ISSN: 2093-5374 / E-ISSN: 2093-5382

Smart Monitoring of Livestock Health and Behavior with Sensor-based Deep Learning Optimized System

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Received: May 26, 2025; Revised: July 05, 2025; Accepted: August 27, 2025; Published: September 30, 2025

Abstract

The livestock sector is so significant in the world that, as a source of basic needs such as meat, milk, eggs, wool, and leather, it has a substantial share of in the economy of every country. It takes a lot of time to care for their lives and welfare (he dwells) on the part of farmers. The developments presented in the SM oL HB Deep LOS project aim to confront these problems by means of sensor technologies and process its output data using a smart algorithm based on deep learning. In turn, once this data has been collected, deep learning algorithms are used to train on this data to develop their patterns and anomalies, for example, changes in behavior that might indicate illness. Machine learning is used to scale the system's deep-learning algorithms, which are fine-tuned for accuracy and to reduce the number of false alarms daily. This allows farmers to identify and treat health issues early on, benefiting their livestock's health. This implies that susceptible hosts can be identified, tracked, and managed, and an early warning of an impending health issue can be provided, thereby reducing the likelihood of disease epidemics. PSAM runs in real-time and on-site very a, allowing ion, farmers to communicate wait buck by monitoring health and behavior immediately and accurately. This news is strongly associated with the early diagnosis and treatment of diseases, directly linked to a reduction in mortality rates and, consequently, of herd productivity.

Keywords: Global Economy, Essential Products, Sensor-Based, Deep Learning, High-Risk.

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 16, number: 3 (September), pp. 219-240. DOI: *10.58346/JOWUA.2025.I3.013*

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1 Introduction

Integrated TAGs, such as Smart Monitoring of Livestock Health &, are the best available technique for monitoring the behavior and health of livestock animals with the aid of modern technology. Farmed animals in these regulations refer to domesticated animals, such as cows, pigs, chickens, goats, and other animals that are farmed and killed for food, fiber, and/or labor (Schmeling et al., 2021; Soni et al., 2025). As presented in Figure 2, the primary focus of the Smart Monitoring approach, concerning livestock animal health and productivity, is on the health and productivity of livestock, providing a real-time snapshot of data and findings to the farmer and veterinarian (Tedeschi et al., 2021; Almudhafar et al., 2024). Med gadget: Your machine can help detect health problems in their early stages. Med gadget: It's always helpful in medicine to detect these issues before the patient is in a critical condition, figuratively speaking. Wearable Sensors and Animal Tracking Devices Wearable sensors and animal tracking devices are one of the pivotal intelligent sensing techniques (Marhoon et al., 2025; Liseune et al., 2021). Something they could have monitored was the temperature, HR, and activity levels. It will enable the monitoring of animals, including their feeding habits (including social behaviors), grazing patterns, and feeding schedules (Hernández et al., 2024).

Data Analysis - At this step, the data from now is compared to Historical Data and Norms to detect deviations or symptoms of certain diseases (Shaik Mazhar & Akila, 2022). This allows farmers to act preventively and decide how to care for their animals, as seen in the life cycle, as illustrated by the picture of the pig. For example, the data may show a diminution of the temperature of activity or a rise in body temperature, indicating to the farmer that some action must be taken to guard against infection or damage (Kaswan et al., 2024). Wireless monitoring and control systems, available from Smart Monitoring, enable farmers to remotely monitor their stock. In larger farms were checking each animal regularly is not feasible, this approach may be useful (Neethirajan, 2024). When abnormalities are detected, it can send out alarms, which is helpful for farmers to take immediate action. Collection and processing of data about the well-being of farm animals and their related activities (to take care of them and to increase their productivity) using technology are the major facilitators of intelligent monitoring of animals' health and behavior (Arshad et al., 2023). While not a cure-all, it has a great list of reasons to get it, but a few key concerns arise. One of the most pressing issues with intelligent surveillance is animal intrusion. Thus, every animal has the right to privacy, and constant surveillance through technology may be considered an invasion of privacy. "Farmers need to know that this data is coming straight from the bottom, not from farm and animal to the consumer — and that they're not getting gouged, and they still own the animals. In other words, the truthfulness on which one can rely in recon is (Hai, 2022) Data collected from smart monitoring devices. The limits. of data accuracy stem at least from their interplay with biometric [–8] and behavioral [–7] data. This can lead to misconceptions about the health and welfare of an animal, which in turn can result in inappropriate treatments and interventions. Privacy issues are also evident in the data captured by such devices. Therefore, datasets of interest could potentially be a mix of sensitive records (e.g., data on RAPID indicators such as genetic information, medical courses, and locations) (Dang et al., 2024). Do not share; Farmers need to ensure that the data is not shared with unauthorized, commercial parties in ways that would be discriminatory or restrictive to competition. Another disadvantage of using intelligent monitoring is the high cost and limited supply of such technology. On large farms, it is highly successful, with small farmers often requiring assistance in acquiring the necessary equipment and systems. Permitting contractual production could widen the gap between the commodifies and smaller, independent farmers (Bosco, 2016). The dubious use of technology for tracking and dictating animal behavior presents a range of ethical issues. Others could argue that it would suppress the instinct of the animals and their freedom to survive. Ultimately, farmers must decide: they must straddle the line between employing technology to make human labor more efficient and respecting the instincts of the animals and their needs. The primary contribution of the study is as follows:

- Enhancing animal well-being and health is one significant research principal benefit and contribution to smart livestock health and behavior monitoring. Using sensors, cameras, and GPS trackers, real-time data about the health and activities of individuals can be collected by farmers, farmers, and researchers. This helps detect health issues earlier on, better manage care, and overall increase the welfare of the animal.
- It is another fundamental research contribution of intelligent livestock monitoring in practice for disease prevention and management in livestock. New technologies allow early detection of disease, and real-time monitoring of emerging epidemics and sources of infection. It could also tip off farmers and researchers to new diseases and help them take steps to stop an outbreak, reducing their impact on livestock and the sector.
- Smart monitoring of livestock health and behavior also serves to optimize livestock production as it provides valuable information about animal behaviors and habits. Through the data of factors such as the amount of feed and eating time, the number of steps per day, or socializations, researchers learn how to generally improve the health and productivity of livestock. It also could result in better and more sustainable farming and better profits for farmers.

The remaining part of the research has the following chapters. Chapter 2 describes the recent works related to the research. Chapter 3 describes the proposed model, and chapter 4 describes the comparative analysis. Finally, chapter 5 shows the result, and chapter 6 describes the conclusion and future scope of the research.

2 Related Words

Sakib et al., (2021) have introduced an IoT-enabled real-time livestock management system that utilizes machine learning techniques for the real-time monitoring of livestock health and behavior. Features secure data transmission and application-level features for convenient system integration. This enables farmers to make science-based choices in livestock health and production management. Wu et al., 202 presented a CNN-LSTM-based multimodal (video and audio) deep learning model to identify the basic activities of a lone dairy cow within a crowded environment. It enables the detection and real-time recognition of behaviors (e.g., feeding, resting, walking) that contribute to cow management and animal well-being. Awan et al., 2022 have presented 'Energy-aware cluster-based routing optimization for wireless sensor networks' in animal husbandry and horticulture to increase energy efficiency and sensor lifetime of a cluster-based network. It is the process of allowing energy-efficient cluster heads to enhance their data transmission, thereby reducing the total energy of the network. Kumar et al., 2021 to * Corresponding author perceive the feasibility of wireless multimedia networks and machine learning algorithms for secure and sustainable cattle recognition. This will identify the individual animal when shown by this trait, behavior pattern, having the ability to manage animal movement by the farmer, and protect animal safety. Gehlot et al., 2022 recently proposed Dairy 4.0 as an emerging solution that integrates blockchain with IoT technology to construct a smart communication network for cattle animal welfare. Retrospective health and behavioral data in real-time may support the general management and welfare of dairy cows (Kumar & Shah, 2021). It ensures complete transparency and traceability to the consumer. (Kandepan & Venkatesan, 2022) A brief history of men's health in the Internet of Things (IoT) and sensor data for status monitoring worldwide. The immediate data acquisition and analysis from various sensors help to enhance the precision of the diagnosis and eliminate the time lag for diagnosing a health condition, thus ensuring early diagnosis and treatment. El (Moutaouakil et al., 2022) present another IoT ecosystem-enabled architecture for a smart livestock farm, featuring a range of connected tools and sensors that collect and analyze data on animals, the environment, and machinery. This framework will enable farmers to monitor and control their livestock operations remotely, providing data-driven projections to enhance farm practices and increase yield and labor efficiency. (Chen et al., 2022) propose cow feeding behavior Recognition, showing that their solution, based on machine learning and a nose band pressure sensor, successfully recognizes and monitors the cattle's behavior in real-time during feeding. It is a helper which enables to control the feeding habits of the animals in a better way, in a way enough for maintaining the health and productivity of the animals". (Wu et al., 2022) presented the deep residual bidirectional LSTM model, a machine learning-based approach that recognizes and understands cattle behavior using data generated by a wearable movement monitoring collar. Residual-connected LSTM cells are utilized for predicting cattle motion and behavior in real time. (Rajendran et al., 2023) reported an IoT-enabled cattle health monitoring system that utilizes wireless sensors to collect health metrics, including body temperature, heart rate, and activity, of the cattle. The data is sent back to a central system, where farmers can track their cattle's health and take action if necessary. (Dang et al., 2023) proposed a Radio-Frequency Energy Harvesting-Based Self-Powered Dairy Cow Behavior Classification System that utilizes radio-frequency energy harvesting technology to continuously power sensors used for tracking cows' behavior on dairy farms. This system enables farmers to track and describe how cows behave, allowing them to provide better care and manage milk production more effectively. (Supriya et al., 2024) have discussed Sensor-Based Intelligent Recommender Systems in Agriculture Operations. (Khodjiev et al., 2025) have discussed that powered by sensors that aggregate information ambiently and then are combined with sensor data that generates personalized recommendations to farmers about what to ripe and when to water their crops and add fertilizers. They utilize complex algorithms and machine learning techniques to analyze data and draw informed conclusions on how to manage crops. (Tang et al., 2021) implemented a smart sensing system to monitor water quality and the consumption of livestock and wild animals. This high-tech system utilizes sensors and analytics to track and measure the water animals that are using it. It's for the safety and well-being of your animals to drink from. (Brandon & Bommu, 2022) SA & HC: Smart Agriculture and Healthy City experts in have mentioned that the fusion of SA and HC may employ artificial intelligence (AI) technologies to improve plant pathogen diagnosis and livestock health monitoring. AI can quickly generate findings about diseases and health hazards by feeding data from sensors and cameras into computers, enabling earlier and more effective action and more sustainable farming. (Achour et al., 2022) also studied the behavior recognition of dairy cows using an energy-saving sensor. This calls for sensors both inside and outside the cow. Then, this data is further analyzed to identify the cow's behavior (eating, resting, walking, etc.) in an energy-efficient manner and present dairy producers with useful information to enhance cow management. Table 1 Summary of the Detailed Analysis.

Table 1: Comprehensive Analysis

Author	Year	Advantage	Limitation
Sakib et al., 2021	2021	Improved accuracy with timely data analysis for efficient and effective livestock management.	Limited usability in remote or under-developed areas due to reliance on internet connectivity and access to technology.
Wu et al., 2021	2021	The integration of both CNN and LSTM allows for better sequential learning of complex patterns and behaviours in a dynamic environment.	One limitation is the potential for overfitting and difficulty in generalizing to different cow or environment conditions.

Awan et al., 2022	2022	The conservation of battery life allows for longer deployment periods, reducing maintenance costs and labour for farmers.	One limitation is that it may not consider other important factors in animal monitoring, such as animal behaviour or health status.
Kumar et al., 2021	2021	The advantage is increased efficiency in cattle management, allowing for better tracking, health monitoring, and overall sustainability practices for cattle farms.	The accuracy of the recognition may be affected by environmental factors such as lighting or obstruction.
Gehlot et al., 2022	2022	Improved animal welfare monitoring and tracking through advanced technology, increasing efficiency and accuracy of data collection and analysis.	One limitation could be the high cost associated with implementing and maintaining the advanced technology systems.
Kandepan & Venkatesan, 2022	2022	Improved accuracy and efficiency in diagnosing animal health conditions, leading to prompt and effective treatment.	One limitation is the potential for inaccurate or faulty data from sensors, leading to incorrect diagnoses.
El Moutaouakil et al., 2022	2022	Better monitoring and management of livestock health and behavior, leading to improved productivity and welfare of the animals.	Limited connectivity or unreliable network infrastructure can hinder data collection and communication between the devices and the farm management system.
Chen et al., 2022	2022	"Improved monitoring and analysis of individual cattle's feeding routines, leading to optimized nutrition and potential health concerns detection."	The limitation is that the system may not accurately identify behaviors that are not well represented in the training data.
Wu et al., 2022	2022	Potential to improve cattle health and productivity by identifying behavioral patterns that indicate stress or illness.	One limitation of using a deep residual bidirectional LSTM model is the potential for overfitting due to a limited dataset.
Rajendran et al., 2023	2023	One advantage is that it allows for early detection and prevention of health issues, leading to better overall herd health and productivity.	One limitation of Iota based tracking cattle health monitoring system is unreliable connectivity in remote or rural areas with limited network coverage.
Dang et al., 2023	2023	The system does not require external power sources, minimizing maintenance and cost.	The signal strength and range of the radio frequency may be hindered by environmental factors, affecting the accuracy of behavior classification.
Supriya et al., 2024	2024	"Increased precision and efficiency in decision-making for farmers, leading to improved crop yield and resource management."	"Sensors may be susceptible to environmental factors, leading to incorrect recommendations in certain conditions."
Tang et al., 2021	2021	The ability to quickly detect any changes in water quality, allowing for prompt intervention and prevention of potential health issues for animals.	"The system may not accurately measure the water quality and intake for all types of animals due to variations in behaviors and physiology."
Brandon & Bommu, 2022	2022	Improved efficiency and accuracy in identifying and addressing plant and animal health issues, leading to better crop yields and animal health.	The high cost of implementing AI-driven solutions may limit accessibility for small-scale farmers and healthcare providers.
Achour et al., 2022	2022	Improved monitoring and detection of reproductive and health issues, leading to timely intervention and increased overall herd health.	The accuracy and reliability of the classification may be affected by the data collected in a specific environment or region.

- As intelligent monitoring depends a lot on sensor-based technology, therefore failures in equipment performance cause a lot of trouble and the integrity of data taken in the process. If there is sensor malfunction or erroneous outputs, it can lead to misreading of animal actions and health conditions, thus resulting in bad decision-making.
- Again, as an enterprise solution, smart monitoring systems involve the transaction of data from the physical devices (sensors) to a central monitoring system, issues may arise in case of poor connectivity, network interruptions, or data loss. It might slow down the process of getting real-time data or rather, missing important data which might make the system work inappropriately.
- With this system, proper processing and the ability to interpret the collected data are key components to the success of intelligent monitoring systems as a lot depends on how accurately the data is processed and analyzed. It involves high-end analytics and data processing that can lead to various technical bottlenecks like issues such as software bugs, system crashes, or compatibility with different devices and platforms. These problems can lead to late or even faulty data analysis, thus reducing the efficiency of the system.

Sensor-based deep learning optimized systems are modern age technology that integrates sensors with artificial intelligence (AI) algorithms to develop high-level level powerful and intelligent systems. Those systems can gather data from a wide variety of sensors and then analyze the data, making decisions using the benefits of deep learning in the process. Such continuous learning and improvement processes lead to optimized performance and efficiency. What makes this technology different from the past is the ability to integrate sensor data (real-time data) with more robust deep-learning algorithms. It enables the system to be adaptive &learning live, ensuring that the AI can deal with/ complex tasks & situations. In the end, deep learning-optimized sensor-based systems could radically change many of our industries, from healthcare to transportation, through the provision of efficient and intelligent solutions.

3 Proposed System

A. Construction Diagram

- **UCI Machine Learning Repository**

The UCI Machine Learning Repository is an online platform for storing and sharing machine learning datasets, algorithms, and experiments. The repository allows researchers and data scientists to access and download various datasets for their research and analysis. The repository's operation is based on a system of contributions and curation.

$$R = \lambda R_L + (1-\lambda) R_D. \tag{1}$$

To balance clustering and network loss, a hyper-parameter between 0 and 1 is employed. In order to solve the lower boundary mutual information, I (c; G (z, c)), which is known as L1(G, Q), or as provided by, INFOGAN developed the variable mutual information maximization.

$$\varepsilon_h \sim E(w,d)\left[\varepsilon_d^{'} \sim f(d|h)\left[\log S(d'|h)\right]\right] + X(d), \tag{2}$$

$$\min_{ES} \max_{D} T_{\inf oGAN}(C,E,S) = T(C,E) - \lambda R_1(E,S), \tag{3}$$

$$Of = \sum_{b=1}^{n} \sum_{y=1}^{Y} z_{ba} \left\| h^b - \mu_y \right\|^2, \tag{4}$$

Researchers can submit their datasets and algorithms to the repository, which are then curated and reviewed by domain experts before being made available to the public. This ensures that the data and algorithms in the repository are of high quality and can be used for reliable research and analysis. The repository also provides data preprocessing and visualization tools, making it a comprehensive platform for machine learning research.

- **Data Pre-Processing**

Data preprocessing is an important part of Data Analysis which includes changing, cleaning, and formatting of raw data into a valuable, homogeneous format in a more processed form of data. It is required because in the real-world data is generally incomplete and inconsistent, with many missing values, outliers, and unwanted information. Data Preprocessing - The very first thing we do is clean the data, i.e., find out NULL values or something that needs to be removed.

This method starts with randomly picked data and clusters it, just as unsupervised learning. In summary, the FCM process consists of three stages: membership, cluster centre, and objective objective function of the FCM is

$$OF_{iter} = \sum_{b=1}^{M} \sum_{a=1}^{md} \left[Mem^{p} \left\| CV_{h_b - DD_a} \right\|^{2} \right], \tag{5}$$

This has N data elements and Nc clusters (the user may supply this depending on the situation).

$$Mem^{f}\left(\frac{c_{ab}}{c_{yb}}\right) = Mem_{iter} = \frac{1}{\left[\sum_{y=1}^{md}\left(c_{ab} / c_{yb}\right)^{2/p-1}\right]} \tag{6}$$

Then, the preprocessing methods, including normalization or standardization, are used to ensure that all variables are on the same scale. Finally, data is prepared for the specific data analysis methods that are implemented. This has the added benefit of increasing the reliability of the data, removing errors, and simplifying its analysis and interpretation.

- **Training Data Set**

In machine learning, a training dataset is a prerequisite. It's a training set of data for a machine learning algorithm to learn from. The data is usually divided into two parts: a training set to train the algorithm and a testing set to validate its performance (Figure 1(a, b))

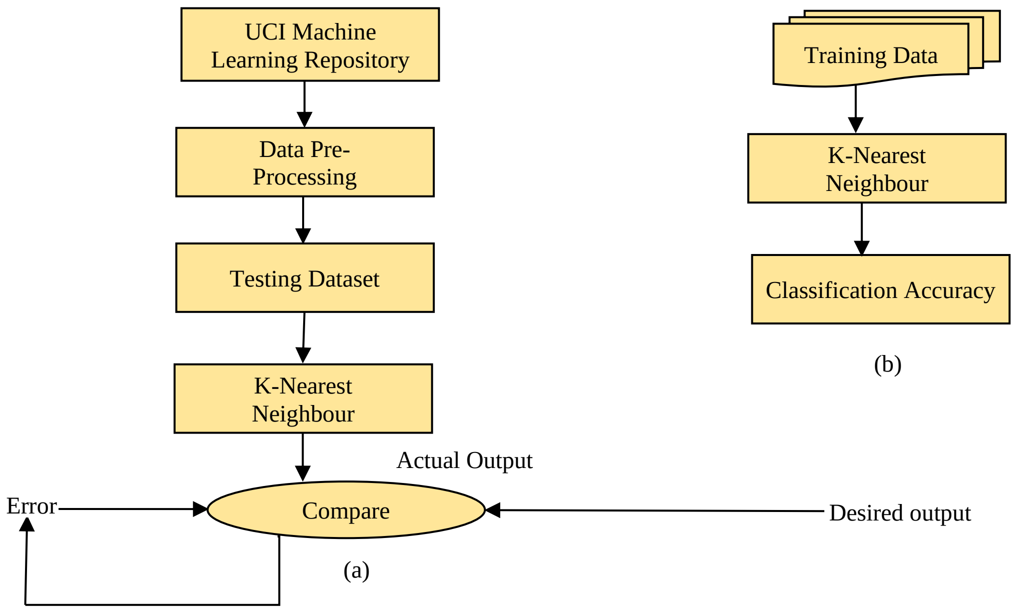

Figure 1(a, b): Construction Diagram

This makes the algorithm robust for the training data and enables it to generalize well for new and unseen data. The initial data set used for training also needs to be appropriately assembled and prepared to simulate real-world data, ensuring that the algorithm learns accurate patterns and yields correct results. The size and quality of the training data are key to the success of a machine-learning model.

- **K-Nearest Neighbour**

K-Nearest Neighbor (KNN) is a supervised machine learning approach for classification and regression tasks. The assumption here is that similar data points belong to the same cluster. The distance between the new data point and all the other data points in the dataset is computed by the algorithm. Here, we draw the K-nearest selected data points that are assigned to the majority class, as all the data points have a new class label for the latest data point. The prediction value is the average of the K nearest points in the case of regression.

To generate new algorithms such as FCMS1 and FCMS2, parameters in FCMS are modified.

$$\varepsilon_b = \frac{1}{1+a}\left(CV_{h_b} + \frac{j}{M_L} \sum_{a \in M_b} h_a \right). \tag{7}$$

$$Q_{ba} = \begin{cases} -\max\left(\left(\left|f_b - f_a\right|, \left|s_b - s_a\right|\right)/\lambda_q\right) - \left(\left\|CV_{h_b} - CV_{h_a}\right\|^2 / \lambda_e \sigma_b^2\right) & \\ g & b \neq a, \\ 0, & b = a, \end{cases} \tag{8}$$

The value of K, i.e., the number of nearest neighbours to be considered, is an important parameter and can be determined through cross-validation. KNN is a non-parametric algorithm, meaning it does not make any underlying assumptions about the data distribution, making it flexible and potentially useful for a wide range of applications. However, it can be computationally expensive, especially for large datasets, and its performance is highly dependent on the choice of distance metric and value.

- **Error**

When a computer program comes across a problem during the execution of a task, it reports it using "error". In case of an error, the program halts and shows us an error with an error message which will tell us why the error occurred and sometimes how to fix it. There are many reasons which are responsible for this kind of error either incorrect input data or unexpected system state or programming error. Programs use try-catch blocks to handle errors, which allow them to try something that may produce an error, and then catch that error to handle it as needed. This will stop the program from crashing and will enable the program to work more efficiently and stably.

- **Actual Output**

Actual Output refers to the final result of a process or operation that has been completed. The physical or tangible outcome is produced after all inputs, resources, and actions have been utilized. Various factors, such as the efficiency of the process, the quality of the inputs, and the performance of the individuals involved, influence the actual Output. It is a crucial indicator of the effectiveness and success of the operations as it reflects the exact performance and productivity.

where the values of the data matrix are taken into consideration for the local window's Centre (p I, q I), and the values of the data matrix are taken into consideration for the center's neighbour. For effective operation, (as and mg) are introduced in this scaling factor.

$$\sigma_b = \sqrt{\frac{\sum_{a \in M_b} \left\| h_b - h_a \right\|^2}{M_L}}, \tag{9}$$

$$\varepsilon_b = \frac{\sum_{a \in M_b} Q_{ba} h_a}{\sum_{a \in M_b} Q_{ba}}, \tag{10}$$

To ensure desired results, organizations constantly monitor and evaluate their actual Output against the desired Output, making necessary adjustments and improvements to the process. Overall, actual Output is a crucial aspect of operational management as it reflects the impact of the organization's activities.

- **Desired Output**

The "Desired output" is the expected result or outcome of the process, system, or software. To be sure that you have already done everything needed you may need to execute the ultimate objective. The outcome is always determined at the start of a project and provides direction for the development and implementation of a project. The so-called Output has to do with the instructions or parameters one feeds into a system or to a piece of software so one gets the desired outcome. Inputs to the system, including (data, commands, or algorithms) that the system processes to get the desired Output. The Operations performing the desired Output differ depending on the system or software. Tasks go from simple calculations and data manipulation to complex algorithms and programming logic. Many times, we have to perform more than 1 operation in a particular order to make the Output correct.

- **Testing Dataset**

The Testing Dataset is an essential part of the machine-learning process and is used to evaluate the performance of a trained model. After a model is trained using the Training Dataset, it is tested on the Testing Dataset to assess its ability to make accurate predictions on new, unseen data. This dataset is separate from the Training Dataset and contains a set of data points that the model has not seen before. The model uses the testing data to make predictions, and the results are compared to the actual values in the dataset. This process helps identify potential issues with the model and improve its overall performance before deploying it in a real-world scenario.

- **Classification Accuracy**

Classification accuracy is how well a predictive model outputs a dataset's groups or classes accurately. Take the number of cases correctly classified and divide by the total number of cases in the dataset. This one matter because it says little about the performance of the model on future new data, and more of its capabilities to predict future unseen (up to now) data. It is important to note that this measure of classification accuracy also does not take into account the possibility of class imbalance in the data set, for that some other classification performance measures are needed. Therefore, in a class imbalance dataset, its performance metrics such as precision, recall, and F1 score may also be considered for creating a deeper evaluation of how well the model has performed. However, even more importantly, classification accuracy might be the least desirable evaluation metric, especially if getting wrong some classes has more severe implications than wronging the rest of the world.

B. Functional Working Model

- **Dataset**

A data box for the data table, where data processing and querying are designed and optimized in a pulley system. Different kinds of information are written on it, including numbers, text, images, and voice. A Dataset provides CRUD operations. To do this, we must first define what our data looks like and what kind of metadata (if any) we have. Read: Data from a Dataset can be updated using this function. Unwanted data from a Dataset is deleted using this operation. Creating a Dataset in Azure using the example ESequence dataset is essential for data analysis and Machine Learning, as it supports the easy storage and manipulation of large data.

- **Data Pre-processing**

Data Preprocessing is an important step in the data analytics process and is responsible for transforming raw data into a more suitable format. The purpose is to enhance the quality of the data by detecting and correcting erroneous or inconsistent data. It also includes handling issues related to missing values, outliers or unrelated data. The following diagram presents the functional block diagram (Figure 2).

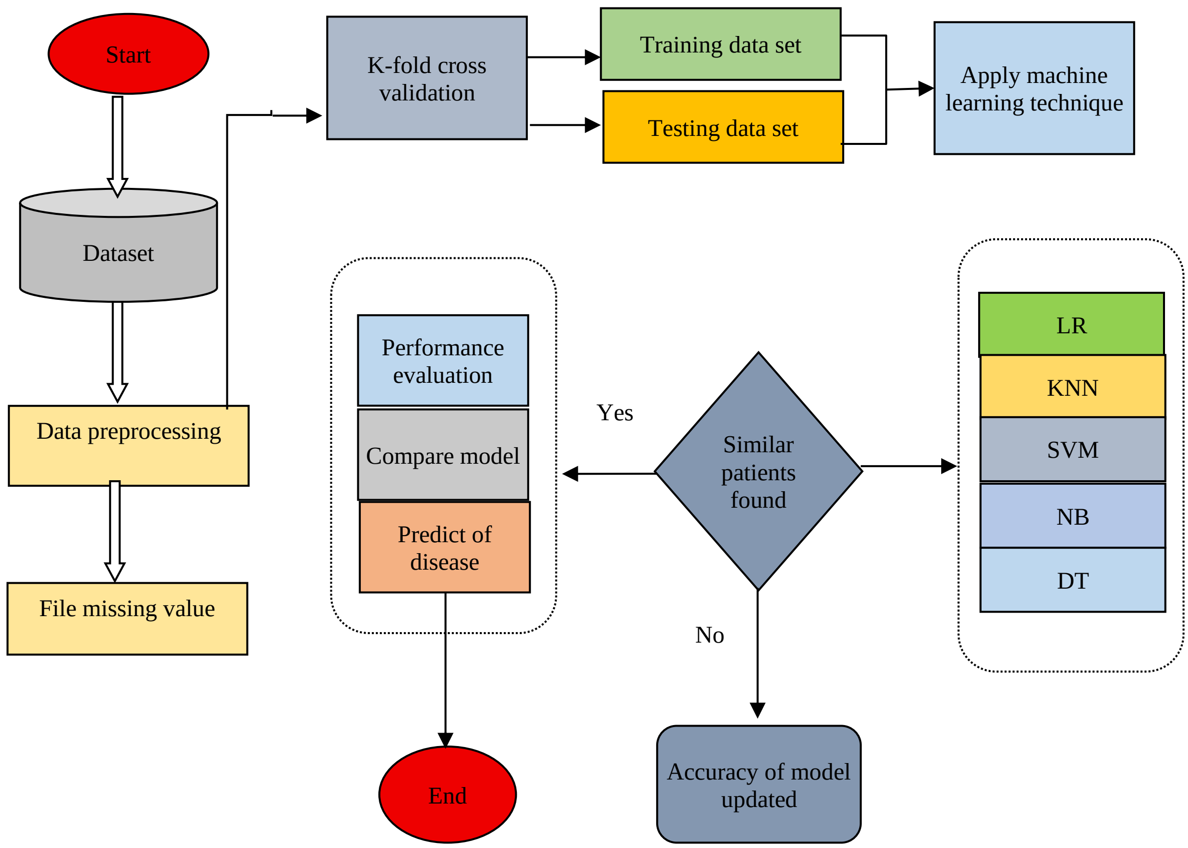

Figure 2: Functional Block Diagram

Preprocessing of data also refers to converting the data to an appropriate format, for example, converting categorical data to numerical values required for different machine learning algorithm analyses. Data preprocessing is an important step to ensure the datasets are accurate, complete, and timely, which will help carry out the analysis effectively and obtain outputs with high accuracy.

➢ File Missing Value

The File Missing Value operation is a data preprocessing task that addresses missing values present in the data. It is the process of finding and replacing these missing values with an appropriate value to preserve the integrity of the Dataset. Firstly, it detects missing value data using statistical methods such as the mean, average, and median.

$$pp_{yb} = \sum_{a \in M_b} \frac{1}{c_{ba}+1} (1-N)^p \left\| C_{h_b} - D_a \right\|^2 \tag{11}$$

As can be seen below, AnsoffKi affects both the FCM's membership function and objective function.

$$A_{iter} = \sum_{b=1}^{M} \sum_{a=1}^{md} \left[N^p \left\| C_{h_b - d_a} \right\|^2 + pp_{yb} \right], \tag{12}$$

$$N_{iter} = \frac{1}{\left[\sum_{y=1}^{md} \left(c_{ab} + pp_{yb} / c_{yb} + pp_{yb} \right)^{1/p-1} \right]}. \tag{13}$$

Subsequently, the missing values are replaced by the mean value for each data type and the way the missing values are missed NA. It does this to prevent dataset bias and ensure that the data can be inspected or used properly in various statistical and machine-learning tasks. It ensures the structure and content of the Dataset remain the same, to do fair analysis and take decisions based on it (keeping the NULL records somewhere stored with some filename value according to its column).

- **K-fold Cross Validation**

K-fold cross-validation is a technique used to validate the performance of a predictive model by splitting the dataset into k number of sections. The model is trained for a k-1 subset and validated using the kth subset and the process is repeated k times. The performance of the model is assessed by averaging the results from the k iterations. This helps prevent overfitting and gives a better estimate of how well the model estimates are going to perform on an independent dataset. It also makes efficient use of the data because it is used to train and validate at some point. Replicating the process k times minimizes the bias and decreases the impact of an outlier in the data set, hence the model evaluation will be more robust.

- **Training Data Set**

A "training data set" is crucial to building a machine learning model. It refers to a specific data set used to train the model and help it learn the underlying patterns and relationships within the data. This data is carefully selected and labelled to represent the real-world scenarios on which the model is meant to learn and eventually make predictions.

These qualities serve as the basis for FLFCM's determination of the fuzzy locals' similarity, which helps shield the data from noise and extraneous information. Primary and secondary celestial magnetic Feld strengths are present in the EM sensor. The magnetizing Feld, or H, that the primary coil erases is represented as

$$X = MB, \tag{14}$$

$$g_2(v) = -M_2 \frac{c\Phi_{21}(v)}{cv}, \tag{15}$$

By dividing the inner area of the coil by the magnetic foxfew, the magnetic Fu density was found. The expression for the magnetic fox density B is

$$I = \mu(X + N), \tag{16}$$

The model is trained on training data, and it learns from the data to adjust its parameters using specific algorithms. The model's fit to these outcomes is measured by how accurately it can predict them in the training data. This process is iterated several times until the model is accurate to the desired level. Therefore, the quality and quantity of training data have a significant impact on model performance and accuracy.

- **Testing Data Set**

The testing dataset is a crucial component of the machine learning model's performance assessment procedure. It is a portion of the large dataset that we train the model on and test it on between ETL: How well is the model able to generalize to new data it hasn't seen before? This data is usually kept separate from the training data to avoid inducing any bias and to mimic the model's real-life performance.

(1928) The Jules-Atherton model. During the past 90 years, several methods have been utilized to model the processes that determine the magnetization of a ferromagnetic material.

$$N = N_{rev} + N_{irr} = d\left(N_{an} - N_{irr}\right) + N_{irr}, \tag{17}$$

$$N_{an} = N_q\left(\cot\left(\frac{X_g}{j} - \frac{j}{X_g}\right)\right), \tag{18}$$

with Mo, Mir, and Mr representing the reversible magnetic susceptibility, irreversible magnetization, and reversible magnetization, respectively.

When the model has been trained, it is validated on the testing dataset to evaluate how accurately the model can predict observations on new data. This stage is useful for uncovering defects or shortcomings in the model and modifying it before it is applied in a practical setting.

- **Apply Machine Learning Technique**

"Machine learning" is an application of artificial intelligence (AI) that enables systems to learn and improve from experience without being explicitly programmed automatically. It utilizes algorithms and statistical models to allow computers to learn from data patterns and make accurate predictions or decisions. The first step is data collection and cleaning – here, your data is separated into training and testing sets. The training data is used to develop and train the model, and the testing data is used to test its performance. The chosen method (e.g., supervised learning via classification or regression) is then implemented on the training data, and the model is fine-tuned until optimal performance is achieved. The model is then used to predict new data. This process requires a trained analyst and knowledge of the data, as well as the right Machine Learning technique, for optimal results.

- **Performance Evaluation**

Performance evaluation involves assessing an employee's job performance, and the process enables the provision of feedback, identification of areas for improvement, and determination of rewards or promotions. The review usually takes into account how employees are performing with respect to their job responsibilities, goals, and expectations that the company sets.

The total power consumption of MTCDs, considering both data transmission standards, is combined.

$$\psi = \sum_{a=1}^{N} \psi_b, \tag{19}$$

where ψ_b represents the MTCD is energy consumption.

$$\psi_b = R_b^c \psi_b^c + \sum_{r=1}^{N} \sum_{y=1}^{Y_1} \alpha_{r,y} R_{b,y}^d \psi_{ba}^d, \tag{20}$$

It can also factor in attendance, team success, and alignment with the company culture. Self-assessment, peer reviews, and manager reviews can all be utilized in the assessment process. The purpose of performance evaluation is to provide employees with a fair and accurate appraisal of their work while helping them grow and develop in their roles. This mechanism also enables firms to identify high performers and address low performance promptly.

C. Operating System

- **Conv Block**

A Conv Block, or Convolutional Block, is a basic building block in a CNN. It is composed of three main operations, namely, convolution, activation, and pooling. A filter (also called a "kernel") is multiplied with the input data to obtain features from the input during the convolution operation.

$$\psi_b^c = \frac{L_b^c}{f_b^c + f_{cir}}. \tag{21}$$

$$L_b^c = I \log_2\left(1 + \frac{f_b^c x_b^c}{\sigma^2}\right), \tag{22}$$

Chill is the channel gain of the Macianimated link. K1 represents the number of CHs in

$$Y_1 = \max y, \exists \alpha_{r,y} = 1, \quad \forall 1 \le r \le R. \tag{23}$$

The clustering policy should adhere to the upper bound on the number of cluster heads (CHs). If the CHs are defined as Nmaps, we then claim the following maximum number of chas:

$$Y_1 \le M_{\max} -- > D1. \tag{24}$$

$$\sum_{b=1}^{N} R_{b,y}^d \le N_1, \quad 1 \le y \le Y_1 -- > d2. \tag{25}$$

$$\sum_{y=1}^{y_1} R_{by}^d \le 1, \quad 1 \le b \le N -- > d3. \tag{26}$$

The operation is followed by an activation operation applying a non-linear transform to the output of the convolution operation to introduce non-linearity in the network. The pooling reduces the spatial dimension of the production by subsampling the feature map. This is beneficial for reducing the complexity of the data and extracting key features. This process is repeated in a network several times to obtain successively complex features, which lead to better performance on more challenging tasks, such as image recognition and classification.

- **MLP**

A Multilayer Perceptron (MLP) is a feedforward neural network that is trained using the backpropagation algorithm. It has an input layer, one or more hidden layers, and an output layer. Neurons are the units in each layer, interconnected by weighted connections. Forward propagation is employed in the MLP to transmit the input and produce the output. In this process, the input data are first multiplied by the weights, followed by the application of an activation function to introduce non-linearity to the model. The operation flow chart is indicated as follows (Figure 3).

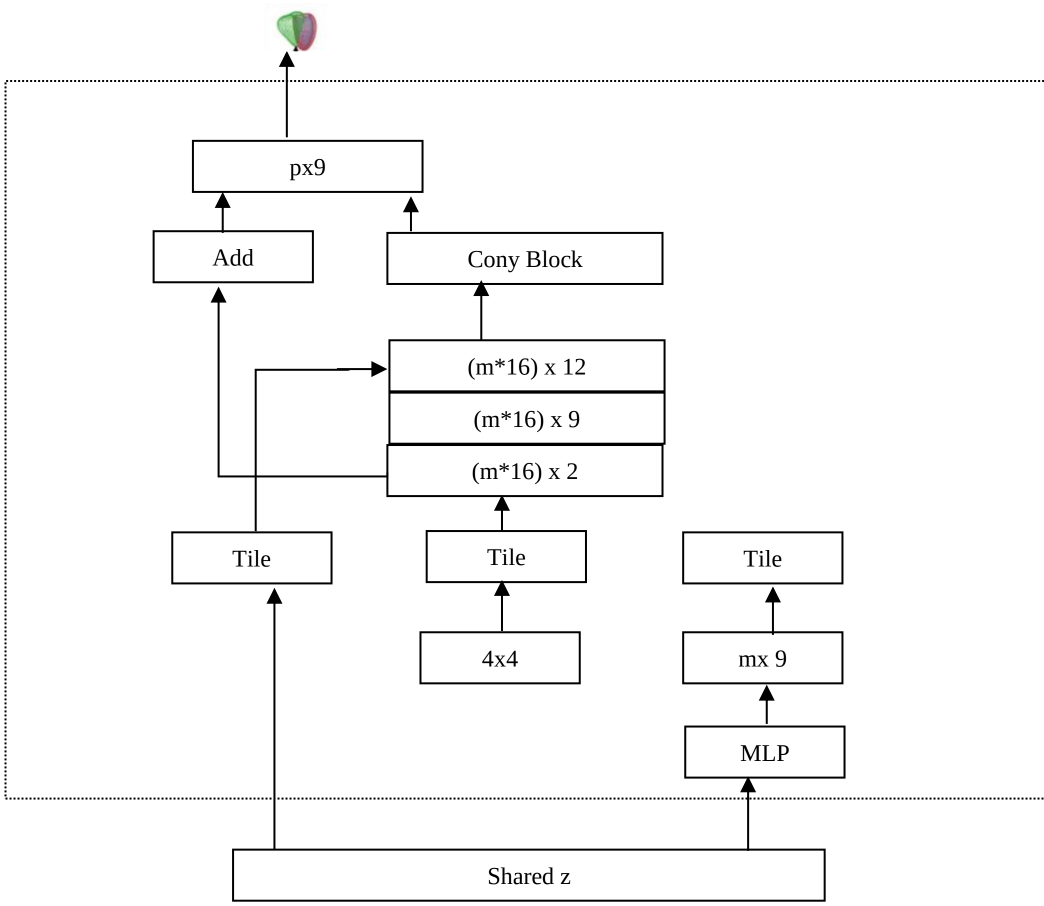

Figure 3: Operational Flow Diagram

This allows the MLP to learn complex relationships between the input and output data. The weights are then adjusted through backpropagation, which uses gradient descent to minimize the error between the predicted and actual outputs.

$$\sum_{r=1}^{N} \alpha_{ry} \leq 1, \quad 1 \leq y \leq Y_1 --> d4. \tag{27}$$

$$\sum_{y=1}^{y_1} \alpha_{r,y} \leq 1, \quad 1 \leq r \leq N --> d5. \tag{28}$$

$$R_b^c + \sum_{y=1}^{Y_1} R_{b,y}^d \leq 1, \; 1 \leq b \leq N --> d6. \tag{29}$$

Interestingly, CHs can only communicate with the BS directly. Cheaply reliable communication to relay CM data packets. The following is the derivative transmission mode.

$$R_r^c = 1, if \sum_{y=1}^{Y_1} \alpha_{r,y} = 1, \quad r \leq N --> D7. \tag{30}$$

The enhanced energy value enhancement in conjunction with resource allocation and clustering issue definition is as follows:

$$\max_{\alpha_{r,y} R_b^c, R_{b,y}^d, f_{b,a}^d} \psi \quad s.t. \quad D1 - D10. \tag{31}$$

CH reselection: Since Maci k′ is selected as a single CH, we denote k′ as the collection of CMs that match the MTCD.

$$\Phi_y = \left\{ MTCD_b \middle| MTCD_b \in \Phi_{cm}, \delta_{b,b_y}^{d,*} = 1 \right\} \tag{32}$$

This process is repeated for multiple iterations until the desired level of accuracy is achieved. Overall, the MLP's ability to handle non-linear relationships and make incremental adjustments to its weights allows it to learn and make predictions on complex datasets effectively.

4 Result and Discussion

The proposed AI-SMLHB (Artificial Intelligence-based Smart Monitoring of Livestock Health and Behavior) has been compared with the existing SMHS-DL (Smart Monitoring of Herd Health with Deep Learning), SBLHO (Sensor-based Livestock Health Optimization) and DLOLS (Deep Learning Optimized Livestock System).

4.1. Sensor Precision and Accuracy

This concerns the resolution that sensors can gather extremely fine data regarding the health and behavior of livestock. The sensors must be sensitive enough to detect small variations and anomalies in the animal's vital parameters and behavioral patterns. Table 2 presents the difference in precision between the present and proposed models. Figure 4 Illustrates the Computation of Sensor precision and accuracy.

Table 2: Comparison of Precision (in %)

No. of Inputs	SMHS-DL	SBLHO	DLOLS	AI-SMLHB
100	81.20	77.02	82.88	84.52
200	81.09	77.04	82.71	84.25
300	81.07	77.92	83.44	84.55
400	84.17	80.75	86.78	88.06
500	85.37	82.07	87.51	89.38

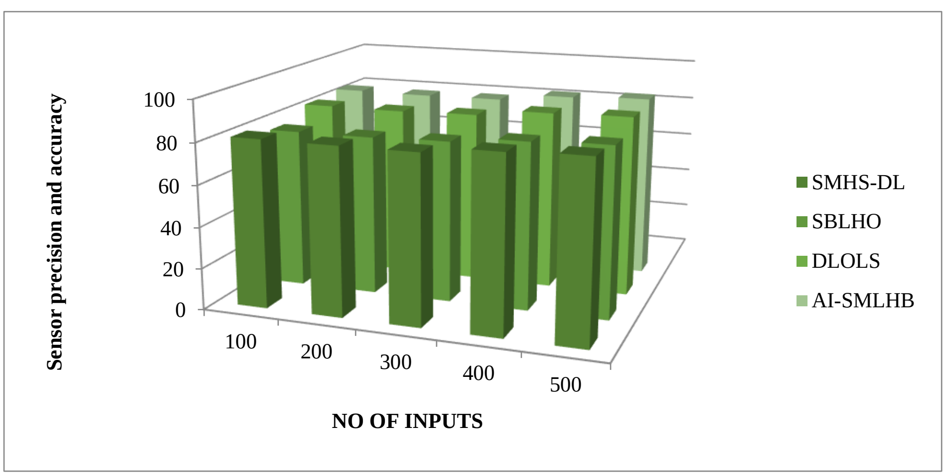

Figure 4: Computation of Sensor Precision And Accuracy

4.2. Deep Learning Algorithm Accuracy

The deep learning algorithms in the system must be properly optimized to analyze and interpret the data generated by the sensors accurately. It could help identify any health-related issues or changes in behavior as soon as possible Table 3. Comparison of accuracy between existing and proposed models. Figure 5 Computation of accuracy of the deep learning algorithm is represented.

Table 3: Comparison of Accuracy (in %)

No. of Inputs	SMHS-DL	SBLHO	DLOLS	AI-SMLHB
100	77.20	73.02	77.88	78.52
200	77.09	73.04	77.71	78.25
300	77.07	73.92	78.44	78.55
400	80.17	76.75	81.78	82.06
500	81.37	78.07	82.51	83.38

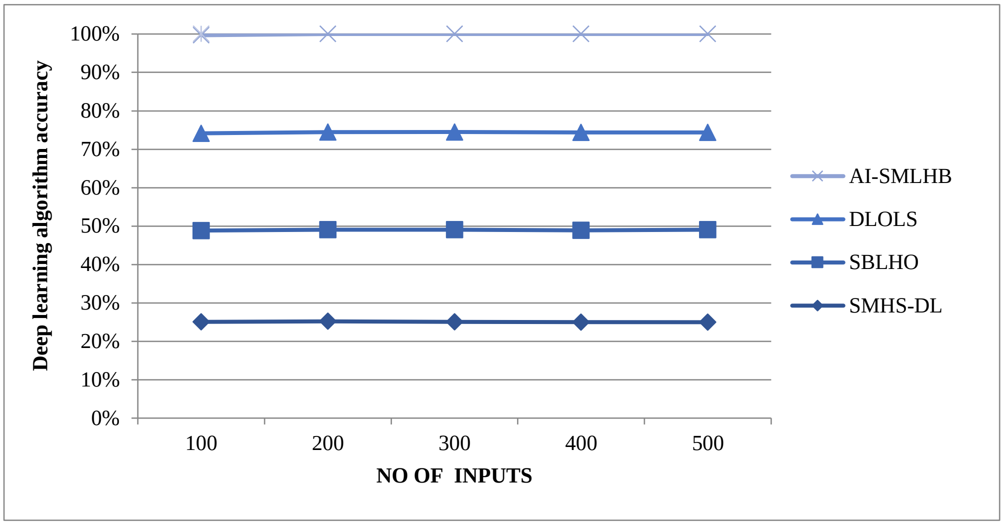

Figure 5: Computation of Deep Learning Algorithm Accuracy

4.3. Real-Time Monitoring and Alerts

The solution should be capable of real-time monitoring of animals ' health and behavior, with the option of immediate notification to owners or animal custodians if any problems are detected. It enables an early response and prevents potential risks to animal health and welfare. Table 4 compares real-time monitoring between the developed model and existing models. Figure 6 Illustrates Real-time monitoring and alerts Computation.

Table 4: Comparison of Real-Time Monitoring (In %)

No. of Inputs	SMHS-DL	SBLHO	DLOLS	AI-SMLHB
100	72.20	70.02	71.88	74.52
200	72.09	70.04	71.71	74.25
300	72.07	70.92	72.44	74.55
400	75.17	73.75	75.78	78.06
500	76.37	75.07	76.51	79.38

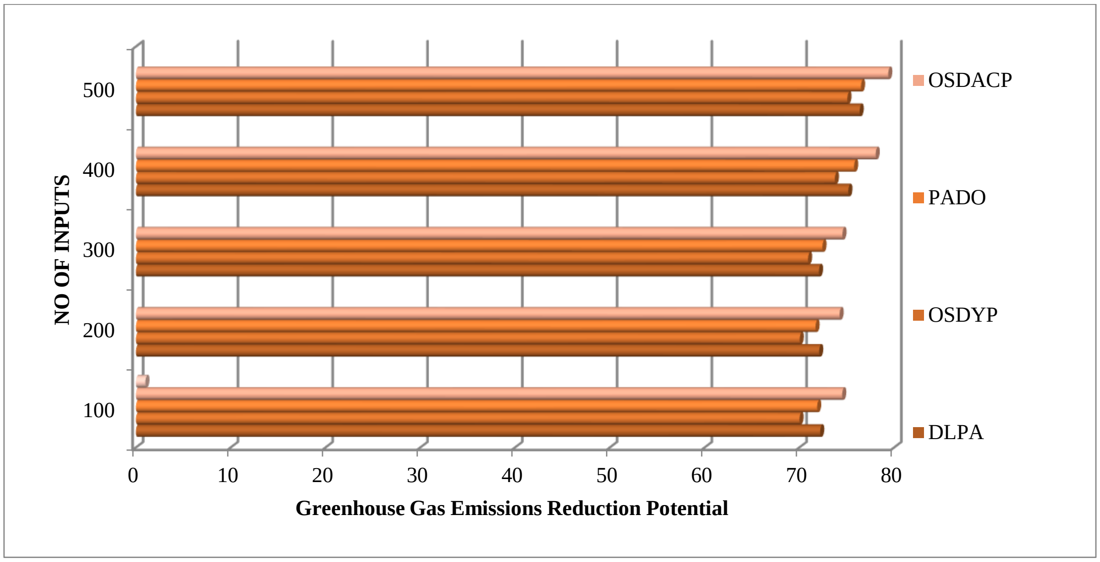

Figure 6: Computation of Real-Time Monitoring and Alerts

4.4. Data Storage and Analysis Capabilities

The systems should have the capability to process and store significant amounts of data detected by the sensors. Historically, the information may be used to track trends and patterns in the health and behavior of animals, which has been useful in making long-term management decisions. Table. 5 A Data storage comparison between existing models and the proposed model is shown in Figure 7 Data Storage and Computing Capacity computation:

Table 5: Comparison of Data storage (in %)

No. of Inputs	SMHS-DL	SBLHO	DLOLS	AI-SMLHB
100	69.20	65.02	67.88	71.52
200	69.09	65.04	67.71	71.25
300	69.07	65.92	68.44	71.55
400	72.17	68.75	71.78	75.06
500	73.37	70.07	72.51	76.38

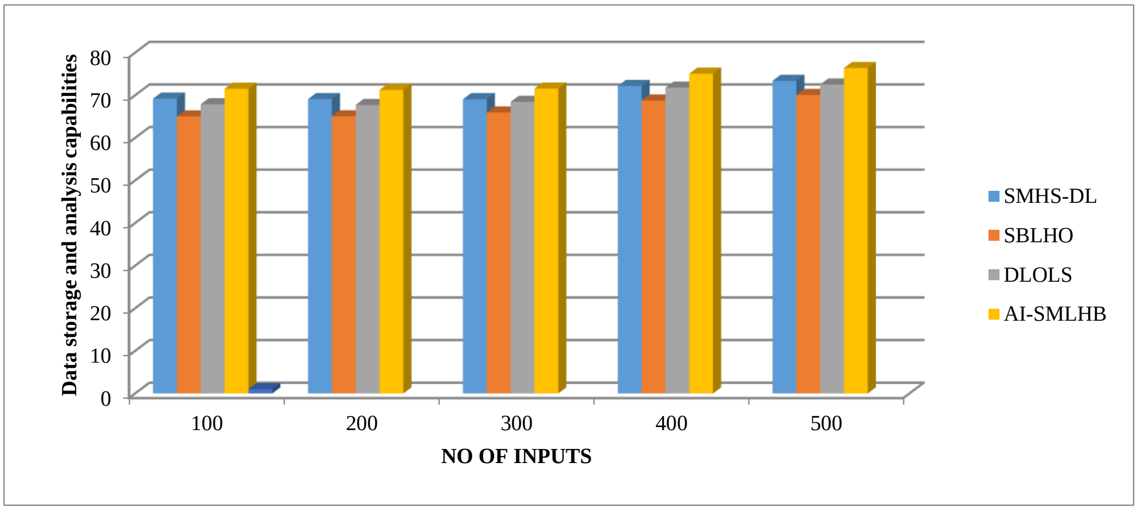

Figure 7: Computation of Data Storage and Analysis Capabilities

5 Conclusion

Therefore, sensor-based deep learning optimization is an effective solution to monitor livestock health and behavior smartly, and this will benefit livestock welfare and the productivity of the whole agriculture industry. The system will enable timely alerts as required for the body temperature, activity levels, feeding behavior, etc to prevent any untoward health issues from developing and to provide proactive health management. This also extends to deep learning algorithms, which improve the level of accuracy and efficiency of the system as a whole, providing farmers with a valuable asset to effectively operate their herds. This innovation will have a lot of appeal to the ever-increasingly health and eco-conscious human demographic, providing assurances to our decisions as consumers and furthering welfare and production capacities in agriculture. More studies and follow-up promotion in this area can result in efficient newer monitoring systems helping to improve the general health of the animals concerning the agricultural farm resources.

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