



Smart Diary Forms: Artificial Intelligence for Efficient Diary Farming

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ABSTRACT

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The dairy industry is experiencing a technological revolution as artificial intelligence transforms traditional farming methods. Modern AI applications are revolutionizing how farmers manage their herds, optimize production, and maintain animal welfare standards. AI technology addresses critical challenges in dairy operations by providing farmers with sophisticated tools for herd management. These systems enhance both productivity and animal care through real-time monitoring and data-driven decision making. The technology creates opportunities for farmers to build more sustainable and profitable operations while ensuring optimal conditions for their livestock. Key applications of AI in dairy farming include comprehensive livestock monitoring systems that track animal behavior and movement patterns throughout the day. Advanced sensors and computer vision technology enable automated health assessments, detecting early signs of illness or stress in individual animals. Automated milking systems optimize production schedules while reducing labor requirements and improving milk quality consistency. Location tracking systems provide farmers with detailed insights into grazing patterns and herd dynamics, enabling better pasture management and resource allocation. Image recognition technology assists in facility design and maintenance, ensuring optimal housing conditions that promote animal comfort and health. This integrated approach to dairy farming represents a significant advancement in agricultural technology. By combining health monitoring, automated milking processes, and comprehensive livestock tracking, AI systems create a foundation for more efficient and humane dairy operations. These innovations not only benefit farm economics but also contribute to improved animal welfare standards and sustainable farming practices. This system will track cow health, do robotic milking, monitor cattle locations. The implementation of AI-driven dairy management systems offers farmers unprecedented opportunities to enhance their operations while maintaining the highest standards of animal care and environmental responsibility.

1. INTRODUCTION

Recent studies highlight the use of artificial intelligence (AI) in agriculture for predictive analytics, autonomous systems, and real-time monitoring. This paper leverages convolutional neural networks (CNN) models, Radio Frequency Identification (RFID), and temperature sensors to address inefficiencies in traditional dairy farms.

Recent advancements in AI, such as convolutional CNN and real-time IoT analytics, are transforming livestock monitoring and disease detection. This study leverages these technologies to propose a unified framework that addresses multiple dairy farming challenges. The dairy sector has adopted innovative methods and tools to improve productivity, herd management, and efficiency [1]. Dairy managers

specifically employ software that has been integrated with precision dairy technologies to manage individual cows within a herd or to determine whether the herd is performing as intended. Precision livestock farming (PLF) is the idea of using data from sensors to make well-informed decisions for managing cattle [2]. For instance, milk capture equipment is used by producers to monitor each cow's milk production. AI technology plays a significant role in intensive animal husbandry by supporting smart farming practices that increase animal health and wellbeing while also producing high economic returns [3]. AI-enabled PLF systems are used by dairy farmers to evaluate and interpret forecasts regarding their livestock [4]. AI can be easily understood by analogizing it to the human brain [5]. The human brain gets more proficient at finishing tasks and finding solutions as it learns and

develops new skills [6]. The following are the primary goals of using AI in dairy farming:

- To analyze and interpret predictions about their cattle using AI.
- To lower transportation costs and waste in order to support a more sustainable and productive dairy business.
- To assess, using precision dairy farming techniques, how animal production affects the amount of ammonium pollution from dairy cattle farms.
- Real-time processing and analysis of large volumes of data.

Many studies in sensors, data processing and transmission, AI models of machine learning (ML), deep learning (DL), artificial neuro networks (ANN), etc., have been conducted recently to address issues about animal identification [7] behavior detection [8], disease monitoring [9], environment control [10], and other related areas. For cattle breeding and dairy farming, numerous Internet of Things sensors and technologies have been developed. The 1980s saw the beginning of the development of cow management on an individual basis. By using an enzymatic reaction, Lactate Dehydrogenase (LDH) in milk can be measured online with Herd Navigator (DeLaval Ltd., Cardiff, UK). Somatic cell counts (SCC) are strongly connected with LDH and are a strong indicator of mastitis [11]. According to De Koning, more than 8,000 farms had the automated milking system installed by the end of 2009, and it can handle bigger herds with less physical effort and labor expense [12].

2. LITERATURE REVIEW

The novelty of this work lies in integrating multiple AI modules—health monitoring, productivity estimation, and cow ID—into one IoT- and ML-driven platform. Existing solutions often address these in isolation.

- Cattle trading and identification: Digital ID, mobile-based AI tools.
- Productivity: CNN for cow ID and feed pattern recognition.
- Milk quality: Image processing for fat detection, Arduino-based pH and gas sensors.
- Health monitoring: ML for mastitis detection, wearable IoT devices.

Achour et al. [13] stated 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, look at the reasons for and effects of smaller holder. The study identifies four important problems with smaller holders. The work explicitly suggest that 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.

Neethirajan [14] developed 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].

Bobbo et al. [15] stated 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 Personal Computer Direct Access to Records by Tele (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 dimension and first-service conception rate, respectively [15].

Rajendran et al. [16] argued because precise crop output estimations are required for the local and international development of effective agricultural and food policy. The work 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. The used farm yield data from multiple sources and regions for model development and evaluation. Random forest outperformed Medical Loss Ratio (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. Root Mean Square Error (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].

Fenlon et al. [17] stated 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. The work was interested in finding out if 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].

Bates and Saldias [18] stated 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. The work 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. The work 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].

Hyde et al. [19] stated 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].

Selvanarayanan et al. [20] proposed the objective of this study was to make and assess expectation models of calving troubles in dairy yearlings and cows for reproduction demonstrating and choice help. 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 sire's breed, the sire's direct calving difficulty, the dam's direct and maternal calving difficulty, projected transmitting abilities (PTA), Body Condition Score (BCS) at calving, assistance or difficulty prior to parity, and the percentage of Holstein breed were the factors in the models. 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. In all four models, calving BCS, calving difficulty PTA, and prior calving assistance were extremely important factors. With average errors in predicted probability of 3.7 and 4.5 percent, respectively, the multinomial regression and neural network models performed better than the others, correctly classifying 75% of calving circumstances and displaying stronger calibration [20].

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].

The condition of animal health is a major problem in the modern world. The work 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, 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, 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 [22]. The proposed Image analysis for individual identification and feeding behaviour monitoring of dairy cows based on CNNs. They developed a non-invasive strategy that only makes use of image analysis. Several classifiers based on the CNN model were used to identify each of the seventeen Holstein dairy cows individually and track their feeding habits. The image of the dairy cow's top served as a Region of Interest (ROI) for these classifiers. According to their findings, their approach achieves high scores at each stage of their algorithm. Also, they proved that out of the three classifiers employed for dairy cow identification, the clustering-multiples CNN classification method yielded the highest accuracy.

Logapriya and Surendran [23] proposed the significance and ethics of digital livestock farming. Animal welfare and sustainability should be prioritized by creating norms and rules of conduct for the adoption and use of digital platforms and tools for livestock farming, which can help address these ethical issues. This can enhance the sustainability of animal husbandry methods and allay stakeholders' worries about privacy. Furthermore, the application of virtual and augmented reality technologies can improve human-animal relationships and provide more individualized care for animals, thus advancing animal welfare. The researcher compared different machine learning algorithm to predict udder health status based on somatic cell counts in dairy cows. All approaches have prediction accuracy greater than 75%. Neural network, random forest, and linear approaches performed the best in forecasting udder health classes on a particular test-day, based on several indicators. Their results point to machine learning algorithms as a potentially useful tool for helping farmers make better decisions. Machine learning analysis could enhance surveillance techniques and assist farmers in anticipating which cows may have elevated somatic cell counts on the next test day. 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 [23].

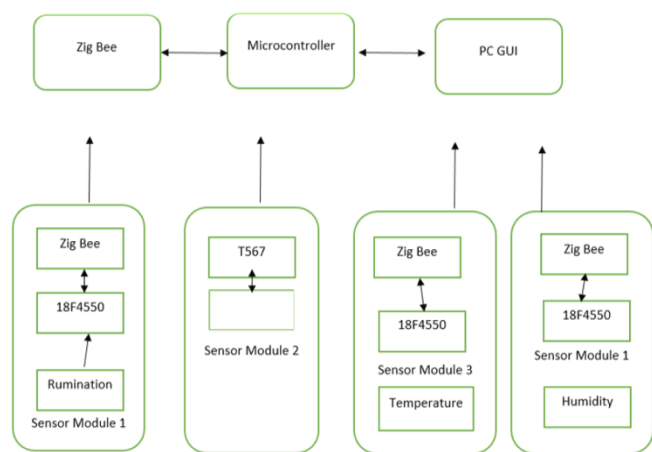


Figure 1. Smart health monitoring animals smart wearable watch for health monitoring for dairy animals

Figure 2 showed a smart wearable watch for dairy farming animals. Here are four ways 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

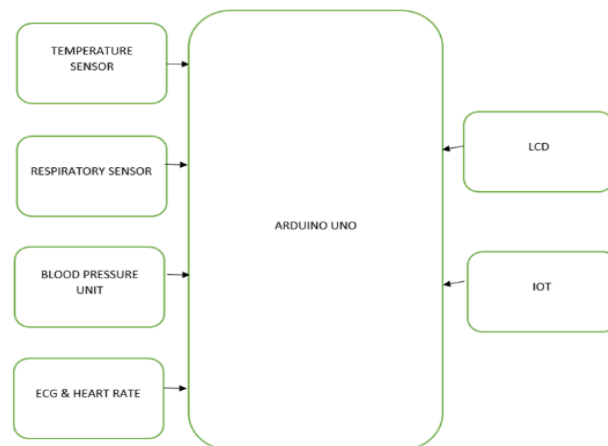


Figure 2. Smart wearable watches for dairy farming animals

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 [24]. Hence, computerized detection and inspection systems can contribute to increased confidence between insurance firms and farmers.

The work is handling this issue differently at Nonfarm. In collaboration with Microsoft, 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 dis colouration to make the prognosis. Also, are currently developing an idea that will allow us to calculate the BCS only based on photographs of the cattle taken from three distinct perspectives [25].

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 [26, 27].

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 [28, 29].

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. The work 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 have access to the history of the cattle, which includes details about dairy productivity, maturity level, health records, sire, and dam [30, 31].

Financial inclusion:

By employing indirect methods to determine the creditworthiness ratings of farmers and awarding loans to them based on tho0se 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 [32].

3. PROPOSED WORK

Evaluation metrics: Accuracy (mastitis prediction > 90%), RMSE (milk yield error < 6%), Precision/Recall (cow ID models > 92%). These were chosen based on classification and regression problem types.

Health monitoring: Sensors record BCS, temperature, and rumination. Data processed using decision trees and Supporting Vector Machine (SVM) models.

Milk quality: Light scattering and gas sensors detect FAT and microbial activity. Results displayed on LCD linked to Arduino.

The system includes temperature, heartbeat, rumination, and motion sensors connected via ZigBee to a central Arduino-based control unit. Sensor data is analyzed by ML algorithms for health and behavior prediction.

Using technology, the work can accurately estimate the performance of farm animals. Their lactation energy expenditures (BCS) can be calculated using their parity, the components of their milk yield, and their body condition score. So that the metabolic state of cows can be assessed using current farm data. Machine learning technologies can be of assistance to farmers in a variety of ways, including the estimation of milk yield, reproduction efficiency, calving time, breeding values, and even the detection of mastitis. Monitoring behavioral changes to identify cows going through the estrous cycle and those with healthy digestive systems are additional applications for sensors.

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. Figure 3 shows an architecture diagram dairy farming using artificial intelligence.

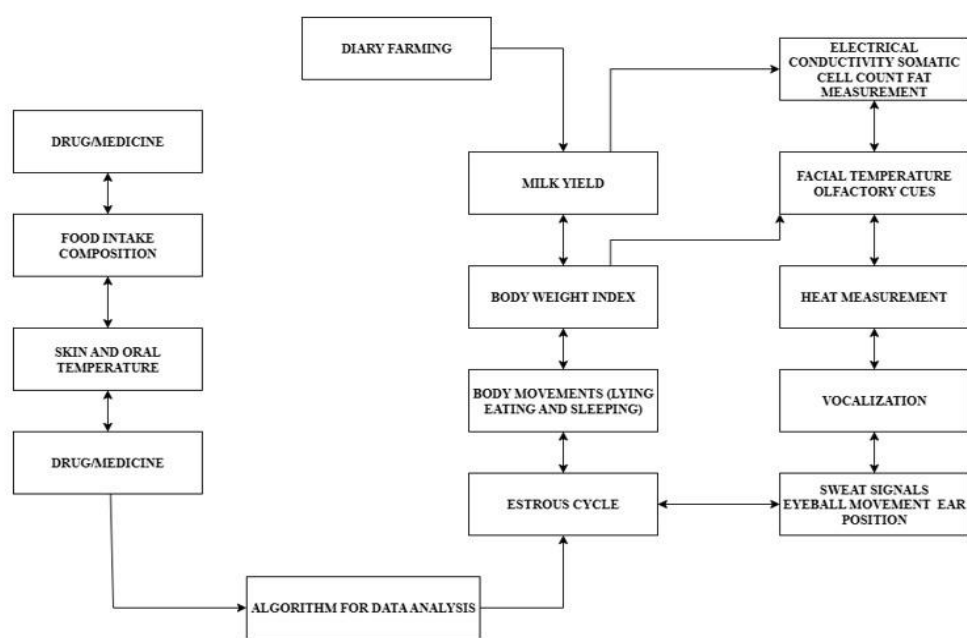


Figure 3. Architecture diagram for dairy farming using artificial intelligence

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, and support vector machine
Algorithms based on regression	General linear model, multivariate linear regression portions of least squares, logistic regression, multiple linear regression

Figure 3 shows the architecture for dairy farming using artificial intelligence and 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 Automated Milking System (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 shown in Figure 4.

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.

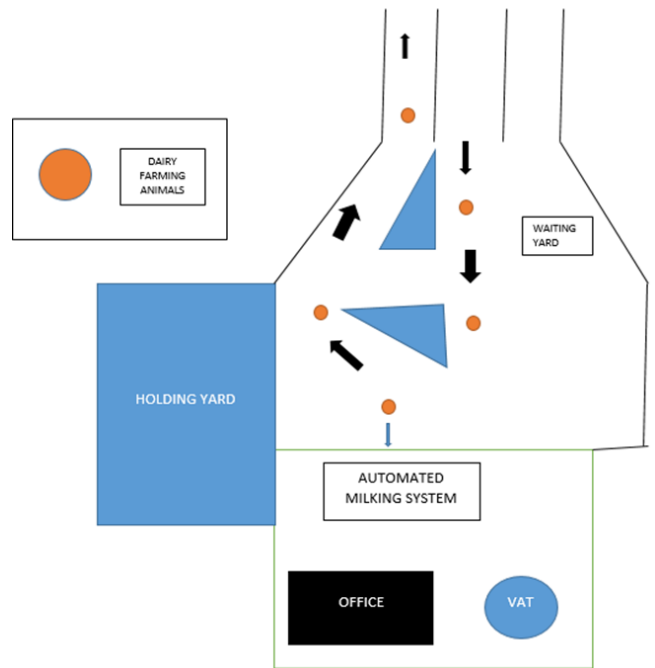
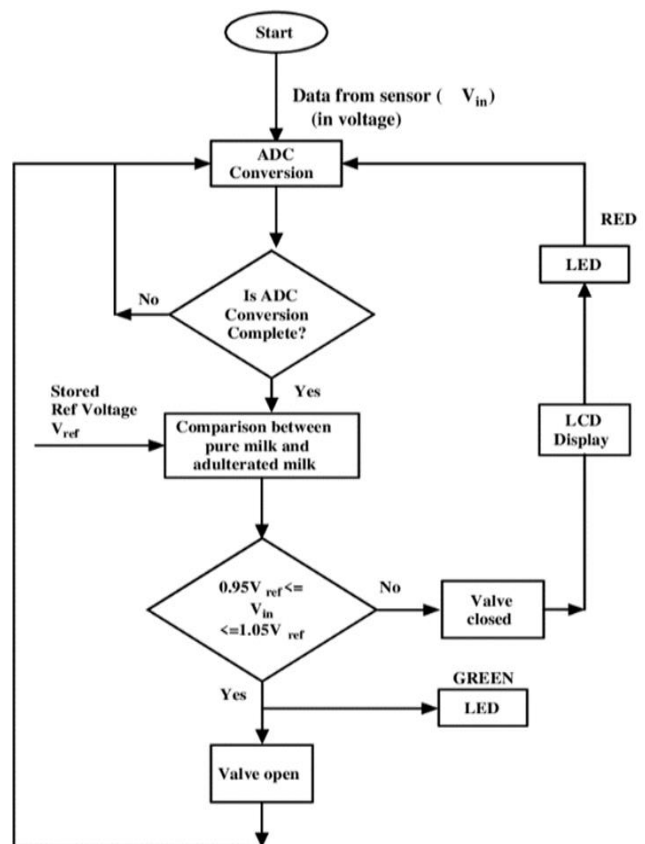
**Figure 4.** Dairy farming using artificial intelligence**Figure 5.** Automated milking system

Figure 6 shows how Audrino is used to check the quality of milk. Farmers can drop off their milk at a nearby dairy or milk dealer to get it to this setup. This instrument can be used as the primary milk analyzer. This gadget is prepared for use whenever it has been introduced accurately and turned on utilizing a 5-volt direct current source through to the power supply module. First, the data from the various sensors connected to the Arduino Controller are read. A pH sensor

measures how acidic a sample of milk is. The pH of milk ought to be between 6.5 and 6.8. This gaseous sensor can detect microbial activity in milk and measure potentially harmful greenhouse gases from a sample of milk.

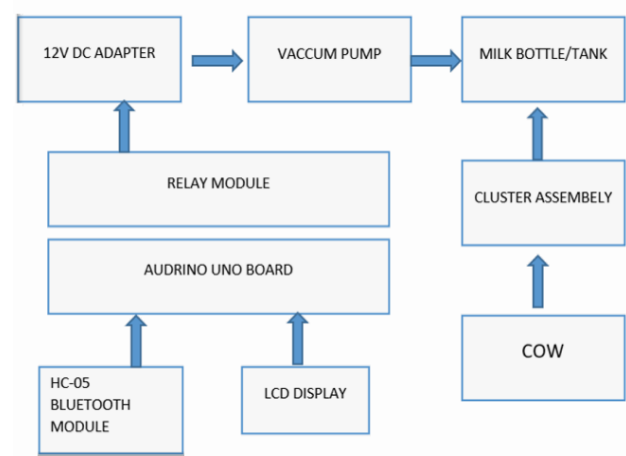


Figure 6. Milk quality check using Audrino

The milk's temperature is determined by a temperature

sensor, and the FAT content is calculated using light scattering theory. LCDs' light beam dispersion can be measured with the help of laser diodes. When light passes through a milk sample, it tends to scatter. The milk sample that the Light Dependent Register collected scatters light, which is then reflected by the milk sample. The LCD resistance changes as the milk sample's light scatters, and the controller board receives the measured data. if there is more fat in the dairy. The sample scatters light widely. The change in LCD resistance is inversely correlated with the amount of light that Milk scatters.

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. Figure 8 shows overall connection set up for farm management.

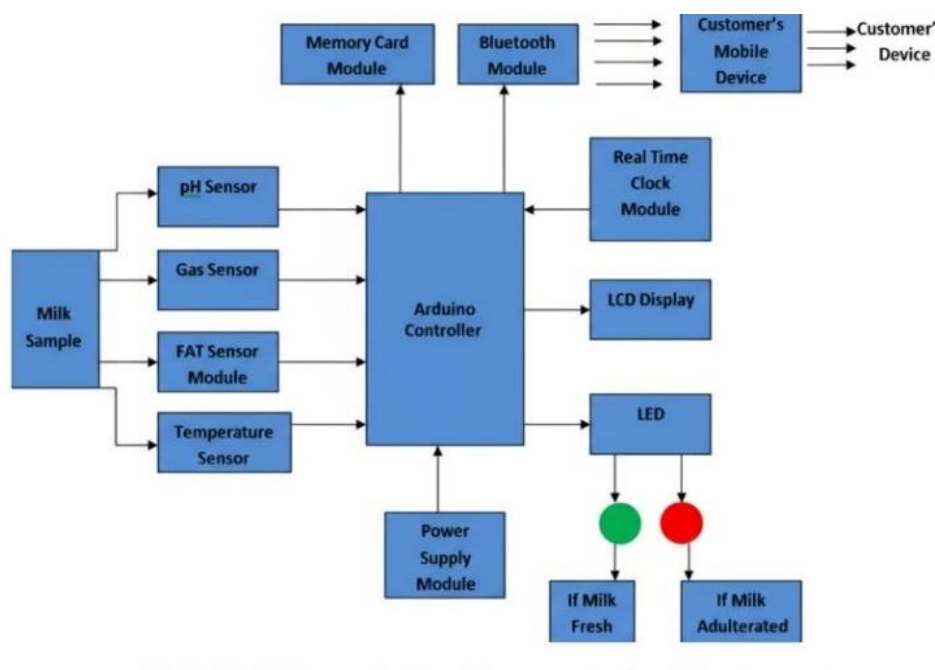


Figure 7. Block diagram for farm management using different sensors

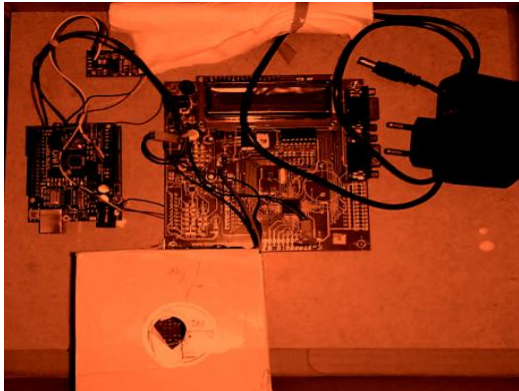


Figure 8. Management of FARM using artificial intelligence



Figure 9. Automated milking machine

Table 2. Reasons for low milk yield and their possible solutions

Category	Reasons	Solutions
Food and Water	Nutrition: The main nutrients that must be included in dairy cow feed are magnesium, calcium, phosphorus, sulphur, salt, chlorine, and potassium.	Automation of data collection to calculate sustenance.
	Feeding: Animal feeding can be a difficult undertaking. Congested forage bunks might restrict feed consumption, resulting in lower milk output.	Robotic system that can nourish itself automatically after seeing the digested meal.
	Water and supply: Dairy milk contains 87% water; therefore, a lack of enough water intake may lower milk production.	Water distribution is automated after observing a thirsty person.
	Body weight: The weight of the animal clearly influences milk output.	Analysis of personal data and clarification of context.
Health	Masitis: Mastitis is caused by bacteria that infect the udder and proliferate in the milk-producing tissues, resulting in decreased milk output.	Milking claws that detect udder illnesses such as mastitis automatically.
	Calving interval: The unusual time period between calves' births may be the reason of lower milk production.	Brilliant idea and placement of historical facts for footage the intermission.

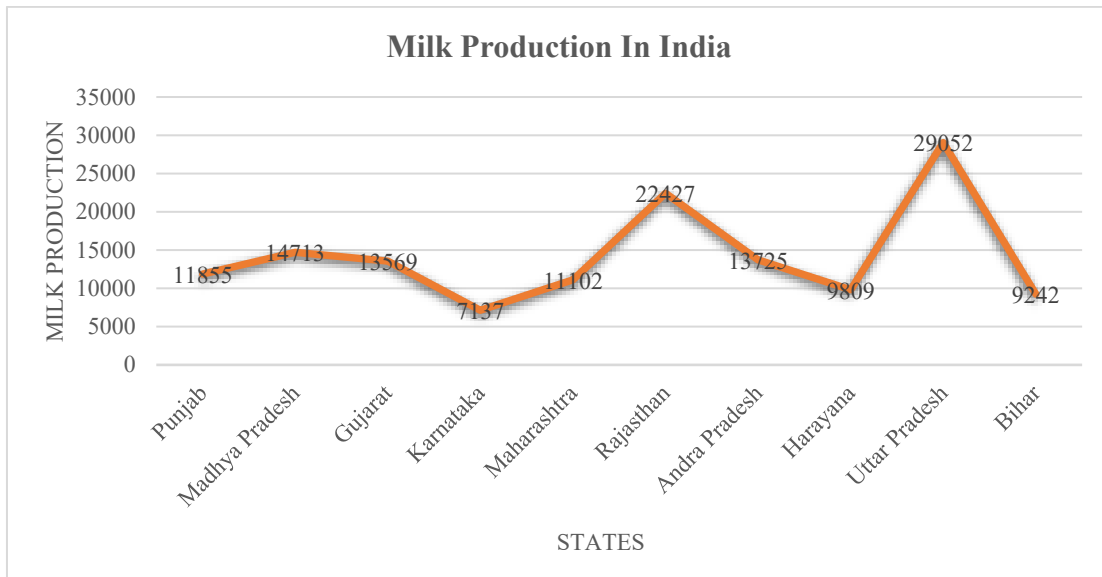


Figure 10. Analysis report of major milk production in India

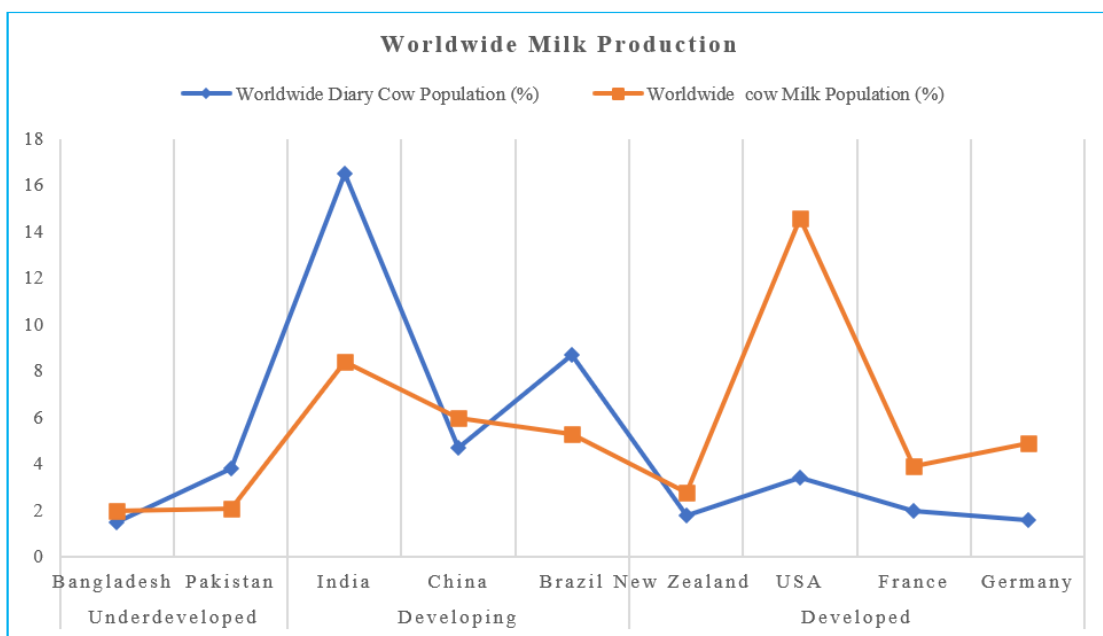


Figure 11. Analysis report of worldwide cow population and milk production in different countries

Implementation: Arduino Uno controller, ZigBee module, temperature and heartbeat sensors. UI developed using Python with GUI for real-time display. Data logged into SQL backend.

Figure 9 shows 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 the work 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. The work 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. Figure 7 shows a smart health monitoring animals smart wearable watch for health monitoring for dairy animals. Figure 10 shows the analysis report of major milk production in India and Figure 11 shows the analysis report of worldwide cow population and milk production in different countries. The work concluded that the reasons for low milk yield and their possible solutions are showed in Table 2.

4. CONCLUSION

Compared to manual methods, the smart dairy reduced health diagnosis time by 40% and increased milk yield consistency by 18%. Costs reduced due to less labor and faster anomaly detection.

Pilot deployment was conducted on a 20-cow farm. System recorded 93% cow recognition accuracy and identified 4 early-stage mastitis cases over 2 weeks, validated by veterinary inspection.

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. From our research on the creation and application of AI in dairy farms, came to the following findings and observations. The work anticipate that AI will eventually find numerous practical benefits in dairy farms, given the explosion of recent literature on the subject, the enthusiasm surrounding AI on college campuses, and the appearance of commercial AI-based services for dairy farms. The anticipate that AI, enabled by technological advancements in hardware and software, will revolutionize the dairy industry by providing better work

environments and eliminating or significantly reducing the need for manual human processing of repetitive activities. AI will also enable intelligent utilization of new large data.

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NOMENCLATURE

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