Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 25, Issues 3, pp. 1702–1715, DOI 10.12694/scpe.v25i3.2785

SCHEMOS – SMART COW HEALTH MONITORING SYSTEM: AN IOT BASED COW HOOF DETECTION AND HEALTHCARE ALERT SYSTEM BY USING LSTM NETWORK

DURAIRAJ.K [*], DHILIP KUMAR.V [†] AND KANAGACHIDAMBARESAN.G.R [‡]

Abstract. Human life and existence are intertwined with a few domestic animals. One of the most important animals of this kind is the cow. Cows play a vital role in daily activities. Most of the people in India consume cow's milk as one of their major nutrients. Monitoring the health of a cow's everyday life is quite challenging. After infertility and mastitis, lameness is typically ranked as the third most economically significant health issue in dairy herds.Lameness are caused due to genetics, lack in nutrition i.e. a diet deficient in essential nutrients such as biotin, which can lead to hoof problems. Due to geographical environments like cows kept in wet, muddy conditions are more likely to develop hoof problems. This investigation analyses the typical characteristics of cow behavior, and a Smart Cow Health Monitoring System (ScHeMoS) using IoT is proposed to identify the cow's health through the data obtained from Internet of Things (IoT) sensors, including position, body temperature, stability, acceleration, and animal feed. IoT is combined with Deep learning (DL) technique to monitor and diagnose animal health. We used the Long Short Term Memory (LSTM) network to predict cow lameness by capturing the body temperature and other parameters, which will aid in predicting their illness. The accelerometer values are stored so that it will further help to determine which cow is lame and which is pregnant or regular and could be intimated to the care takers in the farms. We utilised a self collected dataset to perform the investigation. By implementing this system, we achieved 92.45% accuracy and 0.92 as F1 score.

Key words: Animal Behaviour, Cow Hoof Health, IoT in animal monitoring, LSTM, ScHeMo.

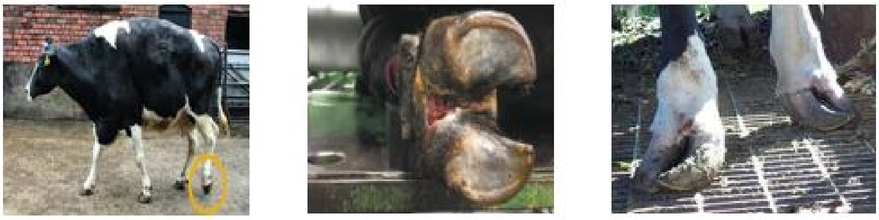
1. Introduction. Cow's milk will be the first choice as one of best nutrient consumed by infant to older people in India or even in most of the countries .The demand for milk in India is raising daily. India's market for dairy products is anticipated to increase dramatically over the next few years due to an increase in consumers, rising incomes, and a growing interest in nutrition. Dairy products that have been pasteurised and packaged are becoming more popular in cities. Numerous national and international brands have joined the market due to increased competition from the private sector, raising consumer expectations for quality. However, a small percentage of people consume these packaged goods. Because of its flavour and perceived freshness, unpackaged, raw milk from a neighbourhood milkman is still preferred in many parts of the nation. [1] Dairy cow productivity is influenced by several factors, one of which is health. A sickness prevents dairy cows from producing milk as efficiently, which lowers milk yield. Dairy cows can have up to 12 to 15 litres of milk per day under normal circumstances, while diseased dairy cows can only generate 3 to 8 litres of milk per day. The incapacity to monitor the ranchers' shared understanding of the disease makes it challenging to identify and treat diseased cows in the early stages.

Lameness in cattle are caused due to genetics, where some cow breeds may be predisposed to hoof problems, lack in nutrition that is ,a diet deficient in essential nutrients, such as biotin, can lead to hoof problems, and due to geographical environments like cows kept in wet, muddy conditions are more likely to develop hoof problems. Fig. 1.1 (a) shows how a Lameness cow walks in a particular motion; (b) the kind of injury a cow would have at the bottom of its hoof, which is something the untrained eyes cannot see,(c) the toes of the cow are crossed because of bilateral damage, which must be cut . A major animal welfare issue in dairy cows is lameness, which causes intense pain and strain, which enervates and decreases milk productivity. For example, in the dairy form, less than 10% of cows are affected by lameness. Lower fertility rate are found among cows

[*]Department of Computer Science and Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi, Chennai 62, India. (duraiit2011@gmail.com)

[†]Department of Computer Science and Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi, Chennai 62, India. (vdhilipkumar@veltech.edu.in)

[‡]Department of Computer Science and Engineering, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Avadi, Chennai 62, India. (kanagachidambaresan@gmail.com)



(a) (b) (c)

Fig. 1.1: Different forms of Hoof problems (a) Lameness (b) Injured cow hoof root (c) Bilateral crossed toes.

affected with lameness. Foot rot is an infection that causes sudden swelling, heat and inflammation in the foot, resulting in severe lameness [2]. When evaluating structural soundness, one of the critical features to assess is the hoof. Some hoof problems, such as excessive or uneven toe growth, may be caused by hereditary, dietary, or environmental factors, or they may be symptoms of other health issues the animal is experiencing. The ideal hoof will be free of cracks and flaws, with two symmetrical claws facing forward. The heel depth should also be carefully monitored because animals with an excessive tilt to their hocks and pasterns might be exceedingly shallow in the heel. The hoof should be dense and capable of supporting the animal's weight without shattering, as this might cause problems [3].

A corkscrew claw, or screw claw, is another symptom to look for while evaluating the hoof. This toe twisting puts the hoof's side wall in direct touch with the ground. At times, the disease manifests itself with the toes pointing inward rather than outward. The typical symptoms of this illness are present in cattle older than two years old. It can damage all hooves or only one of them [4]. Although the mode of inheritance is not fully known, this condition is thought to be heritable. Due to improper weight distribution inside the toe, the issue can cause lameness. Cattle suffering from this disorder must be discarded and eradicated from the herd immediately.

Animals cannot communicate their health issues to human beings. Hence, this research suggests the prototype of a wearable device for animals with the help of a Smart Cow Health Monitoring System (SCHeMo), which shall be mounted on the animals that produce the alert message related to their health issues to both the forest officer's room and the veterinary doctors [5]. The primary parameter is to monitor the animals regularly. It indicates whether they are suffering from diseases or in dangerous situations caused by natural disasters like floods or wildfires. Therefore, this prototype will be user-friendly for evaluating animals' behavioural monitoring.

We propose SCHeMoS model which can serve as health alert system in cow lameness detection. The research brings out:

- From observing to recognition and healing of the diseased cows, our method continuously monitors and manages using IoT and LSTM model.
- A cutting-edge data analytical method aid in the precise detection of the animal behaviour.
- IoT sensors and actuators assist in detecting animal behaviour for early disease analysis and diagnosis.
- We use a rapid prototype model to monitor the animal and maintain a healthy habitat. To recognirmal cows, SCHeMoS can be used by the farmers in identifying the lame cows
- Our proposed model outperformed the existing approaches in detecting the lameness of cows with the accuracy of 92.45%.

The remainder of this article is structured as follows: Section 2 covers the literature review. Section 3 provides specifics on the proposed approach, while Sections 4 contains the implementation and 5 outline the results that were attained. Section 6 concludes the investigation.

2. Related work. There have been numerous research projects on domestic animal surveillance recently. Cow health monitoring is crucial in today's society since it allows for the prediction of milk production. It is essential because milk production is the primary income source for farmers with many cows. A health observing system that focuses on several options are available. The issue with such systems is that they need help forecasting milk production, which is crucial in determining a cow's health. Video-based monitoring with ResNet 3D and other DL approaches can recognise cow behaviours as resting, walking, and roaming [6]. Another untrained ML model [7] was used to assess cow movement patterns and identify anomalies. It used collar, ankle, or neck accelerometers.

Authors of [8] used gait analysis with accelerometers has been done on both people and animals .It has been established that while accelerometer-based gait metrics are still comparatively immature, latest field in the dairy industry includes the use of sensors that can be worn by cows, such as accelerometers. Sheep behaviour and lameness categorization have both been studied using accelerometers and gyroscopes [9].

Use leg-mounted accelerometers [10] to identify cow lameness. Neck, foot, and throat tri-axial accelerometers are used to predict lameness in sheep and have an overall accuracy of more than 85 percent. Wandering, resting, eating, and sleeping were among the monitored actions. In [11] acceleration signal analysis has been shown to have a reported accuracy of 91.9% when applied to the diagnosis of lameness in cows. Two 400-Hz accelerometers were utilised by the authors of [12] to evaluate bilateral front limb impairment and foot disorders by extracting the full rotation, standing phase, and range of motion. In dairy cows with hoof lesions, the connection between gait features and movement score has been studied.

Reviews the use of accelerometer [13] in various clinical applications, including the assessment of gait disorders, fall detection, and the monitoring of patients with neurological conditions. The authors also discuss the advantages and limitations of accelerometer-based gait analysis, including its non-invasive nature and its ability to provide objective measurements. They also highlight the importance of the development of appropriate algorithms and methods for the analysis of accelerometer data. Finally, the authors suggest future research directions to improve the accuracy and reliability of accelerometer-based gait analysis.

Examines accelerometers [14] which are devices that measure the acceleration of a cow's movement, for the categorization of cattle movement and activities in the dairy. The study used data from accelerometers placed on cows in a commercial dairy farm to classify the cows' behaviours, such as lying down, standing, and walking. The authors used ML algorithms, such as RF and SVM, to classify the behaviours and found that the accelerometer data was able to accurately classify the behaviours with a high accuracy. The authors also discuss the potential of using this technology for cow lameness detection and for monitoring cow welfare in dairy barns.

Authors of [15] explores the use of a combination of locating and accelerating the sensors to detect the differences among cows while feeding that are affected with lameness. The study used data from sensors placed on cows to track the cows' movements and feeding behaviours, and analyzed the data using machine learning algorithms. The authors found that the sensor data accurately distinguishes healthy and unhealthy cows based on their feeding behaviours. The authors also covered the possibility of employing this technology to identify lameness among cattles and the significance of taking feeding behaviour into account as a sign of lameness.

Electroencephalogram (EEG) recordings [16] of patients with a range of poor sleep, including restlessness, snoring, and nerve pain, were employed in the study to collect data. and applied deep learning algorithms to classify the patients into different groups based on their disorder. The authors found that the deep learning algorithms were able to accurately classify the patients into different groups with high accuracy. The authors also discussed the potential of using this technology for the diagnosis and treatment of sleep disorders, and the importance of considering multiple bio signals in the analysis. Few limitations of the literature review are presented in Table 2.1. The goal of this investigation is to create a recurrent neural LSTM model to properly and completely categorise cow behavioural traits, particularly those connected to lameness.

3. Proposed Work. This part contains detailed description of the proposed approach, dataset preparation, data pre-processing and methods and materials used to complete the investigation. The proposed architecture is depicted in Fig. 3.1. Initially the data is pre-processed after acquiring it. The cleaned data is given as input to the LSTM model for classifying lameness. The main advantages of LSTM is that they are much better at managing long-term dependencies. This is due to their capability to remember data for prolonged periods of time. Second, LSTMs are much less vulnerable to the vanishing gradient issues. This also give optimal predictions during machine learning when compared to existing algorithms.

Table 2.1: Overall results of the proposed approach

Work	Methodology	Parameters used	Results	Limitations
Casey et. al [17]	MAPE (Mean Absolute Percentage Error) computation method.	Body Temperature Detection, Heart Rate Detection Minutes	The average MAPE value to identify the body temperature and metric for heart beat rate is 1.254, 2.434 respectively.	Small sample size of cows used in the study, which limits the generalizability of the results to the wider population of dairy cows
Lamb et al [18]	TO1 to TO5 is used to synchronise communication protocols.	Breathing frequency sensing rnit, Monitoring the activity of cow.	Monitoring the cow's behaviour, health, and stress.Accuracy rate is measured as 87.61%	The study only used data from accelerometers placed on the front legs of the cows, which may not provide complete picture of the cows gait and lameness status.
Thorup et al [19]	The milk yield prediction model was created using the MATLAB with ThingSpeak.	Temperature & Humidity	Monitor cow's health, and vets, that quickly identifies and treat minor health issues with accuracy of 85.01%	The study only used data from accelerometers placed on the frontlegs of the cows, which may not provide a complete picture of the cows gait which affects the accuracy.
Haug et al [20]	Used IoT techniques. The MQTT protocol is used for data communication within gateway and nodes. HTTP is used for data transmission within server and gateway	Mastitis, Bloat, PMK, Anthrax, Brucellosis, Leptospirosis, Myiasis, Scabies	IoT and smart systems are integrated in monitoring the cattles.	The study used a simple algorithm for lameness detection and did not use advanced machine learning techniques to improve the accuracy of the lameness detection, which could be a limitation in terms of the performance of the system. IoT systems used MQTT which has higher computational complexities.

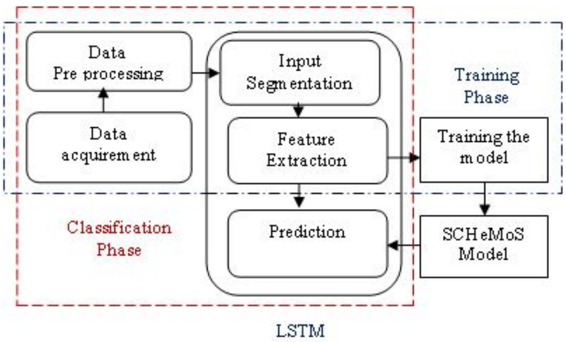


Fig. 3.1: Proposed architecture

3.1. Data pre-processing. To prepare a dataset for cow lameness prediction, we gathered data on cow behavior and physical characteristics, as well as information on their environment and any potential causes of lameness. This may include data on the cow's movement patterns, gait, and posture, as well as information on the flooring and bedding in their living area. Additionally, data on any injuries or conditions that may contribute to lameness specifically hoof infections or joint issues are collected. It is important to have a large

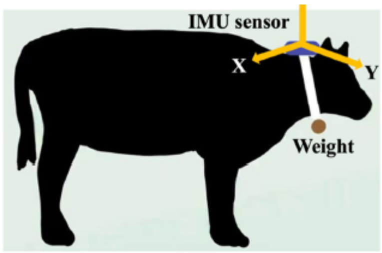


Fig. 3.2: Collar Sensor placed on the cow to collect data

Table 3.1: Category wise cows used for the investigation

Cow breed	Gender	No. of cows used
Angus	Male	12
Angus	Female	11
Brahman	Male	10
Brahman	Female	8
Crossbred	Male	12
Crossbred	Female	14
Charolais	Male	11
Charolais	Female	9
Total		**87**

and diverse dataset, including both healthy and lame cows, to train our model effectively. The data sets include information on the following types of cattle: Angus, Crossbreds and others. Table 3.1 shows statistical information like breeds, gender and number of cows used to collect the data. The data collection was carried out in a farm for 35 days where all the above said breeds are available.

Around four cow breeds are used to prepare the sensor's raw data set, representing different species and ages. Cattle state is divided into eight subcategories, including relaxing, chewing, highly active, moderately active, gasping (heavy breathing), eating, and roaming. The detailed explanation of various conditions of the cow is shown in Table 3.1. The collected dataset contains thorough information for several cattle statuses. Sensors deployed in the neck of the cow as shown in Fig. 3.2 to collect various information Each sensor records the state of the cows for every 30 seconds, and 12,892 data points were gathered for each cow during the time 16:30 IST on December 12,2022.A sample of the collected dataset is shown in Table 3.2.

3.2. Data segmentation. Segmentation is the initial step in the data processing process. Cows belonging to the same breed are grouped together in the statistics. We utilised R programming language to segment the data since the source data were extremely large. The number and breeds of cows used to prepare the dataset is shown in Table 3.1. A large volume of data makes it easier to analyse general characteristics of data and prevent miscalculation brought on by specific and individual data.

We collected data based on various positions of the cow. Table 3.2 shows a few of the cow positions used to collect data for our experiment. The collected data is segmented as per the same breed with a difference in gender. A sample of sensor data from a walking cow of the Brahman breed is shown in Table 3.3. Px, Py, and Pz represent the cow's movement directions. These values are compared to determine the cow's weaning style. To accurately classify hoof foot, the cow's body temperature is also recorded because a change in temperature would also cause a change in the cow's walking style. We collected data and segmented it for all the actions listed in Table 3.2. for all four breeds of cows.

3.3. Data Cleaning. Data cleaning in a cow disease dataset involves a series of steps to ensure that the data is accurate, consistent, and usable for analysis. Removing duplicate records involves identifying and

Table 3.2: Various Positions of Cow used for data collection

Cow ID	Position	Explanation
NC4231	Ideal	The normal cow's position was ideal.
NC4232	Grazing	The average cow here was in a grazing position.
NC4233	Drinking	The normal cow is drinking water.
NC4234	Walking	The normal cow was walking around.
PC6241	Lying Down	The pregnant cow was lying down on the field.
PC6242	Walking	The pregnant cow was walking around.
PC6243	Sleeping	The pregnant cow was sleeping.
LC3351	Ideal	The Lame cow was in an ideal position.
LC3352	Walking	The Lame cow was walking around.
LC3353	Grazing	The Lame cow was in a grazing position.

removing any records that are identical or nearly identical. Handling missing data, involves identifying and addressing missing data, such as by removing records with missing values, imputing missing values, or flagging records with missing data for further investigation. For instance, the relaxed condition of the cow will be marked as zero for specific hour if the cow shows no change in the position. If lot of damage data is collected in that hour; it will affect how the average time stamp is determined. Removing irrelevant data involves identifying and removing data that is not relevant to the analysis. For example Deleting faulty data along with the accompanying time serial number will prevent them from being factored into the average period computation.

In our investigation the sensor delivers very less amount of inaccurate data along with its detection and transmission of the cow's state. Even this less inaccurate data would impact the classification accuracy of the model. Consequently, cleaning up the faulty data is the first step. We used the above methods to clean up the data.

3.4. Prediction using LSTM. Based on the research discussed above, we use the LSTM model in this part to predict the state of a cow lameness whether it is affected with hoof foot.. To be clearer, it is first detailed how to build an LSTM model as well as the characteristics and structure of LSTM. Second, the cow condition is anticipated and simulated using the LSTM model. The model is finally optimised to raise its accuracy. The process of using LSTM to predict lameness in cows would involve the following steps:

Collect data: Collect data related to the cow's behavior, sensor readings, and other relevant factors that may indicate lameness.

Pre-processing: Pre-process the data by cleaning and normalizing it, as well as converting it into a format that can be used by the LSTM model.

Build the LSTM model: Use the pre-processed data to train and build the LSTM model using a suitable deep learning library such as TensorFlow or Keras. Evaluation: Evaluate the model's performance using appropriate metrics such as accuracy, precision, and recall.

Fine-tuning: Fine-tune the model as necessary by adjusting the model parameters, adding additional features, or trying different architectures.

Deployment: Once the model is trained and fine-tuned, it can be deployed for use in predicting the likelihood of lameness in cows.

LSTM (Long Short-Term Memory) is a type of Recurrent Neural Network (RNN) that is particularly well-suited for modelling time-series data and sequences. It can be used to predict the likelihood of lameness in cows by analyzing data from sensor readings, cow behavior, and other related factors. A simple LSTM cell is as shown in Fig. 3.3. Equ. 3.1 to to 3.5 are used by the LSTM network to process the input. The sensor data is given as input through the input gate it ,predicted output is obtained from the output gate o_t and the forget gate f_t is used to analyse the time series data with the help of the memory cell c_t.

$$i_t = \text{sigmoid}\left(W_{ix} \times x_t + W_{ih} \times h\{t-l\} + b_i\right) \tag{3.1}$$

Table 3.3: A sample of male Brahman Cow's walking record

Date	Time	Cow Body Temperature	Px	Py	Px
08 – 12 – 2022	16 : 31 : 02	37.06	2731	7146	9078
08 – 12 – 2022	16 : 31 : 04	37.13	2732	7606	9035
08 – 12 – 2022	16 : 31 : 06	37.19	2730	7466	8872
08 – 12 – 2022	16 : 31 : 07	37.31	2729	7603	8943
08 – 12 – 2022	16 : 31 : 09	37.44	2731	7645	9022
08 – 12 – 2022	16 : 31 : 10	37.5	2732	7630	9021
08 – 12 – 2022	16 : 31 : 12	37.5	2730	7531	8815
08 – 12 – 2022	16 : 31 : 13	37.63	2728	7690	8903
08 – 12 – 2022	16 : 31 : 15	37.75	2729	7738	9062
08 – 12 – 2022	16 : 31 : 17	37.81	2727	7716	9067
08 – 12 – 2022	16 : 31 : 20	37.94	2737	7763	9249
08 – 12 – 2022	16 : 31 : 21	38.06	2731	7591	9140
08 – 12 – 2022	16 : 32 : 14	38.44	2730	7875	9248
08 – 12 – 2022	16 : 32 : 16	38.44	2734	7854	9251
08 – 12 – 2022	16 : 32 : 20	38.5	2734	7913	9292
08 – 12 – 2022	16 : 32 : 22	38.5	2738	7897	9258
08 – 12 – 2022	16 : 32 : 24	38.56	2741	7922	9297
08 – 12 – 2022	16 : 32 : 30	38.63	2739	7811	9226
08 – 12 – 2022	16 : 32 : 59	38.56	2737	7772	9409
08 – 12 – 2022	16 : 33 : 45	38.69	2737	7746	9056
08 – 12 – 2022	16 : 33 : 46	38.75	2737	7779	9044
08 – 12 – 2022	16 : 33 : 49	38.81	2737	7829	9126
08 – 12 – 2022	16 : 33 : 51	38.88	2732	7820	9142
08 – 12 – 2022	16 : 33 : 52	38.88	2734	7829	9183
08 – 12 – 2022	16 : 33 : 54	38.94	2731	7821	9164
08 – 12 – 2022	16 : 33 : 56	39	2733	7831	9190
08 – 12 – 2022	16 : 33 : 57	39	2733	7841	9213
08 – 12 – 2022	16 : 33 : 59	39.06	2733	7837	9241
08 – 12 – 2022	16 : 34 : 00	39.13	2729	7824	9234

$$f_t = \text{sigmoid}\left(W_{f_x} \times x_t + W_{fh} \times h(t-l\} + b_t\right) \tag{3.2}$$

$$o_t = \text{sigmoid}\left(W_{ox} \times x_t + W_{oh} \times h\{t-l\} + b_o\right) \tag{3.3}$$

$$c_t = f_t \times c\{t-l\} + i_t \times \tanh\left(W_{cx} \times x_t + W_{ch} \times h\{t-l\} + b_d\right) \tag{3.4}$$

$$h_t = o_t \times \tanh\left(c_t\right) \tag{3.5}$$

where x_t, h_t, c_t, are the input, hidden state, memory cell for the time stamp t respectively for i_t (input gate), f_t (forget gate), and o_t (output gate) respectively, The weight matrices for the input, output and forget gate are W_i, W_f, W_o and bias terms are b_i, b_o, b_f respectively. We used sigmoid as the sigmoid function; *tanh* is the hyperbolic tangent function [21].

Before applying the created LSTM model for cow status prediction, it is essential to find out the inputs, form of output, time series data. According to the properties of the data sets, predicted output should be the hoof foot affected status of the cow [22]. Hence, one difficult part of this approach is figuring out the input variables. A known fixed periodic function should be the input since periodic changes will be the output. To

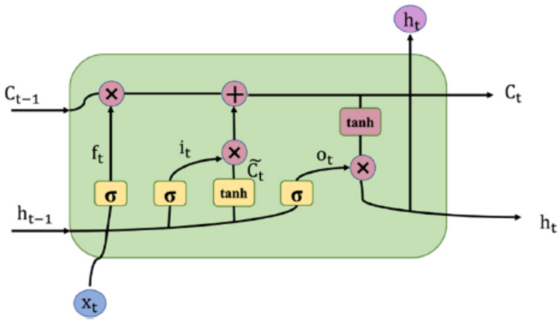


Fig. 3.3: LSTM cell structure

be more precise, it is appropriate to choose total hours as the input variable because the state cycle of cow is one day.

The LSTM model's input and output are periodic. The difference is that while each cycle's output has a different value, this cycle's input has a fixed value[23]. In other words, regardless of time, the same input may produce many results. The matching time series for the input is not the same even though the input is the same [24]. As a result, the LSTM model is capable of handling situations where a single input corresponds to a number of outputs in a time series.

3.5. Feature extraction. In this study, two features RMS (Root Mean Square) and mean were used to extract the features of the sensor data. Equ. 3.6 and Equ. 3.7 are used to perform the feature extraction by the LSTM model.

$$\mathrm{RpX} = \sqrt{\frac{1}{n}\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{PXi}} \tag{3.6}$$

$$\mathrm{m}\left(\mathrm{PX_j}\right) = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{PX_i} \tag{3.7}$$

where PX is PX-axis data, PX_j is the record j of PX, n are the samples number and fixed as n = 32; PX_i is the ith sample of record PX_j; $m(PX_j)$: mean of PX_j, RPX_j : root means square of PX_j.Hence the formulae for $P_x, P_y, andP_z$ axis are similar.

3.6. Hyperparameter optimisation. To further improve the performance of the proposed model we performed hyper parameter optimisation. The number of hidden layers of the LSTM model is selected to be 7,we started with the number of neurons from 32 and gradually increased to 64.The dropout rate is randomly selected from 0.2 and we obtained most optimised accuracy of 92.4% at the rate of 0.1. The learning rate of the model is selected to be 0.001 with the batch size 0f 128.We achieved highest accuracy at the 120th epoch. The results obtained through hyper parameter optimisation are as shown in Table 3.4.

4. Implementation. This article describes a monitoring system that records a cow's heart rate, rumination rate, relative humidity, and body temperature at regular intervals to predict lameness. The parameters collected will then be sent via NodeMCU to a website called Thing Speak for processing and health evaluation. This study focuses on locating cow hoof wounds and keeping tabs on the well-being and behaviour of the subject. Fig. 4.1 depicts the basic layout of the hardware representation of the proposed system. A 4.7K ohm 1/2 Watt Resistor, AD converter (ADS1115), Temperature Sensor (DS18B20), Accelerometer (ADXL335), NodeMCU (ESP8266), 5V Battery, and Micro SD Card Reader Module are used to build the system. Another method for developing NodeMCU using a well-known IDE, the Arduino IDE. We may also use the Arduino programming

Table 3.4: Hyper Parameter Optimisation.

Parameters	Optimised values
No. of LSTM layers	7 Layers
Neurons	64
Learning rate	0.001
Epoch	120
Batch size	128
Dropout	0.1
Trainingloss	0.4357
Testingloss	4.9821
Error rate	0.167

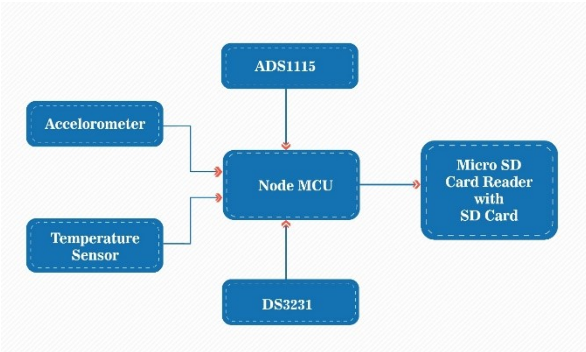


Fig. 4.1: Hardware architecture of SCHeMoS

environment to create applications for NodeMCU. The ADXL335 is used to find the accurate position of the cow. Based on the cow movement, various positions like $P_x, P_y and, P_z$ have been calculated.

4.1. PCB Design of SCHeMoS.

4.2. Product kit (Prototype). Fig. 4.3 (a) shows how all sensors are mounted and fixed by a double-side PCB board, and this process is a preparation for Fig. 4.3 (b), which shows the soldering of all the particulars with a jumper wire. Then, Fig. 4.3 (c) shows how everything is contained in a box to hold the product using a 3D printer. Finally, Fig. 4.3(d) shows the complete design after everything is collected and appropriately adjusted.

Fig. 4.4 (a) shows the ideal position of the cow after applying the device around the neck. Usually, a cow would shake its head in case of finding a burden that affects its liberty of motion, but luckily the device would not cause such a disturbance. As the cow drinks from the bucket, as in Fig. 4.4 (b) 12, it is easy for the cow to bend over and drink without any burden on the device. In Fig. 4.4 (c), the cow can be dragged easily for a walk without harming the device's purpose or the cow's neck. According to the survey, cattle constantly graze for 10- 15 minutes and drink at an average rate for 2-3 minutes. The above three positions have been tested in all three categories of cows. A Timestamp will be generated each minute, and this information will be saved on the MO20's SD card. The comparison after applying the test to the three different categories of cows resulted in various machine-learning algorithms. The system above SCHeMoS will assist the owner in taking preventive and curative steps as soon as possible, preventing catastrophic losses and the owner can take rapid action.

5. Results and discussion. From the results obtained it sounds like the LSTM model used for cow lameness detection is performing well in general, with the exception of the predictions for Brahman males. This could be due to the factors mentioned, such as their continuous rest state and less movement from one

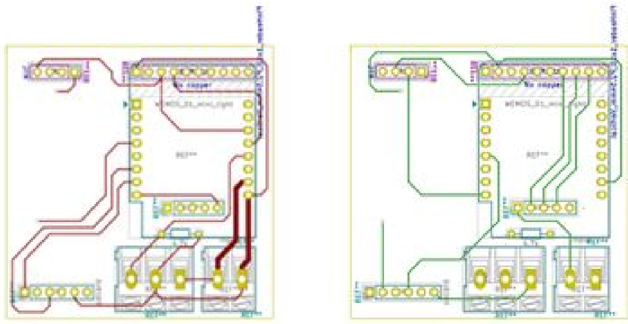
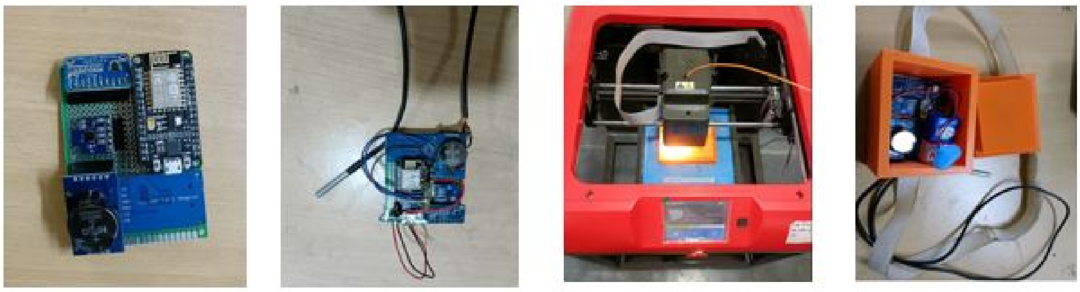


Fig. 4.2: Final PCB board circuit of SCHeMoS using CAD software



(a) (b) (c) (d)

Fig. 4.3: SCHeMoS Hardware design for implementation(a) Sensors with double sided PCB board (b) Circuit of SCHeMoS (c) Preparing box for SCHeMoS in 3D printer (d) Design of SCHeMoS

(a) (b) (c)

Fig. 4.4: Position of the cow after fixing the device (a) Ideal position of the cow (b) Drinking position (c) Walking position

Table 5.1: Performance of the Proposed System

Model Classification	Accuracy	F1 Score	Specificity	Recall	Precision
Affected with lameness	92.45	0.926	0.931	0.925	0.918
Not Affected with lameness	92.36	0.919	0.92	0.919	0.921

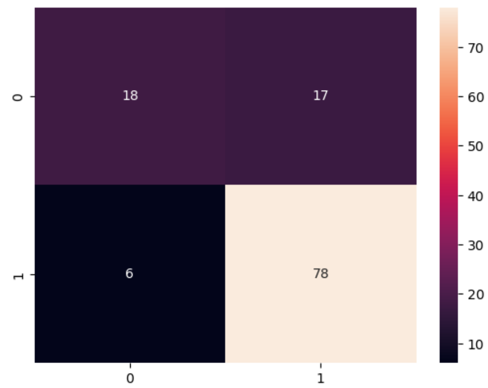


Fig. 5.1: Confusion matrix

place to another. It's important to note that the accuracy of DL models depends on the quality and size of the data used to train them. In this case, the proposed LSTM model is able to precisely calculate the active movement of the next cow, which is a good indication that it is a good fit for predicting cow lameness task. Additionally, the proposed LSTM model could be used for time-series prediction and it is important to pre-process the data accordingly, like normalizing the data, adding time-lag features, etc to obtain more accuracy. We assessed our obtained results by using few of the below ML metrics from Equ. 5.1 to 5.4. tr__pst, are true positive (actually lame and lameness correctly predicted), tr__ngt are true negative (actually not lame predicted as not lame), fp__pst are false positive (actually lame but predicted as not lame),fp__ngt are false negative (actually not lame but predicted as lame). Table 5.1 shows the overall results obtained from the proposed approach.

$$\text{Accuracy} \quad = (\mathrm{tr}\_pst + tr\_ngt) \,/\, (\mathrm{tr}\_pst + tr\_ngt + fs\_pst + fs\_ngt) \tag{5.1}$$

$$\text{Recall} \quad = \mathrm{tr}\_pst/\,(\mathrm{tr}\_pst + fs\_ngt) \tag{5.2}$$

$$\text{Precision} \quad = \mathrm{tr\_pst}/\,(\mathrm{tr\_pst} + \mathrm{fs\_pst}) \tag{5.3}$$

$$\text{F1 Score} \quad = 2 \times (\text{ precision } \times \text{ recall })/(\text{ precision } + \text{ recall }) \tag{5.4}$$

To visualise the results obtained more precisely we represented the classified data in the form of confusion matrix. It summarizes the performance of a classification algorithm. Fig. 5.1 represents the confusion matrix for our approach. A typical confusion matrix for cow lameness detection would have the following structure: We compared our results with few of the existing approaches and the comparison revealed that the proposed approach have outperformed than the existing approaches. The comparison results are shown in Table 5.2. The training and testing accuracy of our SCHeMoS approach is shown in Fig. 5.2. It is observed that the testing accuracy gradually increases when the input data is increased. The training loss of the proposed model reduces to 0.2016 after the 120th epoch. The model stabilises at the learning rate of 0.001.

Table 5.2: Existing versus proposed approach.

Cow Category	SVM	Logistic Regression	Random Forest	K-NN	Proposed SCHeMoS Model
Lameness not affected	79%	83%	86%	90%	92.36%
Lameness affected	80%	85%	90%	90%	92.45%

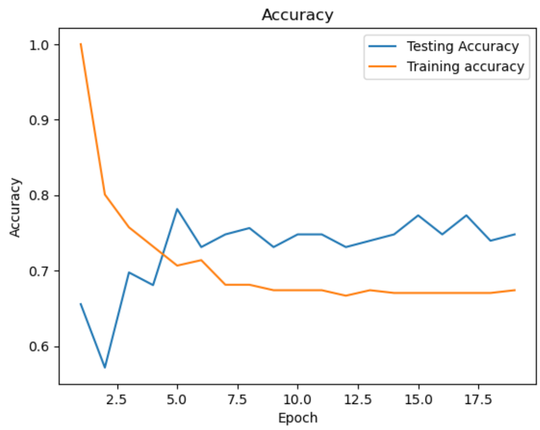


Fig. 5.2: Training and testing accuracy

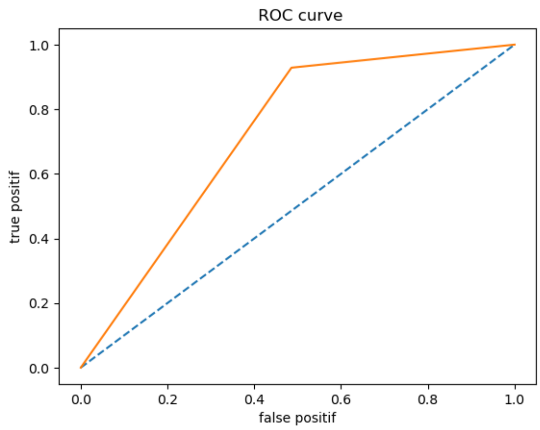


Fig. 5.3: ROC curve for the proposed classifier

A binary classifier's performance is depicted graphically by a Receiver Operating Characteristic (ROC) curve. The true positive rate (tr__pst), often referred to as recall or sensitivity, is represented on the y-axis while the false positive rate (fs__pst) is represented on the x-axis. Sequential and time series data are both well suited for our LSTM-based SCHeMoS model. The time-series data from the cow lameness data set can be analysed and classified using it. The curve line increases as the number of input is increased and stays constant at the 120th epoch with highest accuracy of 92.45%.The ROC of the proposed approach is shown in Fig. 5.3.

6. Conclusion. This research has suggested cow hoof health (lameness) monitoring using the sensor data obtained from the cow's position. We used LSTM network to classify hoof affected or not affected based on the input sensor data of cows performing actions like move, sit,walk,graze and drink. The farmer/diary maintenance person is alerted through IoT devices when the possibility surpasses a specified threshold. As per our result, the SCHeMoS model reduces the computational complexity by classifying in reduced time than few of the existing approaches and also reduced memory storage. In this work, the main goal is to build a cow monitoring model made up of IoT devices on a farm, which is used to collect data of cows in various positions, temperature, grazing habit etc.This collected data is cleaned and given as input to a LSTM network to predict the lameness in cows. After the noise is taken out of the data, a DL based LSTM model for cow lameness detection is built. The model is capable of predicting how the cow's position will transform over the next phase. When the model's predictions are compared to what actually obtained with few of the existing approaches, it shows how accurate and useful it is.The error rate of the model is recorded as 1.201 with the training loss of 0.2016, validation loss as 0.316 and overall accuracy of 92.45%.This model also has its limits. It needs a bunch of input data to learn, and if small amount of data is given as input, the model's prediction accuracy may reduce or sometime may be inaccurate.

REFERENCES

[1] Chao,Ludovico,Korkut,Tokgoz,Jim,Sihan,Hiroyuki, *Integrated Data Augmentation for Accelerometer Time Series in Behavior Recognition: Roles of Sampling, Balancing, and Fourier Surrogates,* in IEEE Sensors Journal, vol. 22, no. 24, (2022), pp. 24230-24241. doi: 10.1109/JSEN.2022.3219594.

[2] Dedi Darwis, Abhishek R Mehta, Novi Eka, Samsugi, Priya, *Digital Smart Collar: Monitoring Cow Health Using Internet of Things* International Symposium on Electronics and Smart Devices (ISESD), (2022), DOI: 10.1109/ISESD56103.2022.9980682.

[3] Boris,Evstatiev,Nikolay,Valov,Seher,Kadirova,Teodo,Nenov *Implementation of a Prototype IoT-Based System for Monitoring the Health, Behavior and Stress of Cows*, 2022 IEEE 9th Electronics System-Integration Technology Conference (ESTC) IEEE,DOI: 10.1109/ESTC55720.2022.9939489.

[4] M. Alsaaod, M. Luternauer, T. Hausegger, R. Kredel and A. Steiner, *The cow pedogram Analysis of gait cycle variables allows the detection of lameness and foot pathologies.* J. Dairy Sci. , vol. 2, no. 100, (2017), pp. 1417–1426, 2017

[5] Akash Trivedi, Pinaki Sankar Chatterjee *CARE: IoT enabled Cow Health Monitoring System*, 2022 International Conference on Intelligent Technologies (CONIT), (2022), IEEE | DOI: 10.1109/CONIT55038.2022.9847701.

[6] Abdul Aziz Chaudhry, Rafia Mumtaz, Syed Mohammad Hassan Zaidi, Muhammad Ali Tahir, Syed Hassan Muzammil School *Internet of Things (IoT) and Machine Learning (ML) enabled Livestock Monitoring*, 2020 IEEE 17th International Conference on Smart Communities: Improving Quality of Life Using ICT, IoT and AI (HONET), (2020) IEEE | DOI: 10.1109/HONET50430.2020.9322666.

[7] G. Suseendran, D. Balaganesh *Cattle Movement Monitoring and Location Prediction System Using Markov Decision Process and IoT Sensors*, 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM).

[8] Varun Mhatre, Vishwesh Vispute, Nitin Mishra, *IoT based Health Monitoring System for Dairy Cows* "IoT based Health Monitoring System for Dairy Cows", IoT based Health Monitoring System for Dairy Cows, (2020).

[9] Achour Brahim, Belkadi Malika, Aoudjit Rachida, Lalam Mustapha, Lalam Mustapha, Laghrouche Mourad *Dairy cows real-time behaviour monitoring by energy-efficient embedded sensor*, IEEE, (2020).

[10] Pratama, Y. P., Kurnia Basuki, D., Sukaridhoto, S., Yusuf, A. A., Yulianus, H., Faruq, F., and Putra, F. B. *Designing of a Smart Collar for Dairy Cow Behavior Monitoring with Application Monitoring in Microservices and Internet of Things-Based Systems.* 2019 International Electronics Symposium (IES), (2019). https://doi.org/10.1109/elecsym.2019.8901676.

[11] S. T. Ahmed, V. V. Kumar and J. Kim *AITel: eHealth Augmented-Intelligence-Based Telemedicine Resource Recommendation Framework for IoT Devices in Smart Cities,* in IEEE Internet of Things Journal, vol. 10, no. 21, (2023) pp. 18461-18468„ doi: 10.1109/JIOT.2023.3243784.

[12] Vannieuwenborg, F., Verbrugge, S., and Colle, D. *Designing and evaluating a smart cow monitoring system from a techno-economic perspective.* 2017 Internet of Things Business Models, Users, and Networks, (2017). https://doi.org/10.1109/ctte.2017.8260982.

[13] Mulla, A. I., Mulik, A. P., Prashant, A., and Gawai, D. D. *Continuous health surveillance system for cattle.* 2017 International Conference on Intelligent Computing and Control Systems (ICICCS), (2017). https://doi.org/10.1109/iccons.2017.8250656

[14] Khanh, P. C. P., Dinh Chinh, N., Cham, T. T., Vui, P. T., and Tan, T. D. *Classification of cow behavior using 3-DOF accelerometer and decision tree algorithm.* 2016 International Conference on Biomedical Engineering (BME-HUST), (2016). https://doi.org/10.1109/bme-hust.2016.7782100.

[15] Smith, K., Martinez, A., Craddolph, R., Erickson, H., Andresen, D., and Warren, S. *An Integrated Cattle Health Monitoring System.* International Conference of the IEEE Engineering in Medicine and Biology Society, (2006).https://doi.org/10.1109/iembs.2006.259693.

[16] Vannieuwenborg, F., Verbrugge, S., and Colle, D. *Designing and evaluating a smart cow monitoring system from a techno-economic perspective.* 2017 Internet of Things Business Models, Users, and Networks, (2017). https://doi.org/10.1109/ctte.2017.8260982.

[17] S. T. Ahmed, V. V. Kumar, K. K. Singh, A. Singh, V. Muthukumaran, and D. Gupta, *6G enabled federated learning for secure IoMT resource recommendation and propagation analysis* Computers and Electrical Engineering, vol. 102, (2022), p. 108210, doi: 10.1016/j.compeleceng.2022.108210.

[18] Khatate, P., Savkar, A., and Patil, C. Y. *Wearable Smart Health Monitoring System for Animals.* 2nd International Conference on Trends in Electronics and Informatics (ICOEI), (2018). https://doi.org/10.1109/icoei.2018.8553844.

[19] Ronghua, G., JingQiu, G., and Jubao, L. *Cow Behavioral Recognition Using Dynamic Analysis.* International Conference on Smart Grid and Electrical Automation (ICSGEA), (2017). https://doi.org/10.1109/icsgea.2017.26.

[20] Junior, R. L. *IoT applications for monitoring companion animals: A systematic literature review.* 14th International Conference on Innovations in Information Technology (IIT), (2020). https://doi.org/10.1109/iit50501.2020.9299045.

[21] 21. Natarajan, R., Lokesh, G. H., Flammini, F., Premkumar, A., Venkatesan, V. K., and Gupta, S. K. *A Novel Framework on Security and Energy Enhancement Based on Internet of Medical Things for Healthcare 5.0.* Infrastructures, 8(2), (2023), 22. https://doi.org/10.3390/infrastructures8020022.

[22] Sindu Divakaran, Lavanya Manukonda, N Sravya, Melinda Morais M, Janani P, Sindu Divakaran, Lavanya Manukonda, N Sravya, Melinda Morais M, Janani P. *IOT clinic-Internet based patient monitoring and diagnosis system.* IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI-2017).

[23] Panda, S., and Panda, G. *Intelligent Classification of IoT Traffic in Healthcare Using Machine Learning Techniques.* 2020 6th International Conference on Control, Automation and Robotics (ICCAR), (2020). https://doi.org/10.1109/iccar49639.2020.9107979.

[24] Ankit Bhavsar, and Harshal Arolkar *ZigBee Based Network Architecture for Animal Health Monitoring*, 2015 1st International Conference on Next Generation Computing Technologies (NGCT-2015).

Edited by: Polinpapilinho Katina
Special issue on: Scalable Dew Computing for Future Generation IoT Systems
Received: Nov 1, 2023
Accepted: Feb 1, 2024