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ORIGINAL ARTICLE **OPEN ACCESS**

IoT Based Smart Dairy Farm based on Machine Learning Prediction

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ABSTRACT
With advancements in technology, there has been a great deal of boost in research towards IoT based concepts and applications in recent times. The data being collected from remote locations and transmitted and conveyed to their respective destinations has been the inherent property of Internet of Things (IoT) platforms. The data being available anytime-anywhere is an added merit to these technology-based applications. Since its inception, many applications ranging from smart governance, smart cities, smart banking, smart data computing, smart agriculture etc. have been on the rising trend replacing much of the manual labor and simultaneously increasing the precision of data being processed. Yet another interesting application of IoT based technology is in the field of dairy also known as smart dairy with IoT being included in it. This paper provides a brief insight into the role of machine learning models in various smart dairy projects and applications. A widespread tool in recent times to improve precision of data is machine learning which has been explored in detail in this paper.
Keywords: Internet of Things (IoT),Smart Dairy Farming, Sensors, Machine Learning, Prediction

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INTRODUCTION

In recent times, technology has undergone a rapid revolution in the past three decades. A great deal of development has been experienced in the data processing fields involving data acquisition, their processing and storage. Communication of data through state-of-the-art technologies has accelerated the development of several hand-held cutting-edge gadgets. Consumers with these gadgets could get all the required data in their hands.This has been greatly aided by development of Internet of Things (IoT) concepts [1]. With data being made available online, transmission and reception of data has been made with much ease and improved efficiency. IoT has further undergone a great boom with advent of cloud-based technologies where the data to consumers are available on the move irrespective of geographical time and location. In view of the inherent and immense potential of IoT based concepts, a wide range of applications have been explored by researchers over a period of time which include smart health care which include patient monitoring, patient data monitoring, to smart agriculture, smart weather monitoring, smart gadgets etc. one such innovative and time-critical application is the smart dairy farming [2-4].This has been taken as the essence of discussion in this paper with special emphasis on the role of machine learning in IoT technologies.

Dairy farming [5] is quite an indispensable application in recent times since the population of any country depends to a large extent on the various dairy products. It could be aptly stated that the day dawns with dairy related products in any home. In conventional and traditional methods, dairy farming is quite an interesting business and yet requires a large amount of labor force.It involves feeding cattle, maintenance, providing veterinary assistance etc. on the other hand, milking process, their handling and storage, distribution etc. form another area of the smart dairy farming process. Yet another division involves reproduction of cattle, their endurance towards heat and required temperature settings, large scale mobility etc. A simple schematic of a conventional dairy farming system is depicted in figure 1shownbelow

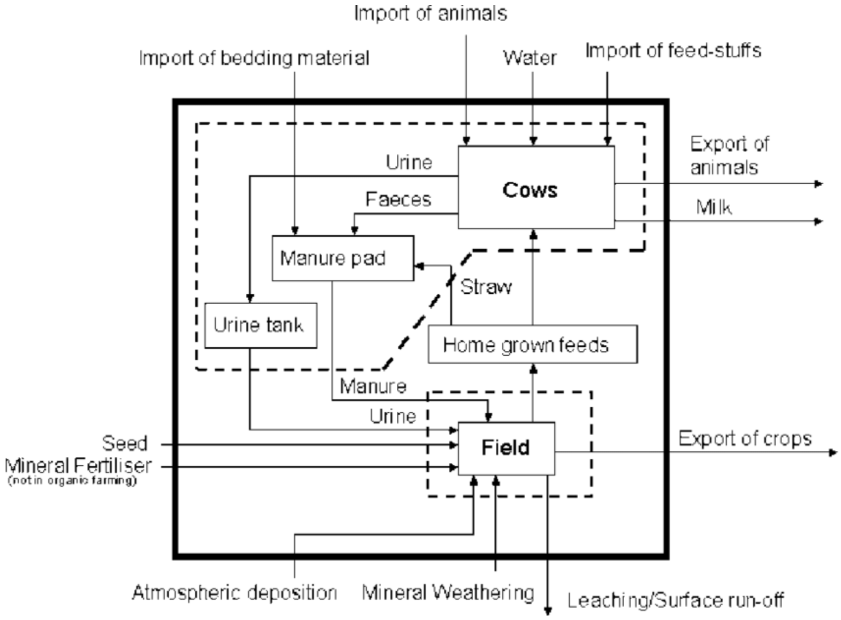

Fig.1. Block schematic of a conventional dairy farming system[6]

Dairy farming, as already mentioned, is quite an interesting yet complicated process. When organized in a well-coordinated manner, yields the maximum output with high accuracy. Several modules are involved in the dairy farming process which starts with import of cattle, selection of apt cattle for maximum efficiency and minimum efficiency costs, their barn constructions, spacious and healthy environments etc. On the other hand, processing of dairy products from the dairy farm is yet another module which involves transportation and distribution, their cold storage preservation, addition of appropriate chemicals for preservation, maintenance of air conditioning, on-time delivery of products etc. The above-mentioned parameters are concerned with logistics aspect of the entire dairy farm.

The next major module comes with the individual cattle whose health and efficiency are dependent on a number of factors related to the animal itself. A simple schematic illustrating the various factors controlling it is depicted in figure2 shown below.

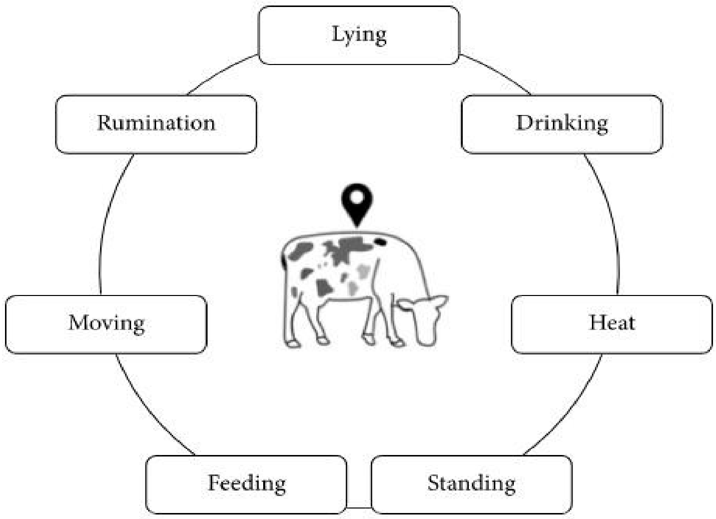

Fig.2. Illustration of various parameters controlling cattle health

A third aspect of dairy farm is the milk production process. It is depicted in figure3 shown below.

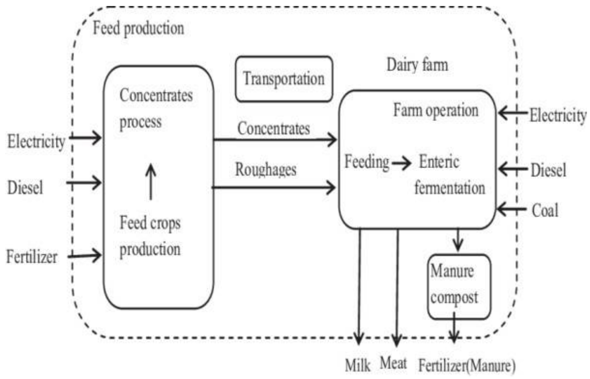

Fig.3. Illustration of milk production system[7]

As observed in figure 3, it could be seen that the generation of milk products by itself demands a high level of complexity. Put together as a dairy farm, conventional method of dairy farming is quite labor intensive and expensive venture.

With the advent of technology and concepts of management, the computational complexity has been drastically reduced. Robotic innovations, communication-based enhancements, data acquisition methods put together have been an effective tool for any kind of smart automation process. Figure 4 projected below depicts avenues in whichvarioustechnology-orientedconceptshavebeeneffectivelyputtouse.

As it can be seen from figure 4, a heterogeneous nature of technology has been applied in various stages and modules of the smart dairy farming (SDF) process easing the complexity at each stage. It is also required to choose the right kind of technology to the right of application process for optimal production. For example, effective robots have been used in the milking process and observation sensors or monitors to observe the various physical parameters at various locations of the SDF.

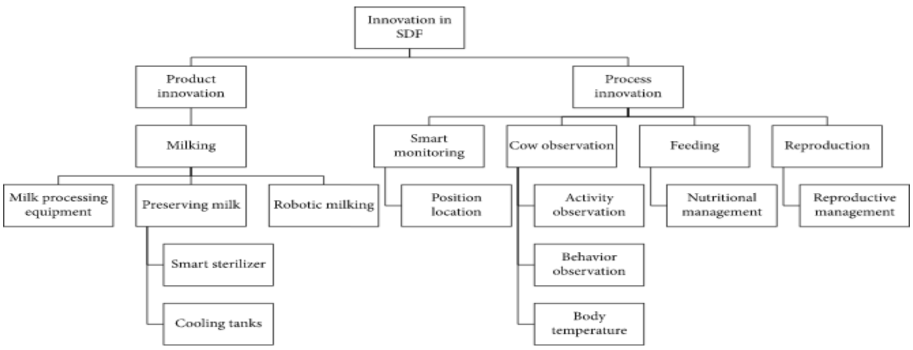

Fig.4. ApplicationoftechnologyinSDF

However, this paper has presented a more specific aspect of SDF wherein application of machine learning techniques has been elaborately explored in the IoT-based SDF project. A general view of the proposed discussion of the IoT-based SDF flow process is depicted in figure 5 shown below.

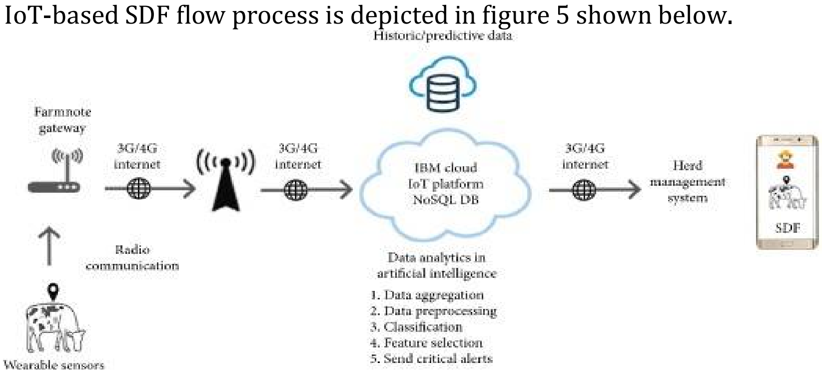

Fig.5. Illustration of IoT–based SDF

As observed in figure 5, IoT is the main gateway connecting the cattle to the user at a remote location. The health status, the location of cattle in the grazing field, their eating patters, their route of grazing and the farm activities which involve production, distirbution and its associated logistics are all monitored by handheld gadget at the user end as shown in figure 5. This means that the user or manager need not be physically present near the cattle or the farm. The efficiency of IoT- based SDF greatly depends on the communication technology installed in the vicinity in the form of 4G, 5G etc. the higher the generation of communication standards, the higher the efficiency and features. Video based monitoring is also possible in cases of 5G network distribution. As mentioned in previous sections, machine learning utility has been effectively addressed in this paper. The role of machine learning is necessitated during the data processing stages as shown in figure 5. Wearable sensors are placed on the cattle which continuously transmit the required data to the cloud IoT gateway where specific processors are used in integration with ML techniques to effectively analyse and process the data in order to predict, extract meaningful information and take counter active measures. The rest of the paper is organized as an elaborate survey of literature related to various aspects or stages of the IoT-based SDF process, the various ML techniques with citations from recent literature related to them.

RELATED WORK

Sensor Technology –Wearable Sensors

As observed in figure 5, the mainstay of the entire IoT-based SDF flow depends on the data transmitted from the sensors. Sensors collect essential data from the point or subject of interest and convey them to the destination through the sequence of forwarding sensor nodes. In the proposed case, wearable sensors offer a convenient solution as the cattle end to form a random movement path and hence choice of wearable sensors is quite optimal. They sense various information like their position of grazing, the movement, speed, health parameters of the cattle etc. and transmit them to the destination which in the proposed case is the IoT-cloud gateway. Figure 6 depicts the typical data being gathered by the wearable sensor.

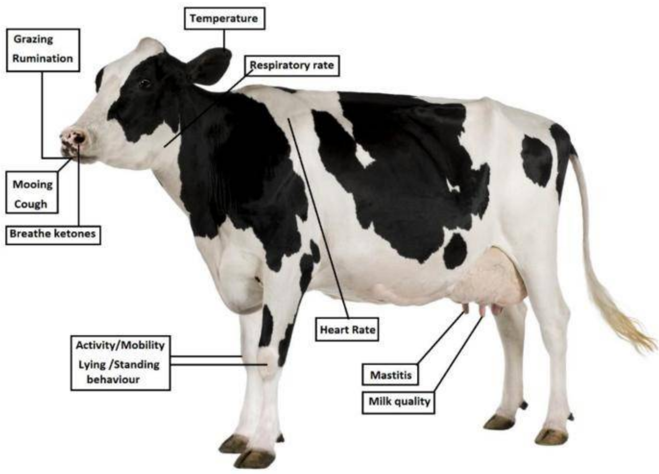

Fig.6. Sensor utility for cattle herd [8]

Normally the wearable sensors are attached to the ear, neck collar, tail portions of the cattle. They are powered by battery power to keep them running. Typical sensors with their make and manufacturer details are listed in table1 shown below.

Table1: Cattle wearable sensors & applications [9]

Sensor	Make	Internal Functions
Data collection Tag	Fever Tags LLC	Temperature data aggregation
Tek SensorTags	TekVet technologies	Temperature data aggregation
Flex Tag	Sense Hub	Health monitoring
Smart Bow	Smart Bowtech	Motion sensing & temperature

Most of the sensors have been observed to be provided with a lifetime of 2 years. The wireless communication technology coupled with limited battery power offer ample scope of research for enhancing the battery life through effective wireless routing protocols of the data sensed by the wearable sensor. Many such protocols are observed in the literature ranging from well-known LEACH (low energy adaptive clustered hierarchical) [10], AODV (Ad-Hocon-demand distance vector routing)[11], optimization-based routing protocols [12] etc. In all the above-mentioned protocols work towards improving the battery lifetime thus reducing the amount of human labor involved in replacement of batteries.

Data Preprocessing

Following the data captured by the sensors, handling of data is of prime importance to provide optimal yield or efficiency in the proposed layout. Multiple data are being captured by the wearable sensor as mentioned in previous section which has to be carefully handled by the processing unit at the IoT-cloud interface. Data preprocessing is crucial as the data transmitted by the wearable sensor may contain several irregularities like in correct data, redundant data etc. In addition, they may be in an unstructured format. Hence, removal of these inconsistent data followed by restructuring of the raw data is a crucial process done by the data preprocessing unit. Several research works have been proposed in this regard.

The first and foremost step in data preprocessing is the data cleaning where missing values, noisy and corrupted values are being removed or eliminated. In addition, the data may also contain imbalance which has been effectively addressed in the works of [13]. SMOTE analysis [14], the modified SMOTE analysis [15] has been effectively used in the literature to handle the class imbalance issues. The raw uncleaned data may also contain redundant or duplicate values which may tend to confuse the further stages of machine learning. Hence, their removal is mandatory. Commonly used data pre-processing methodologies involve the well-known clustering process where the similar likes of data variables are grouped into clusters based on a similarity measure. Normally Euclidean or Manhattan distances [16] are used as the measure of similarity. Binning methods [17] are also popularly used mainly for data sorting. Regression based models [18] are used for data smoothening by removing the in consistencies.

Following the cleaned data, data integration is a very crucial step. It can be observed that in the proposed case of SDF, the wearable sensors are not only placed in on the cattle but also at several points of the SDF to monitor the various activities. Each sensor collects its own type of data to which it is being employed. Hence, the above obtained raw data is a heterogenous mixture of several data types from different cattle as well as different locations of the SDF. Hence, proper grouping or tagging of data identifying its source is essential for effective processing. Metadata

[19] is an effective tool used in recent times which provided adequate information about the source of the data itself. Based on the meta data information, clustering [16] based models could be effectively applied to categorize the data according to their source types.

The cleaned and integrated data is now given to a transformation process wherein the raw data is transformed or scaled to a normalized value such that the ML model can act upon it in a more efficient manner. For example, temperature data from cattle may be in degree Celsius from 93 to 104 while the movement sensor may provide the accelerometer reading as 0.2m/s to 0.5m/s while another sensor may provide a value in a different range and unit. Hence, the ML model may get confused on learning different ranges of different sensors. Hence a normalization mechanism is used to normalize the values from[-1,0,1] based on a set of algorithms.

The final step in data preprocessing involves data reduction. In case of big data applications such as in the proposed case, the information from the cattle is being fed at a constant rate in a continuous manner. Hence, a huge volume of data is being aggregated. Reducing them to a tolerable limit that can be easily processed is of prime importance. A well-known data reduction technique is the principal component analysis (PCA) [20] which effectively scales down the dimension of the raw data with critical information being retained. Other models like histogram, clustering also provide data reduction.

Data Feature Extraction

The preprocessed data from previous stage is now ready to be extracted for its features. A number of feature extraction methods are available in the literature. Feature extraction is vital to any ML model for a specific application as it provides crucial and more relevant information for learning. Features define the overall efficiency of the prediction or classification class. For example, the temperature readings from the wearable sensor placed on the cattle are being continuously monitored. If they exceed a certain threshold, then they are classified to be abnormal. However, in a complex SDF scenario, a multiple set of features describe a particular event or condition related to the cattle or defect in the dairy production process.

Commonly used feature extraction methods involve the above mentioned PCA which also aids in dimensionality reduction, ICA (Independent component analysis) [21] which work on the principle of dependency of any two input variables, LDA (linear discriminate analysis) [22] which works on the principle of maximization of distance between classes thus aiding to improve the classification accuracy. Other methods which working non-linear conditions are local linear embedding, t-distributed stochastic neighbor embedding and the well-known and widely used auto encoders. Auto encoders perform the function of high-dimension to low-dimension mapping effectively and at the same time remove noise data to a certain extent.

Data Classification/Prediction

The final stage involves the ML model which is used to either classify an objective class or predict a future statebasedoncurrentsetofinputvectors(featurevectors).Machinelearningalgorithmshavebeenplayinganind ispensable role in such applications due their high learning potential, quick convergence and ability to handlelargedimensionofdatainrealtime.RandomForest,DecisionTrees,SVM(SupportVectorMachines)arep opularly used classifiers on data sets in recent times. Decision tree is the simples form of supervised classifier ML model where it acts on the input feature vector and takes decisions based on a prescribed set of rules. For example, if the temperature of the cattle is high, the temperature is high, the respiration rate of cattle is high, then the cattle need to be moved to a shady portion or given hydration. In the overall SDF, the total information collected by all sensors are categorized methodologically to formulate a set of rules.A collection of decision trees (DT) constitutes a random forest. SVM is yet another efficient classifier which learns the pattern of feature vectors to arrive at a decision. Another classifier is the kNN classifier which is quite effective but computationally complex as compared to SVM model.

More learning-based models are in practice in recent times. They derive their formulations based on the well-known ANN (Artificial Neural Network)which learn the input pattern and arrive at the decision of prediction/classification using an architecture of nodes and weight-based computations. The overall objective is to reduce the error between computed and expected outcomes. ANNs are iteration based. A typical ANN model is depicted in figure 7.

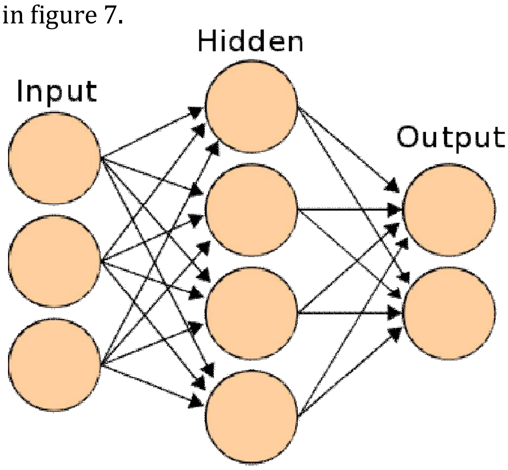

Fig.7.ANN model-based classification

ANNs are composed of input layers, hidden node layers and the output layer. The inputs are utilized to classify the classes into their respective output classes based on computation being done in the hidden layer. The number of input layers vary depending on the number of input feature vectors. The output classes may be classifier outputs like normal/abnormal state of the cattle, Faulty/Non-Faulty running of dairy production machinery, healthy/unhealthy status of the cow, quality grading of the milk etc. incase of prediction classes, it may be sunny/rainy weather in order to direct the cattle for grazing, adjustment of air conditioning systems based on the predicted weather condition etc.

With increasing complexity in data volumes, need for higher precision, ANNs have been explored and extended into deeper architectures like convolution neural networks (CNN) [23], deep convolution neural networks DCNN (Deep convolution neural network) [24], recurrent neural networks (RNN) [25] etc. the latter cases are commonly termed as deep learning architectures or the extreme learning architectures. They are most suited for complex layouts like the SDF proposed in this paper. SDF comprises of several inputs as mentioned in previous sections and hence, analyzing, processing the various types of data from various sources and entities require deep learning layersto provide precise classification/prediction outputs.

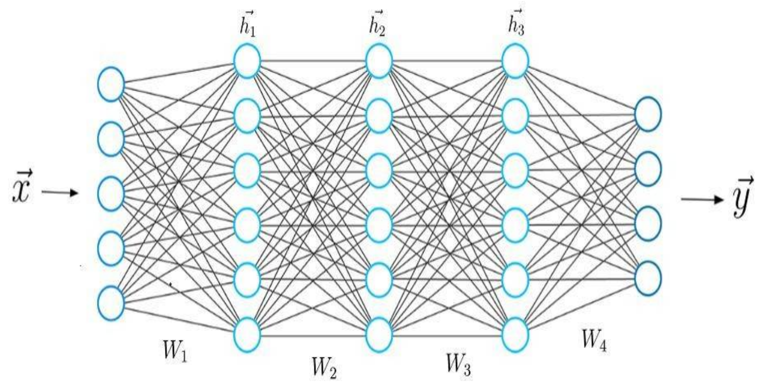

Fig.8. Deep learning architecture for complex ML applications

As it can be seen from figure 8, the single- or two-layer ANN is extended to N layers depending on the level of learning that is to be required. This takes considerable amount of time for the convergence process but provides precise output [26].

A recent trend in ML models is the utilization of hybrid models involving two or more architectures to improve the overall efficiency of the system. Typical models include the ANFIS models [27] which are a hybrid combination of ANN and Fuzzy engines, PCA-SVM models [28] where one performs reduction while other per forms classification, nature inspired evolutionary algorithms like PSO (particles warm optimization) [29], Genetic algorithm, ACO (ant colony optimization) etc. where these algorithms are found to be an excellent choice in finding the most optimal set of features given a raw data set. They are widely adopted as they best mimic the real time scenario. Moreover, they are best suited especially when the volume of data is very high. These evolutionary models are combined either with NN-based classifiers or terminal classifiers like SVM etc.

Performance Metrics

Performance metrics are crucial to understanding the efficiency of the utilized model. Commonly used metrics involves classification accuracy, precision, sensitivity, recall, computation time, computational complexity, response time etc. correlation measures are also being used to establish as to how close the expected values converge to the obtained values.

Communication to user

This is the final stage of the entire SDF automation process. The data after processing through the above-mentioned stages, need to be conveyed to the end-user either through a handheld device/gadget or state-of-the-art monitoring platform. This has to be timely with quick response in order for the monitoring authority to take counteractive measures. With the help of IoT based concepts, small sized controllers are able to take of this process with utmost precision and quick response time. Some of them include the widely utilized Raspberry Pi module. Others include industry ready HX series hybrid model controller, the ESP8266, Arduino, STM, node MCU etc. Arduino cloud enables multiple devices to be connected to it with high precision and quick response time. These controllers also enable android-based OS platforms to provide ease of usage to the monitoring user. A typical node MCU is depicted in figure 9.

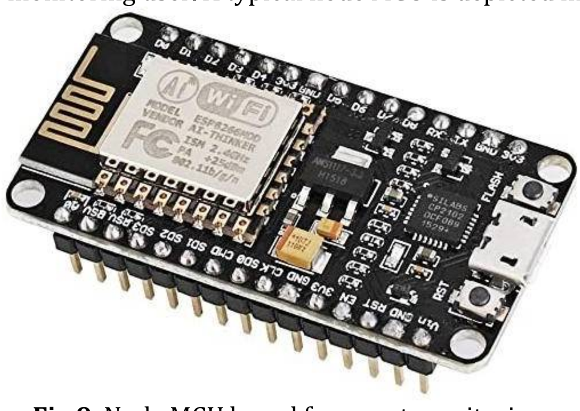

Fig.9. Node MCU board for smart monitoring

An expected snapshot of the user view is projected in figure10.

Fig.10. Mobile APP based monitoring in SDF[Courtesy:https://www.shutterstock.com/image-vector/control-herd-cows-on-dairy-farm-1249065241]

As shown in figure 10, it can be visualized that the application provides a complete picture of what is happening in the cattle farm as well as in the production unit at one go. In the above case, a sample snapshot has been provided from the website as mentioned which illustrates the time that the cattle have been eating, standing still etc. these metrics are quite indicative of the health of the cattle. With upgradation of the communication protocols, video based live streaming can also be facilitated.

ONCLUSION

Smart applications are on the rising trend in recent times with advent of concepts of IoT and cloud technologies. One such interesting and vital application explored in this research paper is the smart dairy farming also known as SDF. The entire process has been visualized as stages and related works in each stage have been discussed in brief.The essence of each stage has been projected with apt citations from recent literature. Dairy farming is a booming industry and offers a wide scope of research in recent times. Machine learning models and their importance in proposed SDF have been discussed in brief with suitable illustrations. With complete involvement of state-of-the-art technology, the manual labor could be completely replaced and providing high yield at the same time.

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