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SMART DIARY FORMS: ARTIFICIAL INTELLIGENCE FOR EFFICIENT DIARY FARMING

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Abstract

Artificial intelligence is improving dairy quality and expanding at an unprecedented rate. It will significantly improve the situation of farm farmers by preserving the health, physiological, and physical conditions of dairy cows. This knowledge-based technology has enormous promise and will address the gaps in dairying, thus strengthening the farm business. In dairying, AI has numerous uses such as monitoring the activities of dairy cows, increasing milk output and farm productivity, detecting redness in dairy cows, police investigating dairy odours, and constructing good cow homes hopped-up by picture analysis. Through a profitable business approach in dairying, it eventually delivers new hope and open prospects for the quality and progress of the farm business. This project suggests employing AI in dairy production. This system will track cow health, do robotic milking, and monitor cattle locations. When these types of technologies are used on dairy farms, they have a new impact on humans and animals.

KEYWORDS: Artificial Intelligence, Health, Dairy-cows, Milk productivity, Image Analysis

I. INTRODUCTION

The automated milking system is used for cutting edges robotics technologies to higher productivity of the milk. The innovations are being created as a result of the dairy industry's rising worldwide market potential, which is expected to grow by 35% by 2030.Due to increased competition, demands for guaranteed milk quality, and concerns about animal welfare, 14 crore dairy farms will stop producing along with the increase in world demand. The latter is a rising consumer issue, which AMS addresses because it is based on the "milking when they want" concept, which improves cow wellbeing and welfare.In recent years, researchers have examined possible advancements in mechanized milking system technology by using biometric monitoring of animals to measure neurobiological changes in production systems. Some of these non-invasive devices measure heart rate, respiration rate, and body temperature using visible imaging/video and infrared thermal picturesThese technologies might lead to better monitoring of heat stress in agricultural animals [1-5]. However, all prior approaches used predictable mathematical equations with insufficient data on the animals in the study, and non - contact biometrics analysis may be too expensive for use in the near future on normal dairy farms.Automation in electronic agriculture is the incorporation of technological knowledge, monitors, and instruments into precision agriculture from the crop to the consumer [6-10]. Modern technologies like artificial intelligence, machine learning, and computer vision are used for data processing. In future, Artificial intelligence applications should benefit not just high-tech systems such as automated milking system, but also traditional dairy farms, enhancing their competitiveness. Autonomous meteorological sensors collected ubiquitous environmental data for this study, and all dairy farms had access to animal data. Autonomous meteorological sensors collected ubiquitous environmental data for this study, and all dairy farms had access to animal data [11-12].

II.LITERATURE SURVEY

Clay N states that dairy production techniques have advanced significantly during the previous several decades. In many parts of the world, dairy farms are expanding and becoming owned by fewer people. Increased productivity has social and environmental consequences in addition to improving general economic benefits. In this study, we look at the reasons for and effects of smaller holder. The study identifies four important problems with smaller holders. We explicitly suggest that we investigate how certain framings and measurements may lead to unjust social outcomes and that research on dairy system reforms be conducted in the context of more general social-environmental change processes. This type of work could be helpful in imagining improvements toward more ethical, ethical, and ecological food systems [13].

Dananjayan S, the ultrafast network will be crucial to farming operations over the next ten years, helping to boost agricultural quality and yields while requiring less manpower.Farmers may become more knowledgeable and productive by using smart and precision farming. The arrival of will drastically alter the nature of farming and agricultural jobs. An exhaustive examination of agriculture technology is provided in this article. The necessity and purpose of intelligent and high accuracy farming, the benefits of implementations for smart agriculture like real-time monitoring, simulated discussion, and preventative analysis, big data, cloud repositories, and career prospects are all covered in this paper's thorough analysis of cloud computing implementation in the agricultural sector [14].

Caraviello states commercial success depends on the fertility of lactating dairy cows, yet over the past three decades, Holstein cows' average reproductive performance has declined. Pregnant status at 150 days in milk and the initial high fertility two features that are influenced by a number of explanatory factors that are specific to various farms or certain cows on these farms. When tackling multicollinearity, missing data, or intricate relationships between variables, machine learning approaches offer a great degree of flexibility. Information from fields taking part in Alta Genetics Advantage's genetic material program were used for this investigation. A total of 153 farms' production and reproduction records were collected using the on-farm herd management programs DHI-Plus, Dairy Comp 305, or PCDART. One assessor rated the physical state of 63 farms while completing questionnaires on administration, infrastructure, labour, nutrients, reproductive, genetics choice, weather, and milk supply on 103 farms' managers' behalf. Nearby weather stations provided data on the temperature. The new data set comprises 14,804 cows, 31,076 lactation records, 317 independent variables, and 341 supporting factors for the reproductive status at 150 DIM and first-service conception rate, respectively[15].

Jeong has argued Because precise crop output estimations are required for the local and international development of effective agricultural and food policy. We compared the effectiveness of random forests and multiple linear regression modeling in forecasting agricultural production responses to climatic and biophysical characteristics for the three crops of grain, maize, and spud on the regional and global scales. We used farm yield data from multiple sources and regions for model development and evaluation. Random forest outperformed MLR benchmarks across the board and was shown to be fairly good at predicting agricultural productivity. Accurate crop output projections are essential for carrying out agricultural and food programs that are both efficient and effective.RMSE for Estimation techniques were almost 6 to 14percentage points of the number of standard yields in all test situations, whereas these numbers ranged from 14% through 49% for Linear regression models. Random Forest could be less accurate when predicting extremes or reactions beyond the bounds of the training data[16].

Cockburn states However, the inability of farmers to evaluate information about their cattle farm due to a lack of data integration suggests that these data are now underused. As a result, dairy farming continues to face a number of difficulties, including low lifespan, subpar performance, and health problems. We were interested in finding out if machine learning (ML) technology could address some of the current issues in the dairy industry. The peer-reviewed and published ML works in the dairy sector between 2015 and 2020 are collected in this study. This review took into account 97 papers from the management, physiology, fertility, prediction, and psychological subdomains. Despite the abundance of research available, the majority of analyzed algorithms have not delivered results that are sufficient for deployment in real-world settings. Insufficient training data may be the cause of this. Longer time horizons and a variety of data farms might be useful to increase forecast accuracy. In conclusion, machine learning is a possible technique in cattle research that might be applied to create and enhance assistance for farmers. The availability of open data is still limited, and integrating a wide variety of data sources is still a challenge [17].

Slob states 97 articles from the management subdomains were ultimately chosen. A variety of academics and experts have addressed various approaches to predict various factors of interest in the setting of family farms in recent years, the majority of which were linked to new ailments. This article's goal is to locate, assess, and synthesize publications that look at machine learning's use in the management of dairy farms. We collected 427 publications using a systematic literature review (SLR) methodology, of which 38 were classified as primary studies and consequently given a detailed analysis. 55 percent of the research were concerned with identifying illnesses. The two additional categories of concerns taken into consideration were milk production and milk quality. There were discovered to be 71 independent variables, which were divided into seven groups. The most common categories were milking variables and milk yield, which were covered in more than half of the studies. Other types of independent factors included information about cow traits, lactation, pregnancy/calving details, milk composition, and farm characteristics. We found 23 algorithms and categorized them into four groups. Regression-based approaches and other methods outside the aforementioned categories were applied in 13 investigations. Seven of the twenty-three assessment parameters that were found were used three times or more. Hardness, accuracy, and RMSE were employed as evaluation measures in more over half of the publications. The most frequent difficulties were with feature selection and imbalanced data, while system size, generalisation, and parameter modification also had a role in the difficulties identified. That will be helpful for both academics and dairy farm operators [18].

Benos states to extract value from the constantly growing amount of data from multiple sources, the digital transformation of agriculture has changed many managerial functions into artificially intelligent systems. Building knowledge-based agricultural systems presents a number of challenges that can be addressed by machine learning, a type of artificial intelligence. Using keyword pattern of "machine learning" coupled with "crop management," "water management," "soil management," and "livestock management," along with principles, the current study seeks to shed light on machine learning in agriculture. The study was limited to journal articles released between 2018 and 2020. The results show that this subject has application in a number of areas that support global convergence research. Additionally, it was established that crop management is to look on attention. Artificial Neural Networks were the most effective of the machine learning approaches that were used. The most extensively studied crops and animals were maize and wheat, along with cattle and sheep.Lastly, to get precise data entry for the big data, a variety of sensors installed on satellites and unmanned land and air vehicles were deployed[19].

Fenlon proposed the goal of this study was to create and evaluate prediction models of calving difficulties in dairy heifers and cows for simulation modelling and decision assistance. To forecast three calving difficulty levels, models were created utilizing four machine learning approaches. 2,076 calving records from 10 Irish dairy cows were the source of the data. Overall, 19.9 and 5.9% of calving experiences required some kind of veterinary care, whether it was small or major. The factors in the models were the sire's breed, sire's direct calving difficulty, the dam's direct and maternal calving difficulty projected transmitting abilities (PTA), BCS at calving, parity prior to calving assistance or difficulty, and the fraction of Holstein breed. Bootstrapping techniques were used to build the models using 70% of the data set. The models' calibration and discrimination performance were evaluated using the remaining 30% of the data. Only specific sire breed subgroups were included in the decision tree and random forest models, which precluded twinning. Only neural networks and multinomial regression explicitly included the simulated relationships. The highly essential factors in all four models were calving BCS, calving difficulty PTA, and prior calving assistance. The multinomial regression and neural network models fared better than the others, accurately classifying 75% of calving circumstances and displaying stronger calibration, with average errors in predicted probability of 3.7 and 4.5%, respectively[20].

According to Bates, the overall health score, which takes into account confounding factors and interactions, has a complicated, dynamic, and non-linear effect on reproductive outcomes. The inherent flexibility of machine learning algorithms in the interpretation of complex data makes them intriguing. This study examined the capabilities of several algorithms using machine learning to determine the likelihood of service after 21 days of the anticipated beginning of mating. Our hypothesis is that if the data contained complicated and unknown interactions or non-linearity, some machine learning techniques would provide superior performance of the model than regression models. Using the federal herd database, information on cows, nursing, and fertility was obtained. This information was used to determine the probability of service within 21 days of the projected start of mating using mixed multivariable regression techniques, decision trees, k-nearest neighbors, regression trees, and neural network analysis. The herd, the maturity level and breed of a cows, the duration that the cows were in dairy, the BCS at stage of lactation, the change in BCS among both calving and copulating, the start changing in BCS after copulating, the perceived loudness milk solids and fat ability to focus before copulation, and the perceived loudness whey proteins and fat density after copulation were all taken into account in the models' adjustments. Nevertheless, a calibration investigation revealed that all algorithms performed better at identifying cows who weren't inseminated than at foretelling cows that had Generalized logistic regression did not perform any better than machine learning techniques overall [21].

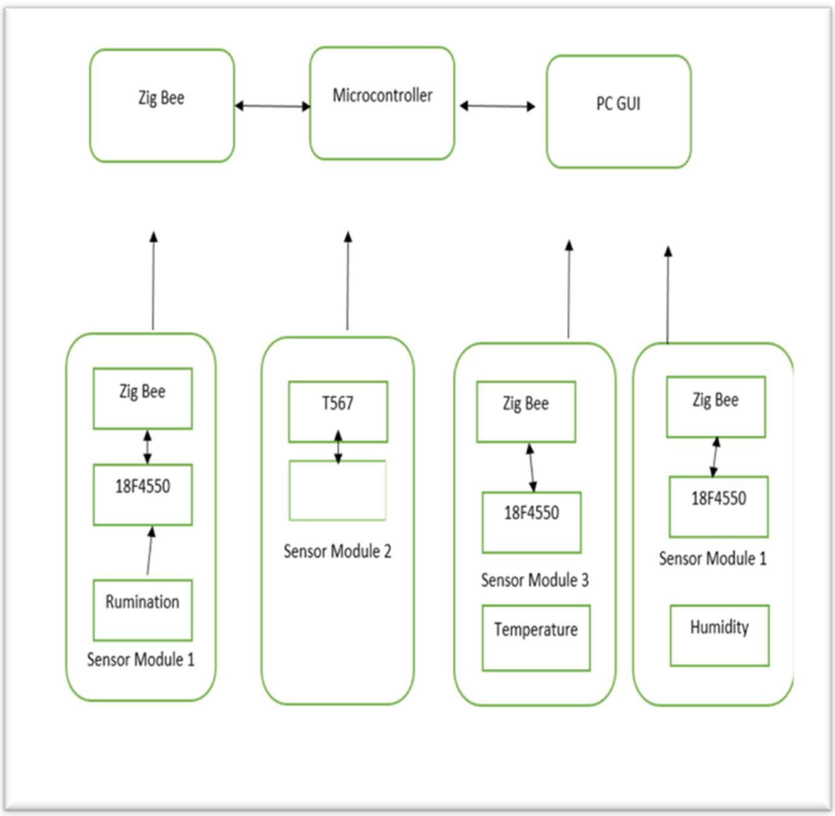

Figure 1: Smart Health Monitoring AnimalsSmart Wearable Watch For Health Monitoring For Dairy Animals

The condition of animal health is a major problem in the modern world. We must wait for an assessment and diagnosis from veterinary professionals in order to monitor an animal health.Delay in therapy and a decrease in animal health are the end outcomes of this. As a result, we recommended creating a system that monitors an animal's health to make it simpler for the animal's owner to do a basic health examination. For this, we have sensors that measure blood pressure, heart rate, temperature, and breathing rate. The relevant physiological data, including hypertension, temp, heart rate, and other vital indicators like the ECG and breathing rate, may be collected by developing a system with devices that can be mounted on an animal's body [41].This method will improve the novelties and viability of animal healthcare. The development of an appropriate medical tracking system for animals follows. Figure 1 showed a Smart Health Monitoring Animals Smart Wearable Watch For Health Monitoring For Dairy Animals.

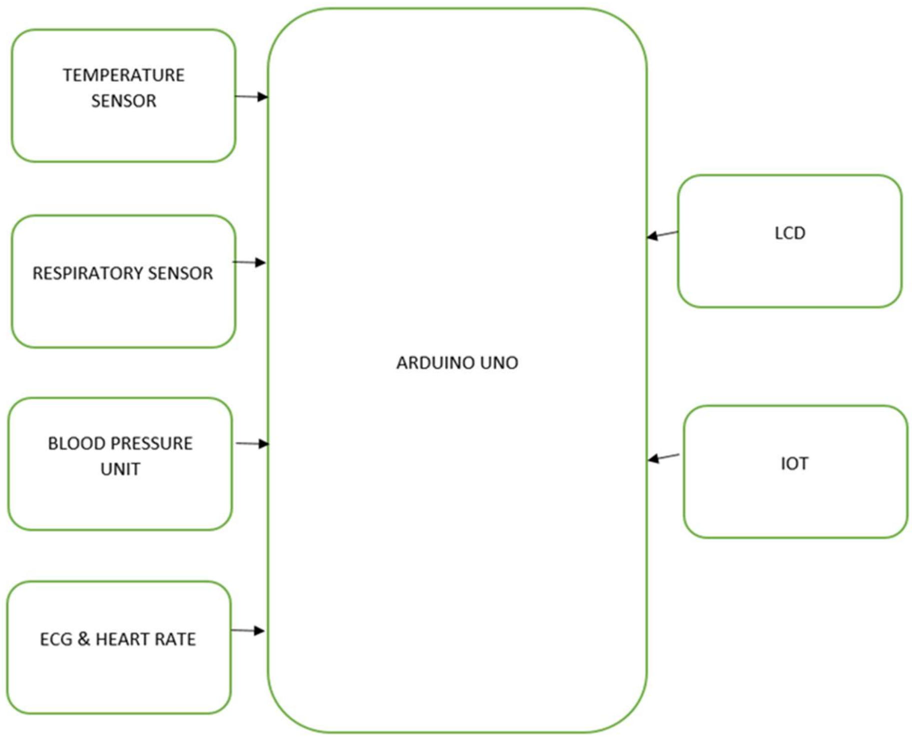

Figure 2. Smart Wearable Watches For Dairy Farming Animals

Figure 2 showed a Smart Wearable Watches For Dairy Farming Animals. Here are four ways artificial intelligence (AI) might change the sector and enhance the lives of small-scale farmers, and how public-private collaborations will be essential to their success.

- DIGITAL IDENTITY
- HEALTH MONITORING
- CATTLE TRADING
- FINANCIAL INCLUSION

HEALTH MONITORING:

Given that it is closely related to milk production; cow wellness is the most crucial component of any dairy operation. One of the more prevalent illnesses in the dairy business, sub-clinical mastitis, costs the Indian dairy sector $billion dollars a year.

IOT devices are now required by the cow health monitoring sector to gather real-time data about cattle, including their movement habits, rumination patterns, and temperature variations. The collar, which is worn around the neck of calves and transmits copious quantities of data every second, is the IOT gadget that is most widely used in the dairy business. Moreover, this information may be utilized to identify preclinical illnesses, such as cattle heat signs. Also, these solutions help strengthen the bond between growers and insurance providers. Due to the high rate of identity fraud, there is a significant level of mistrust between farmers and insurance providers, as seen by the meager 9% market penetration for cattle insurance. Hence, computerized detection and inspection systems can contribute to increased confidence between insurance firms and farmers.

We are handling this issue differently at Nonfarm. In collaboration with Microsoft, we are developing a tool that utilizes photographs of the udder to determine whether a cow has subclinical mastitis. Among many other criteria, the program recognizes changes in marks or udder discolouration to make the prognosis. Also, we are currently developing an idea that will allow us to calculate the Body Condition Score (BCS) only based on photographs of the cattle taken from three distinct perspectives.

DIGITAL IDENTITY:

Many nations, including the EU, the UK, and the US, employ "cattle passports" on their cattle to monitor infectious disease outbreaks, verify the successful implementation of government programs, and process insurance claims. This really implies that many cattle have tags pierced into their ears to identify them. These tags are not only uncomfortable for the creatures, but they are also unreliable. Farmers in certain underdeveloped nations, including India, chop the cattle's ears in order to conduct identity theft and submit false insurance claims.The technology is being produced at scale by Nonfarm, an Aggrotech start up with the objective "to make farmers affluent," and it is collaborating with the government to develop a reliable cow identification system. Many ancillary services, such as cow insurance, cattle loans, and government subsidies, might be built on this technology. In addition to Stelas, Canthus, Tec vantage’s Moo-ID, and other businesses are trying to provide a product that is ready for the market.

Also, these solutions help strengthen the bond with farmers and insurance providers. Due to the high rate of identity fraud, there is a significant level of mistrust between farmers and insurance providers, as seen by the meagre 9% market penetration for cattle insurance. Hence, computerized detection and inspection systems can contribute to increased confidence between insurance firms and farmers.

CATTLE TRADING:

Another sector that is currently quite disorganized and has a lot of room for development is cattle trade. Negotiations between buyers and sellers are now used to determine the price of cattle. We can use machine learning models to create a live cattle price exchange where buyers and sellers can communicate on a transparent platform while the price of the cattle is displayed like stocks on an exchange if we have access to the history of the cattle, which includes details about dairy productivity, maturity level, health records, sire, and dam.

FINANCIAL INCLUSION:

By employing indirect methods to determine the creditworthiness ratings of farmers and awarding loans to them based on those scores, AI can assist in resolving this issue. Several businesses in the sector use unusual data to determine how bankable farmers are and provide loans to them, including psychometric surveys, social networks and network links, mobile usage, SMS, phone conversations, and similar datasets.

III. PROPOSED METHOD

We can accurately estimate farm animal performance with the use of technology. Parity, milk yield components, and body condition score may be used to determine their lactation energy expenditures (BCS). So, utilizing current farm data, the metabolic condition of cows may be assessed. In addition to the previously mentioned estimation of milk yield, reproduction efficiency, calving time, breeding values, and even mastitis detection, machine learning technologies can help farmers. Other uses for sensors include monitoring behavioral changes to spot cows going through the estrous cycle and cows with healthy digestive functions[22-30]. By helping farmers produce high-quality milk, this will enable them to increase their revenue. Utilizing motion and sound sensors to monitor animal behavior may allow for the potential detection of acidosis in cows. Similar to that, calving time may be predicted with an accuracy of more than 90%. This may take the place of currently available pricey, time-consuming, and usually inaccurate choices. Reduced labor discomfort and dystocia are further benefits of predicting the precise moment of calving. This is a tremendous advancement in herd management [31-35].Figure 3 shows a system design of dairy farming using artificial intelligence.

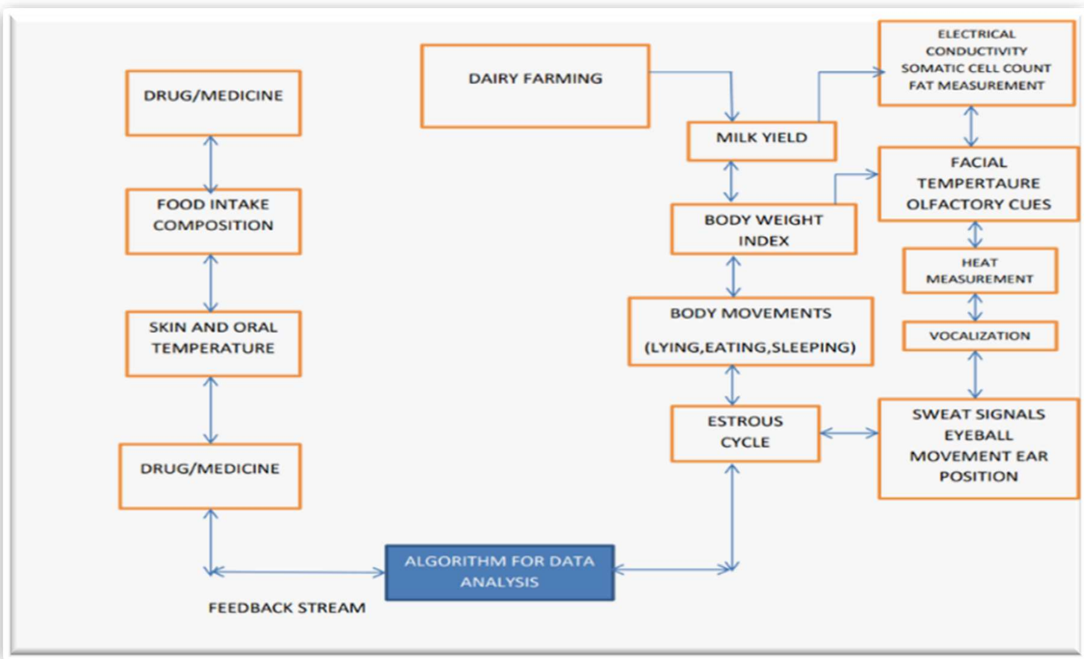

Figure 3.System design of dairy farming using artificial intelligence

Table 1. Smart Health Monitoring for Animals

Types of Algorithms	Beneficial Algorithms
Tree-based decision-making algorithms	regression tree for classification, Gradient boosting machine, Classification tree modelling, Randomized Forest, Judgment stump model, Naive Bayesian model, and Gradient boosting tree

Algorithms based on artificial neural networks	synthetic neural network System for Adaptive Neuro-Fuzzy Interface, network of convolutional neurons, Exogenous input nonlinear autoregressive model, neural network, deep self-contained maps, Perceptron multilayer
Algorithms based on regression	Multi - linear model, multivariate linear regression portions of least square, Logistic regression, multiple linear regression
Others	Network model, fuzzy logic model, support vector machine, and JADE
Algorithms based on regression	General linear model, multivariate linear regression portions of least squares, Logistic regression, multiple linear regression

In Table 1. Describes Smart Health Monitoring for Animals. The production rate and projected yield criteria were used to determine the minimum milk interval, which was then determined using the Crystal program. Depending on how long it had been since their last milking, cows were recognized and routed toward the dairy or the pasture as they departed the cow-operated one-way gates and through a computer-controlled pneumatic gate. A communication line placed above ground in alkathene linked the AMS computer in the dairy to the AMS server that was configured to make this choice. To operate the exit gates, compressed air was employed. A radio transponder identifying device that was installed on the leg of the cow enabled for automatic detection at the AMS. According to the actual yield compared to the projected output for each milking, the milking result was automatically computed. The cow was usually sent to the holding yard for another try at milking after an unsuccessful milking, which was usually due to one or more cups not being securely fastened to the teat or being removed too soon. The cow was permitted to go to the pasture upon leaving the AMS rate if the milk output was high enough to provide an outcome. As a consequence, the cow was permitted to visit the dairy earlier for another milking. The pictorial Representation for Dairy Farming Using Artificial Intelligence is showed in Fig.4.

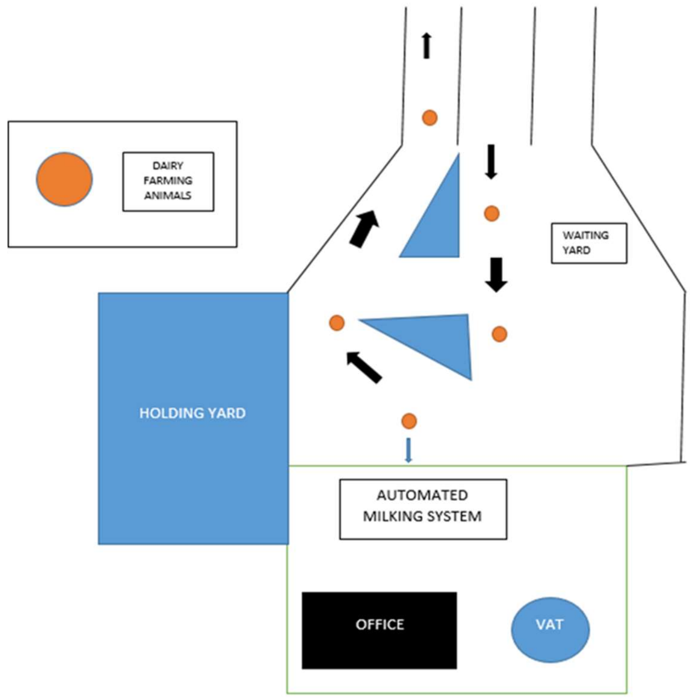

Figure 4. Pictorial Representation For Dairy Farming Using AI

Figure 5 explains the variable structure element-based impedance sensor can identify various forms of contaminated milk and tell the difference between fake milk and real milk. It is stated that milk adulteration may be found using a user-friendly, low-cost instrumentation device. The performance of a circuit to condition signals is investigated in an instrumentation system. A microcontroller-based autonomous sensing system has been claimed to detect synthetic milk, reducing the requirement for trained labor. Modelling the impedance sensor submerged in milk and milk that has been tampered with takes into account the dipole layer capacitor at the interface. A suggested equivalent electrical circuit is verified theoretical and experimental research.

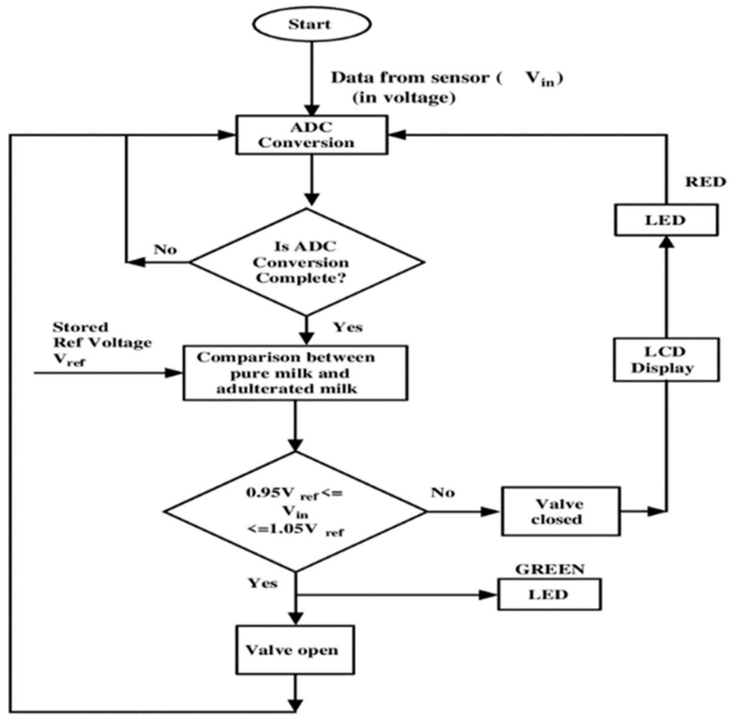

Figure5. Automated Milking System Block Diagram

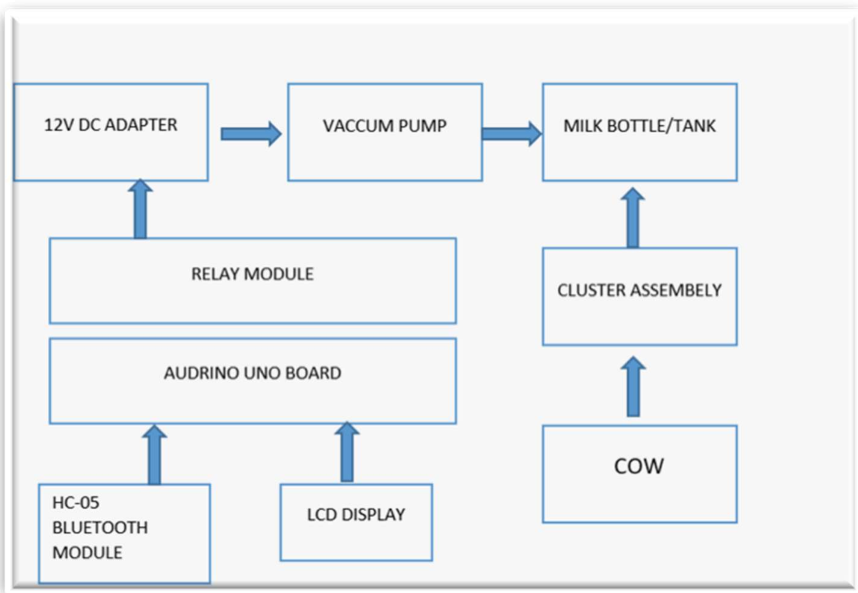

Figure 6: Milk Quality Check Using Audrino

Figure 6 explains how milk quality is checking by using Audrino. Farmers can deliver their milk to this setup at a neighbouring dairy or milk dealer. It is possible to utilize this instrument as a main milk analyser. This device is ready for use once it has been installed correctly and powered on using a 5-volt direct current source through to the power supply module. Data from the different sensors linked to the Arduino Controller are first read. A pH sensor measures the acidity of a milk sample. Milk's pH should range from 6.5 to 6.8. This gaseous sensor can measure hazardous greenhouse gases from a milk sample or identify microbial activity in milk.

A temperature sensor determines the milk's temperature, and the light scattering theory is used to calculate the FAT content. Laser diodes are used to measure the dispersion of light beams that are emitted by LCDs. A milk sample has a tendency to scatter light when it passes through it. Light is scattered by the milk sample that Light Dependent Register gathered, and this light is then reflected by the milk sample [61-66]. As the light dispersed from the milk sample changes, the LCD resistance changes, and the controller board receives the measured information. if the dairy has more fat. Light is widely scattered by the sample. The quantity of light that Milk scatters is inversely related to the change in LCD resistance.

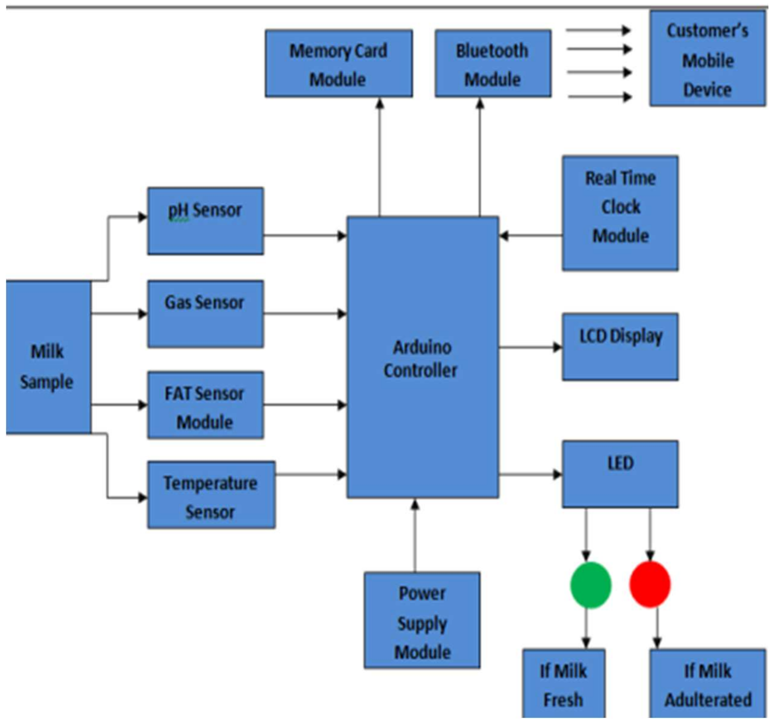

Figure 7. Block Diagram for Farm Management using different sensors

This suggested scheme includes the UNO version. The Arduino Uno is a kind of microcontroller. It's a hybrid hardware and software circuits platform board that is open-source. Direct pre-programming is possible through USB. It is built around the microcontroller ATmega328P. There are also 16 MHz ceramic resonators, electronic I/P and O/P connectors, analog I/P pins, a USB link, a power connector, and a reset button. Connecting to additional circuits modules and sensors is straightforward. Its working voltage is 5 volts DC. The gadget is controlled by a low-cost microcontroller board, which yields speedier and more dependable results.Figure 7. Shows a Block Diagram for Farm Management using different sensors.

IV. EXPERIMENTAL RESLUTS

The functioning of the entire system is controlled by Arduino. This system has been pre-calibrated with criteria for several milk properties that have known values. The Green LED blinks when all parameters are within the usual range. The Green LED blinks when all parameters are within the usual range. It denotes that the milk sample is pure, fresh, and toxin-free.If the test parameters are either below or beyond the standard values, the RED LED will flash. The milk sample has either been tampered with, is toxic, or is otherwise inappropriate for eating. A mobile device can use the Bluetooth module linked to this Controller to obtain the sample data[36-40]. Figure 8 showed overall connection set up for Farm management.

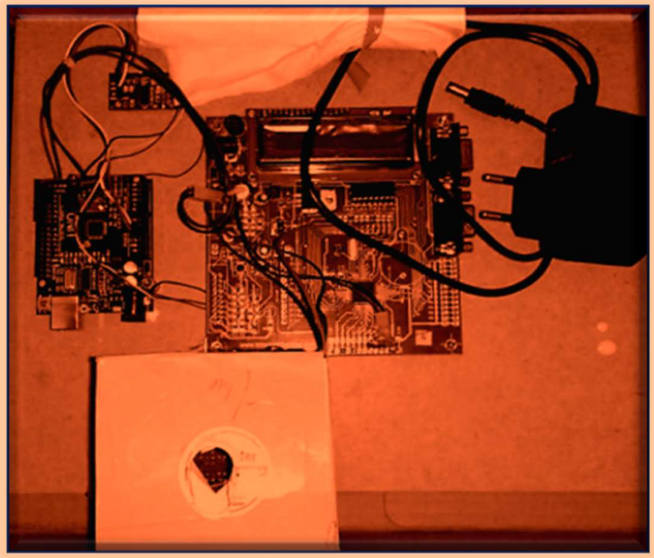

Figure 8. Management of FARM using Artificial Intelligence

Figure 9. Automated Milking Machine

Figure 9 showed a milk quality checker with the help of Artificial Intelligence and Automated Milking Machine. As a result of the vacuum pump replacing the compressor's high level suction pressure, this project aids in the reduction of mortality and disease.Professional approaches for monitoring animal health are inadequate because they produce inconsistent data and need a high level of effort and veterinary expertise. Such technologies that provide data on the animal's present condition do not yet exist. Animal health monitoring systems allocate hardware that will attach on the animal body.These days, it takes a while for veterinary expertise to show up before we can evaluate an animal's health. In addition to improving each individual animal's health, the technology may identify and stop common illnesses, whether they are brought on by biological invaders or other natural causes.Such a technology would aid in the early detection of illnesses. The system has four sensors in total: a digital temperature, a sensor for heart rate, rumination sensor, and rumination sensor. We utilized an Arduino microcontroller and a Zig bee device to construct the sensor module. The values are shown on the Computer using the user interface with graphics (GUI). The tool is crucial and useful for maintaining an animal's health. In Figure 7 showed a Smart Health Monitoring Animals Smart Wearable Watch for Health Monitoring for Dairy Animals. Table 2 shows a comparison for existing authors for SLR study.

Table 2. Title and authors of the identified papers in the SLR study.

S.No	Reference	Title of the Paper
1.	**R [42]**	Detecting the relationship of California mastitis test (CMT) with electrical conductivity, composition, and quality of the milk in Holstein-Friesian and brown swiss cattle breeds using cart analysis
2.	**R [43]**	Using decision trees to extract patterns for dairy culling management
3.	**R [44]**	Predicting first test day milk yield of dairy heifers
4.	**R [45]**	Application of neural network and adaptive neuro-fuzzy inference system to predict subclinical mastitis in dairy cattle
5.	**R [46]**	Investigating associations between milk metabolite profiles and milk traits of Holstein cows
6.	**R [47]**	Short communication: Use of genomic and metabolic information as well as milk performance records for prediction of subclinical ketosis risk *via* artificial neural networks
7.	**R [48]**	Hierarchical pattern recognition in milking parameters predicts mastitis prevalence
8.	**R [49]**	Extraction of Patterns to Support Dairy Culling Management
9.	**R [50]**	On the utilization of deep and ensemble learning to detect milk adulteration
10.	**R [51]**	Comparison of forecast models of production of dairy cows combining animal and diet parameters
11.	**R [52]**	Detection of high levels of somatic cells in milk on farms equipped with an automatic milking system by decision trees technique
12.	**R [53]**	Automated prediction of mastitis infection patterns in dairy herds using machine learning
13.	**R [54]**	Subclinical mastitis prediction in dairy cattle by application of fuzzy logic
14.	**R [55]**	Detection of clinical mastitis with sensor data from automatic milking systems is improved by using decision-tree induction

15.	**R [56]**	Application of Classification Tree Method to Determine Factors Affecting Somatic Cell Count in Holstein Cows
16.	**R [57]**	Detection of dairy cattle Mastitis: modelling of milking features using deep neural networks
17.	**R [58]**	The discrimination of raw and UHT milk samples contaminated with penicillin G and ampicillin using image processing neural network and biocrystallization methods
18.	**R [59]**	Lactation milk yield prediction in primiparous cows on a farm using the seasonal auto-regressive integrated moving average model, nonlinear autoregressive exogenous artificial neural networks and Wood's model
19.	**R [60]**	Effect of introducing weather parameters on the accuracy of milk production forecast models

IV. CONCLUSION

The animal welfare, milk output, and quality could all be automatically measured using the machine learning techniques used for this study. Depending on the model inputs, any dairy farm may apply this machine learning modelling technique. Only modest technological advancements, like as automated gate and cooling systems, will be needed for AI on cattle dairy, including the ML models created there. In order to help small and medium-sized dairy farmers compete more effectively on the global market, this article demonstrated a practical use of AI by utilizing precise data from a robotic dairy farm.

ACRONYMS

AI Artificial Intelligence
ML Machine Learning
SVM Supporting Vector Machine
PCDART Personal Computer Direct Access to Records by Tele
AMS Automatic milking systems
BCS Body Condition Scoring
AMS Automated Milking System
SLR Statutory Liquidity Ratio
PTA Projected transmitting Abilities
RMSE Root Mean Square Error

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