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Modeling of Sensor Enabled Irrigation Management for Intelligent Agriculture Using Hybrid Deep Belief Network

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Abstract: Artificial intelligence (AI) technologies and sensors have recently received significant interest in intellectual agriculture. Accelerating the application of AI technologies and agriculture sensors in intellectual agriculture is urgently required for the growth of modern agriculture and will help promote smart agriculture. Automatic irrigation scheduling systems were highly required in the agricultural field due to their capability to manage and save water deficit irrigation techniques. Automatic learning systems devise an alternative to conventional irrigation management through the automatic elaboration of predictions related to the learning of an agronomist. With this motivation, this study develops a modified black widow optimization with a deep belief network-based smart irrigation system (MBWODBN-SIS) for intelligent agriculture. The MBWODBN-SIS algorithm primarily enables the Internet of Things (IoT) based sensors to collect data forwarded to the cloud server for examination purposes. Besides, the MBWODBN-SIS technique applies the deep belief network (DBN) model for different types of irrigation classification: average, high needed, highly not needed, and not needed. The MBWO algorithm is used for the hyperparameter tuning process. A wide-ranging experiment was conducted, and the comparison study stated the enhanced outcomes of the MBWODBN-SIS approach to other DL models with maximum accuracy of 95.73%.

Keywords: Agriculture; smart farming; hyperparameter tuning; artificial intelligence; irrigation management; sensors; deep learning

1 Introduction

Water is a preventive factor in agricultural productivity. This fact is intensified in areas where water seems to be scarce [1]. Proper management of irrigation becomes an important issue for sustainable productivity. Several agricultural methods made it possible to enhance irrigation management, from drip irrigation mechanisms to regulated deficit irrigation techniques able to sustain yields with fewer irrigation volumes [2]. Information and communication technology (ICT) contributed more to water management in agriculture. Deploying wireless sensor networks (WSN) in crops by utilizing Internet of Things (IoT) technology and remote management of data, including cloud computing (CC), assisted in the immense monitoring of farming parameters that produced an enormous quantity of information [3]. This data will be helpful for the farmers in determining the water condition of the soil–plant–atmosphere and deciding whether various deficit irrigation techniques implemented to the physiology and phenology of the crop must be enforced. However, the consistent modernization of irrigation systems has to adopt equipment that permits an automated preparation of irrigation [4]. It must add sensors to offer several parameters. Usually, such parameters were based on ecological conditions. They rendered data regarding full crop water necessities employing meteorological stations in addition to the water condition of the soil or volumetric content that denotes the plant's water availability [5]. The commonly utilized soil parameter sensors use dielectric properties since it is flexible and inexpensive. Nevertheless, its correct functioning requires complicated calibration, taking factors, namely water salinity, soil structures and texture, temperature, and the spatial inconsistency of the soil. Other sensors, such as multispectral and thermal cameras, infrared radiometers (IR), or satellites, were utilized for estimating water crop requirements [6].

The data produced by various sensors in modern farming operations through IoT platforms could allow a superior understanding of the communication of dynamic variations of the weather, crop, and soil conditions of the greenhouse atmosphere [7], which is utilized for data-driven modelling estimations for precise and faster decision making in real-time in attaining water-saving agriculture [8]. Prediction modelling includes dynamic methods and techniques that integrate data from several physical, operational, chemical, and physiological processes, to predict particular outcomes or trends for deciding on the procedure. It helps improve irrigation productivity and efficiency of crops, along with mitigating the impact of the varying weather conditions dynamics for optimizing agronomic inputs' usage [9]. A smart irrigation scheme with the implementation of sensors and deep learning (DL) was needed because the research works on irrigation systems are still not effective. They cannot be applied to large-scale systems and have minimal efficacy because of the overburdened sensor for every sensing dataset [10]. As a result, a novel intellectual and smart scheme must be devised.

This study develops a modified black widow optimization with a deep belief network-based smart irrigation system (MBWODBN-SIS) for intelligent agriculture. The MBWODBN-SIS algorithm primarily enables the Internet of Things (IoT) based sensors for data collection, which was forwarded to the cloud server for examination purposes. Besides, the MBWODBN-SIS technique applies MBWO with the deep belief network (DBN) model for different types of irrigation classification such as not needed, high needed, highly not needed, average, and needed. The MBWO algorithm is derived by the use of standard BWO with a mutation operator. An extensive range of experiments can occur to ensure the effective irrigation classification performance of the MBWODBN-SIS method.

The rest of the paper is organized as follows. Section 2 elaborates on the related works and Section 3 discusses the proposed model. Later, Section 4 offers experimental validation and Section 5 concludes the study.

2 Related Works

In [11], the long short-term memory (LSTM) model is devised as an alternative technique for solving the irrigation problem. The solution can be tested for smart irrigation systems (SIS) in which neural sensors can substitute physical sensors. The SIS has numerous physical sensors that transfer humidity, soil moisture, and temperature data for calculating transpiration in a specific domain. Kashyap et al. [12] devise a DL-based neural network (DL-NN)-related IoT-assisted intellectual irrigation system to maintain accuracy in agriculture (DLiSA). This was a feedback-compiled system that maintained its functionality well in the weather for some point in time. DLiSA uses an LSTM for predicting volumetric soil moisture level for a day in advance and spatial distribution of water necessitated for feeding arable lands.

Keswani et al. [13] emphases on the effective control of irrigation through exploitations of the abilities of Big Data-based Decision Support Systems (DSS) and IoT for generating suitable valve control commands. Three predictive approaches, the Resilient back propagation neural network (BPNN) method, deep neural network (DNN), and random forest (RF), will be tested for forecasting soil Moisture Content (MC) an hour earlier, considering six numbers of various sensor nodes. Realistic data collection can be executed through the devised IoT node disposition technique tested in the domain. Chang et al. [14] introduce a machine learning (ML)-oriented, accurate, smart irrigation scheme that includes LoRa P2P networks to seamlessly and automatically study irrigation proficiencies from expert agriculturalists for organic crops. The presented mechanism would initially compute the volume of water for every irrigation related to the highly trained irrigation method integrated with atmosphere data like light intensity, humidity or air temperature, soil temperature or humidity, etc., and irrigate the crops mechanically through the low-power and long-distance wireless LoRa P2P network. In [15], the authors devise a DL structure AgriSegNet for automated identification of farmland anomaly utilizing multiscale attention semantic segmentation of drone images. This presented technique method will be helpful in farmland monitoring and raise the efficiency of accurate agricultural methods. Veerachamy et al. [16] solve both alert and irrigation, that is Agricultural Irrigation Recommendation and Alert (AIRA) mechanism that works separately by not having any correlation. The collected data can be processed in a hybrid classifier that integrates a k-nearest neighbour (K-NN) and a NN (k-N4). For faster classification, initially, the NN was utilized. The accumulated data can be gathered by adapted fuzzy clustering, and meteorological conditions were indorsed from the attractiveness-related PSO (APSO) technique.

Singh et al. [17] modelled intelligent systems for accurate irrigation scheduling and monitoring through machine learning, IoT, and low-power (LoRa)-based wireless sensor network (WSN). The devised mechanism uses soil and climatic conditions to predict the water necessity of a crop. The utility of ML approaches offers the devised proposed system capacity of the predictive irrigation prerequisite. Hossam et al. [18] developed an IoT architecture for maintaining accuracy in agriculture. This platform aims to enhance crop production by auto-controlling the plantation atmosphere at less cost. Besides, the platform will use ML for predicting plant diseases through DL techniques that derive hidden knowledge from the leaves of images to produce a method for achieving high possible disease classification accuracy. The platform has three layers. The initial layer will collect the desirable data and implements the required actions. The next layer offers Internet connectivity.

3 The Proposed Model

In this study, a new MBWODBN-SIS approach was formulated for irrigation classification effectively. The MBWODBN-SIS technique exploited the IoT sensors for data collection, which were forwarded to the cloud server for examination purposes. Besides, the MBWODBN-SIS technique applies the DBN model for different types of irrigation classification, such as highly not needed, high needed, needed, not needed, and average. Fig. 1 demonstrates the block diagram of the MBWODBN-SIS system.

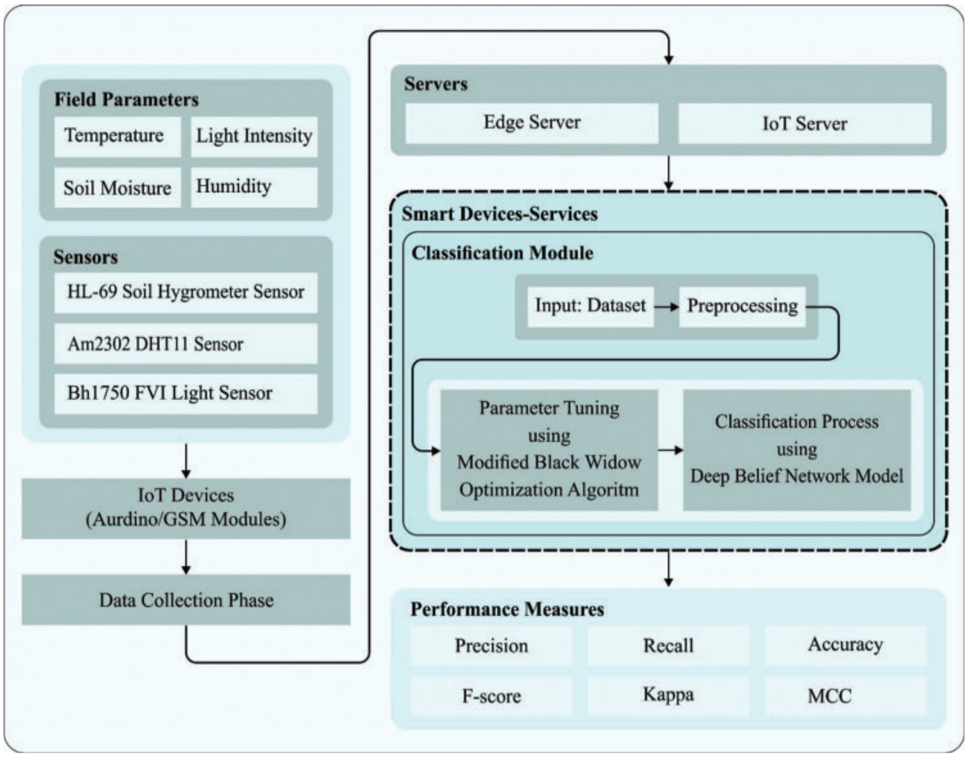


Figure 1: Block diagram of MBWODBN-SIS system

3.1 Data Collection Module

Firstly, the information is gathered via the sensor. In this stage, soil moisture, humidity, and temperature information were collected. The perception layer encompasses the sensor, microcontroller, and actuator. Rest was the part of the residual three layers. Transport and processing layers provide schedules for water crops, supervision, etc. [19]. Afterwards collecting the information, the next stage is to gather information in the data centre for analysis. In the figure, a detailed examination of the physical elements used is presented. Each component effortlessly exists from the market and is reasonable. Light, humidity, and moisture sensors are the implantable device used in this study. The microcontrollers set from the Arduino board accomplish analogy signals, and every 30 s, those values are sent to data centres via the GSM method SIM808. The outcome from these decision-making procedures is visualized through the client using android applications, later, the client directs these systems actuators, and then, water is released in the closed valves.

HL-69 Soil Hygrometer Sensor

This sensor can be used to discover the humidity of the soil. The primary goal is that sensor provides an optimum reading than others. The sensor is applied to observe the real-time soil moisture of plants from tunnel farms. There exist certain key aspects as follows: (i) This sensor has 2 pads and an electronic board that detects the water content, (ii) while the moisturizing content of the soil is high, then the output voltages decreases and output voltage increases if the soil was dry. LM393 comparator chip was deployed on the electrical board. It contains red and green lights; the green light displays the digital switching output indicator, and the red light shows the power indicators.

AM2302 DHT11 Sensor

This sensor was a standard temperature-humidity sensor employed to define the humidity and temperature in the atmosphere. It is comprised of humidity and thermistor sensors. There exist some key aspects as follows: (i) Output or Input voltage to DHT22 sensors was amongst [3, 5 V], (ii) the cost is very low, and (iii) The body size of the sensor was about 15.1 $*$ 25 $*$ 7.7 mm. DHT22 sensor has 4 pins together with 0.1 spacing amongst them. While applying data, the maximum use in the transformation was 2.5 mA.

BH1750 FVI Light Sensor

This sensor was a standard digital light sensor that might regulate light intensity. It refers to a calibrated digital light sensor that measures small traces of light and is transformed into 16 digit number. Generally, it is exploited from mobiles for the screen brightness according to the lighting environments. BH1750 measured the light intensity within [0–65,535] lux (L). There exist some major aspects as follows: (i) it is an in-built 16 bits AD converter that transforms the detection of light to a 16-digit number, (ii) the chip of this sensor contains BH1750FVI, (ii) the power supply can be [3.3–5 V].

3.2 DBN-Based Irrigation Classification

For irrigation classification, the MBWODBN-SIS technique employed the DBN model in this work. Restricted Boltzmann Machine (RBM) is a simple NN model where no discrete layer and every neuron is bi-directional interconnected with other neurons. RBM contains visible and hidden layers [20]. In RBM, the binary value comprises m visible, n hidden neurons, and the weight matrices $W = (w_{i,j}) \times (m \times n)$ are connected between h_i and x_i. RBM comprises input and output layers that have no connections and one-way connections amid neurons of a similar layer. Fig. 2 portrays the architecture of DBN. In the study, the RBM network is expanded effortlessly. Usually, the RBM network is formulated by the hidden layer $h = \{0, 1\}^D$ and visible layer $x = \{0, 1\}^F$:

$$\begin{aligned} E(x, h) &= -\sum_{i=1}^{F} a_i x_i - \sum_{j=1}^{D} b_j h_j - \sum_{i=1}^{F}\sum_{j=1}^{D} w_i x_i h_j \\ &= -a^T x - b^T h - x^T W h \end{aligned} \tag{1}$$

In Eq. (1), $E(x, h)$ indicates the energy function, and a and b refer to the bias value of weight in the hidden and visible layers correspondingly. $P(x, h)$ probability function of RBM has been shown below:

$$P(x, h) = \frac{1}{Z} e^{-E(x,h)} \tag{2}$$

Now, Z indicates the normalization constant and is expressed as follows:

$$Z = \sum\nolimits_{x',h'} e^{-E(x',h')} \tag{3}$$

As well, *the x* probability vector is equivalent to the sum of the equation over the hidden layer.

$$p\left(x\right) = \frac{1}{Z}\sum\nolimits_{h} e^{-E(x,h)} \tag{4}$$

The succeeding expression is exploited for distinguishing the probability of the trained dataset related to W. The suitable value of W is attained in the learning model.

$$\sum\nolimits_{n=1}^{n=N} \frac{\partial \log P(x^{n})}{\partial W_{ij}} = \alpha \left(E_{data}\left[xh^{T}\right] - E_{model}\left[xh^{T}\right]\right) \tag{5}$$

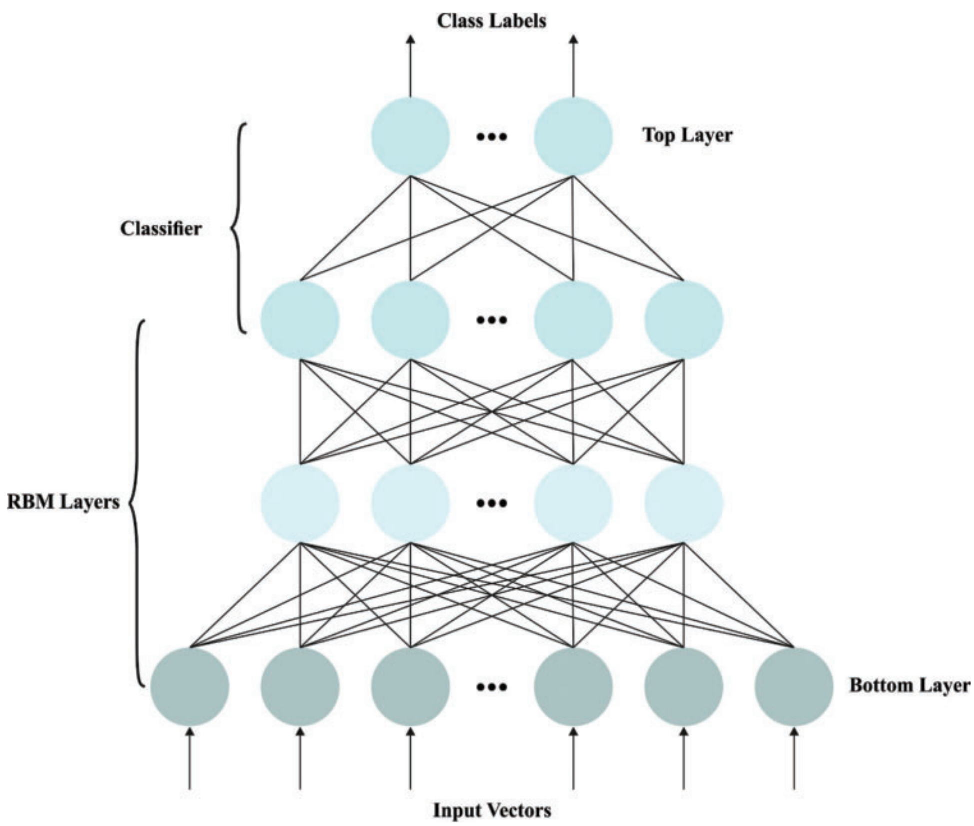


Figure 2: Structure of DBN

In Eq. (5), α indicates the learning rate. E_{data} [.] ve E_{model} [.] shows the expected value in the model or data distribution. DBN, widely employed utilized in the DL algorithm, is a NN that typically employs the basic components of RBM and comprises multiple RBMs. In RBM, having one hidden unit which captures features in the dataset isn't the correct way. Feature learned afterwards training RBM is utilized as input dataset to distinct RBMs. Therefore, the features of concluding RBM become the learned features of whole training models. This kind of layer-wise learning constructs DBN. DBN input datasets are extracted. In the topmost DBN that composes of a layered RBM model was the logistic regression (LR) layer as an output.

Backpropagation (BP) can be frequently used to train conventional NN. In a network with a larger amount of model parameters, the BP approach could trigger an over-reinforcement problem or lower optimization. The solution to these problems was created better through the pre-training model in the earlier study. The pretraining model in the DBN network was in the form of alternated sampling and greedy layer-wise. Alternate sampling was utilized for pretraining the RBM method and each DBN in the greedy layer. Once a classification process is employed for DBN, it is accompanied by another learning process, such as pretraining procedures and distinct learning, which fine-tunes the parameters. Afterwards, an unsupervised preprocess in greedy layer-wise form, $h^K(x)$, indicates the depiction of the abstract x in the kth layer. To accomplish a good execution, the labelled dataset was applied to correct the variable space W. This adjustment of precision can be made by adding the final layers of the variable and preparing the desirable label instance in the trained data. This optimization technique can be given below.

$$f\left(h^K(X), Y\right) = \sum_{i=1}^{n} \sum_{j=1}^{c} T\left(h^K\left(x_i^j\right) \times y_i^j\right) \tag{6}$$

In Eq. (6), T denotes the loss function. The squared error function is widely employed in the BP model, whereby the loss function is shown below.

$$r = h^K\left(x_i^j\right) \times y_i^j \tag{7}$$

3.3 Hyperparameter Tuning

At this stage, the MBWO algorithm is employed for the hyperparameter optimization of the DBN model. Hayyolalam et al. [21] developed the BWO technique based on the lifestyle of BW as mathematical modelling, and it mimics the microscopic and macroscopic laws during spider population development and reproduction process to find a better solution o. On a macro level, the performance of cannibalism and procreating amongst BW reflects the idea of Darwin's evolution theorem, viz., superiority and survival of the fittest. This spider population could be increased competitiveness by these kinds of development and reproduction processes.

The BWO technique was formulated in 4 phases that can be briefly discussed in the following.

3.3.1 Initialization

$W_{N\times D} = [X_1, X_2, \cdots, X_N]$ refers to spider population, including N widows $X_1, X_2, \ldots, X_N$. D characterizes the dimension of the problem.

$$x_{i,j} = l_j + rand\,(0,1)\cdot(u_j - l_j), 1 \le j \le D, \tag{8}$$

whereas $L = [l_1, l_2, \cdots, l_D], U = [u_1, u_2, \cdots, u_D]$ denotes the lower and upper limits of the solution space.

3.3.2 Procreate

The novel generation was generated by the unique mating behaviours of BW. While initiating the mating process, a group of spiders was signed as the father, and mother spiders were randomly chosen from the population to mate according to the procreating rate (Pp) as follows [22]:

$$\begin{cases} Y_i = \alpha X_i + (1-\alpha) X_j \\ Y_j = \alpha X_j + (1-\alpha) X_i \end{cases}, \tag{9}$$

Now, X_i and X_j indicate mother and father spiders correspondingly. Y_i and Y_j show offspring via mating. α refers to a D-dimension array.

3.3.3 Cannibalism

This phase consists of three kinds of cannibalism, such as cannibalism between offspring and mother, sexual cannibalism, and sibling cannibalism. Excellent individuals can be retained by removing the weak spider.

3.3.4 Sexual Cannibalism

After or during the mating, the female BW eats its husband. The survival female spider is preserved for the upcoming generation.

3.3.5 Sibling Cannibalism

The stronger spider eats their siblings because of natural enemies or constrained food sources. The fitness values of spiders were regarded as spider strength. In the presented technique, cannibalism rating (CR) defines the survivor number.

3.3.6 Cannibalism between Mother and Offspring

Certain immensely powerful children spiders may eat their mothers. Specifically, when a solution having higher fitness values is generated by parents, the solution replaces their mom and enters the upcoming generation [23].

3.3.7 Mutation

Here, the population number to mutate can be defined through the mutation rate (Pm) that is provided constantly. The fitness of a novel individual is randomly changed. The pseudocode of the BWO technique is given in the following.

For the optimization process, with the local optimum solution, the BWO will be easier to get trapped local solution instead of obtaining a better outcome because of its simplest mutation process, named premature convergence. Therefore, in the MBWO algorithm, the mutation operator assists the DE technique to escape from local optima. Therefore, the mutation operator is used. According to the mutation rate (Pm), the spider is randomly selected for mutation [24,25].

$$X_{new}^{t+1} = X_{best}^{t} + S \cdot (X_{r1}^{t} - X_{r2}^{t}), \tag{10}$$

From the expression, X_{r1}^t, X_{r2}^t they are randomly selected from the existing population and fulfilled $r1 \neq r2$. X_{best}^t Shows the better individual in *a t-th* generation. $S = t/T$ Indicates a mutation operator that rises by an iteration count.

Smaller diversity of the population illustrates individual gathers together viz., easy to get trapped in local optima.

$$Diversity = \frac{1}{|N| \cdot |S|} \sum_{i=1}^{N} \sqrt{\sum_{j=1}^{D} \left(x_{ij} - \overline{x}_j\right)^2}, \tag{11}$$

Now, D and N denote the size of the dimension and population. S indicates search space sizes. $\overline{x}_j$ Represent average values of *a jth* parameter.

4 Results and Discussion

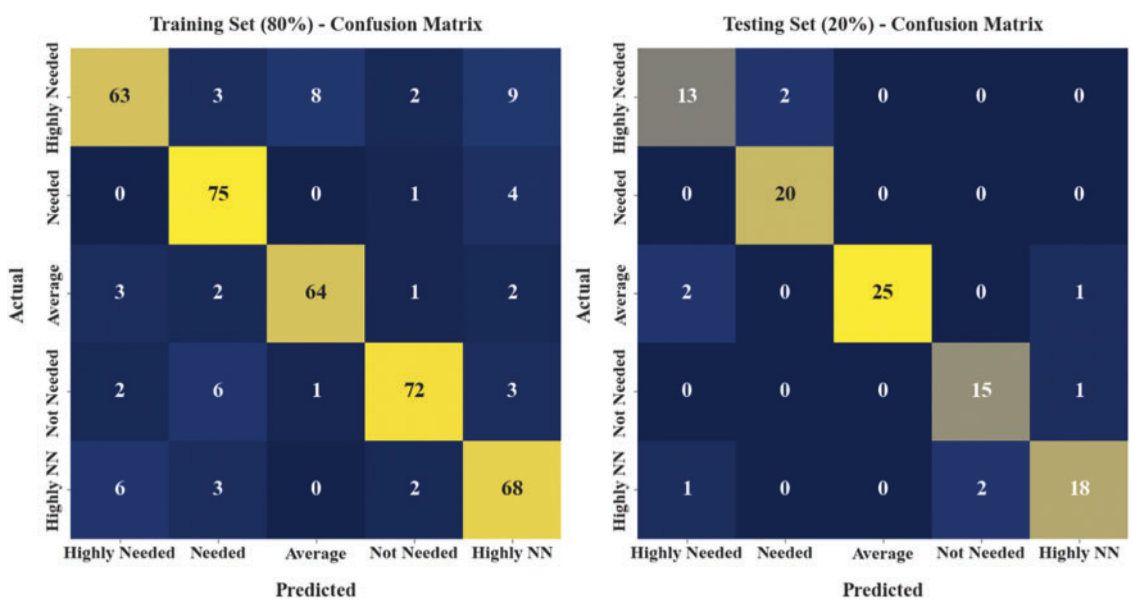
This section establishes the performance of the proposed MBWODBN-SIS method. The proposed method can be tested by utilizing three sensor data such as humidity, soil moisture, and temperatures.

The datasets comprise five class labels high needed, highly not needed, needed, average, and not needed, as depicted in Table 1.

Table 1: Dataset details

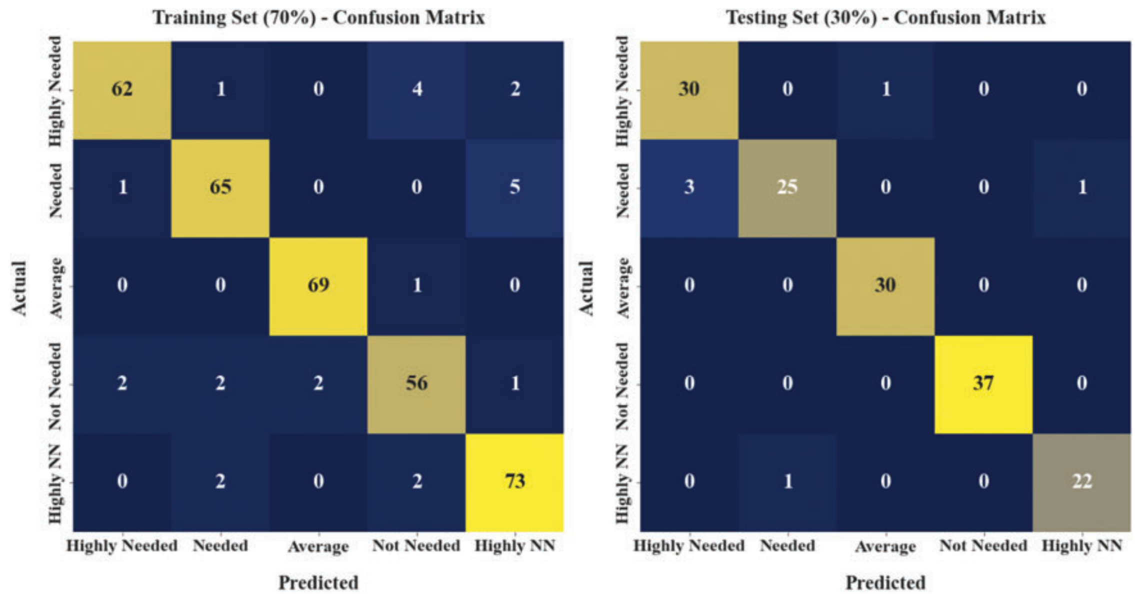
Class	No. of instances
Highly needed	100
Needed	100
Average	100
Not needed	100
Highly NN	100
Total No. of instances	**500**

The confusion matrices generated by the MBWODBN-SIS system on distinct sizes of training (TR) and testing (TS) datasets are reported in Fig. 3. On 80% of TR data, the MBWODBN-SIS method has recognized 63 samples as highly needed, 75 samples into needed, 64 samples into average, 72 samples into not needed, and 68 samples into highly needed. Concurrently, on 20% of the TS dataset, the MBWODBN-SIS methodology has recognized 13 samples as highly needed, 20 samples as needed, 25 samples as average, 15 samples as not needed, and 18 samples as highly needed. In Parallel, on 70% of TR data, the MBWODBN-SIS approach has recognized 62 samples as highly needed, 65 samples as needed, 69 samples as average, 56 samples as not needed, and 73 samples as highly needed. Finally, on 30% of TS data, the MBWODBN-SIS methodology has recognized 30 samples as highly needed, 25 samples as needed, 30 samples as average, 37 samples as not needed, and 22 samples as highly needed.



(a) (b)

Figure 3: (Continued)



(c) (d)

Figure 3: Confusion matrices of MBWODBN-SIS approach (a) 80% of TR data, (b) 20% of TS data, (c) 70% of TR data, and (d) 30% of TS data

Table 2 and Fig. 4 report the overall irrigation classification results of the MBWODBN-SIS approach on 80 of TR and 20% of TS data. The table values represented the MBWODBN-SIS model have shown effectual outcomes under both aspects. For example, on 80% of TR data, the MBWODBN-SIS method has resulted in average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and G_{mean} of 94.20%, 85.69%, 85.71%, 85.52%, and 90.81% respectively. In the meantime, on 20% of TS data, the MBWODBN-SIS algorithm has resulted in average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and G_{mean} of 96.40%, 90.08%, 91.08%, 90.43%, and 94.35% correspondingly.

Table 2: Result analysis of MBWODBN-SIS approach with distinct class labels under 80:20 of TR and TS data

Training/Testing (80:20)					
Class labels	Accuracy	Precision	Recall	F-score	G-mean
Training phase					
Highly needed	91.75	85.14	74.12	79.25	84.58
Needed	95.25	84.27	93.75	88.76	94.68
Average	95.75	87.67	88.89	88.28	92.98
Not needed	95.50	92.31	85.71	88.89	91.70
Highly NN	92.75	79.07	86.08	82.42	90.14
Average	**94.20**	**85.69**	**85.71**	**85.52**	**90.81**
Testing phase					
Highly needed	95.00	81.25	86.67	83.87	91.44

(Continued)

Table 2: Continued

Training/Testing (80:20)					
Class labels	Accuracy	Precision	Recall	F-score	G-mean
Needed	98.00	90.91	100.00	95.24	98.74
Average	97.00	100.00	89.29	94.34	94.49
Not needed	97.00	88.24	93.75	90.91	95.66
Highly NN	95.00	90.00	85.71	87.80	91.40
Average	**96.40**	**90.08**	**91.08**	**90.43**	**94.35**

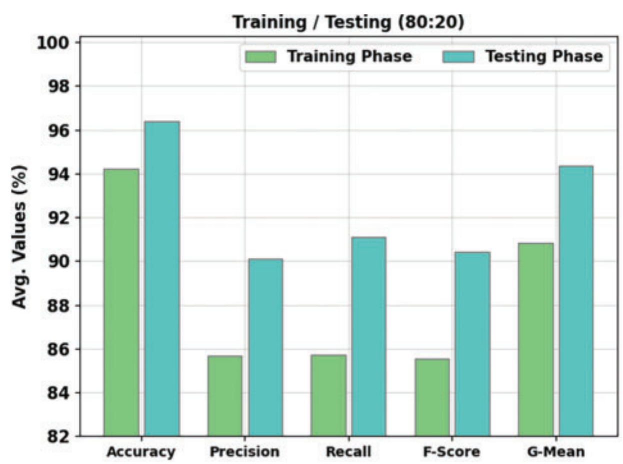


Figure 4: Result analysis of MBWODBN-SIS approach under 80:20 of TR and TS data

Table 3 and Fig. 5 portray the overall irrigation classification outcomes of the MBWODBN-SIS approach on 70 of the TR and 30% of the TS dataset. The table values indicated the MBWODBN-SIS algorithm has exhibited effectual outcomes in both aspects. For example, on 70% of TR data, the MBWODBN-SIS methodology has resulted in average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and G_{mean} of 97.14%, 92.89%, 92.73%, 92.78%, and 95.42% correspondingly. Similarly, on 20% of TS data, the MBWODBN-SIS approach has resulted in average $accu_y$, $prec_n$, $reca_l$, F_{-score}, and G_{mean} of 98.40%, 95.90%, 95.73%, 95.73%, and 97.32% correspondingly.

Table 3: Result analysis of MBWODBN-SIS approach with distinct class labels under 70:30 of TR and TS data

Training/Testing (70:30)					
Class labels	Accuracy	Precision	Recall	F-score	G-mean
Training phase					
Highly needed	97.14	95.38	89.86	92.54	94.28
Needed	96.86	92.86	91.55	92.20	94.82

(Continued)

Table 3: Continued

Training/Testing (70:30)					
Class labels	Accuracy	Precision	Recall	F-score	G-mean
Training phase					
Average	99.14	97.18	98.57	97.87	98.93
Not needed	96.00	88.89	88.89	88.89	93.12
Highly NN	96.57	90.12	94.81	92.41	95.93
Average	**97.14**	**92.89**	**92.73**	**92.78**	**95.42**
Testing phase					
Highly needed	97.33	90.91	96.77	93.75	97.13
Needed	96.67	96.15	86.21	90.91	92.46
Average	99.33	96.77	100.00	98.36	99.58
Not needed	100.00	100.00	100.00	100.00	100.00
Highly NN	98.67	95.65	95.65	95.65	97.42
Average	**98.40**	**95.90**	**95.73**	**95.73**	**97.32**

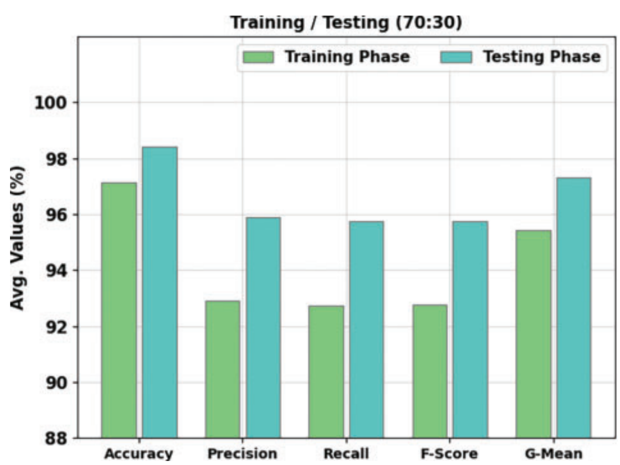


Figure 5: Result analysis of MBWODBN-SIS approach under 70:30 of TR and TS data

The training accuracy (TRA) and validation accuracy (VLA) acquired by the MBWODBN-SIS approach on the test dataset is exemplified in Fig. 6. The experimental outcome inferred that the MBWODBN-SIS approach has obtained higher values of TRA and VLA. Also, the VLA is greater than TRA.

The training loss (TRL) and validation loss (VLL) gained by the MBWODBN-SIS algorithm on the test dataset are shown in Fig. 7. The experimental outcomes denote the MBWODBN-SIS approach has exhibited the least values of TRL and VLL. Particularly, the VLL is lesser than TRL.

A clear precision-recall study of the MBWODBN-SIS algorithm on the test dataset is represented in Fig. 8. The figure implicit the MBWODBN-SIS technique has resulted in enhanced values of precision-recall values in every class label.

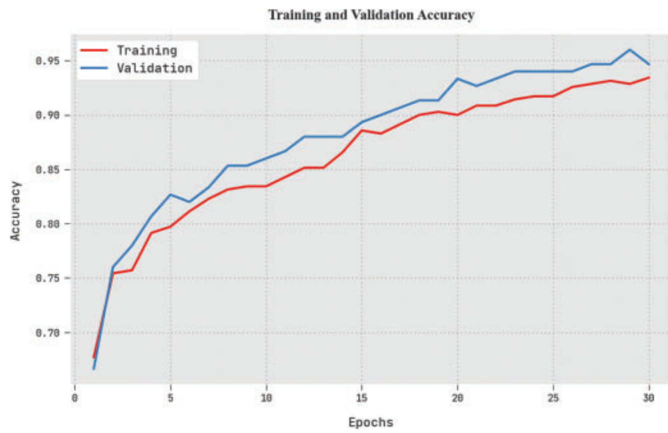


Figure 6: TRA and VLA analysis of MBWODBN-SIS approach

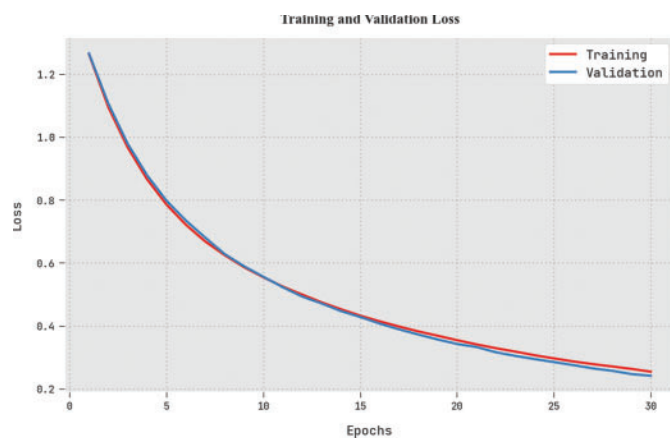


Figure 7: TRL and VLL analysis of MBWODBN-SIS approach

A brief ROC review of the MBWODBN-SIS algorithm on the test dataset is shown in Fig. 9. The outcomes highlighted the MBWODBN-SIS technique has displayed its ability in classifying different class labels in the test dataset.

Finally, a comparative inspection of the MBWODBN-SIS method with recent methods is provided in Table 4. Fig. 10 shows a brief $prec_n$ and $reca_l$ inspection of the MBWODBN-SIS method with other recent models. These results represented that the MBWODBN-SIS model has obtained maximum classification outcomes. For instance, concerning $prec_n$, the MBWODBN-SIS model has offered an increased $prec_n$ of 98.40% whereas the IoTML-SIS, multilayer perceptron (MLP), extreme learning machine (ELM), KNN-11, support vector machine (SVM), and LR models have obtained reduced $prec_n$ of 93.73%, 85.79%, 88.72%, 58.89%, 62.94%, and 73.07% respectively. Moreover, concerning $reca_l$, the MBWODBN-SIS technique has rendered an increased $reca_l$ of 95.90% whereas the IoTML-SIS, MLP, ELM, KNN-11, SVM, and LR approaches have gained a reduced $reca_l$ of 95.15%, 87.97%, 90.26%, 67.64%, 68.28%, and 77.95% correspondingly.

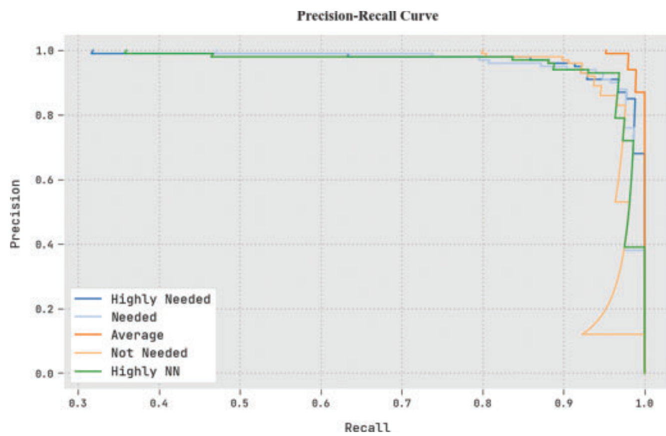


Figure 8: Precision-recall analysis of MBWODBN-SIS approach

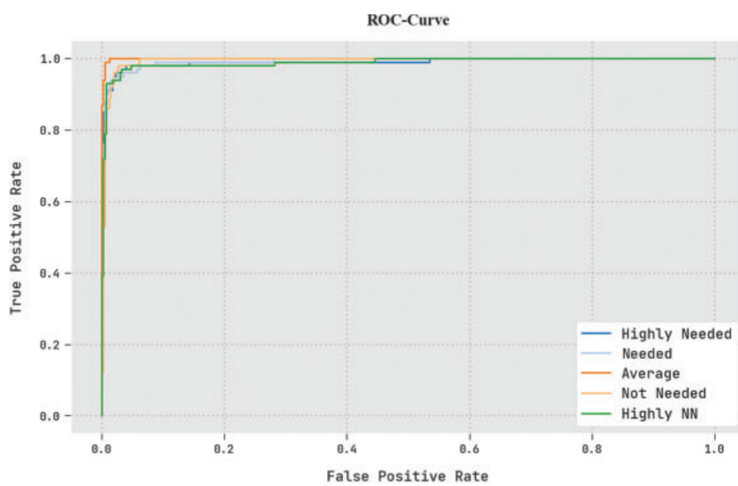


Figure 9: ROC curve analysis of MBWODBN-SIS approach

Table 4: Comparative analysis of MBWODBN-SIS methodology with existing algorithms

Methods	Precision	Recall	Accuracy	F-score
MBWODBN-SIS	98.40	95.90	95.73	95.73
IoTML-SIS	93.73	95.15	93.69	93.20
MLP model	85.79	87.97	87.62	85.31
ELM model	88.72	90.26	87.45	88.23
KNN-11 model	58.89	67.64	64.57	57.56
SVM model	62.94	68.28	67.25	63.38
LR model	73.07	77.95	75.45	74.25

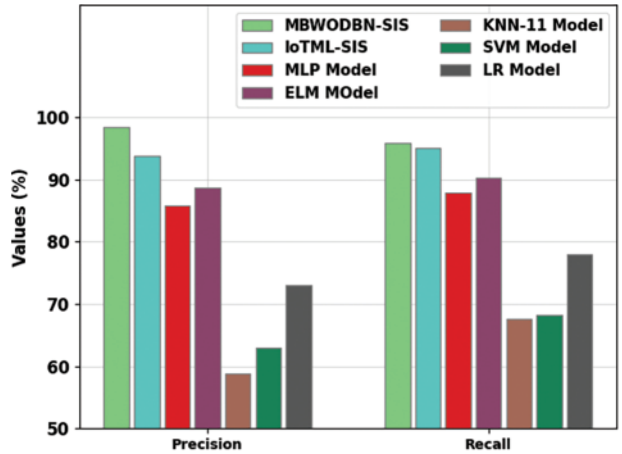


Figure 10: $Prec_n$ and $Reca_l$ analysis of MBWODBN-SIS approach with existing algorithms

Fig. 11 illustrates a brief $accu_y$ and F_{score} examination of the MBWODBN-SIS algorithm with other recent models. These results implicit the MBWODBN-SIS approach has gained maximum classification outcomes. For example, concerning $accu_y$, the MBWODBN-SIS technique has granted an increased $accu_y$ of 95.73% whereas the IoTML-SIS, MLP, ELM, KNN-11, SVM, and LR algorithms have attained a reduced $accu_y$ of 93.69%, 87.62%, 87.45%, 64.57%, 67.25%, and 75.45% correspondingly.

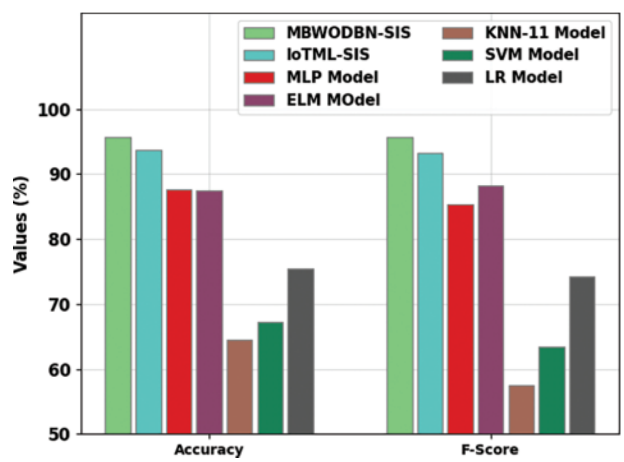


Figure 11: $Accu_y$ and F_{score} analysis of MBWODBN-SIS approach with existing algorithms

Also, concerning $reca_l$, the MBWODBN-SIS approach has presented an increased $reca_l$ of 95.73% whereas the IoTML-SIS, MLP, ELM, KNN-11, SVM, and LR methods have attained a reduced $reca_l$ of 93.20%, 85.31%, 88.23%, 57.56%, 63.38%, and 74.25% correspondingly. These outcomes show the betterment of the MBWODBN-SIS model over other recent models.

5 Conclusion

In this study, a novel MBWODBN-SIS technique was developed for irrigation classification effectively. The presented MBWODBN-SIS technique exploited the IoT sensors for collecting data forwarded to the cloud server for examination purposes. Besides, the presented MBWODBN-SIS technique applies the DBN model for different types of irrigation classification such as highly not needed, high needed, needed, not needed, and average. To enhance the irrigation classification performance of the presented MBWODBN-SIS model the MBWO-based hyperparameter optimization is carried out. The comparison study stated the enhanced outcomes of the MBWODBN-SIS algorithm over other DL models with improved accuracy of 95.73%. Thus, the presented MBWODBN-SIS technique can be utilized for automated irrigation management. In future, feature selection models will be integrated into the presented method for improving classification efficiency.

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