Vol. 05, No. S1 (2023) 69-78, doi: 24874/PES.SI.01.009

Proceedings on Engineering Sciences

www.pesjournal.net

DESIGNING AN IMPROVED NEURAL NETWORK FOR THE EARLY DETECTION OF ANOMALIES IN NUCLEAR POWER PLANTS

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Received 28.04.2023.
Accepted 25.06.2023.

Keywords:

Z-score normalization, kernel principal component analysis (KPCA), nuclear power plants (NPPs), anomaly, recurrent neural network (RNN), bat and grey wolf optimized recurrent neural network (BGWO), improved bat and grey wolf optimized recurrent neural network (IBGWO-RNN).

A B S T R A C T

The effectiveness and dependability of these vital energy infrastructures depend heavily on the early detection of anomalies in nuclear power plants (NPPs). Anomalies in a plant's operations might be signs of the impending equipment failure, a danger to workers' safety, or departure from ideal performance, all of which call for quick attention and preventative actions. Traditional NPP monitoring methods depend on the human inspections and predetermined thresholds, which are only sometimes successful in picking up the complicated irregularities. This Study introduces a new, Improved Bat and Grey Wolf Optimized Recurrent Neural Network (IBGWO-RNN) approach to detect the anomalies in NPPs. In this case, the RNN classification effectiveness is increased by using the IBGWO method. The American Nuclear Society ANSI / ANS-3.5 Nuclear Simulator Standard dataset has been used to assess the success of the suggested approach. Each input feature vector will be normalized by using the Z-score Normalization. A Kernel Principal Component Analysis (KPCA) is performed to extract the properties from segmented data. The results of the research show that the recommended methodology beats earlier approaches in terms of the Accuracy, Precision, Recall, and F1-score. Our suggested approach advances anomaly identification, resulting in safer and more effective operations for NPPs.

1. INTRODUCTION

The term "anomalies" in the context of *NPPs* may refer to various problems or unanticipated occurrences that differ from routine operations. Despite several safety measures and regulations in place, anomalies may still happen in *NPPs* for various reasons, including technological malfunctions, mistakes made by humans, or outside influences. Anomalies might result when crucial machinery like pumps, valves, or cooling systems malfunction. The issues must be addressed immediately to avoid safety risks and impede the plant's operations. It may be quite worrying when radioactive elements are released into the environment abnormally. The Study could occur due to mishaps when handling or maintaining radioactive materials, damaged fuel rods, or breaches in containment systems (Miki et al., 2020). Multiple safety mechanisms exist at nuclear power facilities to stop accidents and lessen their effects. If the designs don't function as planned, anomalies may compromise safety precautions and perhaps dangerous circumstances.

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Anomalies in nuclear power reactors may be caused by errors committed by operators, maintenance people, or other staff. The mistakes that significantly impact plant safety may include misinterpreting data, using inappropriate maintenance techniques, or needing adequate training (Huang et al., 2023). Although catastrophes like earthquakes, floods, or hurricanes might present difficulties, nuclear power facilities are built to survive natural calamities.

Anomalies may happen if the plant's infrastructure sustains more damage than intended or if many safety systems are compromised simultaneously. Nuclear power facilities are now more dangerous due to the growing dependence on digital equipment and network connection (Kravchik and Shabtai 2018).

In context, anomalies may entail illegal access to plant control systems or the alteration of crucial data, which might jeopardize operational integrity or safety. While anomalies occur, it's vital to remember that *NPPs* are subject to stringent laws, extensive safety precautions, and thorough inspections to reduce risks and assure people's and the environment's safety (Xu et al., 2023). Consider learning a compressed representation of typical operating circumstances using an autoencoder-based architecture, such as a variational autoencoder (VAE) (Wang et al., 2019). Set up the neural network's input layer to correspond to the number of sensor inputs. According to how difficult the issue is, add hidden layers with appropriate activation functions (such as sigmoid or ReLU), and change the number of layers.

Depending on the particular use case, design the output layer using a binary classification (standard vs. anomaly) or multi-class classification (various sorts of anomalies) arrangement (Ramezani et al., 2022).

To avoid overfitting, keep an eye on the performance of the validation set and make any required hyperparameter adjustments. To better understand the model's advantages and disadvantages, perform further analysis, such as producing confusion matrices or precision-recall curves. Based on the performance of the model, identify areas that need improvement (Tian et al., 2018). Create a system to continually and instantly monitor data from nuclear power facilities.

To identify abnormalities which include the trained neural network in the monitoring system. Update the model often with new data, retrain it to account for changing operational circumstances, and improve accuracy (Santos et al., 2021). To fully grasp the unique needs and difficulties, carefully collaborate with subject-matter specialists in *NPPs*. Work with subject matter experts to improve the model, analyze the findings, and ensure the network complies with safety and industry requirements (Choi and Lee 2020). Using an autoencoder, a method of unsupervised learning is one such strategy. An autoencoder neural network is trained to reconstruct the input data (Kim et al., 2020).

Key Contributions

The development of an enhanced neural network based on IBGWO-RNN for the early identification of abnormalities in *NPPs* makes many significant contributions to the field:

- The capacity to increase accuracy, efficiency, and flexibility in anomaly detection makes creating an upgraded neural network for early detection of anomalies in *NPPs* based on IBGWO-RNN useful.
- The suggested model has the potential to considerably enhance the safety, dependability, and overall performance of *NPPs* by using the advantages of IBGWO and RNN.

The remainder of the document is structured as follows: Segment 2 discusses the preliminary research about the objectives or goals of the inquiry and points out any shortcomings or discrepancies. Section 3 discusses the research methodology and strategy. In Segment 4, we go through the data and analysis before briefly and systematically outlining the findings, evaluating the aims or objectives of the Study, and providing explanations. An outline of the Study's key sections is given in Segment 5.

2. RELATED WORKS

(Ayo-Imoru and Cilliers 2018) achieved by referring dynamically to the nuclear plant simulator. A flaw is simple to find in a steady state but challenging in transients. Due to the technique, a machine-learning technology called artificial neural networks (ANN) is introduced and used to train both the simulator and the plant's settings. (Caliva et al., 2018) analyzed the feasibility of gleaning helpful information for creating fault/anomaly detection systems from the core reactor neutron flux. (Yong and Linzi 2022) preferred the Multisensor Operation Time Series Data using the Convolutional GRU Encoder-Dncoder (MVCGED) approach for anomaly identification and fault diagnosis. (Roy et al., 2018) developed a technique for automatic feature extraction for online condition monitoring built on the foundation of an Online Sequential Extreme Learning Machine (OSELM) network and a conventional autoencoder. The Method's performance is on par with that of traditional extraction of feature techniques.

(Zhang et al., 2022) suggested a multisensor system signal noise reduction and compression technique using CNN. Simulations of several common function approximations are used to confirm the efficiency of the strategy. (Papaoikonomou et al., 2022) extended the methods to be used in real-world, unsupervised measurements when it is uncertain and actual properties of the perturbation. (Qi et al., 2023) presented an analysis of several Artificial Intelligence (AI) based system-level defect diagnostic techniques for NPPs. The Study starts by going through the history of AI development.

(Ioannou et al., 2021) introduced intelligent techniques, more notably Deep Neural Networks (DNNs), in the Study of neutron flux signals to identify disturbances and other abnormalities in the reactor core that could impact its ability to operate. The preliminary examination of neutron flux signals recorded at pressurized water reactors yielded promising findings, underscoring the viability and potential of the suggested technique.

(Li et al., 2022) compared the proposed transfer learning framework to training an entirely new Convolutional Neural Network (CNN) model from scratch with inadequate labeled target data, the diagnostic results are dramatically improved. As a result, it is shown that transfer learning is better than other methods for diagnosing faults in NPPs, even when there are little labeled data. (Yu et al., 2022) introduced a central transformer maintenance management system using predictive analytics. The information granulation approach is used to preprocess the input data before the suggested condition prediction method based on the online support vector machine (SVM) regression model.

3. EXPERIMENTAL PROCEDURE

In this part, the Method for building the model was specified, the key steps were discussed, and a thorough explanation of how the efforts of the suggested model in (Figure 1) were made was provided. This analysis has five sections: The first phase's primary goal is information gathering. We'll discuss data preprocessing techniques in the next section. The methods for feature selection and extraction are in the third section. The most significant material is provided in the fourth section, which discusses the effort made to develop the suggested model and compile the essential experiences. The fifth step compares the related parameters to assess the performance of each existing and new model.

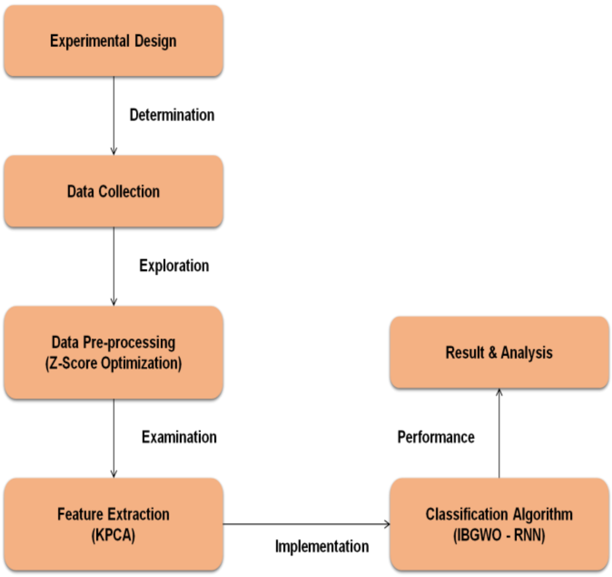

Figure 1. Methodological design of anomalies in nuclear power plants

3.1 Dataset

The Generic Pressurized Water Reactor (GPWR) simulator provides the operational data required to create the anomaly detection predictive model. This simulator was developed based on a reference US nuclear plant that has been in operation and undergoing training for over 20 years. The GPWR reference simulator was built and tested by the American Nuclear Society's ANSI/ANS-3.5 Nuclear Simulator Standard. The simulator's performance has been assessed using data from a real-world working plant, and it includes high-fidelity models that allow the whole plant to operate, including during normal operations, abnormal operations, and emergencies, as specified by ANS-3.5 (Hou et al., 2019). This three-loop facility features a pressurizer in the primary system, three reactor coolant pumps, and three-stream generators. The power escalation from 55% to 100% reactor power has been carried out on the GPWR simulator as a case study, one of the most fundamental reactor control operations, to gather operational data. A large number of plant-wise status variables, totaling 81, are recorded during the operating time of 10291 seconds at a rate of one measurement per second since several plant components, such as the reactor core, steam generators, pressurizer, turbine, etc., are engaged in the operation. A partial list of state variables that have been gathered and processed and will be utilized in the next stage is shown in (Table 1).

Table 1. Example of state variables (Hou et al., 2019).

State variables	Unit
Gross electric power	MW
Percent full power	%
Pressurizer pressure	MPa
Primary hot/cold leg temperature (Loop 1-3)	°C
Steam generator (SG) pressure (#1-3)	MPa
Main feedwater flow (Loop 1-3)	kg/s
Steam generator steam flow (#1-3)	kg/s
Control rod bank position (A-D)	step
Steam (turbine) load	MW
Pressurizer level	%
Governor valve opening (1-4)	%
Steam generator level (#1-3)	%
Total neutron flux	n/cm2 -s

3.2 Data Pre-Processing by using Z-score Normalization

Z-score normalization, sometimes called zero-mean normalization, normalizes each input feature vector by determining each feature's mean (M) and standard deviation (SD) across a training dataset and dividing it by the dataset size. The standard deviation and average for each attribute are computed. The transformation is necessary according to the general Formula (1).

$$n' = \frac{(n-\mu)}{\sigma} \quad (1)$$

The mean and SD of the property mentioned above, n, are and, respectively. The characteristics in the data set are all z-score normalized before training. After gathering training data, each characteristic's mean and standard deviation (SD) should be kept as algorithm weights.

3.3 Feature Extraction by using Kernel Principal Component Analysis (KPCA)

We kept the dimensionality of the data while reducing it for our model, and feature selection was utilized to lower variability. The principal component analysis is one technique for minimizing the number of dimensions. The PCA technique transforms the data into a new feature space, where the starting coordinate represents the majority of variation, the principle of superposition component means the second most variation, and so on. The qualities in this Study that are the most variable will be used as input by the classifiers. This technique increases the computational efficiency and simplicity of the machine learning models by ensuring that only relevant attributes are chosen. The Method may also lessen any potential overfitting by using all the variables.

An approximate covariance matrix of the data in Formula (2) is diagonalized using a basis transformation known as KPCA.

$$D = \frac{1}{k}\sum_{i=1}^{k} \quad v_l v_i^S \quad (2)$$

The orthogonal projections onto the Eigenvectors or the new coordinates in the tile Eigenvector basis are principal components. This work further develops this setting into a nonlinear set of the following kind. If the data were initially nonlinearly mapped onto a feature space using Formula (3),

$$\Phi: Q^M \rightarrow E, v \rightarrow V \quad (3)$$

We'll show that, for specific values, even if it has arbitrarily large dimensionality, we can still do KPCA in E.

Let's assume that Formula (4) translates data into feature space. KPCA for the covariance matrix,

$$\underline{D} = \frac{1}{k}\sum_{i=1}^{k} \quad \Phi(v_l)\Phi(v_l)^S \quad (4)$$

Applications for denoising and wavelet transforms often employ KPCA, a nonlinear variant. The traditional PCA approach reduces the number of dimensions when the manifold is linearly buried in the observation space. The manifold is linearized using the kernel technique, one of the two components, to satisfy the requirements of the PCA, the second component of KPCA. To automatically convert data into a pairwise formula between the mapped data in the feature set, KPCA employs feature mapping. The kernel calculates this pairwise formula. It is challenging to find an appropriate kernel that linearizes the surface in the feature space while considering the geometry of the input space. The nonlinear dimensionality reduction of KPCA would be ineffective for a suboptimal projection that does not satisfy the conditions.

3.4 Classification based on Improved Bat and Grey Wolf Optimized Recurrent Neural Network (IBGWO-RNN)

The IBGWO-RNN is a hybrid model for the early detection of abnormalities in NPPs that combines the Bat Algorithm and the Grey Wolf Optimizer with a Recurrent Neural Network. This model uses the BA and GWO algorithms to optimize the RNN parameters to increase the precision and effectiveness of anomaly detection. Remembering that the precise implementation details, hyper parameters, and optimization techniques may change based on the NPPs unique needs and features is vital. To ensure the IBGWO-RNN model successfully spots abnormalities in the target environment, it should be modified and verified using real-world data. Here are more details about the main parts of BAT and Grey Wolf Optimization and RNN architecture are discussed below:

a) BAT Optimization

The BAT Optimization technique is often disconnected from neural networks. Instead, it employs an optimization technique inspired by bats' echolocation techniques. However, the BAT strategy may function more effectively if neural network techniques were used. The investigation might take into account the following strategies to include neural networks in the BAT method:

- **Initialization using neural network:** Instead of randomly initializing the population of bats, the research may use genetic or neural network methodologies to construct an initial population of bats that is more likely to include workable answers.
- **Adaptive parameters:** Depending on the efficacy and characteristics of the optimization issue, fuzzy logic, and reinforcement learning are neural network methodologies that might be utilized to dynamically adjust the method parameters, such as the volume and heart rate of the bats.
- **Hybridization with neural network methods:** This hybridization may improve searchability and convergence speed by fusing the benefits of the two approaches. It's important to remember that incorporating neural network techniques into the BAT approach is still a research area and may need testing and adaptation depending on the specific problem domain. The effectiveness of the integration will depend on the kind of optimization issue and the neural network techniques used.

Mathematical Model of BAT Optimization

The bat algorithm is a novel global mathematical optimization metaheuristic based on swarm intelligence technique. Its search method draws inspiration from how bats interact with one another and use echolocation to gauge distance. The BAT algorithm is based on idealizing some of the following approximations or idealized laws of bat echolocation:

- All bats use echolocation to gauge distance, and they all innately "know" their environment;
- BATs have a set frequency and fly at a fixed velocity of u_j^s and e_{min} at w_j^s position , changing wavelength and volume to search for prey, as shown in Formulas (5), (6), and (7). Depending on how close their target is, they may spontaneously modify the wavelength (or frequency) of their generated pulses and the rate of pulse production;

$$e_j = e_{min} + (e_{max} - e_{min})\beta \tag{5}$$

$$u_j^s = u_j^{s-1} + (u_j^s - w_*)e_j \tag{6}$$

$$w_j^s = w_j^{s-1} + u_j^s \tag{7}$$

where B^s is a random vector selected at random from an even distribution. Here x represents the current optimal position on Earth, as determined by comparing all of the answers among all of the bats included in Formulas (8), (9) and (10). In general, the frequency is given according to the size of the issue of interest's domain $e_{min} = 0$ and $e_{max} = 100$ in practical implementation. Each bat is first randomly assigned a frequency that is evenly selected from $[e_{max}\ e_{min}]$.

$$w_{new} = w_{old} + \in B^s \tag{8}$$

$$B_j^{s+1} = \alpha B_j^s \tag{9}$$

$$q_j^{s+1} = q_j^0[1 - exp(-\gamma s)] \tag{10}$$

b) Grey Wolf Optimization (GWO)

A metaheuristic optimization method called GWO was developed after studying grey wolves' social interactions and hunting techniques. In GWO, a population of possible answers is repeatedly updated to look for the best one. A pack of grey wolves symbolizes this population. The program mimics how wolves work together to find and catch their prey in a cooperative hunting strategy. Each wolf in the initial population of the GWO algorithm serves as a solution to the optimization issue. Each wolf's location correlates to a specific place in the search space. The wolves' social hierarchy and hunting habits are then considered as the algorithm repeatedly develops their placements. The alpha, beta, and delta wolves, three critical members of the pack, are used to update the wolves' locations during the iteration. The beta and delta wolves indicate the second and third-best answers, respectively, while the alpha wolf represents the finest solution. The wolves' placements have an impact on how the whole pack explores and makes use of their surroundings. Equations in mathematics are used in the updating procedure to establish the new locations of the wolves. The wolves' final sites show the best or nearly the best answers to the given optimization issue. Numerous optimization issues, such as those involving mathematical functions, engineering design, data mining, and neural network training, have been tackled with Grey Wolf Optimization. It is a competitive optimization algorithm for convergence speed and solution quality because it strikes a balance between exploring uncharted territory and capitalizing on promising ones.

Mathematical Model of GWO Optimization

The grey wolves cohabitate and go on hunts in packs. If a prey item is discovered, the seeking and hunting procedure may be summarized as follows: they first track, pursue, and then approach it. In the event that the prey flees, the grey wolves will chase after, surround, and harass the prey until it stops moving. Finally, the assault starts.

The optimization algorithm replicates how grey wolves seek and hunt. The best answer in the mathematical model is known as the alpha (α), Beta is the second-best (β), and consequently, the third best is named the delta (δ).

When a prey is found, the iteration begins ($t = 1$). The omega wolves would then follow the alpha, beta, and delta wolves as they pursued and finally surrounded the prey. Three coefficients $\vec{B}$, $\vec{C}$, $\vec{D}$ and are proposed to describe the encircling behavior in Formula (11), (12), (13):

$$\overrightarrow{C_\alpha} = \left|\overrightarrow{D_1} \cdot \overrightarrow{W_\alpha} - \vec{w}(s)\right| \tag{11}$$

$$\overrightarrow{C_\beta} = \left|\overrightarrow{D_2} \cdot \overrightarrow{W_\beta} - \vec{w}(s)\right| \tag{12}$$

$$\overrightarrow{C_\delta} = \left|\overrightarrow{C_3} \cdot \overrightarrow{W_\delta} - \vec{w}(s)\right| \tag{13}$$

Where (s) indicates the current iteration, $\vec{W}$ is the position vector of the grey wolf, $\overrightarrow{W_1}$, $\overrightarrow{W_2}$, $\overrightarrow{W_3}$ are the position vectors of the alpha, beta, and delta wolves. $\vec{W}$ would be computed as follows in Formula (14),(15),(16) and (17):

$$\overrightarrow{W_1} = \left|\overrightarrow{W_\alpha} \cdot \overrightarrow{B_1} \cdot \overrightarrow{C_\alpha}\right| \tag{14}$$

$$\overrightarrow{W_2} = \left|\overrightarrow{W_\beta} \cdot \overrightarrow{B_2} \cdot \overrightarrow{C_\beta}\right| \tag{15}$$

$$\overrightarrow{W_3} = \left|\overrightarrow{W_\delta} \cdot \overrightarrow{B_3} \cdot \overrightarrow{C_\delta}\right| \tag{16}$$

$$\vec{W}(s) = \frac{\overrightarrow{W_1} + \overrightarrow{W_2} + \overrightarrow{W_3}}{3} \tag{17}$$

The variables and are combinations of the random variable and the controlled parameter numbers $\overrightarrow{q_1}$ *and* $\overrightarrow{q_2}$ which are represented in Formula (18), (19) and (20).

$$\vec{B} = 2\alpha\overrightarrow{q_1} - \alpha, \quad (18)$$

$$\vec{D} = 2\overrightarrow{q_2}. \quad (19)$$

$$\alpha = 2\left(1 - \frac{it}{M}\right) \quad (20)$$

c) Recurrent Neural network

Recurrent Neural Network is referred to as RNN. The capacity of an RNN to keep an internal state or memory, which allows it to handle sequences of different lengths, is its essential characteristic. The RNN receives an input at each time step, combines it with its internal state to create an output, and then updates its internal state. In order to enable the network to recognize relationships and patterns across the sequence, this output turns into the input for the next time step. RNNs are well suited for sequential data applications because of their recurrent nature, including voice recognition, machine translation, sentiment analysis, and time series prediction. RNNs are practical modeling tools for sequential data that have several applications in machine learning and artificial intelligence.

A recurrent unit continuously receives input for a set number of timesteps and a concealed state for that input through a single activation function. Therefore, the amount of timesteps Study has determined how often information will be processed.

It may essentially have an infinite number of input, hidden, and output nodes, all of which are shown in (Figure 2). If we examine RNN, the hidden layers have a feedback loop mechanism that causes information to be transmitted to the same node more than once.

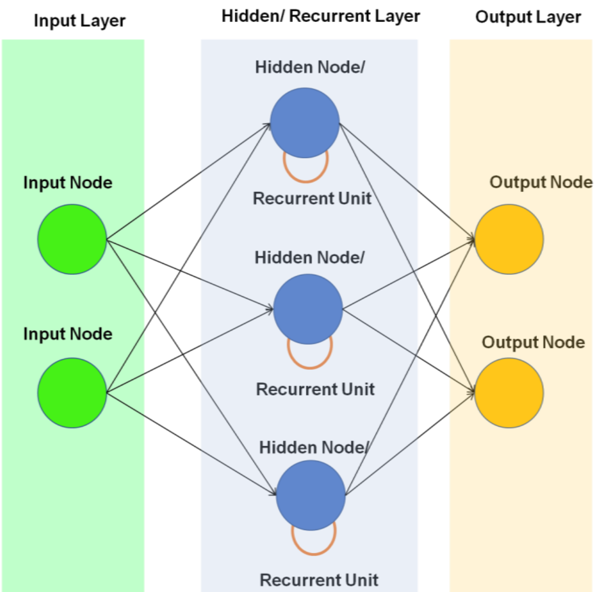

Figure 2. Architecture of RNN

Inputs: It's possible that even if the Study only has one node as input, research still needs to provide it with three temperature figures since {x0, x1, and x2} are necessary.

Recurrent Layer: Bias and weight are the two parameters that a hidden layer or node typically contains. However, the three parameters of a recurrent node are input, bias, and weight. Regardless of the number of timesteps, there will always be three parameters.

Training: RNN trains the network's weights using a slightly modified form of back propagation that accounts for unwinding in time. RNN computes the gradient via back propagation in time.

4. RESULTS AND DISCUSSION

4.1 RESULTS

The design, training, and assessment of the neural network model employing validation approaches will determine the precise outcomes and insights. For the early identification of abnormalities in NPPs, conducting rigorous tests, statistical analysis, and enlisting domain experts will all help to provide relevant and trustworthy findings.

a) Accuracy

In machine learning and statistical analysis, accuracy is a regularly used parameter to assess a prediction model's accuracy or dependability. It is presented as a percentage and indicates how well the model can predict the future. Accuracy in the context of IBGWO-RNN would measure how well the model performed in accurately detecting abnormalities in real-time data from the NPP. The neural network model effectively identifies anomalies and reduces false negatives (missed anomalies) and false positives, according to a high accuracy score. Formula (21) is used to compute the accuracy.

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

Table 2. Numerical Outcomes of Accuracy for Existing and proposed methods.

Methods	Accuracy(%)
CNN (Li et al., 2022)	25
SVM (Yu et al., 2022)	32
DNN (Ioannou et al., 2021)	48
IBGWO-RNN (proposed)	86

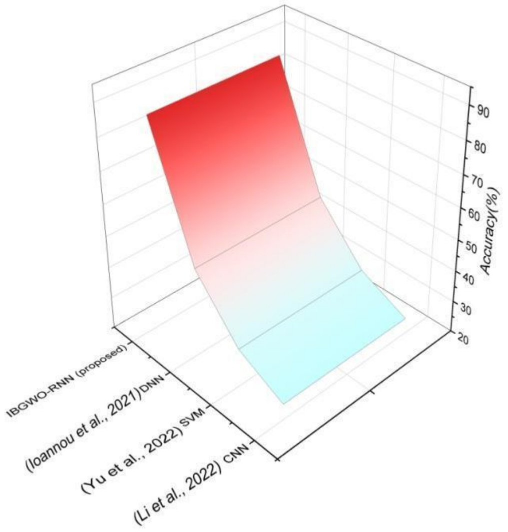

Figure 3. Comparison of accuracy for existing and proposed methods

A comparison of accuracy for current and suggested approaches is shown in (Figure 3). The proposed Method exceeds the already used ones, which include CNN in accuracy (25%), SVM (32%), and DNN (48%), with an accuracy of 86%. (Table 2) shows the suggested approach IBGWO-RNN, which outperformed other methods presently in use in terms of data classification accuracy.

b) Precision

The enhanced neural network based on IBGWO-RNN for early detection of abnormalities in NPPs is one example of a classification or prediction model that uses precision as a performance parameter to assess its accuracy and dependability. Precision is the percentage of all positive cases (anomalies) predicted by the model that is adequately expected. Precision is obtained by dividing the total of accurate optimistic and false positive predictions by the number of true positive predictions (anomalies accurately anticipated). Formula (22) is used to compute the precision.

$$precision = \frac{TP}{TP+FP} \times 100 \tag{22}$$

Table 3. Numerical Outcomes of Precision for existing and proposed methods.

Methods	Precision(%)
CNN (Li et al., 2022)	31
SVM (Yu et al., 2022)	42
DNN (Ioannou et al., 2021)	45
IBGWO-RNN (proposed)	65

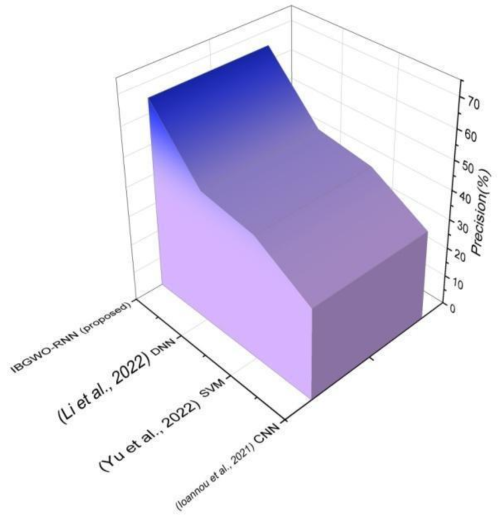

Figure 4. Comparison of accuracy for existing and proposed methods

A comparison of precision for current and suggested approaches is shown in (Figure 4). The recommended technique outperforms the ones already in use, which include CNN (31%), SVM (42%), and DNN (45%), with high performance of 65%. (Table 3) shows the suggested approach IBGWO-RNN, which outperformed other methods presently in data categorization precision.

c) Recall

A classification or prediction model, such as the enhanced neural network based on IBGWO-RNN for early detection of abnormalities in NPPs, is evaluated based on recall, also known as sensitivity or actual positive rate. The recall is measured by dividing the total of accurate positive predictions (anomalies that were successfully predicted) by the total of false negative predictions (occurrences that were mistakenly labeled as non-anomalies and anomalies. Formula (23) is used to determine the recall.

$$Recall = \frac{FN}{FN+TP} \times 100 \tag{23}$$

Table 4. Numerical Outcomes of Recall for Existing and proposed methods.

Methods	Recall (%)
CNN (Li et al., 2022)	35
SVM (Yu et al., 2022)	43
DNN (Ioannou et al., 2021)	52
IBGWO-RNN (proposed)	66

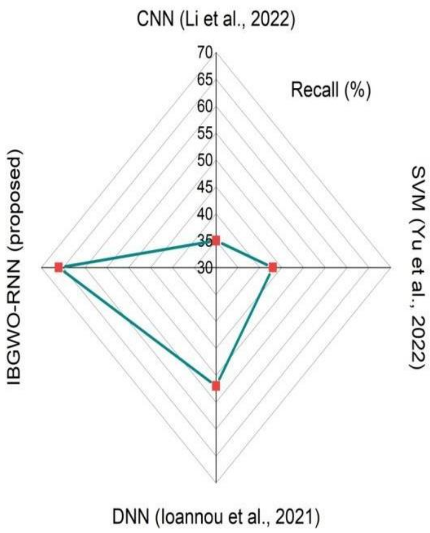

Figure 5. Comparison of recall for existing and proposed methods

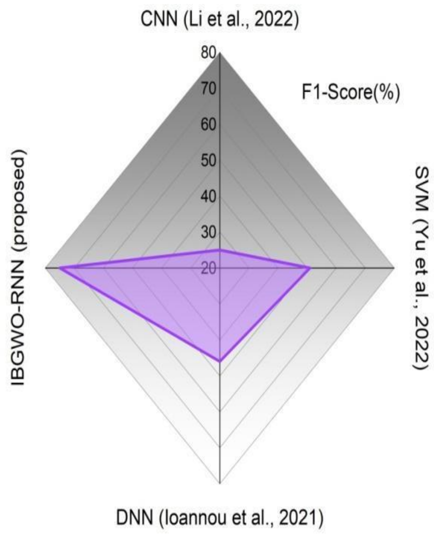

Figure 6. Comparison of F1-score for existing and proposed methods

A comparison of recollection for current and suggested approaches is shown in (Figure 5). The proposed technique performs better than the ones already in use, which include CNN in recall (35%), SVM (43%), and DNN (52%), with a recall of 66%. The suggested technique, IBGWO-RNN, is shown in (Table 4), and it outperformed other presently used methods in terms of data categorization recall.

d) F1-score

The F1 score is used as a performance metric in the updated neural network based on IBGWO-RNN for early identification of problems in NPPs, for instance, to assess the general effectiveness of a classification or prediction model. The F1 score offers a fair evaluation of the model's performance by integrating accuracy and recall data into a single measure. The F1 score is produced by averaging recall and precision. The model's recall (ability to recognize every instance of a true positive case) and accuracy (ability to provide exact positive predictions) are taken into account. The F1-score is obtained by using the Formula (24).

$$F1 - measure \ = \frac{(precision)\times(recall)\times 2}{precision+recall} \times 100 \quad (24)$$

Table 5. Numerical Outcomes of F1-score for existing and proposed methods

Methods	F1-Score (%)
CNN (Li et al., 2022)	25
SVM (Yu et al., 2022)	51
DNN (Ioannou et al., 2021)	46
IBGWO-RNN (proposed)	75

A comparison of recollection for current and suggested approaches is shown in (Figure 6). The proposed technique performs better than the ones already in use, which include CNN in F1-score (25%), SVM (51%), and DNN (46%), with an F1-score of 75%. The suggested technique, IBGWO-RNN, is shown in (Table 5), and it outperformed other presently used methods in data categorization F1-score.

4.2 DISCUSSION

To preserve the safety and effectiveness of these crucial facilities, it is crucial to design an upgraded neural network to identify abnormalities in NPPs early. An efficient neural network may assist in real-time anomaly and possible problem detection, enabling rapid response and preventative actions. The neural network's performance must be rigorously tested, validated, and evaluated at every stage of the design process. An efficient and dependable system for the early identification of abnormalities must be developed via collaboration between domain specialists, data scientists, and NPP operators. The integrity and dependability of the anomaly detection system should also be maintained by implementing safeguards against adversarial assaults and illegal access. By considering these factors, we may work toward creating a better neural network for early anomaly detection in NPPs, eventually improving safety, reducing accidents, and assuring the efficient running of these necessary facilities.

5. CONCLUSION

The IBGWO-RNN technique makes it possible to design a better neural network for detecting abnormalities in NPPs by cleaning and preprocessing the data from different sensors inside the facility, managing missing values, and normalizing the features. Consider domain-specific information when identifying relevant traits that capture the patterns and characteristics of normal and aberrant plant activity. By experimenting with various configurations, choose the best architecture for the IBGWO-RNN model, taking into account the number of recurrent layers, hidden units, and activation functions. To optimize the RNN parameters during training, configure the BAT algorithm and Grey Wolf Optimizer GWO with the appropriate values. The RNN parameters should be optimized using the IBGWO method based on a fitness function that assesses the model's capability for anomaly detection. Adjust the RNN biases and weights as necessary. Utilize testing data and performance assessment criteria, such as accuracy, precision, recall, and F1-score, to rate the trained IBGWO-RNN model. Based on the model's findings and the particular needs of the NPP, choose appropriate criteria for anomaly detection. Integrate the anomaly detection system with the current infrastructure to enable prompt responses and the right action. We determine that we Utilize new data to verify the IBGWO-RNN model's performance in the real world and continue to update and improve the model in response to user input and observations. Our research leads us to conclude that developing a better neural network for early anomaly detection in NPPs is a challenging endeavor that calls for close coordination with subject-matter experts, access to labeled training data, and stringent testing and validation methods. However, by following the suggested procedures and constantly enhancing the model, we may create an accurate and dependable anomaly detection system that enhances NPPs safety and dependability.

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