IOT Driven Bovine Vitalis

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IOT-DRIVEN BOVINE VITALIS

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Abstract. In today's burgeoning global economy, dairy farming has emerged as a pivotal and daily necessity. The productivity of dairy products is intricately tied to the health of the cattle. Even a minor ailment affecting one animal within the herd has the potential to cascade, impacting the entire group and compromising their overall productivity. Recognizing the critical relationship between animal health and dairy output, an innovative Internet of Things (IoT)-driven system has been implemented. This advanced system utilizes sensors to collect data, enabling the early prediction of diseases through the processing of symptoms using supervised machine learning algorithms.

The significance of early disease prediction extends beyond mitigating disease outbreaks; it empowers dairy farmers to make well-informed decisions that contribute to the establishment of sustainable farming practices. The primary objective is to promptly administer the right treatment to cattle, safeguarding them from adverse effects on milk production and the quality of the produced milk. Given the challenge of individually identifying and monitoring each animal in a cattle herd, often comprising a substantial number of individuals, the system adopts a unique approach. Each animal is assigned a distinct identifier, allowing for the separate monitoring of the diagnosis and treatment of each. This meticulous and personalized approach not only facilitates faster treatment but also contributes to the earlier cure of diseases, ultimately enhancing overall production efficiency in the dairy farming industry.

Keywords: IOT, dairy farming, machine learning, algorithms, disease prediction, cattle health, sensors, supervised machine learning.

1 Introduction

In traditional dairy and cattle farming practices, the absence of advanced technology hinders the effective monitoring of individual animals. This lack of a systematic approach, even when technology is available, renders the existing methods ineffective. The conventional practice of physically transporting a veterinary doctor to the location or moving the cow to a veterinary hospital is not only timeconsuming but also introduces delays, posing a risk to the well-being of the cattle.The integration of Internet of Things (IoT) technology into cattle health care systems has the potential to revolutionize and elevate them to the next level, enhancing overall production and optimizing time management. This innovative system entails continuous data monitoring, promptly detecting any symptoms that may indicate potential health issues. In the presence of symptoms, the system employs machine learning algorithms to predict the potential disease.

The insights gathered by IoT devices, comprising various sensors measuring parameters such as temperature, heart rate, respiratory rate, behavior, surrounding humidity, and activity levels, provide a comprehensive understanding of the cattle's health. The predicted analysis serves as a foundation for informed decision-making, particularly in the realm of dietary planning. By ensuring that each animal receives a well-balanced diet based on the predictive analysis, the system contributes to the overall improvement of animal performance and well-being.

2. Literature Review

In the year 2023, a comprehensive system successfully gathered and stored health data from cattle on a centralized server. Utilizing advanced algorithms, the collected data underwent thorough analysis to pinpoint any abnormalities in the health of the cattle. Prompt alerts regarding the detected abnormalities were then transmitted to the farmer's mobile phone, ensuring timely awareness and intervention [1].

By 2023, Wireless Sensor Networks (WSN) had become an integral part of the Internet of Things (IoT), specifically applied in healthcare monitoring. This integration, coupled with artificial intelligence, facilitated the prediction of illnesses. WSN emerged as a crucial component, showcasing its efficacy in advancing healthcare through predictive analytics [2].

In the year 2022, Precision Livestock Farming (PLF) and Industry 4.0 introduced innovative technologies into everyday farming practices. The amalgamation of continuous, real-time monitoring of animal parameters with feeding and production performance had substantial implications for animal welfare and health monitoring. These developments resonated with contemporary public interests [3].

In 2018, Cattle Health Monitoring using wireless sensor networks was developed using small sized motes to monitor the intra-rumenal activity of the steer. The sensors communicate wirelessly with each other and are connected over the mobile telephone network to provide real time view of the data.[4].

In 2017, leveraging sensor technology and intelligent systems, a continuous monitoring approach was implemented for the regular diagnosis and effective treatment of sick cattle at the earliest possible stage [5].

Table 1:Literature Review

Sno.	Author	Year	Name	Abstract
1	Jehengir Arshad,Talha Ahmad Siddiqui, M.Ismail Sheikh	2023	Development of an intelligent and secure health	System forecasts cattle diseases utilizing real-time data from non-invasive body-area sensors and Artificial Neural Networks (ANN) and to display the expected results to authorized personnel via a web application.
2	Bhatla Kikani,Joshi , Jain and Patel	2023	Real time health monitoring using IOT, Thingspeak and app	My Herd, a cattle health monitoring system, employs IoT and ThingSpeak for real-time analysis of physiological data, enabling accurate health condition detection and potential livestock industry improvement.
3	Morrone S,Dimauro C, Gambella F, Cappai MG	2022	Industry 4.0 and Precision Livestock Farming(PLF)	It highlights how real-time monitoring of animal parameters alongside routine farming practices can enhance welfare, health assessment, and productivity
4	Kevin Mayer, Keith Ellis,Ken Taylor	2018	CattleHealth Monitoring using wireless sensor networks	Using small sized motes to monitor the intra-rumenal activity of the steer. The sensors communicate wirelessly with each other and are connected over the mobile telephone network to provide real time view of the data.
5	Prof.Sweta Jha, Vaishnavi Shinde, Komal Salgaonkar	2017	IOT Based Cattle Health Monitoring System	Sensor technology which maps the special aspects of animal behavior temperature, heart rate, this data is aggregating and reprting to health care center.

3. Data Collection

The dataset we acquire comprises numerous attributes, and among them, some are deemed unnecessary for subsequent implementations or procedures. The objective is to streamline the representation of information for enhanced efficiency.

The dataset consists of two distinct files: train.csv, boasting 2044 rows and 92 columns, and test.csv, featuring 25 rows and 92 columns. Within these datasets, various attributes are encompassed, encompassing symptoms such as high fever, mastitis, bloat, and elevated heart rate. The curation and refinement of this dataset aim to optimize its utility by excluding extraneous attributes, ensuring a more focused and efficient dataset for the intended analyses and procedures.

4. Data Preprocessing:

The dataset has undergone a training process where 70% of the data is utilized for the training phase, while the remaining 30% is reserved for testing purposes. As part of the preprocessing steps, categorical features have been encoded using both ordinal and one-hot encoding techniques. This encoding ensures that categorical data, such as labels or attributes with non-numeric values, is transformed into a numerical format, facilitating its inclusion in machine learning algorithms.

Furthermore, Min-Max normalization has been applied to scale the features within a specific range. This normalization technique transforms the numerical values of features, adjusting them to a standardized scale, often between 0 and 1. This step is crucial in maintaining consistency across different features, preventing any particular feature from dominating the learning process due to its larger numerical range. It enhances the model's stability and convergence during training, contributing to improved performance and reliability in subsequent analyses or machine learning tasks.

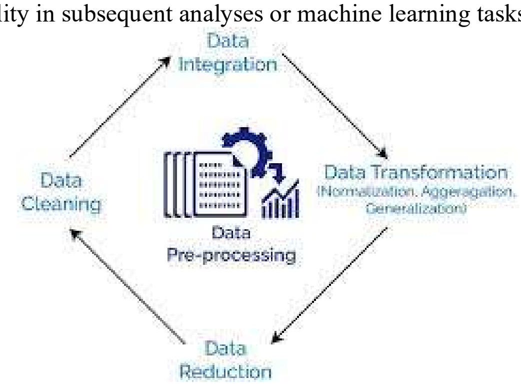

Fig 1:Data Preprocessing

5. Methodology

Algorithms used:

5.1. Support Vector Machine (SVM):

Belonging to the category of supervised learning algorithms widely employed for addressing classification and regression challenges, Support Vector Machines (SVM) primarily find application in classification problems within the realm of machine learning. The algorithm operates by selecting the extreme points or vectors pivotal in constructing a hyperplane, with these critical instances referred to as support vectors. Noteworthy is SVM's versatility, accommodating both linear and non-linear data classification scenarios.
Remarkably, an impressive accuracy of 94% is achieved through the utilization of SVM.

5.2. Decision Tree

Within the realm of Supervised Learning in machine learning, Decision Trees emerge as a significant algorithm capable of addressing both regression and classification problems, although it is typically favored for the latter. This tree-structured classifier is visually represented by key elements: internal nodes correspond to the features of a dataset, branches symbolize the decision rules, and leaf nodes encapsulate the final outcomes of these decisions.
The accuracy achieved by decision tree is 95%.

5.3. KNN(K-Nearest Neighbour) algorithm

KNN, a member of the Supervised Learning techniques, operates by assessing the similarity between a new case and existing cases, subsequently assigning the new case to the category most akin to the available categories. The algorithm, in essence, stores the available cases and employs this repository to classify new cases based on their proximity to existing instances.
Through its mechanism of comparing and evaluating similarities, KNN achieves a notable accuracy rate of 91%.

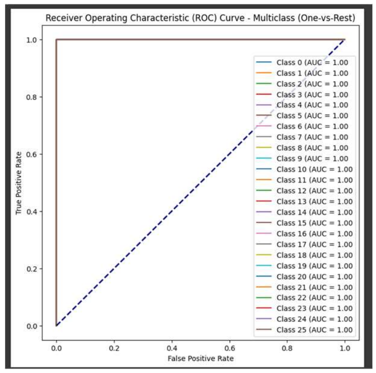

Fig 2:ROC curve (KNN)

5.4. Random Forest Algorithm

This widely adopted algorithm falls under the category of supervised learning techniques and operates on the principles of ensemble learning, a methodology that involves the amalgamation of multiple classifiers to address intricate problems and enhance overall model efficiency.
The achieved accuracy in the case of random forest is 94%.

6. Architecture Diagram:

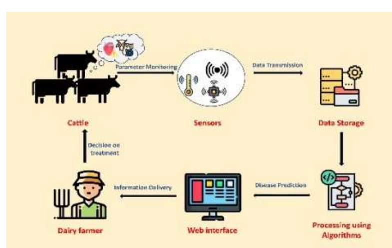

Fig 3:Architecture Diagram

I. Results

In Python, an interface has been developed to facilitate the selection of symptoms, and upon input, the predicted disease is promptly displayed. This interactive interface streamlines the user experience, allowing for seamless symptom selection and providing instant access to the corresponding predicted disease. The Python programming language serves as the foundation for constructing this user-friendly interface, showcasing the versatility and efficiency of Python in developing applications that enhance the accessibility and utility of predictive model.

Table 2:Model Evaluation

Algorithm	Accuracy
SVM	94%
Decision Tree	95%
KNN	91%
Random Forest	94%

Fig 4:Model Evaluation

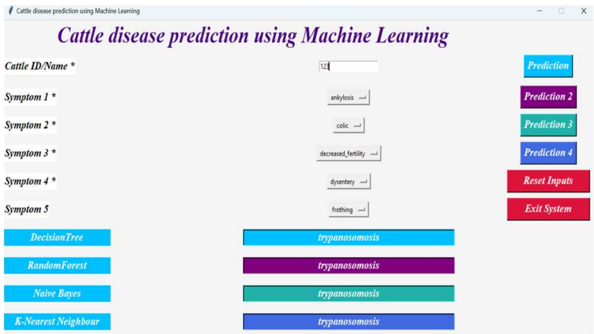

Fig 5:Prediction Interface

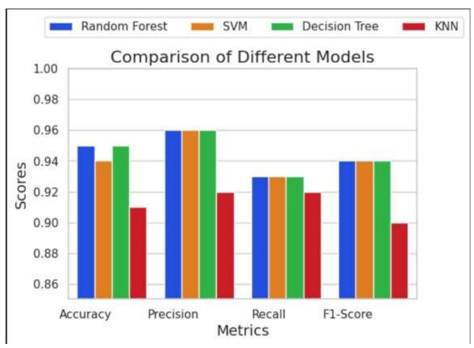

Fig 6: Comparison of Different Models

II. Future Work

In this context, the data acquired from IoT devices is utilized; however, there is potential for further enhancement by implementing a dedicated IoT device equipped with requisite sensors. This comprehensive device would integrate data for in-depth analysis and analytics, offering a more thorough understanding of the monitored parameters. Users would then have access to this information, including alerts, through both a dedicated app and a web application. The inclusion of alert messages ensures that users are promptly informed of any noteworthy developments, fostering a proactive and informed approach to monitoring and managing the associated system.

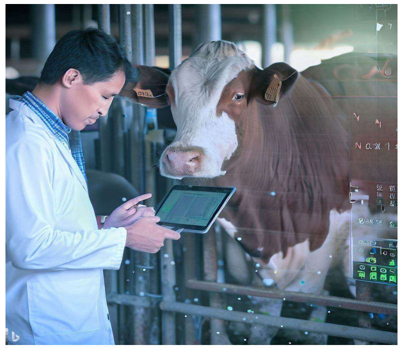
Fig 7:Detailed analytics

III. Conclusion

The envisioned model represents a fusion of IoT and machine learning, where the model undergoes training utilizing specific symptoms and their corresponding diseases through machine learning algorithms. This intricately designed model operates on a premise where, upon symptom selection, the predicted disease is promptly revealed. The acquisition of data is orchestrated through IoT devices, particularly sensors.

The primary objective of this system is to elevate cattle health, bolster production, and refine livestock management practices. By streamlining the identification process for affected animals within a large cattle population, dairy farmers stand to gain financial benefits and save considerable time. The ramifications extend beyond the individual farmer to societal well-being, as the health and purity of the food we consume are inherently linked to the health of the cattle. Thus, the proposed model emerges not only as a boon for farmers but also as a contributor to the broader societal goal of promoting healthier living through the consumption of high-quality produce.

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