Cow Health Monitoring System using Deep Learning

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Abstract - Continuous monitoring of cow health is required in the dairy sector in order to meet the goals of increasing output and preventing diseases at an earlier stage. The conventional approaches to health monitoring are laborious, time-consuming, and primarily reliant on the use of manual observation. The purpose of this research is to offer an automated cow health monitoring system that makes use of a YOLO (You Only Look Once) object detection model that is based on Deep Learning. The system performs an analysis of video or picture data in real time in order to identify important health markers such as abnormal posture, lameness, restricted movement, and feeding behaviour. Because YOLO provides detection that is both quick and accurate, the technology is appropriate for agricultural settings that occur in real time. Following the processing of the detected data, the conditions of cows are classified as either healthy or unhealthy. Through the use of this approach, human interaction is minimized, and prompt health assessment is ensured. The approach that is being proposed improves the welfare of animals, maximizes the efficiency of dairy farms, and provides assistance for precision livestock production. The results of the experiments show that the detection accuracy and real-time performance have been significantly enhanced.

KeyWords: Cow Health Monitoring, Deep Learning, YOLO, Object Detection, Animal Health Assessment, Behavioral Analysis, Livestock Management

1.INTRODUCTION

Agriculture is one of the key sources of food production and rural livelihood, and the livestock and dairy business plays a significant part in the global agricultural economy. Dairy farming is one of the primary sources of food production. When it comes to ensuring high milk productivity, reducing economic losses, and promoting animal welfare, properly maintaining the health of dairy cows is absolutely necessary. Traditional methods of monitoring cow health, on the other hand, rely mainly on the physical observation of farm workers and veterinarians. When it comes to the early diagnosis of health problems like lameness, disease, stress, or odd behaviour, these procedures are not only time-consuming and labour-intensive, but they are also frequently useless.

The rapid development of intelligent agriculture and precision livestock farming has resulted in a considerable increase in the amount of attention that is being paid to automated monitoring systems. In the field of animal health monitoring, computer vision and deep learning technologies offer potential options for continuous monitoring that does not need any invasive procedures. YOLO, which stands for "You Only Look Once," has emerged as a potent real-time object identification method among the many deep learning models. This is owing to the fact that it has a high detection accuracy and a quick processing speed. As a result of its ability to recognize and track animals in real-world agricultural scenarios, YOLO models are suited for use in situations where pictures and video streams are being analyzed quickly.

When it comes to the monitoring of cow health, visual clues such as posture, movement patterns, feeding behaviour, and gait are extremely important in determining the presence of various health issues. The presence of abnormal walking patterns may be an indication of lameness, while a reduction in movement or feeding may be indications of an illness or stress. Through the utilization of the YOLO model, it is possible to automatically detect and analyzed these behavioral and physical indications without having to come into direct physical touch with the individual animals. Because of this, the cows experience less stress, and the need for constant human supervision is reduced to a minimum. The Cow Health Monitoring System that is being suggested makes use of Deep Learning to connect video surveillance with YOLO-based object identification in order to monitor cows in real time. In order to identify deviations from typical behaviour, the system first collects video data from farm cameras, then processes that data with a trained YOLO model, and then interprets the results. Moreover, the data that was extracted can be utilized for the classification of health conditions, the generating of alerts, and the provision of decision support for veterinarians and farmers. Such an automated method makes it possible to detect diseases at an earlier stage, to intervene at the appropriate moment, and to improve farm management.

Taking this method, in general, results in increased productivity, less operational costs, and support for environmentally responsible dairy farming techniques. The system that has been developed makes a contribution to the development of intelligent livestock management and precision agriculture by merging deep learning, computer vision, and intelligent monitoring, among other technologies.

[1] Electrochemical biosensors with three-dimensional geometries are becoming increasingly popular as advanced diagnostic instruments that can be worn and used on-site. These biosensors are particularly useful for illness detection and health management, particularly when they are combined with machine learning algorithms. The specific purpose of these intelligent biosensing systems is to enhance disease diagnosis, optimize operational efficiency, and enable data-driven decision-making. These systems are advanced by artificial intelligence and machine learning. As a result of developments in nanomaterials and three-dimensional printing, sensor sensitivity, affordability, and customization are all being improved, which further advances the usefulness of these technologies. The accuracy of biosensors will be improved by continued research in anomaly detection and data analytics, which will ultimately lead to improved animal welfare and more sustainable agricultural practices. These technologies have the potential to change agriculture, bringing about improvements in productivity, health, and sustainability on a global scale as they continue to develop.

[2] T. H. Dang and colleagues presented a proof-of-concept for a self-powered cow monitoring system that makes use of radio frequency energy harvesting technology for the purpose of classifying cow behavior in the context of a smart dairy farm. A sensor tag device that is worn around the neck and is powered by radio frequency energy and is equipped with an accelerometer is the core component of this system. When the sensor tag was supplied with an input RF power of 7 dBm, it displayed a remarkable power conversion efficiency (PCE) that exceeded 58.76%. Additionally, the complete charging time with a 10-mF supercapacitor is observed to be 5 minutes. The fact that it continued to function without interruption for more than ninety minutes without requiring a recharge is quite remarkable. In addition, the current profiles of the sensor tag demonstrated its suitability to applications that are defined by extremely low power consumption. In order to determine whether or not this self-powered dairy cow monitoring system is feasible in real-world circumstances, a demonstration that lasted for two weeks was carried out. It was successful for the algorithm to classify three different stages of behavior that were recognized by the cow. Using the information that was gathered throughout the experiment, two deep learning models were created in order to perform the classification of these states. Based on the findings, it was determined that both models were successful in classifying the three behaviors demonstrated by dairy cows, with the walking behavior achieving the highest level of accuracy. The Bi-LSTM model achieved an overall accuracy of 96.76%, which was higher than the 1D-CNN model and other standard approaches. This was a significant improvement over the other models. There are several limits to take into consideration, despite the fact that the results of the behavior data measurement are encouraging. The accuracy of behavior classification can be further improved by gathering datasets that are more diverse and extensive, taking into account variances across various breeds of cattle as well as individual features. It is possible that the system's capability to capture a wider variety of behaviors could be improved by combining more sensor modalities and advanced data fusion algorithms. In conclusion, the results of the behavior data measurement obtained from the author's self-powered cattle behavior monitoring system illustrate the usefulness of the system in capturing and evaluating the actions of cattle. The system is a valuable tool for real-time monitoring and management of cow behavior in agricultural settings because it combines energy-efficient data collecting using radio frequency energy harvesting with accurate behavior classification using the Bi-LSTM neural network. This combination establishes the system as a valuable tool. With the help of radio frequency (RF) energy harvesting, the author's system has the potential to function indefinitely, which would eliminate the requirement for frequent battery replacements and, as a result, reduce the costs associated with such replacements. This not only provides a significant economic advantage, but it also improves the monitoring solution's capacity to be maintained over time. The rectifier will be optimized in the future to improve the power conversion efficiency (PCE), which will reduce

the amount of time required for charging and increase its capacity to extend the amount of time that the sensor tag can be used.

[3] The TinyCowNet on embedded devices, which was presented by J. Bartels and others, has the potential to contribute to the improvement of farm efficiency by lowering the incidence of diseases, increasing feed control, and automating fertility distribution. These three distinct sectors have the potential to have a major impact on the decrease of gas emissions produced by livestock farms [6, 8], [9]. This work addressed the problems that are currently being discussed in the literature on Edge AI animal behavior estimation and suggested a solution to these problems using cow behavior distribution regressing RNNs that are referred to as TinyCowNet. Random Search and integer quantization were implemented in order to generate edge-implementable TinyCowNets that are minimum in size yet accurate in their implementation. These TinyCowNets were tentatively estimated using 45nm CMOS experimental literature on SRAM and operation cost. This work indicates that there is a possibility of future low-power but highly accurate cow behavior estimating devices. Although there is still work to be done in terms of ASIC development and implementation on FPGA, this work speaks to the possibilities of development.

The second part of this report examines the prior research that was deemed a Literature Survey. Section 3, labeled "Proposed methodology," provides a comprehensive description of the proposed approach. The experimental evaluation is covered in Part 4, possible modifications are discussed in Section 5, and the essay concludes with a conclusion on the existing plan.

2. LITERATURE SURVEY

[4] In this study, K. Li and colleagues provide a method for determining the body condition score of cows. This method comprises measuring and rating seven characteristics at a variety of distances. Within the framework of this research, the technique is comprised of three basic components. To begin, 19 feature points were localized by utilizing the HR-Net and the positioning locating correction method, in conjunction with an attention mechanism, which was based on the idea of human feature point localization; In the second step, we utilized a database that we had constructed ourselves as well as an image enhancement technique in order to separate the background at various angles and sizes; The third step consisted of the completion of the measurement and scoring of seven cow features. In addition, the author found that the impacts of distance, depth image quality, and various depth image restoration methods had an impact on the accuracy of measurement and scoring. The purpose of this study was to determine whether or not a proposed method for measuring seven characteristics of cows using depth photographs that had complete depth values actually worked. According to the findings, the measurements of chest depth, hip height, ischial width, parallelism of hind, hind leg curvature, length of teat, and depth of teat achieved a coefficient of determination greater than 0.9. Additionally, the relative measurement errors ranged from -5.93% to 8.33% when the camera was positioned at a distance of 1-2 meters from the cow. After being converted into scores, the accuracy of the feature scores was greater than eighty percent. These data provide evidence that the proposed strategy is both successful and feasible in terms of achieving the real production needs at this camera distance. While the average relative measurement error was between -9.84% and 1.26%, the coefficient of determination was greater than 0.8 for camera distances of 2-3 meters. The only exceptions to this were the length and depth of the teat, which were both within the acceptable range. In general, these findings indicate that the method that was proposed is dependable at this distance and has the potential to be applied to manufacturing in the real world. In this investigation, the AR algorithm, the Lerp algorithm, the GAN, and the depth image completion method that were proposed in this study were tested for their capacity to complete and measure the depth values of cow feature points when there was a lack of data. The findings demonstrated that each of the four algorithms had the capability to effectively manage small-scale depth deficiencies for characteristics such as chest depth, hip height, ischial width, length of teat, and depth of teat. At a camera distance of 1-2 meters from the cow, there is a significantly high degree of agreement between machine and manual measurements (with a coefficient of determination more than 0.8 and relative measurement error regulated within a range of -10% to 10%). However, when the camera was two to three meters away from the cow, the AR algorithm, the GAN algorithm, and the Lerp algorithm exhibited higher variations in measurement accuracy than the solution that was provided in this work, which was able to effectively handle large-scale depth loss. In light of this, the method that was suggested in this research is the most appropriate approach for carrying out measurements at distances ranging from one to two meters, as it is capable of satisfying the actual production needs and

guaranteeing reliable findings. In the current study, deep learning techniques were successfully used to the measurement of seven different characteristics. With that being said, there is possibility for future enhancement in the form of expanding the measurement and scoring scope to include other items. This is because there are twenty different items that are used to score cows. In addition, it is recommended that future research investigate more sophisticated methods for dividing and localizing the hoof and udder of cows. The procedure of measuring and scoring simply makes use of image processing techniques at the moment; however, in the future, study will investigate video streaming approaches in order to increase accuracy and completeness.

[5] Using action categorization, J.-W. Chae and colleagues explain the behaviors of cattle, while simultaneously boosting performance through the implementation of the FlowEQ transform. Through the utilization of action classification, it was possible to successfully identify actions shown by cattle that were either difficult to identify or unclear at the frame level. In addition, the recently introduced FlowEQ transform altered the data that was used as input for the classification model by introducing a motion field that represented movement. Consequently, this made it possible to incorporate temporal information into the frames that made up the video. This made it possible for the action classification to learn from data that was more informative and to achieve improved inferential performance without experiencing significant increases in computational costs. This was made possible by the straightforward procedures that were utilized. In addition, the incorporation of temporal information into the photographs was validated by means of verification using a straightforward technique for image categorization. The author anticipates that these developments in development techniques could be utilized in a wide variety of applications, where a better understanding and classification of complex behaviors are essential. For example, automated monitoring and management systems for livestock, wildlife observation, and even the enhancement of surveillance and security measures are all examples of applications that could significantly benefit from these advancements. Although the application of action classification was successful in classifying the behavior of cattle and brought about improvements in performance through the use of the FlowEQ transform, there are still some areas that require additional testing. The first thing to note is that although though we collected 400 movies for each class on the behavior of cattle, this quantity, when broken down into train, validation, and test sets, might not be deemed as thorough. As a result, the authors are carrying on with the process of data collection and want to carry out more research using a more extensive dataset. As a second step, the FlowEQ transform that has been developed will be utilized in a number of different action classification models in order to evaluate its efficiency. Concurrently, the performance in action categorization will be tested based on designs other than the transformer in order to test the applicability of the concept to a wider range of situations. In conclusion, the authors intend to construct new deep learning models that utilize this strategy, expanding on the potential that has been identified in the FlowEQ transform when it is applied to frame-level interpretation.

[6] T. H. Dang and colleagues claim that the results of behavior data measurement collected from the author's self-powered cattle behavior monitoring system illustrate the usefulness of the system in recording and evaluating the actions of cattle. The system is a valuable tool for real-time monitoring and management of cow behavior in agricultural settings because it combines energy-efficient data collecting using radio frequency energy harvesting with accurate behavior classification using the Bi-LSTM neural network. This combination establishes the system as a valuable tool. With the help of radio frequency (RF) energy harvesting, the author's system has the potential to function indefinitely, which would eliminate the requirement for frequent battery replacements and, as a result, reduce the costs associated with such replacements. This not only provides a significant economic advantage, but it also improves the monitoring solution's capacity to be maintained over time. The rectifier will be optimized in the future to improve the power conversion efficiency (PCE), which will reduce the amount of time required for charging and increase its capacity to extend the amount of time that the sensor tag can be used.

[7] In their presentation, Darvesh et al. observe the physical health of the cattle, which led the author to develop a technique for monitoring the bovine's overall health. The author has arrived at the conclusion that the art of animal husbandry employs a system that is automated for the purpose of monitoring the health of cattle. With the method that is described in this work, it is possible to do real-time monitoring of the overall health of a cow. In order to ensure the system's dependability and effectiveness, it was tested on dairy cattle. The cost-effectiveness of the system can be attributed to the low cost of the electronic components.

Because of this, the system is able to properly monitor the overall health of a cow.

[8] In terms of service delivery and accessibility, Isak Shabani and colleagues offered a more comprehensive strategy. This technique was designed to accommodate a greater number of customers that require real-time information from cattle monitoring in real time. By utilizing the system that was built, the authors of this piece were not restricted to the utilization of a particular kind of sensor; rather, they were able to utilize any kind of sensor from any manufacturer. The author was not restricted to a single application, but rather provided the interface via which any existing application could be accessible. The only need was that the application in question possessed the appropriate authorizations to access the data to which it would be referring.

[9] It was proposed by Pawitar Dulari and colleagues that the data acquiring unit would be comprised of various types of biomedical sensors, such as a sensor for measuring body temperature, a sensor for measuring blood pressure, a sensor for measuring humidity, and a sensor for detecting heart beat rate, all of which would be interfacing with a microprocessor. The data gaining units are responsible for acquiring data and making it accessible to the data administering and data interact units, which include the user's web page, server, and cloud. In order to perform straightforward and universal automatic measurements of a wide variety of health parameters, the sensors are utilized. These kinds of health sensors will be attached to the bodies of the cattle, and they will give an output in the form of an electrical signal. These sensors will continuously monitor the body problems of the cattle, such as their temperature and heart rate, among other characteristics. Following that, a comparison is made between these signals and a standard limit of normal values that has been established as the beginning point in the data administering unit. In the event that the administering unit notices significant alterations or abnormal changes in particular cattle, they are able to get in touch with a veterinarian who is located closer to them. It is possible for the controlling person or farm manager to communicate the health graph to the veterinarian using the Internet of Things (IOT) administering unit in some circumstances, such as when a veterinarian is not accessible at the nearby hospital [Fig. 1; Plate 2; Table 1]. Following that, a veterinarian can evaluate the health of the animal (the buffalo) by examining these graphs and other information that is related to it. In the event that the veterinarian is not available, the appropriate therapy can also be administered to cattle in the event of an emergency.

[10] According to X. Zhao and colleagues, illnesses and metabolic abnormalities have a detrimental effect on the quantity and quality of milk produced by dairy cows, as well as on their fertility and overall health. As a robust and promising method for examining metabolic abnormalities linked with health status, as well as for identifying possible biomarkers for illness diagnosis and monitoring metabolic states, metabolomics has emerged as a powerful and promising technique. The purpose of this review is to present an overview of research that was completed between the years 2010 and 2024, with a particular emphasis on metabolic changes in dairy cows in relation to the most prevalent and difficult diseases in dairy farming, as well as physiological states that are indicative of general health. There have been a number of studies that have indicated interesting metabolite candidates; however, many of these studies are restricted by the small sample size and the lack of validation in larger independently controlled cohorts. Therefore, the data that have been obtained up to this point ought to be considered exploratory rather than diagnostic tools. It is recommended that future research give priority to large-scale, well-controlled validation studies that take into account confounding factors and aim to integrate metabolomics with other omics approaches in order to improve biological interpretation and contribute to the development of more comprehensive health monitoring strategies in the future.

[11] A significant step forward in the field of contemporary agriculture is represented by the development of a smart neck collar for the detection of diseases in cows by D. Kaur and colleagues. The implementation of this cutting-edge technology not only guarantees the health and safety of the author's animals, but it also improves the overall efficiency and production of the industry as a whole. The use of this smart collar gives farmers and veterinarians the ability to detect ailments at an earlier stage, which enables them to engage in rapid intervention and treatment. Vital factors such as body temperature, heart rate, and activity levels are continuously monitored by the smart collar. Furthermore, its capabilities of real-time data transmission allow for remote monitoring, which reduces the requirement for persons responsible for the care of these animals to be physically present at all times. As the author moves toward a more sustainable and ethical approach to agriculture, this smart neck collar serves as a testament to the possibilities of technology in protecting the welfare of animals as well as the livelihoods of those who are dependent on agriculture. With the continuation of research and development, it is encouraging to

imagine a future in which precision agriculture becomes the standard. This would result in cows who are healthier and happier, as well as an agricultural business that is more resilient.

[12] The authors Kaur and Virk et al. offer a novel Internet of Things-based system for real-time monitoring of cow health. This system integrates wearable sensor technology that has been specifically created for cows with powerful hybrid machine learning models in order to improve the accuracy of disease prediction. The use of a comprehensive dataset allowed for the thorough examination of both traditional and hybrid approaches. The results showed that the Gradient Boosting (GBoost) network, when paired with Long Short-Term Memory (LSTM) networks, achieved the highest performance in terms of accuracy, precision, recall, and F1-score. In order to address the issue of class imbalance and maximize the efficiency of the model, the SMOTE technique was utilized. The end-to-end design of the system is what makes it stand out. It begins with the collection of data through the use of a smart collar, continues with cloud-based analysis, and concludes with the notification of farmers using a mobile application that is multilingual (English and Punjabi). The real-time alerts that are provided by this pipeline make it possible to detect diseases at an earlier stage and provide support for urgent actions. Because of its low cost, adaptation to local infrastructure, and emphasis on smallholder farmers, it is suitable for use in agricultural contexts with limited resources and may be scaled up to meet the needs of larger populations. The focus of future research will be on expanding the dataset by including a greater number of animals and a wider range of regions, incorporating additional physiological and behavioral indicators, and investigating advanced learning architectures such as attention-based models in order to improve the system's ability to generalize across a variety of regions and breeds of cattle. Continuous collaboration with veterinarians has confirmed the accuracy and dependability of the health alerts issued by the system. This is achieved despite the fact that quantitative benchmarking using publically accessible datasets is currently limited due to differences in testing settings. In the future, research will be conducted with the objective of enhancing benchmarking by including baseline heuristic models and carrying out direct comparisons with conventional veterinary diagnostics. This will further demonstrate the system's robustness and practical application.

[13] It was mentioned by C. C. Mar and colleagues that the cow detection and tracking system is the primary component in the establishment of a reliable livestock monitoring and management system. The author constructed the system out of a cow calving enclosure with the intention of predicting the calving time for each cow based on the behavior that is associated with it, delivering timely alerts to farm management, and enabling prompt provision of the right care and assistance to cows that are calving. The system that the author constructed was developed using data from the actual world, specifically from cattle farms, and it included the normal difficulties that occur in real-world programs. When position and appearance descriptors are combined, it is possible to precisely identify objects and create a strong system for tracking several objects at the same time. In accordance with the performance of the system on video sequences, the author's tracker was able to successfully eliminate noise, re-track cows that had been lost, and identify new cows. The performance was remarkable, and it tracked accurately through some of the more complicated scenarios that were included in the video sequences. A thorough cow-calving detection system requires that each cow be continuously followed without any IDS cases, which could lead to a false calving detection. This is necessary in order to create the system completely. In the work that will be done in the future, the system that has been presented will be developed in order to tackle the IDS problem as a priority and to develop an autonomous tracking tool for predicting the times at which calves will give birth. It is essential to recognize the limitations of the author's current study, despite the fact that it offers vital insights on detection and tracking. For the purpose of addressing this worry, the authors are actively aiming to expand the trials that they have conducted in subsequent rounds of their research.

[14] According to Y. Chen et al., previous research on cow mounting behavior recognition has relied on complicated models to determine the mounting behavior of cows in sparse cow populations. This approach does not provide the maintenance of a high level of accuracy when the number of cows is high. Additionally, more complicated models require a bigger quantity of resources from the necessary hardware. Consequently, the current research proposes a lightweight cow mounting behavior detection model that is based on YOLOv5s for a total of 200 cows. This model is able to accomplish a reduced consumption of hardware resources while still keeping a high level of detection accuracy. In the current study, a lightweight backbone network is constructed with the goal of reducing the number of parameters that are used in the model and

improving the model's capacity to extract shallow features. Following this, a feature improvement module known as C3ECAGhost_3 is developed with the purpose of combining the college attention mechanism, residual structure, and Ghost convolution in order to extract semantic information that is deep. The suggested lightweight cow mounting behavior you recognition model has a mAP value of 87.7%, a model weight size of 4.1 MB, and an inference speed of 333.3 images per second, each of which is determined by the results of the model performance evaluation. Consequently, the performance of the suggested model is significantly better than that of the object detection models that are currently in use. Additionally, the model that is provided in this study beats the other models that have been reported in prior studies in terms of the accuracy and the speed at which it can make inferences regarding cow mounting behavior identification in dense herd cows. As a result, it is possible to prove that the lightweight model that was provided demonstrates high accuracy and high inference speed in identifying calves' mounting behavior while simultaneously minimizing the amount of hardware resources that are consumed. When it comes to computer vision technology, which is employed in smart farming, the wide range of movement that cows are capable of presents a substantial difficulty. In order to facilitate the practice of intelligent cow farming, it is essential to have cameras installed throughout the entire enclosure. As a consequence of this, the model is required to process data simultaneously from several video feeds, which is a considerable difficulty in terms of both the amount of time it takes and the number of resources it consumes from the hardware. The development of lightweight models that are extremely accurate will be given a larger emphasis in the study that will be conducted in the future. Not only does the architecture of the models need to be as lightweight as feasible, but the modules that make up the models also need to maintain a high level of accuracy. In order to successfully implement the algorithms in large-scale farming operations, this is a prerequisite.

3. METHODOLOGY

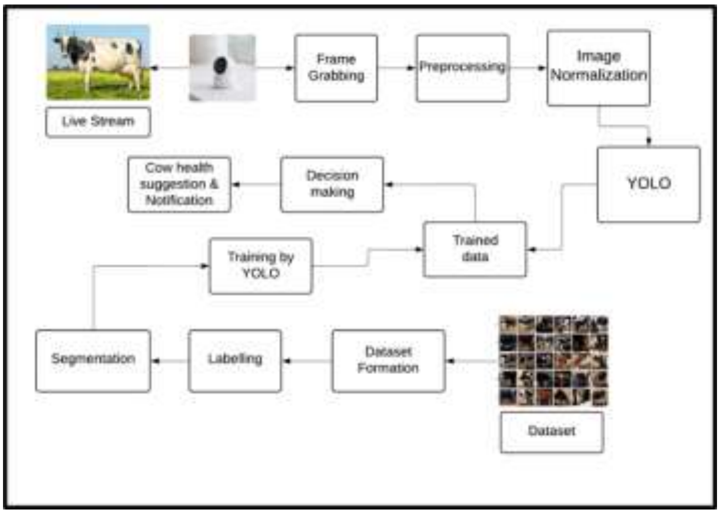

Figure 1: System Overview Design

The presented approach for the purpose of achieving effective realization of cow health detection and monitoring using YOLO has been depicted in the figure given above. The various steps involved in the presented approach are defined in detail in the section given below.

Step 1: Training the Cow Images for YOLO

The system effectively identifies and monitors cow health issues using the image dataset. Identifying and analyzing the cow in the image is the initial stage in the process of generating health suggestions and notifications. Object detection and analysis on cow photos is efficiently performed by the YOLO approach, which is utilized by the cow detection and health monitoring module. Before using this model for real-time cow health monitoring, it needs to be trained.

The training approach initiates with the installation of the ultralytics for the Yolov8 model and the downloading of the roboflow dataset for the implementation of training. The roboflow is connected using an API key and the dataset for the Cow Health recognition is synthetically prepared. The prepared dataset is effectively scanned for extracting the list of the files in the directory. The list of the files is then utilized for extraction of the number of files in the directory. The overall number of files used for dataset is approximately 1000.

Following the successful integration of the roboflow data and the effective shuffling of the Cow dataset, the yolov8 model can be initiated for the yolo task for object recognition. The trained weights are being utilized to initiate the detection model and the training is done the dataset for 200 epochs with the image size as 640 and batch size as 32. The runs of the project are then stored as a zip file in the specified directory after the training of the yolov8 model. The Yolov8 model is described in the table 2 give below.

S.No	Layer Type	Parameters
1	Convolutional Layer	7x7x64 Stride-2
2	Maxpool Layer	2x2 Stride 2
3	Convolutional Layer	3x3x192
4	Maxpool Layer	2x2 Stride 2
5	Convolutional Layer	1x1x128
6	Convolutional Layer	3x3x256
7	Convolutional Layer	1x1x256
8	Convolutional Layer	3x3x512
9	Maxpool Layer	2x2 Stride 2
10	Convolutional Layer	1x1x256
11	Convolutional Layer	3x3x512
12	Convolutional Layer	1x1x256
13	Convolutional Layer	3x3x512
14	Convolutional Layer	1x1x256
15	Convolutional Layer	3x3x512
16	Convolutional Layer	1x1x256
17	Convolutional Layer	3x3x512
18	Convolutional Layer	1x1x512
19	Convolutional Layer	3x3x1024
20	Maxpool Layer	2x2 Stride 2
21	Convolutional Layer	1x1x512
22	Convolutional Layer	3x3x1024
23	Convolutional Layer	1x1x512
24	Convolutional Layer	3x3x1024
25	Convolutional Layer	3x3x1024
26	Convolutional Layer	3x3x1024 Stride 2
27	Convolutional Layer	3x3x1024
28	Convolutional Layer	3x3x1024
29	Fully Connected Layer	
30	Fully Connected Layer	

Figure 2: Model Summary for YOLOv8

The YOLOv8 is derived as a modification of the Convolutional Neural Network. It utilizes the components of the CNN approach in a unique and effective manner to achieve the object recognition with greater accuracy. The Yolo architecture is made up of 24 convolutional layers with varying parameters which are assisted by 4 max pooling layer and various dropout and batch normalizations to regularize the model and avoid overfitting. The model finally culminates in 2 Fully connected layers.

The initial convolutional layers decompose and reduce the channels which are then max pooled with a stride set as 2 and the kernel size 2x2. These max pooling layers are all identical in all the layers of this model. The subsequent convolutional layers have increasing kernel sized to accommodate for the increase in the information. The activation function being utilized for these layers is the RELU activation function. The activation function is identical for all the layers except for the fully connected layers that implement a linear activation function to form the .pt file which is the trained data file for Yolo8. This .pt file will be used in the upcoming steps to alert the blind person for the Cow.

Step 2: Live Stream Testing and Cow Health Monitoring

In this step, a live video stream is captured using a camera device. The live stream is processed by grabbing individual frames, which are then subjected to preprocessing and image normalization to enhance image quality and consistency. The normalized frames are passed to the YOLO model, where real-time cow detection and analysis are performed using the trained data.

Based on the detection results obtained from YOLO, the decision-making module evaluates the health condition of the cow. The decision-making process determines whether the detected parameters indicate a normal or abnormal health condition. Accordingly, cow health suggestions and notifications are generated and sent to the user for timely action.

This integrated approach enables continuous monitoring of cow health using live video streams, trained YOLO models, and automated decision-making, thereby improving livestock health management and early disease detection.

4. RESULT AND DISCUSSIONS

Operating on a Windows-based system with 16 GB of RAM and an Intel Core i7 CPU, the suggested model for monitoring cow health is put into action. In order to train, test, and evaluate the models, the experiments are conducted in the Anaconda IDE environment using Spyder. The accuracy, precision, recall, and macro F1-score, which are common performance metrics obtained from the confusion matrix, are used to systematically analyze the proposed YOLO-based framework. When assessing models for object recognition and classification with many classes, these metrics are commonly used.

In order to calculate the performance evaluation parameters, we use the following formulas:

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN) \quad (1)$$

$$\text{Precision } (P) = TP / (TP + FP) \quad (2)$$

$$\text{Recall } (R) = TP / (TP + FN) \quad (3)$$

$$\text{Macro-F1} = (2 \times P \times R) / (P + R) \quad (4)$$

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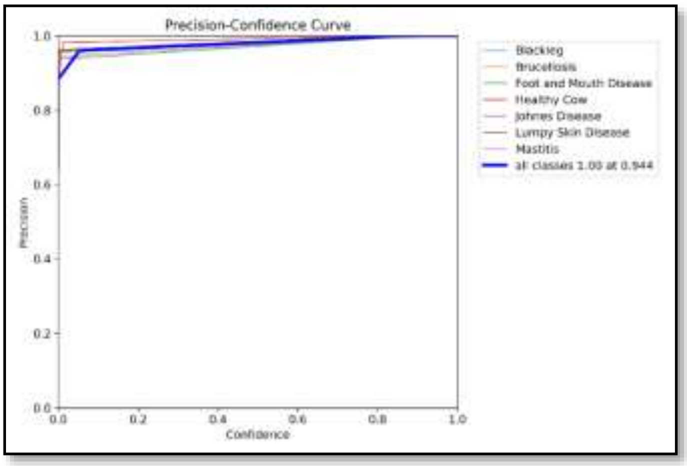
Here, TP represents true positives, TN denotes true negatives, FP indicates false positives, and FN corresponds to false negatives.

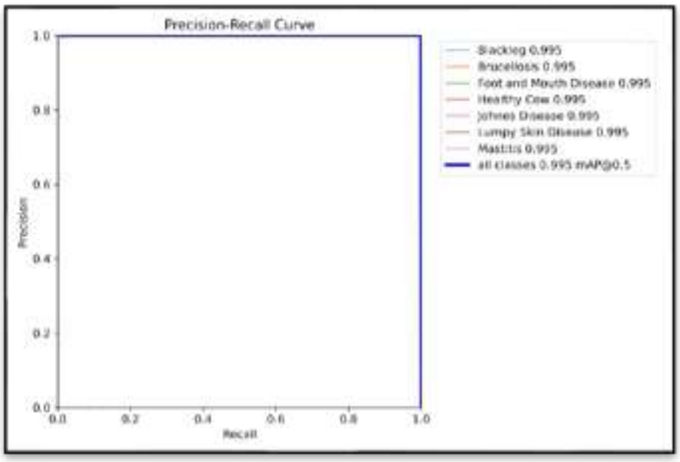
The obtained experimental results are presented using the following evaluation plots:



Plot 1: Precision–Confidence Curve Analysis

For every class—from Blackleg and Brucellosis to Foot and Mouth Disease, Healthy Cow, Johnes Disease, Lumpy Skin Disease, and Mastitis—the Precision-Confidence curve shows the relationship between prediction confidence and precision. The curve clearly demonstrates that, even when using lower confidence criteria, the precision stays quite high, close to 1.0.

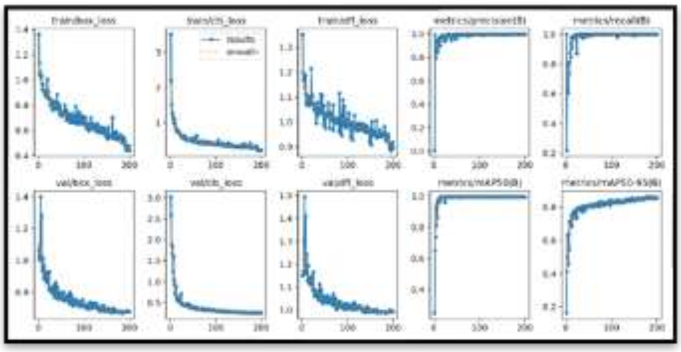
All classes are accurately predicted by the model at a confidence level of around 0.944. This shows that the model consistently makes accurate predictions even as confidence levels rise, and it generates minimal false positives. A stable and dependable YOLO model for cow illness identification is demonstrated by its good performance across all disease categories.



Plot 2: Precision–Recall Curve

The accuracy-recall curve shows how well each disease class balances recall and precision. With an overall mAP@0.5 of 0.995 and an average precision (AP) value of about 0.995 across all classes, the detection performance is top-notch.

Because the curve stays close to the upper right corner, we can see that the model has a high recall and very high precision, meaning it recognizes nearly all-important cases. As a result, there are no discernible compromises between recall and precision when using the trained YOLO model to detect diseases in cows across classes.



Plot 3: Training and Validation Performance Metrics

Over the course of 200 iterations, the model's convergence behavior is shown by the training and validation graphs. A consistent decrease in the training losses (box loss, classification loss, and DFL loss) suggests that the training was effective in learning and optimizing. The model's ability to generalize to new data without suffering from overfitting is further supported by the fact that validation losses tend to decrease.

Accuracy and recall measurements show steady improvement and quick convergence, eventually stabilizing around 1.0. Accurate bounding box localization and classification over different IoU thresholds is reflected in the mAP@50 curve, which approaches 1.0, and the mAP@50-95 curve, which rises steadily and settles around a high value.

Figure 5: Result

The trained YOLO model's real-time detection results for cow health classification are shown in the first batch of photographs. The bounding boxes and class labels show that the model correctly identifies numerous health states, including Healthy Cow and Mastitis. With a confidence score of about 0.9 and a rectangular bounding box highlighting each detected object, we can see that the predictions are very reliable.

Proof of the trained model's resilience in identifying disease-specific visual cues is the consistent recognition of Mastitis instances across different frames. Just as the model successfully differentiates between normal and unhealthy situations, it confidently detects healthy cows. These outcomes prove that the suggested system's dataset preparation, labeling, and training procedure worked.

5. CONCLUSIONS

The purpose of this project is to improve the management of livestock health by presenting an automated Cow Health Monitoring System that makes use of a YOLO model that is based on Deep Learning. Through the utilization of computer vision techniques, the system is able to detect and monitor cow behaviour and physical conditions in real time utilizing an effective method. The approach that has been proposed allows for the early diagnosis of health issues such as lameness and reduced activity; this is accomplished by the analysis of posture, movement, and activity patterns. Using the YOLO model ensures excellent detection accuracy while simultaneously reducing the amount of time needed for computation, which makes it suited for application in real-time farm scenarios. This technique lessens the need on manual observation and reduces the likelihood of errors caused by humans. In addition to this, it improves the welfare of animals by making quick medical intervention possible. The approach that has been proposed helps to improve the productivity of dairy farms and supports precision animal farming practice. Taking everything into consideration, this intelligent monitoring system offers a method of modern livestock management that is scalable, efficient, and cost-effective.

In order to achieve more precise health monitoring, the system can be enhanced by incorporating Internet of Things sensors. The accuracy of detection can be improved with more advanced YOLO models. Real-time alerts can be provided by applications that are either mobile or cloud-based. The prediction of diseases through the use of historical data can also be included.

REFERENCES

1. [1]M. A. Ali, B. R. Howell and L. Zhang, "3D-Printed Wearable Biosensors for Livestock Health Monitoring," in IEEE Open Journal of Instrumentation and Measurement, vol. 4, pp. 1-9, 2025, Art no. 9500709, doi: 10.1109/OJIM.2025.3589706.

[2] T. H. Dang, L. Nkenyereye, V. -T. Tran and W. -Y. Chung, "Self-Powered Cattle Behavior Monitoring System Using 915 MHz Radio Frequency Energy Harvesting," in IEEE Access, vol. 12, pp. 33779-33791, 2024, doi: 10.1109/ACCESS.2024.3360852.

[3] J. Bartels et al., "TinyCowNet: Memory- and Power-Minimized RNNs Implementable on Tiny Edge Devices for Lifelong Cow Behavior Distribution Estimation," in IEEE Access, vol. 10, pp. 32706-32727, 2022, doi: 10.1109/ACCESS.2022.3156278.

[4] K. Li, G. Teng, J. Wang, Y. Zhang, L. Gao and H. Feng, "Body Condition Scoring of Dairy Cows Based on Feature Point Location," in IEEE Access, vol. 12, pp. 5270-5283, 2024, doi: 10.1109/ACCESS.2023.3349320.

[5] J. -W. Chae, H. -S. Sim, C. -W. Lee, C. -S. Choi and H. -C. Cho, "Video-Based Analysis of Cattle Behaviors: Improved Classification Using FlowEQ Transform," in IEEE Access, vol. 12, pp. 42860-42867, 2024, doi: 10.1109/ACCESS.2024.3379277.

[6] T. H. Dang, L. Nkenyereye, V. -T. Tran and W. -Y. Chung, "Self-Powered Cattle Behavior Monitoring System Using 915 MHz Radio Frequency

Energy Harvesting," in IEEE Access, vol. 12, pp. 33779-33791, 2024, doi: 10.1109/ACCESS.2024.3360852.

[7] K. Darvesh, N. Khande, S. Avhad, M. Khemchandani," IOT and AI based smart cattle health monitoring", Darvesh et al 2023/ J. Livestock Sci. 14: 211-218.

[8] Shabani, I.; Biba, T.; Çiço, B. Design of a Cattle-Health-Monitoring System Using Microservices and IoT Devices. Computers 2022, 11, 79. https://doi.org/10.3390/ computers11050079.

[9] Pawitar Dulari, Ajay Bhushan, Brijender Bhushan," IoT-Based Buffalo Health Monitoring System", ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 11 Issue XI Nov 2023.

[10] X. Zhao, P. Tsermoula, and B. Khakimov, "Applications of metabolomics in cow health assessment," Metabolomics, vol. 21, art. no. 159, Nov. 2025, doi: 10.1007/s11306-025-02364-7.

[11] D. Kaur and A. K. Virk, "Smart neck collar: IoT-based disease detection and health monitoring for dairy cows," Discover Internet of Things, vol. 5, no. 12, 2025, doi: 10.1007/s43926-025-00109-5.

[12] D. Kaur and A. K. Virk, "An IoT-driven hybrid AI model for health monitoring of cows," Discover Artificial Intelligence, vol. 5, art. no. 346, 2025, doi: 10.1007/s44163-025-00610-4.

[13] C. C. Mar, T. T. Zin, P. Tin, K. Honkawa, I. Kobayashi, and Y. Horii, "Cow detection and tracking system utilizing multi-feature tracking algorithm," Scientific Reports, vol. 13, art. no. 17423, Oct. 2023, doi: 10.1038/s41598-023-44669-4.

[14] Y. Chen, Z. Wang, J. Li, and H. Zhang, "Vision-based cattle behavior recognition using deep learning," Scientific Reports, vol. 13, art. no. 15457, Sept. 2023, doi: 10.1038/s41598-023-40757-7.