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MOOnitor: An IoT based multi-sensory intelligent device for cattle activity monitoring

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A B S T R A C T

Continuous activity monitoring of dairy cattle is essential to acquire a comprehensive knowledge on health and well-being of the animals. In this research, we have reported the development and deployment of "MOOnitor", a neck-mounted intelligent IoT device for cattle monitoring. The device facilitates classification of salient activities of cattle through appropriately positioned sensors. MOOnitor is an integration of a temperature sensor, a global positioning system (GPS) module, and a 3-axis accelerometer in a lightweight enclosure, which is attached to a halter that allows transmission of data to an IoT server using a microcontroller and a cellular GSM module. After acquiring the necessary sensory information, the most significant features were strategically extracted for enhanced data interpretation. Thereafter, optimally tuned eXtreme Gradient Boosting (XGBoost) and Random Forests classifiers were implemented to classify activities like 'standing', 'lying', 'standing and ruminating', 'lying and ruminating', 'walking', and 'walking and grazing'. The performances of the two classifiers towards identification of different cattle activities were compared in terms of accuracy. Furthermore, the importance of using a temperature sensor and a GPS module in addition to an accelerometer in cattle activity recognition could be justified. An overall classification accuracy as high as ~97% was achieved using the XGBoost based classifier. In addition, accuracy, precision, sensitivity and specificity for standing (0.98, 0.97, 0.97, 0.98), lying (0.97, 0.90, 1, 0.96), standing and ruminating (0.99, 1, 0.97, 1), lying and ruminating (0.99, 1, 0.83, 1), walking (1, 1, 1, 1), and walking and grazing (0.99, 1, 0.75, 1) shows the suitability of the proposed method in effective cattle activity monitoring. Since cattle activity states are indicative of various factors such as estrous and several diseases like mastitis, foot-and-mouth disease, etc, the MOOnitor may be used for early detection of these conditions in addition to general health monitoring.

1. Introduction

Livestock plays a vital role in the socio-economic growth of the developing countries [3]. Recent years are marked with a significant increase in cattle population thereby arising the need for effective cattle monitoring technology so that diseases in animals can be anticipated and immediate actions can be imposed [1]. Regular monitoring of cattle primarily involves critical observation of day-to-day activities of cattle to draw suitable inferences related to health and well-being of the animals. In this context, the existing literature claims that anomalies in cattle activities such as standing, lying, grazing, ruminating, and walking for each animal can help to detect (re)production, health, and welfare problems such as onset of estrous, mastitis, lameness, foot-and-mouth diseases (FMD), etc. These practises have received notable appreciation in recent years with special emphasis on use of non-invasive wearable sensors which are robust enough to fit in free grazing environment [5,10].

Existing literature entailing activity recognition of cattle mostly focuses on use of wearable accelerometer sensors; the use of acoustic sensors, RFID location tags, and cameras coupled with radio

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Table 1
Existing studies related to cattle activity monitoring.

Sl. No.	Author	Method	Algorithm used	Classifier's performance	Activity Classification
1.	Bikker et. al. [12]	Ear mounted accelerometer	Machine learning algorithm not implemented	NA	Monitoring eating, ruminating, and resting behaviour.
2.	Borchers et. al. [15]	Accelerometer placed on neck area and rear leg respectively	Random forest, Linear Discriminant Analysis, Neural Networks	Activity not classified rather calving was predicted.	Calving prediction from activity, lying, and ruminating behaviours.
3.	Tani et. al. [14]	Acoustic sensors placed at horn and nasal bridge, single-axis acceleration sensor on forehead	Machine learning algorithm not implemented	NA	To monitor ingestive and rumination chewing behaviour
4.	Arcidiacono et. al. [13]	Statistical analysis of collar-mounted accelerometer data	Threshold based classifier used. Machine learning algorithm not implemented	NA	Real-time classification of cow feeding and standing behavioural activity
5.	Benaissa et. al. [27]	Neck and leg mounted accelerometer sensor	Calving prediction conducted	NA	Calving prediction.
6.	Wang et. al. [6]	Leg mounted accelerometer sensor and location tag sensor	Multi-Backpropagation-Ada-Boost algorithm	Accuracy for feeding and standing poor (80%)	lying, lying down, standing up, normal walking, active walking, feeding and standing classification.
7.	Tran et. al. [11]	Neck and leg mounted accelerometer	Random Forests	Accuracy for standing 88%	Lying, standing, feeding and walking classification
8.	Diosdado et. al. [26]	Accelerometer based activity	Decision trees, k-means, hidden Markov model (HMM), support vector machine (SVM)	Overall sensitivity and precision for decision trees (83.94,78.53), k-means (68.45, 69.09), HMM (70.78, 71.41), SVM (80.85, 85.89)	Detection of cattle activity

frequency modules for data transmission to nearby nodes are also found. Accelerometer sensors are generally placed in the neck, ear or leg of the animal [2]. The cattle activities that are generally supervised include standing, ruminating/ grazing, walking, lying or a combination of these states [9]. An account of the existing studies related to cattle activity monitoring is presented in Table 1.

A detailed study of advances in cattle activity monitoring using non-invasive sensors, as presented in Table 1, infers the following observations, which need to be considered for enhanced acceptance of the technology in real-time cattle monitoring- (a) Leg mounted accelerometer based devices are claimed to be less effective in classification of feeding and standing behaviour [6], as a result of which researchers have used combination of leg and collar mounted units to achieve better classification accuracy [11]. However, placement of sensors at two different locations is equally complex and challenging for continuous monitoring of animals. A neck mounted device that adequately classifies the aforementioned activities is hence desired for ease of access; (b) Research in veterinary science reveals that the body temperature of cows increases significantly during active hours irrespective of the duration [4]. For instance, a standing and ruminating cow exhibits a slightly higher temperature than a lying or resting one. However, current studies have not mainly focussed on this factor. Inclusion of a temperature sensor that would continually log a cow's body temperature might lead to more accurate activity monitoring; (c) Majority of the reported research focuses on activity classification within farm or barn environment [12,13,15,26]. However, in developing countries cattle are mostly found to move around freely in the outdoors during the day time which calls for a need of a sensory technology that would meet out-of-farm consequences. This is where the temperature and walking speed of the cattle become the dominant factors for activity analysis. Hence, installation of a Global Positioning System (GPS) module along with a temperature sensor would be a prospective solution; (d) The reported studies deal with the data collection and interpretation of cattle activity wherein the data is either manually off-loaded [13] or transmitted via radio frequency modules [11]. This becomes impractical for walking and grazing cattle since data transmission is limited by the effective range of radio frequency module. A SIM based module which can provide cellular internet connectivity can alleviate this issue.

Considering the aforementioned findings, in this research we have presented "MOOnitor"- a device housing a temperature sensor, a 3-axis accelerometer sensor, and a GPS module measuring the cattle body temperature, acceleration due to movements, and walking speed respectively to effectuate seamless monitoring of various cattle activities in real-time scenario both in and off the farm. A group of healthy, lactating crossbred cows from three different barns was selected for experimental purpose. The MOOnitor was installed on a halter and fastened to the neck of each cow for data acquisition. An onboard microcontroller captured the necessary data and transmitted the information via a SIM based GSM module to a remote server. The acquired data was then subjected to feature extraction, following which, intelligent algorithms were deployed to draw suitable inferences.

Bagging and boosting algorithms are the two popular ensemble methods wherein multiple learning algorithms are used to train models with same dataset to achieve a better prediction accuracy, avoid overfitting, and effectively handle bias-variance trade-off. The RFs that comprises many decision trees are trained through bagging and the predictions are made based on the average of the output of the decision trees. This enhances the prediction accuracy and consequently, the limitations of decision trees are alleviated. On the other hand, XGBoost algorithm deals with gradient boosted decision trees for enhanced performance. Considering several factors such as regularization, apprehension of missing value, flexibility, etc. leading to speedy and accurate predictions, XGBoost based classification and regression algorithms are gaining importance in recent times. Here, the feature-extracted dataset was trained using optimally tuned XGBoost and RF classifier and the results of both were compared. Although the bagging and boosting algorithms are popular in related literature [6,15], very few researchers have implemented XGBoost in sensor-driven cattle monitoring. For instance, [8] studied the feasibility of an automated detection system in classifying sick and healthy cattle using a motion sensor and necessary on-farm health recordings. Results of the research indicated a decent F1-measure of 81% and much lesser computational time allowing implementation of the methodology in online and/or cloud platforms [8]. However, classification of cattle activity using XGBoost is not attempted till date to the best of our knowledge. Motivated by the aforesaid findings and considering the exceptional performance of XGBoost based classification in other data-driven applications reported in recent literature [7], the authors implemented XGBoost in this research for classification of cattle activities. Further, benefits of using multi-sensory approach over accelerometery have been discussed to reach at interesting inferences.

2. Materials and methods

The MOOnitor is an assembly of a temperature sensor, a GPS module, and a 3-axis accelerometer on a microcontroller platform used for the measurement of associated physical quantities pertaining to cattle activities. The sensory information was transmitted to an IoT server using a GSM module for further interpretation. Intelligent algorithms were implemented thereafter to classify different activity states. The methodology is elaborated in the following sections. A block diagram representing the sensor integration and a glimpse of the developed device used for field experiments are shown in Fig. 1(i) and Fig. 1(ii) respectively.

2.1. Device development and system integration

The device comprised of a negative temperature coefficient (NTC) thermistor (make: Vishay Instruments, India, Part No: NTCLE413E2103F102L, resistance at 25 °C-10 KOhm), a GPS module (make: Ublox, type: NEO6M), and a motion processing unit (MPU)/ 3-axis accelerometer (make: InvenSense, model: MPU6050) for measurement of cattle's body temperature, location or walking speed of the animal and acceleration along X, Y, and Z axes in g units respectively. The sensors were interfaced with an ATMEL328P microcontroller that received the data from the sensors in form of a data array sampled at 1 Hz frequency. Supported by the findings of the available literature [27] and the scan rate of GPS module being 1 Hz, the sampling frequency of the sensor data was fixed to 1 Hz. ATMEL328P microcontroller was used considering its compatibility with Arduino UNO board wherein the microcontroller chip was programmed prior to use in the developed printed circuit board (PCB).

The thermistor was interfaced with the microcontroller using a voltage divider circuit bearing a divider resistance of 10 K (Fig. 2(i)). It is well known that a thermistor changes its resistance (R_{th}) with temperature variations. Here, one end of the thermistor was connected to an analog pin of the microcontroller that read the analog value (val) ranging between 0 and 1023, which was mapped with voltage (V_{th}) ranging between 0 and 5 V as in Eq. 1. The thermistor resistance computed from V_{th} is shown in Eq. 2.

$$V_{th} = \left(\frac{5}{1023}\right) \times val \tag{1}$$

$$R_{th} = \frac{5 \times 10K}{V_{th}} - 10K \tag{2}$$

The temperature in °C (T) is calculated using Steinhart-Hart equation [17], as in Eq. 3, with coefficients- A = 0.001129148, B = 0.000234125 and C = 8.76741 * 10^{-8} standard for 10 K thermistor.

$$T = \frac{1}{A + B^{*}\ln(R_{th}) + C^{*}(\ln(R_{th})^{3})} - 273 \tag{3}$$

The aforementioned aspects were considered while programming the microcontroller. The temperature measured from the thermistor was validated using standard digital laboratory thermometer (Make: Elnico Innovations, Model: TFX111) and measurement errors were noted.

The GPS module transmitted the latitude and longitude information as NMEA (National Marine Electronics Association) sentences using software serial mode of communication to the microcontroller at a navigation update rate of 1 Hz. The GPS had a velocity accuracy of 0.1 m/s as claimed by manufacturer. Since the speed of cattle during normal walk can be as low as 3.4 Km/h (~ 1 m/second) and as high as 40 Km/h (~ 11 m/s) during run [18], the latitude and longitude information was recorded every 1 s to estimate the distance travelled. TinyGPS+ + library for Arduino was emulated in the microcontroller programming and was used to extract the latitude, longitude, and speed related information of the cattle in m/s. The speed in m/s was validated using "GPS Speedometer: Speed Tracker, HUD, Odometer" android application.

The MPU6050 module recorded the acceleration along X, Y, and Z axes and transmitted the data using inter-integrated circuit (I2C) mode of communication to the microcontroller. MPU6050 is a MEMS based 3-axis accelerometer and 3-axis gyroscope. To obtain the desired information from the accelerometer, the full-scale range of accelerometer was selected as + /− 2 g with sensitivity scale factor of 16,384 LSB (Count)/g, where g is acceleration due to gravity. Thereafter, acceleration was noted along X, Y, and Z axes after dividing sensor raw data with its sensitivity scale factor [19]. Since the

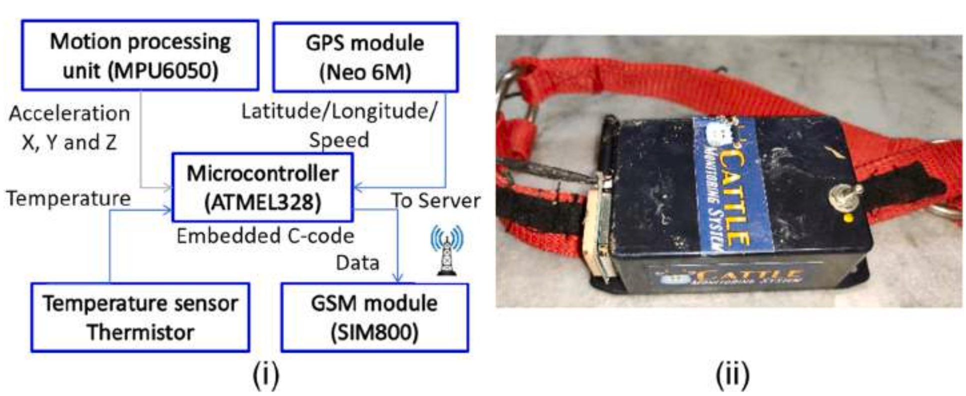

Fig. 1. (i) Block diagram representing sensor integration (ii) The MOOnitor device attached with a cattle halter.

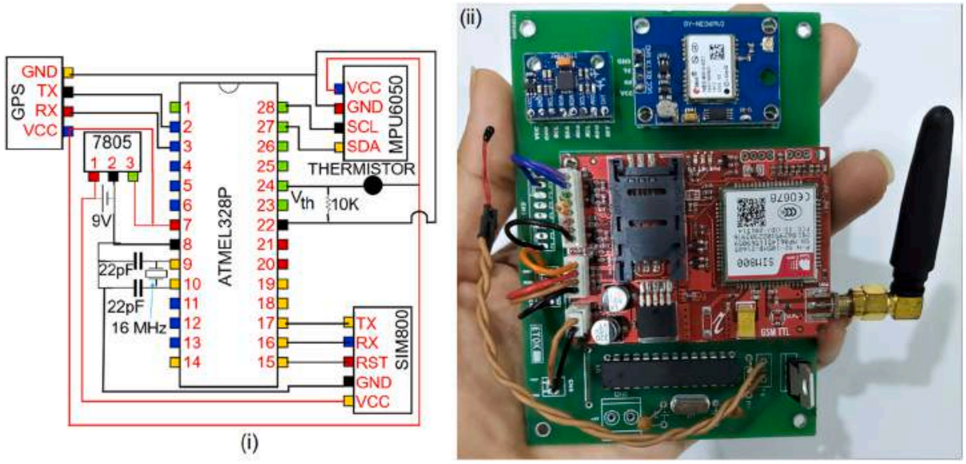

Fig. 2. (i) The circuit diagram for the developed device "MOOnitor" (ii) The fabricated PCB assembly for the device.

MPU6050 comprises of an accelerometer along with pre-calibrated motion processing unit (MPU) we considered the values suitable to be used as it is.

The data collected from the sensors was stored in the microcontroller as a character array comprising of temperature, latitude, longitude, speed, and acceleration along X, Y and Z axes. The microcontroller transmitted each character array to a server over internet network using GSM / GPRS Quad Band TTL UART Modem (make- rhydoLABZ, India, model- SIM800) to a user specified API (Application Programming Interface) defined in the server. The entire circuitry along with the modem was assembled on a printed circuit board (PCB) for appropriate packing and installation on a neck mounted halter set-up. The system was powered by a rechargeable lithium polymer battery (Make: Orange, Capacity: 850mAh 2 S 30 C/ 60 C, peak voltage: 8.4 V) coupled with a 5 Volts voltage regulator (L7805) to supply constant voltage to all the integrated modules. The developed PCB and battery assembly was packed in a waterproof plastic enclosure and was attached to a cattle halter using screws at appropriate location. During packaging, it was ensured that the thermistor was fixed at the external surface of the device touching the cattle body. The thermistor was installed such that it is always in contact with the upper neck region of the animal. Furthermore, the GPS antennae and the GSM antennae were fixed outside the plastic enclosure. The developed PCB is shown in Fig. 2 (ii). The size of the packaged device was 44 mm × 82 mm × 110 mm and the net weight was ~130 g.

The received signal strength indicator (RSSI) of SIM800 varies with location. Consequently, the battery lifetime of the device may be different at different locations. Hence, the battery lifetime was computed for each location of concern. The battery lifetime (L) in hours of a wireless sensory node is given by $L= B_c/I_L$, where, B_c is the battery capacity in mAh and I_L is the total load current consumed by the sensors, microcontroller, and GPRS module in mA. Thus, $L= B_c/C_s+C_m+C_r$ where C_s, C_m, and C_r are sensory, microcontroller, and radio unit currents respectively. For any wireless sensor network (WSN), more than 60% of the load current is consumed by the radio unit itself. A 5 A, ACS712 (ACS712–05B) current sensor module was used to measure the current drawn by the device. This methodology was adapted from earlier literature [28].

The character array transmitted by the microcontroller was received on ThingSpeak server which is a platform for user friendly data collection in cloud backed by mobile application. The server received data through different channels with unique API keys, each channel being assigned for a single device. The API key needs to be specified for each channel while programming the microcontroller with respect to the device under consideration. This set up facilitated hooking up of multiple number of MOOnitor devices through different API keys. Each channel contained several fields where each field corresponded to readings from each sensor. Therefore, the number of animals monitored simultaneously was equal to number of channels on the server and number of fields in each channel were 7 (temperature, latitude, longitude, walking speed, acceleration along X axis, acceleration along Y axis and acceleration along Z axis). The data for temperature, speed and acceleration along 3 axes were plotted for visualization and were downloaded as.csv files for algorithm implementation resulting in activity classification. The latitude and longitude data were fed to an HTML plugin script created on ThingSpeak server combined with Google Maps API key to display real time location of the cattle on the map.

2.2. Experimental protocols and data collection

Prior to field deployment of the MOOnitor, the thermistor and the GPS module were validated in laboratory environment. Temperature validation was conducted using a hot plate arrangement wherein the temperature was varied from 20 °C to 50 °C (measured using a laboratory thermometer) and corresponding temperatures measured by the thermistor were noted. The efficacy of the GPS module in measuring walking speed was validated using a smart phone application imposed with speed ranging between 1 m/s and 9 m/s. Here, a passenger vehicle was used as a speed simulator. The device as well as the smartphone loaded with GPS application was housed in the vehicle and the vehicle was driven in a smooth empty terrain such that the speed measured using the smartphone application was constant for each value of speed ranging from 0 to 9 m/s. Simultaneously, the MOOnitor device transmitted the time stamped speed information. For each speed instance, the data from the MOOnitor was logged for 60 s at a sampling rate of 1 Hz. Subsequently, the average of the readings of the MOOnitor for each speed instance were compared with the speed given by the smartphone application. However, the GPS signal was found to be discontinuous while a cow was housed in a roofed barn; this did not affect the intended objective as the cow was mostly stable inside the barn and the role of the GPS signal was insignificant in this state.

Field experiments were carried out at three different locations (i) the barn of West Bengal University of Animal and Fishery Sciences (WBUAFS), Mohanpur campus, West Bengal, India (Latitude: 22.9418°N, Longitude: 88.5247°E) (ii) barn at Namkhana Uttar Para village, under Block- Namkhana CD Block, PS-Namkhana, South 24 Parganas district, West Bengal, India (Latitude: 21.7699° N and Longitude: 88.2315°E) and (iii) barn at Palashdiha Village, Durgapur,

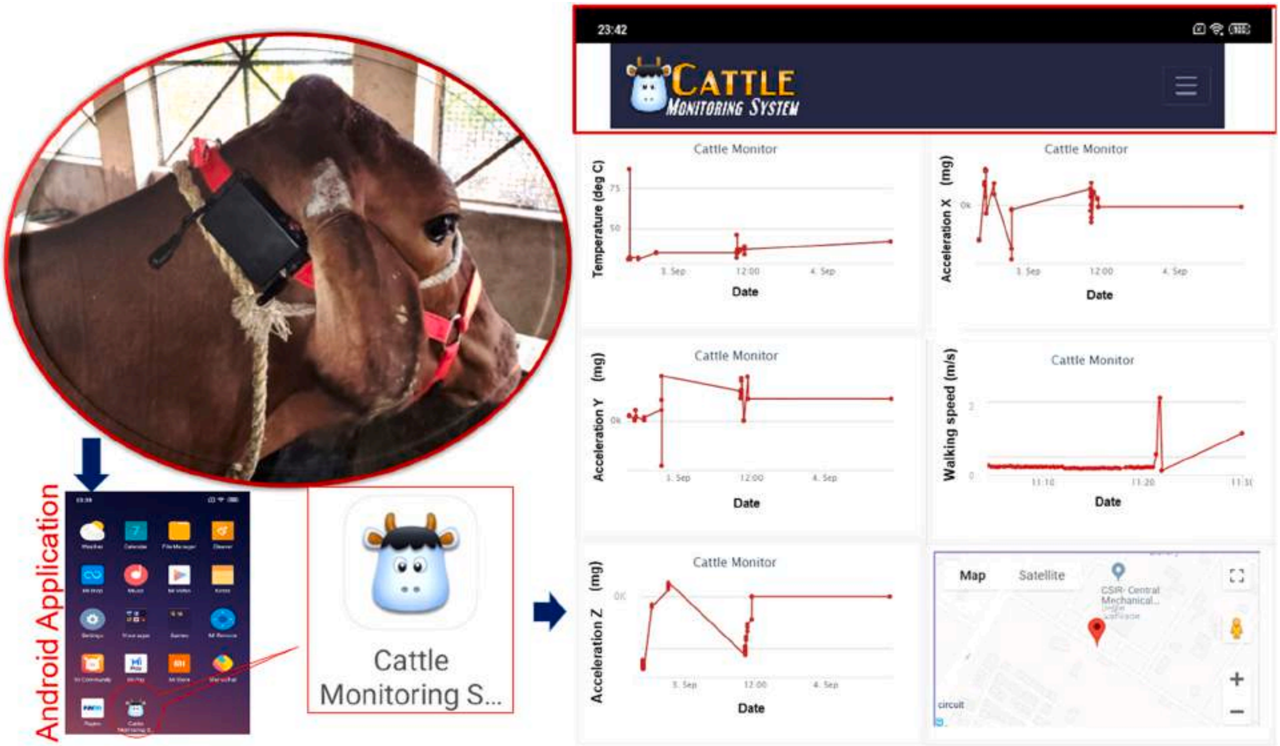

Fig. 3. Image depicting the developed device MOOnitor mounted to cattle, the android application and the data seen on smartphone using the android application received in the server.

West Bengal, India (Latitude: 23.5356°N, 87.2921°E). Locations (i), (ii) and (iii) were at an altitude of 17, 4 and 65 m above sea level respectively, with locations (ii) and (iii) having pastures in close vicinity. The experiments were conducted during from September 2018 to November 2020. The data was collected in a server located at CSIR-Central Mechanical Engineering Research Institute, Durgapur, WB, India (Latitude: 23.5493°N, Longitude: 87.2943°E). The server was located at a maximum distance of approximately 250 km from the aforementioned locations.

Thirteen lactating crossbreed healthy cows were selected randomly for the study with an average body weight of 465 ± 16 kg, at the age of 6 ± 0 years and milk yield of 10 litres approximately. Six, five, and two numbers of cows were selected from location (i), (ii), and (iii) respectively. The cows were checked clinically and confirmed that they were free from any anatomical, physiological or infectious disorders. Cows were milked twice daily by hand milking. The cows were provided with required concentrate feed and roughages and had free access to water in all the three locations. Green fodders (local grass) and commercially available concentrate feeds were fed according to the standard feeding regimen. The animals chosen for experiments were housed in a space with brick flooring, asbestos roofing and well-ventilated shed situated in a sheltered paddock under the natural day light and environmental conditions. The sheds were cleaned and washed every day. Antiseptic solution like phenyl was applied at regular intervals on the floor of the shed. Clean drinking water was made available ad libitum. As per the standard schedule deworming and vaccination were done. Location (i) supported a surface area of 45 sq. ft. per animal, whereas, locations (ii) and (iii) offered a surface area of approximately 25 sq. ft. per animal with access to pastures. The minimum area of the pastures close to the barns was 100 m^2.

The MOOnitor devices were fixed on the upper neck region of the animal under observation and sensor data received in the server was visualized using the android application as shown in Fig. 3. Several trials were conducted under the supervision of qualified vet prior to collection of actual data used in classification. The skin temperatures of the cattle as received on IoT platform were validated using a standard handheld portable IR thermometer (Make: Bentech, Model: GM320).

To establish the significance of a temperature sensor towards cattle activity monitoring, temperature information was noted at 4 different states: 1) before feed intake, 2) after feed intake, 3) before grazing and, 4) after grazing. The experiments were conducted in a field/pasture wherein the MOOnitor was mounted on the selected animals. The skin temperatures were recorded using the MOOnitor and IR thermometer (IRT) at specific time intervals during 09:00 am to 11:30 am (IST). Additionally, the core body temperature was measured using a digital clinical thermometer (CT) to observe its relation with skin temperature. The experiments were conducted for 15 days on a randomly selected animal and the mean temperature readings for each state were considered. Activity details along with corresponding time durations were noted by a field supervisor for future reference. The activities taken into consideration in this research are defined in Table 2. A one-way ANOVA analysis with a significance level of 0.05 was conducted on the skin temperatures acquired from the MOOnitor and the IRT to draw conclusions related to the variability between the two.

Furthermore, the raw sensor data acquired was studied to understand the relationship of sensors with the corresponding cattle activities. A field supervisor was always present during the experiments and the time of the activities were logged carefully. Additionally, the time-stamped videos were captured using "Timestamp Camera" application of a smart phone. Now, since the raw sensor data received in the IoT server was already time-stamped, the sensor data could be correlated with the cattle activity videos.

A total of 605 valid datasets corresponding to the six activities as in Table 2 were recorded in the IoT server from 13 cows under observation. The experimental protocols were approved by the Institutional Animal Ethics Committee (IAEC) of the West Bengal University of Animal and Fishery Sciences, Kolkata, India.

Table 2
List of activities recorded and definitions.

S. No	Activity	Definition
1	Standing	The cattle stand on its four feet with its head up or down.
2	Lying	The cattle sit on the surface with its head up or down.
3	Standing and Ruminating	The cattle stand on its four feet and ruminates with its head up or down.
4	Lying and Ruminating	The cattle sit on the surface with its head up or down and ruminates.
5	Walking	The cattle walk in a non-enclosed area with its head up or down.
6	Walking and Grazing	The cattle walk in a non-enclosed area and grazes green grass with its head down.

NB: Activity was noted only if the cattle conducted the same continuously for at least 32 s

2.3. Feature extraction

The datasets for all the animals on each day of the experiments were downloaded from the IoT server. All the datasets collected throughout the experimental process were combined suitably and used without any filtering. The window size was selected after repeated manual iterations to optimize the classification accuracy. As reported in the existing literature, window sizes varied between 10 s and 1 min to the best of our knowledge [6,9,11]. Hence, to select an optimum window size trials were conducted with window sizes of 16, 32, 48 and 64 s and the corresponding classification accuracies were computed. Each dataset exhibited sensor readings collected for temperature, walking speed and acceleration along X, Y and Z axes respectively. Feature extraction is necessary to understand a large set of raw sensor data in a better way. Considering the nature of the present study, the features extracted were (i) mean (average of absolute values of sensor readings), (ii) standard deviation (square root of variance of sensor readings) and (iii) Root-Mean-Square (RMS) value (square root of the arithmetic mean of the squares of the sensor readings). Cattle activity states along with respective time durations were previously noted by the field supervisor and this information was used for labelling the dataset. The nomenclature of the extracted features are shown in Table 3.

2.4. Extreme gradient boosting (XGBoost) based classification

The feature extracted and suitably labelled dataset was subjected to an optimally tuned XGBoost classifier. 80% of the data was used for training and 20% was used for testing. Data collection, feature extraction and implementation of classification algorithm is detailed in Fig. 4.

XGBoost is a scalable and regularized form of gradient boosting algorithm built by Tianqi Chen in the year 2016 [22]. Of late, XGBoost based classification has gained immense popularity in data-driven applications due to enhanced efficacy, reduced computational time, and altogether an exceptional performance. It has an option to penalize complex models through L1 (Lasso) and L2 (Ridge) regularization thereby assisting in preventing overfitting [20,21].

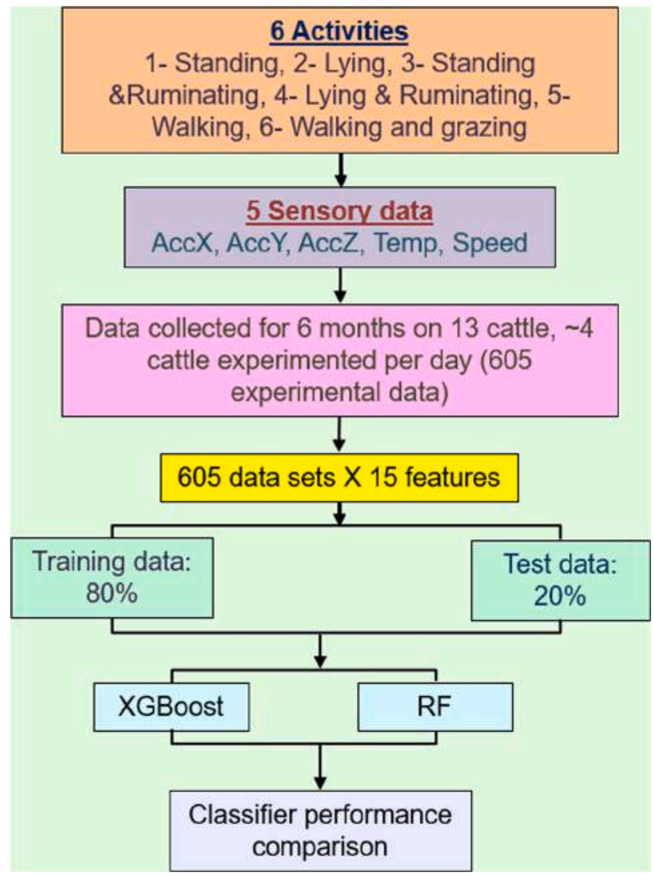

Fig. 4. Flowchart for data collection, feature extraction and implementation of classification algorithm.

Performance of classification algorithms are evaluated by residuals which is the difference between observed and predicted values that shows how good the initial prediction was. In gradient

Table 3
Nomenclature of the features extracted.

S. No	Extracted feature	Relevance
1	Mean_AccX	Mean of acceleration measured along X axis.
2	SD_AccX	Standard deviation of acceleration measured along X axis.
3	RMS_AccX	RMS value of acceleration measured along X axis.
4	Mean_AccY	Mean of acceleration measured along Y axis.
5	SD_AccY	Standard deviation of acceleration measured along Y axis.
6	RMS_AccY	RMS value of acceleration measured along Y axis.
7	Mean_AccZ	Mean of acceleration measured along Z axis.
8	SD_AccZ	Standard deviation of acceleration measured along Z axis.
9	RMS_AccZ	RMS value of acceleration measured along Z axis.
10	Mean_Temp	Mean of cattle body temperature.
11	SD_Temp	Standard deviation of cattle body temperature.
12	RMS_Temp	RMS value of cattle body temperature.
13	Mean_Speed	Mean value of cattle walking speed.
14	SD_Speed	Standard deviation of cattle walking speed
15	RMS_Speed	RMS value of cattle walking speed.

Table 4
Chosen set of hyperparameters and their maximum and minimum values for XGBoost and RF classification algorithm.

	S. No.	Hyperparameters	Definitions	Search range	
				Maximum	Minimum
XGBoost	1	eta	Learning Rate: amount of weight shrinkage used in update to prevent overfitting	0.01	0.6
	2	subsample	Percentage of samples selected for each tree	0.3	0.9
	3	max_depth	The maximum depth of a single tree	3	9
	4	colsample_bytree	Percentage of features selected for each tree	0.5	0.9
	5	min_child_weight	Minimal sum of weights a split needs to have before it stops	1	4
RF	1	n_estimators	Number of trees in the forest	200	800
	2	max_depth	Maximum number of levels in each decision tree	10	50
	3	min_samples_split	Minimum number of data points placed in a node before split	2	10
	4	min_samples_leaf	Minimum number of data points allowed in a leaf	1	4
	5	max_features	Maximum number of features considered for splitting a node	Tuned between 'auto' and 'sqrt'	
	6	bootstrap	method for sampling data points with or without replacement	Tuned between 'true' and 'false'	

boosting, this is done by loss function. For XGBoost based classification, loss function is defined as in Eq. 4.

$$L(y_i, p_i) = -[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)] \tag{4}$$

where, y_i is the outcome of the i^{th} instance.

p_i indicates the probability of the i^{th} instance assuming the value y_i.

XGBoost uses the above loss function to build trees by minimizing expression 5.

$$\left[\sum_{i=1}^{n} L(y_i, p_i)\right] + \gamma T + \frac{1}{2}\lambda O_{value}^2 \tag{5}$$

where, $\sum_{i=1}^{n} L(y_i, p_i)$ is the loss function.

γ or gamma is a user definable penalty meant to encourage pruning.

T is the number of nodes or terminals in a tree.

$\frac{1}{2}\lambda O_{value}^2$ is the regularization term.

O_{value} is the output value to be estimated.

λ or lambda is the (L2) regularization parameter.

The objective is to find an O_{value} for the leaf that minimizes the whole equation. The O_{value} is being optimized from the first tree, therefore p_i can be replaced with p_i^0 plus the O_{value} from the new tree and expression 5 can be re-written as expression 6.

$$\left[\sum_{i=1}^{n} L(y_i, p_i^0 + O_{value})\right] + \gamma T + \frac{1}{2}\lambda O_{value}^2 \tag{6}$$

The more the regularization penalty is emphasized by increasing λ, the optimal O_{value} gets more closer to '0'. Therefore, λ decreases the O_{value} in a more smoothing way.

XGBoost uses the second order Taylor approximation to estimate the loss function as Eq. 7.

$$L(y, \quad p_i + O_{value}) \approx L(y, \quad p_i) + \left[\frac{d}{dp_i}L(y, p_i)\right]O_{value} + \frac{1}{2}\left[\frac{d^2}{dp_i^2}L(y, p_i)\right]O_{value}^2 \tag{7}$$

XGBoost uses gradient (g) and Hessian (h) to represent derivative and second derivative of the loss function respectively. Hence, the Eq. 7 may be written as:

$$L(y, \quad p_i + O_{value}) \approx L(y, \quad p_i) + gO_{value} + \frac{1}{2}hO_{value}^2 \tag{8}$$

The expression 6 can be re-written as expression 9.

$$\left(\sum_{i=1}^{n} g_i\right)O_{value} + \frac{1}{2}\left(\sum_{i=1}^{n} h_i\right)O_{value}^2 + \frac{1}{2} \quad \lambda O_{value}^2 + \gamma T \tag{9}$$

The constant terms have no effect on O_{value} and can hence be omitted.

After minimizing expression 8, the O_{value} and Similarity Score for classification ($SS_{classification}$) for each are computed as in Eqs. 10 and 11:

$$O_{value} = \frac{(\sum Residual_i)}{\sum\left[p_i(1 - p_i) + \lambda\right]} + \gamma T \tag{10}$$

$$SS_{classification} = \frac{(\sum Residual_i)^2}{\sum\left[p_i(1 - p_i) + \lambda\right]} + \gamma T \tag{11}$$

Therefore, XGBoost approximates the final decision boundary by combining a set of weak learners in an iterative manner just like original gradient boosters with an additional regularization added to the loss function to establish the objective function.

In this research, the machine learning models were trained on scikit-learn python 3.8.1 libraries. The learning task was set to "multi:softprob", using the non-linear "gbtree" algorithm and number of estimators was fixed at 800. Tuning of hyperparameters is crucial for achieving the best performing classification model. Random search approach was executed for tuning the hyperparameters where random combinations of hyperparameters are used to build the best classification model. Compared to grid search, random search technique is computationally inexpensive as well as demonstrates good results as found in literature [23]. The hyperparameters chosen for tuning along with the search ranges are tabulated in Table 4.

RFs is an ensemble machine learning method introduced by Breiman [24] by adding an extra layer of randomness to bootstrap aggregating or bagging method. Considering substantial use of RFs in few similar researches [25], an optimally tuned RF classifier was also implemented in this research. The hyperparameter tuning information is detailed in Table 4. Eventually, performance of the classifiers were analysed using confusion matrices and evaluation metrics like accuracy, precision, sensitivity, and specificity.

3. Results and discussions

Observations related to validation of sensors, profiles for sensory information pertaining to various cattle activity and activity classification using machine intelligence are discussed in the following subsections.

3.1. Validation of sensors

The temperatures measured using a thermistor were validated using a clinical thermometer and the experimental results are graphically represented in Fig. 5(i). Simultaneously, for validation of the

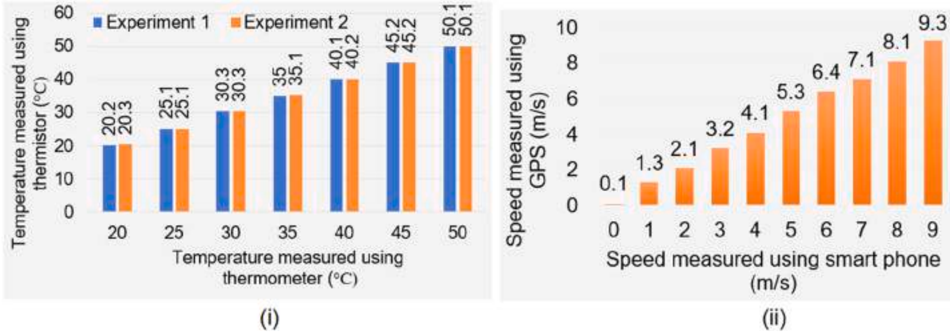

Fig. 5. (i) Comparison of temperature measured using thermistor and laboratory thermometer (ii) Comparison of walking speed measured using GPS module and smart phone application.

GPS module, the average of the readings of the MOOnitor for each speed instance was plotted against the speed given by the smartphone application as shown in Fig. 5(ii). It can be found that the maximum errors in temperature and walking speed measurements are 0.3 °C and 0.4 m/s respectively. Hence, it can be understood that the temperature and GPS information acquired during the walking-related activity of the cattle was satisfactory; this motivated the authors to deploy the proposed device for field trials.

The temperature recorded using MOOnitor and IRT and the core body temperature recorded using clinical thermometer at different time intervals before and after feed intake and before and after grazing is presented in Table 5.

It can be inferred from Table 5 that the skin temperatures measured by MOOnitor did not deviate much from the temperatures measured by IRT. The maximum difference between the two for all the said states was found to be 0.27 °C. However, the core body temperatures measured using CT was always found to be slightly higher than the skin temperatures for all states [29] with a maximum difference of 1.91 °C between the two.

The results of ANOVA, as presented in Table 6, depict a much lower sum of squares (SS) and mean-size-squared (MS) for between-group variance ($SS_{between}$=0.085, $MS_{between}$=0.085) when compared to within-group variance (SSwithin=27.086, MSwithin=1.504). This infers that the individual means of the temperatures measured using the MOOnitor and the IRT do not differ much and hence their differences with the grand mean won't vary significantly either. Here, SS and MS for the total sample indicated the sum of the squared deviations from the grand mean and the variance for the total sample respectively.

An F-ratio as low as 0.05 and a significantly high F-critical value of 4.41 indicated major statistical similarity between the two groups. Furthermore, a P-value of 0.81, which is much greater than the significance level (=0.05), confirmed the null hypothesis i.e., the two groups have statistically insignificant differences. Based on these inferences, it is evident that the measurements of the MOOnitor are in conformity with those of the IRT. Now, since an IRT is already clinically acceptable for recording skin temperatures [30], MOOnitor may be used for recording real-time body temperature of cattle. Also, the increase in temperature after grazing and feeding indicated the relevance of temperature sensor in activity monitoring.

Table 6
One-way ANOVA for the temperature data acquired from the MOOnitor and IRT.

Source of Variation	SS	df	MS	F-ratio	P-value	F-critical
Between Group	0.08	1	0.08	0.05	0.81	4.41
Within Groups	27.08	18	1.50	–	–	–
Total	27.17	19	1.58	–	–	–

The sensory information obtained from accelerometer, temperature sensor, and GPS module concerning all the activities for a randomly selected animal are shown in Fig. 6. In connection with the resultant acceleration profile, walking activities could be prominently distinguished from standing and/or lying activities. In order to establish the same, the standard deviations of the data were computed for each activity interval. The standard deviations of standing or lying activities ranged between 0.05 and 0.08 and that of walking activities lied between 0.56 and 0.60. Although substantial differences in standard deviations were found between 'lying' (=0.05), 'lying and ruminating' (=0.07) and 'standing' (=0.08), it was difficult to discriminate 'standing' (=0.08) and 'standing and ruminating' (=0.084). Difficulty in discrimination of 'standing' and standing and ruminating' activities using accelerometer data is also reported earlier [11]. However, the mean body temperatures observed during 'standing' and 'standing and ruminating' were 36.3 °C and 37.7 °C respectively indicating a notable difference in temperature. This would be a significant contribution in discriminating the said activities, which was otherwise difficult to be identified based on only accelerometer readings. It was also found that the maximum temperatures identified during each activity differed from each other. Again, unlike acceleration profile that could efficiently discriminate between 'standing and ruminating' and 'walking', mean temperatures identified during these activities did not differ much. On the other hand, walking speed during 'walking and grazing' was considerably less than walking speed during only 'walking'. Since 'walking' and 'walking and grazing' exhibit almost similar acceleration profiles, the walking speed information at this stage can help in

Table 5
Comparison of cattle temperature measured using MOOnitor, IR thermometer and clinical thermometer for different states.

Sl. No.	Device	9:00 am	9:30 am	10:30 am	11:00 am	11:30 am
		Before feed intake (°C)		After feed intake (°C)		
1	MOOnitor	34.40	35.20	36.92	36.74	36.33
2	IRT	34.38	34.91	36.82	36.51	36.38
3	CT	35.78	37.04	38.59	38.45	38.24
		Before grazing (°C)		**After grazing (°C)**		
1	MOOnitor	34.01	34.59	37.06	37.02	36.84
2	IRT	33.94	34.32	36.97	36.78	36.79
3	CT	35.92	36.11	38.70	38.62	38.52

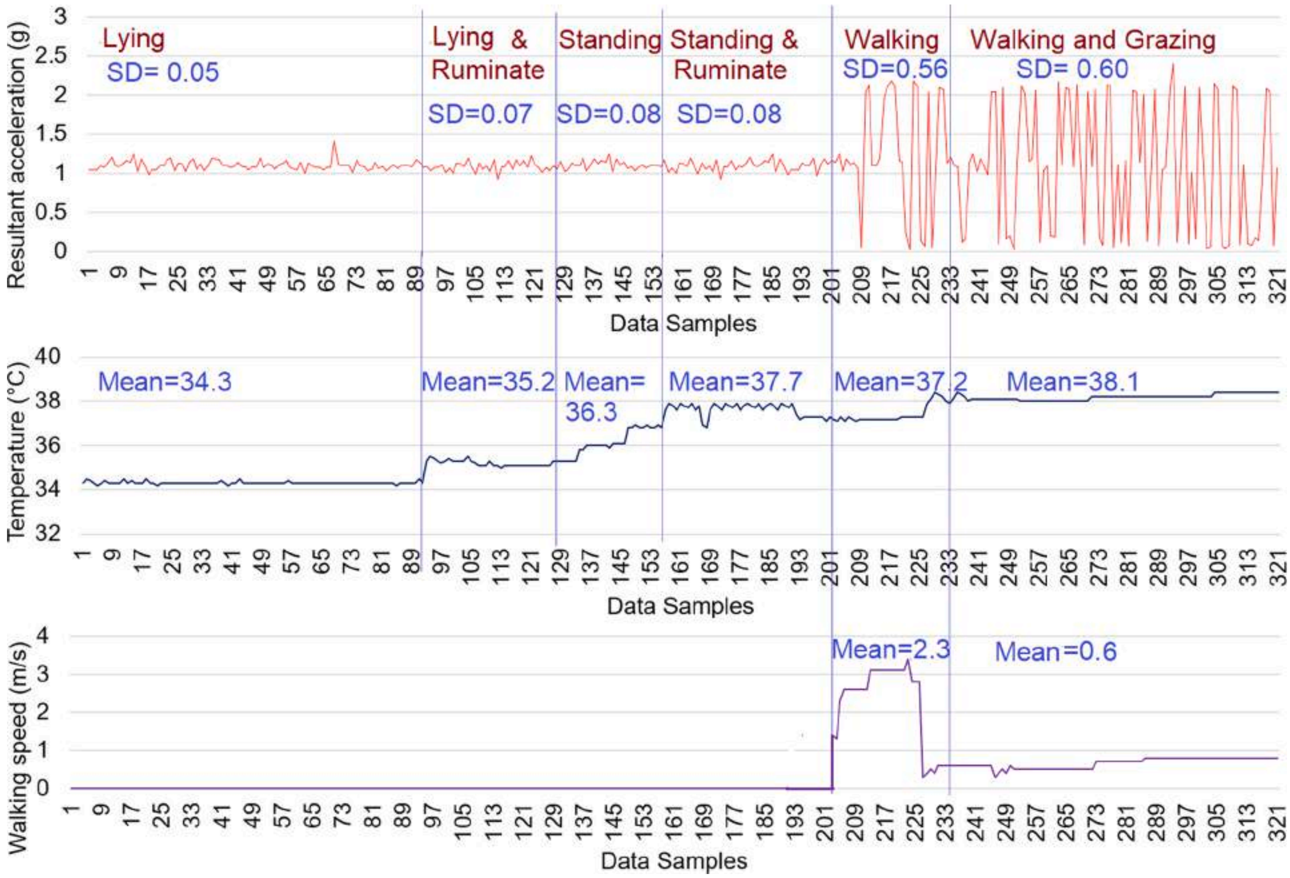

Fig. 6. Raw sensor data profiles concerning all the significant activity states of a cow.

better analysis. Collectively, the aforementioned findings demonstrate that the sensory information acquired from each sensor needs to be efficiently integrated while assessing cattle activities thereby leading to more accurate classification.

The computed battery lifetimes at different locations, the corresponding RSSI values, and the average values of load current are summarized in Table 7. The tested battery lifetime on single charge for the developed device was ~11 h.

3.2. Classification

After training an optimally tuned XGBoost classifier with 80% of the dataset, 20% of the dataset was tested for classification accuracy. A classification accuracy of 96.69% and mean absolute error (MAE) of 0.07 was achieved. On the other hand, an optimally tuned RF classifier demonstrated an accuracy of 94.21% and MAE of 0.08. The hyperparameters chosen through random search for both the classifiers are shown in Table 8.

It could hence be understood that XGBoost based classifier outperformed RF in the present research. Subsequently, to exhibit class-specific comparison between the two classifiers, the classification reports and the confusion matrices/heatmap are reported in Table 9 and Fig. 7 respectively.

Table 8
Hyperparameter set chosen for XGBoost and RF.

	S. No.	Hyperparameters	Chosen values
XGBoost	1	eta	0.23
	2	subsample	0.84
	3	max_depth	7
	4	colsample_bytree	0.98
	5	min_child_weight	4
RF	1	n_estimators	600
	2	max_depth	22
	3	min_samples_split	2
	4	min_samples_leaf	1
	5	max_features	‘auto’
	6	bootstrap	‘false’

The overall accuracy for trials conducted with window sizes of 16, 32, 48 and 64 s are reported in Table 10. A significant improvement in classification accuracy was observed when the window size was increased from 16 to 32, whereas a nominal or almost no change in classification accuracy was observed when the window size was increased beyond that. Hence, the window size was set to 32 s

Table 7
Details of cattle location, average load current, and calculated lifetime of the device.

Location	RSSI value (dBm)	Average load current I_L (mA)	Calculated lifetime in hours (B_c=850 mAh)
West Bengal University of Animal and Fishery Sciences (WBUAFS), Mohanpur campus, West Bengal, India (Latitude: 22.9418°N, Longitude: 88.5247°E)	-53	78	10.89
Namkhana Uttar Para village, under Block- Namkhana CD Block, PS-Namkhana, South 24 Parganas district, West Bengal, India (Latitude: 21.7699° N and Longitude: 88.2315°E)	-61	84	10.11
Palashdiha Village, Durgapur, West Bengal, India (Latitude: 23.5356°N, 87.2921°E)	-57	81	10.49

Table 9
The classification reports while using XGBoost and RF during activity classification on use of window size as 32.

	XGBoost			RF					
Activity/ Class	Precision/ PPV	Recall/ Sensitivity	Overall accuracy	Specificity	Precision/ PPV	Recall/ Sensitivity	Overall accuracy	Specificity	Support
Standing/0	0.97	0.97	0.98	0.98	1	0.97	0.99	1	34
Lying/1	0.9	1	0.97	0.96	0.84	0.96	0.95	0.94	28
Standing and Ruminating/2	1	0.97	0.99	1	0.97	0.87	0.95	0.98	39
Lying and Ruminating/3	1	0.83	0.99	1	1	1	1	1	6
Walking/4	1	1	1	1	0.90	1	0.99	0.99	10
Walking and Grazing/5	1	0.75	0.99	1	1	1	1	1	4

Accuracy = (TP+TN)/(TP+FP+FN+TN), Precision = TP/(TP+FP), Sensitivity = TP/(TP+FN), Specificity= TN/(TN+FP)
TP-True Positive, TN- True Negative, FP- False Positive, FN- False Negative

It could be inferred from Table 9 that the overall accuracy of all classes while using XGBoost was higher than that of RF classifier thereby suggesting XGBoost to be a better classifier. The higher classification accuracy of XGBoost is possibly due to the distinctive regularized boosting feature of the classifier that reduces the complexity of the tree thereby enabling it to handle the outliers more often by penalizing them. It is also noted that the overall classification accuracy for the 'lying' activity is the lowest for the XGBoost as well as the RF classifier i.e. 97% and 95% respectively, which may be due to random lying postures of the cattle. However, for the standing and ruminating activity, XGBoost classifier outperformed the RF classifier with a classification accuracy of 99%.

Unlike earlier literature, where accelerometry could not classify 'standing' and 'standing and feeding/ruminating' satisfactorily, it is interesting to note that in this research even the RF classifier could adequately discriminate 'standing' and 'standing and ruminating' behaviour of the cattle. This might be due to the acceleration and temperature data being collectively used towards the classification. It could thus be understood that use of multi-sensory data in classification of cattle activity is phenomenal. XGBoost classified all the activities with a higher precision, specificity and sensitivity except that the sensitivity of 'walking and grazing' activity was higher in case of RF. The lower sensitivity of class 5 for XGBoost would not affect the classification significantly since higher precision and specificity indicates a high true positive rate for the said activity.

The importance of the extracted features towards the classification was observed using 'model.feature_importances_' function of Python. The feature importance plot is shown in Fig. 8.

Table 10
Overall with variation in window size.

Activity/ Class	Window size	Overall accuracy XGBoost	Overall accuracy RF
Standing/0	16	0.81	0.76
	32	0.98	0.99
	48	0.98	0.99
	64	0.98	0.99
Lying/1	16	0.79	0.75
	32	0.97	0.95
	48	0.97	0.96
	64	0.97	0.96
Standing and Ruminating/2	16	0.80	0.76
	32	0.99	0.95
	48	0.99	0.95
	64	0.99	0.96
Lying and Ruminating/3	16	0.78	0.76
	32	0.99	1
	48	0.99	1
	64	0.99	1
Walking/4	16	0.86	0.80
	32	1	0.99
	48	1	0.99
	64	1	0.99
Walking and Grazing/5	16	0.82	0.81
	32	0.99	1
	48	0.99	1
	64	0.99	1

From Fig. 8 it was found that the features related to acceleration (Mean_AccY, SD_AccX) were the most significant ones whereas, features related to temperature (RMS_Temp) and speed

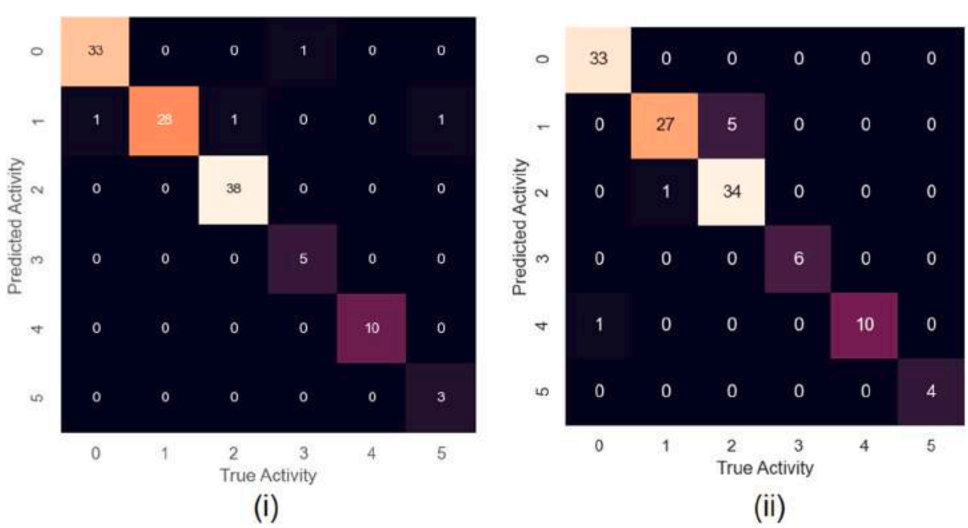

Fig. 7. The confusion matrices/ heatmap for (i) XGBoost classifier (ii) RF classifier wherein following activity conventions are followed- 0: Standing, 1: Lying, 2: Standing and Ruminating, 3: Lying and Ruminating, 4: Walking, 5: Walking and Grazing.

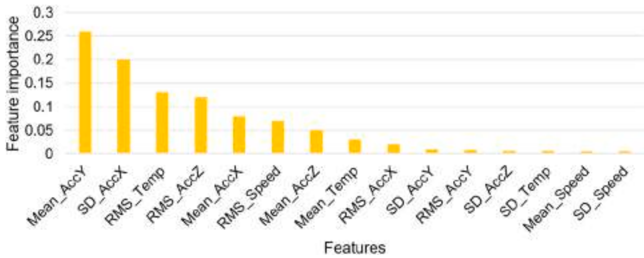

Fig. 8. Feature importance sorted as decreasing order of feature importance used in XGBoost algorithm.

(RMS_speed) appear among the six most significant features thereby proving the importance of incorporating temperature and speed data for accurate classification of cattle activities.

4. Conclusions

In this research we have demonstrated the construction, working and deployment of a neck mounted intelligent IoT aided device called 'MOOnitor' for cattle activity monitoring inside the barn as well as in the pasture. The device is capable of recording acceleration, temperature and walking speed information of cattle and transmitting the data directly to a server over SIM based GSM module. Thereafter, implementation of intelligent algorithm with the acquired information would facilitate an automated cattle activity classification. Since nature of an animal's activity is strongly related to its health and well-being, such a methodology would enable the farmers or owners to monitor the cattle in a better way. With reference to the technologies reported in earlier literature, only data storage feature existed in most of them and few of them allowed transmission to a nearby IoT node via RF modules thereby imposing functional constraints to a predetermined zone. Besides, the device developed in this research transmits the sensory information directly to a server and can seamlessly operate in presence of GSM network regardless of boundary or terrain. In addition to the novelty in design, the research brings forth the fact that cattle temperature and walking speed are two important aspects to be considered in addition to already established acceleration data in order to achieve more accurate classification of activities. This facet is even more striking with regards to discrimination of nearly similar activities such as 'standing' and 'standing and ruminating'. Subsequently, shortcomings of existing neck or collar-mounted devices could be alleviated using the proposed methodology as well as a higher classification accuracy was achieved using XGBoost classifier.

The accuracy, precision, sensitivity, and specificity were (0.98, 0.97, 0.97, 0.98) for standing, (0.97, 0.90, 1, 0.96) for 'lying', (0.99, 1, 0.97, 1) for 'standing and ruminating', (0.99, 1, 0.83, 1) for 'lying and ruminating', (1, 1, 1, 1) for 'walking', and (0.99, 1, 0.75, 1) for 'walking and grazing' computed for 34, 28, 39, 6, 10, and 4 observations respectively. This shows the suitability of the method in accurate cattle activity classification. The classification accuracy while using XGBoost classifier is ~97% which is highest compared to that reported in existing literature to the best of our knowledge.

The 'MOOnitor' is hence expected to find huge prospects in field deployment as well as veterinary research. For instance, the device is capable of providing information related to standing behaviour of cattle which would assist farmers detect the estrous in a more effective way. Furthermore, health conditions such as foot and mouth disease, lameness, mastitis, etc. can be detected and appropriate prognosis measures can be taken beforehand. These applications could be taken as a scope for future work in this direction. Experiments with higher number of animals and more number of observations under each activity category could be attempted in future for a more robust classification. In addition, to improve upon the device portability and fidelity, a light and compact microcontroller board with in-built sensors such as an Arduino BLE sense board can be used. To further automate the prediction process, the learning algorithms can be implemented on the cloud platform so that the required inferences can be achieved seamlessly on user interfaces such as mobile applications. Again, this facility can be effectuated by an Arduino BLE sense, which is a more energy-efficient AI enabled board in the smallest available form factor.

Author Statement

Debeshi Dutta (DD) conducted the hardware assembly and software integration of MOOnitor and worked for the manuscript preparation, Dwipjyoti Natta (DN) conducted field trials and field experiments, Dr. Soumen Mandal (SM) coordinated the work, was involved in IoT integration and manuscript preparation, Dr. Nilotpal Ghosh (NG) coordinated the work and was involved in field testing and trials of the MOOnitor device.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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