Current Transformer Status Online Monitoring Platform Based on Big Data

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Transformer failures are currently a major issue due to the widespread use of electronic transformers in smart grid monitoring systems. To stimulate regular upkeep practices, and raise grid reliability and efficiency, this work developed a sophisticated fault diagnosis approach for electronic current transformers (ECTs) utilizing analytics from big data. For efficient defect diagnosis in the ECT, the dynamic eagle perching optimized long-short term memory (DEPO-LSTM) technique is proposed. Fault sample datasets for ECTs are collected from big data to train the proposed approach. Min-max normalization is used in data preprocessing to remove noisy or redundant information. From the normalized data, important features are extracted using principal component analysis (PCA). Next, we apply the proposed technique in the framework for fault diagnosis, and the DEPO technique is used to improve the parameters of the LSTM. The simulations are carried out using the Matlab platform to assess the proposed DEPO-LSTM technique for ECT defect diagnostics. Based on the results, we deduced that our proposed approach outperformed other approaches presently in use for diagnosing ECT faults. The DEPO-LSTM algorithm is evaluated in terms of precision (97.15%), recall (97.42%), accuracy (96.23%), and F1-score (96.36%).

Povzetek: Opisana je platforma za spletno spremljanje stanja tokovnih transformatorjev (ECT) na podlagi algoritmov velikih podatkov. Predlagana metoda DEPO-LSTM izboljšuje napovedi in diagnosticiranje napak.

1 Introduction

Electric energy is the primary energy source in modern civilization, and as the social economy has grown, it has become increasingly associated with people's daily lives, along with manufacturing and construction [1]. Modern power systems must operate with the ability to generate and supply power reliably and consistently while maintaining the quality of the authorized power supply. A crucial component of core technology in the power system is the transformer. When a failure happens, people's productivity and quality of life are severely impacted and wasted [2].

The most expensive component of equipment in every power sector utility, the power transformer indirectly brightens every environment and provides all forms of real-world entertainment. Systems for wireless monitoring are generally selected for checking different industrial metrics from different places. For actual creation, the majority of organizations require monitoring various parameters, none of which can be physically observed [3]. An essential component of electrical distribution networks is the transformer, which is positioned at distinct locations across the network at varied voltage and power levels. The distribution transformer's maintenance and protection are crucial. Technicians constantly monitor the transformer environments, and all identified issues are accurately corrected. Distribution transformers can be used for a very long period if they are properly and continuously checked. In electrical power systems, economic considerations are crucial, and cost reduction is primarily associated with the production of dependable and high-quality power [4].

Distribution transformers are among the most costly and essential parts of electricity distribution networks.Distribution service transformer problems can be caused by a variety of factors, such as operating stresses, oil leaks, thermal overload stress, harmonics, and irregular loading.Transformers may experience a reduction in lifespan or failure if one or more of these situations persistently exceed the limitations of both their layout and operation.Strategies are proposed and outcomes are evaluated in the online condition monitoring.A distribution transformer's status was assessed using various standards, including transformer loading, humming sound, temperature, and oil level [5].The findings displayed were based on an extremely short time frame, making it difficult to determine the transformer's exact status. The wireless monitoring system evaluates distribution transformers' conditions in real time. Every 90 seconds, the system stores data on a server, ensuring excellent dependability and rapid findings [6].

Monitoring transmission and distribution equipment includes measuring fundamental characteristics that affect the asset's ability to operate as designed. In traditional monitoring systems, sensors are integrated and data is collected to identify indicators of failure, alert users to anomalous level quantities, create trend curves, and correlate occurrences with servicing employees [7]. One significant advancement within the electrical power sector is the ability to remotely monitor transformers, which is intendedto ensure that these key substation assets operate both firmly and reliably. The use of online transformer monitoring will help the power utilities with the reliability and efficiency of the operation. They also reduce the length of the utilization cycle of transformers, help to detect faults earlier, and prevent their occurrence as well. It reduces communication costs caused by the need for on-site employees, thus also decreasing transportation costs [8]. The DEPO-LSTM technique is introduced to enhance the predictive accuracy and real-time fault detection in the ECT.

This study's remaining sections are as follows: Section 2: Related works; Section 3: Methods; Section 4: Results; and Section 5: Conclusion

2 Related works

Table 1 shown as summary of work below;

Table 1: Summary of related work

Reference	**Methods/Algorithm**	**Merits**	**Limitations**
[10]	This research presents a unique integration of an Internet of Things (IoT) architecture with deep learning against cyber attacks for online monitoring of the power transformer status.	Compared to earlier approaches in the literature, the new deep 1D-CNN is more accurate with 94.36 % in the ordinary situation and 92.58 % when considering cyber attacks, with ±5% uncertainty.	This paper is challenging the diagnosis of the transformer condition.
[11]	EL-CSO-NN algorithm is proposed in this paper	Their study also supported the effectiveness of the proposed EL-CSO-NN model, which was useful in predicting transformer problems, improving its management, and reducing the impact of such problems.	The DGA fault samples gathered via the online DGA monitor are typically restricted, resulting to the inadaptability of most AI algorithms due to their demand for huge training samples.
[12]	proposed the use of an enhanced density clustering algorithm coupled with an association algorithm	Based on the results of the tests, it was possible to conclude that the use of the proposed approach could improve the efficiency of searching for sources of abnormally measured data in the online monitoring of transformers.	anomaly detection methods for non-smooth characteristic- state quantities are required An anomaly detection approach for non-smooth characteristic state values is needed.
[13]	Power Transformer-Transformer Neural Network	For power transformer state control transformer and thermal fault detection, the PT-TNNet	The proposed method is not beneficial for systems that require a speedy reaction.

	(PT-TNNet) model based on data fusion is proposed	method integrated data fusion with transformer neural network	
[14]	Boosting learning and random forest methods was proposed in the research	As a result, the one-click sequencing system worked well and reduced the time spent on each sequential action while increasing its effectiveness.	less accurate condi- tional monitoring element less accuracy conditional monitoring element
[15]	ML techniques to analyze DGA data	The proposed model combines the design of four ML classi□ers and enhances diagnosis accuracy and trust between the transformer manufacturer and power utility. The suggested model integrates the design of four ML classifiers and improves the diagnosis accuracy and confidence between the transformer maker and power utility.	On the other hand, understanding DGA samples isn't good enough for detecting early faults, and it mostly depends on how good the test engineers are at their jobs.
[16]	multimodal mutual neural network was presented in the paper	The results show that the proposed method is better and more efficient than the comparison ways because it is more accurate and takes less time to fault diagnosis of the power transformer.	The data from the power transformer will get mixed up with data from other modes, which will cause sensor devices to fail.
[17]	evaluation model based on CNN and GCA were introduced	According to the study, their proposed model was more accurate, as well as provided higher identification results	lacking of training samples
[18]	k-means clustering	Proposed method to identify transformer condition anomalies using transformer power, current, and voltage data in their study	the transformer’s current state in real time using the electrical data, making it beneficial to engineering applications

The investigation demonstrated that the proposed approach could determine the transformer’s current state in real time using the electrical data, making it beneficial to engineering applications.

3 Methods

ECT fault sample dataset was first gathered. The data collected is preprocessed using min-max normalization technique to normalize it at this point. The next step is the PCA approach that helps to select the important features from the data. For the purpose of enhancing the ability of the ECT regarding the fault detection and prediction in real-time, the DEPOLSTM approach is recommended.

3.1 Circuit for detecting electronic current transformers

The fault categories and the structural features of ECTs were used to create a detecting circuit for ECT defect diagnostics. This allowed gathering different kinds of defect samples from ECTs efficiently. A single signal can detect certain ECT defects, while other faults need to be detected by several signals. The voltage and current characteristics on both the secondary and the primary sides of the transformer can be identified by placing several key detecting points. This will facilitate to obtain the general characteristics of the ECT and determine whether the transformer is operating as designed. The ECT's detection circuit's principal structure is displayed in Figure 1.

The ECT is represented by CT in Figure 1. The current in the C, B, A and phases is represented by I_C, $I_B, and\ I_A$. The calculated current and voltage of metering units one and two are denoted by the current I_a, I_c, and voltage $V_a, V_c.CT_1\ and\ CT_2$have corresponding secondary side voltages of $v_a, and\ v_c$. The impedance shift is measured when the ECT is short-circuited by applying a $1\ KHz$ signal and accumulating several signals. When a secondary short circuit occurs in CT, the defect is identified by many observed characteristics, and the network impedance changes based on the load.

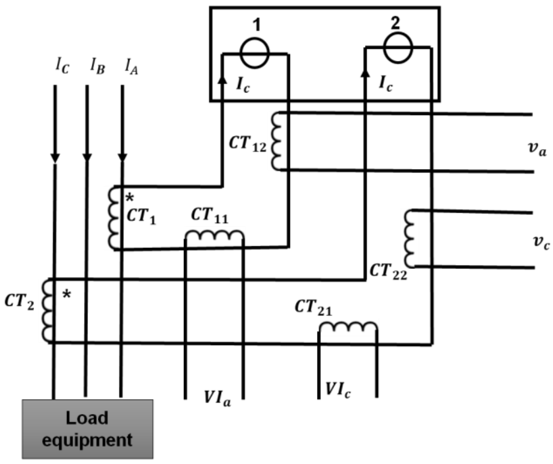

Figure 1: Principal diagram for ECT fault detection

3.2 Data collection

A single signal can identify defects on the primary side, while numerous signals are sometimes needed to identify defects on the secondary side. Seven critical parameters were collected as sample data for the primary and secondary ECT defects using the evaluation environment platforms.100 groups of data in ordinary operating mode and 100 groups of data in each of the 7 failure circumstances were gathered. After that, 20% of the dataset was used for testing, and 80% of the samples in each category were chosen at random for training.

3.3 Min-Max normalization

Min-max normalization is a technique for normalization that involves linearly transforming the initial data to provide value comparisons that are balanced between the before and after process data. This approach could utilize the subsequent Equation (1).

$$W_{new} = \frac{W - \min(W)}{\max(W) - \min(W)} \quad (1)$$

W- Old value

W_{new}- The new value derived from normalized outcomes

$\min(W)$- The dataset's minimum value

$\max(W)$- The dataset's maximum value

3.4 PCA

Principal Component Analysis is a data processing technique for unlabeled extraction of features. Features will be displayed on a newly created, smaller feature space. The features with the most essential data are the new features that were discovered from the PCA extraction findings. By optimizing data variance, the primary constituents are acquired. Data visualization is possible in a low-dimensional principal component space since the number of additional dimensions (features) is less than the number of initial attributes. Calculate the mean based on each attribute as follows,

$$\overline{w}_i = \frac{1}{m}\sum_{j=1}^{m} w_{ji},\ \ j = 1,2,\ldots\ldots,m \quad i = 1,2,\ldots\ldots,m$$
(2)

Where,

n - Number of features,

w_{ji} - Data j-sample with i-feature,

m - Number data of sample, and

$\overline{w}_i$ - Data i-feature.

Calculate Φ with the following Equation,

$$\Phi = [\Phi_{ji}] = [w_{ji} - \overline{w}_i] \quad (3)$$

Φ - Matrix of size $m \times n$.

Calculate the covariance matrix using the following Equation,

$$D = \frac{1}{m-1}\Phi^S\Phi \quad (4)$$

D - Matrix of size $n \times n$.

Calculate the eigenvalues of the D matrix by calculating the subsequent Equation.

$$Det\ (\lambda J - D) = 0 \quad (5)$$

D - Covariance matrix, and

J - Identity matrix.

After that, calculate the subsequent equation to determine the eigenvectors w that correspond to the eigenvalues λ,

$$(\lambda.J - D)w = 0 \quad (6)$$

Form matrix w' using the associated eigenvectors after sorting the eigenvectors according to the eigenvalues, starting with the greatest. Calculate the principal components as follows.

$$PC = \Phi w' \quad (7)$$

3.5 Dynamic eagle perching optimized long-short term memory (Depo-LSTM)

The proposed DEPO-LSTM approach combines DEPO and LSTM networks to dynamically modify the parameters of the LSTM method. DEPO iteratively modifies the LSTM parameters to enhance the model's prediction and detecting capabilities in ECT.

3.5.1 Dynamic eagle perching optimization (DEPO)

The inspiration for the DEPO algorithm will be covered first in the following section. Then the exploration of the algorithm and mathematical formulation is provided.

Inspiration: A large number of predatory birds that are members of the Accipitridae family are commonly referred to as eagles. Their average length is between$30 - 31\,inches$, and their wingspan is between$6 - 7\,feet$. They typically reside in the upper sky, and even during the reproductive season, the female and male engage in rather unusual courtship behavior. They fly at a great height. There, while doing an aerobic motion, they locked their clays together and fell, breaking apart just before they reached the earth. The five stages of a female's life cycle are hatching, fledgling, juvenile phase, and maturity. Typically, a female will hatch two to four eggs. They are members of a predatory class. Their typical food source consists of fish, aquatic organisms, and small animals. They hunt distinctively; they fly through the sky to a potentially high point, where they then look for their prey. After tracking it, they dive down to grab their prey. As previously stated, they live at higher altitudes, typically on top of cliffs, mountains, and long trees. They use a technique that was provided to them by nature to discover the highest place to go. Initially, they simply drop from a great height, look at the landscape, examine some locations, and identify which point is the highest position among those samples. As they get closer, they sample a few more points and make their opinions about the top spot even more apparent. They modify this technique iteratively to find the ideal place to reside.

To find the BS, we will take advantage of this characteristic and use it in optimization. We will create a group of eagles in the algorithm to search for the best height to stay. Each of them will search for the ideal solution on their own. Subsequently, the method will select one BS from every eagle and contrast it with the already gathered BS. Iteratively, this procedure will continue until the method finds its BS, at which point no more advancements can be made.

3.5.2 DEPO-LSTM model

DEPO-LSTM is an effective approach to continuous online assessment of ECT conditions. The ECT modern technologies are incorporated into this system to enhance the reliability and precision of continuous real-time monitoring of ECT. Employing the concept of LSTM networks, DEPO-LSTM was able to process and forecast the sequence of the inputs. This suggests that the system can perform an effective evaluation of previous information in the context of ECT monitoring and at the same time, is capable of changing its predictions based on new information. The dynamic eagle perching demonstrates the capacity and percentage precision of the way to identify deviations or irregularities in ECT performance.

Mathematical formulation: The perching behavior of an eagle is represented by the EPO algorithm. Similar to eagle, this technique also determines the solution's highest point or BS. The minima and maxima of a function have a special relationship in optimization; for example, for function e, $\min(e) = \max\,(-e)$.The algorithm that works for all of its residents is defined by nature. Eagle has a very basic but distinctive method of covering ground. An eagle can reach its highest position in the sky by repeatedly looking around and repeating a similar process while it is flying at a high altitude. It does this by traveling toward the highest position and sampling a few locations along the way. The eagle explores the entire area at first by flying overhead, then it repeats this process multiple times until it gets close to the ground, which is known as exploitation. For stochastic optimization methods, the transition from E-E is crucial. In the EPO algorithm, this is expressed mathematically as below.

$$k_{scale} = k_{scale} * eta \quad (8)$$

The scaling variable k_{scale} is anticipated to decrease recurrently as it moves from E-E. Meanwhile, eta is the shrinking constant $0 < eta < 1$ can be derived using the final value resolution as a basis.

$$eta = \left(\frac{res}{k_{scale}}\right)^{1/s_t} \quad (9)$$

Where $0 < res < k_{scale}$ is limited to a range of 0 to 1, $s_t$represents the maximum number of iterations, and res represents a resolution range. If $eta > 1$, then the region of exploration will grow with every run and we will not be able to fulfill our intended goal of E-E. To attain optimality more quickly, we shall utilize a cluster of eagles. To make the process simpler, these will collectively search the SS.

$$K = \begin{bmatrix} K_{1,1} & K_{1,2} & K_{1,3} & \cdots & K_{1,n} \\ K_{2,1} & K_{2,2} & K_{2,3} & \cdots & K_{2,n} \\ K_{3,1} & K_{3,2} & K_{3,3} & \cdots & K_{3,n} \\ K_{4,1} & K_{4,2} & K_{4,3} & \cdots & K_{4,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ K_{m,1} & K_{m,2} & K_{m,3} & \cdots & K_{m,n} \end{bmatrix} \quad (10)$$

Where n is the number of sizes in the SS and m is the number of particles we utilize in it. To comprehend the erratic movement of particles, or eagles, in SS, assume a particle at location k that is free to move in all directions at random. At every iteration, a random number called Δf is given to its current location, indicating that $k + \Delta k$.Consequently, we have:

$$K = K + \Delta K \quad (11)$$

$$\Delta K = \begin{bmatrix} A_{1,1} & A_{1,2} & A_{1,3} & \cdots & A_{1,n} \\ A_{2,1} & A_{2,2} & A_{2,3} & \cdots & A_{2,n} \\ A_{3,1} & A_{3,2} & A_{3,3} & \cdots & A_{3,n} \\ A_{4,1} & A_{4,2} & A_{4,3} & \cdots & A_{4,n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{m,1} & A_{m,2} & A_{m,3} & \cdots & A_{m,n} \end{bmatrix} \quad (12)$$

$A \in (0,1)$ - Random values.

For every component in K, we have,

$$K_{j,i} = K_{j,i} + \Delta K_{j,i} \quad (13)$$

Where i denotes the i^{th} size of the corresponding place and j denotes the j^{th} particle.

Given that eagles live in the upper atmosphere, some of their samples are searching for the highest point on Earth. They determine who came in first by analyzing their sets of samples. We will use our technique to reproduce that outcome, passing the $K_{j,i}$ to the function we wish to reduce.

$$Z_{j,i} = e(K_{j,i}) \quad (14)$$

Equation (14) demonstrates how every particle's position is assessed.

The optimum answer among all the eagle places, shown by Z_{min}, represents the value we want to find by minimizing the specified function. Two additional variables, Z_{Best} and K_{Best}, will be defined. The following is how Z_{Best} and K_{Best} are anticipated to develop,

$$if: Z_{min} < Z_{Best} \quad (15)$$

$$Z_{Best} = e(K_{j,i}) \quad (16)$$

$$K_{Best} = K_{j,i} \quad (17)$$

The ideal solution for a specific function will eventually be found using this method's recursion.

An alteration was presented that will accelerate the EPO's convergence. This change relates to the computation of eta.Particularly, the value of eta in each iteration will be changed, as demonstrated below.

$$eta = eta_{max} - s * \frac{eta_{max} - eta_{min}}{s_t} \quad (18)$$

Where,

eta_{min}- Minimum value (ending value of eta), and

eta_{max}- Maximum value (starting value of eta).

As a result, the transformation will be more rapid and effective, and the dynamic method with different eta in Algorithm (1).

Algorithm 1: DEPO-LSTM
Procedure

```
Initialize all the variables
for < maximum number of iterations do
Calculate ΔK using Formula. (12)
        Calculate K = K + ΔK
for < total number of particles position accessed > do
    Implement Z_{j,i} using Formula. (14)
end for
Implement Z_min from using Formula. (14)
compare Z_min with Formula. (15)
if: Z_min < Z_Best satisfies then
Implement Equ. (16) and Formula. (17)
Repeat k_scale using Formula. (8)
Calculate eta using Formula. (18)
   End if
End for
End procedure
```

The DEPO- LSTM cell is an effective structure using gate units to regulate the data flow, but it has the same outputs and inputs as a regular RNN cell. A present-time input of $w^{(s)}$ and an output of $g^{(s-1)}$ from the prior moment determine the weight of the self-loop cell status that the FG uses to refresh the memory cell.

$$E_j^{(s)} = \sigma\left(a_j^E + \sum_i V_{j,i}^E w_i^{(s)} + \sum_i X_{j,i}^E g_i^{(s-1)}\right) \quad (19)$$

Where,

σ - Sigmoid function,

X^E- RWs of the FG,

V^E- IWs of the FG, and

a^E- Respective biases of the FG.

The value that the FG sets in the range of 0 to 1. The data delivered into the memory cell is regulated by the IG.

$$J_i^{(s)} = \sigma\left(a_j^J + \sum_i V_{j,i}^J w_i^{(s)} + \sum_i X_{j,i}^J g_i^{(s-1)}\right) \quad (20)$$

Where,

X^J- RWs of the IG,

V^J- IWs of the IG, and

a^J- Respective biases of the IG.

Following that, the LSTM cell's internal condition is modified in the manner described below.

$$T_j^{(s)} = E_j^{(s)} T_j^{(s-1)} + J_j^{(s)} \tanh\left(a_j + \sum_i V_{j,i} w_i^{(s)} + \sum_i X_{j,i} g_i^{(s-1)}\right) \quad (21)$$

X- RWs into the LSTM cell,

V- IWs into the LSTM cell, and

a- Respective biases into the LSTM cell.

The weight of cell output is controlled by the OG,

$$P_j^{(s)} = \sigma\left(a_j^P + \sum_i V_{j,i}^P w_i^{(s)} + \sum_i X_{j,i}^P g_i^{(s-1)}\right) \quad (22)$$

Where,

X^P - RWs of the OG,

V^P - IWs of the OG, and

a^P - Respective biases of the OG.

Subsequently, the DEPO- LSTM cell's output is:

$$g_j^{(s)} = \tanh\left(T_j^{(s)}\right).P_j^{(s)} \quad (23)$$

Long-term dependencies can be acquired by DEPO-LSTMs using these gated units.

4 Result

The proposed DEPO-LSTM is evaluated through explorations that are performed on MatlabR2024a platform and the results of which are presented in the subsequent sections together with other relevant analysis. The efficiency of the proposed DEPO-LSTM method is confirmed using the original classification algorithms, such as GBDT [19], DT [19], and RF [19]. The effectiveness of ECT online monitoring should be measured using different metrics like recall, accuracy, precision, and F1-score. Table 2, displays the main parameters of DEPO.

Table 2: Main parameters of DEPO

Population size	50
Maximum iteration number	3000
Initial temperature	50
$\boldsymbol{\eta}$	0.05
Nonlinear adjustment factor	1.2
Annealing factor	0.85

The diagnostic outcomes of the proposed DEPO-LSTM method are displayed in Figure 2. It contrasts the expected and actual fault kinds. It provides a visual representation of the model's effectiveness, demonstrating how closely the expected values correspond to the actual fault incidents. This shows how accurate and dependable the model is at identifying faults.

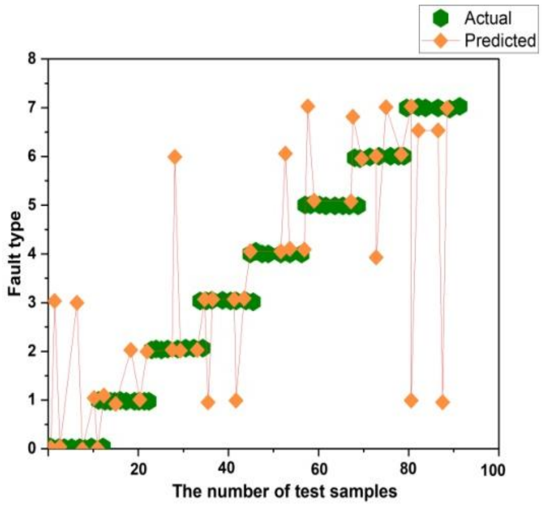

Figure 2: Fault diagnosis outcome of DEPO-LSTM

The recall calculates the percentage of actual transformer issuesthat the system was capable of identifying, to show its capability to recognize all the events of interest and ensure completemonitoring, and timely maintenance. The recallrates of the conventional GBDT, DT, and RF approaches are 94.25%, 91.93%, and 92.69%, respectively, while our proposed DEPO-LSTM method's recallrate of 97.42%, which is higher than the proposed approach, is shown in Figure3.

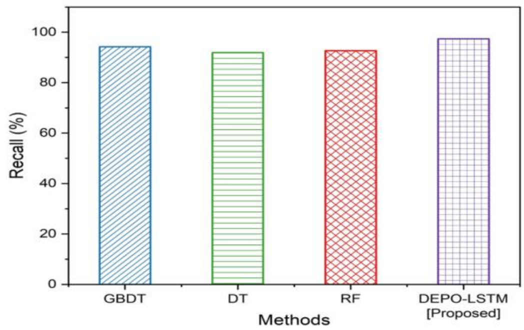

Figure 3: Result of recall

The precision evaluates how well the transformer’s status is identified as being in its functioning state. It determines the ratio of true positive outcomes to the total of false positives and true positives. The precision values of the traditional GBDT, DT, and RF techniques are 94.25%, 91.38%, and 92.53%, respectively, whereas the precision value of our proposed DEPO-LSTM method is 97.15%, which is displayed in Figure 4.

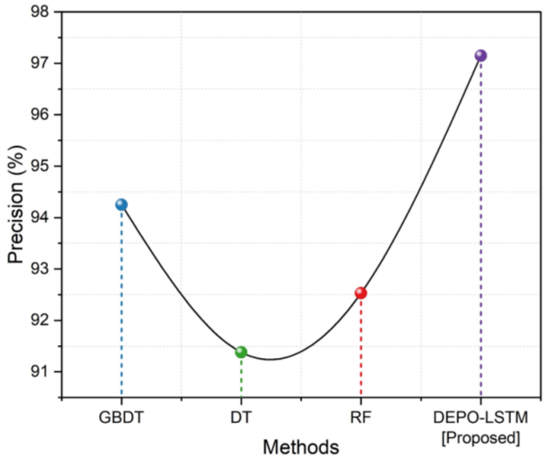

Figure 4: Output of precision

The F1-score metric measures the equilibrium of precision and recall when measuring efficacy, which is critical for determining both the accuracy of identifying online conditions and the system's dependability in real-time monitoring environments. In comparison to our proposed DEPO-LSTM strategy, traditional methods yield F1 scores for GBDT (94.25%), DT (91.65%), and RF (92.61%), whereas our proposed DEPO-LSTM method has a high F1 score of 96.36%, as shown in Figure 5.

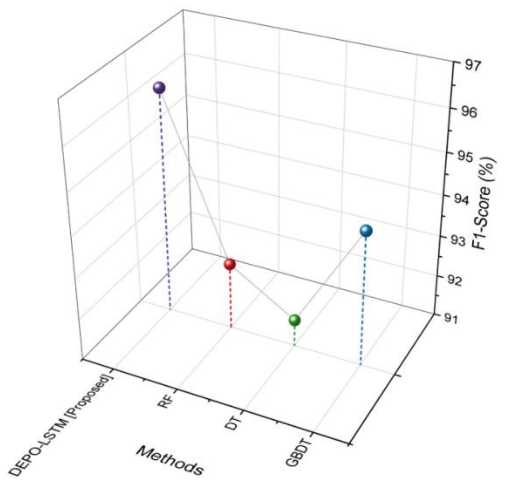

Figure 5: Result of F1-score

The accuracy represents the system's capacity to accurately determine the transformers' operating condition, guarantee the accuracy of real-time data, minimize false alarms, and improve predictive maintenance by precisely identifying anomalies and performance problems. Conventional approaches yield accuracy values for GBDT (93.18%), DT (89.83%), and RF (91.17%) compared to our proposed DEPO-LSTM strategy, which has a high accuracy value of 96.23%, as shown in Figure6. Table 3, shows the comparison results of DEPO-LSTM with traditional approaches.

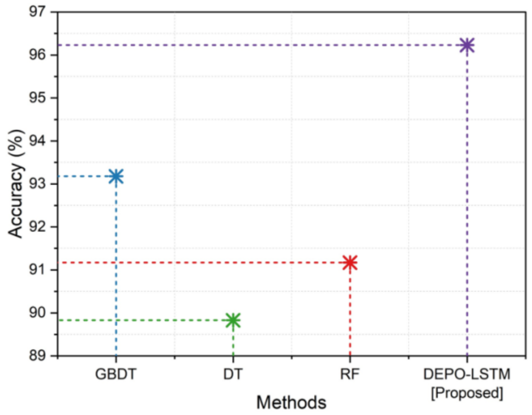

Figure 6: Output of accuracy

Table 3: Overall result comparison

Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
GBDT	93.18%	94.25%	94.25%	94.25%
DT	89.83%	91.38%	91.93%	91.65%
RF	91.17%	92.53%	92.69%	92.61%
DEPO-LSTM [Proposed]	96.23%	97.15%	97.42%	96.36%

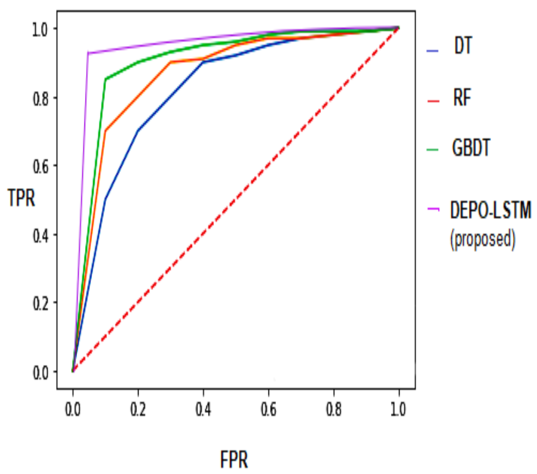

Figure 7: ROC Curve

Figure 7 shows a visual depiction of the model's performance over all thresholds is the ROC curve. The true positive rate (TPR) and false positive rate (FPR) are computed at each threshold (practically, at predetermined intervals), and the TPR is then graphed over the FPR to create the ROC curve. In the event that all other thresholds are disregarded, a perfect model, which at some threshold has a TPR of 1.0 and an FPR of 0.0, can be represented by either a point at (0, 1) The ROC is a helpful metric for evaluating the performance of distinct models, provided that the dataset is fairly balanced. In general, the better model is the one with a larger area under the curve. The suggested model [DEPO-LSTM] shows ROC curve has highest accuracy with 0.95.

5 Discussion

DEPO-LSTM can use the advantage of operators for enhancing predictive maintenance, as proposed by increased accuracy. When applied with a proactive approach to analyzing any problems or the degradation of functionality in ECT, the system optimizes the potential issues of downtime and ineffectiveness. DEPO-LSTM real time analysis means any anomalies such as the above occurrences are immediately identified and one can promptly act or perform maintenance, thus preventing possible equipment breakdowns or disruption of power transfer. This DEPO-LSTM is a great advancement to monitoring technologies in ECT; when used for efficient ECT condition monitoring in industries and power transmission it provides the stability required for constant sensitivity while at the same time provides the flexibility of LSTM networks. The DEPO-LSTM algorithm is evaluated in terms of precision (97.15%), recall (97.42%), accuracy (96.23%), and F1-score (96.36%). In ROC curve figure shows the suggested method has highest accuracy, precision, Recall than the other existing methods.

6 Conclusion

Ensuring the dependable functioning of ECT is crucial when it comes to electrical power systems. In this research, a novel DEPO-LSTM technique was introduced for efficient problem diagnostics in the ECT.The efficacy of the proposedDEPO-LSTM technique is assessed in terms of precision (97.15%), recall (97.42%), accuracy (96.23%), and F1-score (96.36%). DEPO-LSTM models can be very complicated and computationally demanding. This may render real-time monitoring difficult, particularly in circumstances with low computing power or resource constraints. Future developments in DEPO-LSTM models might concentrate on addressing complexity and improving viability for broad use in a variety of sectors, as well as maximizing computing effectiveness for real-time monitoring in environments with limited resources. In our future work of DEPO-LSTM model is to handle domains like sensor networks and the Internet of Things, which are sources of time-series data that DEPO-LSTM can collect, store, and process. Our next research will expand DEPO-LSTM to accommodate these data sources, which is feasible due to the adaptable and effective nature of the DEPO-LSTM model. By adding data collectors intended to gather data from additional devices that are present in the expanded domain, the primary changes in the data collection layer must be made. Additionally, a new set of aggregations should be built to extract the information for the consumers of data in this domain, based on the type of information contained in these data.

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Appendix

1D-CNN - One-dimensional convolutional neural network	EL-CSO-NN - Ensemble learning based criss-cross-optimized neural network
DGA - Dissolved gas analysis	IoT - Internet of Things
EML - Ensemble machine learning	OG – Output gate
PT-TNNet -Power Transformer-Transformer Neural Network	OIT - oil-immersed transformers
CNN - Conventional neural networks	GCA - Gray clustering algorithms
ML - Machine learning	BS - Best solution
E-E - Exploration to exploitation	SS - Search space
FG - Forget gate	RW - Recurrent weight
IW - Input weight	IG – Input gate