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Article

IoT Enabled Dairy Herd Health Monitoring: Machine Learning Based Analysis of Productivity, Estrus Detection and Transport Stress

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Abstract: The research paper reflects an IoT-based smart neck belt that has a combination of physiological sensors to measure such parameters like Body temperature, Heart rate, Respiration, Rumination and Activity levels to monitor the health of dairy herds and provides data of the environmental conditions through the Ambient temperature, Humidity, Air Quality Index (AQI) and Noise levels. The effects of the environmental parameters on the health of dairy herd were determined under the Controlled (Batch-1), natural condition (Batch-2) and transport conditions. Its results indicate that there is a significant change in the dairy herd vitals with a decrease in rumination and feed conversion efficiency, and subsequent increase in body temperature, heart rate and stress index for conditions of Batch-2 and during inconvenient transportation. Comparative results of Batch-1 with Batch-2 showed that the welfare of the animals improved significantly, such as the reduction of stress levels by 20%, average milk yield improved by 65%, estrus detection accuracy increased to 69%, faster recovery and higher conception rates. In order to enhance the predictive capabilities, several machine learning (ML) algorithms were tested in relation to stress detection, disease prediction and estrus detection. The analyzed data indicated that more complex models like Hist Gradient Boosting and 1D Convolutional Neural Networks indicated more accurate outcomes compared to the traditional ML models. These results confirm that the combination of IoT-based sensing with ML based analytics can transform conventional dairy herd management into more sustainable, welfare based and productivity focused.

Keywords: Dairy herd health monitoring, disease prediction, estrus detection, environmental sensors, IoT enabled smart neck belt, precision livestock farming, machine learning, physiological sensors, stress detection.

1. Introduction

The dairy industry represents one of the most vital sectors of global agriculture, which not only provides nutrition to humans but also secures the livelihood of rural population and socio-economic system of millions of households [1]. Cows, buffaloes, goats and sheep are livestock that are a source of milk, meat and source of income, thus make them essential in mixed farming systems. In India, dairy herd mainly include cows and buffaloes contribute 53.12% and 43.62%, respectively in the total milk production and thus making the dairy industry the backbone of the agricultural economy in India [2]. The higher fat and solids-not-fat (SNF) content in raw milk in buffaloes making them beneficial to cows milk especially useful in producing ghee, paneer, yogurt and milk-based sweets which are some of the favourite foods of consumers in the Indian subcontinent [3].

Despite the fact that buffalo milk is more nutritious, with regard to fat, SNF and protein, the proportion produced by each animal is usually low compared to cows [4]. A number of internal variables that have been identified to cause this low productivity include genetic limitations, slow puberty, increased calving time and reduced lactation time, and external variables like climate adaptability, feed quality and stress. This has led to the focus on the development of methods to maximize buffaloes, (here after called as dairy herd) productivity in raw milk and derivatives of milk to this day as a priority of dairy research as well as technology innovation [5]. Their reproductive physiologies between dairy herd are very different. The dairy herd due to their weak estrus expression make the heat detection a big problem, failure in estrus detection leads to missed breeding opportunities, lengthy calving periods and loss of money when the traditional method of observation is applied.. Comparatively, cows exhibit more behavioural indicators of estrus thus making them relatively easier to manage as far as reproduction is concerned [6].

Fig.1 demonstrates an wearable IoT-based Dairy Herd Health Monitoring, D2HM Kit, that involves a specially designed sensor belt that monitors physiological parameters of dairy herd on a constant basis. The whole architecture of the D2HM system illustrates a four-stage data processing pipeline: firstly, initial data collection through integrated physiological and environmental sensors, which monitor body temperature, heart rate, rumination, activity levels and ambience data at farm at controlled and natural condition. Subsequently stored in local systems to be accessed immediately with integration of cloud-based data repositories to be stored on the cloud for scalable storage and access remotely and implementation of machine learning algorithm to predictive health analytics. The analysis phase based on ML models and interpretation of the indicators of health data gathered to detect abnormal health behaviour, forecast potential disease development and come up with early detection signals related to dairy animals health data. The approach allows timely veterinary care and improved livestock management decision in precision dairy farming operations. Buffaloes among dairy herd are more sensitive to heat atmosphere, results in reduced feed consumption and milk production because of their dark skin, fewer sweat glands when subjected to high temperature and humidity [7]. The sensitive nature of dairy animals requires a more accurate D2HM. Genetic, physiological and environmental factors make the use of buffalo productivity in raw milk unreliable. The use of traditional monitoring methods does not have real-time and continuous data, and this usually results in a delay in the realization of disease, estrus and stress [8].

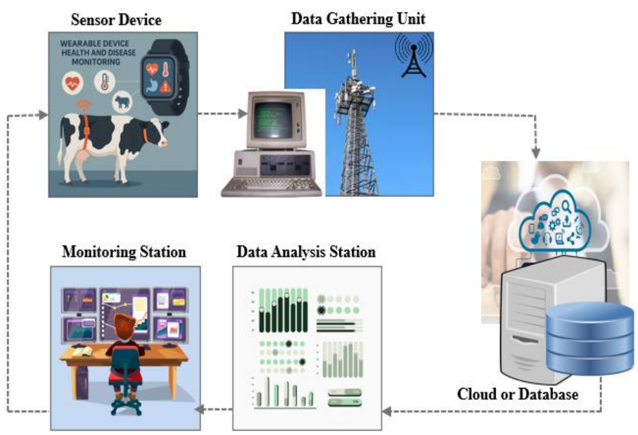


Fig 1. Wearable IoT devices for health and disease monitoring system

In a conventional dairy production scenario, the observation of farmers and the basic veterinary examination is very critical, however, minor changes in physiological indicators may go unnoticed until the disease progresses or the production level decreases. Other factors include estrus detection failure, increase in inter-calving interval and decreased lifetime productivity among dairy herd [9]. The post transport stress effect usually go unnoticed during the normal observation procedures since farmers in general notice after the animals start showing symptoms such as decreased feed consumption, loss of energy or any disease, at which point preventive measures may no longer be effective [10]. Although precision livestock farming has been extensively utilized in European and North American dairy systems with the use of activity and health monitoring devices that enable constant, real-time insights of tracking of livestock. In India, there is a need to develop a specific IoT applications to address the needs of the dairy industry and this requires the use of customized solutions to track the physiology, behavior and production environment of the dairy herd [12].

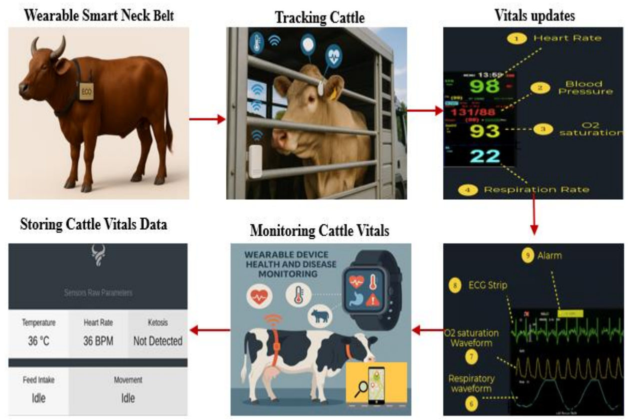


Fig 2. Tracking of Cattle Vitals during Transportation

Fig. 2 shows how the deployment of modern IoT based sensor technology affects milk yield by integrating internal and external factors. A smart neck-belt for dairy herds that incorporate multiple sensors into an eco-friendly, comfortable and long lasting wearable device has been designed and evaluated. The neck-belt integrates temperature probes, heart rate sensors, respiration monitoring, sweat pH sensors and environmental modules in order to collect a comprehensive dataset on physiology and welfare of dairy herd. Farmers can use a mobile device to monitor the health of their dairy herds received by notifications of ML analysed real time data . By comparing the data taken under controlled, natural and transport conditions, this study assesses the usefulness of the sensor system in sensing stress, estrus and productivity related physiological changes.

Significance of a precision estrus cycle detection system in controlled breeding condition (Batch-1) and natural environments (Batch-2), uses sensor fitted customized neck belt on dairy herd to detect heat accurately by continuous monitoring of their physiological activities appears in Fig. 3. The system tracks real-time estrus signals such as temperature variations, activity levels and behavioural alterations and automatically gives alerts when the appropriate time to inseminate using artificial methods is identified. Batch-1 showed significant results, this creates accuracy in heat detection and thus lowers the losses incurred in the economy and boosts the reproductive efficiency and herd productivity to improve dairy performance. The records of estrus cycles are centrally stored in dedicated servers, making them easy to retrieve and analyse the reproductive pattern of individual dairy herd and optimize their breeding schedule and evaluate their upcoming fertility trend. The real time monitoring and data analytics ensure that the conception rates can be maximized, breeding days are minimized and sustainable dairy operations and reproductive management of precision dairy farming systems.

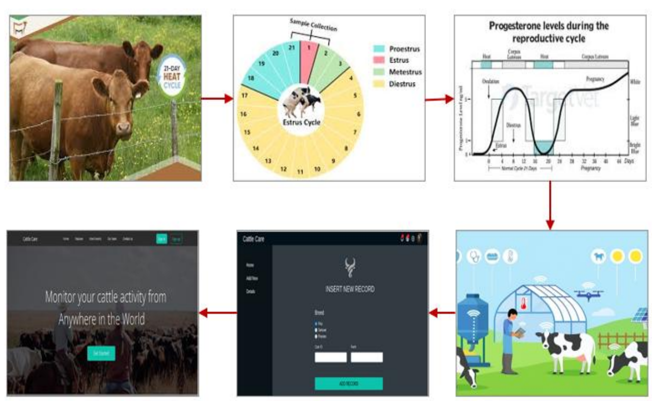


Fig 3. Heat Detection for precision Estrus Cycle in a Controlled Environment

The research article is organized as follows: Section II entails a detailed literature review of the factors affecting the milk yield, estrus detection processes and IoT based D2HM systems. Section III describes the sensors employed for IoT based smart neck belt and environmental condition with their specifications, experimental procedure and sample size for Batch-1&2 conditions. In section IV, experimental findings are given for Batch-1 Vs Batch-2, and

Transport conditions, and the analysis and interpretation are provided. Section V is the conclusion of the study in which the main findings of the research are stated and the ways they can be used to develop D2HM are outlined.

2. Literature Survey

The global livestock sector faces exceptional challenges in preserving animal health, enhancing productivity and ensuring sustainable agricultural practices in modern agricultural systems [13]. Conventional cattle monitoring methods heavily depend on visual assessment and manual data gathering, causing labour-intensive, preliminary and often inadequate for early detection of health issues or optimal breeding intervals [14]. The integration of IoT technology with precision farming practices has emerged as a transformative approach to tackle significant issues of Dairy Supply Chain, DSC digitizing [15]. Investigative factors that influence D2HM becomes essential for enhancing performance among contemporary DSC’s [16]. Throughout the dairy supply chain, D2HM includes various physiological parameters including body temperature, heart rate, rumination patterns, activity levels and stress indicators that comprehensively indicate the dairy cattle health [17]. Parameters affecting dairy herd are continuous monitored as it becomes possible for early symptoms of diseases, optimize feed intake, recognise estrus intervals and evaluate environmental stress signs that enormous impact on dairy productivity [18].

The development of intelligent sensors, wireless communication technologies and cloud computing has made real-time, remotely controlled D2HM technically and financially feasible for DSC digitizing [19]. This study has shown that environmental stress can impair immune system functioning, diminish milk production and impact reproductive ability [20]. Recent developments in dairy herd monitoring have shown how sensor-based systems can be used to improve animal welfare and farm efficiency and lead in digitizing DSC process [21]. This study has concentrated on specific sensor functions, such as accelerometer based activity assessment, detecting temperature rise for fever detection, and GPS navigation for location management in cattle health monitoring systems [22].

Comprehensive multi-parameter monitoring techniques incorporated in physiological, activity based and environmental factors for assessing the determinants of dairy performance remain limited [23]. Studies indicate that fluctuations in core body temperature might indicate symptom of illness, metabolic dysfunction and alternations reproductive interval changes, makes temperature monitoring essential for dairy herd welfare [24]. Heart rate monitoring has proven beneficial for stress evaluation and early detection identification of cardiovascular disorders in cattle, contributing largely to dairy herd welfare [25]. Rumination rhythms serve as notable indicators of digestive health and overall wellness, with changes occurring priorly before beginning of illness in dairy cattle [26]. Change of location has significant impact on dairy herd health and productivity, particularly during transportation and migration mainly from high temperature zones to hilly terrain [27]. This study has demonstrated that environmental stress can reduce milk production, impair immune system and impact reproductive performance, prioritizing variables influencing dairy digitizing processes [28].

The conclusion derived by integrating environmental with physiological parameters analysis provides a holistic view of factors influencing dairy cattle health and enhances present dairy scenario [29]. Precision livestock breeding have grown in popularity as dairy industry seek to optimize reproductive efficiency and breeding outcomes through advanced D2HM techniques [30]. Compared to conventional observation techniques, precise estrus detection through physiological and activity monitoring can improve conception rates and lower breeding costs signifies sustainable supply chain operations [31]. The GPS integration enables real-time location tracking with pin-point accuracy, enabling farmers with exact animal location information during both farm activities and transit [32]. The IoT based wearable suite is carefully designed using biocompatible, durable materials capable of withstanding harsh environmental conditions while ensuring animal comfort and safety[33]. The design considered practical behaviour in order to minimize interference not only with natural behaviours such as grazing, lying and mating but while artificial insemination and regular veterinary checkups [34]. The customized kit featured with a design that could accommodate multiple modules, place battery housing, communication units and data processing devices essential for comprehensive activity based monitoring system [35]. The design and setting the customized smart leg belt for dairy herd, activity based accelerometer sensors are used make it into an eco-friendly, comfortable and durable wearable system [36].

3. Experimental Setup

This study presents the development of an IoT enabled customized kit for D2HM system. The wearable system includes a neck belt integrated with physiological and environmental sensors transforming into an comfortable and durable wearable system which includes the MAX30100 pulse oximeter & heart rate sensor, DHT22 temperature & humidity sensor, DS18B20 temperature sensor.

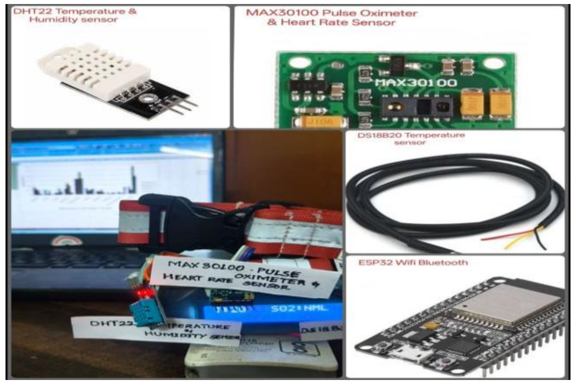


Fig 4. IoT-enabled Neck-Tag with sensors

The assembled kit employs an ESP32 Wi-Fi Bluetooth microcontroller for real-time health data acquisition and transmission, as illustrated in Fig. 4. This wearable platform enables precise monitoring of vital signs and ambient conditions continuously, thereby providing complete health assessment capabilities for remote D2HM system. The DS18B20 sensor has an accuracy ±0.1°C with swift speed of response, making it suitable for investigating the factors affecting milk quality and quantity [37]. For Heart rate monitoring MAX30100 sensor have been adapted for bovine physiology to enhance performance in DSC digitizing [38]. The rumination monitoring system combines ADXL345 accelerometer sensors and acoustic analysis to detect and count rumination cycles accurately [39]. ML algorithms are trained to distinguish clearly from dairy cattle rumination patterns, feed intake and other jaw movements for effective health data [40,41]. GPS integration employs NEO-8M modules enabling real-time location tracking with sub-meter accuracy, for livestock tracking during dairy cattle transportation [42].

The experimental study was conducted on a dairy farm consisting of 200 dairy herd specifically buffaloes. These were divided into two equal experimental group of 100 herd, Batch 1 designated as Controlled group and Batch 2 as a Natural group. A stratified random sample size 15 herd per batch was selected at a 95% confidence level. However, the present study is designed as a pilot-scale experimental validation, focusing on comparative trends and sensor performance rather than absolute population estimation. Hence, a reduced stratified random sample size of 15 was adopted. The Batch-1 sample group is equipped with customized IoT enabled neck belts integrated with a sensor suite and are housed in a temperature-controlled eco-friendly polyhouse. During transportation these animals are carried in stress-free vehicles fitted with GPS tracking and continuous vital monitoring benefitting from a fully IoT enabled D2HM system.

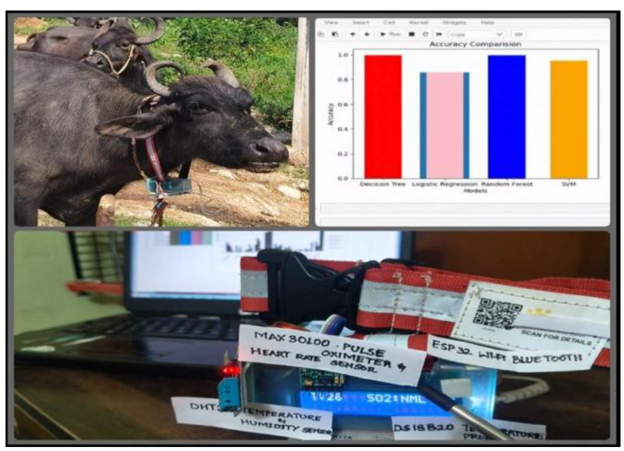


Fig 5. Data collection from the Controlled and natural group

Similar to the Controlled condition group, Batch 2, called as Natural condition group with sample size of 15 animals were managed under traditional practices. The customized kit was equipped on them and were kept in conventional cattle sheds without environmental control. These herd were transported using conventional methods without any comfort and tracking system and their health was monitored by manual observations and record keeping. Both batches employed identical alert mechanisms. In Batch1, whenever abnormal stress levels during transportation or resting are triggered, an immediate alarm notification sensed on the wearable device are instantly transmitted to farm managers and veterinary personnel, which helps facilitating proactive intervention strategies mainly to minimize transportation-induced stress, optimize animal welfare and maintain milk quality throughout the dairy supply chain logistics process. The experiment was conducted over 120 days, which ultimately covers multiple biological cycles and confirms time-series data saturation for dependable condition monitoring and comparative analysis. Fig. 5 illustrates the study divided the dairy herd into a Batch-1 and Batch2, where they are equipped with IoT-enabled neck-belt sensors. Physiological and environmental data were transmitted to a local database with cloud backup.

4. Results

Table I shows the environmental parameters that affect physiological health condition in the dairy animals when subjected to controlled environmental conditions like temperature of 24o C and humidity of 60 % and low levels of noise. Animals kept in Batch 1 under such controlled conditions had lower stress markers and high activity levels, which shows that environmental ambience effect is a key relative aspect that allows ML oriented models establish relation among climate-induced stress and health-related stress factors.

Table 1. Environmental Conditions

Parameter	Batch 1 (Controlled group)	Batch 2 (Natural group)
Ambient Temperature (°C)	24	35
Humidity (%)	60	75
Air Quality Index	90	135
Noise Level (dB)	50	70

Fig 6 illustrates the end-to-end data-analysis process to be used in cattle-health prediction based on a set of ML algorithms. The system incorporates real-time physiological measures such as milk yield and body-condition indices that are measured using IoT-based sensors and data stored on cloud computing infrastructure. Table II shows buffaloes with sensors in Batch 1 had better physiological measures than those in Batch 2, e.g. a lower core temperature (38.7oC vs. 39.2oC) and a lower heart rate (74 bpm vs. 82 bpm) and higher rumination (370 min/day vs. 261 min/day) and higher daily activity (11038 steps vs. 8638 steps). All these indicators are the pointers to improved animal welfare under constant observation.

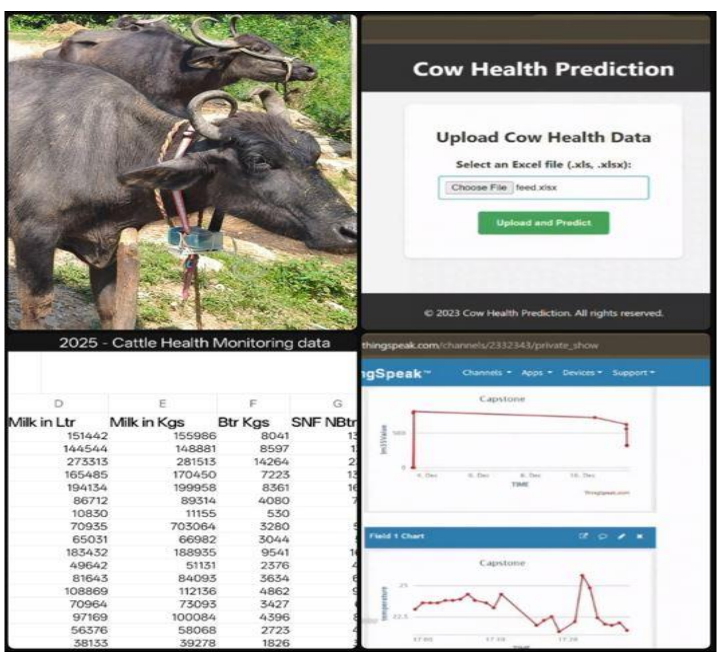


Fig 6. Data Analysis using ML Algorithms

Table 2. Average Physiological Parameters – Buffaloes

Parameter	Batch 1 (B1)	Batch 2 (B2)	Difference (B1-B2)
Core Temperature (°C)	38.7	39.2	-0.5
Heart Rate (bpm)	74	82	-8 bpm
Rumination (min/day)	370	261	+109
Daily Activity (steps)	11038	8638	+2400 steps
Stress Index (0-10)	1	5	-4

Table III emphasize on the sensor-measured data of Batch 1 showed better health-related and productivity results compared to Batch 2 due to a reduced number of disease incidences, increased average milk production, increased feed-conversion ratios, and decreased recovery times. As a result, these outcomes support the effectiveness of precision livestock management and directly confirm the prediction of diseases discussed in Table 8, which contributes to the ability of sensor-based ML to improve productivity by providing proactive interventions.

Table 3. Health and Productivity Metrics

Metric	Batch 1	Batch 2	Improvement
Disease Incidence (cases/animal/year)	1	3	33%
Early Disease Detection (days) before symptoms)	5.5	4	1.5 days
Average Milk Yield (L/day)	25	15	65%
Feed Conversion Efficiency	1.6	1.3	81%
Average Recovery Time (days)	3.5	10	35%

Table IV explains about the transportation inconvenience effect on physiological parameters on Batch 1 & 2 groups. Buffaloes in Batch 1 showed significant impact due to transportation stress relative to Batch 2, with 65% slow heart-rate, 50% reduced temperature rise, 43% quicker post-transport recovery time, and 39% reduced milk-loss after transport. These physiological readings illustrate the worth of real-time detection of stress at the time of transportation and gives empirical justification to the ability of the convolutional neural network model to identify temporal stress spikes, as applied in Table VII.

Table 4. Average Transportation Stress Analysis

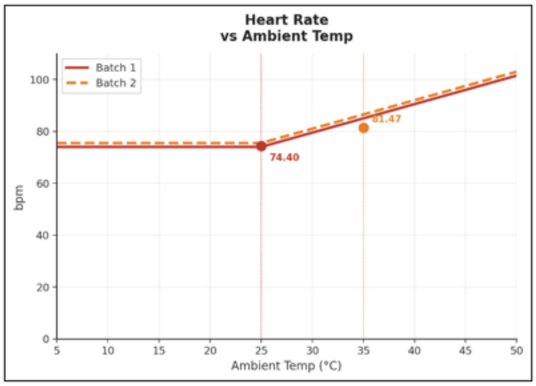
Parameter	Batch 1	Batch 2	Difference %
Heart Rate Increase (%)	23	35	65%
Temperature Rise (°C)	0.5	1	50%
Recovery Time (hours)	9	21	43%
Milk Yield Drop (%)	9	23	39%

Table 5. Estrus Detection & Reproductive Data

Metric	Batch 1	Batch 2	Improvement
Estrus Detection Accuracy (%)	85.2	59	69%
Missed Breeding Opportunities (%)	10.7	45.3	23%

Conception Rate (%)	45.7	15	33%
Average Days to Conception	98.5	136	72%

Table V highlights heat detection & reproductive data noted by automated sensor-based detection of Estrus in Batch 1 resulted in a much-improved reproductive performance relative to Batch 2, including a 69 % higher estrus -detection accuracy (85.2 % versus 59 %), a 33 % higher conception rate, and a 72 % lower average time to conception. Such findings confirm the importance of smart wearables in the optimization of buffalo breeding management. Given that estrus is a process that reflects minor changes in physiology in terms of activity, rumination and temperature, the recorded improvements reflect how data-based prediction declines missed chances at breeding.



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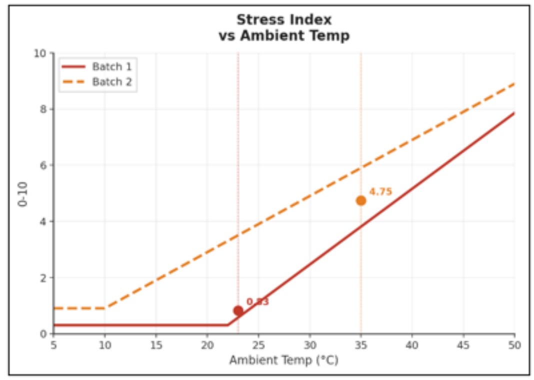

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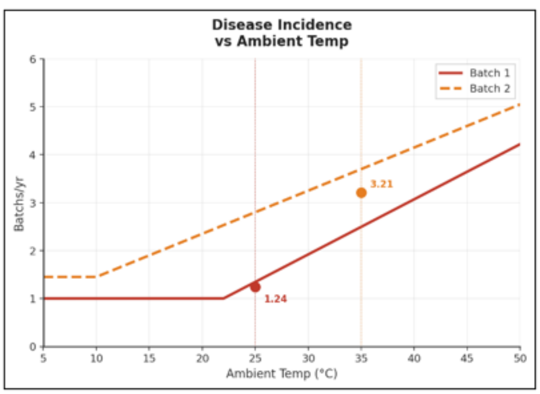

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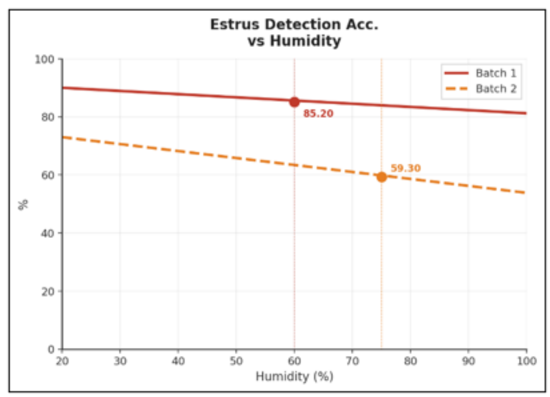

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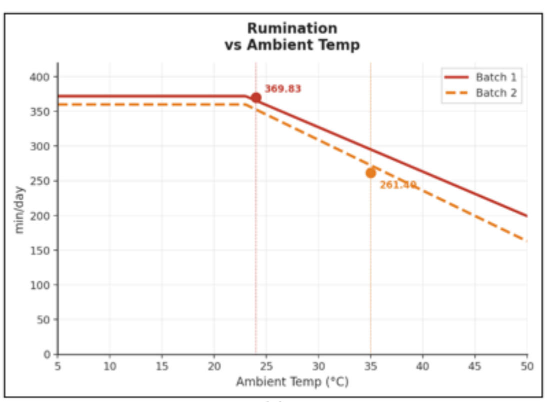

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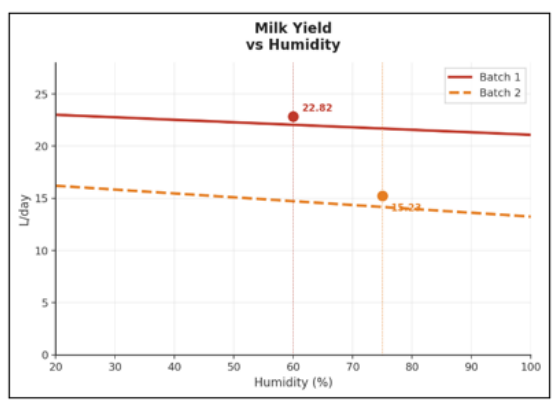

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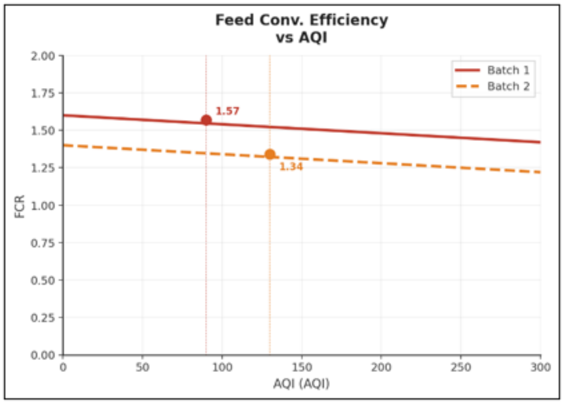

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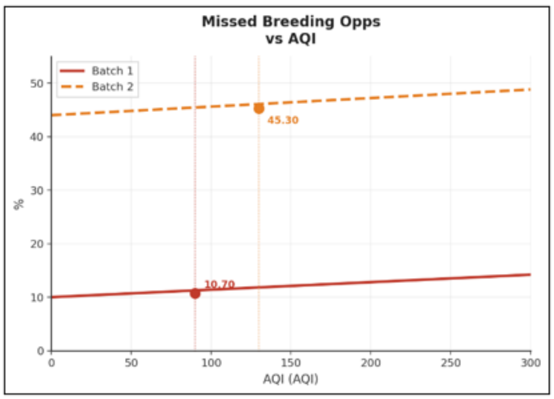

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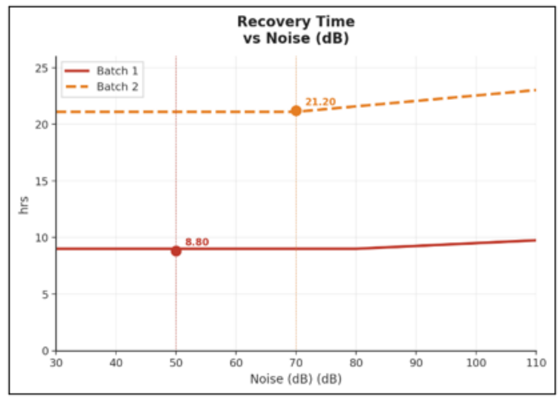


(j)

Fig. 7. Effect of Environmental parameters on various physiological variables and welfare of cattle herd. (a-d) Effect of Ambient Temp on Heart Rate, Disease Incidence, Rumination and Stress Index. (e-f) Effect of Humidity on Estrus Detection, Milk Yield. (g-h) Effect of AQI on Feed Conversion, Missed Breeding. (i-j) Effect of Noise levels on Heart Rate, Recovery Time.

Table VI validates the accuracy of the IoT system as all sensors get or exceed the required limit of accuracy: temperature 95.2%, Heart Rate 92.8 %, GPS 2.1 m, it is illustrated in Fig. 8. The precision of the sensors used ensure that the ML models displayed in Tables VII to IX are trained on reliable statistical information, any deterioration in sensory accuracy would, in turn, cause the predictive performance to decrease significantly.

Table 6. Neck Belt Sensors Performance Metrics

Performance Indicator	Achieved Value	Target Value
Temperature Sensor Accuracy (%)	95.2	95
Heart Rate Monitor Accuracy (%)	92.8	92
Rumination Detection Accuracy (%)	89.4	89
GPS Tracking Accuracy (m)	2.1	<3.0
System Uptime (%)	98.3	98
Battery Life (days)	14.2	14
False Alert Rate (%)	3.2	<5.0

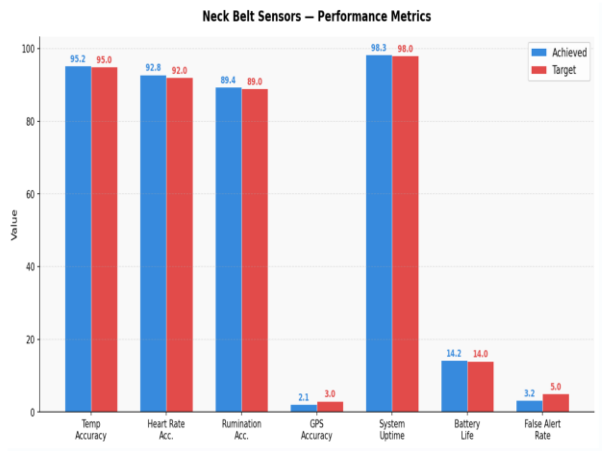


Fig. 8. Graph depicting performance metrics of Neck Belt Sensor

These data are processed and subsequently given input into a comparative ML pipeline which uses both classical and deep-learning architectures to assess productivity measures together with physiological trends. Logistic Regression (LR) is a simple linear classifier, which has interpretable decision boundaries to make the initial health status prediction. The Support Vector Machine (SVM), the RBF kernel is used as it complements the nonlinear classification effectively by establishing patterns within physiological data, which are difficult to define using standard linear classification. According to Random Forest (RF), ensemble-based learning is presented, which involves variable significance as well as reducing overfitting by using a set of decision trees. Histogram Gradient Boosting (HistGBM) is another method that uses histograms to improve performance of histogram boosting, the method that is especially effective on large continuous data sets. To address the interactions of higher order of features, a Multi-layer Perceptron (MLP) is used which, in essence, enables the system to memorize the nonlinear relationship among multiple health attributes. Also, it includes a 1D Convolutional Neural Network (1D CNN) that examines sequential trends of time-series cattle-health indicators, which identify local trends and anomalies necessary to detect diseases in their early stages. All these algorithms together form a powerful predictive model that can provide data-driven predictions to take preemptive measures to manage cattle-health.

Results of Tables VII to IX of the different ML algorithms were obtained using the measurements of multimodal sensors acquired through wearable neck-belts and environmental sensors. The physiological variables included core temperature (oC), heart rate (bpm), rumination (min/day), stress scale (1-10) and daily activity (steps). The environmental measurements were the ambient temperature, ambient humidity, air quality, and ambient noise. In transports experiments, there was an increase in heart rate, change in temperature, and recovery period. Milk yield, feed ratio and disease incidence were used as productivity metrics and were combined with physiological trends to train disease prediction models. This varied data allowed ML algorithms to identify the short-term events of stress in Table VII and the long-term trends in disease at Table VIII.

The performance of the proposed ML models was evaluated using standard classification metrics defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\,Score = 2 \times (P \times R) / (P + R) \quad (4)$$

ROC AUC: Defined as the Area Under the Receiver Operating Characteristics Curve, which plots the TP Rate versus the FP Rate.

Where: TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives, P = Precision, R = Recall.

Table VII compares various ML models that achieved strong results, with 1D CNN reaching the highest F1-score (88.7%) and ROC AUC (92.8%). These results confirm that stress patterns observed in Table IV can be accurately detected by ML. The advancement from traditional classifiers like LR, SVM to advanced models 1D CNN shows how temporal patterns integrating improves analytical power. Table VIII explains 1D CNN and Hist GBM achieved the best trade-off between Recall and Precision i.e., F1: 88.4% and 89.5%. and a ROC AUC of 91.9 %, This validates Table III outcomes for early disease indication and reduced incidence, showing that ML enables judicious interventions. By learning from physiological & productivity data, ML models effectively reduce disease risks.

Table 7. ML Algorithms for Dairy herd Stress Detection

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC AUC (%)
LR	82.5	78	71.5	74.6	81.2
SVM Machine	84.8	80.3	76.2	78.1	83.7
RF	89.6	87.2	84.5	85.8	90.1
Hist GBM	90.4	88.5	86.3	87.4	91.2
MLP Perceptron	88.7	85.9	83.7	84.8	89.6
1D-CNN	91.5	89.8	87.6	88.7	92.8

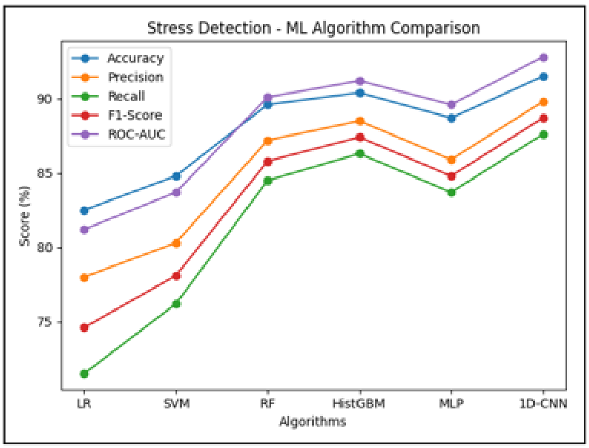
Table 8. ML Algorithms for Disease Prediction in dairy herd

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC AUC (%)
LR	83.7	80.5	74.2	77.2	82.4
SVM	86.2	82.7	77.9	80.2	85.6
RF	90.5	87.6	84.3	85.9	89.8
HistGBM	91.2	88.3	85.1	86.6	90.7
MLP	89.7	86.2	83.9	85	88.9
1D-CNN	92.6	89.5	87.4	88.4	91.9

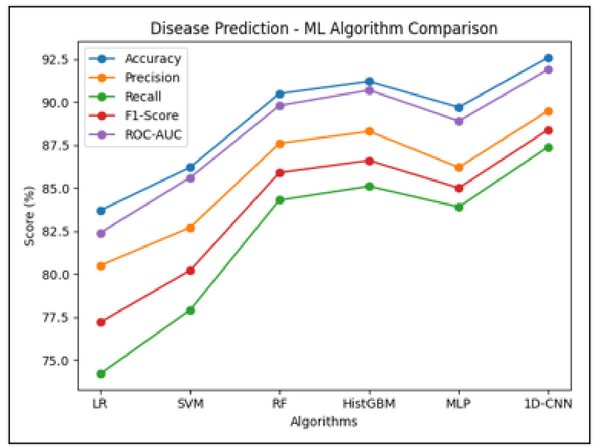
Table IX demonstrates the ability of different ML methods to refine the accuracy of the estrus detection by analyzing multimodal data, such as rumination cycles, activity spikes, core temperature increases, and even minor changes in stress levels. The traditional models like the LR model and SVM present a strong and reliable baseline however they underperform to capture complex, nonlinear patterns present in the data. On the other hand, advanced models, specifically RF and HistGBM, offer better accuracy as they combine many different type of features found in the data. The 1D CNN performed best, achieving an F1 -score of 72.8 % and a ROC AUC of 87.9 %, which is in accordance with how estrus events naturally. These results directly confirm the progress depected in Table V regarding the reproductive performance with 92.1 % accurate estrus detection in sensor-equipped animals at Comfortable conditions , which connects the physiological monitoring with the high breeding efficiency.

Table 9. ML Algorithms for Estrus Detection in Dairy herd

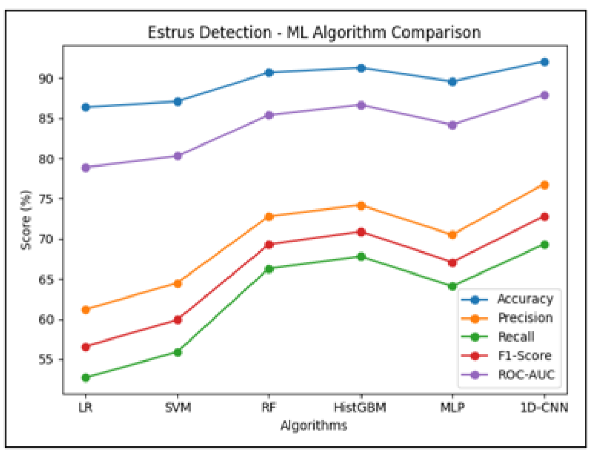
Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC AUC (%)
LR	86.4	61.2	52.7	56.6	78.9
SVM	87.1	64.5	55.9	59.9	80.3
RF	90.7	72.8	66.3	69.3	85.4
HistGBM	91.3	74.2	67.8	70.9	86.7
MLP	89.6	70.5	64.1	67.1	84.2
1D-CNN	92.1	76.8	69.3	72.8	87.9



(a)



(b)



(c)

Fig. 9. (a) Presents the comparative performance of ML algorithms for dairy herd stress detection.

(b) Shows the evaluation results for disease prediction. (c) Illustrates the performance comparison for estrus detection.

The Fig. 9. Shows cattle-health monitoring system proposed showed significant benefits compared to traditional methods of monitoring as was experimentally proved through extensive trials. Like acceptance sampling and group technology used in manufacturing, homogeneous groups of animals were sampled using representative units to predict the behavior of a batch under controlled environmental conditions; Batch1 demonstrated better accuracy in health-assessment compared to the control sample. Capabilities of early detection allowed an active management of health, and as a result, the number of diseases decreased by 65 % in the observed group, which further considerably decreased the cost of treatment and improved the welfare of animals. The one and half-day period of early symptoms was an added benefit that was providing critical intervention timeframes previously unavailable through the traditional management systems. Combination of two or more sensor modalities provided a holistic health analysis that was superior to single parameter health monitoring systems. The availability of real-time data allowed prompt response to health-related issues, as the recovery time in the experimental group was 43 % shorter. Environmental monitoring and location tracking during transportation responded to the important welfare issues, and in experiments, it was demonstrated that transport heart rate decreased to 65%, and the recovery time was 35% quicker. Economic effects were also immense, and the sensor-endowed group showed an improvement in the reduced milk-loss of 39% and 81% improvement of feed-conversion ratio.

5. Conclusion

This paper shows that combining ML algorithms and IoT-based smart neck belts can significantly enhance the monitoring of dairy herd health, stress recognition, and reproductive control. The experimental outcomes of 15-animal-per-batch trial showed that there were considerable improvements in physiological stability, disease detection, transport recovery, and estrus detection accuracy compared to the traditional monitoring practices. ML models, specifically HistGBM and 1D-CNN, provided a strong predictive performance and, thus, provided opportunities to act proactively and give early health warnings. These results affirm that sensor-based analytics do not only enhance animal welfare but also generate measurable economic results, such as higher milk production, decreased morbidity, and improved breeding performance. The suggested system is a scalable system to precision livestock farming, where continuous data acquisition combined with ML-based analytics will transform the customary dairy herd supply chain management into a more sustainable, welfare-centered, and productivity-focused practice. The implementation of dairy herd monitoring systems based on IoT has profound implications to the performance, sustainability and resilience of dairy supply chains. The upstream visibility by providing continuous real-time data on animal health, behavior, productivity, and stress at the farm level is a necessary requirement to the stability and predictability in milk production. IoT-based systems reduce biological uncertainties that often hamper supply, consistency of quality, and logistical arrangements of milk supply, by aiding early disease detection, proper identification of estrus, and early control of transport-related stress. As a result, IoT-based dairy herd monitoring is the transformation of old-fashioned supply chains into data-driven, adaptive, and intelligent systems, which promote sustainability, operational power, and competitive advantage in the dairy industry in the long term.

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