Internet of Things Enabled Smart Animal Farm Prototype

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Abstract. Livestock plays very important economic, social and cultural roles in the well being of rural communities across the world. Quality environmental conditions, automation and monitoring are the key necessities of running a good and profitable livestock farm. Air quality, temperature of the surroundings and humidity play a major role while deciding the fan speeds of the exhaust System used in all aspects of livestock farming. Another important part of livestock production is increasing incubation speeds of eggs by performing artificial incubation. It is a requirement to maintain the temperature at a constant value in this system. This paper describes two mutually exclusive Fuzzy Logic algorithm-based systems to automate the exhaust system and an artificial egg incubator. The other important part of a livestock farm is production of milk and milk products. It is required to monitor the health of cows by overseeing their activities at any point of time. This can be done by determining and monitoring the activities performed by the cow. This paper describes a simple Deep Learning Model to classify the activities of a cow broadly as standing, walking or grazing. The Exhaust and the Incubator system are controlled and monitored using Internet of Things (IOT) System using a native web application developed using the Flask framework.

1. Introduction

Quality control of the environmental conditions, automation and monitoring facilities are the key necessities of a Smart Livestock Farm. One such system is that of a smart exhaust fan where the speed of the fans is varied depending on the temperature, humidity and concentration of Carbon di oxide (CO$_2$) of the surroundings. In a livestock farm it is a common practice to have large number of animals in a relatively small room to reduce maintenance cost. In such cases a proper exhaust fan is a necessity for any type of livestock like cows, chickens, sheep etc. The major factors in deciding the speed of the fans are the temperature of the surroundings and the humidity of the surroundings [1]. Several authors have discussed the optimal environment conditions for milk yield in cows and egg yield of laying hens. Another important factor in determining the fan speeds is the concentration of CO$_2$. Large concentrations of CO$_2$ are harmful to both animals and workers and can induce health issues. Artificial incubation is a newly developed method in which eggs are hatched by imitating the avian hatching conditions. During natural hatching the hen maintains the temperature at which the egg is situated to a constant optimum temperature. The temperature at which any particular egg is to be maintained depends on the type of egg. But in general, the optimum temperature ranges between 36 °C to 38 °C. The exact temperature can be gauged using trial and error methods. Further the temperature should be kept constant throughout
the process of incubation which is generally about 21 days. Artificial incubation plays a key role in livestock farming as it speeds up the generally tedious process of egg hatching [2]. Furthermore, in such a system a large number of similar types of eggs can be hatched at the same time which increases production and thus profits. Both of the above-mentioned systems are to serve different purposes but both the systems can be implemented using the same underlying principle of fuzzy logic. Fuzzy logic control is one of the most used and easiest type of control to implement. In general, fuzzy logic control is applied to plants where there is no prior quantitative knowledge of working of the plant and has a poor mathematical model. The main aspect of a fuzzy logic controller is the use of operator intuition for modelling the controller [3]. This paper describes the modelling of a fuzzy logic based automatic exhaust fan speed regulator for moderating the temperature, humidity and concentration of CO$_2$ to an optimum value and a fuzzy logic based closed loop temperature control to maintain the temperature of the system at a optimum value based on the error and change in error of the temperature [7]. Both the systems are developed using the Fuzzy Logic Toolbox in MATLAB and also implemented using the Python dependency Scikit-Fuzzy in Python. The results of both the systems are obtained, observed and tabulated for a range of Test conditions. The outputs and corresponding sensor inputs for both the systems can also be remotely monitored using a simple Native Web Application developed using the Flask Framework [6].

Livestock activity monitoring is an emerging field of science where there is potential to monitor the health of various animals like cow and sheep by monitoring their day-to-day activities. Cattle Activity Recognition can be drawn from the strides in work done on Human Activity Recognition over the past few years. In humans several lifestyle diseases can be prevented by continually monitoring day to day activities and recognizing the shortcomings from a Healthy Lifestyle [4]. In this paper we have tried to extend the developments in this area to cattle wherein the activities of cattle are recognized. The results of a Cattle Activity Recognition Algorithm can be used to determine sickness in cows and also determine beginning Estrous Cycle of Cows [13]. In this paper we are using a simple set of Tri-Axial accelerometer values to classify the activities performed by the cow into three categories namely grazing, standing and walking [5]. A cow primarily rests in its standing position and using the time for which the cow grazes and walks, it is possible to standardize the time it takes to rest, eat and remains active in a day. Any discrepancies in this time can be used to conclude that the cow is facing some sort of discomfort. Pre-determining health issues in cows can enable the worker to take necessary actions to compensate for the reduced milk yield. Further using the activity analysis of a cow, it is possible to predict beginning of Estrous Cycle in the cow which if delayed requires the farmer to employ artificial insemination which is an expensive service with a relatively low success rate [12]. In this paper Cattle Activity Recognition is carried out using a simple Deep Learning Algorithm and the results obtained are analysed [10].

2. Internet of Things in Livestock Farming

The most important aspect of a Smart Farm is the use of Internet of Things based systems to Monitor and Control the different sensor-based systems used in the farm.

In this paper we present the use of an Internet of Things based system namely a Web Application to control various subsystems used to aid in livestock farming. The web application can be accessed from any part of the world with proper Internet connection and user credentials. Monitoring can be carried out in real time once the application is accessed. The Web Application is developed using the FLASK Framework in Python. It is hosted to the Internet using the Heroku Command Line Interface. There is also the need of a Database to act as the interface between the controllers and the display or the application. For this particular system a Google Firebase Real Time Database is used as shown in Figure 1.
The controller input and output values are continually pushed into the database. The application keeps extracting the last row of data from the database and displays it to the user. This way monitoring can be done in real time over the internet. One essential constraint for the proper working of this system is that the Raspberry Pi used for implementing the controller system should be connected to the Internet. If at any point the connection is lost the Raspberry Pi will no longer feed data into the database and thus the real-time values will not be updated in the application. The application was styled in a simple manner using various CSS and Javascript files. The home page of the application is as shown in Figure 2.

The native web application is used to monitor two different systems based on a Fuzzy Logic Controller. The two systems are an exhaust system and an incubator system.

3. **Fuzzy Logic Controller Based Systems**

3.1. **Software Implementation**

The term ‘fuzzy’ refers to things which are not clear. In most of the real-life scenarios we encounter problems which have outputs which do not explicitly belong to the category True or False. In such scenarios we can use fuzzy logic instead of traditional digital logic. Fuzzy logic differs from traditional digital logic as fuzzy logic is based on degrees of truth rather than the traditional either true or false model. Digital logic can be considered as a special case of fuzzy logic. In Boolean system ‘1’ represents absolute truth and ‘0’ refers to absolute false. There is no middle ground. But using fuzzy logic it is possible to represent scenarios of Partial Truth and Partial False as shown in Figure 3.
In this project two different Fuzzy based systems are implemented namely an exhaust System and an incubator system. The inputs to both systems are sensor based and thus analog or crisp. These different crisp inputs are fuzzified and the controller arrives on a output state based on these fuzzified values as in Figure 4. This output is converted to a crisp value which is fed to the corresponding actuators for each system. The key difference between both systems is that the exhaust system is an open loop system i.e., the output is directly fed to the actuator, but the Incubator System is a closed loop system i.e., the output of one Iteration is used as one of the dominant inputs for the next iteration. The sensor inputs to both systems along with their permissible ranges is as shown in Table 1(a) and Table1(b).

**Table 1. Range of all Input and Output parameters accepted by Controllers**

| Variable                          | Range   |
|-----------------------------------|---------|
| a) Exhaust Fan System             |         |
| Temperature (in Celsius)          | 10-30   |
| Humidity(%)                       | 20-100  |
| Concentration of Carbon Di Oxide(ppm)| 400-1000|
| Output Speed (rpm)                | 0-2000  |

| b) Egg Incubator System           |         |
|-----------------------------------|---------|
| Error in Temperature(in degree Celsius)| -5 to +5|
| Change in Error                   | -2 to +2|
| Bi Linear Output                  | -250 to +250|

Fuzzy system makes use of membership functions to convert crisp inputs to fuzzy inputs and fuzzy outputs to crisp outputs. The membership functions for both these systems are defined based on logical intuition as either a triangular function or a trapezoidal function. The output of the fuzzy logic controller
is defuzzified and a crisp output is obtained. Results were obtained using the Fuzzy Toolbox in MATLAB for ten different sets of crisp inputs as shown in Table 2. Input sets 11 and 12 correspond to the extreme cases of the system where it can be observed that under simulation the speed ranges from 160 rpm to 1840 rpm. This range is for a machine which is assumed to be rated at 2000 rpm which implies that for any common DC motor with a rated speed of `N` the output speed will range from 0.08N to 0.92N. For all the other inputs the speed increases as any one of the inputs is increased. This validates the logical facts that speed of the exhaust fan should increase if any of the temperature, humidity or concentration of CO2 increases. In the implementation of the system, it is assumed that the sensor inputs range within the permissible limits in Table 2. If any of the inputs goes out of bounds it is assumed that the value of the input will be constrained to the nearest possible value.

**Table 2. Results of Exhaust Fan System**

| S.No. | Temperature (°C) | Humidity (%) | Concentration of CO2 | Output Speed |
|-------|-----------------|--------------|----------------------|--------------|
| 1     | 12.5            | 33           | 545                  | 170          |
| 2     | 18.1            | 52.3         | 1065                 | 469          |
| 3     | 21.2            | 27.2         | 814                  | 377          |
| 4     | 23              | 73           | 1528                 | 1070         |
| 5     | 27.7            | 91.8         | 1836                 | 1830         |
| 6     | 23.9            | 60           | 1330                 | 1050         |
| 7     | 10.8            | 38.6         | 488                  | 166          |
| 8     | 15.2            | 29.5         | 1630                 | 472          |
| 9     | 27.7            | 70.6         | 1150                 | 1170         |
| 10    | 16              | 90.8         | 904                  | 666          |
| 11    | 10              | 20           | 400                  | 160          |
| 12    | 30              | 100          | 2000                 | 1840         |

Unlike the exhaust, the incubator system requires the controller to maintain a particular value rather than control it. This means that the system needs to operate as a closed loop one with the output being fed back. In this case the process variable to be maintained is the temperature of the system. To do this the current temperature is recorded using the sensor and compared to the required reference temperature. The error is normalized to be in the range -5 to 5 and is fed as one of the inputs to the fuzzy logic controller. Another input required by the system is the rate of change of error. In this case it is sufficient to find the change of error as the acquisition occurs in regular intervals. The output of the system is a bipolar value as in both the magnitude and sign of the output have relevance. As shown in the last two rows of Table 3 the range of the output is -210 to 210. The sign of the output is used to choose the actuator as either a fan for cooling or a heating element for heating. The magnitude is to control the intensity of operation. For each iteration, the recorded temperature is expected to get closer to the required value. Once the error reduces below a threshold value both the error and the change in error will be very close to 0. In this system it is required that both the inputs be normalized to the ranges as specified in Table 1(b).
Table 3. Results of Incubator System

| S.No. | Input Error (°C) | Delta Error (°C) | Output |
|-------|-----------------|------------------|--------|
| 1     | -3.76           | -1.47            | -203   |
| 2     | -2.02           | -0.782           | -205   |
| 3     | -0.275          | 0.273            | -139   |
| 4     | 2.39            | 1.15             | 60.6   |
| 5     | 3               | 2                | 128    |
| 6     | -1.09           | 0.642            | -92.3  |
| 7     | 3.43            | 1.11             | 77.8   |
| 8     | -3.58           | 1.14             | -137   |
| 9     | -5              | -2               | -210   |
| 10    | 5               | 2                | 210    |

3.2. Hardware Implementation

Hardware testing of the controllers were carried out using the Raspberry Pi Micro controller, the DHT11 sensor and the MQ135 sensor as shown in Figure 5. The input range of the DHT11 and the MQ135 sensor is as shown in Table 4. The output of both controllers is ensured to be within the permissible range and is converted to an appropriate duty ratio for a Pulse Width Modulation (PWM) based signal generator.

![DHT11](image1.png) ![MQ135](image2.png)

Figure 5. Sensor Circuits.

Table 4. Ranges of Sensors used for Hardware Implementation

| Sensor Name | Range               |
|-------------|---------------------|
| DHT11       | Temperature(0°C-50°C) and Humidity (20% - 95%) |
| MQ135       | CO₂ (10 ppm - 1000 ppm) |

To test the controller working, a small-scale prototype using a 12V DC motor and an incandescent lamp as actuators was implemented as shown in Figure 6. The working of the controllers was observed and it was ensured that the controller responds to various sets of inputs as expected.
4. Cattle Activity Recognition Using Convolutional Neural Networks

4.1. Introduction

Cattle Activity Recognition is an upcoming advancement in livestock farming to help farmers predict, moderate and monitor the day-to-day activities of different livestock. In this paper a simple Convolutional Neural Network (CNN) based algorithm is used to carry out activity recognition in cattle as grazing, standing or walking. A combination of two datasets in the ratio 1:1 is used for training and validation purposes [9]. One dataset is from [4] where the activity walking is focused. The second dataset was one collected from a nearby dairy farm using a similar setup as in [4]. This dataset focuses on the activities grazing and standing.

The results yielded using cattle activity recognition can be of use in predicting the health of the animal and predicting behavioral changes which can be directly linked to normally unpredictable acts like beginning of Estrous Cycle in Cows or infections due to certain viruses etc. Furthermore, determining the time an animal grazes can be used along with the grazing rate of the animal to counter overgrazing in livestock which can reduce the chances of obesity. Such a system is better than a camera-based system because it is cheaper, gives activity data for each individual cow and unlike the camera-based systems visibility during the night is not an issue. The algorithm presented in this paper can be further extended to other livestock like goats, sheep, oxen and even to non-domesticated animals to aid in behavioral analysis of animals in the wild [11].

4.2. Data Collection using Accelerometer

To collect the data a setup using the ADXL345 accelerometer sensor was used along with a Raspberry Pi. The data was sampled at 50Hz and the setup developed was mounted on the neck of the cow as shown in Figure 7. and Figure 8.
The collected data was sent to a Google Firebase database and accessed from there. The complete dataset after merging and scaling using the inbuilt standard scaler function in Keras amounts to 16800 samples equally classed into walking, grazing and standing.

4.3. Model Architecture and Implementation

The network is a relatively small one and comprises of two convolution layers followed by a flatten layer and two dense layers as shown in Figure 9. The Network accepts inputs as a frame of data points rather than a single data point. The Frame Size was chosen as 20 samples which is equivalent to 24s of data. The activation function used in the Convolution Layers is Rectified Linear Unit function. Each of the 16800 samples correspond to a label as the training is supervised. After the data is divided into frames, each frame is assigned a label corresponding to the majority label of its samples. It is ensured that the data is not shuffled as the data is collected with respect to time. As the input size is relatively less the network performance is not affected due to size of input and thus pooling is not required.

4.4. Model Performance Analysis

To tune the hyperparameters of the network a manual grid search for different epochs and different optimization functions was carried out. The results are as shown in Table 5.

Table 5. Manual Grid Search results for Hyperparameter Optimization

| S.No | Optimizer | Number of Epochs | Validation Accuracy (%) |
|------|-----------|------------------|-------------------------|
| 1    | Adam      | 10               | 82.14                   |
| 2    | Adam      | 13               | 80.16                   |
| 3    | Adam      | 15               | 82.54                   |
| 4    | Adam      | 17               | 82.14                   |
| 5    | SGD       | 10               | 36.90                   |
| 6    | SGD       | 13               | 59.52                   |
| 7    | SGD       | 15               | 59.33                   |
From Table 4, it is observed that the best performance is achieved when the optimizer used is the Adam Optimizer and the number of epochs is 15.

|   |   |   |   |
|---|---|---|---|
| 8 | SGD | 17 | 60.12 |
| 9 | RMSprop | 10 | 84.13 |
| 10 | RMSprop | 13 | 82.34 |
| 11 | RMSprop | 15 | 81.35 |
| 12 | RMSprop | 17 | 80.75 |
| 13 | Adamax | 10 | 77.98 |
| 14 | Adamax | 13 | 80.36 |
| 15 | Adamax | 15 | 80.95 |
| 16 | Adamax | 17 | 78.17 |

From Table 4, it is observed that the best performance is achieved when the optimizer used is the Adam Optimizer and the number of epochs is 15.

**Figure 10.** Accuracy and Loss Plots of Model.

From the accuracy and loss plots as shown in Figure 10, the validation accuracy over the span of 15 epochs is always lesser than the training accuracy which implies that the model is not overfitting and apart from a few spikes both the accuracy and loss follow the expected trends. The accuracy of 82.54% is a relatively good number considering the activities performed by a cow are very closely related. The confusion matrix for the hyperparameter configuration is obtained as in Figure 11.

**Figure 11.** Confusion Matrix of Test Results.
The minimum and maximum accuracy across each of the three classes ranges from 79% to 90%. The difference is just 11% which implies that the model is not skewed or biased in any manner and that each class is identified nearly as accurately as the overall accuracy of the model. For a complex task like cattle activity recognition the model is found to perform extremely well considering not a single feature was extracted manually and that the model with a mere 2 convolution layers was fed with raw scaled data. The algorithm used in this paper can be extended to do the same as a Real Time Model and thus predict the activity every 24s in real time.

5. Conclusion

5.1. Results and Inference

In this paper a diverse system to aid in Smart Livestock Farming is presented to control and monitor various aspects of the farm using techniques like Internet of Things and Deep Learning Algorithms. Two controllers based on Fuzzy Logic are designed and interfaced with a native Web Application to aid in Monitoring. The results obtained using the design were observed and inferred upon. Both the systems are found capable to work independently and are interfaced with the user with the help of the web application. The application is deployed to the Internet to ensure that it is accessible from any part of the world as long as there is proper internet connection. A Cattle Activity Recognition System was implemented using a Convolutional Neural Network and the results were obtained. The designed Fuzzy Logic Controllers were tested physically using a simple DC motor and Incandescent Lamp setup.

5.2. Future Scope

For the exhaust system and the incubator system the number of variables used by the controller can be increased and further better actuators can be used so that the developed prototype is as close to the actual system as possible. The external environment can also be considered while determining the output as certain features like the size of the room or external temperature can prove important. For Cattle Activity Recognition the system can be extended to different animals both wild and domesticated. Upon collecting data for different animals, a pattern in certain activities can be found and a more generic model can be implemented. In this project accelerometer data from a single sensor is used, but the accuracy of the model can be improved by using multiple sensors for each limb and sensors to predict position like the gyroscope sensor. Furthermore, the same algorithm can be extended to work as a Real Time Model and the resultant prediction can be monitored using the web application.

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