LiveCare: An IoT based Healthcare Framework for Livestocks in Smart Agriculture

Pinaki S. Chatterjee, Niranjan K. Ray, Senior Member, IEEE and Saraju P. Mohanty, Senior Member, IEEE

***Abstract*—In the field of smart agriculture health monitoring of livestock is an important field of research. Maintaining the good health of cows is very much essential for the steady growth of milk production. Unfortunately, in a large dairy cow farm, day-to-day monitoring of the health status of individual cows is a complex and time-consuming activity. This paper proposed LiveCare, an IoT-based framework that automatically monitors the health of cows in a large cow farm. It tracks the cow's behavioral changes on a daily basis. This paper also proposed the Cow Disease Prediction (CDP) algorithm, which is an unsupervised multi-class classifier that serves as the LiveCare framework's central component. The CDP algorithm can predict several cow diseases by analyzing the cows' behavioral changes. In this framework, we have also tabulated a few common cow diseases, their measurable symptoms, and the various sensors used to record them. We compared the efficiency of the proposed CDP algorithm to that of other machine learning algorithms.**

***Index Terms*—Cow health monitoring, Wireless sensor networks, Cow disease prediction, Precision livestock farming.**

I. Introduction

AGriculture and animal husbandry are the two fields which play the most important role in the economic growth of a country. Almost 18% of the Gross Domestic Product of India comes from agriculture. Around 50% of India's population are employed in the field of agriculture and animal husbandry [1]. Animal husbandry is a field where animals are nurtured for different animal products. Mainly, the animal product includes food products like milk, egg, meat etc and non-food products like wool, bone products, pharmaceuticals etc. Dairy cow farming is an important section of animal husbandry. Here the health of the cows is an important factor to increase the quantity and quality of milk. It requires day-to-day monitoring to maintain the good health of cow's. Day-to-day monitoring of cow's health is again a challenge for a big dairy cow farm where thousands of cows are there. Manually one-to-one checking of cows health is a tedious job.

To solve this problem, the traditional methods of cow health monitoring must be replaced by the advanced automated monitoring and disease prediction system which includes different types of sensors and IoT devices [2, 3]. Such automated cow health monitoring and disease prediction system is also very useful for the dairy farms which are located in the remote areas of the country where doctors are not easily available. This system can be helpful for timely treatment of some common cow diseases. Already different IoT applications are used in the field of agriculture like field monitoring, greenhouse monitoring, agricultural drones, smart irrigation control, agriculture warehouse monitoring and many other applications [4, 5, 6, 7]. LiveCare the proposed IoT based cow health monitoring framework is depicted in Fig. 1. Here, each cow has a different sensor attached to their body. The sensory data is sent to the proposed Cow Disease Prediction (CDP) system. The CDP system predicts the cow's health and stores the results in the cloud, as explained in Section III. The farmer uses a web application to track the health of each cow.

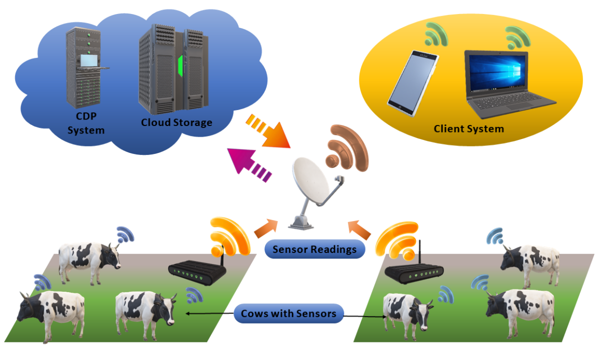

Fig. 1: LiveCare framework.

The majority of the works in the existing literature has been presented to produce an alarm [8, 9, 10, 11, 12] or to detect a specific cow illness [13, 14, 15, 16, 17, 18]. Our proposed LiveCare platform predicts multiple cow illnesses and sends warning messages to the farmers.

The organization of the paper is as follows: Section II discusses about related works. The contributions of the current paper are highlighted in Section III. Section IV is the proposed framework for livestock healthcare, Section V is implementation and analysis of the proposed system. The paper concludes in Section VI.

II. Related Research Works

Currently, one of the most important topics in the next era of consumer electronics (CE) and consumer technology (CT) is IoT based healthcare. Any revolutionary technologies allow the production of these innovative technologies, facilitating their mass market adoption. The emergence of new applications in this field includes low-cost devices which are interconnected to enhance the consumer's lifestyle [19, 20, 21, 22].

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It may be noted from the above that while consumer electronics research for human healthcare is ongoing, the healthcare frameworks for in the context of animal husbandry is seriously lacking.

At present, few approaches are available in the literature. They are broadly classified into two categories as follows-

(a) Approaches to generate an alarm for behavioural changes: There is an analysis in [8] and [9] of the various diseases that can affect cows and their symptoms. Such diseases may cause changes in the parameters of the cow's body that are recognized and sensors are selected to effectively sense these changes. In [10] the author uses Arduino UNO to measure cattle body parameters and LabVIEW to view real-time graphical representations of the signals. In [11], a cloud-based mobile gateway operating system is suggested. A lightweight structure has been developed for cloud-based mobile devices. [12] proposed a framework consisting of data collection, mobile nodes and IoT cloud platform. The nodes for collecting cow's health parameters are equipped with different sensors. The mobile node serves as a portal to the IoT cloud platform to identify unhealthy cattle by carrying out data analytics on the sensor data.

(b) Approaches to predict a particular cow disease using different Machine Learning (ML) algorithms: ML has recently been used in the study of pathogen transmission patterns of mastitis in cattle [13] as well as in the diagnosis of both subclinical [14] and clinical [15] mastitis at the level of individual animals. In [16] the author has proposed an algorithm to detect lameness from the accelerometer readings fixed on cows body and they have also listed the wearable sensor device for cows. In [17] the authors have proposed a system to detect foot and mouth disease and mastitis using IoT framework. They have considered various parameters like Temperature, Motion, Sound etc. along with micro-controller and machine learning algorithm in their system. In [18], a system is proposed to analyze the 3-axis acceleration information from IoT sensors and detect the pattern-recognition performance for three behavioral patterns of breeding cows, estrus start, peak estrus activities, and estrus finish using ML algorithm.

Table I shows the comparisons of different approaches. The following are the key concerns that are not adequately addressed in the majority of current research:

- Sensor node management for the framework is not properly discussed.
- Most of the work are primarily concerned with raising an alarm in response to behavioral changes.
- The majority of the work for disease detection is not generic in nature. They are mainly interested in predicting a particular disease.

TABLE I: Comparison of different approaches.

Approaches	**Behavior monitoring**	**Disease detection**	**Limitations**
Jha, et al. [8] and Meenakshi, et al. [9]	Yes	No	Reports Only about the behavioral changes due to different disease.
Swain, et al. [10]	Yes	No	Limited to display real time health graphs.
Suresh, et al. [12]	Yes	No	Limited to identify unhealthy cattle based on sensory readings.
Esener, et al. [13]	No	Yes	Identify subclinical or clinical level mastitis.
Haladjian, at al. [16]	Yes	Yes	Detect lameness from the accelerometer readings.
Vyas, et al. [17]	Yes	Yes	Detect foot and mouth disease and mastitis
Lee [18]	Yes	Yes	Detect breeding cows, estrus start, peak estrus activities, and estrus finish.
LiveCare (Proposed)	Yes	9 different diseases can be detected	–

III. Contributions of the Current Paper

The main objective of the proposed work are the following:

1) Convenience to the farmer: The person, who is the direct in-charge of the cow farm, can identify cow health problems within a minute or an hour. This job becomes very difficult when the number of cows grows to a few hundred in a big cow farm. Sometimes the proper precautions become late. To avoid such loss, an IoT based health monitoring of cow is very useful.
2) Automated abnormal behaviour monitoring: A certain health disorder can be identified in an animal by minutely studying the changes that occur in their behavioural appearances. Here different sensors always record the behavioural changes of the cattle. If any abnormal values are recorded, then specifically that can be sent to the stock person as an alarm.
3) Automated multi-disease prediction: The proposed CDP algorithm predict few common cow diseases by monitoring the changes in the cow's behaviour. This is useful for the quick treatment of some not so serious disease in the region where the doctors are not available very easily.

The proposed solutions are novel and significant in the following ways:

- An efficient IoT-based framework for monitoring cow health has been proposed.
- The proposed framework is suitable to capture behavioural changes of cows in a big dairy cow farm.
- Several common cow diseases, their symptoms, measurable behavioral changes in cows caused by those diseases, and the sensors used to accurately record those changes has been tabulated.
- The CDP algorithm has been proposed.
- The CDP algorithm is an unsupervised multi-disease prediction algorithm.
- The placing of different non-invasive sensors on the cow

body is mentioned.

- The performance of the CDP algorithm is compared with other classification algorithms.

IV. LiveCare: The Proposed Framework for Livestock Healthcare

The LiveCare framework consists of a sensor module and a base station, a cloud system module and a web application module for the farmer as shown in Fig. 2. The sensor module consists of different sensors with wireless transmission capability attached on the cow's body. The cloud system consists of the servers hosting the web application and the databases. The sensors capture the activities of the cow and it is sent to the base station through a wireless link. The base station runs the CDP algorithm on those sensed data and predicts whether the cow has some illness or the cow is in a healthy state. The base station sends those information to the cloud server. The result of the prediction can be seen by the web application. To make an efficient wireless communication between the sensors and the base station in the presence of many sensor nodes transmitting simultaneously, we could use cognitive wireless sensor nodes [23].

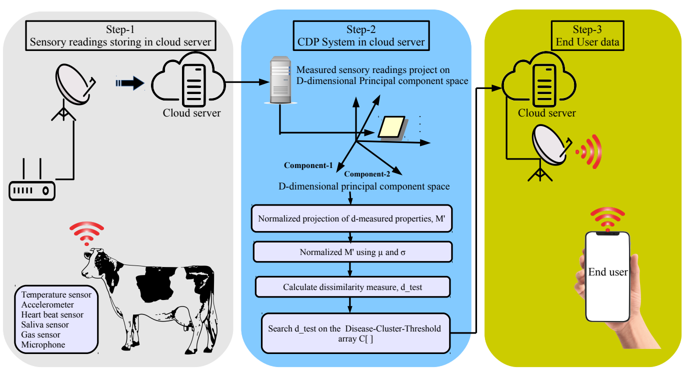


Fig. 2: Overviw of the proposed LiveCare monitoring system.

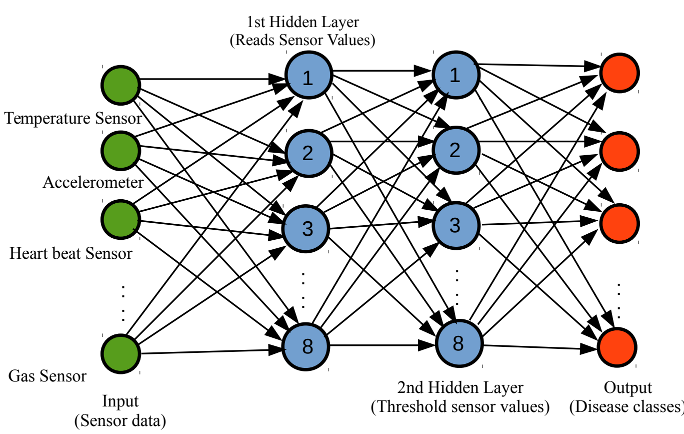
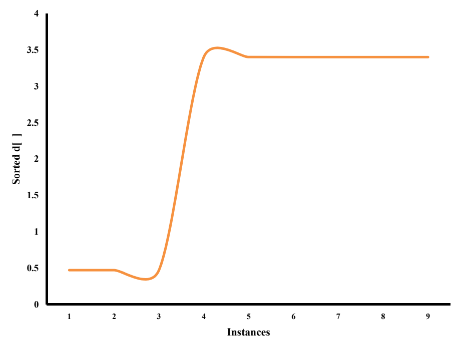


Fig. 3: FCNN model representation in CDP.

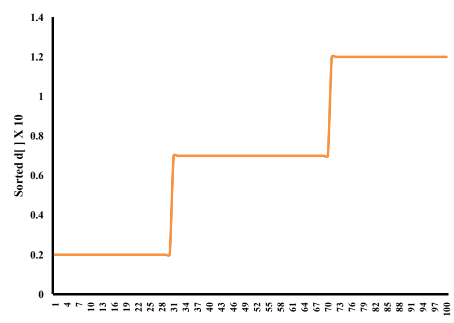
As shown in Fig. 3, the CDP system can be represented using a Fully-Connected Neural Network (FCNN) model with 1 input layer, 2 hidden layers, and 1 output layer with 8 neurons each to determine the relationship between cow behavior and cow disease. After feeding the data into the model, the data is routed through all of the hidden layers, where the weighted inputs to each layer are measured using the defination of the dissimilarity measure as follows:

$$d[k] = \sum\{(m_i)^2/\lambda_i\} \tag{1}$$

Where, i represent the choosen principal components, m_i is the $score$ of the i^{th} feature on the d-principal component space, and λ_i is the eigenvalue of the i^{th} principal component. Here $k \in [1, T]$ and T is the number of unlabeled instances. The word $score$ refers to an instance's projection into the eigenspace consisting of all principal components obtained from the training data set.



(a)



(b)

Fig. 4: Ploting of sorted d[] for mixed data set.

Fig. 4 represents the ploting of the sorted dissimilarity measure value, $d[\ ]$ in MATLAB. Fig. 4a shows the ploting of $d[\ ]$ where the training instance cantains two different classes. Fig. 4b shows the ploting of $d[\ ]$ where the training instance cantains three different classes. From this graphs we can observe that each different classes has different dissimilarity measure values which are parallal to the x-axis. Section B describes in detail the disease class classification and detection mechanism.

A. A study of sensors and their sensory outputs for the different health disorder

Changes in cow's behaviour is an indicator of the changes in the cow's health. In this section, we have conducted research on the changes in cow's behaviour on the case of the different health diseases. Those changes are captured by a set of sensors. We have tabulated the different type of sensors required to capture the behavioural changes in different health diseases in the bellow Table II.

B. The Cow Disease Prediction (CDP) algorithm

In this section, we have used an unsupervised multi-class classifier to predict the possible health disease from the above sensory output. To classify the measured symptoms we have used the Unsupervised Principal Component Classifier [27]. The CDP algorithm has two phases namely Disease-profile learning phase (*Training phase*) and Disease-profile classification phase (*Testing phase*).

1) Disease-profile learning phase (Training phase): Different sensors are attached to the cow's body as mentioned in Table II. During the system setup time, all the sensors send their readings to the central device. There could be T number of such readings $\{R_1, R_2, ...R_i, ...R_T\}$. In every reading, there are d numbers of measured properties.

$$R_i = \begin{bmatrix} q_1 \\ q_2 \\ \vdots \\ q_d \end{bmatrix} \tag{2}$$

The T number of readings are completely unlabeled and includes all the possible disease listed in Table II along with the reading of some healthy cows. Our job now is to identify the various classes of disease on the basis of the properties obtained. First, we use Principal Component Analysis (PCA) to decrease the dimensions of this data. We maintain just n number of main components that differentiate the various types of illnesses. Then we compute the dissimilarity measures d_{train}. We save these d_{train} values in the array $D_{TRAIN}[\,]$ in ascending order. The Automated-Cluster-Threshold-Discovery (ACTD) Algorithm 2 [27] will use the $D_{TRAIN}[\,]$ array as input. The ACTD algorithm determines which d_{train} value is the threshold for a certain illness class. These threshold values are kept in the $C[\,]$ array. If $C[\,]$ array has k entries, means we have $k-1$ different diseases and one extra class for healthy cows. The steps of the disease-profile learning phase are shown in Algorithm 1.

In Algorithm 2, $D_{TRAIN}[m_0]$ and $D_{TRAIN}[m_{max}]$ be the $0.5\%^{th}$ and $99.5\%^{th}$ percentiles of the sorted distribution vector. Here, m_0 and m_{max} are indexes corresponding to the nearest integers to $0.005 \times T$ and $0.995 \times T$, respectively, and are used to filter some extreme values from both ends of the $D_{TRAIN}[\,]$ distribution vector.

Algorithm 1: Disease-profile learning $(R[\,], T)$

Input : $R[\,], T$

Output: The disease-cluster threshold values, stored in $C[\,]$

1. First, the obtained multi-disease class data were normalised by the mean μ and the standard deviation δ .
2. The PCA [28] approach is then used to evaluate the main components, their eigenvalues values λ_i, and the data instance scores $Z = \{z_{ij}\}$. Z is a $d \times T$-dimensional normalized projection onto the d-dimensional eigenspace of the unlabeled training data matrix, where $i \in [1, d]$ represents the d key components, and $j \in [1, T]$ represents each training instance. The score matrix, z_{ij}, is the projection of each T training instance on the d-principal component space.
3. Then, n number of main components are automatically selected which effectively capture the differences between the different classes in the training data set through a threshold function. To indicate the degree of dissimilarity of a score array, this function is based on the standard deviation values of the features in the principal component space. Assume that $SCORE_i = (z_{i1}, z_{i2}, ..., z_{iT})$, $i \in [1, d]$, is the score row vector corresponding to the i^{th} feature in the eigenspace. To avoid the impact of score arrays with very low standard deviation values, which may correspond to very low eigenvalues and their corresponding score row vectors generated by the PCA projection, we first refine the number of score row vectors by selecting those that satisfy Equation 3 and discarding all others:
   $$STD(SCORE_v) > \phi \tag{3}$$
   Where, ϕ is an adjustable coefficient whose value is set to 0.01 as the default value, based on our empirical studies and $STD(SCORE_v)$ is the standard deviation of the score row vector satisfying the refinement equation and corresponding to the the v^{th} principal component.
4. These key components are used to find the dissimilarity measures between the various groups of training cases, d_{train} .
   $$d_{train} = \Sigma_{i=1}^{n}\{(z_i)^2/\lambda_i\} \tag{4}$$
5. The d_{train} estimated for T training instances is then sorted in ascending order and stored in the $D_{TRAIN}[\,]$ array.
6. The Automated-Cluster-Threshold-Discovery (ACTD) procedure is then applied on $D_{TRAIN}[\,]$ to find which d_{train} will be the threshold for a particular class of disease. In the $C[\,]$ array, the threshold values are stored. Since $D_{TRAIN}[\,]$ is sorted in ascending order, $C[\,]$ is sorted in ascending order as well.
7. If $C[\,]$ has K entries, then we have $K-1$ disease classes and one class which belongs to the healthy cows in the training data set. We have set the names of the disease as the marker for each entry of the $C[\,]$ array and also the class for healthy cows.

TABLE II: Measurable diseases symptoms and sensors.

Disease [24]	Symptoms [25, 26]	Measurable behavioral changes	Sensors
(1) Fever	Discomfort	Lethargic	Accelerometer(neck)
	High temperature	Increase in body temperature	Temperature sensor(neck)
	Ache	Mooing	Microphone(neck)
(2) Mastitis	Prostration	Laying down less frequently	Accelerometer(neck)
	Activity during milking	Kicking	Accelerometer(feet)
	Discomfort and pain	Restlessness	Accelerometer(feet and neck), Microphone(neck)
	Less food intake	Less grazing	Accelerometer(feet and neck)
	Weight distribution	Weight shifting	Load sensors (under feet)
(3) Lameness	Less consumption of food	Less grazing	Accelerometer(feet and neck)
	Mounting	Less movement	Accelerometer(feet and neck)
	Hitch	Uneven load distribution on legs	Load sensor (under feet)
(4) Ovarian cysts	Abnormal estrous behavior	Restlessness	Accelerometer(feet and neck)
	Bellowing	Mooing	Microphone(neck)
	Body temperature	High body temperature	Temperature sensor(neck)
	Quality of milk	Conductivity	Electrical conductivity sensor (udder)
(5) Oestrus	Increased estrogen and progesterone level	Restlessness	Accelerometer(feet and neck)
	Less consumption of food	Less grazing	Accelerometer(feet and neck)
(6) Ketosis	Weight loss	Weight loss	Load sensor (under feet)
	Reduced appetite	Less grazing	Accelerometer(feet and neck)
	Smell of breath	–	Gas sensor(nose)
	Fever	High temperature	Temperature sensor(neck)
(7) Pneumonia	Rapid pulse	Rapid breathing rate	Heartbeat sensor (vein on neck)
	Fever	High temperature	Temperature sensor(neck)
	Coughing	Coughing	Microphone
	Loss of appetite	Less grazing	Accelerometer(feet and neck)
(8) Black quarter	Fever	High temperature	Temperature sensor(neck)
	Loss of appetite	Less grazing	Accelerometer(feet and neck)
	Dullness	Less activity	Accelerometer(feet and neck)
	Suspended rumination	less rumination	Microphone (neck), Accelerometer(neck)
	Rapid pulse	Rapid heart rate	Heartbeat sensor (vein on neck)
	Lameness	Lameness on effected leg	Accelerometer(feet and neck), Load sensor (Under feet)
	Prostration	Prostration	Accelerometer(feet and neck)
(9) Foot and mouth disease	Fever	High temperature	Temperature sensor(neck)
	Saliva	Saliva hangs from mouth	Saliva sensor (mouth)
	Lameness	Lameness	Accelerometer(feet and neck), Load sensors (under feet)

2) Disease-profile classification phase (Testing phase): During the course of regular day, the sensors connected to the cow's body detect behavioural changes and transmit them to the central unit. The measured properties are then projected onto d-dimensional principal component space once more. We next compute the dissimilarity measures d_{test}. Finally, we look for the d_{test} value in the $C[\ ]$ array. We stop when the $d_{test} > C[i]$, and the cow's illness class is i-1. The steps for disease-profile classification is shown in Algorithm 3.

V. Implementation and Validation of LiveCare

In this section, the implementation details are presented to evaluate the performance of the proposed CDP algorithm in the presence of similar and dissimilar diseases of cows. The placement of different sensors on the cow body is shown in Fig. 5. These sensors help to monitor the behavioural changes of the cow. In our work, we have attached only those sensors on the cow body which are noninvasive. The electrical conductivity sensors are invasive. They are placed at the milking parlour. The load sensors can not be put under the feet of the cow as they are used to measure the load on the individual legs. Load sensors are also kept at the milking parlour.

In our work, we have identified eight basic sensors for the reading of the cow's behavioural changes. Table III shows the sensors and their basic sensory values for cows health monitoring.

To test the classification performance of our proposed algorithm we have collected data from two local dairy farms. The data is the sensors reading according to Table II. These data

Algorithm 2: Automated-cluster-threshold-discovery ($D_{TRAIN}[\,]$)

Input : $D_{TRAIN}[\,]$
Output: $C[\,]$
$ini = D_{TRAIN}[m_0]$
$C[1] = ini$
$i = 2$
for $(m = 1; m < m_{max}; m++)$ **do**
  if $(((D_{TRAIN}[m] - ini) \div ini) > 1)$ **then**
    $ini = D_{TRAIN}[m_0 + m]$
    $C[i] = ini$
    $i = i + 1$
  end
end
K=i-1

Algorithm 3: Disease-profile classification ($C[\,], n, \mu, \sigma$)

Input : $C[\,], n, \mu, \sigma$
Output: disease-class

The system projects them on the d-dimensional principal component space to calculate the score $M^{'}$.

$$M^{'} = \begin{bmatrix} m_1{'} \\ m_2{'} \\ \vdots \\ m_d{'} \end{bmatrix} \quad (5)$$

$M^{'}$ is the normalized projection of the cow's d-measured properties on the d-dimensional eigen space.

$M^{'}$ is normalized using the mean μ and standard deviation σ obtain from the training dataset.

Then, the dissimilarity measure of the testing instance d_{test} is:

$$d_{test} = \sum_{j \in n} \{(m_j^{'})^2 / \lambda_j\} \quad (6)$$

The disease class to which the cow belongs can now be found by checking the d_{test} in the $C[\,]$ array linearly. If $d_{test} > C[i]$, then we stop and the cow 's disease class is i-1.

include the sensor readings for the different health conditions of the cows. The final data set consisted of 500 records from 150 cows. This data set was separated into a training data set and a testing data set using the following approaches: the training data set consisted of records from both the farms for the period of January 2019 to December 2019, inclusive, and the testing data set included data from the period of January 2020 to July 2020 inclusive. In the training data set we have 300 records of the year 2019 and in the testing data set we have 200 records of the year 2020. The performance of our proposed algorithm is evaluated on this data set and shown in the experimental result section.

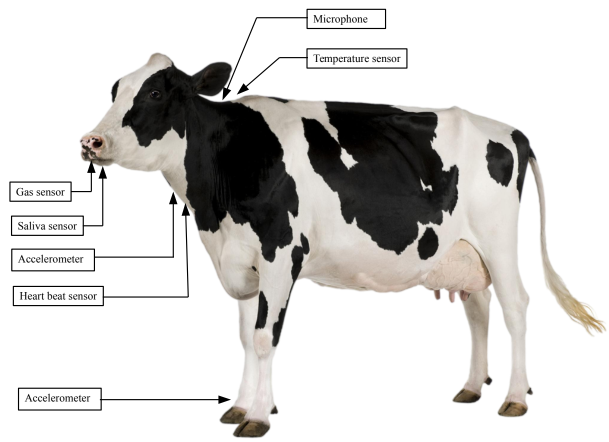


Fig. 5: Placing of different sensors on cow body.

A. *Experimental results*

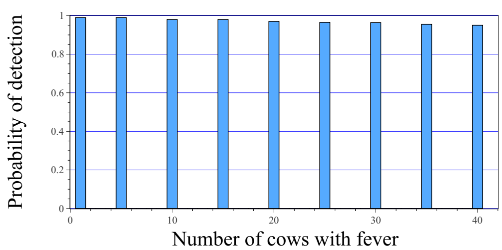
In this subsection, we have evaluated the performance of our proposed disease detection algorithm for the following experiments. The 300 training records are the first input for our algorithm. These training records are completely unlabeled and include all types of disease mentioned in Table II and also it includes the records for healthy cows. Since our proposed algorithm is unsupervised, thus it will form different disease clusters on this unlabeled data set. The next 200 records are used for the testing of the prediction accuracy of the algorithm. We have tested the prediction accuracy of the proposed algorithm for the individual diseases separately and also combinedly. We have also compared the classification accuracy of our proposed algorithm with few other supervised (Random forest and C 4.5) and unsupervised (K-means and Expectation Maximization) classification algorithms.

1) Experiments on individual diseases separately: Experiment-1: Detection probability of fever and comparison of classification performance with other algorithms
Here, in each iteration, we have calculated the detection probability of fever. Fig. 6a shows the probability of fever detection with the increase of the number of cows in each iteration. In our experiment, the probability of fever detection never goes bellow 95%. We have compared the performance of our proposed CDP algorithm with other supervised algorithms namely Random forest, C 4.5 and unsupervised algorithms namely K-means, Expectation-Maximization (EM) on the same data set. Fig. 6b shows the comparison of ROC curves for each classification algorithms for fever detection on the same data set. The proposed CDP algorithm and random forest show almost similar performance.

Experiment-2: Detection probability of cyst and comparison of classification performance with other algorithms
Fig. 7a shows the detection probability of cyst with the increase of the number of cows at different iterations of the experiment. The detection performance does not go bellow 90%. Fig. 7b shows the comparison of ROC curves of the proposed CDP algorithm with other algorithms. CDP algorithm shows

TABLE III: Basic sensory values for cow health monitoring.

Sensor	**Behavior**	**Value [9][29]**		
(1) Temperature Sensor	Cold	$35.5°C$ to $38.5°C$		
	Normal	$38.5°C$ to $39.5°C$		
	Low fever	$39.5°C$ to $40.5°C$		
	Middle fever	$40.5°C$ to $41.5°C$		
	High fever	Above $41.5°C$		
(2) Three-axis Accelerometer		**X**	**Y**	**Z**
	Standing still	constant	–	constant
	Moving	variable	variable	variable
	Prostration	constant	constant	constant
	Lameness	variable	–	variable
	Discomfort	variable	variable	variable
(3) Microphone	Mooing or Coughing	yes No		
(4) Gas sensor	Smell of breath	yes No		
(5) Load sensor	Load shifting	yes (load varies on four legs) No (load constant on four legs)		
(6) Heartbeat sensor	Heart rate (normal for adult cow)	48 to 84 beats per minute		
	Heart rate (anxiety)	Above 84 beats per minute		
(7) Electrical conductivity sensor	For healthy cow	4 to 6 milliSiemens (ms)		
	Clinically infected cow	Above 6 milliSiemens (ms)		
(8) Saliva sensor	Saliva hangs from mouth	Present Not present		



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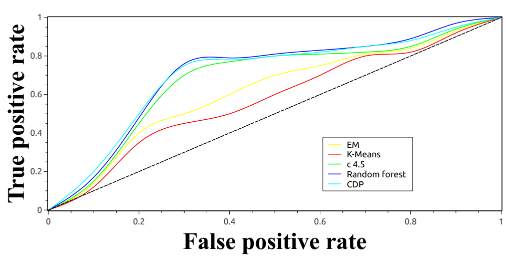

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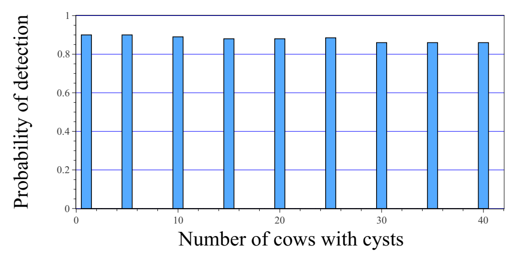
Fig. 6: Detection probability and ROC curve - fever



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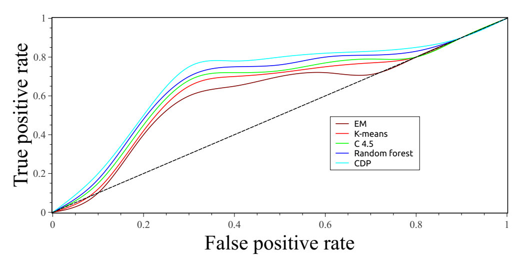


(b)

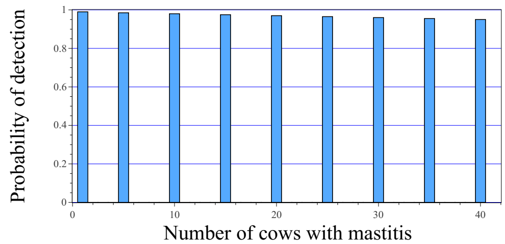
Fig. 7: Detection probability and ROC curve - cyst

better performance.

Experiment-3: Detection probability of mastitis and comparison of classification performance with other algorithms Fig. 8a shows the detection probability of mastitis at the different iteration of the experiment. The detection probability never goes bellow 95%. Fig. 8b shows the comparison of ROC curves. CDP algorithm shows better performance.

Experiment-4: Detection probability of pneumonia and comparison of classification performance with other algorithms Fig. 9a shows the detection probability of pneumonia at the different iteration of the experiment. The detection probability is never going bellow 85%. Fig. 9b shows the comparison of ROC curves. CDP algorithm shows better performance.

Experiment-5: Detection probability of Black quarter and comparison of classification performance with other algorithms Fig. 10a shows the detection probability of Black quarter at the different iteration of the experiment. The detection probability



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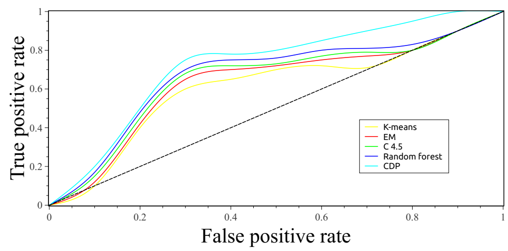
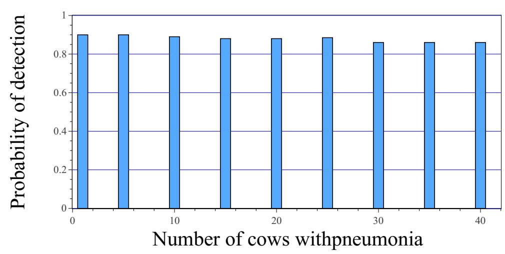
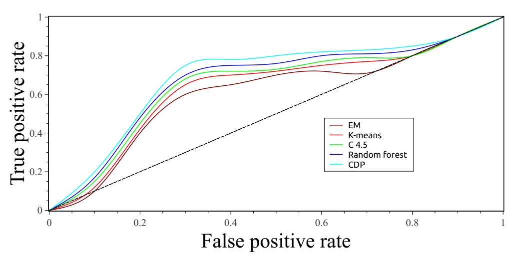


(b)

Fig. 8: Detection probability and ROC curve - mastitis

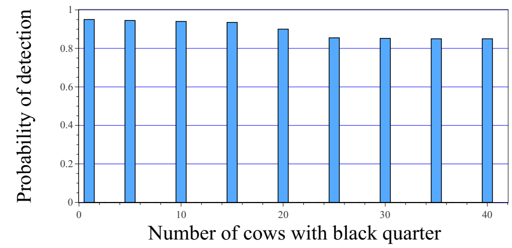


(a)

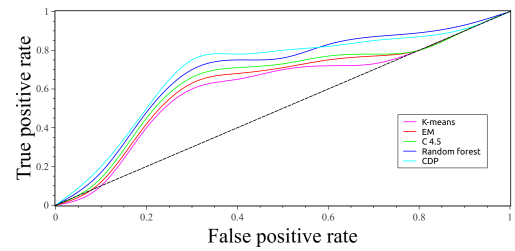


(b)

Fig. 9: Detection probability and ROC curve - pneumonia

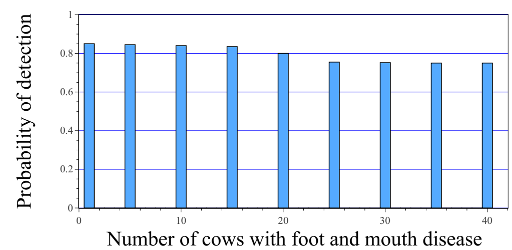


(a)

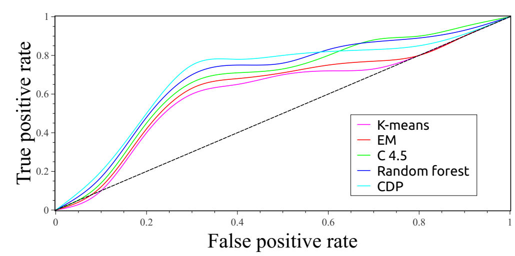


(b)

Fig. 10: Detection probability and ROC curve - black quarter



(a)



(b)

Fig. 11: Detection probability and ROC curve - foot and mouth disease

is never going bellow 83%. Fig. 10b shows the comparison of ROC curves. Again the proposed CDP algorithm and random forest show almost similar performance.

Experiment-6: Detection probability of Foot and mouth disease and comparison of classification performance with other algorithms
Fig. 11a shows the detection probability of Foot and mouth disease at the different iteration of the experiment. The detection probability is never going bellow 72%. Fig. 11b shows the comparison of ROC curves. Here C 4.5 and K-Means shows better performance in some iterations.

2) Experiments on individual diseases combinedly: In this experiment, we have taken records randomly from the test data set. Those records can have any type of disease symptoms as listed in Table II. Those randomly selected records are the inputs for our classification algorithms. At different iterations, we have measured the detection probability of different diseases. Fig. 12 shows a comparison graph of the detection probability of different algorithms when different diseases are considered combinedly. Proposed CDP algorithm shows better detection probability over other algorithms as a whole. It has never gone below 87%.

Table IV shows the comparison of clustering accuracy(%) of different classification algorithms on the data set.

B. Analysis

Using the proposed CDP algorithm we were able to predict the common cow-diseases correctly. Although, in general, the proposed algorithm is generic we could classify and test only

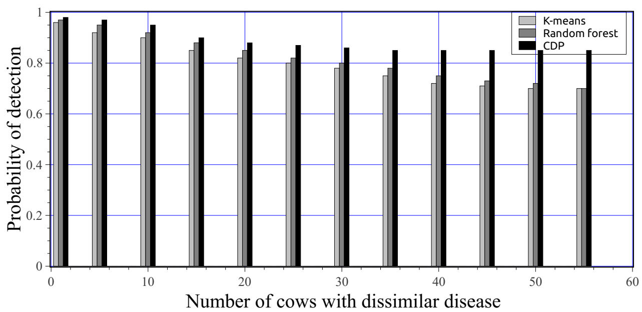


Fig. 12: Probability of detection of dissimilar disease.

TABLE IV: Clustering accuracy

Machine Learning Algorithms	**Accuracy** %
Proposed CDP	100%
κ-means	98%
Expectation-Maximization (EM)	80%

a few disease classes as listed in Table II. The accuracy of prediction is increased with the number of attributes we could measure for a particular disease class and how correctly we could measure the values of the attributes. The proposed CDP algorithm does not include any information relevant to a priori disease class, such as the number of different diseases(clusters) and the maximum number of cases per disease class, since it is an algorithm of strictly clustering or/and unsupervised classification.

The proposed CDP algorithm only store the principal components, eigenvalues, and threshold values in the testing phase. There is no need to store the training instances. This makes it lightweight.

Practically, in testing-phase for the CDP algorithm, the d_{test} can be calculated in $O(n)$ time, where the number of observed variables is denoted as n. The computational complexity to search (linear search) a disease class on the $C[\,]$ array is $O(m)$, where m is the different disease classes present. Practically, $m > n$, is the complexity of the linear search dominates. However, in the learning phase needs $O(NP^2)$ time to compute, where N is the size and P are the dimension of the training set. Thus, in testing-phase, the algorithm takes very less computation.

As per our knowledge, such a generic algorithm for cow disease prediction is new to the literature. In the experiment section, we have compared the performance of the proposed CDP algorithm with the performance of other classifiers on the same data set. It is found that the proposed algorithm performs better in this scenario.

VI. Conclusion

The proposed system tracks the behaviour of dairy cows effectively and reliably and ensures a particular physiological state such as certain health issues like fever, cyst, mastitis, pneumonia, black quarter, foot and mouth disease etc. to be identified. The IoT infrastructure consisting of hardware devices, a cloud system, and an end-user framework facilitates this purpose.

In the future, extended research can be done to find more number of measurable disease symptoms for different diseases and the sensors to record them. This will help the proposed CDP algorithm to predict more number of cow disease accurately.

References

[1] M. L, “Agriculture role on indian economy,” *Bus Eco J*, vol. 6, no. 4, 2015.

[2] O. Unold, M. Nikodem, M. Piasecki, K. Szyc, H. Maciejewski, M. Bawiec, P. Dobrowolski, and M. Zdunek, “IoT-based cow health monitoring system,” in *Int. Conf. on Computational Science*. Springer, 2020.

[3] P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. K. Ganapathiraju, “Everything you wanted to know about smart health care: Evaluating the different technologies and components of the internet of things for better health,” *IEEE Conum. Electron. Mag.*, vol. 7, no. 1, 2018.

[4] M. A. Safayet and A. U. Zaman, “IoT-based smart agriculture monitoring system with double-tier data storage facility,” in *Int. Joint Conf. on Computational Intelligence*. Springer, 2020.

[5] A. Al-Ali, I. A. Zualkernan, M. Rashid, R. Gupta, and M. Alikarar, “A smart home energy management system using iot and big data analytics approach,” *IEEE Trans. Conum. Electron.*, vol. 63, no. 4, 2017.

[6] P. Sundaravadivel, K. Kesavan, L. Kesavan, S. P. Mohanty, and E. Kougianos, “Smart-Log: A deep-learning based automated nutrition monitoring system in the iot,” *IEEE Trans. Conum. Electron.*, vol. 64, no. 3, 2018.

[7] P. Chanak and I. Banerjee, “Internet-of-things-enabled smart villages: An overview,” *IEEE Consum. Electron. Mag.*, vol. 10, no. 3, 2021.

[8] S. Jha, A. Taral, K. Salgaonkar, V. Shinde, and S. Salgaonkar, “E-Cattle health monitoring system using IoT,” *J. Network Commun. and Emerging Tech.*, vol. 7, no. 8, 2017.

[9] M. Meenakshi and S. S. Kharde, “Advanced cattle health monitoring system using Arduino and IoT,” *Int. J. of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 5, no. 4, 2016.

[10] K. B. Swain, S. Mahato, M. Patro, and S. K. Pattnayak, “Cattle health monitoring system using arduino and labview for early detection of diseases,” in *Int. Conf. on Sensing,Signal Processing and Security*. India: IEEE, 2017.

[11] M. Li, G. Xu, P. Lin, and G. Q.Huang, “Cloud based mobile gateway operation system for industrial wearables,” *Robotics and Computer-Integrated Manufacturing*, vol. 58, 2019.

[12] A. Suresh and T. V. Sarath, “An iot solution for cattle health monitoring,” in *IOP Conf. Ser.: Mater. Sci. Eng.* IOP Publishing, 2019.

[13] N. Esener, M. J. Green, R. D. Emes, B. Jowett, P. L. Davies, A. J. Bradley, and T. Dottorini, “Discrimination of contagious and environmental strains of streptococcus

uberis in dairy herds by means of mass spectrometry and machine-learning," *Sci Rep*, vol. 8, 2018.

[14] M. Ebrahimi, M. Mohammadi-Dehcheshmeh, E. Ebrahimie, and K. R. Petrovski, "Comprehensive analysis of machine learning models for prediction of sub-clinical mastitis: Deep learning and gradient-boosted trees outperform other models," *Comput. Biol. Med.*, vol. 114, 2019.

[15] S. Sharifi, A. Pakdel, M. Ebrahimi, J. M. Reecy, S. F. Farsani, and E. Ebrahimie, "Integration of machine learning and meta-analysis identifies the transcriptomic bio-signature of mastitis disease in cattle," *Plos One*, vol. 13, no. 2, 2018.

[16] J. Haladjian, J. Haug, S. Nüske, and B. Bruegge, "A wearable sensor system for lameness detection in dairy cattle," *Multimodal Technol. Interact.*, vol. 2, no. 2, 2018.

[17] S. Vyas, V. Shukla, and N. Doshi, "FMD and mastitis disease detection in cows using internet of things (IoT)," *Procedia Computer Science*, vol. 160, 2019.

[18] M. Lee, "IoT livestock estrus monitoring system based on machine learning," *Asia-pacific J. of Convergent Research Interchange*, vol. 4, no. 3, 2018.

[19] R. K. Nath, H. Thapliyal, A. Caban-Holt, and S. P. Mohanty, "Machine learning based solutions for real-time stress monitoring," *IEEE Consum. Electron. Mag.*, 2020.

[20] B. K. Wiederhold, I. T. Miller, and M. D. Wiederhold, "Using virtual reality to mobilize health care: Mobile virtual reality technology for attenuation of anxiety and pain," *IEEE Consum. Electron. Mag.*, vol. 7, no. 1, 2018.

[21] L. Rachakonda, S. P. Mohanty, E. Kougianos, and P. Sundaravadivel, "Stress-Lysis: A dnn-integrated edge device for stress level detection in the iomt," *IEEE Trans. Conum. Electron.*, vol. 65, no. 4, pp. 474–483, Nov 2019.

[22] L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iLog: An intelligent device for automatic food intake monitoring and stress detection in the IoMT," *IEEE Trans. Conum. Electron.*, vol. 66, no. 2, pp. 115–124, May 2020.

[23] P. S. Chatterjee and M. Roy, "Maximum match filtering algorithm to defend spectrum-sensing data falsification attack in cwsn," *Int. J. of Wireless and Mobile Computing*, vol. 15, no. 2, 2018.

[24] B. Sharma and D. Koundal, "Cattle health monitoring system using wireless sensor network: a survey from innovation perspective," *IET Wirel. Sens. Syst.*, vol. 8, no. 4, 2018.

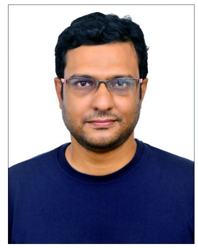
[25] M. A. G. V. Keyserlingk, K. L. Proudfoot, L. Vickers, and D. M. Weary, "Using cow behaviour to predict disease," *WCDS Advances in Dairy Technology*, vol. 23, 2011.

[26] A. Singh, "Common cattle diseases: Symptoms, treatment and prevention," *Dairy Year Book*, 2014.

[27] Z. Xie, T. Quirino, and M. L. Shyu, "UNPCC: A novel unsupervised classification scheme for network intrusion detection," in *Int. Conf. on Tools with Artificial Intelligence*, 2006.

[28] I. T. Jolliffe and J. Cadima, "Principal component analysis: a review and recent developments," *Phil. Trans. R. Soc. A*, vol. 374, no. 2065, 2016.

[29] J. Barwick, D. W. Lamb, R. Dobos, D. Schneider, M. Welch, and M. Trotter, "Identifying sheep activity from tri-axial acceleration signals using a moving window classification model," *Animals (Basel).*, vol. 8, no. 1, 2020.



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