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Sparrow Search Algorithm based BGRNN Model for Animal Healthcare Monitoring in Smart IoT

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Abstract— Rural regions rely heavily on agriculture for their economic survival. Therefore, it is crucial for farmers to implement effective and technical solutions to raise production, lessen the impact of issues associated to animal husbandry, and improve agricultural yields. Because of technological developments in computers and data storage, huge volumes of information are now available. The difficulty of extracting useful information from this mountain of data has prompted the development of novel approaches and tools, such as data mining, that can help close the informational gap. To evaluate data mining methods and put them to use in the Animal database to create meaningful connections was the goal of the suggested system. The study's primary objective was to develop an IoT-based Integrated Animal Health Care System. Various sensors were used as the research tool to collect physical and environmental data on the animals and their habitats. Temperature, heart rate, and air quality readings were the types of information collected. This research contributes to the field of health monitoring by introducing an Optimised Bidirectional Gated Recurrent Neural Network approach. The BiGRNN is an improved form of the Gated Recurrent Unit (GRU) in which input is sent both forward and backward through a network and the resulting outputs are connected to the same output layer. Since the BiGRNN method employs a number of hyper-parameters, it is optimised by means of the Sparrow Search Algorithm (SSA). The originality of the study is demonstrated by the development of an SSA technique for hyperparameter optimisation of the BiGRNN, with a focus on health forecasting. Hyperparameters like momentum, learning rate, and weight decay may all be adjusted with the SSA method. In conclusion, the results demonstrate that the suggested tactic is more effective than the current methods.

Keywords- Animal Health Care System, Bidirectional Gated Recurrent Neural Network, Internet of Things, Heart Rate, Sparrow Search Algorithm, Temperature.

I. INTRODUCTION

Internet of Things (IoT) is an expanding intent-based information architecture that facilitates commerce and seeks to create a means by which "things" may be traded in a straightforward, safe, and unobtrusive manner [1]. The (IoT) is a phenomenon that links commonplace items like phones and computers to one another over the web. Layered architecture is used by IoT to automate things, which in turn provides intelligent solutions to applications and a middleware system that streamlines the creation of apps for devices [2-3]. In recent years, wireless sensors—also called wireless sensor nodes or just sensor nodes—have had a profound effect on people's daily lives. Because RFID and WSNs are complementary technologies, combining them increases their overall utility for gathering long-range information about people's whereabouts [4, 5]. In the IoT, any object may be linked to the cloud, allowing for remote access, monitoring, and control through any device with an internet connection. IoT has also been implemented for monitoring the health of cattle [6]. A dairy cow monitoring system that uses a wireless body area network and the Internet of Things is simulated. IoT animal health monitoring prototype built using Raspberry-Pi and a variety of sensors.

Care for animals is an important public health measure since it helps prevent the transmission of disease. Because of the potential for infection in all animals, including humans, it is crucial to keep an eye on animal health conditions. This is because humans have extensive interactions with both domesticated and wild animals. Animal husbandry entails more than just checking on the animals' well-being [8]. This entails supplying the animals with a space that is not only habitable but also neat, clean, and dry, allowing them freedom of movement and access to food and water. Because of this, the animal is able to reach its full potential in terms of health, reproduction, and general well-being [9, 10]. These days, sensors are just one tool among several that may be used to keep tabs on an animal population's health. Animals' physiology and behaviour may be measured with the use of sensors. Attached and removable sensors are both in use. Non-attached sensors are implanted inside the animal during surgery, whereas attached ones are worn on the outside [11]. The collected data from the sensors is then communicated to the pet's owners in a number of ways, including wirelessly over Wi-Fi and without Wi-Fi. Using long-range communication technologies is one approach that doesn't rely on Wi-Fi.

Vision-based animal behaviour monitoring is becoming increasingly important alongside sensors measuring animals' physiological signs. Using a deep learning-powered automated system, researchers can pinpoint individual pigs, monitor their movements, and analyse key behavioural data. The system is now assessing camera-captured pig photos. This analysis only works with monocular pictures. Previously, it could identify any odd mouse behaviour. In [13], the pros and cons of using machine learning algorithms to analyse animal behaviour in videos are examined. The suggested system, which is based on IoT technology, is a functional, low-cost, and environmentally friendly Animal Health Monitoring (AHM) System. In this context, AHM is applied to the problem of animal health management. Using a number of sensors, AHM will be able to get information on the animal's physical state. With the use of sensor reading computations, AHM will automatically determine whether or not the animal's health is good. The health of agricultural animals' benefits and problems with diagnosing animal diseases are resolved [14, 15].

This research creates an SSA-BiGRNN method, which uses the BiGRNN method for the majority of the prediction process, due to the DL model's efficacy in solving forecasting difficulties. The SSA algorithm then makes the best possible adjustments to the BiGRNN method's hyper parameters. Optimal selection of the BiGRNN technique's hyper parameters is aided by an SSA algorithm inspired by bird mating behaviour, improving the method's overall prediction performance. The experimental consequences are analysed from several angles, and a broad variety of simulation analyses are performed on the benchmark dataset. This section of the paper is structured as shadows: In Section 2, we summarise the relevant literature, and in Section 3, we briefly describe the suggested model. In Section 4, we compare and contrast the projected model to the state-of-the-art validation approaches. Section 5 deliberates the final results of the study.

II. RELATED WORKS

An autonomous beef-production farm's architectural framework is presented in Garcia et al. [16]. In specifically, the design incorporates three ACODATs (data investigation tasks) to provide beef producers with proper coordination, optimisation, and planning of the productive process. As a first step towards automated and successful methods of beef production, this study also implements the autonomous animal-fattening cycle in a farm setting. Two of this architecture's most notable features are (i) the incorporation of everything mining to enhance system understanding and decision creation, and (ii) the use of three ACODAT for continuous in-the-moment analysis in support of eco-friendly, low-impact cattle farming. Positive outcomes may be expected since the ACODAT facilitates intelligent management of the cattle production process by organically incorporating AI approaches to develop these activities. In particular, an accurate description of an exactness livestock procedure may be modelled with the help of ACODAT. In a similar vein, the first findings of several ACODAT activities are encouraging since they permit assessing the proposal's practicality. ACODAT will utilise a Mean Absolute Error (MAE) of 5.4 kg on a first job for identifying cattle fattening to spot irregularities in the process. The success and durability of this approach are demonstrated by the implementation of the animal-fattening cycle.

To monitor the whereabouts of chickens and spot any issues with their well-being before they become serious, Yang et al. [17] create an automated monitoring system. In this research, an unobtrusive machine vision technique was created to track where the chickens are all the time. To evaluate the dispersal of hens in research cage-free facilities approach was created and trained. Perch zone, nesting zone are only some of the spatial distributions of hens that the system tracked. From day one to day 252, the full span of a chicken's development is represented in the dataset. For the purposes of model training, validation, and testing, around 3000 pictures were taken at random from recorded movies. It is estimated that 2400 training photos and 600 test images were used. The new approach tracked the dispersal of hens and pullets throughout different zones with an accuracy of 87–94%. Younger birds had a lower body size and were difficult to identify due to their darkness or occultation by tackle, hence their age had an impact on the model's performance. The model's performance for spotting perching

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behaviours ranged from 0.891-0.942 for birds less than 10 days old and older than 10 days old, correspondingly, and from 0.874-0.932 for the two age groups, respectively. If there were a lot of chickens in a small area (more than 18 per square metre) and their bodies were obscured by nesting boxes, feeders or perches, then the sensors failed to pick them up. The model should be integrated with other research, such as efforts to identify chicken behaviour in a commercial housing system, to create an automatic detection system.

In order to detect birds on open litter, Guo et al. [18] developed the YOLOv5-C3CBAM-BiFPN perfect for hens. The model has three components: Three models are used to improve the accuracy of the laying hen target detection algorithm: 1) convolution block attention module integrated with C3 module (C3CBAM) to improve the detection effect of targets and occluded targets; and 3) the (BiFPN). To properly assess the performance of the new model, 720 photos were chosen to generate complicated datasets with varying degrees of occlusion and densities of laying hens. In addition, a YOLOv5 model that included additional attention processes was compared to the suggested model in this work. Based on the evaluation findings, the enhanced YOLOv5-C3CBAM-BiFPN model performed with a 98.1 percent accuracy rate, a 92.9 percent recall rate, a 96.7 percent mean absolute percentage, a 156.3 frames-per-second classification rate, and a 95.4 percent F1 score. That is to say, the suggested deep learning-based technique for laying hen identification in the current work performs admirably, rapidly and reliably identifies the target, and may be used for in-process, detection of laying hens in a production setting.

Using real-time data from Artificial Neural Networks (ANN), Arshad et al. [19] hopes to predict illnesses in cattle and present the anticipated findings to authorised staff via a web application. Since this system may be hacked and needs strong network security to keep its resources private, secure, and always available, it employs a number of widely used authentication methods. The results demonstrated here verify the almost 99 percent accuracy of the suggested innovative approach for cow illness prediction. The planned CHMS can let worried farmers keep tabs on their animals from afar, so they can respond quickly to any health issues that arise. Automation in agriculture uses technology to increase yield while decreasing costs and labour requirements.

Using four different types of sensory information, including a radar device for detecting respiration rate, an embedding system for monitoring feeding time, a thermal imaging system for measuring eye temperature, and an IMU for collecting daily activity of dairy cows, Huang et al. [20] established health indicators for three major issues. Many sensors and functional modules were designed into system architecture for the Internet of Things. The data was analysed and models were constructed using machine learning and multi-sensor data fusion techniques. Multiple sensing information's, necessary for developing health indicators, was automatically gathered by the designed system. The time it takes an individual to finish eating might vary greatly. The sensing data were compared to the daily average value using a dynamic balance approach to see if the feeding condition was unusual. Data fusion using the K-means machine learning model was used to categorise the effects of heat stress on dairy cows, which was incorporated in the heat stress health indicator. To alert the dairy farmer in a timely manner when the cows are in estrus, an algorithm was developed using data on rumination and walking time. This health status evaluation methodology is able to more precisely depict the health state of dairy cows than information from a single sensor. Additionally, the technology is useful to dairy producers since it alerts them to aberrant circumstances of dairy cows, allowing for proactive management to be conducted before any harm comes to the cows.

Using a Hybrid Visual Geometry Group (VGG)-19+ (Bi-LSTM) networks, Natarajan et al. [21] are able to identify animal behaviour and issue alerts accordingly. Short Message Service (SMS) notifications are transmitted to the regional forest service office for quick action. With an average classification accuracy of 98%, a mAP of 77.2%, and an FPS of 170, the suggested model shows significant gains in model performance. Over 98% mean accuracy and precision were attained in both qualitative and quantitative tests utilising 40,000 photos from three separate benchmark datasets totalling 25 classes. This technique is an effective means of saving lives by disseminating precise data based on animal behaviour.

III. PROPOSED SYSTEM

This study applies optimised deep learning in internet of things technology to the problem of monitoring animal health. The next subsection provides a synopsis of the suggested model.

3.1. Materials and Methods

The tools and techniques for connecting the various parts of the projected implementation are described in this section. Figure 1 depicts the suggested model's process.

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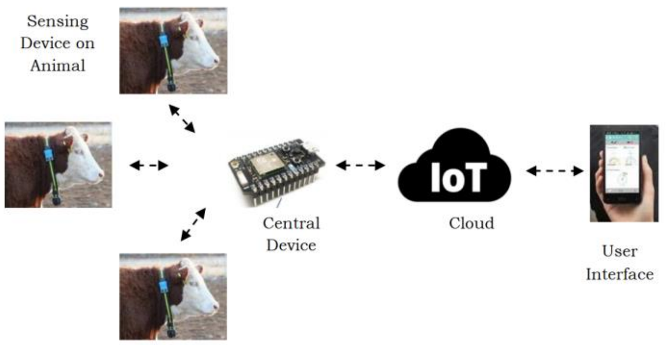

Figure 1: Workflow of the Research Model

Body area module has been included into the cow collar system. The health of the cows in the barn depends on the measurements taken by each individual node, which are in charge of monitoring certain environmental conditions. With the aid of front-end development, the owner of a smart dairy farm may view information about the farm at any time, from any location, through the internet. Information from the cow collar and environmental factors is sent to a database, where it is regularly updated. The modules to be utilised in the projected system and the parameters for each module were defined with the help of the prototype development. Vaccine reminders have also been included into the scheme. A reminder push notification is sent to the veterinarian's mobile on the day of the planned immunisation.

- A novel application is presented in this system, one that includes architecture for monitoring animal health, with the goal of attaining smart Animal Health Monitoring and bridging the gap between farmers and specialists by providing remedies to animal sickness.
- It's important to have a body temperature sensor because the average core temperature varies depending on the species. The average temperature for cattle is 38.5 degrees Celsius, for buffalo it's 38.2 degrees Celsius, for cats it's 38.1 to 39.2, and for dogs it's 38.3 to 39.2. When someone is sick, their body temperature fluctuates. At a specific temperature, the body is able to function optimally.
- Moisture Detector: Because of their impact on metabolism and behaviour, environmental factors like humidity must be constantly monitored. Directly and indirectly, the criteria have impacted performance and animal health. The effects of humidity on animal health are significant. The ability of animals and plants to cool off through evaporation is negatively impacted.
- Monitor of the Heart: The measurement of heart rate is an indirect one. The effects of anxiety and stress on an animal can be reliably detected by monitoring its heart rate.

The study included 13 healthy, nursing cows of mixed breeds, with a mean body weight of 465 16 kg, and a mean milk output of 10 0.5 l. Six cows were chosen from location (i), five from location (ii), and two from place (iii), in that order. Clinical examinations indicated that the cows were healthy across the board anatomically, physiologically, and microbiologically. The cows were milked by hand twice a day. The cows have access to unlimited water and all necessary concentrate feed and roughages at any of the three facilities. The usual diet consisted of green fodders and concentrate feeds purchased from outside sources. The experimental animals were kept in a shed with brick floors, asbestos roofing, and enough ventilation, all of which was located in a naturally lit and ventilated pasture. Every day, the outbuildings were washed down and scrubbed. The shed floor was treated with an antiseptic solution, maybe phenyl, at regular intervals. Pure water for drinking was provided freely. The routine procedures of deworming and immunisation were carried out. Location (i) allowed for 45 square feet of space per animal, whereas Locations (ii) and (iii) provided grazing space of around 25 square feet per animal. Nearby pastures had an area of at least 100 square metres.

Pre-feed, post-feed, pre-grazing, and post-grazing temperatures were recorded to determine the usefulness of a temperature sensor for keeping tabs on cow activities. The chosen animals had the Monitor attached to them while the tests were done in a field or pasture. Using a Monitor and an infrared thermometer (IRT), we took readings of their skin at regular intervals from 9:00 am to 11:30 am (IST). To further investigate the connection between internal and external temperatures, we used a digital (CT) to take readings from the subject's core. A randomly selected animal underwent 15 days of trials, with average temperatures from each state being taken into account. A field supervisor recorded information about the activities and how long they took. The skin temperatures measured by the Monitor and the IRT were analysed using a one-way ANOVA at the 0.05 level of significance to make conclusions about the degree of variation between the two.

In addition, the correlation between sensors and the associated cattle actions was analysed using the raw sensor data collected. The studies were overseen by a supervisor in the field at all times, and their duration was meticulously recorded. The "Timestamp Camera" app on a smart phone was also used to take the time-stamped footage. Time-stamped raw sensor data conventional in the IoT server allowed for correlation with videos of cow activities.

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3.2. Feature Extraction

The IoT server provided the datasets for each animal on each day of the studies. All the data obtained throughout the experiment was collated, cleaned up, and then utilised. Manual iteration was used to find the optimal window size for the classifications. Therefore, trials were run with window dimensions of 64 s, and the related classification exactitudes were calculated in order to identify an optimal window size. Sensor data for temperature, velocity, and acceleration in the X, Y, and Z axes were included in each set. In order to better comprehend a sizable amount of raw sensor data, feature extraction is required. Because of the specifics of this investigation, we were only interested in extracting three measures: (i) the mean (the average of the absolute values of the sensor interpretations), (ii) the standard deviation (the square root of the variance of the sensor readings), (iii) root mean square (RMS) value. The field supervisor kept a log of the different activity stages of the cattle and how long each lasted, and this information was used to categorise the data. Table 1 displays the names given to the characteristics that were extracted.

Table 1: Nomenclature of the features extracted.

Relevance	Extracted feature
Standard nonconformity of cattle walking speed	SD_Speed
RMS value of cattle walking speed.	RMS_Speed
Mean of acceleration slow along X axis	Mean_AccX
Standard acceleration measured along X axis.	SD_AccX
RMS value of acceleration measured along X axis.	RMS_AccX
Mean of acceleration slow along Y axis.	Mean_AccY
Standard of acceleration measured along Y axis.	SD_AccY
RMS value of acceleration measured along Y axis.	RMS_AccY
Mean of acceleration measured along Z axis.	Mean_AccZ
Standard deviation of acceleration measured along Z axis	SD_AccZ
RMS value of acceleration measured along Z axis.	RMS_AccZ
Mean of livestock body temperature	Mean_Temp
Standard deviation of cattle body temperature.	SD_Temp
RMS value of livestock body temperature.	RMS_Temp
Mean value of livestock walking haste.	Mean_Speed

3.3. Classification using Optimized BiGRNN Model

The BiGRNN method takes the characteristics as input during the first stage of the forecasting process and generates a future health status estimate. The predictive power of the RNN makes it an excellent choice for sequential information. The RNN is equipped with a hidden state h that makes predictions based on the input value x and the state before it. The RNN is denoted by Eq. for assessing the output y_t, given the input series x_1,x_2,...x_n. The hidden state at time t is denoted by h_t, and the weights of the connections between hidden layers, between hidden and the input layer, and between hidden and the output layer are denoted by W_hh, W_hx, and Wyh. The bias towards the hidden state, and hence the bias towards the output state, is denoted by b_h. The activation function f used on input and output nodes of the network.

$$h_t = f(W_{hh}h_{t-1} + W_{hx}x_t + b_h) \quad (1)$$

$$y_t = f\left(W_{yh}h_t + b_y\right) \quad (2)$$

GRU can capture long-term and solve the problem that arises frequently if training RNN [22]. RNNs cannot. In this step, we calculate GRU's hidden state h_t using the formula:

$$h_t = u \otimes \tilde{h}_t + (1-u) \otimes h_{t-1} \quad (3)$$

where u is an element-wise multiplication and ht is the update gate that determines whether or not ht has been improved. The sigmoid logistic function is used to improve the upgrade gate u, and the resulting expression is,

$$u_t = \sigma(W_{uh}h_{t-1} + W_{ux}x_t + b_u) \quad (4)$$

Following is an update to the candidate cell calculated with the hyperbolic tangent:

$$\tilde{h}_t = \tanh(W_{hx}x_t + W_{hh}(r \oplus h_{t-1}) + b_h) \quad (5)$$

where r is the reset gate used to determine how h_(t-1) compares to h_t. Estimation of the reset gate r is then performed by,

$$r_t = \sigma(W_{rh}h_{t-1} + W_{rx}x_t + b_r) \quad (6)$$

The BiGRNN's enhanced 2-layer architecture provides the output layer with input context data at all times. Bi-GRNN works on the premise that a forward NN and a backward NN are used to process the input order, and then their respective outputs are coupled by a common resulting layer. The Bi-GRU model's architecture is seen in Fig. 2.

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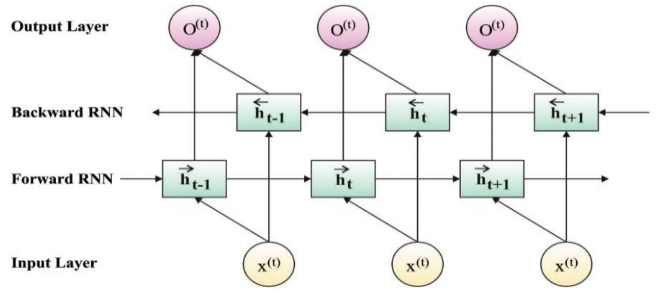

Figure 2: Architecture of Projected model

When running Bi-GRNN on all levels, the forward layer always calculates the backward result of the hidden layer always calculates the forward result of the hidden layer. The resulting layer is a constant superposition and normalisation of the forward and inverse layers' outputs.

$$\overrightarrow{h}_t^1 = f\left(w_{x\overrightarrow{h}^1} x_t + w_{\overrightarrow{h}^1\overrightarrow{h}^1}\overrightarrow{h_{t-1}^1} + b_{\overrightarrow{h}^1}\right) \quad (7)$$

$$\overleftarrow{h}_t^1 = f\left(w_{x\overleftarrow{h}^1} x_t + w_{\overleftarrow{h}^1\overleftarrow{h}^1}\overleftarrow{h_{t-1}^1} + b_{\overleftarrow{h}^1}\right) \quad (8)$$

$$\overrightarrow{h}_t^2 = f\left(w_{\overrightarrow{h}^1\overrightarrow{h}^2}\overrightarrow{h_t^1} + w_{\overrightarrow{h}^2\overrightarrow{h}^2}\overrightarrow{h_{t-1}^2} + b_{\overrightarrow{h}^2}\right) \quad (9)$$

$$\overleftarrow{h}_t^2 = f\left(w_{\overleftarrow{h}^1\overleftarrow{h}^1}\overleftarrow{h_t^1} + w_{\overleftarrow{h}^2\overleftarrow{h}^2}\overleftarrow{h_{t-1}^2} + b_{\overleftarrow{h}^2}\right) \quad (10)$$

$$y_t = g\left(w_{\overrightarrow{h^2}_y}\overrightarrow{h_t^2} + w_{\overrightarrow{h^2}_y}\overrightarrow{h}_t^2 + b_y\right) \quad (11)$$

where $\overrightarrow{h}_t^1 \in R^H$ and $\overrightarrow{h}_t^2 \in R^H$ are the vectors of layers from 1st and 2nd layers of Bi-GRNN at period t, H mentions to the sum of units from the GRU cells, $\overleftarrow{h_t^1} \in R^H$ and $\overleftarrow{h_t^2} \in R^H$ are the resultant vectors of the backward layer from 1st and 2nd layers of the Bi-GRNN at time t, $y_t \in R^T$ is the score of corresponding word on all labels at time t, T mentions to the count of tags, x_t indicates the NN input at time t, f validates the GRNN modelling, g mentions to functions, where $g(x)_i = \frac{e^{x_i}}{\sum_{k=1}^{n} e^{x_k}}$. w and b represent the weight matrices.

3.3.1. Hyperparameter Optimization Using SSA Algorithm

Sparrows, in general, are social birds, and there are many different kinds. They may be found in most regions, preferring those with stable human populations. Additionally, they are omnivorous birds that mostly consume plant matter in the form of grain or weed seeds. It's widely knowledge that sparrows are widespread local breeders [23]. The sparrow stands out from the crowd of little birds due to its superior intelligence and long-term memory.

Mathematical Model and Algorithm:

We can develop the exact perfect to build the sparrow search procedure based on the earlier description of the sparrows. The following sparrow conduct was idealised and laws were developed to govern it.

(1) The producers usually have plenty of stamina and provide the scavengers clear instructions on where to look for food or where to find it. Its job is to locate places with abundant food supplies. The evaluation of fitness levels of individuals determines the extent of energy reserves.

(2) When a sparrow spots a predator, the birds start making worrisome chirping noises to warn one other. When the alarm value exceeds the critical value, producers must direct all survivors to the secure zone.

(3) Each potential to become a producer if it diligently seeks out the best food sources, but the ratio of creators to scavengers remains constant across the board.

(4) The more active sparrows would play the role of producers. Several famished scavengers are more prone to travel great distances in search of food.

(5) In their quest for sustenance, the scavengers go where the finest food is produced. Meanwhile, some scavengers may keep a close eye on the producers and engage in intense competition for food to boost their own predation rate.

As soon as they become aware of danger, the sparrows at the group's periphery make a beeline for the safe zone to get a better position, group's core wander aimlessly in an attempt to stay in close proximity to one another.

The project requires us to utilise digital sparrows to scavenge for virtual grub. The locations of sparrows can be shown as a matrix, as seen below:

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,d} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ X_{n,1} & X_{n,2} & \cdots & X_{n,d} \end{bmatrix} \quad (12)$$

where n is the total sum of sparrows and d represents the depth of the optimisation space. The following vector reflects the whole sparrow population's fitness level:

$$F_X = \begin{bmatrix} f([X_{1,1} & X_{1,2} & \cdots & X_{1,d}]) \\ f([X_{2,1} & X_{2,2} & \cdots & X_{2,d}]) \\ \vdots & \vdots & \vdots & \vdots \\ f([X_{n,1} & X_{n,2} & \cdots & X_{n,d}]) \end{bmatrix} \quad (13)$$

where n is the total sum of sparrows and the values in F_X are each bird's fitness. In the SSA, the producers with the highest fitness levels are given favourite during the quest for food. Furthermore, producers are accountable for steering the population's mobility and looking for food. Therefore, unlike scavengers, producers have more options regarding where to

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look for food. Following principles (12) and (13), the producer's location is revised in each cycle as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{i,j}^{t}.\exp\left(\frac{-i}{\alpha.iter_{max}}\right) \text{ if } R_2 < ST \\ X_{i,j}^{t} + Q.L \quad \text{if } R_2 \geq ST \end{cases} \tag{14}$$

where t designates the current iteration, $j = 1, 2, \ldots, d$. $X_{i,j}^{t}$ characterizes the value of the jth dimension of the ith iteration $t.iter_{max}$ is a constant with the largest figure of iterations. $\alpha \in (0, 1]$ is a random numeral. R_2 ($R_2 \in [0, 1]$) and ST ($ST \in [0.5, 1.0]$) represent the alarm value and the safety threshold correspondingly. Q is a random sum which obeys normal distribution. L demonstrations a matrix of $1 \times d$ for which each element inside is 1.

When $R_2 < ST$, which no marauders around, the creator mode.

If $R_2 \geq ST$, Some of the sparrows have spotted the danger, so the rest of them must rapidly relocate.

Scroungers, meantime, must strictly enforce clauses 15 and 16. Some freeloaders, as was noted before, keep closer tabs on the manufacturers. In response to the producer's discovery of palatable food, they promptly abandon their existing location in order to secure a feeding advantage. If they win, they can immediately begin consuming the producer's food; otherwise, they must continue carrying out the rules (16). Here we give the formula for the scrounger's position updates:

$$X_{i,j}^{t+1} = \begin{cases} Q.\exp\left(\frac{X_{worst}^{t} - X_{i,j}^{t}}{i^2}\right) \text{ if } i < n/2 \\ X_p^{t+1} + |X_{i,j}^{t} - X_p^{t+1}| A^{+}.L \quad \text{otherwise} \end{cases} \tag{15}$$

where X_P is the optimal position engaged by the producer. X_{worst} signifies the current global worst location. A signifies a matrix of $1 \times d$ for which each component inside is arbitrarily assigned 1 or -1, and $A^{+} = A^{T}(AA^{T})^{-1}$. When $i > n/2$, The ith scavenger with the lowest fitness value is probably famished, according to this.

These sparrows' starting placements in the population are determined by chance. The mathematical model may be written as shadows using rule (16):

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^{t} + \beta.\left|X_{i,j}^{t} - X_{best}^{t}\right| \quad \text{if} f_i > f_g \\ X_{i,j}^{t} + K.\left(\frac{\left|X_{i,j}^{t} - X_{worst}^{t}\right|}{(f_i - f_w) + \varepsilon}\right) \quad \text{if } f_i = f_g \end{cases} \tag{16}$$

where X_{best} is the current location. β, as the step size parameter, is a distribution of random statistics with a 0 and a alteration of 1. $K \in [-1, 1]$ is a random number. Here f_i is the current sparrow. f_g and f_w are the current fitness values, correspondingly. ε is the smallest continuous so as to avoid zero-division-error.

For simplicity, when $f_i > f_g$ designates that the edge of the group. X_{best} represents the location of the centre around it. $f_i = f_g$shows that The sparrows in the centre of the flock know they need to go closer to the rest of the flock because they are in danger. The sparrow's direction of flight, denoted by K, is also the control coefficient for the size of its steps.

IV. RESULTS AND DISCUSSION

All pet owners and veterinarians may benefit greatly from the proposed strategy for keeping tabs on their animals' health. The suggested system utilises four crucial sensors, including ones for measuring temperature, respiration rate, pressure, and heart rate. The ESP8266 Wi-Fi module relays information from the pet part to the receiver section. The data is received by the Received Signal Strength Indicator from the system's microcontroller and then transmitted to the device using the Universal Asynchronous Transmitter-Receiver protocol. After that, the hardware's data values will be sent to a website for analysis. All the data values, together with analyses, will be available on the website or webpage. In order to keep up with the times, we've adapted our system so that it can be used on any Internet-enabled device. The example output from the hardware implementation is shown in Figures 3 and 4.

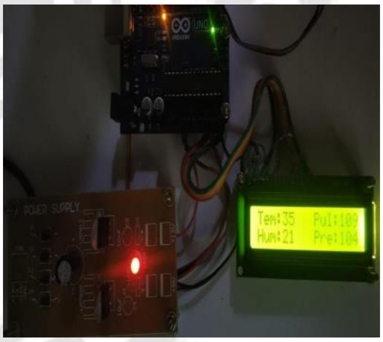

Figure 3: Project setup for Animal monitoring system.

Figure 4: Processing output

4.1. Evaluation Metrics

In this part, we'll go through the most popular tools for gauging a method's efficacy. The Confusion Matrix, a two-dimensional criteria.

- True Positive (TP): The data instances correctly predicted as a disease by the classifier.
- False Negative (FN): The data instances wrongly predicted as Normal instances.
- False Positive (FP): The data instances wrongly classified as a disease.
- True Negative (TN): The instances correctly classified as Normal instances.

Elements outside the confusion matrix represent incorrect predictions made by a given classifier. In Table 2 we can see the confusion matrix characteristics.

Table 2: Confusion Matrix

		Predicted Class	
		Fault	Normal
Actual-Class	Fault	True Positive	False Negative
	Normal	False Positive	True Negative

Further, the diverse evaluation metrics used in the fresh studies are,

Precision: It is the share of cases that were successfully recognized relative to the total sum of cases that were expected.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (17)$$

Recall: This metric compares the proportion of diseased samples that were properly labelled to the total sum of diseased samples.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (18)$$

False Alarm Rate: It is the percentage of cases in which an illness was erroneously diagnosed compared to the total number of cases in which a disease was correctly diagnosed.

$$\text{False Alarm Rate} = \frac{\text{FP}}{\text{FP+TN}} \quad (19)$$

True Negative Rate: Correctly identifying Normal samples as a proportion of total Normal samples is the definition of this metric.

$$\text{True Negative Rate} = \frac{\text{TN}}{\text{TN+FP}} \quad (20)$$

Accuracy: It represents the fraction of training data that was successfully categorised. When used to a balanced dataset, it provides a reliable indicator of performance.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (21)$$

F-Measure: It is the exact middle ground among Precision and Recall. It's a arithmetical method for assessing a scheme's reliability by looking at how well it performs in terms of both precision and recall.

$$\text{F} - \text{Measure} = 2\left(\frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}}\right) \quad (22)$$

Table 3. Comparative analysis of Proposed models without SSA.

Algorithm	Accuracy	Precision	Recall	F-score
AE	81.10	84.32	75.91	83.45
CNN	87.70	92.43	85.21	91.68
LSTM	92.50	93.48	90.98	91.81
BiLSTM	92.50	90.21	91.38	89.03
RNN	92.70	96.61	91.93	92.24
GRNN	93.27	96.17	92.47	92.10
BiGRNN	94.32	98.32	93.24	94.53

In above table 3 represent that the Comparative analysis of Projected models without SSA. In this investigation of we evaluate the diverse model to evaluate the model performances. In the analysis of AE model reached accuracy of 81.10 and the precision performance as 84.32 and also the recall value as 75.91 and finally the F-score value as calculated in term of 83.45 respectively. And another CNN model reached accuracy of 87.70 and the precision performance as 92.43 and also the recall value as 85.21 and finally the F-score as 91.68 respectively. After that the LSTM model reached accuracy of 92.50 and the precision performance as 93.48 and also the recall value as 90.98 and finally the F-score as 91.81 respectively. In next BiLSTM model reached accuracy of 92.50 and the precision performance as 90.21 and also the recall value as 91.38 and finally the F-score as 89.03 respectively. By the RNN model reached accuracy of 92.70 and the precision performance as 96.61 and also the recall value as 91.93 and finally the F-score as 92.24 respectively. Also, the GRNN model reached accuracy of 93.27 and the precision performance as 96.17 and also the recall value as 92.47 and finally the F-score as 92.10 respectively. And finally, the BiGRNN model reached accuracy of 94.32 and the precision performance as 98.32 and also the recall value as 93.24 and finally the F-score as 94.53 respectively.

Table.4. Comparative analysis of Proposed algorithm with Hyper-parameter tuning process.

Algorithm	Accuracy	Precision	Recall	F-score
AE	85.71	99.41	85.93	86.72
CNN	92.10	99.41	92.15	91.82
LSTM	92.46	99.82	92.44	95.27

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BiLSTM	89.52	99.63	89.54	95.18
RNN	94.53	99.90	92.52	95.32
GRNN	94.16	99.91	92.32	95.63
BiGRNN	95.62	99.95	94.62	96.02

The comparative analysis of the proposed approach with the hyper-parameter tuning process is shown in table.4 above. As the AE model achieved the accuracy of 85.71, the precision value of 99.41, the recall value of 85.93, and finally the F1-score of 86.72 in this comparison procedure, we examine several ways. Another CNN model achieved accuracy and precision values of 92.10 and 92.15, respectively. Then, the LSTM scored 92.46, with precision scores of 99.82 and recall scores of 92.44 and 95.27, respectively. Next, the BiLSTM model achieved accuracy values of 89.52, 99.63, and 89.54, precision values of 99.63, recall values of 89.54, and ultimately an F1- score of 95.18. The RNN model eventually achieved an accuracy of 94.53, a precision of 99.90, a recall of 92.52, and a final F1- score of 95.32. Following that, the GRNN model attained accuracy and precision values of 94.16 and 99.91, and 95.63, respectively. Finally, the BiGRNN model achieved accuracy of 95.62, precision of 99.95, and recall of 94.62 and 96.02, respectively.

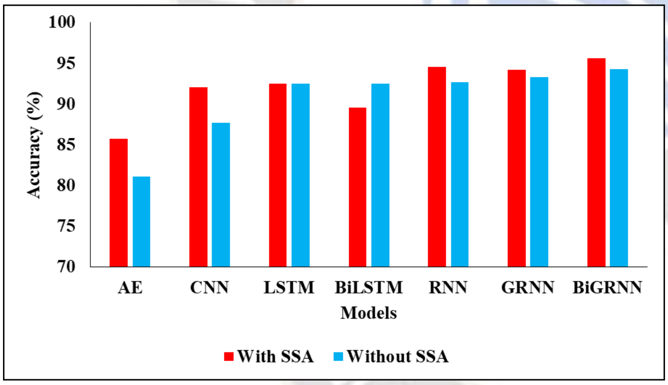

Figure 5: Graphical Comparison based on Accuracy

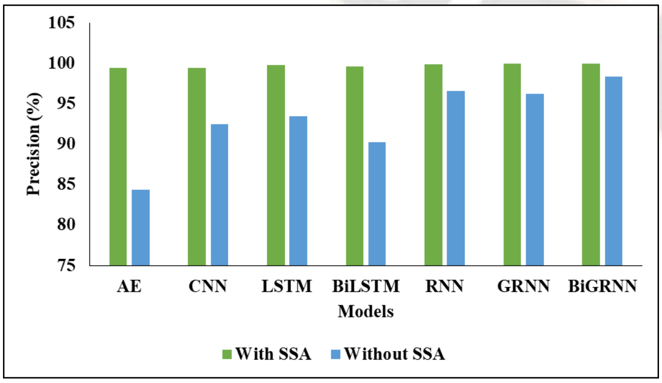

Figure 6: Precision analysis of proposed model

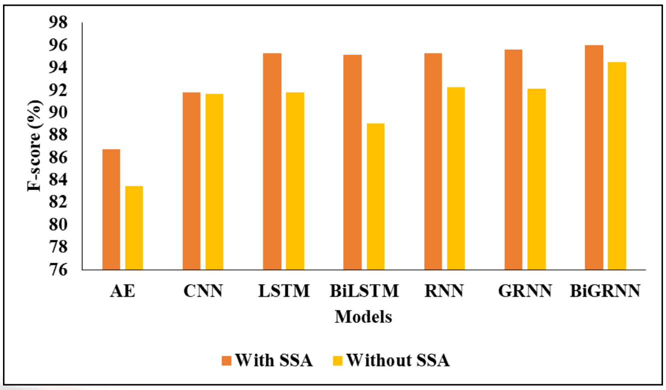

Figure 7: F-score analysis of various DL models

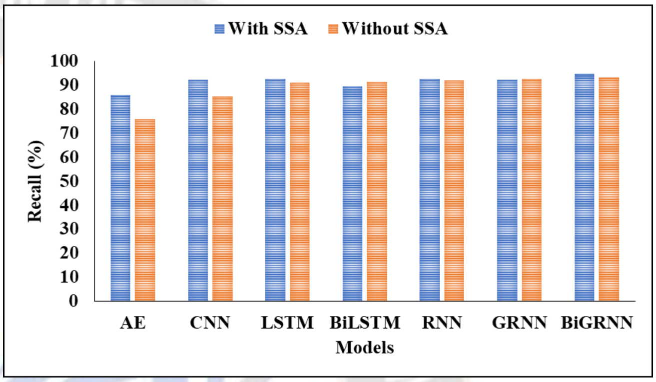

Figure 8: Graphical Representation based on Recall

V. CONCLUSION

Improvements in the ability to track animal health are happening at a breakneck pace these days. Animal Health Monitoring (AHM) is a new method designed to aid farmers in tracking and improving animal health and welfare and puts into action a reliable and cost-effective method of tracking animal health conditions. The suggested system is totally automated and requires no human intervention; the user may check on the animal's health from afar and receive alerts on his phone if any changes are detected. Node MCU is a microcontroller used in the system together with sensors for measuring temperature, humidity, heart rate, and strain on the animal. In this research, a novel BiGRNN approach was developed to analyse and classify data for predicting animal healthcare issues. The BiGRNN method consists of two phases: a prediction phase based on the BiGRNN model, and a hyperparameter tuning phase based on the Support Vector Machine. The BiGRNN model relies heavily on the feature data in order to make healthcare condition predictions. The SSA approach may then be used to fine-tune the BiGRNN method's hyper parameters. The benchmark dataset is subjected to a broad variety of simulation analyses, and the experimental findings are analysed from several angles. The comprehensive evaluation of the outcomes shows that the BiGRNN method is greater to the most recent state-of-the-art tactics on a variety of metrics. The online accessibility of the

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animal's medical history makes round-the-clock monitoring possible. It's useful for the farmer to keep an eye on his livestock around the clock. Faster treatment after early diagnosis helps keep animals healthy and helps prevent needless deaths. More sensors will soon be able to be integrated into the wireless body area network, providing comprehensive health data and boosting productivity.

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