Indonesian Journal of Electrical Engineering and Computer Science
Vol. 34, No. 2, May 2024, pp. 1192~1203
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v34.i2.pp1192-1203

Smart livestock management: integrating IoT for cattle health diagnosis and disease prediction through machine learning

Satyaprakash Swain[1], Binod Kumar Pattnayak[1], Mihir Narayan Mohanty[2], Suvendra Kumar Jayasingh[3], Kumar Janardan Patra[3], Chittaranjan Panda[4]
[1]Department of Computer Science and Engineering, Institute of Technical Education and Research (ITER), Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, India
[2]Department of Electronics and Communication Engineering, Institute of Technical Education and Research (ITER), Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, India
[3]Department of Computer Science and Engineering, Institute of Management and Information Technology (IMIT), BPUT, Cuttack, India
[4]Mavenir Systems, Bengaluru, India

Article Info

Article history:

Received Nov 24, 2023
Revised Dec 25, 2023
Accepted Dec 26, 2023

Keywords:

Boosting models
Cattle health analysis
Ensemble learning
IoT
Machine learning

ABSTRACT

Cattle diseases can significantly impact on livestock health and agricultural productivity is substantial. Timely detection and prognosis of these diseases are essential for prompt interventions and preventing their spread within the herd. This study delved into employing machine learning models to anticipate cattle diseases based on relevant parameters. These parameters encompass milk fever, milk clots, milk watery, milk flake, blisters, lameness, stomach pain, gaseous stomach, dehydration, diarrhea, vomiting, abdominal issues, and alkalosis. A dataset of 2,000 samples from diverse cattle populations was amassed, each tagged with the presence or absence of specific diseases. The primary goal was to compare the efficacy of five well-known machine learning models: Naïve Bayes multinomial (NBM), lazy-IBk, partial tree (PART), random forest (RF), and support vector machine (SVM). The findings underscored the consistent superiority of RF in comparison to the other models, boasting the highest accuracy in predicting cattle diseases. The RF model exhibited an accuracy rate of 88% on the test dataset. This achievement can be ascribed to its capacity to handle intricate interactions among input features and mitigate over fitting through ensemble learning. These insights can furnish valuable information about early indicators and risk factors associated with diverse cattle diseases.

Corresponding Author:

Satyaprakash Swain
Department of Computer Science and Engineering, Institute of Technical Education and Research (ITER)
Siksha 'O' Anusandhan (Deemed to be University)
Bhubaneswar, Odisha, India
Email: satyaimit@gmail.com

1. INTRODUCTION

Cattle health management holds a pivotal role in ensuring the livestock industry's well-being, productivity and profitability. The prompt identification and precise diagnosis of ailments or health issues in cattle are imperative for effective prevention and treatment. With the evolution of technology, machine learning methods have emerged as a potent instrument for medical prognosis and anticipation in various fields, including veterinary science. By harnessing machine learning algorithms and computational models, researchers and veterinarians can scrutinize extensive datasets to enhance the precision and efficiency of cattle health diagnosis. This manuscript presents an outline of the machine learning application in the realm of cattle medical diagnosis and anticipation. It delves into the possible advantages, obstacles, and future potential of incorporating machine learning techniques into cattle healthcare frameworks. Machine learning algorithms possess the capability to process diverse data categories, ranging from clinical records, and laboratory test outcomes to genetic information and sensor data. This capacity facilitates the detection of disease patterns and markers, thereby permitting the early identification of health concerns in cattle. This, in turn, enables swift intervention and treatment. By training machine learning models on extensive datasets containing labelled cattle health records, these algorithms can grasp intricate patterns and associations that might elude human observation. This ameliorates diagnostic precision and dependability, consequently mitigating the risk of misdiagnosis. Machine learning models can be instructed to predict the probability of forthcoming diseases or health complications founded on historical data and risk elements. This ability facilitates proactive management methodologies, including targeted vaccinations, pre-emptive measures and optimized herd supervision strategies, all geared towards minimizing the impact of potential outbreaks. Machine learning algorithms are equipped to amalgamate real-time data from wearable gadgets, sensors and automated surveillance systems to uphold continual monitoring of cattle health. This enables the early identification of abnormal behaviours, deviations from standard vital signs, or indications of distress, thereby enabling timely corrective action.

2. LITERATURE REVIEW

Bobbo *et al.* [1] ministry-supported research highlights machine learning's success over 75% accuracyin predicting dairy cows' udder health. Through various algorithms, including neural network and random forest (RF), their study emphasizes data-driven approaches for early mastitis detection, signaling a pivotal role for advanced analytics in bolstering farming practices and surveillance. Gorczyca and Gebremedhin [2] used machine learning models to predict the physiological reactions of dairy cows to environmental heat stress. Nonlinear algorithms fared better than linear ones, illuminating the effects of stressors. Rao *et al.* [3] in the meantime, presented a Python/R-based real-time cattle disease detection system that makes use of RF, Naïve Bayes, k-nearest neighbor (K-NN), support vector machine (SVM), and decision tree. It seeks to transform cow healthcare by bridging the comprehension gap in animal discomfort by linking symptoms to remedies. Shah *et al.* [4] propose a deep learning-powered health check system for the cattle industry, emphasizing its global and Indian economic importance. Utilizing cattle images, this system aims to bolster health monitoring, curbing losses from infections. Wang *et al.* [5] introduce the BLCKG model, merging deep learning and a knowledge graph for precise dairy cow disease diagnosis, leveraging veterinary expertise to outshine other models with additional diagnostic insights.

Zhou *et al.* [6] research investigates eight algorithms to predict dairy cow disorders, highlighting Rpart's superior generalization. They highlight machine learning's potential in detecting common health issues, advocating for AI integration in management software to enhance forecasting and identify nursing cow and calf problems through new disease-related features. These advancements promise to enhance cattle healthcare and management, mitigating economic losses and enhancing industry efficiency. The various research endeavors highlight machine learning's potential in transforming dairy cattle management, particularly in predicting lameness and assessing metabolic status. Shahinfar *et al.* [7] investigate lameness prediction using milk production and conformation factors, singling out Naïve Bayes as a promising method despite data limitations. They stress the need for expanded datasets incorporating environmental and management factors to enhance predictive accuracy. Taneja *et al.* [8] present an internet of things (IoT)-based application employing pedometers and hybrid techniques for early lameness detection, emphasizing specialized models and edge computing's value in prompt intervention. Volkmann *et al.* [9] utilize acoustic analysis for lameness detection, achieving significant sensitivity and specificity, suggesting an automated, on-farm potential, while noting the importance of addressing false positives and negatives. Xu *et al.* [10] focus on clustering cows' metabolic status using plasma markers, with RF and SVM emerging as strong predictors. Their findings highlight on-farm data's relevance in early detection and management of metabolic issues. Collectively, these studies emphasize machine learning's pivotal role in advancing cattle welfare. They signal the need for further research to develop comprehensive predictive models encompassing environmental, health and production factors to optimize dairy cattle management and well-being.

Hossain *et al.* [11] investigate dairy cow clustering using plasma metabolites and hormones, employing machine learning to predict metabolic status from on-farm data. Particularly, RF, and SVM show promise among eight algorithms, suggesting potential for predicting metabolic status with error rates spanning 12.4% to 49.8%. These findings hint at early detection possibilities for managing metabolic issues in dairy cattle, shedding light on the significance of specific milk production traits in the prediction process. Rony *et al.* [12] underscore the severe impact of foot-and-mouth disease (FMD) and lumpy skin disease (LSD) in cattle farming, advocating for machine learning in early disease prediction to improve identification and containment. They emphasize the necessity of high-quality data and thoughtful considerations of technical constraints, implementation costs and maintenance for effective machine learning solutions. Further research is crucial to optimize the role of machine learning in addressing FMD and LSD in the cattle industry. Guitian *et al.* [13] discuss machine learning's contribution to veterinary public health surveillance, handling tasks ranging from pattern identification to health record analysis. They stress the importance of integrating machine learning with traditional statistical analysis and highlight the need for combining domain expertise with machine learning proficiency for successful implementation in surveillance systems. Hyde *et al.* [14] introduce a RF based automated mastitis diagnosis tool, exhibiting accuracy in replicating herd-level diagnoses made by specialized veterinarians. This tool demonstrates potential in swiftly detecting mastitis transmission channels during lactating and non-lactating phases, aiding non-specialist veterinary professionals in implementing controls against this detrimental disease at the herd level.

3. TECHNIQUES USED

3.1. Naive basis multinomial

Naïve Bayes multinomial (NBM) [15] is a revolutionary paradigm for interpretable machine learning that combines neural networks and generalized additive models. NBM improves scalability in sparse, high-dimensional datasets by using a small set of shared fundamental functions among features [16]. The interpretability problem in complicated machine learning models is addressed by NBM, which is a ground-breaking method thanks to its capacity to record intricate feature interactions.

3.2. SVM

One of the most popular supervised learning algorithms, mostly for classification tasks, is the SVM. In a multi-dimensional space, it creates an ideal decision boundary known as a hyperplane that successfully divides classes for upcoming data points. Support vectors are key elements in SVM [17] that define the hyperplane's classification capability and have a significant impact on its development. The algorithm's name, which represents these crucial moments, derives from how the algorithm operates. A distinct difference between two groups is seen in Figure 1, demonstrating the effectiveness of SVM in defining discriminating decision boundaries for classification [18].

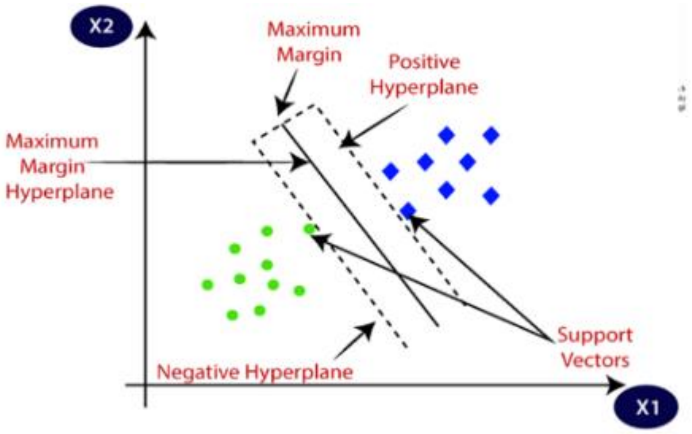

Figure 1. Diagrammatic representation of SVM

3.3. Lazy IBk

Lazy learning, exemplified by KNN algorithms, stores training instances and defers extensive computations until classification. It offers localized approximation, enhancing adaptability to varying problem scenarios and effective individual query solutions. This approach facilitates concurrent problem resolution but demands significant storage for the entire dataset as shown in Figure 2, especially with noisy data, lacking concept formation in training. While the evaluation process may be slower, the training phase is quicker, distinguishing lazy learning methods. Techniques like instance-based learning, local regression, KNN, and lazy Bayesian [19] rules fall under lazy IBk, showcasing the versatility of this approach.

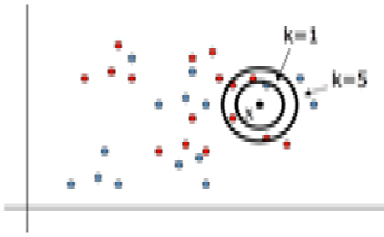

Figure 2. Lazy learner

3.4. Partial decision trees

Partial decision trees (PART) [20], this approach integrates the divide-and-conquer methodology of RIPPER with the decision tree approach of C4.5. In greater detail, PART functions by generating a collection of rules using the divide-and-conquer strategy. It initiates by crafting a rule, subsequently removing all instances from the training dataset that adhere to this rule. This process iterates recursively until no instances remain unaccounted. For the creation of an individual rule [21], PART constructs a partial decision tree based on the current set of instances. The leaf node with the most extensive coverage is then selected as new rule.

3.5. Random forest

RF is an ensemble learning technique used for a range of tasks including classification and regression [22]. This approach involves creating numerous decision trees during the training phase. In scenarios requiring classification, the output of the RF is determined by the class most frequently chosen across the trees. Conversely, for regression tasks, the outcome is derived from the mean or average prediction yielded by the individual trees. In Figure 3 by aggregating multiple trees, this ensemble method mitigates this tendency. While RF generally surpass individual decision trees in performance, it's worth noting that their accuracy falls short of gradient boosted trees.

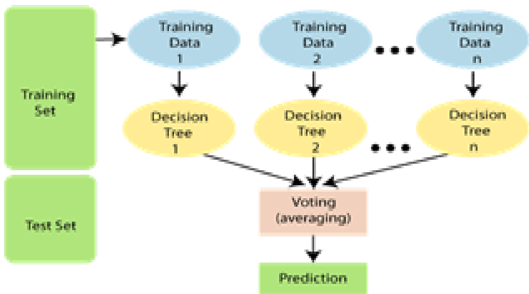

Figure 3. Graphical representation of RF

3.6. Boosting methods

In the field of machine learning, boosting [23] stands out as an ensemble meta-algorithm aimed at primarily mitigating bias and additionally, addressing variance in supervised learning. It belongs to a category of machine learning techniques that transform feeble learners into robust ones. The fundamental idea behind boosting traces back to the query raised by Kearns and Valiant, pondering whether a collection of feeble learners can collaboratively yield a potent learner. A weak learner is defined as a classifier that holds only slight correlation with the actual classification but can perform better than random guessing in labeling examples. Conversely, a strong learner is a classifier that exhibits a high degree of correlation with the true classification, effectively capturing intricate patterns in the data.

4. DATA COLLECTION

4.1. Data collection

Data are gathered from different IoT devices which are planted by internally or externally on cattle including relevant features such as cattle characteristics (age, breed, gender), environmental factors (temperature, humidity) and disease-related attributes (symptoms, previous diseases). The data/parameters are anorexia (loss of appetite), abdominal pain, anaemia (low red blood cell count), abortions (in pregnant animals), aggression, coughing, depression, diarrhoea, dehydration, lameness (difficulty in walking), lethargy (lack of energy), milk flakes, milk watery, milk clots, milk fever, nausea, pain, pneumonia, rapid breathing, reduced fertility, salivation (excessive drooling), swelling in various body parts (e.g., pharyngeal, udder), tachycardia (elevated heart rate), weight loss and weakness. These parameters are used to predict 26 numbers of diseases like mastitis Blackleg, bloat, Coccidiosis, Cryptosporidiosis, Displaced_abomasum, Gut_worms, Listeriosis, Liver_fluke, Necrotic_enteritis, Peri_weaning_diarrhoea, Rift_valley_fever, Rumen_acidosis, Traumatic reticulitis, Calf diphtheria, Foot rot, Foot-and-mouth, Ragwort poisoning, Wooden_tongue, Infectious_bovine_rhinotracheitis, Acetonemia, Fatty_liver_syndrome, Calf pneumonia, Schmallen_berg_virus, Trypanosomiasis, and Fog fever. These sensor technologies can be seamlessly integrated into an IoT framework to capture and analyze real-time data concerning various cattle health conditions. These are:

- Anorexia (loss of appetite): by employing feed intake monitors, changes in feed consumption can be detected, facilitating the identification of altered appetites.
- Abdominal pain: motion sensors, such as accelerometers or posture sensors, can pinpoint unusual movements that may indicate abdominal discomfort.
- Anemia (low red blood cell count): blood oxygen sensors can provide valuable insights into anemia by continuously monitoring blood oxygen levels.
- Abortions (in pregnant animals): estrus monitors are adept at tracing reproductive cycles, aiding in the early detection of potential pregnancy issues.
- Aggression: behavior sensors analyzing animal interactions offer the capability to identify patterns of aggression.
- Coughing: sound sensors, like microphones, can recognize coughing sounds, helping to identify respiratory distress.
- Depression: activity monitors, gauging activity levels, can be used to track changes related to depressive behavior.
- Diarrhea: fecal analysis sensors possess the ability to analyze fecal composition, aiding in the detection of diarrhea.
- Dehydration: water intake monitors, which track water consumption, play a crucial role in predicting dehydration.
- Lameness (difficulty in walking): gait analysis sensors interpret walking patterns, enabling the prediction of lameness.
- Lethargy (lack of energy): activity monitors, observing activity reductions, are valuable in predicting periods of lethargy.
- Milk flakes: integrated within milking systems, milk quality sensors are equipped to forecast abnormalities in milk consistency.
- Milk watery: milk quality sensors can predict milk wateryness by analyzing milk consistency.
- Milk clots: milk quality sensors are capable of detecting milk clotting issues.
- Milk fever: temperature sensors can predict milk fever by recognizing elevated body temperatures.
- Nausea: behavior analysis utilizes changes in behavior and activity to predict episodes of nausea.
- Pain: behavior and motion analysis leverage abnormal behaviors and movements to predict instances of pain.
- Pneumonia: respiration rate monitors are proficient in predicting pneumonia by analyzing respiration patterns.
- Rapid breathing: respiration rate monitors predict rapid breathing through increased respiration rates.
- Reduced fertility: estrus monitoring systems predict reduced fertility based on reproductive cycle patterns.
- Weight loss: weight sensors predict gradual weight loss over time.
- Salivation (excessive drooling): specialized saliva detection sensors predict excessive salivation.
- Swelling in various body parts: imaging sensors, encompassing thermal or visual imaging capabilities, forecast inflammation and swelling.
- Tachycardia (elevated heart rate): heart rate monitors predict elevated heart rates, indicative of tachycardia.
- Weakness: behavior monitors predict periods of weakness by analyzing movement and posture changes.

These sensors would be seamlessly integrated into an IoT framework [24], thereby enabling the real-time collection and analysis of cattle health data. As shown in Figure 4. Dataset has been assembled, encompassing diverse parameters such as age, breed, gender, environmental conditions like temperature and humidity, as well as disease-related attributes including symptoms and medical history. This information has been acquired through IoT devices attached to cattle bodies [25] and manual observations and has been systematically organized into a tabular format. The dataset comprises a range of attributes like anorexia, abdominal pain, anaemia, abortions, and aggression, providing a valuable resource for in-depth analysis and predictive modelling in cattle health management.

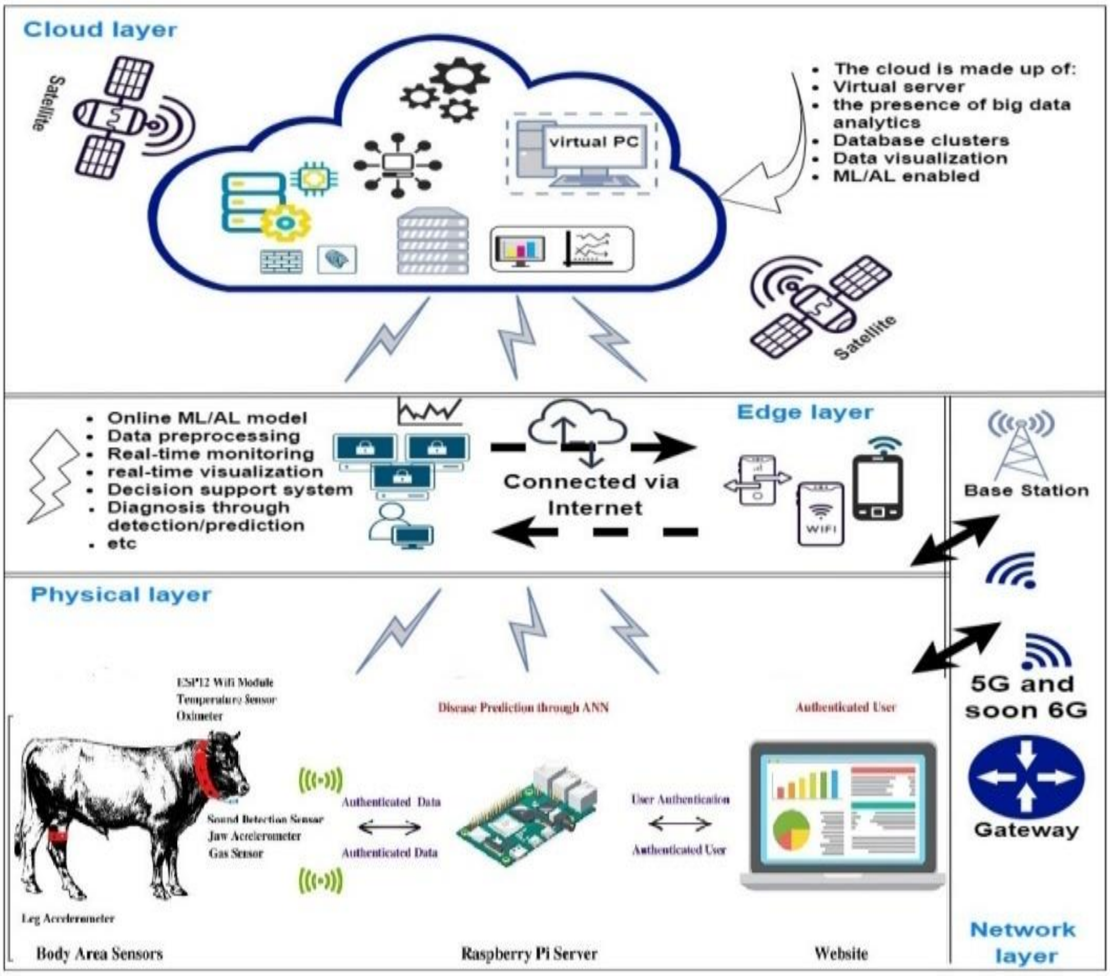

Figure 4. Data collection of cattle using IoT devices

5. METHOD

Data preparation is a crucial step in machine learning model training. It involves cleaning, transforming and organizing the data to make it suitable for input into the models. Figure 5 showing step-by-step methods for data preparation in the context of predicting cattle diseases using machine learning models.

Figure 6 shows the flow of work using machine learning models. After data collection and cleaning, we split our collected dataset into 70% training purpose, 20% for validation and 10% for testing. Here we used five different model i.e., NBM, SVM, lazy-IBk, PART, and RF for find best prediction.

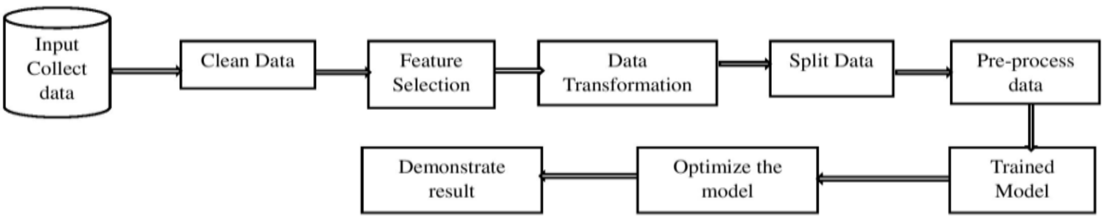

Figure 5. Dataset preparation steps

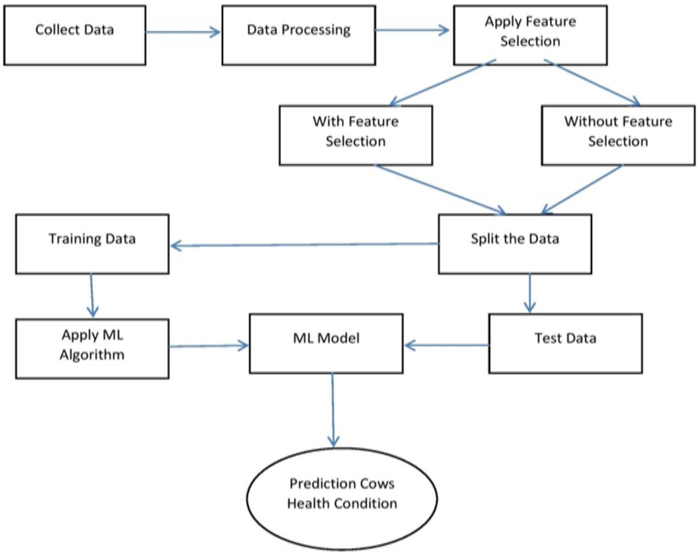

Figure 6. Flow chart for prediction of cow's health condition

6. COMPARISON AND ANALYSIS

The proposed model employs implant devices within various parts of cattle bodies to gather time series data concerning different parameters associated with cattle diseases. The acquired data is stored in a cloud-based repository for subsequent analysis through diverse machine learning techniques such as NBM, SVM, lazy-IBk, PART, and RF. Table 1 contains the accuracy levels by different machine learning models from the data 2,000 data sets divided into five sections. Figure 7 is representing the diagrammatical analysis of Table 1 data to find out best model. Here our objective is to predict potential instances of disease in cattle, enabling proactive care. The selection of parameters is tailored to the specific requirements of different machine learning models enhancing disease prediction accuracy and reducing potential errors. Table 2 contains mean absolute error values of different machine learning models which is generated from five diffent batch of data sets and Figure 8 representing its graphical analysis. Table 3 contains root mean square error values generated by different machine learning models from five batches of data sets and Figure 9 representing its graphical analysis. Table 4 contains the relative absolute error values generated by different machine learning models from same 5 batches of data set and Figure 10 representing its graphical analysis. Table 5 contains the values of root relative squared error which is resulted from five different batch of data sets and Figure 11 showing is graphical analyze representation.

Table 1. Comparison of NBM, SVM, lazy-IBk, PART, and RF on the basis of accuracy values

No. of data	NBM	SVM	Lazy-IBK	PART	RF
1-400	76.88	58.54	81.15	78.89	81.65
400-800	79.19	58.39	83.7	77.44	84.21
800-1,200	88.72	75.43	92.23	86.21	90.97
1,200-1,600	77.85	67.13	86.01	82.28	86.48
1,600-2,000	78.52	65.39	87.35	81.14	87.58

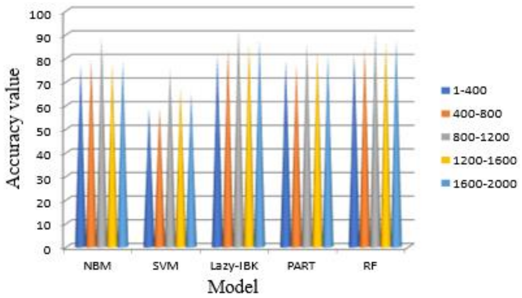

Figure 7. NBM, SVM, lazy-IBk, PART, and RF on the basis of accuracy values

Table 2. Comparison of NBM, SVM, lazy-IBk, PART, and RF on the basis of MAE values

No. of data	NBM	SVM	Lazy-IBK	PART	RF
1-400	0.03	0.03	0.02	0.02	0.02
400-800	0.03	0.03	0.01	0.02	0.01
800-1,200	0.02	0.02	0.01	0.01	0.01
1,200-1,600	0.03	0.03	0.01	0.02	0.02
1,600-2,000	0.03	0.02	0.01	0.01	0.01

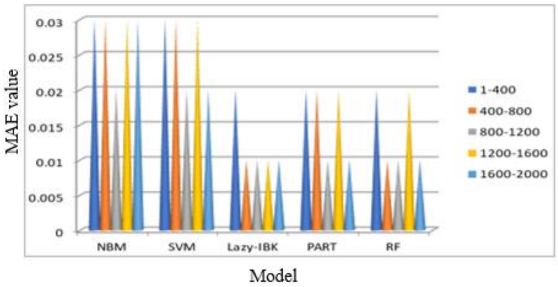

Figure 8. NBM, SVM, lazy-IBk, PART, and RF on the basis of MAE values

Table 3. Comparison of NBM, SVM, lazy-IBk, PART, and RF on the basis of RMSE values

No. of data	NBM	SVM	Lazy-IBK	PART	RF
1-400	0.12	0.18	0.1	0.12	0.1
400-800	0.11	0.17	0.09	0.11	0.09
800-1,200	0.1	0.15	0.08	0.1	0.08
1,200-1,600	0.12	0.18	0.1	0.11	0.1
1,600-2,000	0.1	0.16	0.08	0.1	0.08

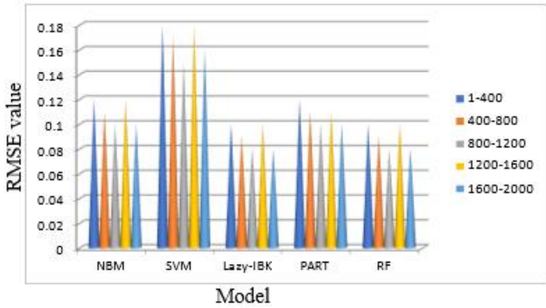

Figure 9. NBM, SVM, lazy-IBk, PART, and RF on the basis of RMSE values

Table 4. Comparison of NBM, SVM, lazy-IBk, PART, and RF on the basis of RAE values

No. of dataset	NBM	SVM	Lazy-IBK	PART	RF
1-400	45.55	43.71	25.11	29.39	26.37
400-800	43.54	44.66	22.7	28.73	24.33
800-1200	32.48	26.22	14.31	21.69	16.1
1200-1600	36.83	36.1	20.97	24.31	22.22
1600-2000	41.58	36.56	18.43	24.42	20.26

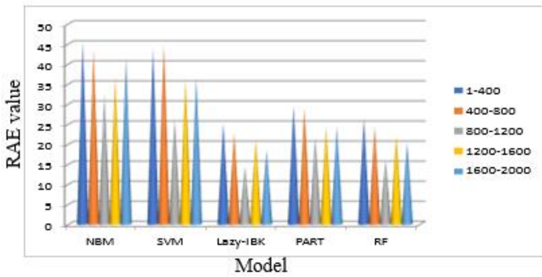

Figure 10. NBM, SVM, lazy-IBk, PART, and RF on the basis of RAE values

Table 5. Comparison of NBM, SVM, lazy-IBk, PART, and RF on the basis of RRSE values

No. of dataset	NBM	SVM	Lazy-IBK	PART	RF
1-400	59.8	93.5	51.9	59.55	51.7
400-800	58.78	94.59	49.49	60.01	49.88
800-1,200	47.79	72.45	38.12	50.88	40.13
1,200-1,600	56.38	85.05	47.16	53.82	47.9
1,600-2,000	56.27	85.54	44.04	55.19	45.14

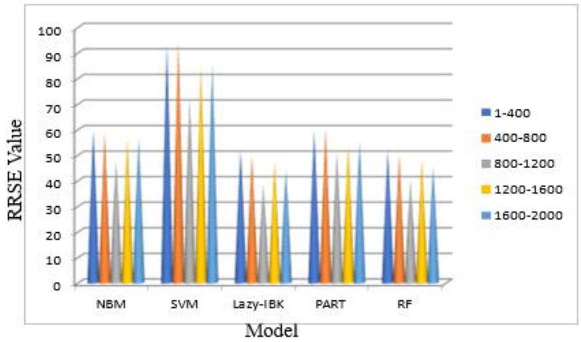

Figure 11. NBM, SVM, lazy-IBk, PART and RF on the basis of RRSE values

The prediction in different models like NBM, SVM, lazy-IBk, PART, and RF are compared on the basis of the accuracy and different error parameters and it is found that RF performs the best. After finding RF gives accuracy of 84% over our collected data set, we add some boosting model i.e., gradient boost, Lp boost, cat boost, and light GBM individually with RF model for boost accuracy and predict better than previous prediction. We found the increase accuracy after apply these models are given in Table 6.

Table 6. Comparison table of four different boosting models adding with RF model

Name of boosting models	Accuracy in (%)
Gradient boost	66
Lp boost	34
Cat boost	88
Light GBM	84

In Table 6 containing the accuracy value which is received after adding four different boosting models with RF model and Figure 12 representing its diagrammatical analysis. The prediction in different boosting models like gradient boost, Lp boost, cat boost, and light GBM are compared on the basis of the accuracy score and it is found that RF with cat boost performs the best and gives 88%.

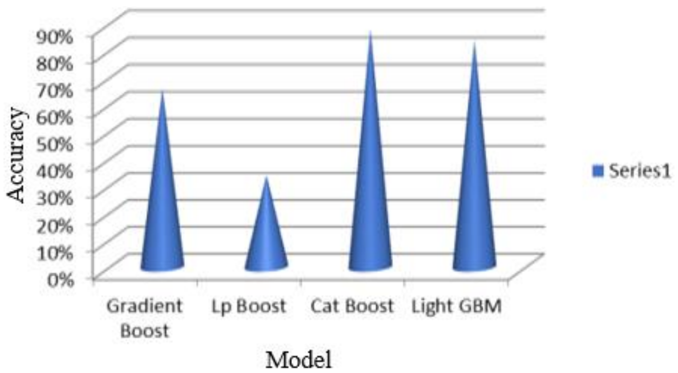

Figure 12. Graphical representation of different boosting model accuracy after adding with RF

7. CONCLUSION AND FUTURE WORK

This investigation utilized an extensive dataset that included diverse parameters such as age, breed, gender, environmental variables (temperature and humidity) and disease-related attributes to anticipate cattle health concerns. The parameters covered a wide spectrum, encompassing symptoms, previous medical history and physiological markers. Various machine learning models, including NBM, SVM, lazy-IBk, PART, and RF, were assessed for their predictive capabilities. Notably, RF achieved the highest accuracy of 84% across the dataset. To further enhance predictive accuracy, boosting models such as gradient boost, Lp boost, cat boost and light GBM were combined with the RF model. This comprehensive analysis revealed that the RF model paired with cat boost produced the highest accuracy at 88%, underscoring its exceptional performance in forecasting cattle health issues. The amalgamation of diverse machine learning techniques, particularly the synergy of RF and cat boost, presents substantial potential for precise and advanced prediction of cattle health conditions. This approach holds promise for proactive livestock management, bolstering animal well-being and providing valuable insights for informed decision-making in veterinary care. Future work in this domain could focus on exploring advanced feature engineering methods, incorporating ensemble approaches for improved predictive accuracy and robustness, developing real-time monitoring systems using IoT devices for early disease detection, augmenting the dataset to enhance model generalization and delving into model explain ability techniques to foster greater trust and usability in the context of cattle disease prediction systems.

REFERENCE

[1] T. Bobbo, S. Biffani, C. Taccioli, M. Penasa, and M. Cassandro, "Comparison of machine learning methods to predict udder health status based on somatic cell counts in dairy cows," *Scientific Reports*, vol. 11, no. 1, p. 13642, Jul. 2021, doi: 10.1038/s41598-021-93056-4.

[2] M. T. Gorczyca and K. G. Gebremedhin, "Ranking of environmental heat stressors for dairy cows using machine learning algorithms," *Computers and Electronics in Agriculture*, vol. 168, p. 105124, Jan. 2020, doi: 10.1016/j.compag.2019.105124.

[3] M. A. Rao, H. R. Monika, B. C. Rakshitha, and S. Thaseen, "Cattle disease prediction using artificial intelligence," *International Journal for Research in Applied Science and Engineering Technology*, vol. 11, no. 4, pp. 2184–2189, Apr. 2023, doi: 10.22214/ijraset.2023.50535.

[4] H. J. Shah, C. Sharma, C. Joshi, Y. Engineer, and S. K. Educare, "Cattle medical diagnosis and prediction using machine learning," *International Research Journal of Engineering and Technology*, no. May, pp. 3867–3870, 2022.

[5] H. Wang *et al.*, "Diagnosis of dairy cow diseases by knowledge-driven deep learning based on the text reports of illness state," *Computers and Electronics in Agriculture*, vol. 205, p. 107564, Feb. 2023, doi: 10.1016/j.compag.2022.107564.

[6] X. Zhou *et al.*, "The early prediction of common disorders in dairy cows monitored by automatic systems with machine learning algorithms," *Animals*, vol. 12, no. 10, p. 1251, May 2022, doi: 10.3390/ani12101251.

[7] S. Shahinfar, M. Khansefid, M. Haile-Mariam, and J. E. Pryce, "Machine learning approaches for the prediction of lameness in dairy cows," *Animal*, vol. 15, no. 11, p. 100391, Nov. 2021, doi: 10.1016/j.animal.2021.100391.

[8] M. Taneja, J. Byabazaire, N. Jalodia, A. Davy, C. Olariu, and P. Malone, "Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle," *Computers and Electronics in Agriculture*, vol. 171, p. 105286, Apr. 2020, doi: 10.1016/j.compag.2020.105286.

[9] N. Volkmann, B. Kulig, S. Hoppe, J. Stracke, O. Hensel, and N. Kemper, "On-farm detection of claw lesions in dairy cows based on acoustic analyses and machine learning," *Journal of Dairy Science*, vol. 104, no. 5, pp. 5921–5931, May 2021, doi: 10.3168/jds.2020-19206.

[10] W. Xu *et al.*, "Prediction of metabolic status of dairy cows in early lactation with on-farm cow data and machine learning algorithms," *Journal of Dairy Science*, vol. 102, no. 11, pp. 10186–10201, Nov. 2019, doi: 10.3168/jds.2018-15791.

[11] M. E. Hossain, M. A. Kabir, L. Zheng, D. L. Swain, S. McGrath, and J. Medway, "A systematic review of machine learning techniques for cattle identification: Datasets, methods and future directions," *Artificial Intelligence in Agriculture*, vol. 6, pp. 138–155, 2022, doi: 10.1016/j.aiia.2022.09.002.

[12] M. Rony, D. Barai, Riad, and M. Z. Hasan, "Cattle external disease classification using deep learning techniques," in *2021 12th International Conference on Computing Communication and Networking Technologies, ICCCNT 2021*, Jul. 2021, pp. 1–7, doi: 10.1109/ICCCNT51525.2021.9579662.

[13] J. Guitian, M. Arnold, Y. Chang, and E. L. Snary, "Applications of machine learning in animal and veterinary public health surveillance," *OIE Revue Scientifique et Technique*, vol. 42, pp. 230–241, Jan. 2023, doi: 10.20506/RST.42.3366.

[14] R. M. Hyde *et al.*, "Automated prediction of mastitis infection patterns in dairy herds using machine learning," *Scientific Reports*, vol. 10, no. 1, p. 4289, Mar. 2020, doi: 10.1038/s41598-020-61126-8.

[15] S. Swain *et al.*, "Application of IoT framework for prediction of heart disease using machine learning," *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 11, no. 10s, pp. 168–176, 2023, doi: 10.17762/ijritcc.v11i10s.7616.

[16] R. Dutta *et al.*, "Dynamic cattle behavioural classification using supervised ensemble classifiers," *Computers and Electronics in Agriculture*, vol. 111, pp. 18–28, Feb. 2015, doi: 10.1016/j.compag.2014.12.002.

[17] H. A. Fayed and A. F. Atiya, "Decision boundary clustering for efficient local SVM," *Applied Soft Computing*, vol. 110, p. 107628, Oct. 2021, doi: 10.1016/j.asoc.2021.107628.

[18] L. Niu, C. Yang, Y. Du, L. Qin, and B. Li, "Cattle disease auxiliary diagnosis and treatment system based on data analysis and mining," in *2020 5th International Conference on Computer and Communication Systems, ICCCS 2020*, May 2020, pp. 24–27, doi: 10.1109/ICCCS49078.2020.9118590.

[19] T. A. Shaikh, T. Rasool, and F. R. Lone, "Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming," *Computers and Electronics in Agriculture*, vol. 198, p. 107119, Jul. 2022, doi: 10.1016/j.compag.2022.107119.

[20] E. O. Kiyak, G. Tuysuzoglu, and D. Birant, "Partial decision tree forest: a machine learning model for the geosciences," *Minerals*, vol. 13, no. 6, p. 800, Jun. 2023, doi: 10.3390/min13060800.

[21] M. I. Kareem and M. N. Jasim, “DDOS attack detection using lightweight partial decision tree algorithm,” in *Proceedings of the 2nd 2022 International Conference on Computer Science and Software Engineering, CSASE 2022*, Mar. 2022, pp. 362–367, doi: 10.1109/CSASE51777.2022.9759824.

[22] J. M. Bowen, M. J. Haskell, G. A. Miller, C. S. Mason, D. J. Bell, and C. A. Duthie, “Early prediction of respiratory disease in preweaning dairy calves using feeding and activity behaviors,” *Journal of Dairy Science*, vol. 104, no. 11, pp. 12009–12018, Nov. 2021, doi: 10.3168/jds.2021-20373.

[23] S. Mondal, R. Maity, Y. R. Singh, S. Ghosh, and A. Nag, “Early prediction of coronary heart disease using boosting-based voting ensemble learning,” in *IBSSC 2022 - IEEE Bombay Section Signature Conference*, Dec. 2022, pp. 1–5, doi: 10.1109/IBSSC56953.2022.10037445.

[24] A. Herlin, E. Brunberg, J. Hultgren, N. Högberg, A. Rydberg, and A. Skarin, “Animal welfare implications of digital tools for monitoring and management of cattle and sheep on pasture,” *Animals*, vol. 11, no. 3, pp. 1–20, Mar. 2021, doi: 10.3390/ani11030829.

[25] G. Suseendran and D. Balaganesh, “Cattle movement monitoring and location prediction system using markov decision process and IoT sensors,” in *Proceedings of 2021 2nd International Conference on Intelligent Engineering and Management, ICIEM 2021*, Apr. 2021, pp. 188–192, doi: 10.1109/ICIEM51511.2021.9445360.

BIOGRAPHIES OF AUTHORS

Satyaprakash Swain completed his Masters of Technology (M.Tech.) in Computer Science from Utkal University, Odisha, India in 2015 and has since been actively involved in research, teaching and mentoring the students. He is currently working as a faculty in Institute of Management and Information Technology, Cuttack, India and as well as a part time Ph.D. scholar in Siksha 'O' Anusandhan University, Bhubaneswar, India. His research interest includes IoT, machine learning, network security, cloud computing, computational intelligence and soft computing. He has 11 years of teaching and research experience. He is a life member of ISTE. He can be contacted at email: satyaimit@gmail.com.

Binod Kumar Pattnayak is currently working as a Professor in the Department of Computer Science and Engineering, Institute of Technical Education and Research (ITER), Siksha 'O' Anusandhan University, Bhubaneswar, India since 1999. He got his Ph.D. from Siksha 'O' Anusandhan University, M.S. in Computer Engineering from National Technical University, Kharkov, Ukraine and B.Sc. from Revenshaw University, Cuttack, India. He has 25 years of teaching and research experience. He has published more than 400 papers in different journals, conferences including book chapters. His research interests include Ad-hoc networks, compiler design, software engineering, computer architecture, intelligent-systems. He can be contacted at email: binodpattanayak@soa.ac.in.

Mihir Narayan Mohanty is currently working as a Professor in the Department of Electronics and Communication Engineering, Institute of Technical Education and Research (ITER), Siksha ‘O’ Anusandhan (Deemed to be University), Bhubaneswar, Odisha. He has received his M. Tech degree in Communication System Engineering from the Sambalpur University, Sambalpur, Odisha and obtained his Ph.D. degree in Applied Signal Processing. He is the fellow of IE (I), and IETE. Also, he is the member of many professional societies including IEEE, and IET. He has 25 years of teaching and research experience. He has published more than 400 papers in different journals, conferences including book chapters. He has authored two books. He is the successive reviewer of manuscripts from IEEE, Elsevier, Springer, and IGI Global. His areas of research interests include applied signal and image processing, speech processing, antenna and intelligent signal processing. He can be contacted at email: mihirmohanty@soa.ac.in.

Suvendra Kumar Jayasingh completed his Bachelor of Engineering (BE) in Computer Science and Engineering (CSE) with Honours from the University College of Engineering (UCE), Burla, Odisha, India (Now VSSUT, Burla) in 2003. He got selected by Odisha Public Services Commission (OPSC) in 2005 to serve in the Institute of Management and Information Technology (IMIT), Cuttack, a Constituent College of Biju Patnaik University of Technology (BPUT), Odisha, India. He completed M. Tech. in Computer Science and Engineering (CSE) from JRN RVU, Udaipur in 2007. He got his Ph.D. in Computer Science and IT from North Orissa University, Baripada in 2020. His main research work focuses on machine learning, data mining, database design, computational intelligence, and soft computing. He can be contacted at email: sjayasingh@gmail.com.

Kumar Janardan Patra completed his Master of Technology (M.Tech) degree in 2023 from the Institute of Management and Information Technology (IMIT), Cuttack, a Constituent College of BijuPatnaik University of Technology (BPUT), Odisha, Indiain Computer Science and Engineering (CSE). He has a deep passion for data analytics, data mining, machine learning, and AI, soft computing, visual computing, demonstrating strong interest, and enthusiasm in these fields. He can be contacted at email: janardanpatra1997@gmail.com.

Chittaranjan Panda completed his MCA degree from CET Bhubaneswar (Presently OUTR) in the year of 2004. He has a wide range of experience in the field like IT, Networking and Administration with the posts like Senior Director and Telecom Engineer in different IT related organisations. Also he has experience on openstack, Kubernet, SDN cloud profesional. His research area is data analytics, data mining, machine learning and AI, soft computing, and visual computing. He can be contacted at email: chittaranjan.panda@mavenir.com.