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SMART FARMING USING IOT FOR HEALTHCARE OF CATTLE

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Abstract. Smart farming was a growing field of research, and monitoring the health of livestock played a significant role within it. Keeping cows healthy was crucial for milk production, but it was challenging and time-consuming to monitor each cow individually on a large dairy farm. In this paper, Live Care was proposed, an IoT-based system that automatically tracked the behavioral changes of cows in a large cow farm to monitor their health. Live Care also included the Cow Disease Prediction (CDP) algorithm, which used machine learning to predict the risk of cows developing different diseases based on their behavioral changes. The CDP algorithm served as the core of the Live Care framework. Additionally, the paper listed some common cow diseases, their symptoms, and the sensors used to record these symptoms. The performance of the CDP algorithm was compared to other machine learning algorithms.

Keywords: Monitoring the well-being of cows, using wireless sensors, predicting cow diseases, and practicing precise livestock management.

Introduction

Smart farming was a growing field of research, and monitoring the health of livestock played a significant role within it. Keeping cows healthy was crucial for milk production, but it was challenging and time-consuming to monitor each cow individually on a large dairy farm.

In this paper, Live Care was proposed, an IoT-based system that automatically tracked the behavioral changes of cows in a large cow farm to monitor their health. Live Care also included the Cow Disease Prediction (CDP) algorithm, which used machine learning to predict the risk of cows developing different diseases based on their behavioral changes. The CDP algorithm served as the core of the Live Care framework. Additionally, the paper listed some common cow diseases, their symptoms, and the sensors used to record these symptoms. The performance of the CDP algorithm was compared to other machine learning algorithms[3].

Agriculture and animal husbandry played a pivotal role in a nation's economic development. In India, agriculture contributed to nearly 18% of the Gross Domestic Product (GDP)[4], and about half of the population was employed in these

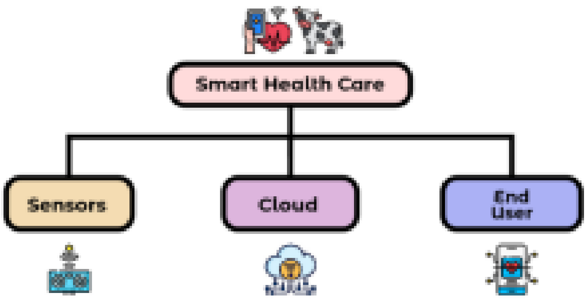

Fig. 1. Flow of the suggested Live Care monitoring system

sectors. Animal husbandry involved raising animals to produce various goods, including food items like milk, eggs, and meat, as well as non-food products such as wool, pharmaceuticals, and bone-related items. Dairy cow farming was a significant aspect of animal husbandry, and the health of cows had a profound impact on both the quantity and quality of milk production. Ensuring cow health required consistent daily monitoring, which was quite challenging, especially in large dairy farms with numerous cows. Manually checking the health of each cow was a labour-intensive task [3].

To address this challenge, it was essential to replace traditional cow health monitoring methods with advanced automated systems that utilized various sensors and IoT devices. Such automated systems were particularly valuable for dairy farms in remote areas where access to veterinarians was limited. They enabled timely treatment for common cow illnesses. In the broader field of agriculture, IoT applications were already being used for a range of purposes, including monitoring fields and greenhouses, employing agricultural drones, implementing smart irrigation control, and overseeing agricultural warehouses [6].

One such proposed solution was Live Care, an IoT-based framework designed for monitoring cow health. Each cow was equipped with individual sensors that transmitted data to the Cow Disease Prediction (CDP) system. The CDP system assessed the health of cows and stored this data in the cloud, as described earlier. Farmers could access this information through a web application to keep track of the health status of each cow[3]. While previous research mainly focused on generating alarms or detecting specific cow illnesses, our Lifecare platform was designed to predict multiple cow illnesses and notify farmers accordingly as shown in Fig. 1.

Previous Studies in the Field

Presently, IoT-based healthcare was a significant focus in the emerging phase of consumer electronics (CE) and consumer technology (CT). Pioneering technologies paved the way for the development of these innovative solutions, making them more accessible to the public. In this field, new applications had emerged, including cost-effective devices that were interconnected to enhance the consumer's way of life [2]. It’s worth noting that, while research in consumer electronics for human healthcare had been advancing, the healthcare frameworks associated with animal husbandry were noticeably underdeveloped.

1) Methods for creating alerts in response to behavioral shifts: An examination is conducted to explore various diseases that can impact cows, along with their associated symptoms. These illnesses may lead to alterations in [3] the cow's bodily parameters, which are recognized, and appropriate sensors are chosen to effectively detect these changes. The author utilizes an Arduino UNO to measure the body parameters of cattle and employs Lab View to visualize real-time graphical representations of the signals. Furthermore, a cloud-based mobile gateway operating system is proposed, featuring a streamlined structure designed for mobile devices connected to the cloud. Reference presented a framework that encompasses data collection, mobile nodes, and an IoT cloud platform [7]. The nodes responsible for gathering health parameters from cows are equipped with a variety of sensors. The mobile node functions as a conduit to the IoT cloud platform, where it identifies unhealthy cattle by performing data Analytics on the sensor data.

2) Methods for forecasting specific cow illnesses through the utilization of various machine learning (ML) algorithms: ML has recently been applied in the examination of mastitis pathogen transmission patterns in cattle. It has also been utilized for diagnosing both sub clinical and clinical mastitis at the individual animal level [1], [3]. Furthermore, the author has put forth an algorithm for identifying lameness by analyzing accelerometer data attached to cows' bodies and has cataloged wearable sensor devices designed for cows. In another context, the authors have introduced a system that utilizes an IoT framework to detect foot and mouth disease and mastitis. This system takes into account various parameters, including temperature, motion, sound, and more, in conjunction with micro controllers and machine learning algorithms. Lastly, a system is proposed for scrutinizing 3-axis acceleration data from IoT sensors. This system employs

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machine learning algorithms to identify behavioral patterns in breeding cows, encompassing estrus start, peak estrus activities, and estrus completion [1],[3].

The contributions outlined in the present paper

The primary goals of the proposed work are as follows:

1) Ease for the farmer: The person in charge of the cow farm could quickly identify cow health issues when dealing with a small number of cows, often within minutes or an hour. However, this task became quite challenging in large cow farms with hundreds of cows. Sometimes, taking timely precautions was delayed, which could lead to potential losses [4]. To prevent such setbacks, an IoT-based health monitoring system for cows proved highly beneficial.

2) Automatic monitoring of strange behaviour: A specific health disorder could be identified in an animal by closely studying the changes that occurred in their behavioral patterns. Different sensors continually recorded the behavioral changes of the cattle. If any abnormal values were recorded, they were sent as alerts to the stock person.

3) Automated prediction of multiple diseases: The CDP algorithm could predict certain common cow diseases by observing the cows' behaviour. This was beneficial for promptly addressing less severe illnesses in areas where finding a doctor was not easy.

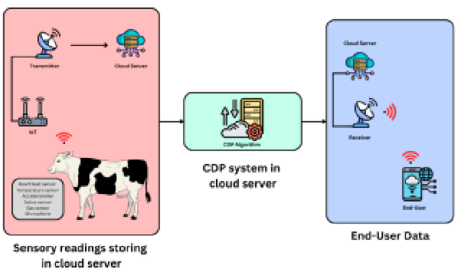

Fig. 2. Live Care monitoring system.

The suggested solutions are innovative and carry significance in the following manners:

- A highly effective IoT-based system for tracking the health of cows has been put forward as shown in Fig. 2.
- The suggested system is well-suited for capturing changes in the behaviour of cows in a large dairy farm.
- A table summarizes common cow diseases, symptoms, related behavioral changes, and the recording sensors.
- The introduction of the CDP algorithm is presented.
- The CDP algorithm stands as an unsupervised, multi-disease prediction approach.
- The use of various non-invasive sensors on the cow's body is discussed. • The CDP algorithm's effectiveness is assessed in comparison to other classification methods.

The suggested framework for livestock healthcare

The Live Care framework comprises several key components:

Sensor Module and Base Station: The sensor module is equipped with various sensors as shown in Fig. 4. capable of wireless data transmission, attached to the cow's body. These sensors capture the cow's activities and transmit the data to the base station through a wireless link [9].

Cloud System Module: The cloud system includes servers hosting the web application and databases. Data from the base station is sent to the cloud server for further processing and storage.

Web Application Module: Farmers can access the results of the monitoring through a web application as shown in Fig. 2. The web application displays the predictions made by the system regarding the cow's health.

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Predictive Algorithm: The base station runs the CDP (Cow Disease Prediction) algorithm on the sensed data to determine whether the cow is healthy or if it shows signs of illness. The results of this analysis are then transmitted to the cloud server [3].

Efficient Wireless Communication: To ensure efficient wireless communication between the sensors and the base station, especially when multiple sensors are transmitting simultaneously, cognitive wireless sensor nodes are utilized as shown in Fig. 2.

Machine Learning Model: The CDP system employs a Fully Connected Neural Network (FCNN) model. This model consists of one input layer, two hidden layers, and one output layer, each with eight neurons. It serves to establish the connection between cow behaviour and cow disease. Data is input into the model, which is then processed through the hidden layers, with the weighted inputs calculated using the dissimilarity measure definition as shown in Fig. 3. Sensor data Readings Diseases

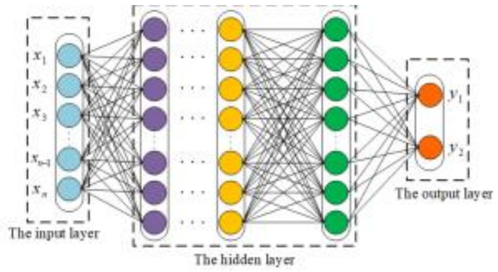

Fig. 3. Representation of a Fully Connected Neural Network (FCNN) model in CDP.

The Live Care system integrates sensors, predictive algorithms, and cloud-based tools to monitor livestock health, providing valuable insights to farmers through a user-friendly web application. Additionally, cognitive wireless sensor nodes are used to optimize data transmission, and a machine learning model helps in predicting cow health based on behaviour data

��(��) = ∑{(��)^2/��} (1)

In this context, "i" denotes the selected principal components, "mi" stands for the score of the ith feature in the d-principal component space, and "λi" represents the eigenvalue of the ith principal component.

I) *Examining Sensors and Their Output Responses in Various Health Disorders:*

Variations in a cow's behaviour serve as a key indicator of its health status. This section focuses on our research into monitoring changes in cow behaviour across various health conditions using a set of sensors. The following Table I lists the specific types of sensors necessary to detect and record these behavioral changes in different health diseases.

Table I. Diseases and their corresponding sensors

Disease	Symptoms	Measurable behavioural changes	Sensors
Fever	Discomfort	Lethargic	Accelerometer (neck)
	High temperature	Increase in body temperature	Temperature sensor (neck)
	Ache	Mooing	Microphone (neck)
Mastitis	Prostration	Laying down less frequently	Accelerometer (neck)
	Activity during milking	Kicking	Accelerometer (feet)
	Discomfort and pain	Restlessness	Accelerometer (feet and neck)
	Less food intake	Less grazing	Micro-phone (neck)
	Weight distribution	Weight shifting	Accelerometer (feet and neck)
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)
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)
Foot and mouth disease	Fever	High temperature	Temperature sensor (neck)
	Saliva	Saliva hangs from mouth	Saliva sensor (mouth)
	Lameness	Lameness	Accelerometer (feet and neck)

I) The Cow Disease Prediction (CDP) Algorithm: In this part, we employed an unsupervised multi-class classifier to anticipate potential health diseases based on the sensory data mentioned earlier [1]. To categorize the observed symptoms, we utilized the Unsupervised Principal Component Classifier. The CDP algorithm comprises two stages: the Disease-profile learning phase (Training phase) and the Disease-profile classification phase (Testing phase) [3].

1) Training Phase for Disease Profiles: In the initial phase, various sensors are affixed to the cow's body. As the system is configured, all the sensors transmit their data to the central device. These readings are denoted as {R1, R2, ..., Ri, ..., RT}, where T represents the total number of readings. Each reading encompasses d distinct measured properties.

(2)

2) Testing Phase for Disease Profiles: Throughout a typical day, the sensors attached to the cow's body identify alterations in behaviour and relay this information to the central unit. The recorded properties are subsequently re-mapped to a d-dimensional principal component space. Following this, we calculate the dissimilarity measures denoted as dtest [1],[3].

Table 2. Cow Health Monitoring: Fundamental Sensory Parameters

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Sensor	Behaviour	Value		
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		
		X	Y	Z
Three-axis Accelerometer	Standing still	constant	-	constant
	Moving	variable	variable	variable
	Prostration	constant	constant	constant
	Lameness	variable	-	variable
	Discomfort	variable	variable	variable
Microphone	Mooing or Coughing		Yes No	
Gas sensor	Smell of breath		Yes No	
Load sensor	Load shifting	yes (load varies on four legs)		
Heartbeat sensor	Heart rate (normal for adult cow)	48 to 84 beats per minute		
	Heart rate (anxiety)	Above 84 beats per minute		
Electrical conductivity sensor	For healthy cow	4 to 6 milliSiemens (ms)		
	Clinically infected cow	Above 6 milli Siemens (ms)		
Saliva sensor	Saliva hangs from mouth	Present Not Present		

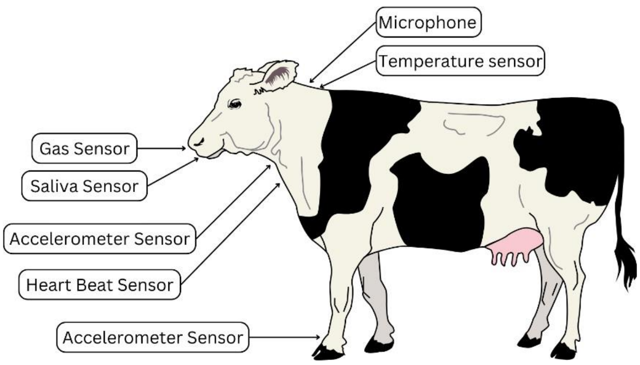

Fig. 4. Placing of different sensors on cow body

Experimental Results

Table 3. Sensors and their output measurable data

Disease	Sensor	Function
Fever	Accelerometer	Accelerometers are a promising tool for detecting fever in cows. By measuring changes in a cow's movement patterns, accelerometers can help farmers to identify sick cows early on and provide them with the necessary treatment.
	Temperature sensor	Temperature sensors are used to detect fever in cows by measuring their body temperature. By monitoring the cow's body temperature, temperature sensors can help farmers to identify sick cows early on and provide them with the necessary treatment.
	Microphone	Microphones are used to detect fever in cows by measuring changes in their respiratory patterns. cows that are sick typically have different respiratory patterns than healthy cows. This data can then be analysed to identify changes in the cow's respiratory patterns that may indicate fever.
Mastitis	Accelerometer	Accelerometers are used to detect mastitis in cows by measuring changes in their movement patterns. This data can then be analysed to identify changes in the cow's movement patterns that may indicate mastitis.
Mastitis	Micro-phone	Microphones can be used to detect mastitis in cows by measuring changes in their vocalizations. Cows with mastitis often make different sounds than healthy cows.
Ketosis	Load sensor	Load sensors can be used to detect ketosis in cows by measuring changes in their standing and lying time. Cows with ketosis typically spend more time lying down than healthy cows. This is because ketosis can cause cows to feel lethargic and weak.
	Accelerometer	Accelerometers can be used to detect ketosis in cows by measuring changes in their movement patterns. Cows with ketosis typically have different movement patterns than healthy cows. For example, a cow with ketosis may have less frequent and shorter rumination periods, decreased walking activity, increased lying time, and increased kicking of the hind leg.
Ketosis	Gas sensor	Gas sensors can be used to detect pneumonia in cows by measuring changes in the composition of their breath.
	Temperature sensor	Temperature sensors can be used to detect pneumonia in cows by measuring changes in their body temperature. Cows with pneumonia typically have a fever, which is an elevation in body temperature above normal levels.
Pneumonia	Heartbeat sensor	Heartbeat sensors can be used to detect pneumonia in cows by measuring changes in their heart rate.
	Temperature sensor	Temperature sensors can be used to detect pneumonia in cows by measuring changes in their body temperature. Cows with pneumonia typically have a fever, which is an elevation in body temperature above normal levels.
	Microphone	Microphone sensors can be used to detect pneumonia in cows by measuring changes in their respiratory patterns. Cows with pneumonia often have different respiratory patterns than healthy cows.
	Accelerometer	Accelerometer sensors can be used to detect pneumonia in cows by measuring changes in their movement patterns. Cows with pneumonia typically have different movement patterns than healthy cows.
Foot and mouth disease	Temperature sensor	Temperature sensors can be used to detect foot and mouth disease (FMD) in cows by measuring changes in their body temperature. Cows with FMD often develop a fever, which is an elevation in body temperature above normal levels.
	Saliva sensor	Saliva sensors can be used to detect foot-and-mouth disease (FMD) in cows by measuring changes in the composition of their saliva. Cows with FMD often have elevated levels of certain proteins and other biomarkers in their saliva.
	Accelerometer	Accelerometers can be used to detect foot-and-mouth disease (FMD) in cows by measuring changes in their movement patterns. Cows with FMD often have different movement patterns than healthy cows

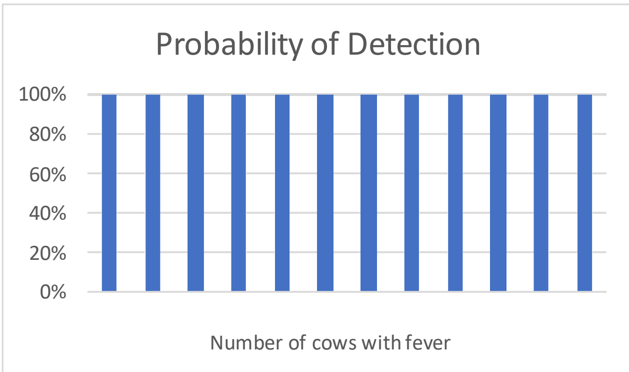

Fig. 5. (a) Probability of detection of cows with fever

In this study, we randomly sampled data from the test dateset, encompassing a variety of disease symptoms as outlined in Table II. These randomly chosen records served as inputs for our classification algorithms. Throughout multiple iterations, we assessed the detection probability for various diseases.

The proposed CDP algorithm consistently demonstrates.

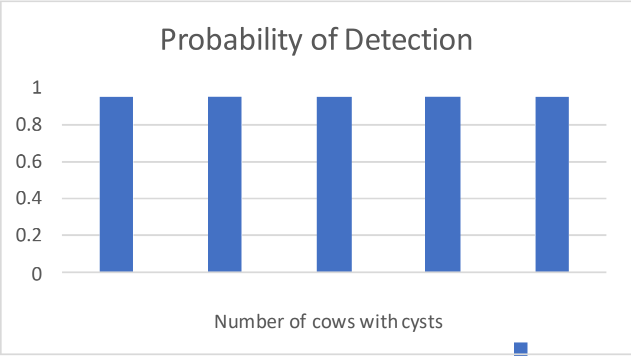

Fig. 5. (b) probability of detection of cows with cysts

Conclusion

The suggested system effectively and dependably monitors the behaviour of dairy cows, enabling the identification of specific physiological states, such as various health issues like fever, cysts, mastitis, pneumonia, black quarter, foot and mouth disease, and more. This is achieved through an IoT infrastructure comprising hardware devices, a cloud system, and an end-user framework. In the future, further research could expand the range of measurable disease symptoms for various illnesses and develop sensors to record them. This advancement would enhance the predictive capabilities of the proposed CDP algorithm for cow disease detection.

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