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Cattle Monitoring System

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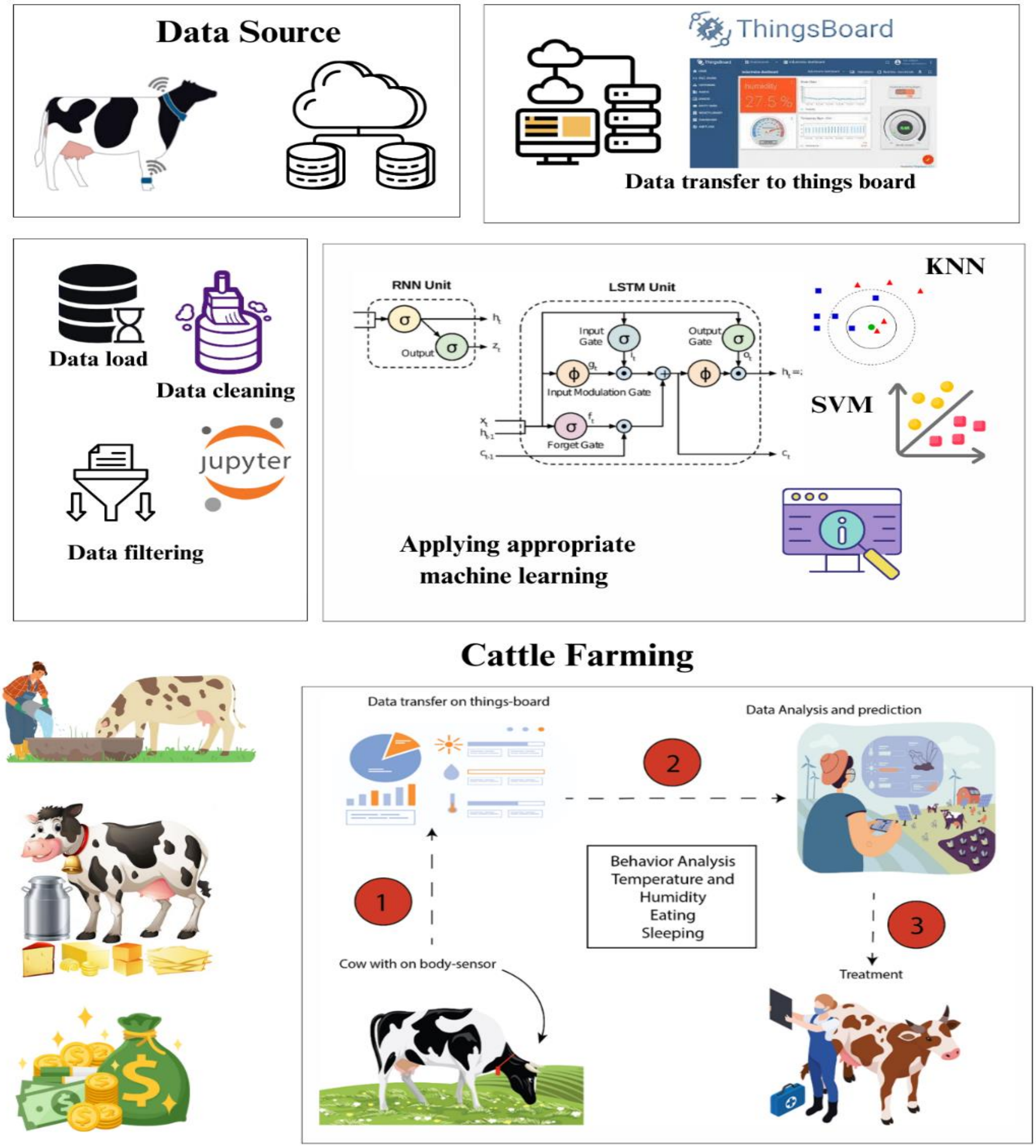
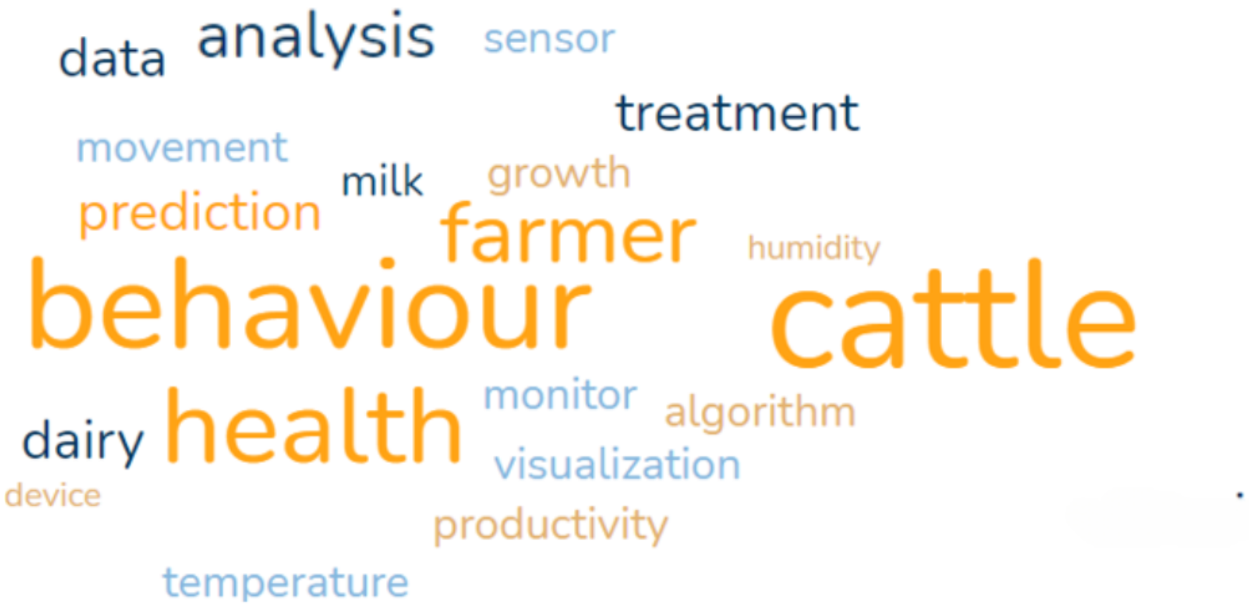


Abstract
The Internet of Things (IoT) has become one of the solutions to low agricultural and livestock efficiency and productivity. In this paper, a gyro sensor integration system was created in the context of cow behavior monitoring and milk productivity optimization. The goals and benchmarks for studying cow behavior and

increasing milk yield were established. The machine learning models' insights and predictions were rigorously investigated to find patterns and trends in cow behavior. The categorization of the behaviors shown by cows is the primary emphasis of this research. The research focuses on biosensors and wearable technologies with the potential to enhance operations, management, and early illness detection in cattle. There is a need for detection technologies that can foresee possible consequences for a particular population, educate on diagnostic and treatment choices, and predict when and in what group an event is likely to occur.

Keywords

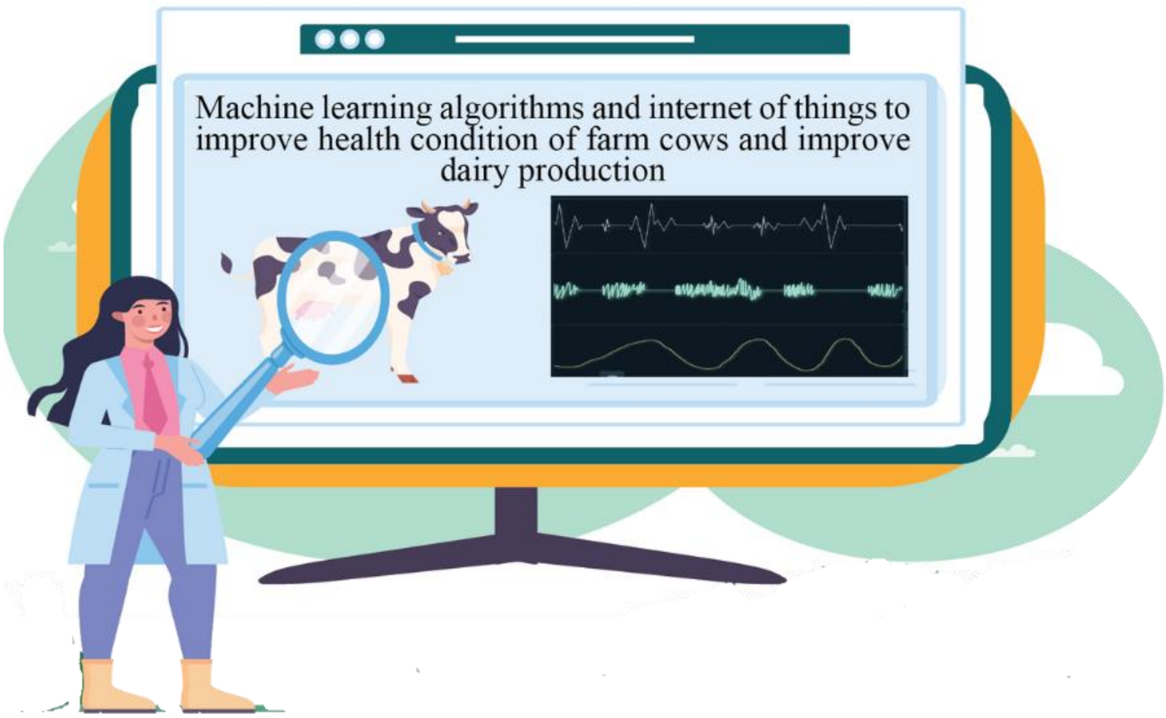


Introduction

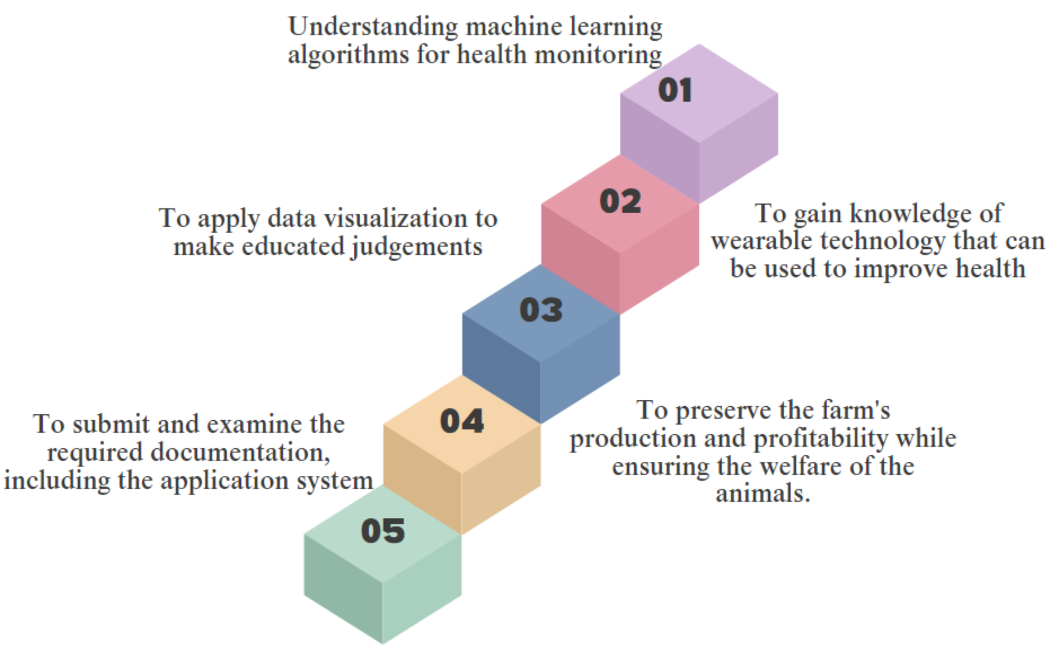
For optimal health, development, and milk production, cattle are raised on large farms and ranches where they are fed a variety of food and grains. Successful cow farming requires knowledge of many other fields, such as animal nutrition, reproductive medicine, and pasture management. Livestock farmers must familiarize themselves with and abide by the various regulations designed to protect consumers, animals, and the environment. (Wesley patterson & Garrigus, 2022) . The integration of Machine Learning (ML) algorithms and the Internet of Things (IoT) has revolutionized the agricultural sector, particularly in enhancing farm cow health and increasing dairy production. The dairy industry is crucial for meeting the global demand for high-quality milk and dairy products. Traditional methods of managing dairy farms often rely on manual monitoring and subjective decision-making. IoT technology offers vast opportunities for data collection and real-time monitoring, allowing farmers to gather vital data on physiological and behavioral parameters. A gyro sensor is used to track the cow's motion. Machine Learning algorithms can interpret patterns, predict outcomes, and provide valuable insights from the collected data. Farmers must be able to recognize signs of disease or injury in their animals and provide the necessary care to keep them healthy. The success of a cow farming enterprise is significantly influenced by the health of the animals on the farm. Numerous health issues, such as parasites, traumas, and infectious illnesses, can harm cattle. These issues may be avoided with the right care and management, which will also guarantee the cattle's continued health. Inadequate farm animal care reduces output and increases animal suffering. Surpluses and financial losses result from an incorrect forecast of demand for animal products. Surpluses are widespread in intensive agricultural production, when investors are primarily concerned with high output rates and quick turnover regardless of demand. Excess production losses are less harmful since they may be deducted from tax returns, lessening the motivation to avoid this form of agricultural mismanagement. Framers can prevent fatal diseases by tracking the health of cows based on their behavior. They can look after the cows if they find out they are in bad condition.. Tracking their health is critical for agricultural production. Farmers may lose production if they are unaware of the health of their cows. Farmers should conduct proper health tracking to identify problems to avoid production losses and sudden deaths.

Most people today use tools that help them monitor their health and fitness. The wearable can monitor a person's heart rate, blood pressure, and sleep patterns. These records are intended to keep track of a person's health and make sure they get immediate medical care if they notice something out of the ordinary. People wear Fitbits on their wrists to track how many steps they take each day and help them get healthier and fitter. Depending on the Fitbit model, a person might also use it to keep track of how they sleep. tracking and keeping an eye on their heart rate. Examples of activities include moving around the office, climbing stairs, or chasing your boss down the hallway. Walking your dog, playing with your kids, or engaging in any other activity can be fun. The device tracks steps, miles, calories burned, water consumed, weight loss, and more. Some are monitored automatically; others you must enter. It's also fashionable. They come in many shapes, sizes, colors, materials, and models, and they make a statement. The Internet of Things (IoT), a mature and successful technology, looks to be one of the answers to low agricultural and animal production and efficiency. Latest Dairy manages cows, milk, and the herd with artificial intelligence. They provide sensors for anything from calving and heat sensing to health monitoring, such as the Sense Time Solution sensor, which monitors a cow's daily activity, such as rumination, eating, and movement patterns (Singh Rajesh, 2019). Farmers may now use a range of widely accessible sensors to monitor changes in animal movements, feed intake, sleep cycles, and even air quality in animal quarters. When paired with artificial intelligence software, this sensor provides users with quick and proactive problem-solving answers. The sensor provides farmers with alternatives for each cow while also recording reproductive, health, and nutritional data (Joshi Naveen, 2019). Furthermore, the AI tells the farmer when the cow's behavior changes, allowing for human intervention as needed. Without AI, it would be practically impossible for the farmer to keep a close eye on every cow in the herd. Farmers may now detect, forecast, and prevent disease outbreaks even before they become prevalent by using cutting-edge AI and machine learning algorithms to identify deviations or abnormalities. (Kumari Maina, 2021).

Aim

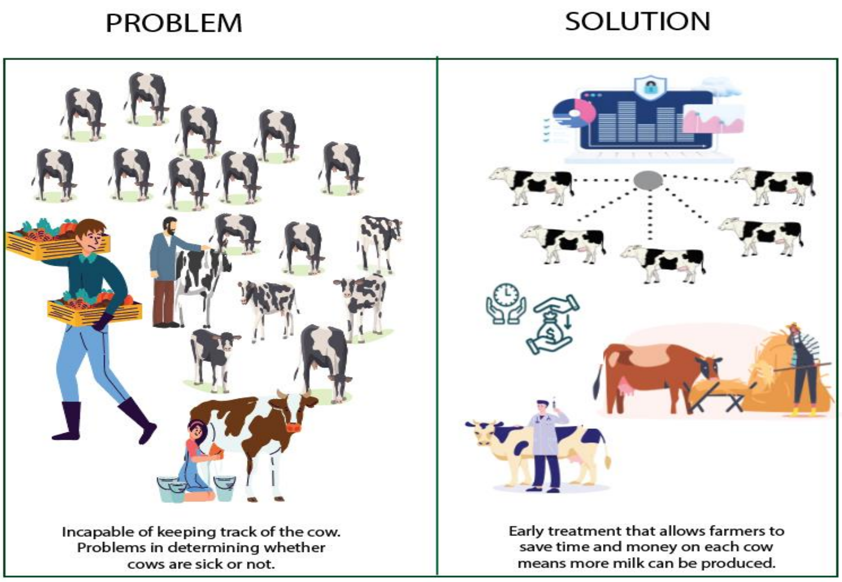


Objectives

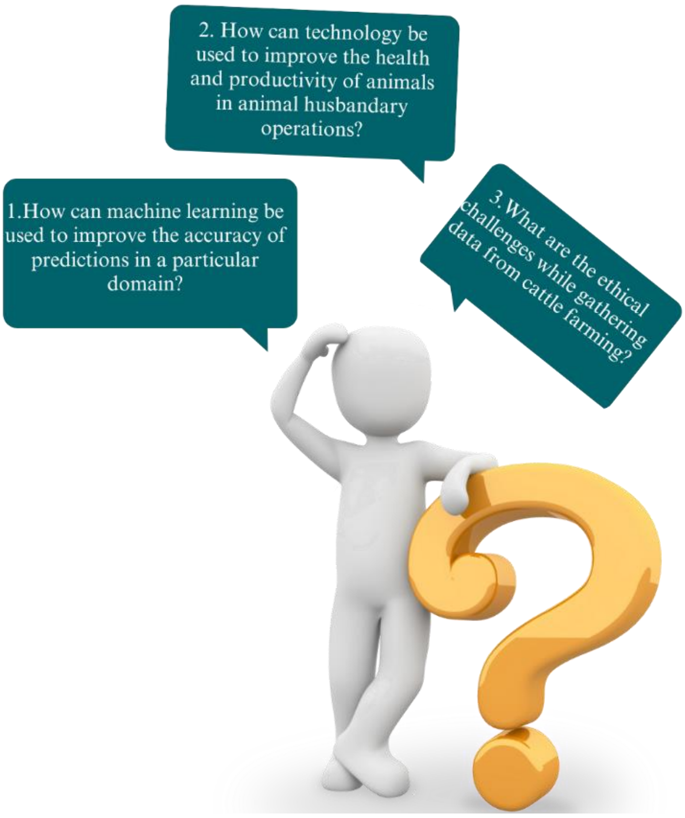


Justification

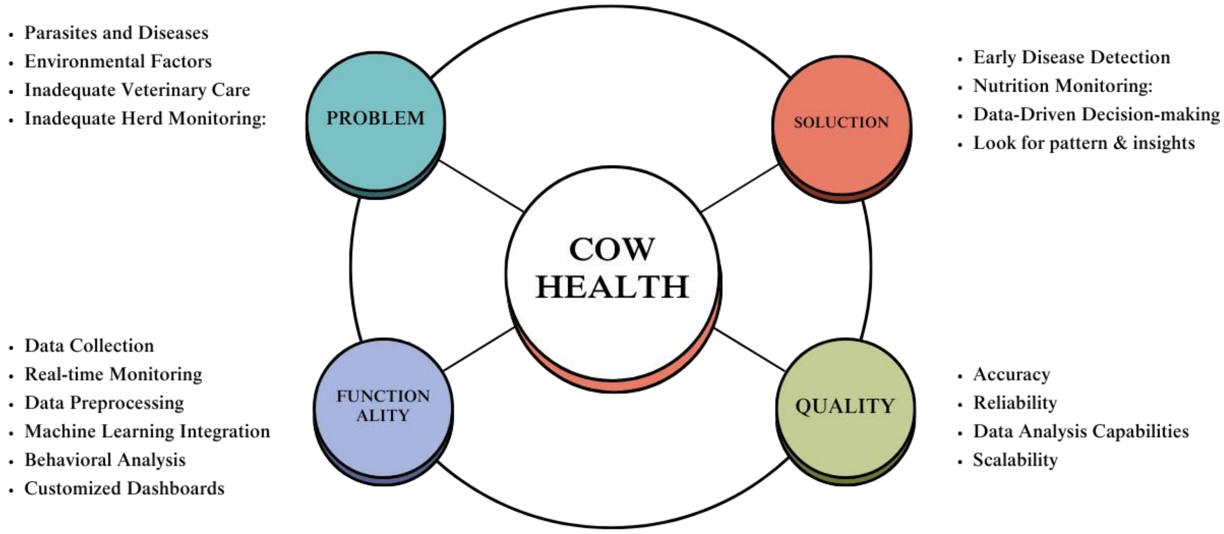
Commercial dairy farms confront numerous obstacles in keeping track of cow well-being and comfort, which are directly tied to dairy output volumes. Medium-to-large farms find it difficult to manage their herds by observation, resulting in a financial loss for the farm. Animal health and agricultural output are inseparable. Farmers have a difficult time keeping track of all the cows on their farms. They are completely unaware of the symptoms. Failure to treat the disease in the first place can result in fatal illnesses that directly impact business. Due to poor production margins and animal mortality, farmers are losing money in the business sector (Rodriguez Iris, 2020).To solve the problem, farmers must identify and address all health issues in their herd. Cows change their behavior in response to stressors such as infection, satiety, or social and environmental changes. As a result, because behavior is an indicator of dairy cow health and well-being, detecting changes in cow behavior daily can help provide alerts to execute specific management tasks that improve dairy farm management. Health inspection involves regularly observing animals for signs of illness or injury and taking steps to correct any identified problems. This will minimize the impact of the disease on the herd and prevent its spread. By monitoring herd health through the sensor of wearable technology, Farmers can detect and manage probable disease epidemic sources, such as contaminated feed and water, and take steps to prevent them. Cow health monitors identify health concerns such as infections or diseases early, allowing farmers to take appropriate action. This contributes to better herd management by allowing for more informed decisions regarding feeding, breeding, and culling. Monitoring systems identify heat cycles and estrus activity, allowing for healthier pregnancies and enhanced herd expansion, resulting in improved reproductive management. Early diagnosis and proactive management of health conditions can save veterinarians money by allowing for preventative measures and prompt treatment. Healthy cows are more productive, and monitoring their health allows you to discover and fix problems impacting milk output. Efficient resource allocation is done by recognizing underperforming or sick cows and focusing on specific animals that require special attention. Cow health and well-being monitoring demonstrate a dedication to animal welfare by maintaining a pleasant and compassionate environment for their animals. Farmers can receive warnings and messages if abnormal circumstances or crises arise thanks to remote monitoring and alerts available via cell phones or PCs. Data analysis allows for data-driven decision-making, allowing farmers to make data-driven decisions, identify trends, and constantly improve their management techniques for improved herd health and performance.



Research Question



Scope



Ethical considerations

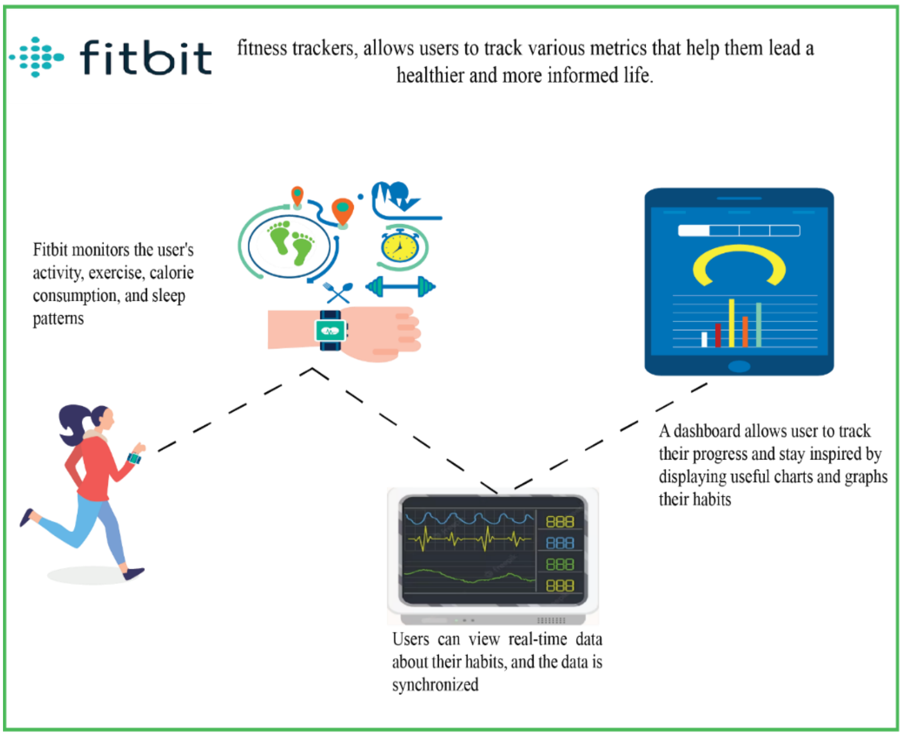
Ethical standards in research require the truthful reporting of research results, findings, methodology, and data. It is strictly prohibited to fabricate data, exaggerate results, or deceive readers. In this research and academic pursuits, integrity and honesty are prioritized, actively avoiding errors, negligence, and biases across all aspects, including data interpretation, experimental methods, result analysis, peer review, and collaborator selection. Discrimination against collaborators, coworkers, pupils, reviewers, and mentors is firmly considered unethical and impermissible. A core principle driving the work is openness, firmly believing in advancing both science and society (Ph.D. assistance, 2020). Transparent communication of ideas, findings, and methodologies fosters the growth of knowledge and contributes to overall societal development. Plagiarism is strictly forbidden, and proper credit is given to all contributors to the research. Furthermore, ethical concerns related to self-plagiarism are diligently addressed. Respecting privacy and maintaining confidentiality is integral to research ethics. The protection of human rights and handling of sensitive data, such as diagnostic results, grant information, and patient records, are prioritized with the utmost care and security. To ensure the highest ethical standards, responsible publication practices are adhered to, actively avoiding any form of fabrication, manipulation, or duplication of work. The commitment to presenting research cohesively entails refraining from splitting research papers into multiple publications that cover the same questions, hypotheses, methodologies, results, and samples, as such practices do not align with ethical principles.

Desk-based Research

The project is based on the material published in reports and similar documents that are available in public libraries and websites, as well as data obtained from surveys already carried out. Once the research topic is identified and approved by the academic leader, relevant sources of information with the most relevant data are identified on the internet through reliable websites and books. The data that is collected through secondary or desktop research gives organizations or companies an idea about the effectiveness of primary research.As a result, a hypothesis may be developed, and the cost of carrying out primary research can be calculated.. It is a less expensive and time-consuming process, as the required data is readily available and does not cost much if it is extracted from authentic sources. The availability of data makes desk research faster. It can be done in a few weeks, depending on the firm's objectives or the size of the data necessary.

Fitbit

Fitbit, a pioneer in wearable fitness technology since 2007, established in San Francisco, is the market leader in the linked fitness wearables sector. Their devices function as fitness trackers, allowing users to track a variety of metrics that will help them live healthier and more informed life. They manufacture a variety of devices, ranging from basic trackers that measure how many daily steps you take to smartwatches that display phone messages and notifications. In 2014, the company sold about 11 million gadgets. (big data book) Fitbit has become known for its software, which includes a smartphone app, a social network, sleep tracking, and subscription coaching, in addition to its accessible hardware. Fitbit has over 28 million active users and has sold over 100 million units worldwide. Fitbit monitors the user's activity, exercise, calorie consumption, and sleep patterns. Users can view real-time data about their habits, and the data is synchronized (wirelessly and automatically) from the gadget to the user's smartphone or computer. A dashboard allows users to track their progress and stay inspired by displaying useful charts and graphs. Aria, Fitbit's Wi-Fi smart scale, monitors users' weight, BMI, lean mass, and body fat percentage. The scale can recognize up to eight distinct users (allowing the entire family to use it) and keep their results separate and private. The numbers are synced to the user's home Wi-Fi network and are also compatible with Fitbit's wearable devices (Guidance,). Again, an online dashboard assists the user in setting goals and tracking progress. Health data like this is extremely instructive and valuable, and it extends far beyond the individual user (guidance,). Fitbit collects information about fitness habits and health statistics to share with strategic partners. With the user's agreement, personal, and individual data can also be shared. For example, Microsoft's HealthVault service lets users upload and share data from their fitness trackers with health professionals, potentially providing doctors with a more complete picture of a patient's general health and habits than consultations and examinations alone. The consequences are heightened by the recent announcement by insurance company John Hancock that clients who wear a Fitbit gadget will receive a discount (Cadmus-Bertram et al., 2015). Policyholders can exchange Fitbit data for prizes based on their physical activity and diet. This suggests an increased propensity among individuals to "trade" their private data in exchange for a better product or service or monetary incentive, all of which is excellent as long as the transaction is transparent.Fitbit's market share was beginning to decrease as large tech businesses like Apple, Xiaomi, and Huawei increased their investments in health monitors. To reclaim worldwide market share and compete more effectively in the health and fitness industry, they required a fast-deployed global cart and checkout experience that is adaptable to the specific needs of over 20 different nations and consumers (Chu et al., 2017). Fitbit's in-house e-commerce platform, like many others, was designed in the early days of desktop e-commerce but was no longer capable of scaling to the degree of agility and reliability that Fitbit required. The platform's inherent inefficiencies (such as the lack of a content management system) were putting a burden on internal resource.



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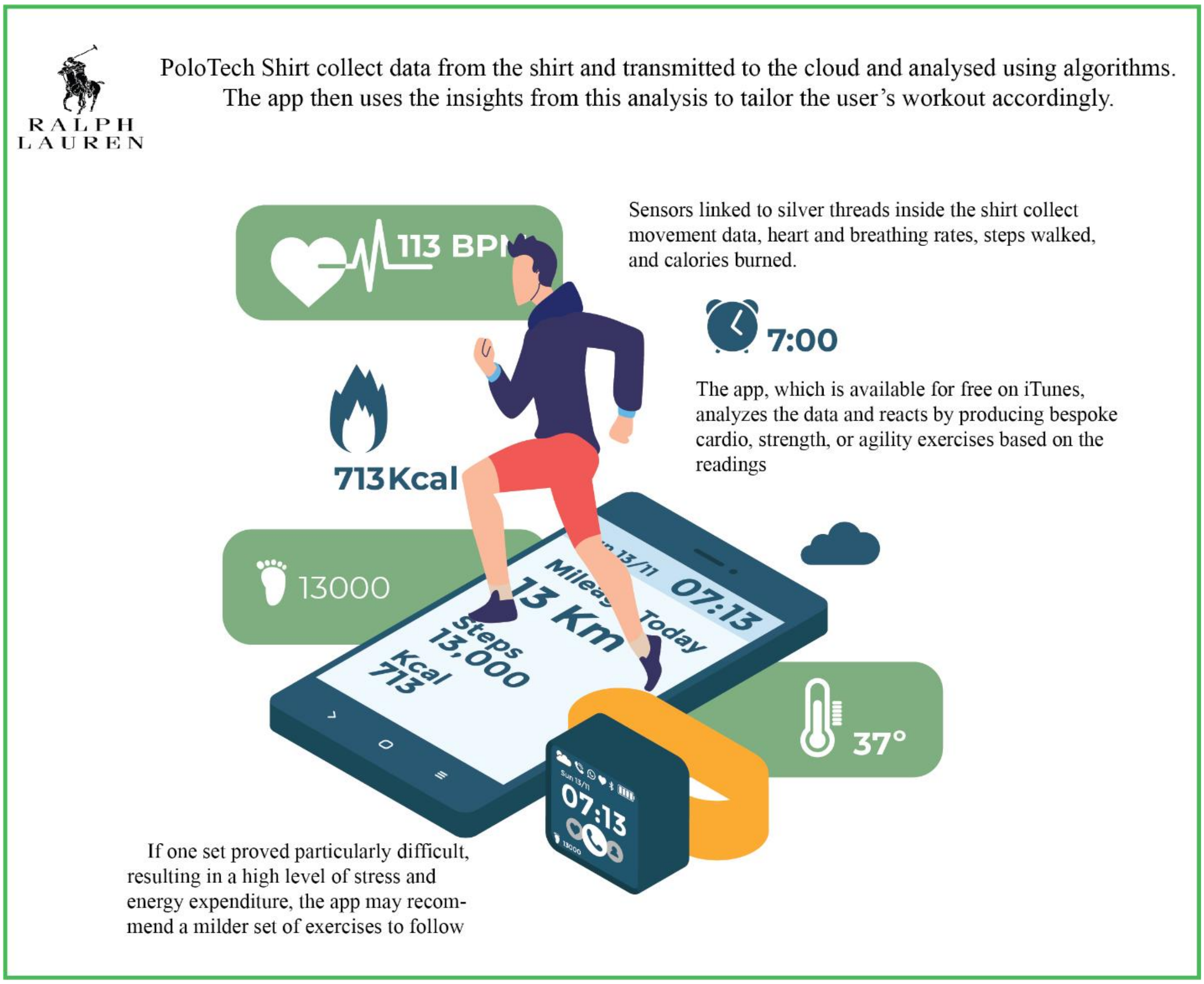


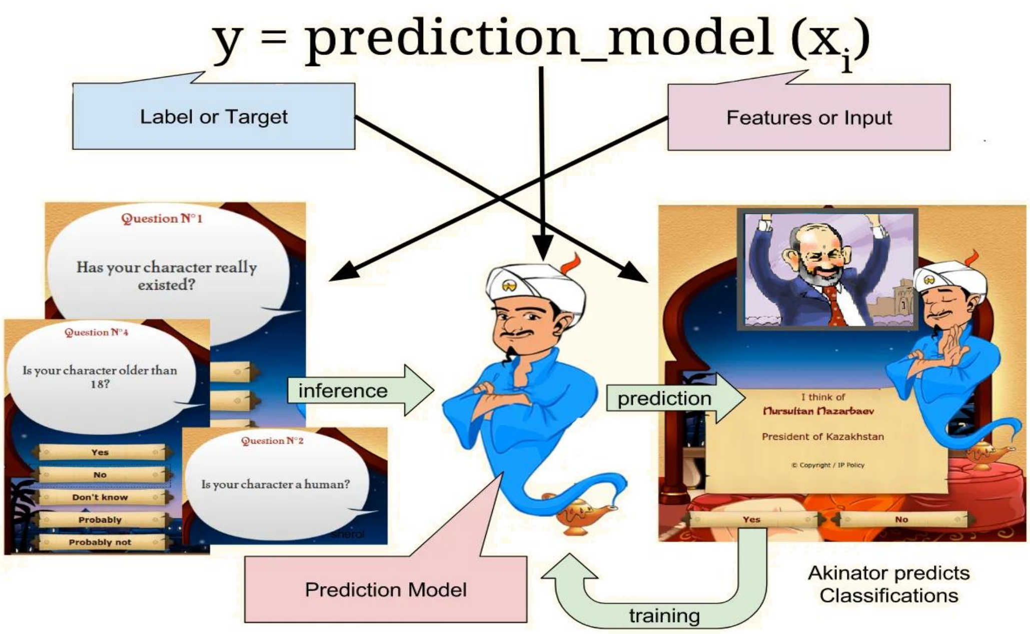
Our world is getting increasingly technologically connected. This tendency is having an impact on everything, including fashion. Wearable technology, colloquially known as "wearables," is predicted to grow in popularity as the Internet of Things (IoT) takes off, a process that is likely to quicken with the recent release of the Apple Watch. Ralph Lauren, which debuted its connected PoloTech Shirt during the 2014 US Open tennis event, is one of the great brands in high-end consumer fashion to show their eagerness to embrace this new industry. (Gross, 2014) The shirt went on sale to the general public in August 2015.

Sensors linked to silver threads inside the shirt collect movement data, heart and breathing rates, steps walked, and calories burned. The companion software, which is available for free on iTunes, analyzes the data and reacts by producing bespoke cardio, strength, or agility exercises based on the readings (Shore et al., 2022). The app includes three workouts — aerobic, strength, and agility created by Galvanized, David Zinczenko's media and fitness company, with trainer Chris Ryan on hand to demonstrate the shirt's features. The garment is essentially one huge sensor that collects real-time data on direction and movement, as well as biological data like heart rate. The device saves a user's personal information, such as height, weight, and age, and combines it with data collected during an exercise to decide what to do next (Edelson, 2014). For example, if one set proved particularly difficult, resulting in a high level of stress and energy expenditure, the app may recommend a milder set of exercises to follow. There are almost

10,000 different workout combinations. The shirt also works with standalone workouts, such as SoulCycle or personal training sessions. Big data is increasingly being used in trend forecasting in the fashion industry, where social media data, sales data, and reporting from fashion shows and important newspapers are pooled to help designers and stores figure out what the season's must-have looks are. We can wash the PoloTech shirt, but we must first remove the slightly larger-than-credit-card-sized Bluetooth transmitter. The company is currently investigating ways to shrink the device, possibly to the size of a button, or to embed it into the fabric in such a way that removal is unnecessary. And, while the PoloTech Shirt is firmly in the realm of sportswear, an industry already brimming with smart IoT technology such as the Babolat smart racquet and Adidas miCoach smart ball, Ralph Lauren has bigger plans.

Akinator

Akinator is a worldwide popular online game created in 2007 by the French company Elokence. Because of its outstanding performance and success rate, this game has sparked a lot of curiosity about its process. In the game, a mystical genie named the Akinator asks players to imagine a character (actual or imaginary), an object, or an animal. Akinator will ask the user questions until it figures out who or what the user is thinking about. This is a variation on the "20 questions game," in which one player asks the other player up to 20 questions to guess what they thought. The player must imagine a person or figure (fictional or not) and respond to yes-or-no questions. Akinator manages ambiguity by providing options such as "probably", "probably not", and "I don't know." The program picks the ideal question to ask next based on each answer and eventually guesses as to whom the player is thinking of. It is a fascinating artificial intelligence program that incorporates aspects of decision trees, binary trees, probabilistic approaches, and machine learning. If the initial guess is incorrect, Akinator continues to ask questions, and so on up to three times, with the first guess usually coming after 15–20 questions. If the player's third guess is still incorrect, he or she is asked to enter the character into the database. Although the exact algorithm used by Akinator is unknown, we can assume that a decision tree is constructed based on the character entries in the database and that several searches are performed in this tree.



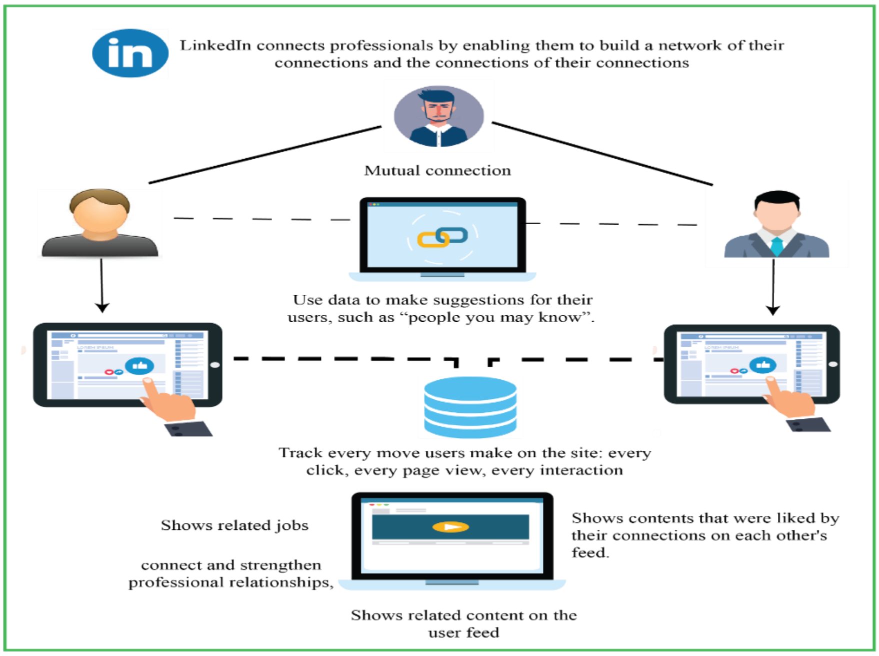
The Akinator program may use a probabilistic strategy to lower the complexity of the search for binary decision trees to reduce the number of questions required to determine which character best suits the responses. The first question Akinator asks is about the root of the decision tree. In actuality, the initial question is not always the same, but it is always a query that would efficiently split the search space, such as "Is this person real?" or "Is this person a man?" The interior nodes of the decision tree are the questions that the player answers to progress to the next node of the tree. The characters who fit the answers on the way to that leaf might be considered the leaves of the decision tree. The full character collection should be used to build a tree that is as binary-balanced as feasible, allowing you to divide the search space by two for each query. Although using a binary tree reduces the cost of the search, it would still be very expensive to ask every question that yields an element corresponding to a character. As the player answers questions, the program must eliminate characters that do not match the answers given thus far. If the data is represented as a decision tree, answering should indicate moving on to the next node. Gathering all of the information on the character the player is considering is expensive and should necessitate asking too many questions (Damassino, 2020). As a result, the search cost must be decreased in some way. Based on previous experience, the authors offer a probabilistic strategy to reduce search costs in this work. As games are played, Akinator collects a large amount of data that can be used. The goal is to bypass some decisions for specific nodes, i.e., not ask the question of that specific node if the chance of following this path is high enough based on experience.

Akinator undoubtedly has a database that saves every character it knows as well as their traits. The authors argue that for AI software to behave more humanly, it must be able to develop its knowledge dynamically rather than having everything coded manually by a human. One limitation is that the software must be in some form of observation or learning mode to gather new knowledge (Sasson & Kenett, 2023). For Akinator, this simply means that it must fail one or more times before it can predict a character that was not previously in the database. Akinator, on the other hand, overcomes this constraint in some ways. When the likelihood of having found the character is high enough, the program will ask the player several seemingly unimportant questions to learn more about the guessed character for future games. Changes to the database may also affect the decision tree and thus the program's behavior in terms of the order of the questions. Although Akinator is portrayed as a genie with more knowledge than a human, there is an emphasis on the player's human-like interaction with the program. For example, the genie appears to be thinking through animations while the program searches for the next, most appropriate question. It's also worth noting that Akinator has some scripting to respond to some specific case scenarios, such as answering "I don't know" to all inquiries (A.R., 2020). It is possible to improve both gaming behavior and human-like robotics by working on dynamic learning. Even though Akinator has a fairly efficient learning capability, it lacks some human-like behavior, such as when it backtracks, some questions are repeated or are irrelevant.

LinkedIn

LinkedIn is the world's largest online professional network. It connects professionals by allowing them to build networks of networks. Social network rivalry is stronger than ever, and what's fashionable one year may not be the next. LinkedIn must guarantee that its site remains a crucial tool for young professionals, assisting them in becoming more successful. Whether they use the premium (paid-for) service or the free service, they are more productive and successful.

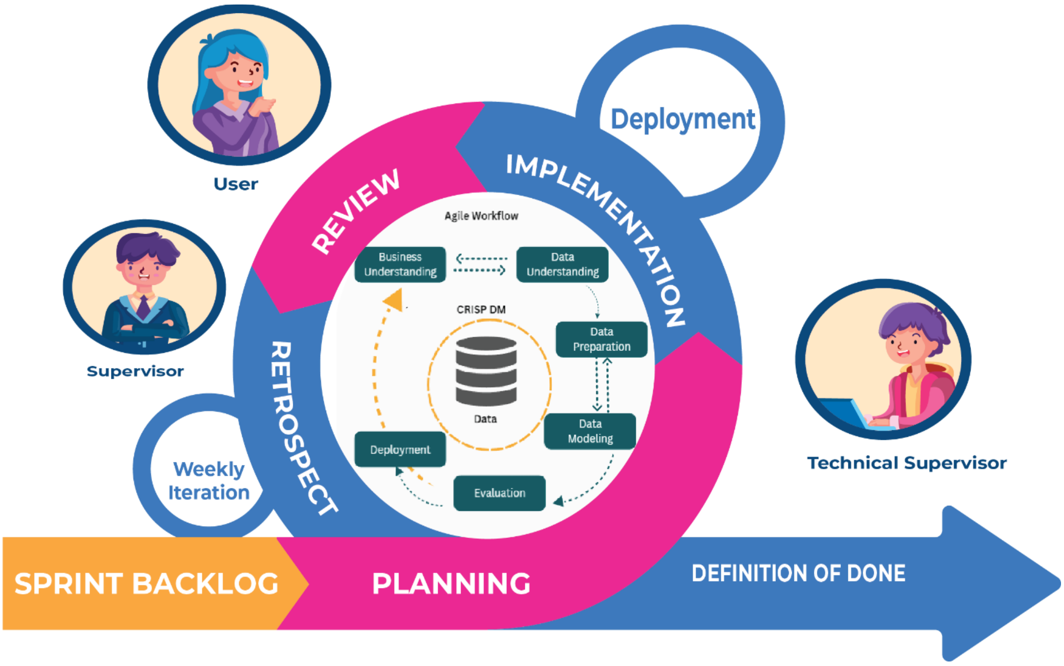
LinkedIn tracks every action a user takes on the site: every click, every scroll. Every interaction, every page view LinkedIn's data scientists and researchers analyze this avalanche of data to help with decision-making. creating and designing data-driven goods and features LinkedIn, like Data is used by various social networking sites to provide suggestions to users, such as "people you may know." These recommendations are based on a variety of criteria, such as clicking on someone's profile (in which case, it's plausible to suppose we may know them or someone else by that name), working at the same firm during the same period, or sharing certain connections. Furthermore, because users may upload their email contacts, LinkedIn uses this information to generate recommendations—not only for individuals you may know on the site but also for people your contacts may know if they join the site. LinkedIn applies machine learning techniques to enhance its algorithms and provide better suggestions to users. LinkedIn applies machine learning techniques to enhance its algorithms and provide better suggestions to users. Assume LinkedIn routinely suggests individuals you might know who work at Company A (where you worked eight years ago) and Company B (where you worked two years ago). If you practically never click on the profiles of people from Company A but frequently check out the ideas from Company B, LinkedIn will prefer Company B in future suggestions. This tailored method allows users to create networks that are most effective for them. LinkedIn utilizes stream-processing algorithms to guarantee that the most recent data is presented when users visit the site, from information on who has joined the site and who has gotten a new job to relevant articles that connections have liked or shared. To summarize, the site is continually collecting and showing fresh data for visitors (Yap & Wang, 2015). This continual stream of data not only makes the site more engaging for users but also speeds up the analytic process. Traditionally, a company would collect data and store it in a database or data warehouse for further analysis. However, using real-time stream-processing technology, LinkedIn may stream data directly from the source (such as user activity) and analyze it on the fly. LinkedIn must generate income, which they do through recruiting services, paid membership, and advertising. Big data may help businesses increase income while also enhancing the customer experience. For example, in advertising, which generates 20–25% of LinkedIn's yearly income, analysts collaborate with the sales team to determine why users click on some advertisements but not others. These insights are subsequently shared with advertisers to improve the effectiveness of their advertisements.



Development Methodology

This project is being completed using the agile development process. Agile points out adaptability to changing needs, which may be very effective in fast-paced workplaces with shifting requirements.The agile methodology is a good fit for projects that use machine learning. Machine learning is still in the process of developing a considerable number of industry-standard techniques for the generation of software (Chan & Thong, 2009). Because it is difficult to create reproducibility in artificial intelligence systems, repeatability is an essential component of software systems. This is because software systems are more easily modified. Not only is it possible for machine learning systems to have dependencies in their code, but it's also possible for such dependencies to exist in their data. Maintain a very close eye on these interconnections (Cao et al., 2009). The iterative and incremental approach that is part of the agile methodology makes room for flexibility and adaptation, which is particularly useful for projects that include machine learning. The industry-standard methods are always changing to handle the one-of-a-kind problems offered by artificial intelligence systems in light of the continual technological developments that are being made in the field of machine intelligence.

The CRISP-DM methodology is appropriate for initiatives involving machine learning, such as the development of a bovine health monitor. It consists of six phases: Business Knowledge, Data Knowledge, Data Preparation, Modeling, Evaluation, and Deployment. Business Understanding entails delineating objectives and requirements, identifying stakeholders, and comprehending how the monitor will enhance bovine health and farm management (Jaggia et al., 2020). Data Understanding collects and evaluates pertinent information, such as cow health records, sensor data, and environmental data. Data Preparation is the preparation and purification of data, whereas Modeling is the use of machine learning methods to build prediction models for bovine health monitoring. The evaluation compares the performance of models to predetermined objectives and criteria, considering limitations, biases, and uncertainties. The deployment of the model ensures that it is integrated into a real-world cattle monitoring system, making its predictions accessible and actionable (Schröer et al., 2021). Throughout the process, collaboration with domain experts, veterinarians, and stakeholders is essential to ensure that the cow health monitor meets their requirements and resolves practical challenges on the farm.

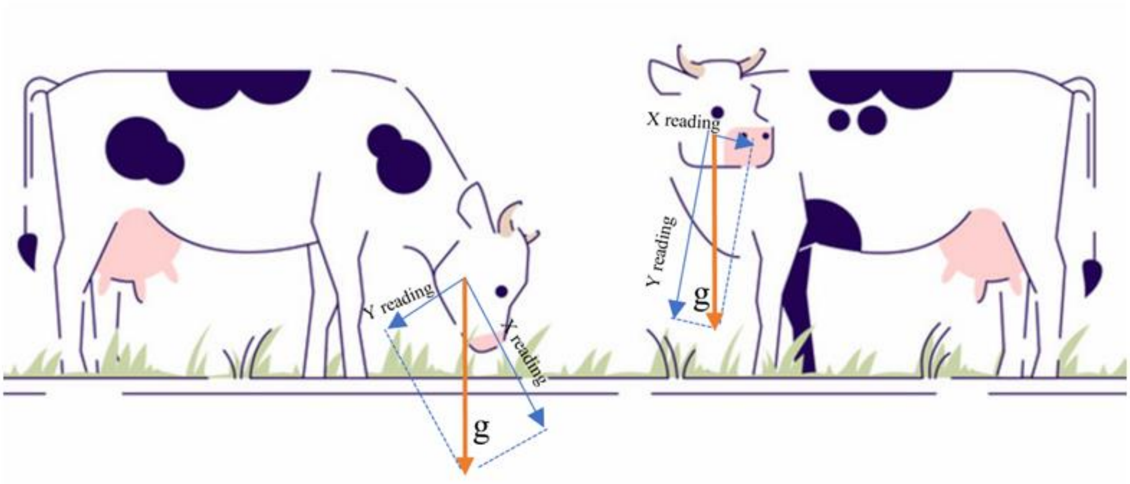


Development

Creating a project involves organizing and preparing various elements, including resource allocation, budget establishment, and role delegation. It is crucial to align multiple tools and technologies with the project objectives, working in collaboration with the chosen agile methodology for product development. Typically, the development phase follows the planning and designing phases, during which a tangible project blueprint is conceived.

IoT-Based Sensor Integration Sensor

A sensor integration system was created in the context of cow behavior monitoring and milk productivity optimization. Initially, suitable sensors capable of gathering data on movements, weight, temperature, and humidity were carefully selected and mounted in appropriate positions on the cattle. The gyro sensor was carefully chosen for its ability to provide valuable insights into the cow's balance, orientation, and body positioning. The sensors were calibrated to ensure reliable data capture (USAMI et al., 2019). This data is particularly useful in understanding the cow's behavior patterns, detecting signs of discomfort, and assessing its overall health and wellbeing .The sensors were then linked to IoT devices, and microcontrollers, such as the ESP32. These gadgets were designed to collect and transmit sensor data. An IoT platform named Things Board was created to help with data management and analysis.The IoT devices were set up to connect to the Things board through multiple protocols, allowing for smooth data flow. Data ingestion techniques were created inside the Things board to manage the incoming sensor data (Bestari & Wibowo, 2023). These techniques effectively received and stored sensor data in the Things board's database. Things board was then used to develop customized dashboards that allowed the viewing of real-time and historical data on cow behavior, such as sleeping patterns, feeding habits, and environmental variables. The sensor data was obtained from the Things board's database to do an in-depth analysis.



An Iterative Machine Learning Approach

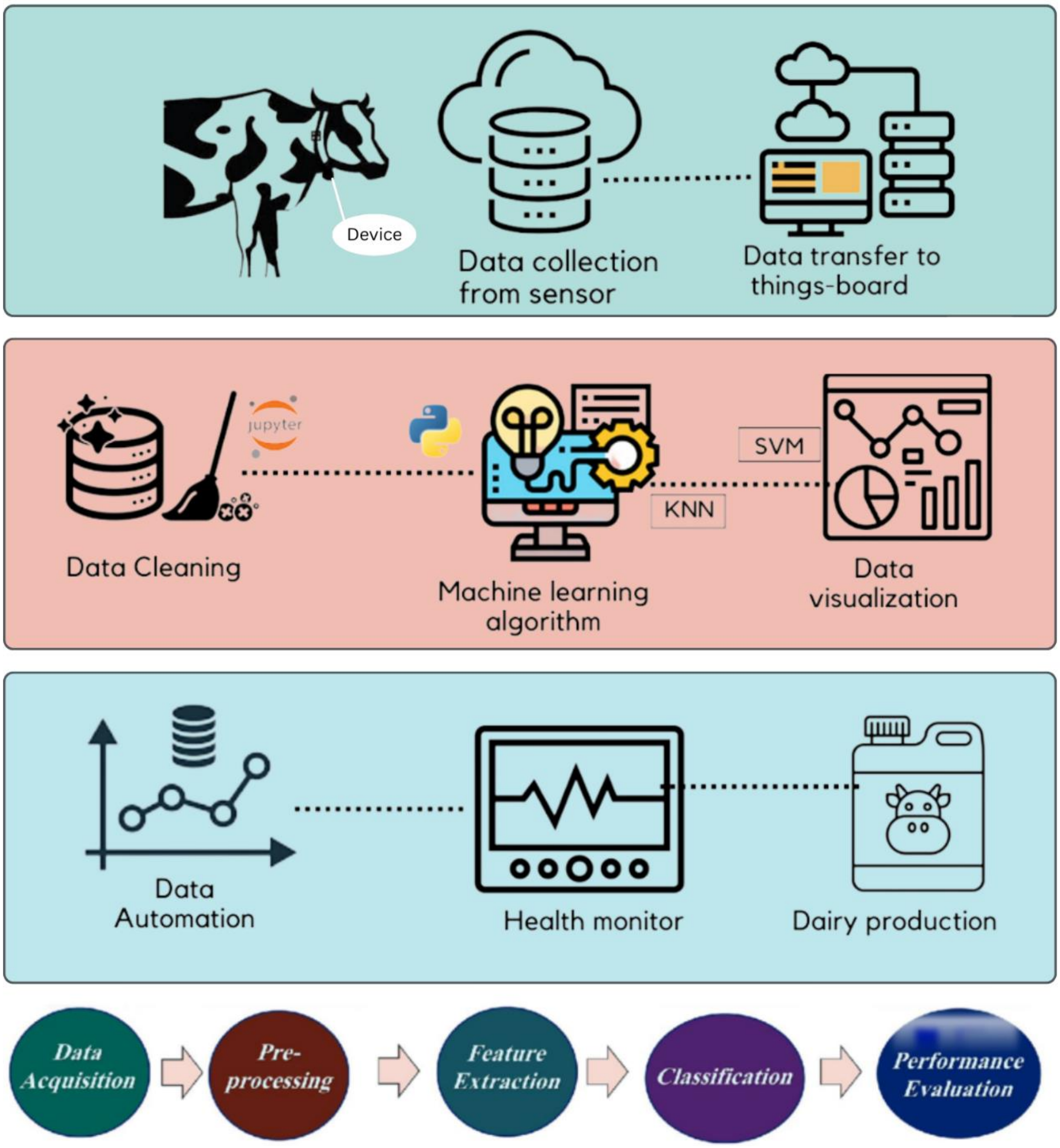
Several data preparation operations, such as cleaning, filtering, and normalizing, were carried out to assure the quality and consistency of the data. The preprocessed data was then saved in a manner that would allow machine learning models to be deployed more easily. The goals and benchmarks for studying cow behavior and increasing milk yield were established. Based on these goals, important variables from the preprocessed data were retrieved, considering parameters such as sleep length, eating frequency, and temperature and humidity fluctuations. To construct and test machine learning models, the data was divided into training and testing sets. The training dataset was used to choose and train appropriate algorithms such as KNN and SVM. To enhance their performance, the models were tested and fine-tuned using the testing dataset. (Zhang, 2020) The learned machine learning models were connected with the Things board to provide real-time predictions or analysis. This connection enabled automatic decision-making based on the collected data. The accuracy and performance of the deployed models were constantly reviewed, and improvements were made as needed. The acquired data was monitored regularly to assure its dependability and correctness (Pfeuffer et al., 2023). The machine learning models' insights and predictions were rigorously investigated to find patterns and trends in cow behavior. The models and the system as a whole went through modifications based on feedback and fresh data to constantly enhance milk productivity and optimize the analytical process. This iterative method is intended to maximize the sensor integration system's performance and influence on milk production.

Tools and Technique

Utilizing easily accessible, user-friendly, and effective tools and technologies allows for the achievement of the goal. Python's extensive library of pre-installed tools and modules makes it an attractive choice for a wide range of applications (Datacamp, 2022). There is also a lot of online help and resources for Python due to its vibrant developer and user community.

System workflow and Integration

The information gathered by the sensor will be uploaded to the Things board. Then, with the help of proper machine learning, the farmer will be able to anticipate the health of the cow, which will be helpful for the production of dairy products. It was determined with the help of the labeling tool what the suitable window sizes were for each activity that was labeled. Grazing activities normally take between four and twenty-four seconds, whereas ruminating might take anywhere from five to fourteen seconds. The labeling technique that was used was aimed at capturing the vast majority of operations while also reducing noise and disruptions. The fact that various classes were assigned to different instances was another source of concern. The classes that made up the majority were busy grazing and ruminating, whereas the classes that made up the minority were lying, standing, and walking. Because of this mismatch, the models were flawed, with grazing behaviors being given more weight than walking. To solve this problem, the models were trained using sampling strategies or weights that were determined by their class. The classification of head position-related activities was accomplished through the use of the distribution of acceleration data. To categorize activities that are connected to head position, the machine learning models learned how to learn the distribution of acceleration data. The computation of features was done to quantify relations and spread outs, such as the correlation between the various acceleration axes, the mean, the percentiles, the movement variation, the minimum, the maximum, and the integral of accelerations. The median was chosen because it provides a more accurate depiction of the normal acceleration, while the variance was chosen because it describes how the data differ from predicted values. Entropy, which is a measure of the probability distribution of accelerations, was utilized to determine the degree to which accelerations were generated at random. The data was divided into fixed window widths before the characteristics of the data were computed and the data was analyzed. The window sizes that were selected were determined by their capacity to record the vast majority of actions while also reducing noise and disruptions. The dataset was flawed, and the algorithms were trained with sampling strategies and class weights as inputs. The performance of the models was evaluated based on their balanced accuracy since the recall of each class was employed regardless of the class's size. SVM was utilized because of its performance in high-dimensional space and its ability to use kernel techniques for complicated decision surfaces. To solve the issue of nonlinear classification, the Radial Basis Function (RBF) kernel and a soft margin were implemented. To solve problems with data separability, the RBF kernel and the soft margin were implemented. The efficient non-parametric classification technique k-NN, which classifies input based on the similarity of previously collected data, was selected as the method of choice. The algorithm was trained with either the random oversampling approach or the class weight method. The Nearest-Neighbor algorithm is used to classify unlabeled observations by locating the labeled instances that are the most similar based on distance measurement. There was no need that the variables to be independent, identically distributed, linear, or linearly separable. According to the findings of the research, the Nearest-Neighbor classifier is the one that is most suited for determining the best model for the behavior categorization of cows. The results of the experiments and training approaches served as the foundation for the machine learning models used in the study. According to the findings, the RBF kernel performed slightly better than the polynomial of degree three and the Linear, while the k-NN classifier performed better than the RBF kernel. The results also revealed that the linear kernel performed slightly better than the RBF kernel. The categorization of the behaviors shown by cows is the primary emphasis of this research, which makes use of machine learning models and assessment criteria. Because the dataset that contains the selected features is unbalanced, the algorithms need to be trained with the use of sampling approaches and class weight, and they also need their hyperparameters fine-tuned. When evaluating the performance of models, balanced accuracy is utilized since each class's recall, regardless of size, serves as a representation of that class's performance.



Technical Specification

Scalability and availability are fundamental design considerations for a cattle monitoring system to ensure its efficacy, dependability, and longevity.

Scalability in Cattle Monitoring System

Cattle monitoring systems must be able to accommodate more cattle and data points without compromising performance or data accuracy. Horizontal scalability involves distributed systems and load balancing, whereas vertical scalability entails upgrading hardware components. Horizontal scalability requires distributed databases, load balancers, and microservice architecture for efficient and dependable monitoring, whereas vertical scalability entails upgrading hardware components.

Availability in Cattle Monitoring System:

Cattle monitoring systems require constant and dependable services in order to monitor cattle behavior, health, and production in real-time. High availability decreases data loss and downtime, allowing essential information to be accessed on time. Redundancy, fault tolerance, cloud-based infrastructure, and proactive monitoring are all important components. Redundancy guarantees continuous backups in the event of a breakdown, whereas fault tolerance enables gentle recovery from hardware or network faults. Cloud architecture provides built-in redundancy and high availability, while proactive monitoring detects possible issues early and reduces downtime.

Finding

1. **How can machine learning be used to improve the accuracy of predictions in a particular domain?**

Machine learning algorithms are trained on existing datasets to learn and improve. To build reliable models, training datasets must be of sufficient quantity and quality. Finding, collecting, or even creating (in certain cases) the training dataset is the initial step in a machine-learning process. Of course, this will heavily depend on the final goal of the model we're trying to train. Normalization and cleansing are prerequisites for making use of data. Using physical or chemical knowledge-based criteria, you'll identify any outlying, suspicious, or otherwise suspect data points. When utilizing machine learning to create better predictors, cleaning and homogenizing the data is crucial. This may be essential depending on the approach used; for instance, certain ML algorithms are more tolerant of outliers than others (Jain, 2021). The null value is not accepted by certain algorithms (such as those in the Random Forest family) but is accepted by others. Once the data has been cleaned and homogenized, the next stage in the machine learning workflow is to encode it into a set of specific variables that will be directly modified by the ML algorithm. The data obtained is frequently in raw format and must be translated into a format suited for the learning technique, typically as a series of scalar or vector variables for each dataset item. This stage may include transforming existing data (such as physical attributes) by rescaling, normalizing, or binarizing it to make it easier for the algorithm to parse (Misra et al., 2019a). Some simple preprocessing approaches are widely available in ML software, such as Scikit-Learns Min Max Scaler and Standard Scaler methods. Three primary types of ML models use the curated and pre-processed dataset as input: supervised, unsupervised, and semi-supervised. Consider chemical structures and their characteristics as a common example of a dataset that would contain both input variables and their matching output variables in supervised learning (chibani siwar, 20202). Then, using this training data, the ML algorithm aims to learn the function that maps the input (the structures) to the output (the qualities). Unsupervised learning operates very differently, attempting to infer conclusions about the input data without any associated output variables. It is used to search for previously unnoticed patterns in data with little to no human supervision or direction.The family of k-nearest neighbor (k-NN) algorithms can be used for classification and regression tasks in supervised ML. The k-NN algorithm assumes that similar objects in the data are near each other and uses the output variable associated with these nearest neighbors to predict the value of X. Decision trees (DTs) are another family of learners that can handle both classification and regression-supervised ML (forming classification trees and regression trees, respectively) (Misra et al., 2019b). Decision trees in machine learning are straightforward to comprehend and interpret because the trees can be represented graphically. Numerous kinds of decision tree-based learners exist, including Random Forest (RF) and Gradient Boosting Decision Tree (GBDT). RF uses averaging to reduce overfitting and

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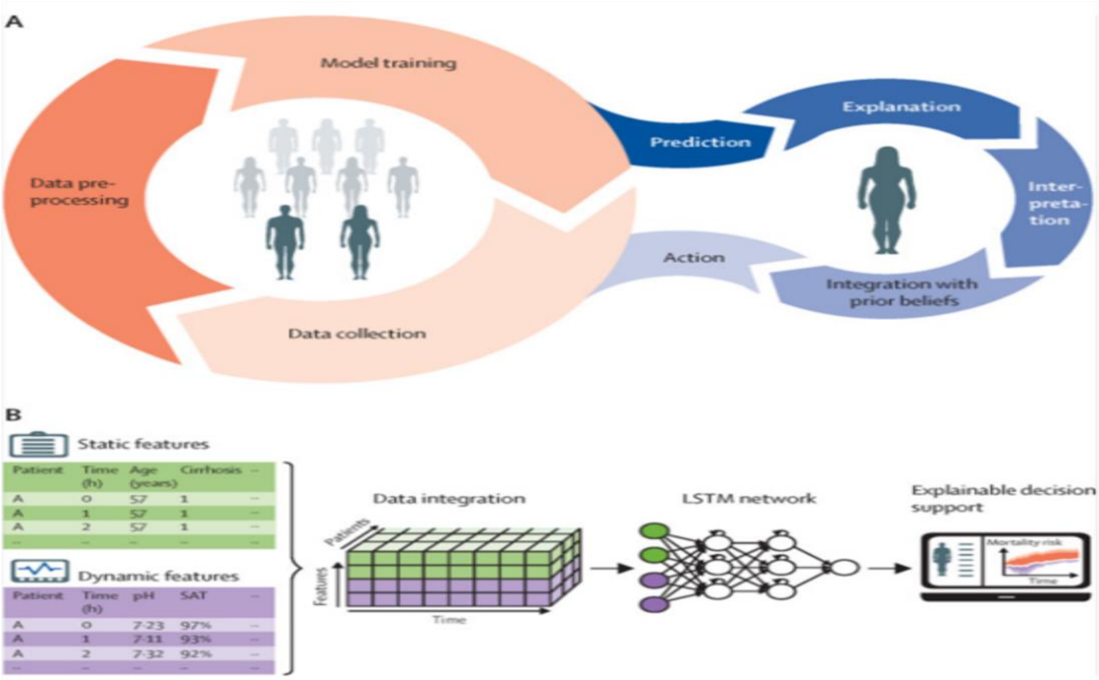
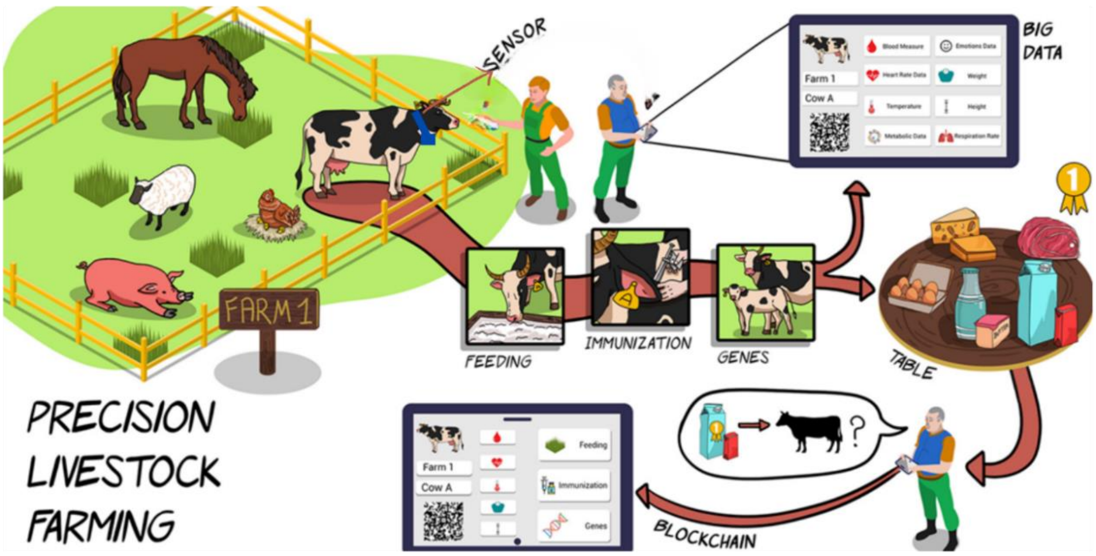
improve predictive accuracy, while GBDT tries to correct the error of previous trees by merging several trees at smaller depths.



2. How can wearable technology be used to improve the health and productivity of animal husbandry operations?

Autonomous cow behavior monitoring systems have gained relevance in recent years. Sensor-based solutions are now being recognized as an improvement over traditional visual examination, which is both time-consuming and labor-intensive. Systems for monitoring dairy and beef cattle, such as neck-mounted collars and leg and ear tags, are becoming more popular. Such systems give early information on health and welfare concerns, as well as the commencement of estrus, which serves as the foundation for a decision support system that advises farmers on the most relevant measures that improve the efficiency of present methods. Innovative technologies and sensors are becoming more and more crucial as the value of farming grows. The use of robotics and automation in agriculture has the potential to significantly contribute to society's ability to meet its future food supply needs. Wearable sensors attached to or inside cows can track a variety of behaviors, including feeding, ruminating, pH levels, body temperatures, laying patterns, animal movement, location or placement, and more. Research focuses on biosensing technologies with the potential to enhance operations, management, and early illness detection in cattle. Traditional diagnostic techniques need the knowledge of trained professionals utilizing specialized equipment and are notoriously labor-intensive, time-consuming, and complex. New technologies are being used to address these challenges and provide quick-response, inexpensive, and highly reliable biosensor devices. Improving biological metrics in cattle by automated remote monitoring, detecting animal well-being, and identifying potential body and body weight issues may be possible. The use of biosensors and wearable technologies in managing animal health is becoming more and more crucial. These tools can help in early illness identification in animals, reducing financial losses. Around the world, several animal health management sensors are in varying stages of commercialization (karina & dzermaika, 2023). The current level of medical technology makes it difficult to diagnose illnesses early on and expensive to test animals in a lab. There is a need for detection technologies that can foresee possible consequences for a particular population, educate on diagnostic and treatment choices, and predict when and in what group an event is likely to occur. These instruments can expedite the monitoring process, and they can be trustworthy and easy to use in addition to being accurate and sensitive to the parameters being studied. Utilizing portable devices in place of more traditional methods, including taking notes, keeping a farm diary, or utilizing basic equipment without data-sharing features, can make general farm monitoring simpler and more dependable. We can boost milk output by monitoring the health of cows. Because milk output is one of the key sources of income for farmers with more cows, and due to advanced technology and agricultural automation, the number of farms increases daily. It is extremely tough to care for cows in a large herd. There is now a monitoring system in place that solely measures dairy cows' body temperature, relative humidity, rumination, and heart rate. This monitoring system collects real-time data and alerts farmers in the event of abnormalities. By tracking these vital signs, farmers can identify early signs of illness or distress in cows, allowing for timely intervention and treatment. This enhances the overall health and welfare of the cows and ensures optimum milk production and farmer profitability. Farm monitoring has grown more efficient with such modern technology in place, allowing farmers to supervise their herds with simplicity and assurance.

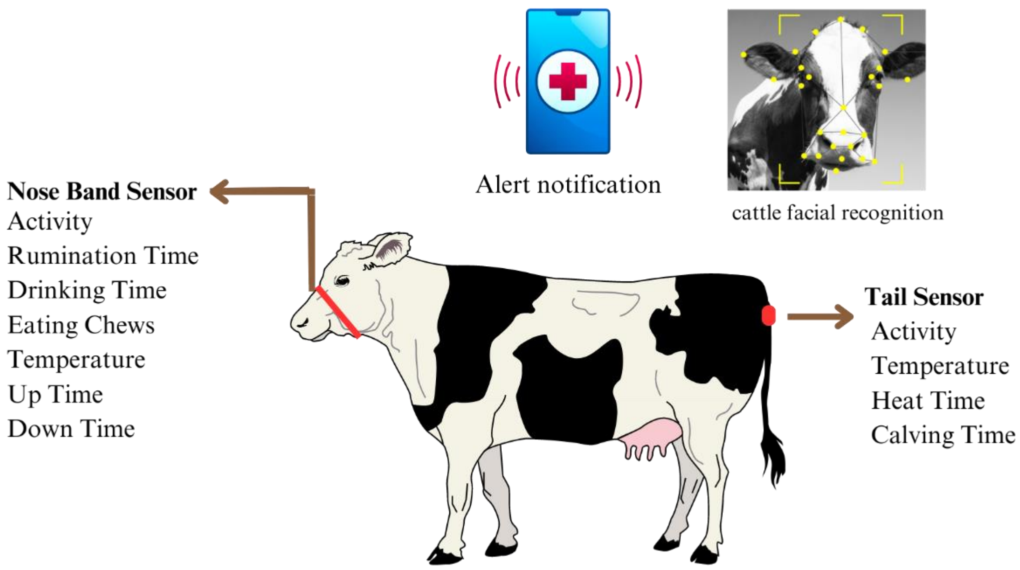


3. What are the ethical challenges while gathering data from cattle farming?

There are a lot of different ethical questions that come up when animals are used in scientific studies. The vast majority of people believe that animals have some sort of moral significance and that human behavior toward them should be subject to some sort of code of ethics. The following positions are reflective of the aforementioned points of view: It is necessary to acknowledge the intrinsic worth that animals possess. Considering the needs of animals is necessary given that they are conscious beings with the capacity to experience discomfort. Our perspectives and beliefs are reflected in the way that we treat animals, including the use of animals in scientific studies. Researchers and anyone who works with live animals are required to have current knowledge of animals as well as proven prior experience. This involves specific information about the biology of the animal species in issue as well as the willingness and aptitude to properly care for animals. In addition, this demands specific knowledge about how to properly care for animals. Researchers and research managers alike are responsible for ensuring that their practices are in line with applicable national laws and guidelines, as well as international treaties and agreements that govern the use of laboratory animals. Anyone who wants to research animals is required to become familiar with the regulations that are already in place. Researchers are responsible for investigating the likelihood that laboratory animals would experience pain and weighing that probability against the potential advantages that the research may have for other animals, people, or the environment (Ingrid Synnøve Torp, 2019). The responsibility of assessing whether the experiment will be beneficial to humans, animals, or the environment lies with the researchers. The study's immediate and long-term possible benefits need to be investigated, verified and explained in detail. As part of the tasks, it is necessary to assess the level of scientific rigor present in the experiments and to ascertain whether or not the studies will result in significant advancements in scientific knowledge. It is the responsibility of the researchers to cause as little disturbance as possible to the normal behaviors of the animals they study, including those creatures that are not the primary focus of their investigations, as well as the populations of animals and the ecosystems in which they live. Implementing some scientific and technological projects, such as those involving environmental technology and environmental surveillance, may affect animals and the environments in which they live. These projects include activities such as the construction of radar towers, antennas, and other measurement equipment. In situations like these, researchers have a responsibility to work toward adhering to the proportionality principle while also attempting to minimize the possible negative impact.

Recommendation

Implementing alert notifications in the system is a crucial part of this upcoming improvement, as it will immediately inform farmers if a cow's body temperature rises beyond the safe threshold. Farmers will be able to keep a close eye on the health of their livestock and respond quickly if they see any problems. Extending the scope beyond cattle, our vision entails adapting the monitoring device to the specific requirements of a variety of animals. For example, sensors could be designed specifically for canines and cats, enabling pet owners to easily monitor their creatures' health and behavior. Additionally, the



incorporation of a lactation sensor system will be of great benefit to cattle breeders. By being notified when a cow is about to give birth, producers can provide opportune assistance during the calving process, thereby promoting the health of the cow and the newborn calf. Using advanced computer vision technology, the incorporation of a cattle facial recognition system will enable individual animal tracking, behavior surveillance, and health issue detection. This will revolutionize the way we observe and care for our cattle, allowing us to detect anomalies and early symptoms of distress. To aid producers in their decision-making, our future research will analyze bovine behavior patterns using machine learning algorithms. The dashboard will provide producers with the most comprehensive comprehension of their herd and promote healthier environments by displaying insights into the behavioral issues of cattle along with suitable solutions. Essential to this next-generation system is the surveillance of grazing patterns and the provision of individualized dietary recommendations. Farmers can ensure their animals receive a balanced diet that promotes optimal health and productivity by analyzing the weight and activity levels of their cows. In addition to providing real-time data, this innovative device will assist in identifying any aberrant behavior that could indicate illness or distress. Interventions based on these insights will enable the prevention of potential maladies and injuries, thereby enhancing the cattle's overall health. This future cattle monitoring system provides a customizable, all-inclusive, and technologically advanced solution for farmers, allowing them to efficiently manage and care for their livestock. Through the use of machine learning and computer vision technology, we aim to transform the livestock management industry, thereby improving animal welfare and agricultural operations. Through this system, farmers can monitor the behavior, temperature, and vital signs of each animal in real-time. This data will be analyzed using advanced algorithms to detect any abnormalities or signs of illness, enabling proactive intervention before the condition worsens. This system will also provide insights into the overall herd's health and allow farmers to make informed decisions regarding breeding, nutrition, and disease prevention. Overall, this technological advancement promises to not only improve the well-being of cattle but also enhance the efficiency and productivity of the entire agricultural sector.

Conclusion

The Internet of Things (IoT) is a promising solution to low agricultural and livestock efficiency and productivity, as it helps to monitor animal health and reduce financial losses. Ethical standards in research require truthful reporting of results, findings, methodology, and data, and it is essential to maintain openness and transparency in the research process. Factors such as Fitbit, which monitors users' activity and sleep patterns, are utilizing wearable technology to track health and reduce stress. However, Fitbit's in-house e-commerce platform has limitations, such as a lack of a content management system, which burdens internal resources. With the recent release of the Apple Watch, wearable technology, such as the Apple Watch, is expected to grow in popularity as the IoT takes off. Akinator, a game where players imagine characters, objects, or animals, uses probabilistic strategies to reduce the complexity of binary decision trees. LinkedIn, the largest online professional network, continuously collects and displays data for decision-making. The CRISP-DM methodology is suitable for machine learning initiatives, such as the development of a bovine health monitor. A sensor integration system was created for cow behavior monitoring and milk productivity optimization, calibrated to ensure reliable data capture. The learned machine learning models were connected to the Things board for real-time predictions or analysis. The accuracy and performance of the deployed models were constantly reviewed and improved as needed. The use of biosensors and wearable technologies in managing animal health is becoming increasingly crucial as medical technology makes it difficult to diagnose illnesses early on and expensive to test animals in labs. It is essential to acknowledge the intrinsic worth of animals and investigate both the immediate and long-term benefits of these technologies.

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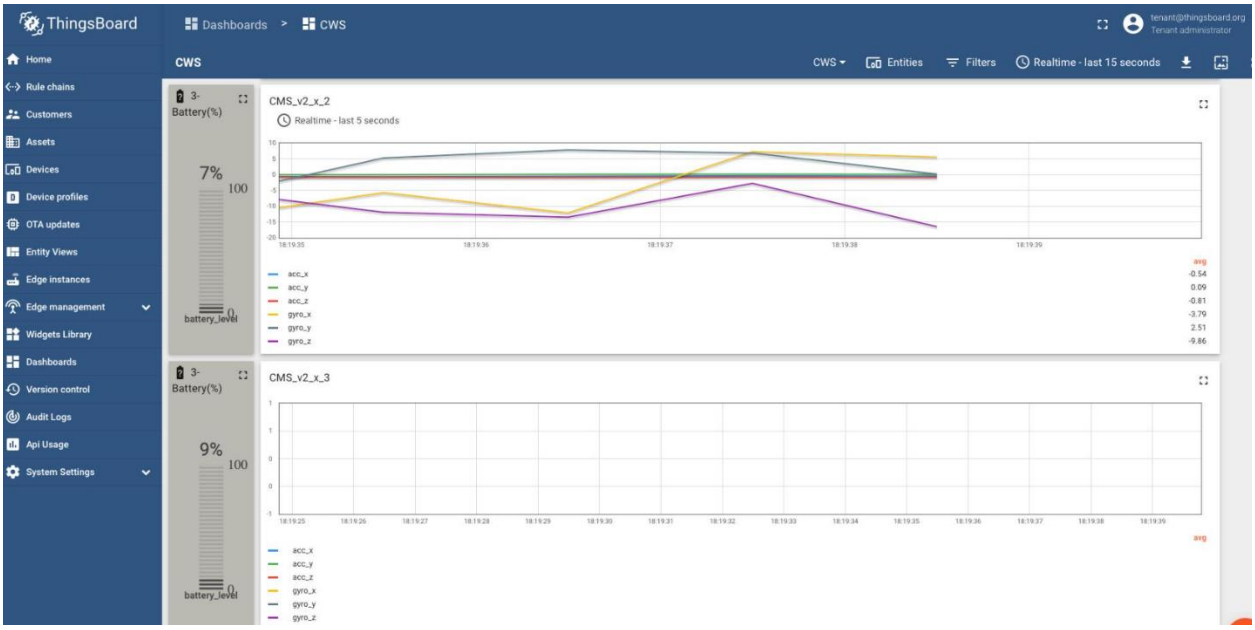
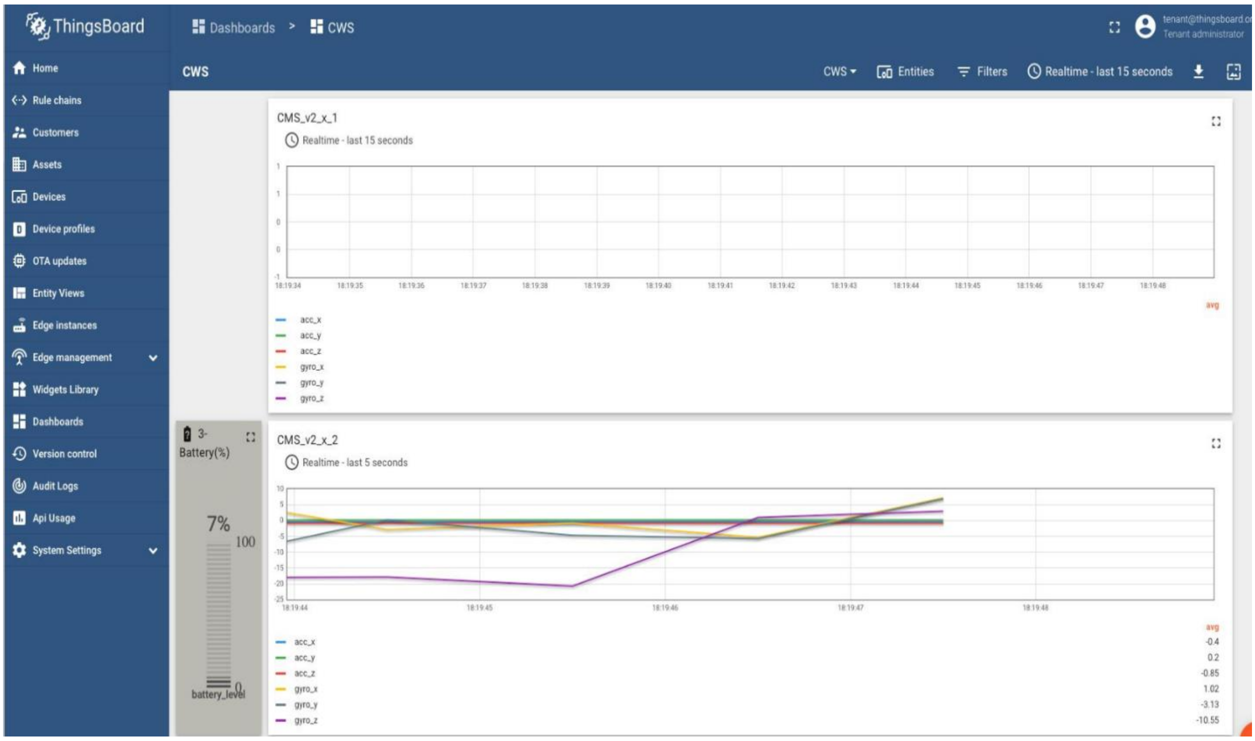
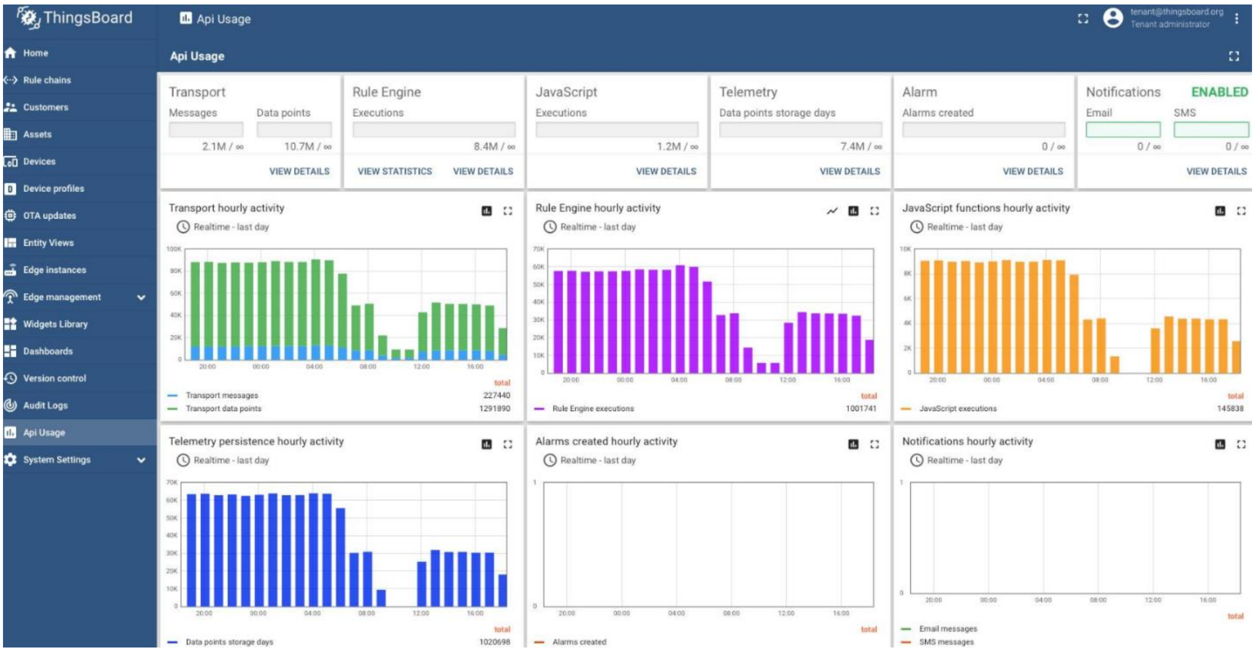
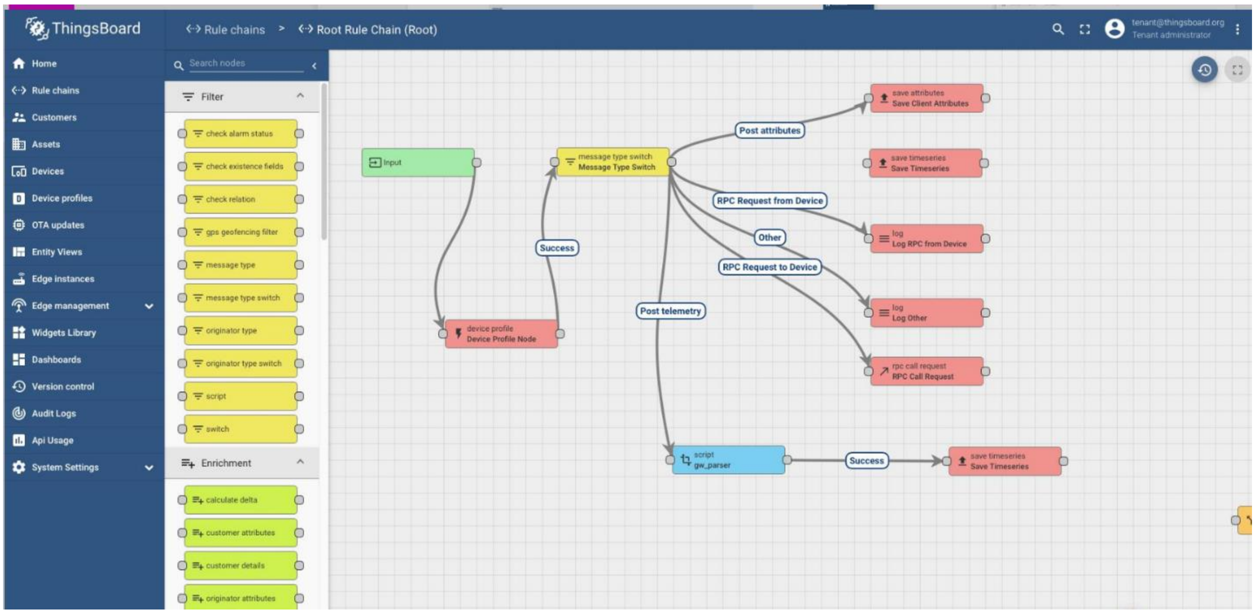
Things board




ThingsBoard
Dashboards > CWS
CWS
CMS_V2_x_1
Realtime - last 15 seconds
CMS_V2_x_2
Realtime - last 5 seconds
Battery(%)
7%
battery_level


ThingsBoard
Api Usage
Transport
Rule Engine
JavaScript
Telemetry
Alarm
Notifications
ENABLED
Transport hourly activity
Rule Engine hourly activity
JavaScript functions hourly activity
Telemetry persistence hourly activity
Alarms created hourly activity
Notifications hourly activity


ThingsBoard
Rule chains
Root Rule Chain (Root)
Home
Rule chains
Customers
Assets
Devices
Device profiles
OTA updates
Entity Views
Edge instances
Edge management
Widgets Library
Dashboards
Version control
Audit Logs
Api Usage
System Settings
Search nodes
Filter
check alarm status
check existence fields
check relation
gps geofencing filter
message type
message type switch
originator type
originator type switch
script
switch
Enrichment
calculate delta
customer attributes
customer details
originator attributes
Input
Success
device profile
Device Profile Node
message type switch
Message Type Switch
Post attributes
save attributes
Save Client Attributes
save timeseries
Save Timeseries
RPC Request from Device
Other
log
Log RPC from Device
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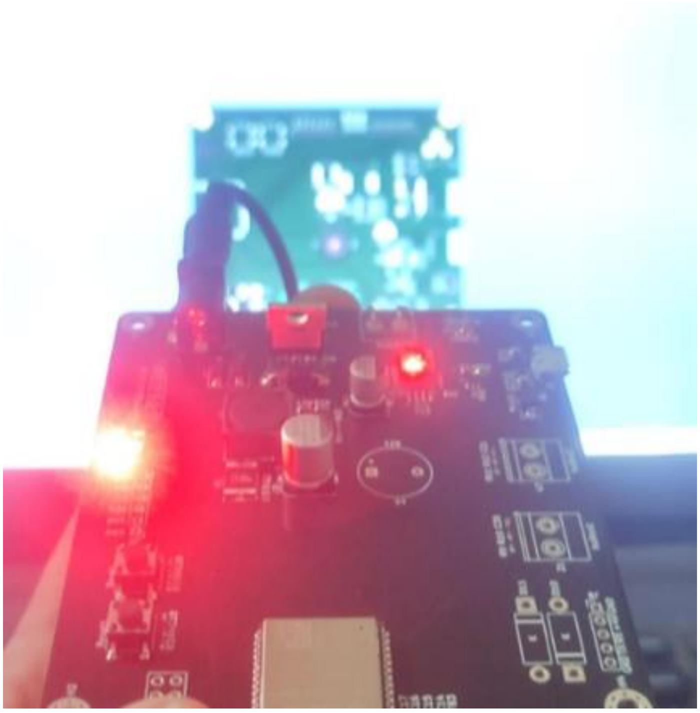
Post telemetry
log
Log Other
rpc call request
RPC Call Request
script
gw_parser
Success
save timeseries
Save Timeseries

Real Device



This autoencoder neural network model is created using Long Short-Term Memory (LSTM) recurrent neural network (RNN) cells within the Keras / TensorFlow framework.

```
# import libraries
import os
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.externals import joblib
import seaborn as sns
sns.set(color_codes=True)
import matplotlib.pyplot as plt
%matplotlib inline

from numpy.random import seed
from tensorflow import set_random_seed
import tensorflow as tf
tf.logging.set_verbosity(tf.logging.ERROR)


from tensorflow.keras.layers import Input, Dropout, Dense, LSTM, TimeDistributed, RepeatVector
from tensorflow.keras.models import Model
from tensorflow.keras import regularizers
```

Data loading and pre-processing

```
# Read in the csv file exported from Django backend into a dataframe
data = pd.read_csv("new_format_data_cowdy.csv", sep=',', header=0)
```

```
from Functions import pre_process_data
```

```
df = pre_process_data(data)
```

```
from Functions import remove_duplicates
```

```
# subset for one animal
df = df[df['device_id']=='262B']
```

```
df = remove_duplicates(df)
```

Define train/test data

Before setting up the models, we need to define train/test data. To do this, we perform a simple split where we train on the first part of the dataset (which should represent normal operating conditions) and test on the remaining parts of the dataset leading up to the anomalous behavior.

```
train = df.iloc[0:9946, :]
test = df.iloc[9947:12432, :]
print("Training dataset shape:", train.shape)
print("Test dataset shape:", test.shape)
```
[5] Python

```
Training dataset shape: (9946, 3)
Test dataset shape: (2485, 3)
```

```
fig, ax = plt.subplots(figsize=(14, 6), dpi=80)
ax.plot(train['x'], label='x', color='blue', animated = True, linewidth=1)
ax.plot(train['y'], label='y', color='red', animated = True, linewidth=1)
ax.plot(train['z'], label='z', color='green', animated = True, linewidth=1)
#ax.plot(train['Bearing 4'], label='Bearing 4', color='black', animated = True, linewidth=1)
plt.legend(loc='lower left')
ax.set_title('Sensor Training Data', fontsize=16)
plt.show()
```
[6] Python

Distribution of Loss Function

By plotting the distribution of the calculated loss in the training set, one can use this to identify a suitable threshold value for identifying an anomaly. In doing this, one can make sure that this threshold is set above the “noise level” and that any flagged anomalies should be statistically significant above the background noise.

```
# plot the loss distribution of the training set
X_pred = model.predict(X_train)
X_pred = X_pred.reshape(X_pred.shape[0], X_pred.shape[2])
X_pred = pd.DataFrame(X_pred, columns=train.columns)
X_pred.index = train.index

scored = pd.DataFrame(index=train.index)
Xtrain = X_train.reshape(X_train.shape[0], X_train.shape[2])
scored['Loss_mae'] = np.mean(np.abs(X_pred-Xtrain), axis = 1)
plt.figure(figsize=(16,9), dpi=80)
plt.title('Loss Distribution', fontsize=16)
sns.distplot(scored['Loss_mae'], bins = 20, kde= True, color = 'blue');
plt.xlim([0.0,.5])
```
Python

```python
# frequencies of the healthy sensor signal
fig, ax = plt.subplots(figsize=(14, 6), dpi=80)
ax.plot(train_fft[:,0].real, label='x', color='blue', animated = True, linewidth=1)
ax.plot(train_fft[:,1].imag, label='y', color='red', animated = True, linewidth=1)
ax.plot(train_fft[:,2].real, label='z', color='green', animated = True, linewidth=1)
#ax.plot(train_fft[:,3].real, label='Bearing 4', color='black', animated = True, linewidth=1)
plt.legend(loc='lower left')
ax.set_title('Sensor Training Frequency Data', fontsize=16)
plt.show()
```

One-class SVM with non-linear kernel (RBF)

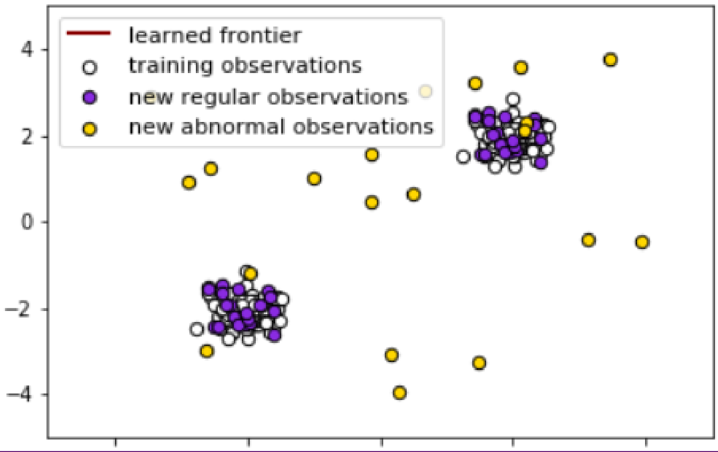
```python
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.font_manager
from sklearn import svm
```

```python
xx, yy = np.meshgrid(np.linspace(-5, 5, 500), np.linspace(-5, 5, 500))
```

```python
# Generate train data
X = 0.3 * np.random.randn(100, 2)
X_train = np.r_[X + 2, X - 2]
# Generate some regular novel observations
X = 0.3 * np.random.randn(20, 2)
X_test = np.r_[X + 2, X - 2]
# Generate some abnormal novel observations
X_outliers = np.random.uniform(low=-4, high=4, size=(20, 2))
```

```python
# fit the model
clf = svm.OneClassSVM(nu=0.1, kernel="rbf", gamma=0.1)
clf.fit(X_train)
y_pred_train = clf.predict(X_train)
y_pred_test = clf.predict(X_test)
y_pred_outliers = clf.predict(X_outliers)
n_error_train = y_pred_train[y_pred_train == -1].size
n_error_test = y_pred_test[y_pred_test == -1].size
n_error_outliers = y_pred_outliers[y_pred_outliers == 1].size
```

```
s = 40
b1 = plt.scatter(X_train[:, 0], X_train[:, 1], c='white', s=s, edgecolors='k')
b2 = plt.scatter(X_test[:, 0], X_test[:, 1], c='blueviolet', s=s,
                 edgecolors='k')
c = plt.scatter(X_outliers[:, 0], X_outliers[:, 1], c='gold', s=s,
                edgecolors='k')
plt.axis('tight')
plt.xlim((-5, 5))
plt.ylim((-5, 5))
plt.legend([a.collections[0], b1, b2, c],
           ["learned frontier", "training observations",
            "new regular observations", "new abnormal observations"],
           loc="upper left",
           prop=matplotlib.font_manager.FontProperties(size=11))
plt.xlabel(
    "error train: %d/200 ; errors novel regular: %d/40 ; "
    "errors novel abnormal: %d/40"
    % (n_error_train, n_error_test, n_error_outliers))
plt.show()
```



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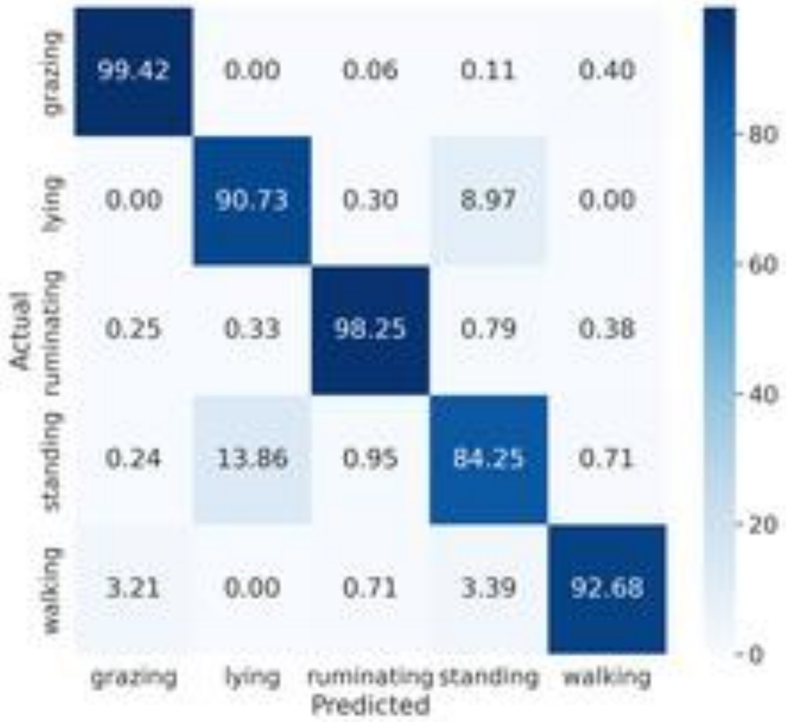

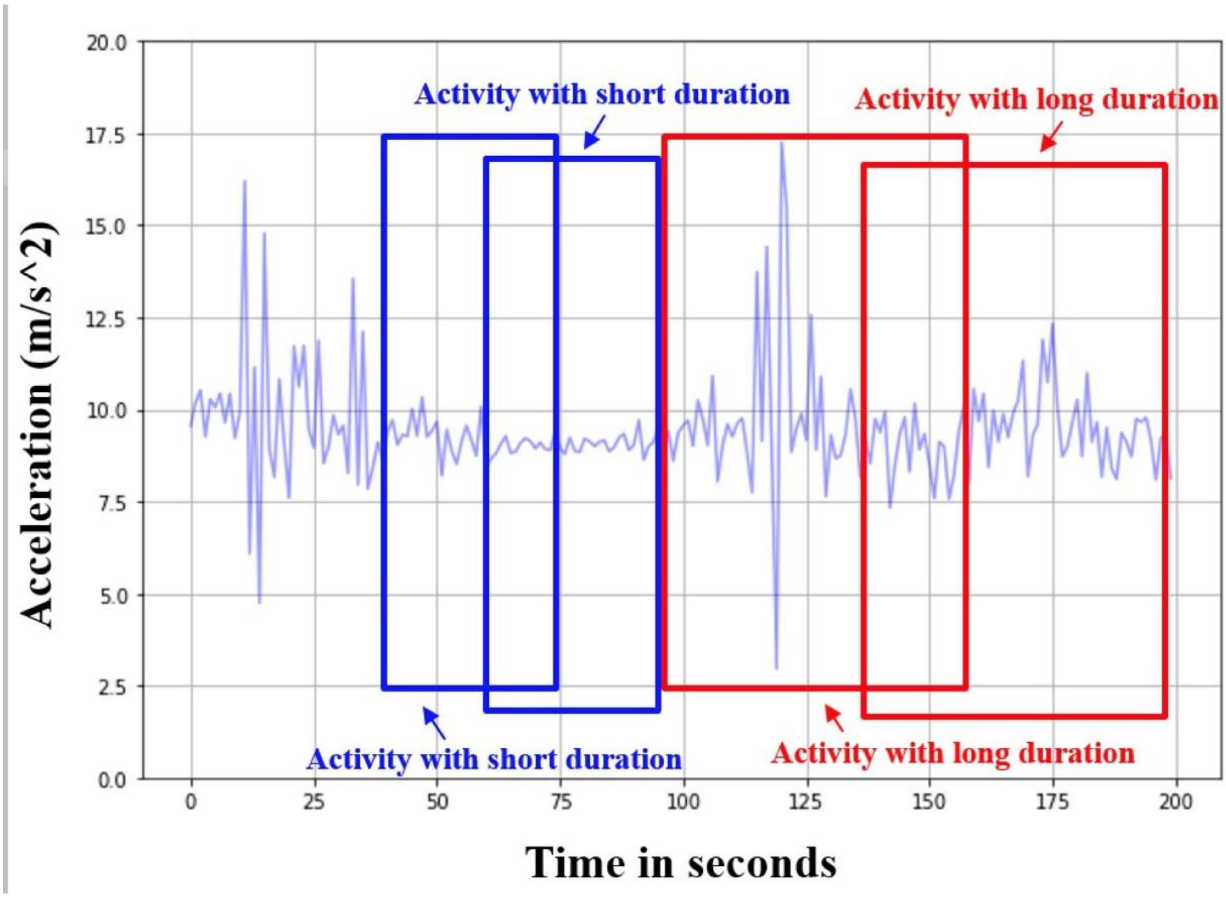

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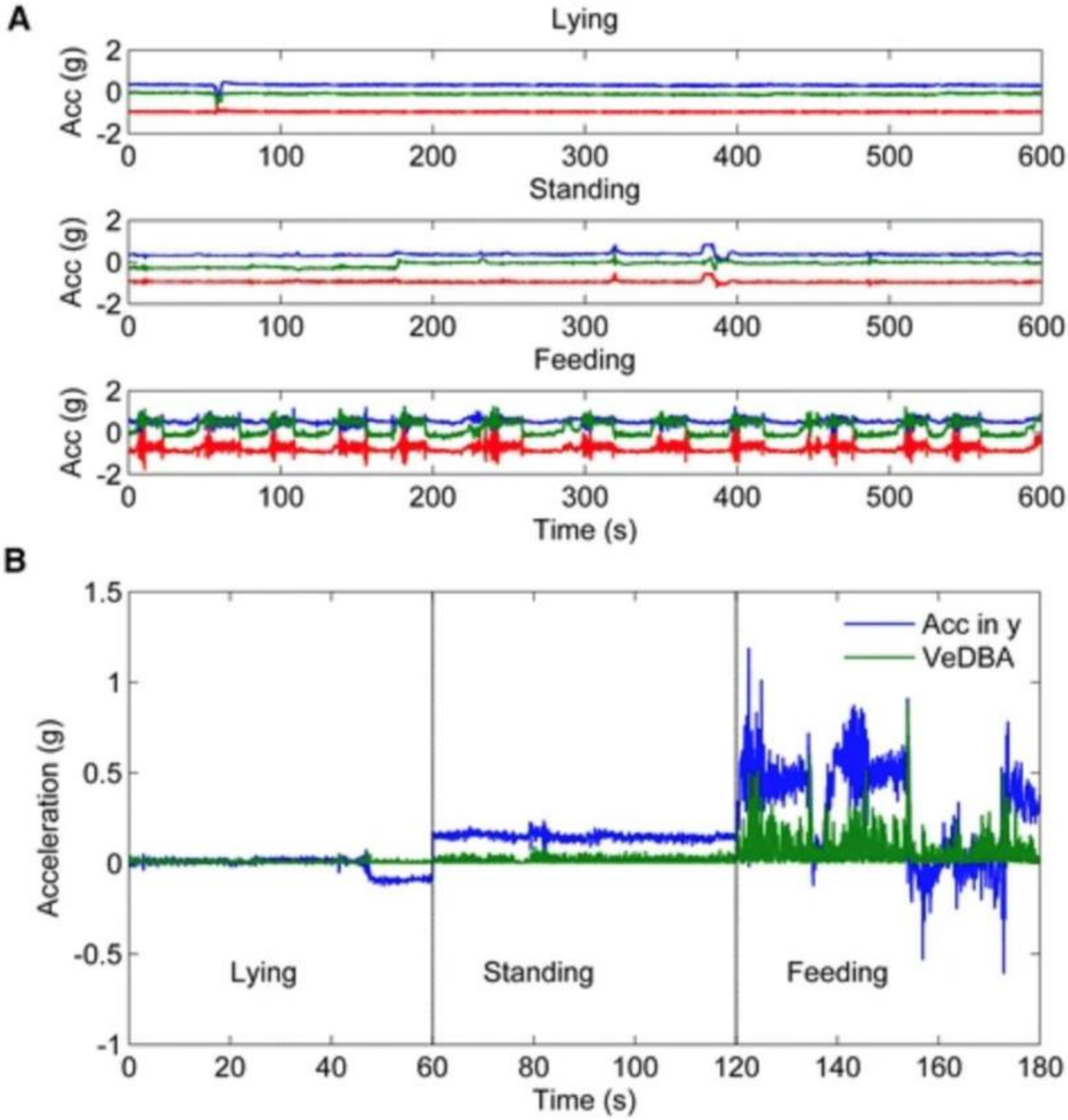

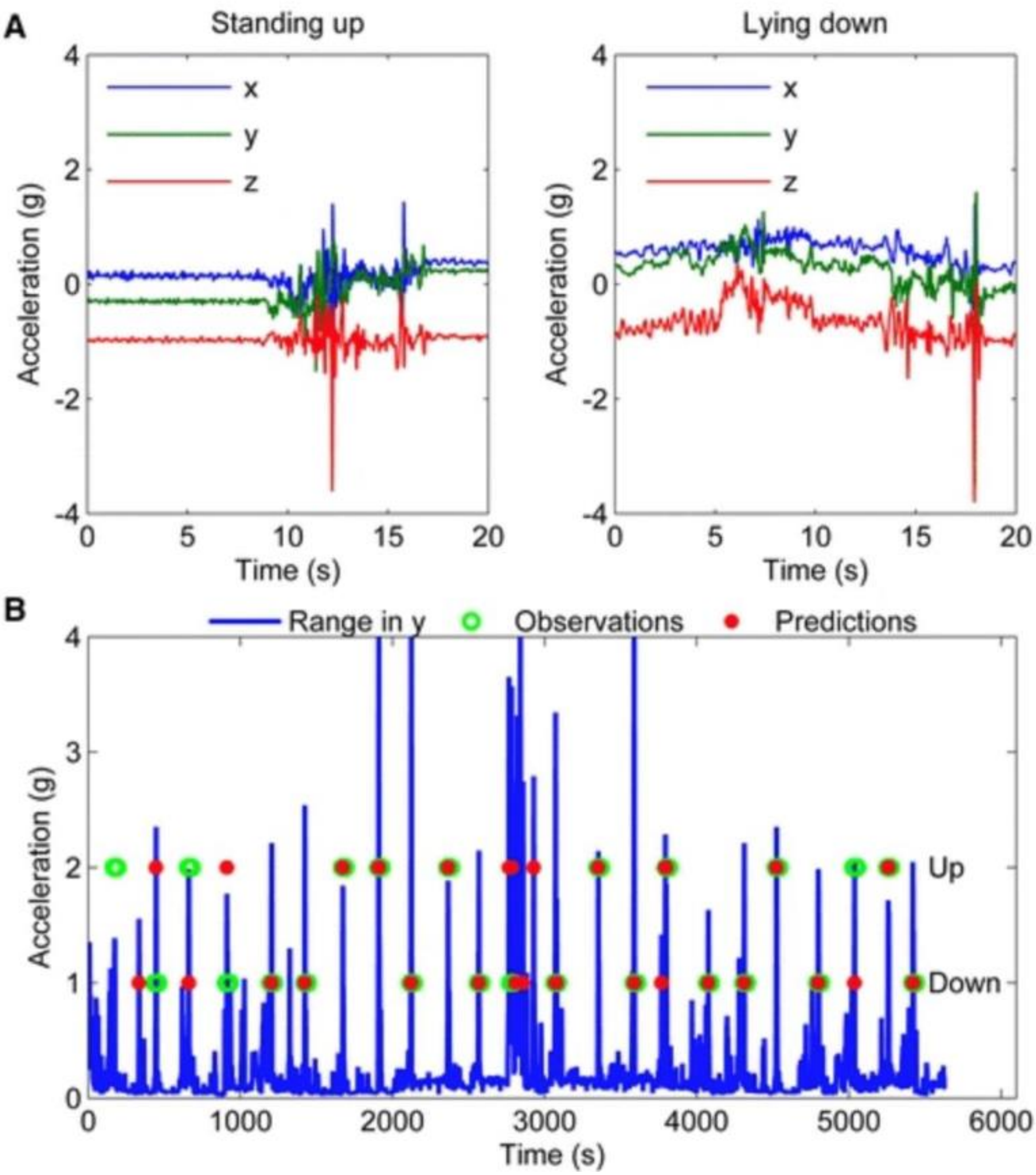
A
Standing up
Lying down
x
y
z
Acceleration (g)
Time (s)
B
Range in y
Observations
Predictions
Up
Down
Acceleration (g)
Time (s)