Deep Learning with IoT-Based Solar Energy System for Future Smart Agriculture System

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***Abstract*—Agriculture has a considerable contribution to the economy. Agriculture automation is a serious issue that is becoming more prevalent around the world. Farmers' traditional practices were insufficient to achieve these objectives. Artificial Intelligence (A1) and the Internet of Things (IoTs) are being used in agriculture to improve crop yield and quality. Distributed solar energy resources can now be remotely operated, monitored, and controlled through the IoT and deep learning technology. The development of an IoT-based solar energy system for intelligent irrigation is critical for water- and energy-stressed areas around the world. The qualitative design focuses on secondary data collection techniques. The deep learning model Radial Basis Function Networks (RBFN) is used in conjunction with the Elephant Search Algorithm (ESA) in this IoT-based solar energy system for future smart agriculture. Sensor systems help farmers understand their crops better, reduce their environmental impact and conserve resources. These advanced systems enable effective soil and weather monitoring, as well as water management. To provide the required operating power, the proposed system, RBFN-ESA, employs an IoT-based solar cell forecasting process. The proposed model RBFN-ESA will collect these data to predict the required parameter values for solar energy systems in future smart agriculture systems. The results of the RBFN-ESA model are effective and efficient. According to the findings, RBFN-ESA outperforms CNN, ANN, SVM, RF, and LSTM in terms of energy consumption (56.764J for 100 data points from the dataset), accuracy achieved (97.467% for 600 nodes), and soil moisture level (94.41% for 600 data).**

Keywords*—*Precision agriculture; smart monitoring; Internet of Things; Radial Basis Function Networks; Elephant Search Algorithm (ESA)

I. Introduction

Food manufacturing in the 20th century is a pressing issue as long as population growth continues to increase. Between 9.4 and 10.1 billion people will rely on biodiversity for their livelihood by 2050, which would raise the demand for locations set aside for agricultural production, especially for farming and the rearing of farm animals [1]. Human-induced changes to the environment can result in conditions that make it difficult for new crops to flourish. Similarly, rising urbanization raises food prices while decreasing food.

Production and employment in food-producing regions. In an effort to address the challenges of fulfilling the demands of food production and the working population decline, smart agriculture aims to lower farm management expenses [2–3]. It employs techniques and technology at various agricultural production scales and levels. Precision farming, for example, can employ a range of sensing devices to collect data (heat, moisture, light, stress, presence, etc.), connectivity networks to receive and send that data, information management systems to keep and process that data, and analysis tools to do so [4]. "IoT" is a term used frequently to describe this network of connected devices [5]. The right actions can be taken thanks to the knowledge that intelligent farming generates.

Recent developments in wireless technology have completely changed how farmers can interact with their crops and track their growth [6]. Advanced management concepts can be used to monitor crops using new technologies and respond to their needs appropriately. Precision agriculture (PA) is one method that combines technology and conventional farming methods [7, 8]. Using PA in farming can increase control and accuracy when raising animals and crops. Farmers are becoming increasingly productive and cost-effective by utilizing new technology to enable agriculture because they can use more precise solutions rather than simply attempting to manage the many elements of their farming systems.

Instead of using modern technology, traditional farming practices are used to manage fields. More experience is required to maintain proper efficiency. With traditional farming methods, the best course of action for a successful harvest must be determined by considering both the current weather and historical data when making decisions about planting, harvesting, and irrigation. Contrarily, PA helps farmers use less labour while giving their crops more attention as needed by using tools like sensors, actuators, the Global Positioning System (GPS), robots, and data analysis software. Monitoring livestock and vegetation with Internet of Things (IoT) devices is one effective method for achieving PA [9]. IoT devices are minuscule, energy-efficient embedded electronics with network data transmission capabilities. An IoTs network is frequently used to describe a group of connected devices that work together to accomplish a common objective. Sensors, for example, can be installed in an IoT-based agricultural system to collect environmental information about soil moisture. An automated irrigation system can use the measured data to water plants appropriately, avoiding over- and under-watering. Farmers might be able to instantly and remotely monitor field conditions thanks to an IoT system. It is just as crucial to keep an eye on the vegetation in a field as it is to keep an eye on livestock to ensure that they are fed and cared for properly. The use of IoT devices can lower labour costs significantly and enhance animal welfare. IoT devices can be used to find the livestock's location and assess its health.

II. Literature Survey

Systems remain a type of feedforward neural system that activates using radial basis functions and universal approximators. Classification, regression, pattern recognition, and time series forecasting problems are frequently solved using RBFN [10–11]. In addition to their strong ability to approximate any continuous network, RBFNs also possess strong characteristics like their compact structure, noise tolerance, and ability to approximate any global approximation. The new elephant algorithm is among the most recent meta-heuristic methodologies to be suggested. The search areas of elephant males are widened as they travel farther and farther. The female elephants focus on seeking out the best response locally. A lifespan mechanism that regulates birth and death gives all agents a gradually increasing chance of dying as they age. The heuristic knowledge of these elephants' forebears will be passed down to them, and this mechanism is designed to keep whole agents from entering the local optimum. The solar energy-driven polygene ration system configurations and classified them based on design, benefits, technical potentials, challenges, and market prospects. A solar-driven multigeneration system enhances the system's efficiency and reduces the capital and operation costs as well as carbon dioxide emissions to improve the environment [12].

Soil temperature modelling to assess the viability of using soil air exchangers for agricultural structures. In this context, the ability of soil to cool or heat agricultural structures such as greenhouses was determined by modifying temperature behaviour at various depths [13]. A solar thermal system produces inexpensive, environmentally friendly heat using the sun's energy. Temperature pushes, electronic warmers, and rotation forces are all controlled in accordance with the need for hot water in a building. First, take into account clear, cloudy, rainy, and dark weather[14]. The network's overall node count could be decreased while the sampling frequency was raised. Although reducing the number of sensor nodes has been shown to result in a similar network lifetime, it is unknown how much data is lost from specific locations within a field. Even though there are more samples, most agricultural systems don't need quick responses because the environment doesn't change quickly over short periods of time [15]. The temperature readings taken by the drone while it was flying over the crop were incorrect, according to experiments. The drone was able to get more precise readings when it was nearer the area of interest. The devices had to be in constant time sync for the data collected among the drone and nodes to be accurate [16]. In order to implement multiple networks, the system was built with nodes that could switch between two operating frequencies. Nodes were organized into clusters, and the cluster leader forwarded data from each cluster to the target node. The outcomes showed that the design used very little energy and could work for a whole season on just one charge of the battery [17].

Wen-tai Li et al. presented by [18]. Building managers can achieve their energy management objectives with the aid of the Solar Water Heating (SWH) control mechanisms. The methods are based on the price of electricity, the weather, and the demand for hot water. An important source of solar energy for buildings, solar thermal systems are the subject of this study. A solar thermal system produces inexpensive, environmentally friendly heat using the sun's energy. Temperature pushes, electronic warmers, then rotation forces remain all controlled in accordance with a building's need for hot water. First, take into account clear, cloudy, rainy, and dark weather. To run the simulations, three different days were picked: a cloudy day, a sunny day, and a semi-synthetic day with no solar. The ideal control mechanism for heat pumps, electric heaters, and circulator pumps has been researched to enhance the SWH system's performance.

Mohammadi et al. [19] reviewed various solar and hybrid solar energy driven polygene ration system configurations and classified them based on design, benefits, technical potentials, challenges, and market prospective. Solar-driven multigeneration system enhances the system efficiency and reduces the capital and operation costs as well as carbon di-oxide emissions to build environment.

Faridi et al. [20] Soil temperature modelling was used to assess the viability of using soil-air exchangers for agricultural structures. The ability of soil to heat or cool agro constructions like greenhouses was detected by means of modifying the behavior of temperature at various depths in this context.

The objective of the paper is

1) First this IoT-based solar energy system for a future smart agriculture system, a deep learning [36, 37] model called Radial Basis Function Networks (RBFN) with the Elephant Search Algorithm (ESA) has been used.

2) IoT and automation are linked with agriculture and farming practises in order to recover the efficacy and efficiency of the entire process.

3) Sensory systems promoted resource conservation, decreased detrimental environmental effects, and improved farmers' understanding of crops. These innovative systems allow for effective soil and weather monitoring as well as efficient water management.

4) To supply the necessary operating power, the proposed system, RBFN-ESA, makes use of a forecasting method from an IoT-based solar cell.

5) The IoT controller reads the data from the humidity, field-based temperature and soil moisture sensors and then outputs the required actuation command signals to drive irrigation pumps.

6) The proposed model RBFN-ESA will collect these data to predict the values of the important solar energy system parameters for a future smart agriculture system.

III. Proposed System

Every aspect of conventional farming practices can be drastically altered by integrating the most recent sensing and IoT technologies. Now that the IoTs and wireless sensors are available, smart agriculture [35] can reach new heights. By implementing smart farming techniques like drought response, yield enhancement, land applicability, irrigation [34], and pest control, the Internet could really help improve options for so many traditional farming problems. The RBFN-ESA method's block diagram is shown in Fig. 1.

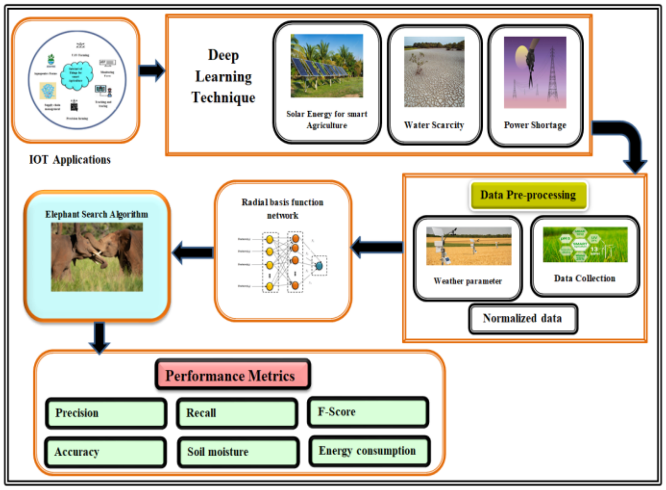

Fig. 1. Block diagram for the approach proposed by RBFN-ESA.

A. Data Pre-processing

The method for considering the weather parameter, data collection, and normalised data during the data pre-processing is described as follows.

1) Weather metric: Accuweather is used to get the daily weather parameters and their measurement units. Based on the temperature (in degrees Celsius), date (dd/mm/yy), season, and daily rainfall, this parameter is used to calculate the amount of rain that will fall on a specific day. The probability of rainfall is taken into account when choosing the aforementioned parameters. The chosen parameter is only equipped to predict the weather.

2) Data collection: For this experiment, we made use of actual data, particularly weather information from Kolkata, West Bengal. The data has been standardized. This data was gathered from the online weather resource Accuweather.com. Data from the first year is used for training, and data from the next 50 days is used for testing.

3) Normalized data: The next stage of data processing, known as "normalization," has arrived after the choice of weather parameters and completion of data collection. Random data in GA must be in normalized form for training and testing. It might be challenging to combine when the GA is trained using real data. Every bit of data is fixed and changed to a value of 0 or 1.

B. Web-Based Water Motor Control Service

A web server built atop the HTTP protocol has been developed to stop and start the water motor. The programming language in R-Pi has accessed this web service to start or stop this same water motor. The Pic Microcontroller's programming language sends signals to the Arduino-Uno, which controls the spread circuit to start and stop the fluid motor.

C. Digital Water Pump

In this subsystem, an aquatic force is attached to a convey button that is managed by a base station with Bluetooth capabilities. For real time monitoring, the web service stimulates base station control from the flexible web-based interface. The water pump can be controlled remotely, both automatically and manually, using this web-based interface.

D. Internet of Things

The IoT is a station of smart, interrelated substances that can transmit information and generate useful data about the market environment. As a result, almost any object that can connect to the Internet can be referred to as a "thing" in the context of the IoTs, including furniture, electronics, appliances, agricultural or industrial machinery, and level public [21-23].

The IoT concept is not new-fangled, but acceptance has recently risen. Some of the technologies that have developed to support it include big data, cloud computing, artificial intelligence, and hardware advancements that have reduced the scope and control of feasting and improved connectivity via the Internet and among plans via wireless connections [24]. Together, these technical parts make a net of nodes that can send and receive information and data and react to interference from the network.

Even though the structure of an IoT network is similar to that of other computer system architectures, [25] says that the identification, sensing, and control of remote devices, as well as the limited computing power of the equipment, are some of the unique aspects of this framework that must be taken into account.

E. Classification using RBFN

The most basic RBFN configuration is a three-layer feed-forward neural network. The network's inputs are represented by the first layer, and its final output is represented by the second layer, which is a hidden layer made up of numerous RBF non-linear activation units. Gaussian functions are frequently used in RBFNs to implement activation functions [26]. An illustration of the RBFN framework can be found in Fig. 2. Let's say we have a dataset D that contains N structures of (xp, yp), where xp is the data set's input.

Eq. (1) can be used to calculate the production of the ith initiation function φi in the net's unseen coating based on the separation among the input pattern x and the centre i.

$$\phi_i(\| x-d_i \|) = exp\left(-\frac{\| x-d_i \|^2}{2\sigma^2{}_j}\right) \tag{1}$$

The ||.|| hidden neuron j's centre and width are represented by d_i and σ_j, the Euclidean norm.

Then, Eq. (2) can be used to determine the output of node k of the network's output layer:

$$yk = \sum_{j=1}^{n} \omega jk \phi_j(x) \tag{2}$$

The majority of conventional training methods for RBFNs described in the literature consist of two step [27]. For example, in the first stage, an unsupervised clustering algorithm is used to compute the widths and centers. In order to reduce an error criterion, such as the common mean squared error (MSE) over the whole dataset, the hidden layer and output layer's connection weights must be determined in the second step.

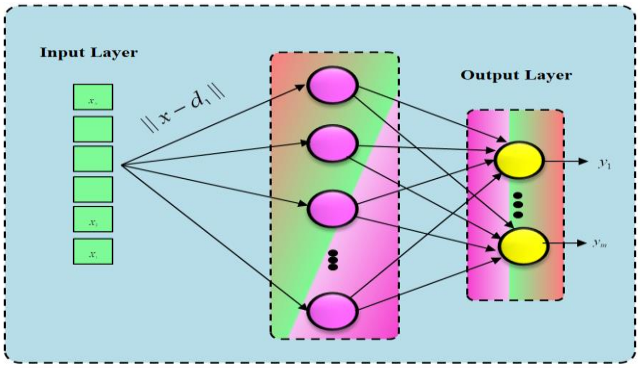

Fig. 2. The RBFN's structure.

F. Elephant Search Algorithm (ESA)

The most recent generation of meta-heuristic search optimization algorithms includes ESA. A dual search mechanism, or the ability to divide the search agents into two groups, is the foundation of this algorithm's approach, which mimics the characteristics and behaviours of an elephant [28]. Elephants live in herds, and each herd is made up of several smaller clans or groupings, each led by the eldest elephant in the herd. The ESA mimics elephant herds' major characteristics and qualities. Elephants have different social systems, with males preferring solitary living and females preferring family units. Female elephants are more concerned with improving their surroundings, whilst male elephants are in charge of discovering new locations to explore.

In this case, ESA is a good search optimization algorithm that has the following three main traits:

1) The search process enhances the present response iteratively in order to identify the ideal one. Chief female elephants also conduct extensive local searches in regions where they believe there is a better chance of finding the greatest solution.

2) Male elephants are in charge of foraging outside the neighborhood's ideal range.

3) Elephants possess a variety of traits, making it crucial to draw inspiration from their biological behaviour. Here is a description of the ESA.

Algorithm 1: Elephant Search Algorithm (ESA)

```
Input: SearchSpace, HerdSize, MaxIterations
Output: BestSolution
Initialize the herd
Herd ← InitializeHerd(HerdSize, SearchSpace)
BestSolution ← None
Main search loop
for iteration = 1 to MaxIterations do
Evaluate the herd's position
   for each elephant in Herd do
elephant.fitness ← EvaluateFitness(elephant.position)
if BestSolution is None or elephant.fitness is better than
BestSolution.fitness then
    BestSolution ← elephant
end if
  end for
Communication among elephants (sharing the best known solution)
BestElephant ← FindBestElephant(Herd)
for each elephant in Herd do
   if elephant ≠ BestElephant then
elephant.position ← MoveTowards(BestElephant.position,
elephant.position)
   end if
end for
Random exploration to avoid local optima
for each elephant in Herd do
   if rand() < ExplorationProbability then
elephant.position ← RandomMove(SearchSpace)
   end if
end for
Memory retention (remembering good positions)
for each elephant in Herd do
    if rand() < MemoryRetentionProbability then
elephant.position ← elephant.bestKnownPosition
   else
elephant.bestKnownPosition ← elephant.position
   end if
end for
end for
Return the best found solution
return BestSolution
End Algorithm
```

Each elephant must be a member of a clan since they all live together in a herd under the leadership of the oldest elephant [29]. The equation below can be used to represent the animal j in the cli clan.

$$Y_{new,cli,j} = Y_{cli,j} + c(Y_{Best,cli} - Y_{cli,j}).r \tag{3}$$

where $Y_{Best,cli}$ denotes the clan cli and $r \in [0,1]$, and $Y_{new,cli,j}$ and $Y_{cli,j}$ are the elephant j's newly updated and old places in clan cli, separately. $c \in [0,1]$ determines how clan cli influences $Y_{cli,j}$. Eq. (3) cannot be applied when $Y_{cli,j} = Y_{Best,cli}$, but the fittest elephant can be determined using the formula shown below.

$$Y_{new,cli,j} = \alpha.Y_{center,cli} \tag{4}$$

where $\alpha \in [0,1]$ stands for the $Y_{center,cli}$ s impact on the $Y_{new,cli,j}$. The d th dimension of the new individual $Y_{new,cli,j}$ is then updated using the formula below.

$$Y_{center,cli,d} = \frac{1}{n_{cli}} \cdot \sum_{j=1}^{n_{cli}} X_{cli,j,d} \quad (5)$$

There are that many elephants in the cli clan, $1 \leq d \leq D indicate\ the\ dth\ \dim ension$e, D is its overall dimension, and $Y_{cli,j,d}$ is the d th of the individual $Y_{cli,j}$ elephant.

As mentioned earlier, adult male elephants continue living alone in a remote area after leaving their families [30]. By using a separating operator to solve challenging optimization problems, this scenario can be simulated. Let's assume that the animal individual people with worst fitness particular instance will use the trying to separate operator in compliance with the appropriate equation to enhance the search functionality of ESA [31].

$$Y_{worst,cli,d} = Y_{Min} + (Y_{Max} - Y_{Min} + 1).Rand \quad (6)$$

where Y_{Max} and Y_{Min} are the highest and lowest limits of an elephant's position, $Y_{worst,cli}$ is the worst elephant member of clan cli, and $Rand \in [0,1]$ is a random distribution [32]. The description of the clan updating and separating operator has been included in the ESA development.

IV. Result and Discussion

The main goal of this experiment is to use sensors to gather the physical characteristics of a farming area. From there, an algorithm will be developed using the sensor data and weather forecast information to predict soil moisture for the upcoming days [33]. This study compares the proposed MPNN-MCOA algorithm with the convolution neural network, support vector machine, artificial neural network, long short-term memory and random forest as five machine learning algorithms.

A. Assessment Criteria

- True Positives (TP) are instances where both the actual yield and our expectations came true.
- True Negatives (TN): Occurrences in which the true yield turned out to be incorrect, as predicted.
- False Positives (FP): We expected real results, but the yield was incorrect.
- False Negatives (FN): When an outcome that we anticipated to be untrue proved to be accurate.

Precision: It is also known as the ratio of results that were correctly predicted as positive to results that were actually positive.

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

Recall: It is determined by separating the total amount of successful results by the total amount of conjugate samples.

$$Recall = \frac{TP}{TP+FN} \quad (8)$$

F1-score: It also goes by the name "harmonic mean" and aims to balance precision and recall. The computation works well on an unbalanced dataset and allows for both false negatives and false positives.

$$F1-score = \frac{2TP}{2TP+FP+FN} \quad (9)$$

Accuracy: The percentage of precise predictions to all input models is referred to by this expression.

$$Ac\chi\upsilon\rho\alpha\chi\psi = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

B. Precision Analysis

Fig. 3 and Table I provide a comparison of the RBFN-ESA method's precision with that of other methods now in use. The precision with which the deep learning with IOT method has enhanced performance is illustrated by the graph. For example, the precision of the RBFN-ESA method for data 100 is 86.743%, whereas the CNN, ANN, SVM, RF, and LSTM methods have precision values of 83.487%, 78.256%, 75.187%, 69.664%, and 72.387%, respectively. However, the RBFN-ESA method has shown optimal performance over a range of data set sizes. Under 600 data points, the RBFN-ESA methods precision value is 92.864%; in contrast, the CNN, ANN, SVM, RF, and LSTM methods have precision values of 84.754%, 81.242%, 77.854%, 71.643%, and 74.532%, respectively.

TABLE I. Precision Analysis of the RBFN-ESA Method

No of data from dataset	CNN	ANN	SVM	RF	LSTM	RBFN-ESA
100	83.487	78.256	75.187	69.664	72.387	86.743
200	82.954	78.654	75.533	70.532	72.854	87.953
300	82.843	79.054	76.863	70.843	73.454	88.435
400	83.543	79.435	77.095	69.853	72.964	91.653
500	84.864	80.774	76.346	71.254	73.964	93.643
600	84.754	81.242	77.854	71.643	74.532	92.864

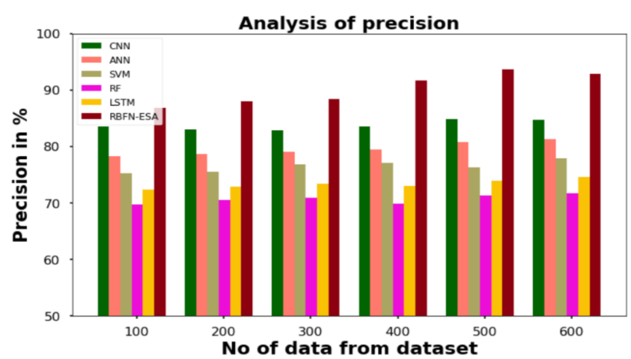

Fig. 3. Precision analysis for RBFN-ESA method.

C. Recall Analysis

Fig. 4 and Table II compare the recall analysis of the RBFN-ESA method with existing methods. The graphic shows how recall performance has increased with the deep learning with IOT method. For example, the recall value for data 100 for the RBFN-ESA method is 90.542%, whereas the corresponding values for the CNN, ANN, SVM, RF, and LSTM methods are 77.76%, 86.543%, 80.187%, 74.875%, and 85.765%. The RBFN-ESA method has performed at its best with various data sizes, though. Similar to this, for 600 data, the recall value of the RBFN-ESA is 94.765%, while for CNN, ANN, SVM, RF, and LSTM methods, it is 79.942%, 88.864%, 84.854%, 78.543%, and 87.912%, respectively.

TABLE II. RECALL ANALYSIS FOR RBFN-ESA METHOD

No of data from dataset	CNN	ANN	SVM	RF	LSTM	RBFN-ESA
100	77.765	86.543	80.187	74.875	85.765	90.542
200	76.643	86.954	81.286	75.278	85.265	89.542
300	77.923	87.254	84.543	73.478	87.397	91.467
400	78.743	87.854	83.567	76.187	86.093	93.965
500	79.654	88.145	82.864	77.098	87.743	92.376
600	79.942	88.864	84.854	78.543	87.912	94.765

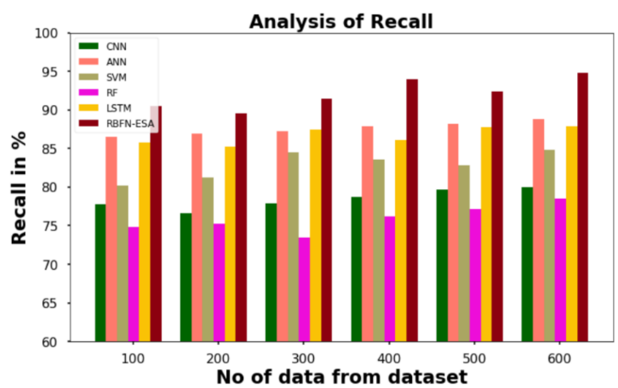

Fig. 4. Recall analysis for RBFN-ESA method.

D. F-Score Analysis

Fig. 5 and Table III provide comparative f-score analyses of the RBFN-ESA method with other existing methods. The graph shows that the f-score performance has improved with the deep learning with IOT method. For example, the f-score value of the RBFN-ESA method for data 100 is 94.095%, whereas the corresponding values for the CNN, ANN, SVM, RF, and LSTM methods are 88.643%, 85.865%, 78.543%, 91.754%, and 81.765%. However, the RBFN-ESA method has shown optimal performance over a range of data sizes. In comparison to the CNN, ANN, SVM, RF, and LSTM methods, which have respective f-score values of 90.345%, 86.324%, 80.864%, 94.865%, and 83.265%, the RBFN-ESA method has an f-score value of 97.565% under 600 data points.

TABLE III. F-SCORE ANALYSIS FOR RBFN-ESA METHOD

No of data from dataset	CNN	ANN	SVM	RF	LSTM	RBFN-ESA
100	88.643	85.865	78.543	91.754	81.765	94.095
200	87.045	84.345	79.465	92.865	82.644	94.345
300	87.345	85.234	78.843	91.245	81.438	95.346
400	88.934	84.846	80.245	92.533	82.835	95.755
500	87.834	86.987	81.258	93.546	83.095	96.346
600	90.345	86.324	80.864	94.865	83.265	97.565

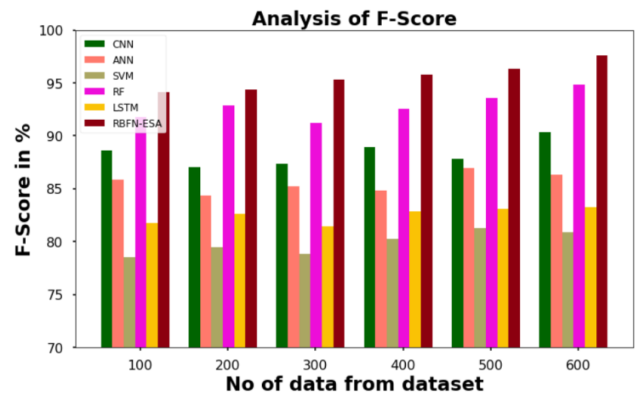

Fig. 5. F-Score analysis for RBFN-ESA method.

E. Accuracy Analysis

Fig. 6 and Table IV compare the accuracy of the RBFN-ESA method to other methods. The graph shows how applying the deep learning with IOT method has improved performance with accuracy. For example, the RBFN-ESA method accuracy value for data 100 is 94.509%, while the accuracy values for CNN, ANN, SVM, RF, and LSTM methods are 79.346%, 89.453%, 84.578%, 90.353%, and 81.756%, respectively. However, the RBFN-ESA method has shown optimal performance over a range of data sizes. Comparing the accuracy values of CNN, ANN, SVM, RF, and LSTM method, which are 83.653%, 88.245%, 86.953%, 92.465%, and 83.543%, respectively, to the RBFN-ESA, which has an accuracy value of 97.467 % is 600 data.

TABLE IV. ACCURACY ANALYSIS FOR RBFN-ESA METHOD

No of data from dataset	CNN	ANN	SVM	RF	LSTM	RBFN-ESA
100	79.346	89.453	84.578	90.353	81.756	94.509
200	79.754	89.775	84.965	91.654	82.467	94.356
300	80.645	87.464	85.196	93.464	82.776	95.864
400	80.356	87.865	85.853	92.098	83.854	96.245
500	81.246	88.353	86.257	93.834	81.943	96.865
600	83.653	88.245	86.953	92.465	83.543	97.467

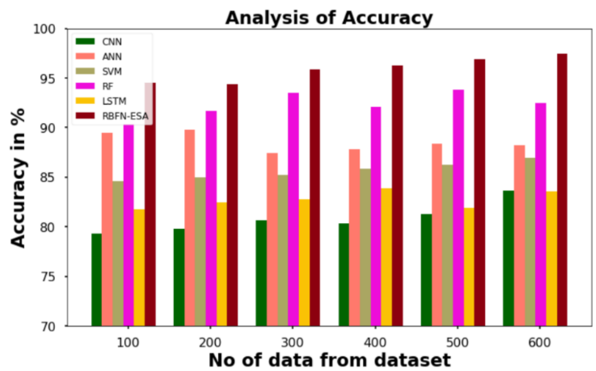

Fig. 6. Accuracy analysis for RBFN-ESA method.

F. Training Validation and Training Loss

Fig. 7 shows training validation and training loss analysis for RBFN-ESA method.

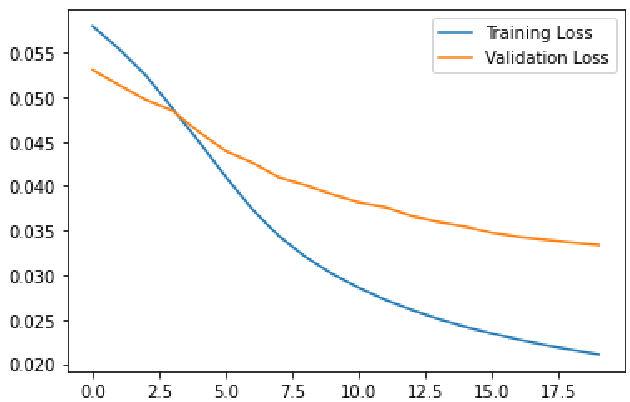

Fig. 7. Training validation and training loss analysis for RBFN-ESA method.

G. Soil Moisture

Fig. 8 and Table V compare the RBFN-ESA method with existing methods for examining soil moisture. The graph shows how soil moisture performance has increased with the deep learning with IOT method. For example, with 100 data, the RBFN-ESA method's soil moisture is 90.16%, whereas the CNN, ANN, SVM, RF, and LSTM methods' soil moisture values are 71.87%, 77.76%, 76.17%, 79.96%, and 84.67%, respectively. However, the RBFN-ESA method has shown optimal performance over a range of data sizes. Similarly, the RBFN-ESA has soil moisture of 94.41% under 600 data, while CNN, ANN, SVM, RF, and LSTM methods have 73.18%, 79.17%, 76.62%, 82.78%, and 88.76%, respectively.

TABLE V. SOIL MOISTURE ANALYSIS FOR RBFN-ESA METHOD

No of data from dataset	CNN	ANN	SVM	RF	LSTM	RBFN-ESA
100	71.87	77.76	76.17	79.96	84.67	90.16
200	73.43	76.17	74.36	77.12	83.87	92.65
300	73.12	78.19	75.42	79.65	85.15	91.76
400	70.98	76.54	74.17	81.65	88.44	93.43
500	72.98	78.66	75.77	80.32	88.91	95.17
600	73.18	79.17	76.62	82.78	88.76	94.41

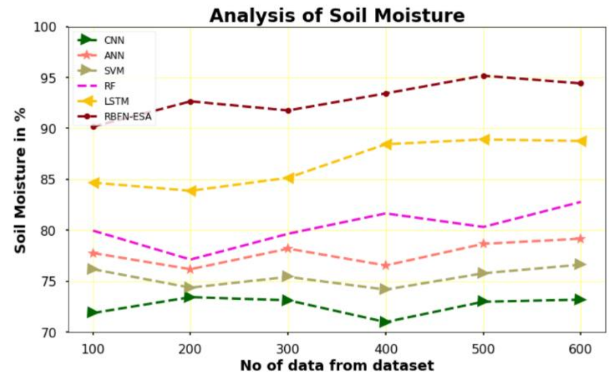

Fig. 8. Soil moisture Analysis for RBFN-ESA method.

H. Energy Consumption Analysis

Table VI and Fig. 9 provide a comparison of the energy consumption of the RBFN-ESA method with existing methods. With 100 data, the CNN, ANN, SVM, RF, and LSTM methods consume 59.324J, 57.276J, 64.865J, 67.897J, and 69.256J of energy, respectively, whereas the proposed RBFN-ESA method uses 54.632 J. In a similar vein, the proposed RBFN-ESA method uses just 56.764 J with 600 data, compared to 62.543 J, 58.721 J, 65.443 J, 68.432 J, and 73.876 J for CNN, ANN, SVM, RF, and LSTM. The recommended method shows enhanced performance with lower energy usage.

TABLE VI. ENERGY CONSUMPTION ANALYSIS FOR RBFN-ESA METHOD

No of data from dataset	CNN	ANN	SVM	RF	LSTM	RBFN-ESA
100	59.324	57.276	64.865	67.897	69.256	54.632
200	60.633	57.642	63.269	66.265	70.765	55.853
300	61.287	58.973	64.249	66.875	70.236	53.842
400	62.843	58.423	63.865	65.854	69.246	55.062
500	61.865	59.053	65.089	68.532	71.663	55.187
600	62.543	58.721	65.443	68.432	73.876	56.764

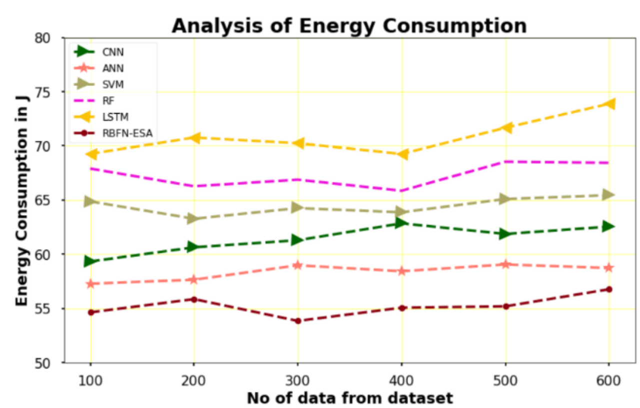

Fig. 9. Energy consumption analysis for RBFN-ESA method.

V. CONCLUSION

Environmental variables, such as relative humidity, temperature, soil temperature, UV rays, etc., impact soil moisture. Technology advancements have greatly enhanced the precision of weather forecasts, and the information can now be used to predict variations in soil moisture. The intelligent irrigation system described in this week's IoT-based planet comprehensive liveliness classification is essential for areas of creation where water and energy are uncommon. Using a qualitative methodology and focusing on secondary data collection, a deep learning model called Radial Basis Function Networks (RBFN) with the Elephant Search Algorithm (ESA) was used for this IoT-based solar energy system for a Future intelligent agriculture system. To supply the necessary operating power, the proposed RBFN-ESA uses a forecasting process from an IoT-based solar cell. The IoT controller reads the data from the humidity, field-based temperature and soil moisture sensors and then outputs the required actuation command signals to drive irrigation pumps. In forecast the value systems of the crucial solar power system variables for a future intelligent agriculture system, the suggested framework RBFN-ESA will gather these data. In terms of defining whether a user will belong to a specific group, the proposed model performed better than other models like Random Forest (RF), Artificial Neural Network (ANN), Support Vector Machine (SVM), Convolution Neural Network (CNN) and Long Short-Term Memory (LSTM). This approach makes use of existing models, such as SVM, RF, LSTM, and convolution neural. We want to conduct further assessments of water savings based on the proposed algorithm with numerous nodes and system cost reduction.

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