Condition Monitoring Method for Oil-Immersed Power Transformer based on Convolutional Neural Network and Metaheuristic OOBO Algorithm

[1]Pushpinder Kumar, [2]Dr. Ved Parkash, [3]Naveen Kumar Sharma

[1]PhD Scholar, Electrical Engineering Department, MRSPTU, Bathinda, Punjab, India. pushpinder.numwas@gmail.com

[2]Assistant Professor, Electrical Engineering Department, MRSPTU, Bathinda, Punjab, India. dr.vparora@mrsptu.ac.in

[3]Assistant Professor, Electrical Engineering Department, I. K. Gujaral Punjab Technical University Main Campus Kapurthala, Punjab, India. naveen31.sharma@gmail.com

Abstract: In this paper, a novel condition monitoring method is presented for an oil-immersed power transformer based on the Convolutional Neural Network (CNN) and metaheuristic One-to-One-Based-Optimizer (OOBO) algorithm. The CNN algorithm is employed for classifying the various faults, whereas metaheuristic OOBO is utilized to fine-tune the parameters of the CNN algorithm to enhance the classification accuracy. In addition, the unbalanced database is balanced using the SMOTE algorithm and normalized using the min-max normalization algorithm. The simulation evaluation is performed for the standard dataset, and various parameters are measured to evaluate the proposed method. The result shows the proposed method achieves a high value of accuracy for classifying the various faults. The proposed method achieves an accuracy value of 0.99 for discharge fault, 0.98 for partial discharge, 0.98 for thermal, and 0.99 for no fault.

Keywords: Condition Monitoring, CNN, DGA, Diagnostic, Fault, Metaheuristic, OOBO, Power Transformer.

1. Introduction

Because oil-immersed power transformers can withstand greater voltage levels than dry-type transformers, they are often utilized in power systems. Power transformers are vulnerable to various types of defects due to their continuous operation under severe electrical, thermal, and mechanical stresses [1]. As a result of these faults, the grid collapse, power supply interruptions, and other impacts occurred. To guarantee the safety of the electricity system, it is essential to ensure that oil-immersed transformers are functioning properly [2].

The Dissolved Gas Analysis (DGA) approach is one of the most used techniques in industry for analyzing power transformer oil to find initial issues [3]. This method has become a crucial asset management tool as it is shown to be successful in recognizing any problems with power transformers. The main idea of DGA is to monitor dissolved gases in transformer oil. These gasses occur from arcing, overheating, and partial discharge [4]. We can detect any problems and evaluate the rate of insulation degradation by assessing the type and concentration of dissolved gases in transformer oil samples. This allows us to plan for maintenance and repairs immediately, preventing serious damage to the transformer. Transformer oil contains dissolved gases such as methane, hydrogen, ethylene, ethane, carbon monoxide, acetylene, and dioxygen, as observed in previous studies [5]. These gases are signs of transformer problems, and their concentrations may indicate the transformer's condition.

In the literature, several conventional methods are utilized for identify fault in the oil immersed power transformers [6]. These methods consist of the Rogers Ratios, Key gas method, Duval Triangles, Doernenburg Ratios, and Pentagons graphical methods. But all of these methods have some problems, like using out-of-code ratios, specific limits, or not considering gas evolution, which can make fault checks wrong and unreliable [5]. Thus, test practitioners' expertise determines diagnosis accuracy. Several artificial intelligence (AI)-based techniques have been developed by researchers to increase diagnostic accuracy to overcome such subjective views. In this paper, we have presented a condition monitoring method for oil-immersed power transformers using the deep learning algorithm to classify the fault condition. Besides that, the performance of the deep learning algorithm is enhanced by fine-tuning the parameters of it using the metaheuristic algorithm. The main contribution of this research is as follows.

- The metaheuristic OOBO algorithm is employed to fine-tune the CNN algorithm at the learning level based on the accuracy parameter to enhance the classification accuracy.
- The pre-processing of the database is done using the SMOTE and Min-Max Normalization method to balance and normalize the database.

The rest of the paper is as follows. Section 2 shows the related work is done in the condition monitoring method. Section 3 outlines the preliminary steps, providing an overview of the CNN and the metaheuristic OOBO algorithm. Section 4 presents the proposed condition monitoring method for oil-immersed power transformers. Section 5 shows the results and discussion parts. Finally, the conclusion and future scope are drawn in Section 6.

2. Related Work

This section covers the related work done in the condition monitoring of the oil-immersed power transformer based on deep learning. Jin et al. [3] showed a CNN-based condition monitoring method that could sort the different faults by dividing the dataset into three parts: 65% for training, 15% for validation, and 20% for testing. Additionally, they have performed pre-processing on the data using the normalization and data balancing technique to prepare it for classification purposes. Arsya et al. [7] designed a health condition monitoring method for power transformers using several machine learning algorithms. The simulation evaluation shows that the gradient boosting algorithm achieves the highest accuracy of 95% for assuming the complete data. Ghoneim et al. [8] designed an ensemble learning approach-based fault detection method for dissolved gas analysis. Additionally, they use the Adaptive Dynamic Polar Rose Guided Whale Optimization algorithm (AD-PRS-Guided WOA) to select features. They have achieved an accuracy of 97.1%. Al-Sakini et al. [9] showed a model for predicting faults in power transformers that uses six machine learning algorithms: RF, SVM, DT, BPNN, KNN, and NB. In their research, they consider three cases: case A, which involves the Duval triangle method; case B, which involves Doernenburg's method; and case C, which involves the Rogers method. The result indicates that the RF outperforms for case A and achieves an accuracy of 95.2%, whereas for cases B and C, RF and DT outperform others and achieve an accuracy of 100% and 99.2%, respectively. Bjelić et al. [10] monitored the health of power transformers using the analysis of sweep frequency response. In their work, k-mean clustering, ANN, and adaptive neuro-fuzzy interference system (ANFIS) are considered. The result indicates that the ANN and ANFIS outperform the k-means clustering algorithm. El-Rashidy et al. [11] used the concept of a digital twin and utilized the LSTM for predicting the health index and life expectancy of the power transformer. The result shows that their method achieves a low value for error parameters (MSE, MAE, and MedAE) and a high value (0.98) for correlation determination. F. Guerbas et al. [12] developed a fault detection method by performing dissolved gas analysis using the ANN algorithm. Besides that, the PSO algorithm is employed to fine-tune the parameters of the ANN algorithm. Rao et al. [13] presented a fault classification method by considering the several machine learning algorithms. They then proceeded to refine the optimal machine learning algorithm through the application of the Bayesian optimization algorithm. They have achieved an accuracy of 88.34%.

From the previous studies, we found several machine learning algorithms are utilized for fault classification in the power transformer. However, in these methods, the feature selection is done manually and outperforms for the supervised dataset. In addition, the ensemble learning approach enhances the classification accuracy but, on the other hand, increases the computation complexity. In order to overcome this issue, deep learning algorithms are utilized, which automatically extract the features. Further, the performance of the deep learning algorithm is highly dependent on the parameter values. In the literature, PSO and Bayesian optimization are utilized for fine-tuning the parameters. However, these algorithms have a low convergence rate and face a local optima problem. These challenges are taken in this paper to enhance the classification accuracy of the condition monitoring method.

3. Preliminaries

This section gives an overview of CNN and metaheuristic OOBO algorithm is utilized for design the condition monitoring method for oil-immersed power transformer.

3.1 CNN

Three main parts comprise a CNN: the convolution layer, the activation function, and the pooling layer. An FC layer is further used during classification job processing to finalize the input-to-label mapping [14]. This study's CNN has two convolutional layers, two pooling layers, and an FC layer. The CNN's key component is the convolutional layer. It comprises several stacked convolutional kernels and can retrieve local features through a convolution process. The convolution technique allows the convolution kernels to learn and remember the spatial relationship of various characteristics in the input data. Then, maximal pooling preserves the most significant features. Maximum pooling is better than other pooling tools at reducing the error in the expected value that is caused by the convolution layer's parameter error. Lastly, the softmax function is used to input the features into the FC layer, finishing the feature-to-label mapping. The following is the definition of the CNN term [15]:

$$\begin{cases} X_i = f(w_i \otimes X_{i-1} + b_i) \\ Q_j = Max(P_j^0, P_j^1, P_j^2 ... P_j^t) \\ Y_j = f(w_j \otimes y_{j-1} + b_j) \end{cases} \tag{1}$$

In the above equation, bi and wi shows the bias and weight of the ith convolutional kernel. The convolution operation is represented by $\otimes$. The activation function is denoted by f(x), the pooling outcome of the j-th region is represented by Qj, the maximum pooling operation is denoted by Max, and the t-th element of the j-th pooling region is expressed by Pt j. The weights and biases of the j-th neurons in the FC layer are represented by wj and bj, while the input and output of the convolution kernel and FC are given by Xi, Xi−1, and yj−1, respectively.

3.2 Metaheuristic OOBO Algorithm

The foundation of OOBO is the initial generation of many viable options based on the problem's limitations. The fundamental principle of the method is then used to update the positions of those solutions in the search space in each iteration. The problem's search space can't be accurately scanned when the update process relies too much on individual population members. This may cause the algorithm to converge toward nearby optimum regions. The OOBO algorithm updates the population by using information on all population members to avoid over-reliance on best, worst, and mean members [16]. Therefore, in this updating process, (a) population updates are not reliant on specific members, (b) all members are involved, and (c) each population member guides another member in the search space one-on-one.

4. Proposed Condition Monitoring Method for Oil-Immersed Power Transformer

This section presents the proposed condition monitoring method for oil-immersed power transformer. The main novelty of the proposed method is that the performance of the deep learning algorithm is optimized by fine-tuning the parameters of it using the metaheuristic algorithm. The flowchart of the proposed condition monitoring method is shown in Figure 1.

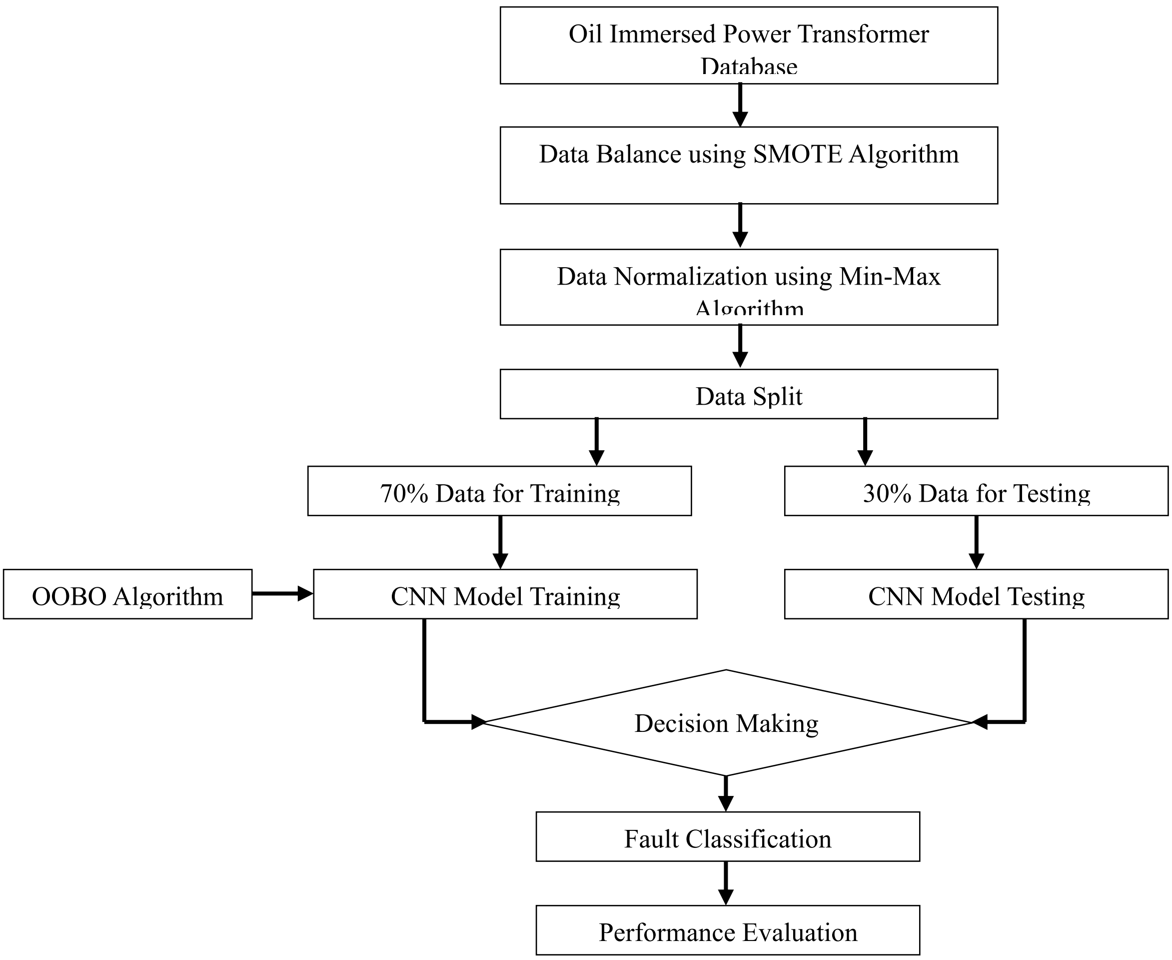

Figure 1. Flowchart of the Proposed Condition Monitoring Method

In the proposed method, initially, the database of the oil-immersed power transformer is read. The database contains 1000 samples. Further, each sample has five input attributes (‘H_2, CH_4, C_2H_4, C_2H_6, C_2H_2’) and one output attribute that defines the fault condition. The fault condition has four stages, namely, discharge fault, partial discharge, thermal discharge, and no fault. Next, the database is balanced and normalized using the SMOTE and min-max algorithm. After that, the database is split into a training and testing ratio. In this work, a 70:30 ratio is taken into consideration. The 70% database is utilized to train the model, whereas the 30% database is for testing the model. The CNN algorithm is employed for fault classification purposes. In addition, the parameters of the CNN algorithm are fine-tuned at the learning level by determining the learning rate and number of hidden layers and considering accuracy as the objective function. Finally, after fault classification, the proposed method is evaluated using the various parameters.

5. Results and Discussion

Here, we present the simulation results for the proposed condition monitoring method and perform a comparative analysis with the existing methods for validation. MATLAB 2018a software was used to design and simulate the proposed method, and the system configuration is an Intel i7 processor, a 64-bit Windows operating system, and 8GB of RAM. Table 1 shows the detailed description of the dataset. In this dataset, there are five input parameters that denote the various gases and one output parameter that denotes the type of fault condition.

Table 1. Dataset Description

Parameter	Value
Total Sample	1000
Input Parameters	‘H_2, CH_4, C_2H_4, C_2H_6, C_2H_2’
Output Parameter	‘Condition’

Table 2 shows the parameter setup configuration for the OOBO algorithm. These parameters are setup to find the best parameter value of the CNN algorithm based on the accuracy objective function.

Table 2. Parameter Setup Configuration for OOBO Algorithm

Parameter	**Value**
Pop_{size}	2
Pop_{dim}	2
$Iteration_{size}$	50
Learning Rate Parameter	[0.001-0.99]
Number of Hidden Layers	[0.01-0.99]
Objective Function	Accuracy

Figure 2 shows the convergence rate graph for the OOBO algorithm for the objective function, accuracy. The result indicates that the OOBO algorithm achieves the maximum accuracy value in the 45^{th} iteration while exploring the solution space for the parameter value of the CNN.

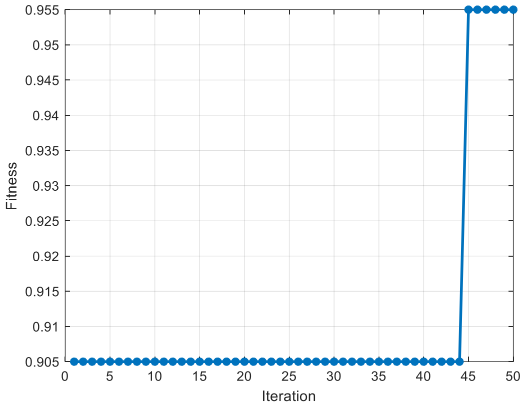

Figure 2 Convergence Rate graph for OOBO Algorithm

Table 3 shows the parameter setup configuration for the CNN algorithm. These parameters are setup to classify the fault conditions. In the proposed method, two filter of size 8 and 16 is taken into consideration.

Table 3. Parameter Setup Configuration for CNN Algorithm

Parameter	Value
Max Epoch	50
Activation Layer	'Relu'
Padding	'Same'
Filter Size	[8,16]

Figure 3 shows the confusion matrix is evaluated for the different fault classifications. The confusion matrix denotes the true positive, true negative, false positive, and false negative cases classified by the proposed method.

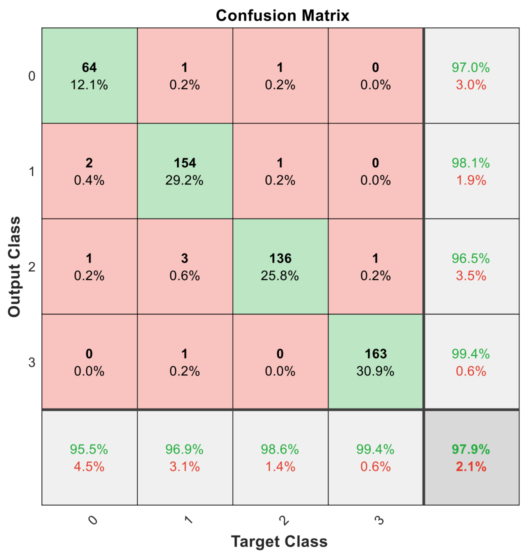

Figure 3. Confusion Matrix for the Proposed Method

Table 4 shows the different parameters are evaluated for the different classes of faults. The result shows that on average the proposed method achieves an accuracy of 0.98769, a recall value of 0.97246, a precision value of 0.97006, and an F-score value of 0.97122.

Table 4. Performance Analysis of the Proposed Method

N-Classes	Accuracy	Recall	Precision	F-score
1	0.98674	0.95522	0.94118	0.94815
2	0.98485	0.96855	0.98089	0.97468
3	0.98485	0.97826	0.96429	0.97122
4	0.99432	0.98780	0.99387	0.99083
Average	**0.98769**	**0.97246**	**0.97006**	**0.97122**

Figure 4 shows the accuracy analysis for classifying various faults for oil-immersed power transformers. The result shows the proposed method achieves a high value of accuracy for classifying the various faults. The proposed method achieves an accuracy value of 0.99 for discharge fault, 0.98 for partial discharge, 0.98 for thermal, and 0.99 for no fault.

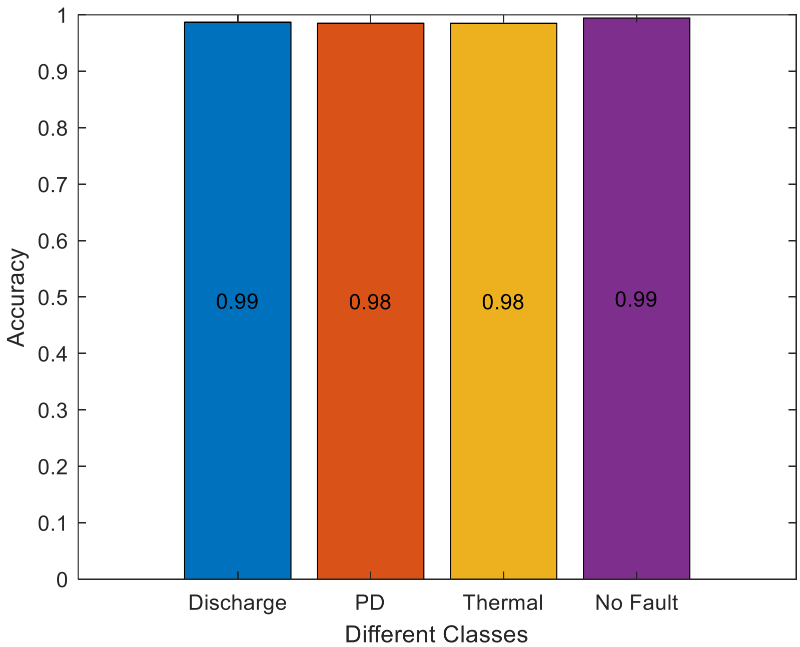

Figure 4 Accuracy Parameter Analysis for Classify Various Faults for Oil Immersed Power Transformer

Figure 5 illustrates the recall analysis for the classification of diverse faults in oil-immersed power transformers. The results indicate that the proposed strategy attains a high recall value for categorizing different faults. The proposed technique attains a recall value of 0.96 for discharge faults, 0.97 for partial discharge, 0.98 for thermal faults, and 0.99 for no faults.

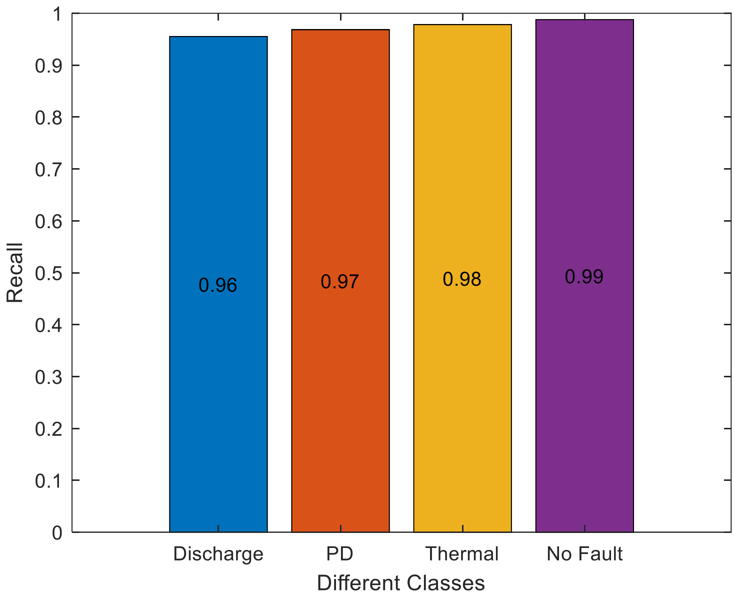

Figure 5. Recall Parameter Analysis for Classify Various Faults for Oil Immersed Power Transformer

Figure 6 shows the precision analysis for classifying various faults for oil-immersed power transformers. With no fault, the propsed approach attains a precision value of 0.99, while with partial discharge it reaches 0.98; thermal, 0.96; and discharge fault, 0.94.

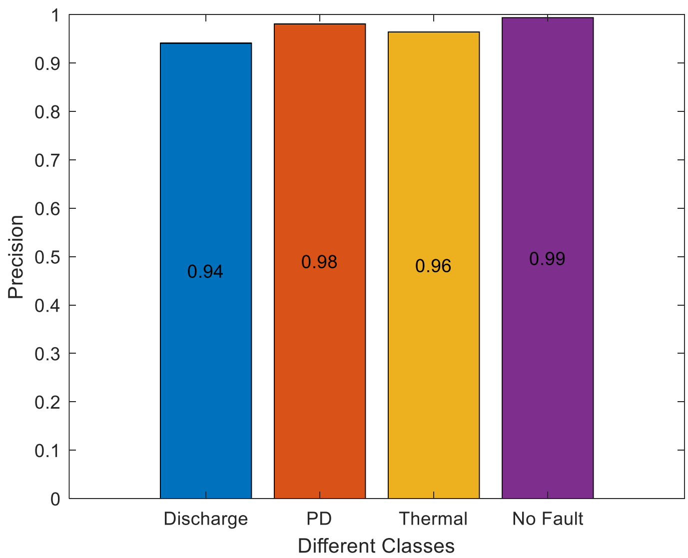

Figure 6. Precision Parameter Analysis for Classify Various Faults for Oil Immersed Power Transformer

The analysis using F-scores for fault classification in oil-immersed power transformers is illustrated in Figure 7. The outcome demonstrates that the suggested approach successfully classifies the different faults with a high F-score. At discharge fault, the suggested approach achieves an F-score of 0.95; at partial discharge, it drops to 0.97; at thermal, it stays at 0.97; and in the absence of fault, it reaches 0.99.

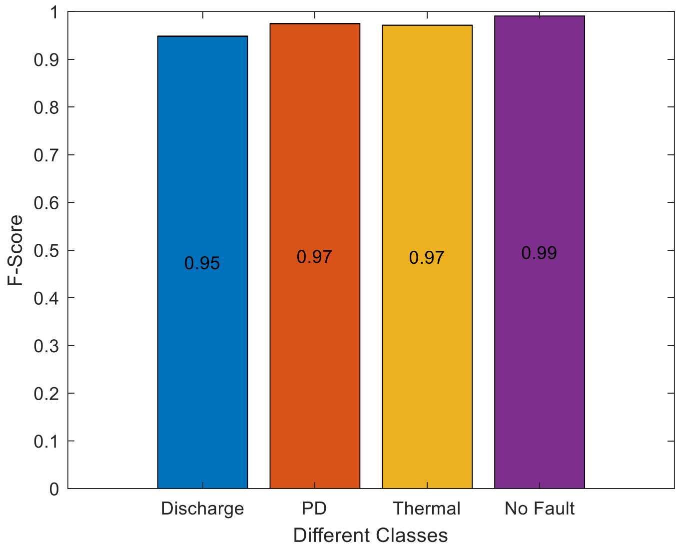

Figure 7. F-Score Parameter Analysis for Classify Various Faults for Oil Immersed Power Transformer

Finally, the proposed condition monitoring method is compared with the existing method based on the CNN algorithm for classifying the various faults in the oil-immersed power transformer [3]. The result shows that the proposed method achieves a high accuracy value of 98.77% in classifying the various faults due to fine-tuning the parameters of it using the metaheuristic OOBO algorithm.

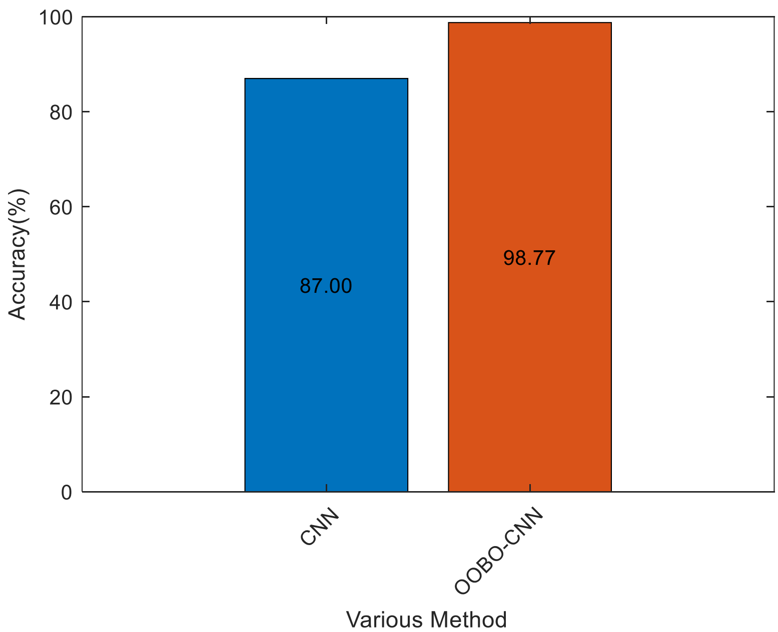

Figure 8. Comparative Analysis based on Accuracy Parameter

6. Conclusion and Future Scope

This paper presents a condition monitoring method for oil-immersed power transformers, which fine-tunes the CNN parameters at the learning level using the metaheuristic OOBO algorithm, with accuracy serving as the objective function. In addition, the pre-processing of the database is done using SMOTE and Min-Max normalization algorithms to balance and normalize the database. The simulation evaluation is done on the standard database. This database contains five input attributes and one output attribute, which defines the fault condition. The performance evaluation using the various parameters shows that the proposed method achieves high values of accuracy, precision, recall, and F-score. Finally, the comparative analysis shows that the proposed method achieves an accuracy value of 98.77% over the existing method, which achieves an accuracy of 87%. In the future, the CNN algorithm can be optimized at the architecture and layer level.

References

[1], Jin et al., "Oil-Immersed Power Transformer Condition Monitoring Methodologies: A Review," *Energies,* Vol. 15, no. 9, pp. 3379, 2022.

[2] J. Shao *et al.*, "Probabilistic modeling of dissolved gas concentration for predicting operating status of Oil-Immersed transformers," *IEEE Transactions on Industrial Informatics*, pp. 1–10, Jan. 2024, doi: 10.1109/tii.2024.3476550. Available: https://doi.org/10.1109/tii.2024.3476550

[3] Jin et al. "Deep Machine Learning-Based Asset Management Approach for Oil Immersed Power Transformers Using Dissolved Gas Analysis," *IEEE Access*, Vol. 12, pp. 27794-27809, 2024.

[4] A. Wajid *et al.*, "Comparative Performance Study of Dissolved Gas Analysis (DGA) methods for identification of faults in power transformer," *International Journal of Energy Research*, vol. 2023, pp. 1–14, Sep. 2023, doi: 10.1155/2023/9960743. Available: https://doi.org/10.1155/2023/9960743

[5] Y. Chen, Z. Wang, Z. Li, H. Zheng, and J. Dai, "Development of an online detection setup for dissolved gas in transformer insulating oil," *Applied Sciences*, vol. 11, no. 24, p. 12149, Dec. 2021, doi: 10.3390/app112412149. Available: https://doi.org/10.3390/app112412149

[6] G. Karthigaiselvi and B. Vigneshwaran, "Recognition of Type of Faults in Power Transformer Using Dissolved Gas Analysis," *2024 Third International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS),* pp. 1–5, 2024. doi: 10.1109/incos59338.2024.10527661. Available: https://doi.org/10.1109/incos59338.2024.10527661

[7] N. R. Arsya, N. Suwarno, R. A. Prasojo, G. A. Sudrajad, and A. Abu-Siada, "A holistic integration of conventional and machine learning techniques to enhance the analysis of Power Transformer Health Index considering data unavailability," *IEEE Access*, vol. 12, pp. 124549–124561, Jan. 2024, doi: 10.1109/access.2024.3450110. Available: https://doi.org/10.1109/access.2024.3450110

[8] S. S. M. Ghoneim, T. A. Farrag, A. A. Rashed, E.-S. M. El-Kenawy, and A. Ibrahim, "Adaptive dynamic Meta-Heuristics for feature selection and classification in diagnostic accuracy of transformer faults," *IEEE Access*, vol. 9, pp. 78324–78340, Jan. 2021, doi: 10.1109/access.2021.3083593. Available: https://doi.org/10.1109/access.2021.3083593

[9] S. R. Al-Sakini, G. A. Bilal, A. T. Sadiq, and W. A. K. Al-Maliki, "Dissolved gas analysis for fault prediction in power transformers using machine learning techniques," *Applied Sciences*, vol. 15, no. 1, p. 118, Dec. 2024, doi: 10.3390/app15010118. Available: https://doi.org/10.3390/app15010118

[10] M. Bjelić, B. Brković, M. Žarković, and T. Miljković, "Machine learning for power transformer SFRA based fault detection," *International Journal of Electrical Power & Energy Systems*, vol. 156, p. 109779, Jan. 2024, doi: 10.1016/j.ijepes.2023.109779. Available: https://doi.org/10.1016/j.ijepes.2023.109779

[11] N. El-Rashidy, Y. A. Sultan, and Z. H. Ali, "Predecting power transformer health index and life expectation based on digital twins and multitask LSTM-GRU model," *Scientific Reports*, vol. 15, no. 1, Jan. 2025, doi: 10.1038/s41598-024-83220-x. Available: https://doi.org/10.1038/s41598-024-83220-x

[12] F. Guerbas *et al.*, "Neural networks and particle swarm for transformer oil diagnosis by dissolved gas analysis," *Scientific Reports*, vol. 14, no. 1, Apr. 2024, doi: 10.1038/s41598-024-60071-0. Available: https://doi.org/10.1038/s41598-024-60071-0

[13]U. M. Rao, I. Fofana, K. N. V. P. S. Rajesh, and P. Picher, "Identification and application of machine learning algorithms for transformer dissolved gas analysis," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 28, no. 5, pp. 1828–1835, Oct. 2021, doi: 10.1109/tdei.2021.009770. Available: https://doi.org/10.1109/tdei.2021.009770

[14] R. Yao, N. Wang, P. Chen, D. Ma, and X. Sheng, "A CNN-transformer hybrid approach for an intrusion detection system in advanced metering infrastructure," *Multimedia Tools and Applications*, vol. 82, no. 13, pp. 19463–19486, Dec. 2022, doi: 10.1007/s11042-022-14121-2. Available: https://doi.org/10.1007/s11042-022-14121-2

[15] K. Li, J. Li, Q. Huang, and Y. Chen, "Data augmentation for fault diagnosis of oil-immersed power transformer," *Energy Reports*, vol. 9, pp. 1211–1219, Jun. 2023, doi: 10.1016/j.egyr.2023.05.110. Available: https://doi.org/10.1016/j.egyr.2023.05.110

[16] M. Dehghani, E. Trojovská, P. Trojovský, and O. P. Malik, "OOBO: a new metaheuristic algorithm for solving optimization problems," *Biomimetics*, vol. 8, no. 6, p. 468, Oct. 2023, doi: 10.3390/biomimetics8060468. Available: https://doi.org/10.3390/biomimetics8060468