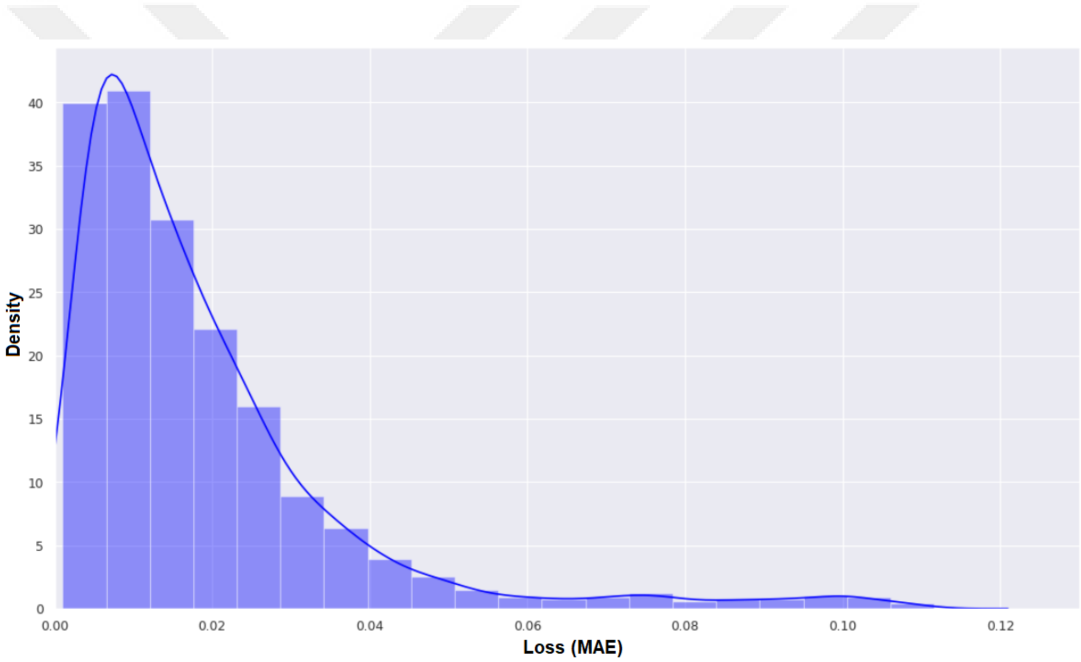

Figure 3.8: Loss of distribution of the LSTM model

So far, the machine learning model has been trained in a Python environment with a virtual computer with 16 GB of RAM. However, the control center of the monitoring system is equipped with Arduino UNO with 2 KB of RAM. In addition, the Arduino environment supports and uses simplified versions of the C and C++ programming languages to develop software for Arduino boards.

For the reasons explained above, necessary changes were made to implement and execute the code on the Arduino UNO. First, Python and its libraries were replaced by the C++

programming language and the layer math of LSTM algorithm of Recurrent Neural Networks, respectively. Next, the code was transferred to the Arduino board and executed for several times to test whether it works without any issues.

It should be taken into account that the tests are carried out at room conditions (approximately 25°C and 40% relative humidity) and that there may be various malfunctions due to ambient conditions under real operating conditions (average 35°C and 70% relative humidity).

4. OBTAINED RESULTS

A total of 12146 registrations were collected from 3 different beehives between 21.08.2021 and 01.05.2022. Important dates of the study shown in Table 4.1.

Table 4.1: Important dates of the study

Date	Description
10.08.2021	End of honey harvest.
21.08.2021	Inspection and dataloggers were placed in hive 17 and 85.
22.08.2021	Feeding sugar syrup.
05.09.2021	Inspection and data collection.
13.09.2021	Feeding sugar syrup.
17.09.2021	Amitraz treatment in hive 85.
22.09.2021	Amitraz treatment in hive 17 and 36.
28.09.2021	Formic Acid treatment in hive 85.
30.09.2021	Feeding sugar syrup.
03.10.2021	Formic Acid treatment in hive 17 and 36.
05.10.2021	Feeding sugar syrup.
08.10.2021	Feeding sugar syrup.
31.10.2021	Inspection. Loss of hive 17.
06.11.2021	Inspection and data collection. Dataloggers were placed in hive 36 and 85.
08.11.2021	Formic Acid treatment in hive 85.
10.11.2021	Formic Acid treatment in hive 36.
15.11.2021	Hives winterized and closed down.
16.04.2022	First inspection after winter. Feeding sugar cake and data collection.
01.05.2022	Inspection and data collection. Sensor kit was placed in hive 36.

The results of the study are explained in order according to the flow chart shown in Figure 3.1.

4.1 Results of Problem Definition

In the applications made with the preliminary results and objective of the study, a grand prize of 10.000 Euros was won from TÜBİTAK and poster presentation was accepted from 47th APIMONDIA - International Apicultural Congress.

Apimondia is the biggest non-governmental apicultural organization that brings together beekeepers, manufacturers of beekeeping equipment and scientists working on apiculture, apitherapy, pollination, development, and economics. Since 1893, Apimondia has been organizing apiculture events and the biennial International Apicultural Congresses. The abstract of the study was submitted in November 2021, and the acceptance of poster presentation was announced in May 2022.

TÜBİTAK 1512 Entrepreneurship Support Program (BIGG) is the biggest individual technological venture capital support program that enables entrepreneurs to turn their technology and innovation-oriented business ideas into qualified business plans and become companies with capital support. The theory of the study was presented in April 2021, and the winners of the program were announced in January 2022.

4.2 Results of Data Collection and Development Processes

Figure 4.1 shows ambient and internal temperature of the beehives. The internal temperature remained between 8°C and 38°C for the entire period while the ambient temperature showed a high variability: 34°C maximum and -6°C minimum. The average temperature difference between day and night was 4.9°C.

Measures of the internal temperature of colony 17 started around 33°C and dropped below 15°C while hive 85 maintained its internal temperature between 36°C and 25°C. After training, the model detected anomalies in colony 17 (Figure 4.2) in mid-September (Table 4.2). Eventually, despite the Amitraz and Formic Acid treatments, the colony 17 couldn't restore its descending temperature and failed in October.

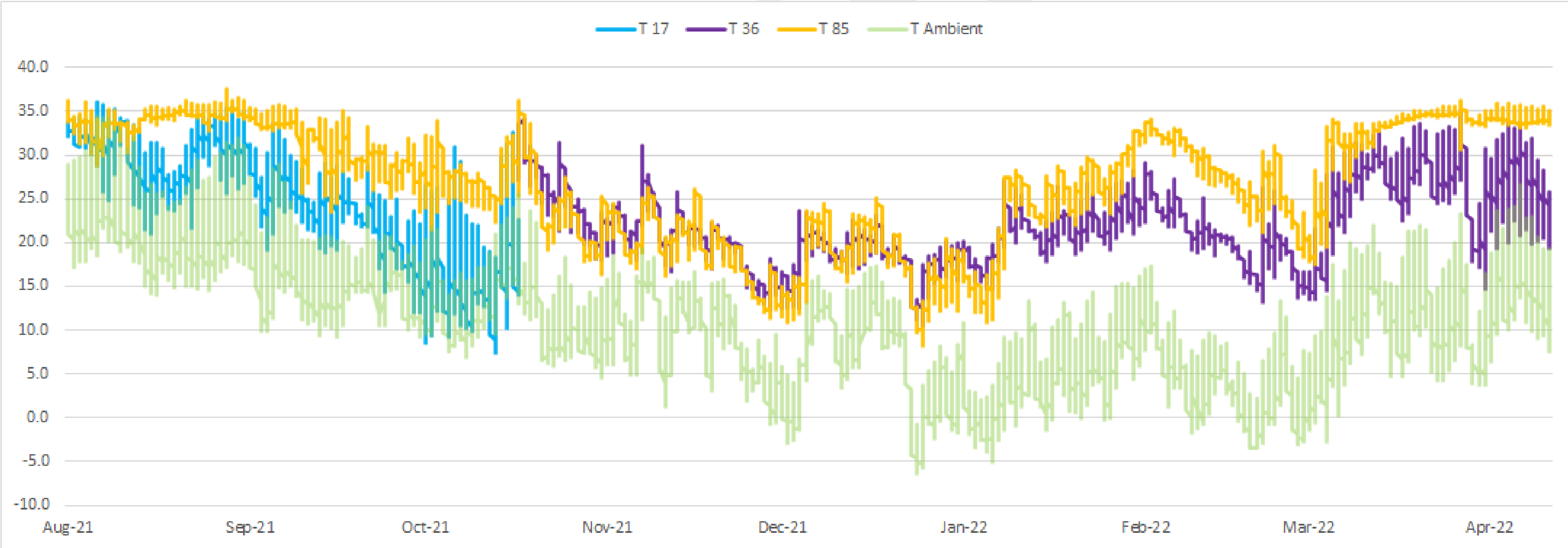

Figure 4.1: Temperature values of ambient, hive 17, hive 36 and hive 85

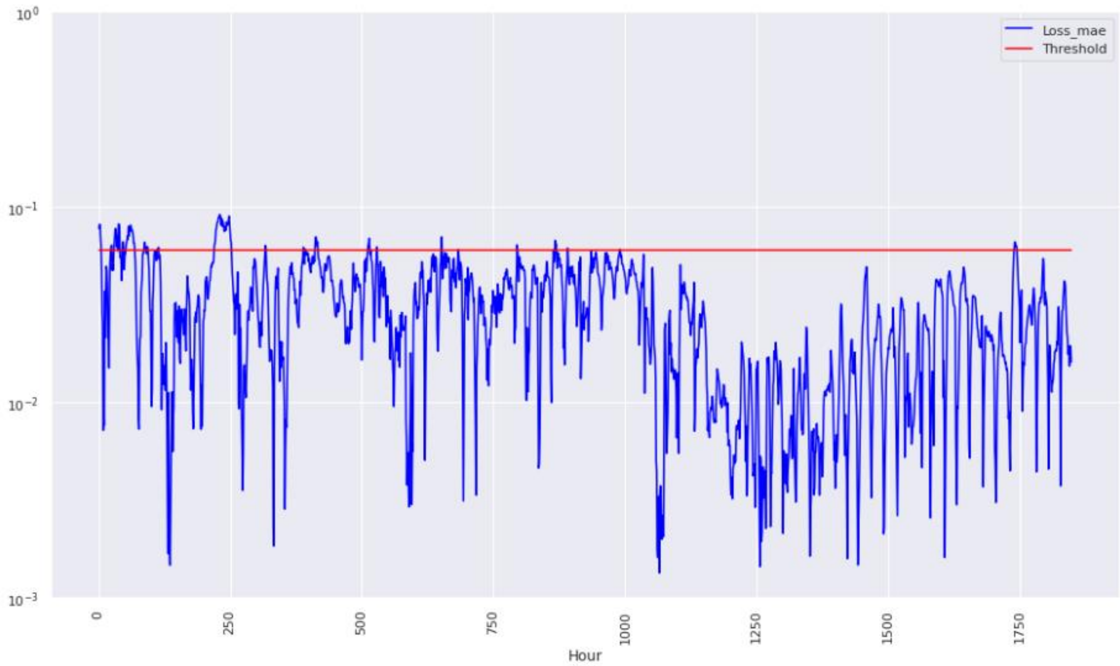

Figure 4.2: Detected anomalies in colony 17

Table 4.2: Detected anomalies in colony 17 in September

Date	Loss (MAE)	Threshold	Anomaly
01.09.2021	0.067420	0.06	True
03.09.2021	0.063319	0.06	True
06.09.2021	0.062028	0.06	True
07.09.2021	0.070148	0.06	True
11.09.2021	0.065070	0.06	True
17.09.2021	0.070220	0.06	True
19.09.2021	0.060372	0.06	True
26.09.2021	0.067274	0.06	True

As of mid-March, the model detected anomalies in colony 36 (Figure 4.3 and Table 4.3) possibly due to lack of food. After the first feeding session of the spring in mid-April, the anomalies stopped in colony 36. The deterioration in thermoregulation can be observed from temperature (Figure 4.1) and relative humidity (Figure 4.5) data. Throughout the study, colony 85 displayed a strong and stable appearance with negligible number of anomalies.

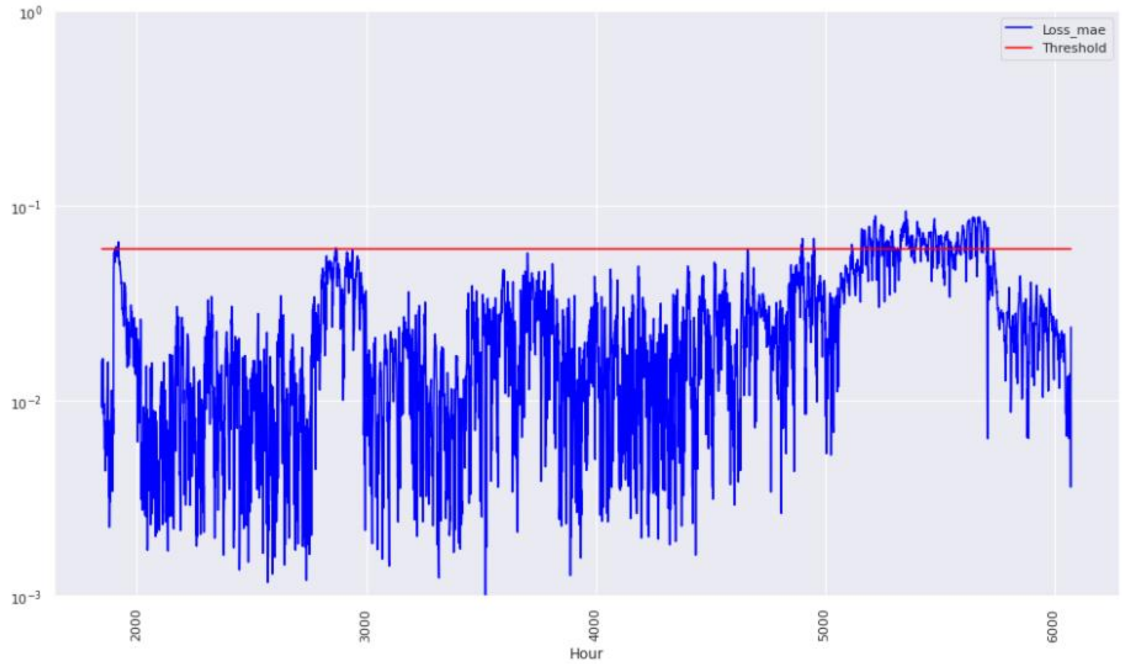

Figure 4.3: Detected anomalies in colony 36

All the anomalies detected in colony 85 (Figure 4.4 and Table 4.4) were on the days that the hive was inspected, fed sugar syrup, or treated with Formic Acid. Considering its honey production, hive 85 was known to be one of the strongest hives in the apiary, and the anomaly results confirmed this.

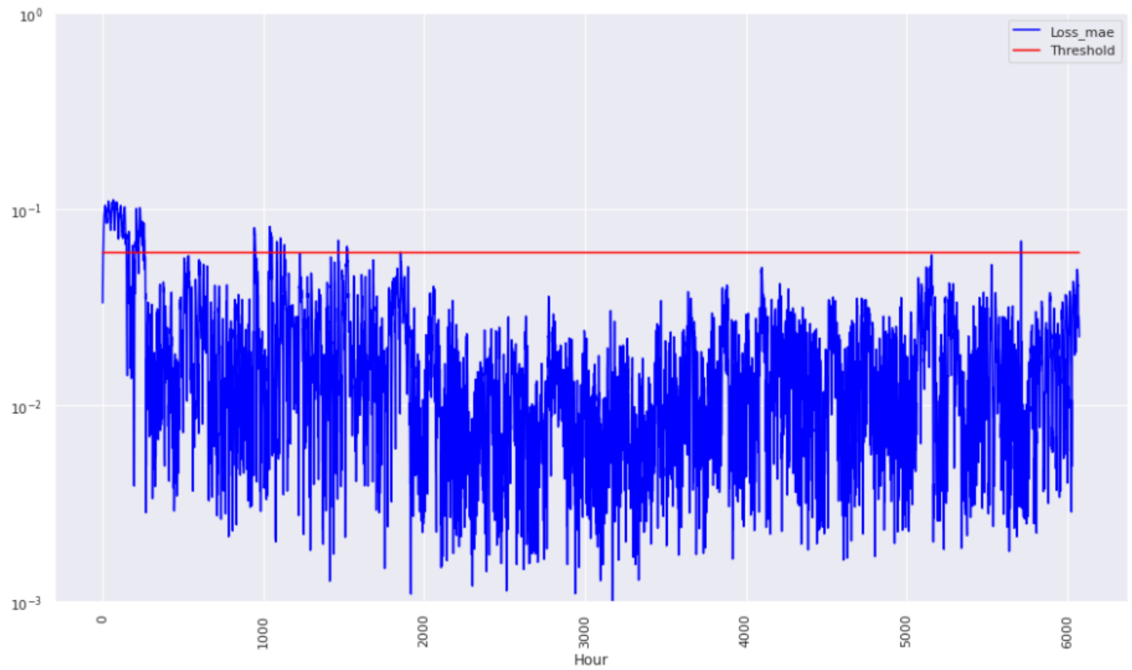

Figure 4.4: Detected anomalies in colony 85

Table 4.3: Detected anomalies in colony 36

Date	Loss (MAE)	Threshold	Anomaly
13.03.2022	0.067854	0.06	True
15.03.2022	0.067961	0.06	True
16.03.2022	0.060219	0.06	True
22.03.2022	0.063344	0.06	True
24.03.2022	0.076177	0.06	True
25.03.2022	0.078276	0.06	True
26.03.2022	0.083008	0.06	True
27.03.2022	0.088519	0.06	True
28.03.2022	0.078104	0.06	True
29.03.2022	0.070183	0.06	True
30.03.2022	0.074305	0.06	True
31.03.2022	0.072873	0.06	True
31.03.2022	0.076165	0.06	True
01.04.2022	0.081010	0.06	True
02.04.2022	0.070541	0.06	True
03.04.2022	0.08278	0.06	True
04.04.2022	0.07204	0.06	True
05.04.2022	0.073001	0.06	True
06.04.2022	0.085763	0.06	True
07.04.2022	0.070601	0.06	True
08.04.2022	0.072583	0.06	True
09.04.2022	0.072556	0.06	True
10.04.2022	0.067699	0.06	True
11.04.2022	0.072883	0.06	True
12.04.2022	0.083265	0.06	True
13.04.2022	0.084653	0.06	True
14.04.2022	0.086117	0.06	True
15.04.2022	0.084357	0.06	True
16.04.2022	0.079339	0.06	True

Table 4.4: Detected anomalies in colony 85

Date	Loss (MAE)	Threshold	Anomaly
21.08.2021	0.090818	0.06	True
22.08.2021	0.102220	0.06	True
23.08.2021	0.101275	0.06	True
24.08.2021	0.111592	0.06	True
25.08.2021	0.108409	0.06	True
26.08.2021	0.100963	0.06	True
27.08.2021	0.097267	0.06	True
28.08.2021	0.076996	0.06	True
30.08.2021	0.100586	0.06	True
31.08.2021	0.086474	0.06	True
01.09.2021	0.084777	0.06	True
29.09.2021	0.078509	0.06	True
30.09.2021	0.074631	0.06	True
03.10.2021	0.081491	0.06	True
04.10.2021	0.076226	0.06	True
05.10.2021	0.068389	0.06	True
06.10.2021	0.068337	0.06	True
07.10.2021	0.065824	0.06	True
21.10.2021	0.069353	0.06	True
23.10.2021	0.064399	0.06	True
24.10.2021	0.062714	0.06	True
06.11.2021	0.060272	0.06	True
16.04.2022	0.068652	0.06	True

Additionally, Figure 4.5 shows ambient and internal relative humidity of the beehives. The internal relative humidity remained between 29% and 100% with an average of 65% during the study. Meanwhile, the ambient relative humidity of the apiary has minimum, maximum and average values of 17, 100 and 71, respectively.

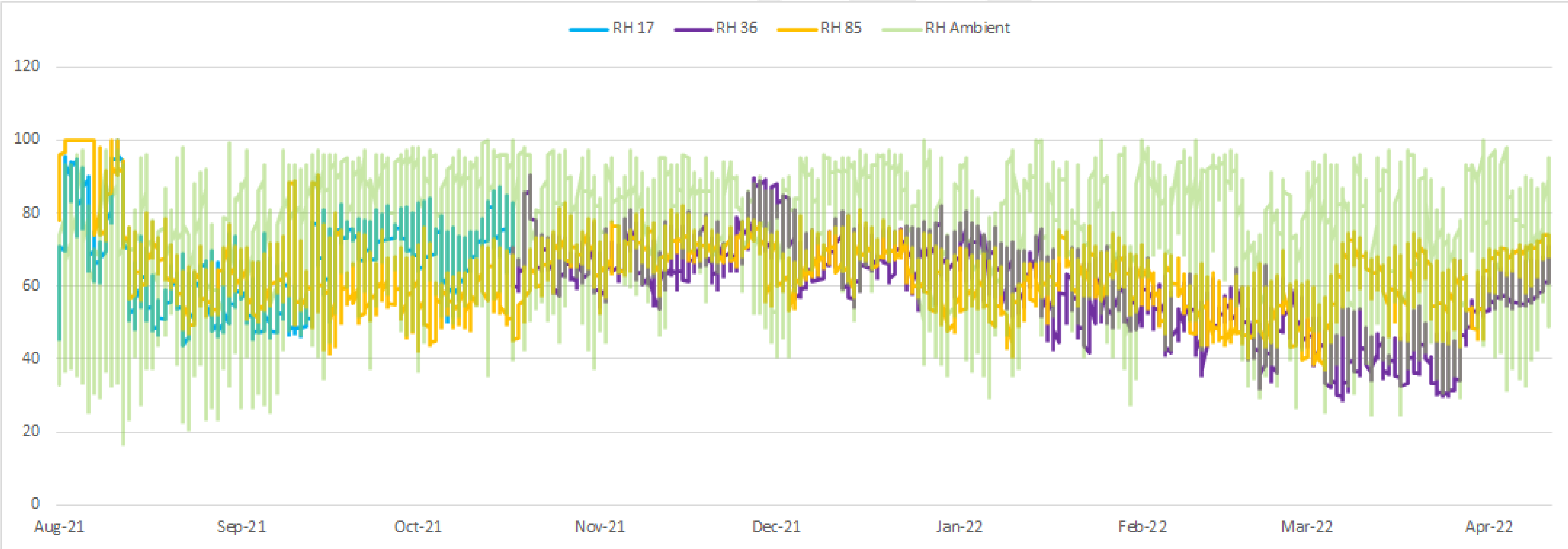

Figure 4.5: Relative humidity values of ambient, hive 17, hive 36 and hive 85

Critical values of the beehives are shown in the Table 4.5. Maximum values were generally recorded around 13:00, and minimum values were recorded after sunset. Therefore, the best time for a beekeeper to inspect the hives is between 12:00 and 19:00.

Table 4.5: Critical values of the beehives

Source		Mean	Std. Dev.	Min	Max
Ambient	Temperature	11	7	-6	34
	Relative Humidity	71	18	17	100
	Apparent Temperature	11	9	-10	36
Hive 17	Temperature	25	7	8	36
	Relative Humidity	67	12	44	100
	Apparent Temperature	28	9	6	48
Hive 36	Temperature	22	5	11	35
	Relative Humidity	60	12	29	90
	Apparent Temperature	23	6	9	44
Hive 85	Temperature	27	7	8	38
	Relative Humidity	64	10	38	100
	Apparent Temperature	31	10	6	52

Training accuracy of the LSTM model, evaluated with Mean Absolute Error (MAE), is shown in Figure 4.6. The MAE of the model is less than 0.025, which means that the model detects anomalies with great accuracy.

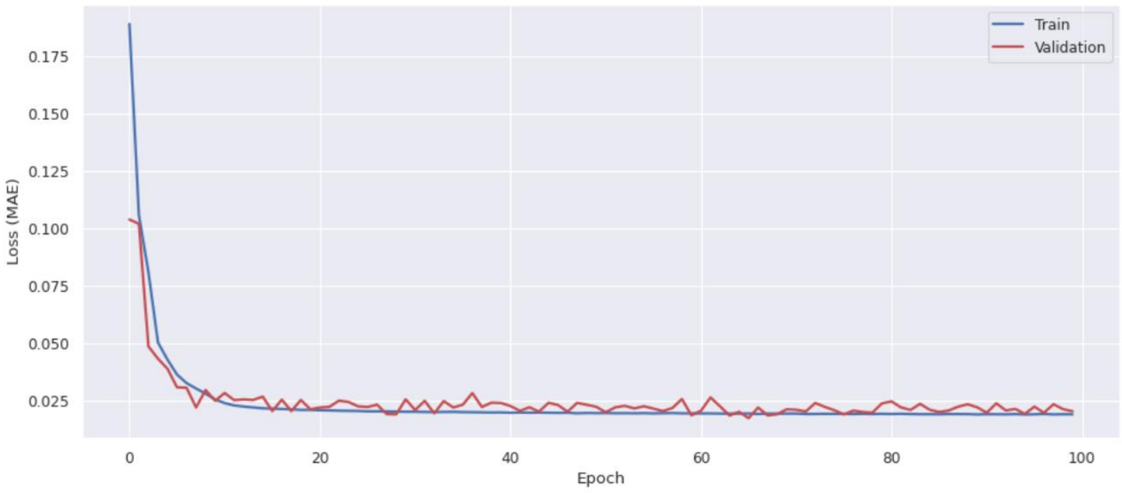

Figure 4.6: Training accuracy of the LSTM model

The best housing variation is a combination of PVC case and nylon wrap. Wrapping the system housing is necessary since the honeybees cover the sensors with honey, wax and propolis. Pouches made of cotton were heavily deformed while nylon wraps were intact. On the other hand, PVC was preferred due to its accessibility and diversity over wood. Before and after photos of all variations are shown in Figure 4.7 through Figure 4.11.

Figure 4.7: Cotton pouch with PVC data logger – Before

Figure 4.8: Cotton pouch with PVC data logger – After

Figure 4.9: PVC data logger in cotton pouch – After

Figure 4.10: Nylon wrap with PVC data logger – After

Figure 4.11: PVC data logger in nylon wrap – After

4.3 Results of Solution Deployment

After the hardware and model development was completed, the monitoring system was placed in the hive 36 with the data logger on May 1, 2022. In the month of June 2022, when this article was completed, the system has not detected any anomalies yet.

In the next inspection, the accuracy of the monitoring system results will be checked when comparing with the data logger measurements. Possible system errors and their causes are explained in the discussion section.

5. DISCUSSION

The results of this study, which lasted more than 6000 hours, showed that the model was able to detect anomalies weeks before failure, providing sufficient time to avoid colony loss. Also, it was obtained in this study demonstrate that ambient temperature shows a high variability; there are daily differences up to 17°C. However, inhive temperature values always remained above 8°C even when the ambient temperature was around -3°C. The honeybees kept the colony within a temperature range of 8°C – 38°C. Otherwise, it could mean hive is starving, queen is failing or brood diseases.

Meanwhile, relative humidity of the beehives remained between 29% and 100% while the ambient relative humidity fluctuated between 17% and 100%. The 100% relative humidity values of the hives implies that there was honey to be harvested in the hives. It is known that if the relative humidity inside the beehive is below 50%, eggs in the brood cells do not hatch. Moreover, during winter period, it can be understood that colony is starving if the relative humidity is too low.

When the data of hive 17 was implemented to LSTM model, the model detected anomalies 4 weeks prior to the loss of colony. This period of anomaly intercepts with manual inspections (i.e: feeding, medicating etc.) done by the beekeeper. However, the weakening of the hive 17 wasn’t recognizable with bare eyes.

Even if the hive 85 was the stronger and more stable colony used in the study, it also has the lowest temperature and apparent temperature records. This was probably due to the extreme cold of January, hive parameters improved later on.

In November, a sudden and sharp decrease in relative humidity which later stabilized around 10 days was observed at hive 36 (Figure 5.1). This anomaly intersects with Varroa destructor treatment with Formic Acid.

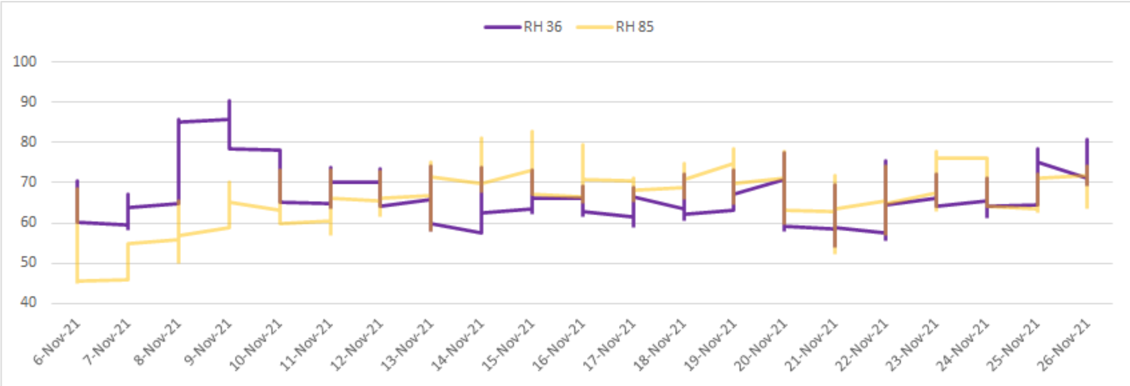

Figure 5.1: Relative humidity change of hive 36 due to Varroa treatment

In the view of the results, it is unlikely to define a function and/or fixed limit values for the monitoring system. Doing so would trigger a large number of false positive outputs. The RNN algorithm makes its decisions not only by evaluating the inhive measurements, but also considering the ambient parameters.

After the calibration with winter data was completed, the monitoring system (Figure 5.2 and Figure 5.3) was placed in hive 36 (Figure 5.4 and Figure 5.5) to provide data for further studies.

At the time this article was completed (early June 2022), the monitoring system did not detect any anomalies. Several reasons for this situation and their solutions are shown in Table 5.1.

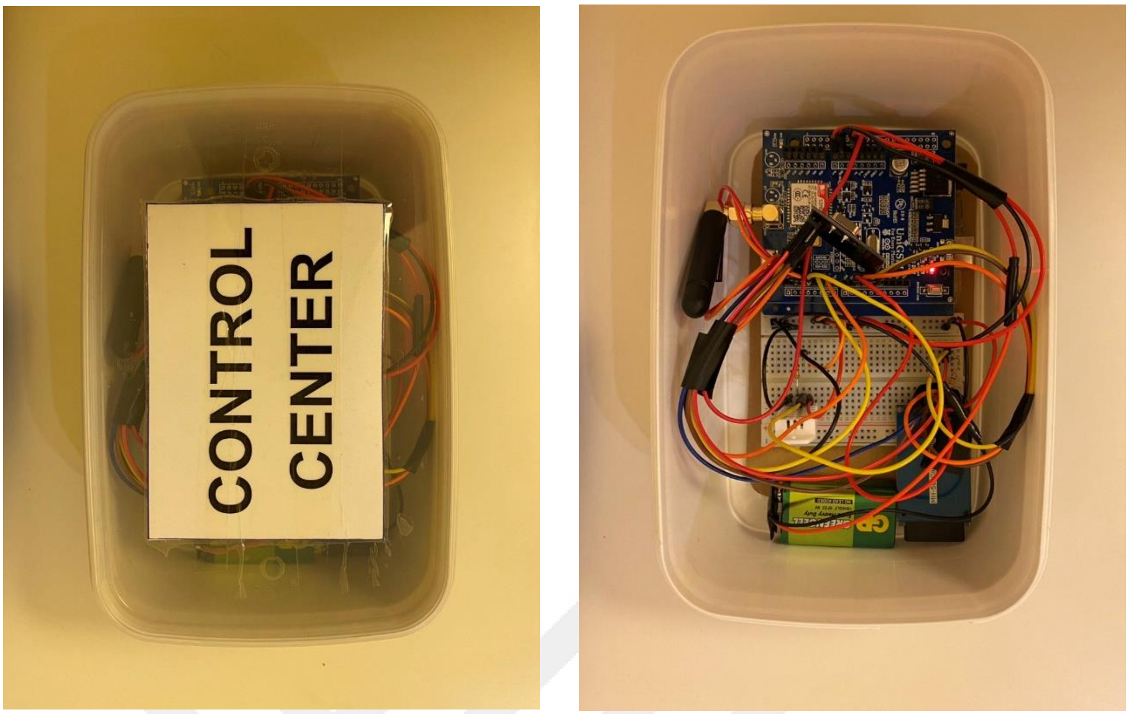

Figure 5.2: Control center

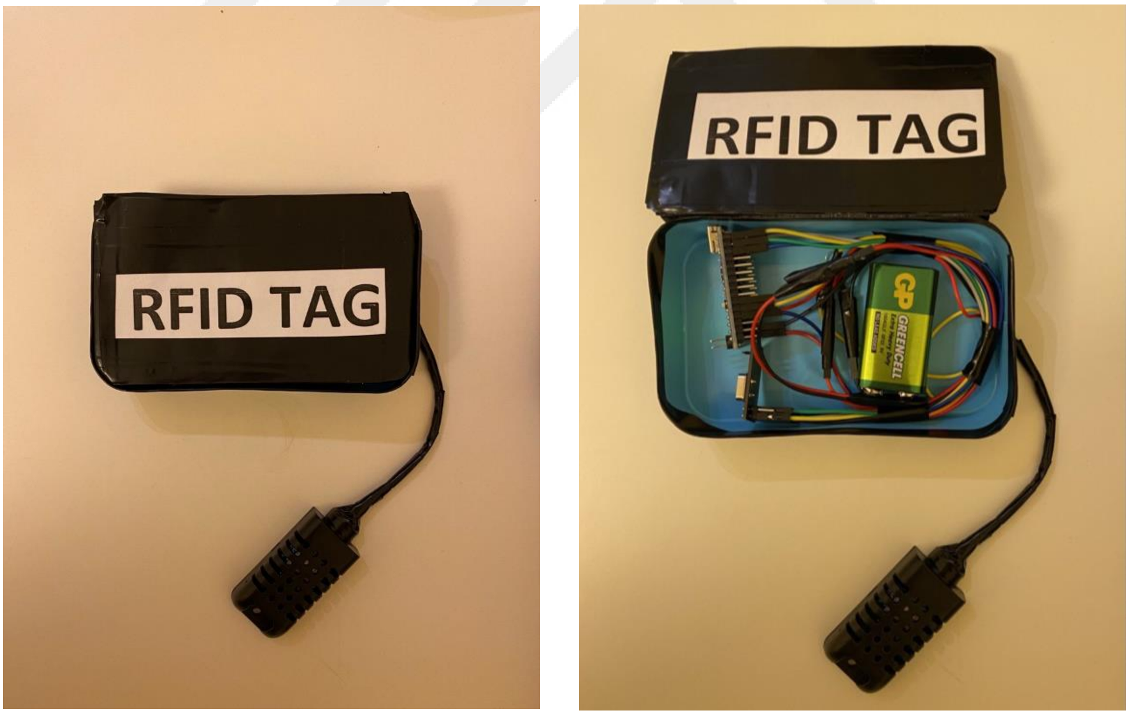

Figure 5.3: Sensor kit/RFID tag

Figure 5.4: Deployment of control center to apiary

Figure 5.5: Deployment of sensor kit/RFID tag to apiary

Table 5.1: Possible system failure reasons and solutions

Reason	Solution
No anomaly occurred in the hive 36.	This is not a problem.
RAM capacity of Arduino has been exceeded and the network cannot be trained.	Use another board with larger RAM. For example: Arduino Mega.
The training process gets stuck, oscillating indefinitely.	Simplify the model. (This will trigger false positives.)
Hardware failure. For example: sensor, wiring, battery etc.	Replace with new one.
The sensor kits are damaged and not working.	Redesign the housing.
The GSM module is faulty or out of range.	Check for signal. Try sending a test SMS.
The system is down due to an unknown error.	Check the above items one by one.

6. CONCLUSION

In this study, data collection and development (both hardware and software) processes were carried out simultaneously. In this period, colony of beehive 17 was totally lost but their data offered valuable information about the process of colony failures. To illustrate, it was observed that the colony weakening could be identified weeks before the colony loss. Furthermore, the effects of hunger and drug treatment could be observed with beehive 36 and desired threshold values were reached with beehive 85.

The results showed that the smart beehive monitoring system can detect fatal anomalies up to 4 weeks prior to colony loss. The calibration made by unsupervised machine learning algorithm of Long Short-Term Memory was effective in achieving these results. However, the system can only warn beekeeper to inspect the colony in need. Therefore, the beekeeper will have to decide whether to feed or medicate the colony or replace the queen.

During the winter period, 28 out of the 101 beehives in the apiary were lost. It is estimated that most of the deaths were due to starvation, as there was no food left in the beehives. It should be taken into account that the winter of 2022 was longer and colder than in previous years.

Future studies should be evaluated in two separate sections as hardware and software. As hardware studies, weight measurement of the beehives can be added to gain more insight about the colony health by monitoring the honey production and food consumption. As software studies, repeating this study in different climates and locations would be useful to better calibrate the system by increasing sample data.

Finally, some numbers related to this study are listed below.

- Lasted more than 6000 hours.
- 18219 rows of data were collected (3 hives and ambient data).
- 425 Euros were spent (excl. transportation, accommodation etc.).
- A total of 2400 km has been traveled (İstanbul – Çanakkale).
- 28% of the colonies were lost in winter.

An agreement has been reached with the beekeeper Servet Yavuz to expand and continue the study in the apiary.

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BIOGRAPHICAL SKETCH

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