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Enhanced Deep Learning Approaches for Smart Monitoring Oil Validity in Power Transformer

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Abstract: Transformers are essential and costly elements in the transmission and distribution of electrical energy. Consequently, electrical utility companies must prioritize the monitoring of transformer conditions. Insulating oil is a crucial element in transformers, serving a significant function in heat transfer and overseeing the scheduled performance of the transformer. The oil ageing procedure can enhance transformer conditions and improve power grid reliability. The ageing of oil is mostly attributed to thermal forces. Mechanical forces induce chemical deterioration of the oil. Consequently, the oil's health may be verified through multiple assessments. Prior research has employed many methods to monitor transformers oil, including spectroscopy, color and acidity for oil, acidity measurement, current transformers, and dissolved gas analysis (DGA), followed by data classification utilizing machine learning and deep learning approaches. Nonetheless, precise fault detection in transformers continues to be a formidable challenge. This study presents an innovative method for transformer oil evaluation using intelligent monitoring through Fabry-Perot fiber interferometer (FPI) for transformer oil analysis. Machine learning techniques (Random Forest and Gaussian NB) and deep learning methods (1D-CNN and CNN-LSTM) were used in our experimental approach to improving the decision-making process regarding oil health. They included data pre-processing before using the classification model. The algorithms showed superior performance and higher data classification accuracy than previous experiments. Classification accuracy, precision, recall, F1-score, and specificity for transformer oil reached 100%.

Keywords: Fabry perot interferometer (FPI), Oil validity, Machine learning (ML), Deep learning (DL), Convolution neural network (CNN).

1. Introduction

The primary function of power transformers is to convert voltage levels in power transmission lines. They represent a highly crucial and costly component inside the electrical grid [1]. Consequently, utility companies must priority failure avoidance and maintain optimal operational conditions of their electrical networks. Ensuring these assets remain optimal and efficient is a primary objective for numerous electric companies worldwide [2]. Consequently, so as to improve the reliability of the electrical power transmission, it has become absolutely necessary to improve the efficiency of the transformer Therefore, the transformer needs constant maintenance and monitoring to be reliable and available. Numerous statistics indicate that insulation degradation is the primary cause of transformer failure [3]. Transformer oil plays a crucial function in several aspects of transformer performance, including insulation, iron formation prevention, heat transfer, corrosion protection for metal components, and prevention of moisture infiltration in the transformer chamber. The transformer insulation system, consisting of oil and paper, naturally deteriorates and loses its insulating qualities over time due to factors such as temperature, heat, moisture, and air exposure [4]. Consequently, the infiltration of moisture leads to an acceleration in the formation of X-wax (Chemical deposits in transformer oil) and an increase in the acidity characteristics of the oil. Moreover, increasing temperatures and thermal stress expedite the process of aging [5]. The acidity of oil degrades the insulating paper and accelerates the oxidation of transformer metal components. Particles resulting from the corrosion and oxidation of metals are mixed with oil. These particles diminish the insulating characteristics and hinder its effectiveness. A drop in the breakdown voltage, which in turn leads to an increase in the amount of partial discharge (PD), is caused by a rise in the amount of moisture that is absorbed by the oil [6]. In addition, the amount of moisture that is absorbed by the oil increases. There are several gases that are created during the process of breaking down insulating oil. These gases include hydrogen (H2), methane (CH4), ethane (C2H6), ethylene (C2H4), and acetylene (C2H2) [7]. The presence of these gasses is a sign that there are deficiencies in both thermal and electrical energy. Furthermore, the breakdown of insulation paper in the oil results in the production of carbon monoxide (CO) and carbon dioxide (COz) gases, both of which are suggestive of the likelihood of a thermal fault. Both of these gases are formed when the paper is broken down. The existence of these flaws in the transformer has the potential to significantly shorten its lifespan and put the dependability of the electrical grid at risk and threaten its reliability. Hence, it is crucial to continuously monitor the condition of the transformer by evaluating the state of the insulation system through transformer oil [5].

Several techniques exist for analysing transformer oil and assessing its quality, including using Dielectric Gas Analysis (DGA) to measure the aging of transformer oil [8] and the gas chromatography (GC) technology [9]. Furthermore, by the comprehensive examination of the oil's characteristics, it becomes possible to assess the quality of the oil and ascertain its aging process [10]. The influence of oil aging on these variables was examined. One of these factors is color, commonly employed as an indicator of deterioration potential. Extending the duration of oil operation leads to alterations in oil color and aging of the oil. Hence, it is possible to conduct some analysis by considering the color of the oil [11]. However, these and other techniques are very expensive and their test results do not provide an accurate interpretation later.

The analysis of transformer oil test findings is challenging due to the intricate structure and mechanisms underlying transformer degradation [5]. The technical analyst must be present during the diagnosis [12]. The correct decision-making is crucial since erroneous interpretation may lead to transformer damage, endangering workers, incurring substantial economic losses, and resulting in network shutdowns and service termination. Consequently, the exploration of artificial intelligence and its applications, which facilitate the storage of human experience and enable intelligent, automated interactions to assist novice analysts in making accurate conclusions, is warranted. Limited literature exists that examines the assessment of transformer oil quality using artificial intelligence. Researchers have examined the efficacy of artificial neural networks, Gaussian Naive Bayes [13], Decision Tree [8], Random Forest [14], LSTM [15], and other methodologies for evaluating transformer oil quality. These studies exhibit certain limitations, maybe resulting from either the Analysis Technology of the oil or the intelligence technology employed.

In this study, fiber optic infrared (FPI) technology was used as a temperature sensor, a technique used to investigate material composition and qualitative assessment. This technique involves decomposing the electromagnetic wave into its individual wavelengths and then emitting it by radiation on a medium. The determination of the content quantity can be achieved by evaluating the differences in the cross-wave, thus determining the specific properties and quantities of its components. Spectroscopy devices consist of two main components: a light source and a light detector [16]. It is a cost-effective methodology for analysing transformer oil qualities that requires less time than other monitoring methods. To assess the validity of transformer oil, machine learning algorithms (Random Forest, Gaussian NB) and deep learning techniques (1D-CNN, CNN-LSTM) were employed. The data underwent pre-processing, a crucial step that enhances predictive accuracy compared to the use of raw data, thereby distinguishing our methodology from prior approaches.

The main contributions to the suggested model include the following:

1. Gathering the dataset for the proposed system by acquiring samples of oil obtained from both aged and recently manufactured transformers. This collaboration was undertaken with the Diyala General Company for Electrical Industries and the Ministry of Electricity of Iraq. Following that, the oil samples underwent analysis at the Laser Institute for Postgraduate Studies Laboratory located at the University of Baghdad.

2. In this paper, a unique technique for oil state classification of power transformers is presented. The approach makes use of (ML) RF and Gaussian NB, (DL) 1D-CNN, and hybrid CNN-LSTM models. This study presents a method that is comprised of many pre-processing, crucial step that enhances predictive

accuracy compared to the use of raw data, thereby distinguishing our methodology from prior approaches. Stages that, when combined, lead to the achievement of a high degree of precision in the evaluation of the state of transformer oil.

The organization of this paper is as follows: A review of recent literature is given in Section 2, a proposed system architecture is presented in Section 3, experiments and analysis are shown in Section 4, and the study is concluded in Section 5.

2. Literature review

There are only a few articles in the literature that address the problem of transformer oil quality assessment through artificial intelligence and hence the use of machine learning and deep learning models for the purpose of transformer oil quality assessment has been the focus of recent research.

In 2020, D. Firouzimagham et al. [13], this study proposed and implemented a laboratory-based approach for online transformer analysis of oil using the spectroscopic methodology. Gaussian NB algorithm was implemented in the system results to classify the oil quality and achieve an accuracy of up to 92%. The drawbacks of the proposed oil analysis technique are that it relies on optical methods (light and transmission spectrum) and the spectral analysis device (light source and light detector); for oil analysis, it is very expensive to connect to each transformer.

In 2021, G. Odongo et al. [8] This work introduced a DGA method for transformer oil analysis, and KosaNet, a classification system based on decision trees, was utilised to interpret the findings. The accuracy of the suggested approach for assessing transformer oil was 99.9%. The drawback of this approach is that the accuracy and dependability of the observed gas concentrations are crucial to the DGA technique of correct fault identification in transformers using dissolved gas analysis. Apart from the expensive nature of the oil analysis apparatus.

In 2021, M. Senoussaoui et al. [14] The suggested method employed laboratory analysis of the oil based on its color and acidity. The results were interpreted using the J48 decision tree and random forest machine learning classifiers. Random forest demonstrated improved accuracy and performance with minimal data. The k-means method was used to preprocess the raw data before putting it into the classification model. This processing improved the classification performance of the used algorithms, especially the random forest, which reached an accuracy of 89%. One of the drawbacks of the used technique is that oil parameters usually affect each other. As the moisture content increases, the electrical strength of the insulating oil decreases. Although the oil to be filtered is better than the oil to be extracted according to most parameters (color, viscosity, acidity, and tgδ), this is not the case according to the comparison of their insulating strengths because the water content in the oil to be extracted is less than that in the oil to be filtered. In 2022, J. Ramesh et al. [15] This study proposed an IoT system for real-time monitoring of transformer oil based on a three-phase current transformer CT technique and oil levels/temperature. The LSTM algorithm was implemented to evaluate the oil, and it achieved an accuracy of 67%. The drawbacks of the proposed approach are the cost of the equipment used to conduct oil tests. Moreover, the results obtained are not satisfactory.

3. The proposed methodology

The proposed system comprises three stages: Data Collection, Pre-processing, and Classification, employing Machine Learning and Deep Learning approaches, as seen in Fig. 1. Initially, the stage of Building a dataset, the stage of Data processing that involves several operations: clean data using remove null, apply unsupervised learning using Sieve Diagram, supervised learning using label data, Exploratory Data Analysis (EDA) technique, remove outlier. Ultimately, these data are put into (Random Forest and Gaussian NB) Machine Learning and (1D-CNN and CNN-LSTM) deep learning approaches to categorize transformer oil as Good, Not Bad, Poor, or Very Poor.

3.1 Dataset collection stage

This stage has several steps. The following delineates these steps:

A. Transformer Oil Samples: The transformer oil samples were collected from both new and old transformers. This was done with the Diyala General Company for Electrical Industries and the Iraqi Ministry of Electricity. Five different samples were collected as shown in Fig. 2.

A refined oil lighter than the other oils is known as Sample 1. Sample 5 is a darker, more refined sample, while samples two to four are oils with a lower age than sample 5.

B. Preparing the experimental environment: This environment was prepared in the Laser Institute for Postgraduate Studies laboratory at the University of Baghdad. Fig. 3 shows the experimental environment inside the laboratory and the experimental

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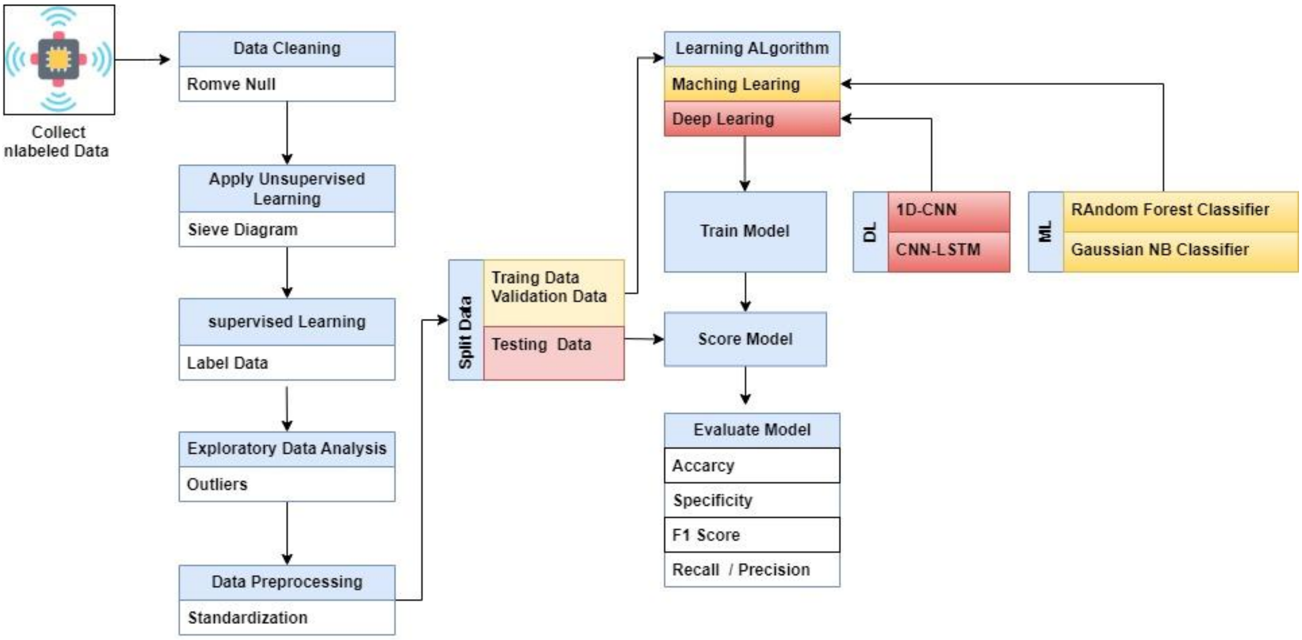

Figure. 1 The Proposed System

Figure. 2 Transformer oil samples

configuration of the FPI sensor through FBG-PCF-FBG, where the fabrication procedure was conducted using the Fujikura type FSM-60S fusion splicing machine, a small length of PCF was prepared and fused with a 30 cm length of SMF-28s and connected between two identical FBG.

The source Broad Band Spectrum has an optical spectrum that spans from 1450 nm to 1650 nm. The integrated circuit (IC) chipset is the most critical component of the BBS, which generates the optical spectrum. Its maximal optical power is 31.2 mW. The optical signal that was emitted was supplied with the necessary power by the laser diode controller (LCD).

The emitted wavelengths and output power were regulated by temperature electrical control (TEC). The oil chamber to preserve oil samples during analysis. An optical spectrum analyzer (OSA) is a device designed to measure and show the power distribution of an optical source throughout a specific wavelength range.

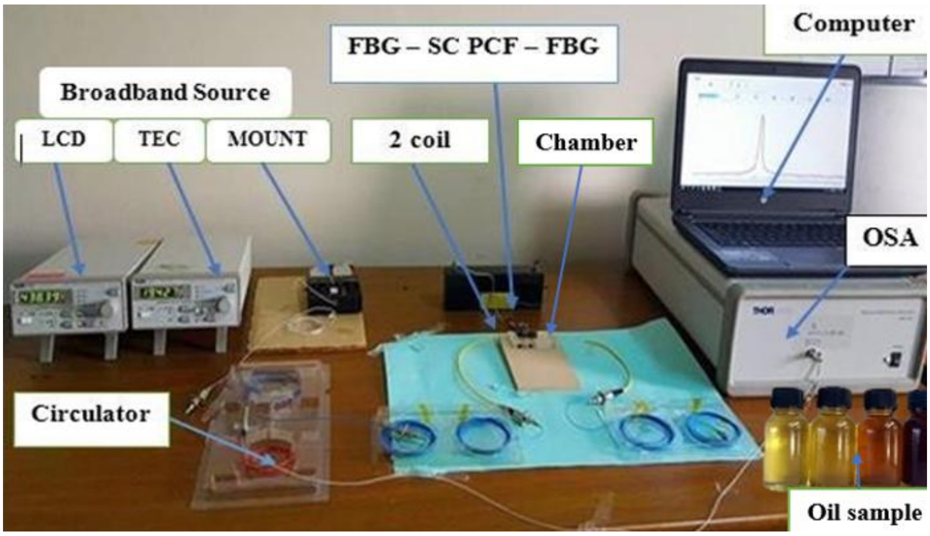

Figure. 3 Experimental setup in the lab

C. Testing Process:

A sample of transformer oil is placed in the chamber, and the device is initiated, where samples are examined by introducing a small amount into the chamber and transmitting the spectrum from a broadband source to an FPI-based FBG sensor. The temperature of the two coils shifts the wavelength. This information is transmitted to a computer or smartphone software via a wireless connection. An optical spectrum analyzer (OSA) measures the intensity of reflected light as it passes through an oil sample. The data on light intensity is graphically displayed on the PC. As the temperature increased to degrees Celsius, the interference pattern of FPI caused the center wavelength to shift toward a longer wavelength (red shift). The proposed sensor achieved a sensitivity of approximately 18 pm/°C within the temperature range of 25 to 60 °C, as the wavelengths λB1, λB2, and λR share the same operating wavelength λc. In contrast, the thermal expansion coefficients of PCF and FBG are equivalent, which leads to a similar temperature sensitivity between λB and λR. The oil is illuminated with the entire broadband spectrum centred at 1549 nm.The light sensor detects the spectrum after it has passed through the oil, as the light passing through the oil causes changes in amplitude in certain parts of the initial light spectrum. Fig. 4 illustrates the light-passing characteristics in the BBS for each oil sample. The oil samples of varying ages exhibit a variation in the spectrum traveling through them. The light intensity is conveyed more in No. 1 oil sample, which has the lowest levels of contamination, than in the other oils Nevertheless, oil No. 5, which contains the highest levels of contamination, exhibits the lowest level of light intensity. The oils 2 to 4 exhibit identical light passage as a result of their high degree of similarity in operation and aging. The system then measures these changes to display the oil's characteristics, and the OSA records these changes in the form of a file. These changes are the database used in the subsequent stages that will be described in section 4.

3.2 Data pre-processing stage

Data pre-processing is an initial step that prepares raw data for analysis. Analytics tools may yield inaccurate results and mislead if the data contains impurities such as missing data or outliers. Hence, it is imperative to enhance the data quality before conducting any analysis. The following steps demonstrate the data preparation conducted for this study.

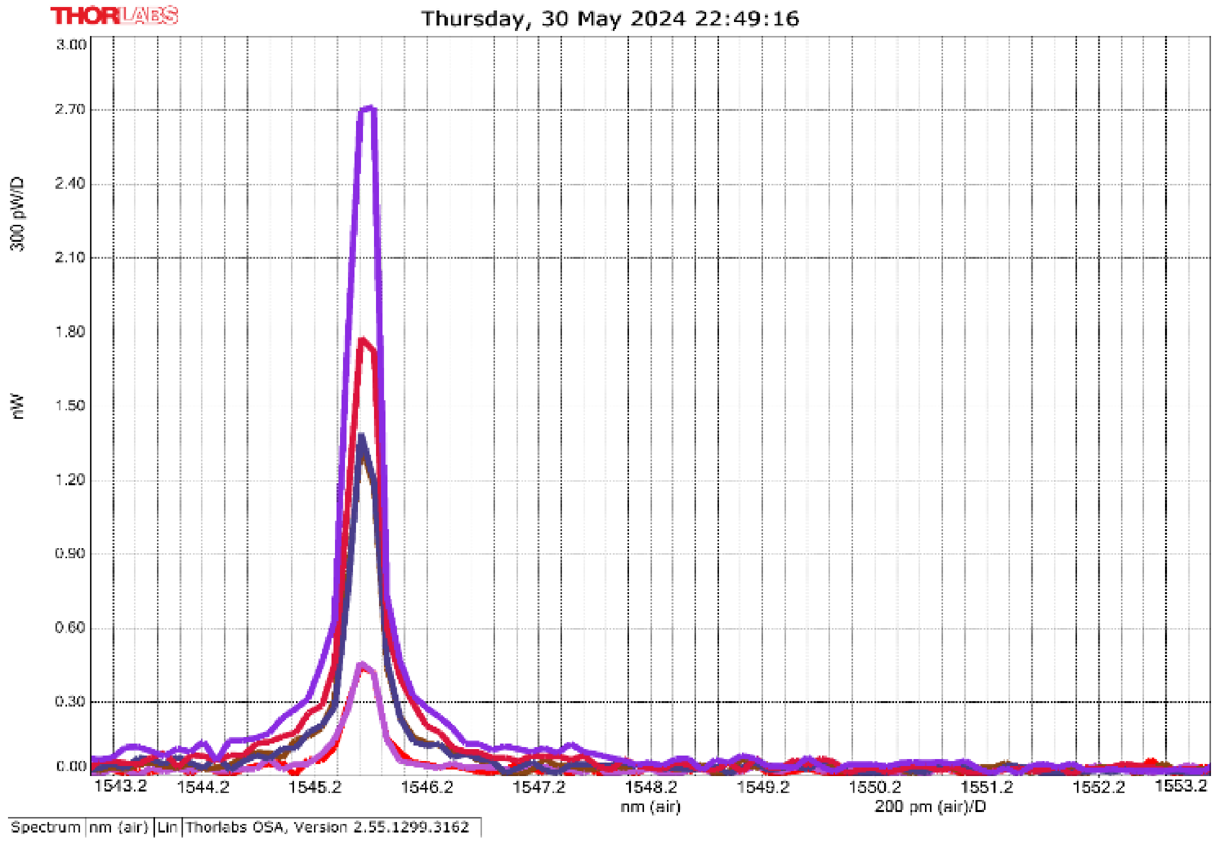

Figure. 4 Reflection Spectrum when the light passing oil sample at different temperature

A. Data Cleaning:

In many datasets, data values are not recorded for all attributes because some attributes do not apply to some cases. This causes missing values. These missing values negatively affect the performance of the classifier created using the dataset as a training sample. For this reason, all records were inspected, and null values were removed.

B. Unsupervised learning (Sieve Diagram):

Sieve diagrams are useful for visualizing the separation or classification of data according to specific conditions or thresholds in data analysis. A sieve diagram shows the number of data points that remain after each layer of filtering, giving insight into the structure of the data and the impact of the applied filters. In this study, the database was filtered using the following logical conditions:

If temperature for transformer oil > o and ≤ 25 is labelled "Good".
If temperature for transformer oil > 25 and ≤ 50 is labelled "Not bad".
If temperature for transformer oil > 50 and ≤ 75 is labelled "Poor".
If temperature for transformer oil > 75 and ≤ 100 is labelled "Very poor".

In this step, the dataset was converted from unsupervised to supervised data.

C. Supervised learning (Data labelling):

For each class in the training dataset, the suggested system applied a Label encoder library in Python to convert the labels into a numeric form learning-readable form. Fig. 5 shows that each class will be assigned a unique code number.

D. Exploratory Data Analysis (EDA):

It involves detecting and removing outliers from the input dataset to enhance data comprehension and optimize classification model performance. Data outliers can be detected by checking if the data points are beyond the range of Eq. (1):

$$Q1 - 1.5(Q3 - Q1) \& \; Q3 + 1.5(Q3 - Q1) \quad (1)$$

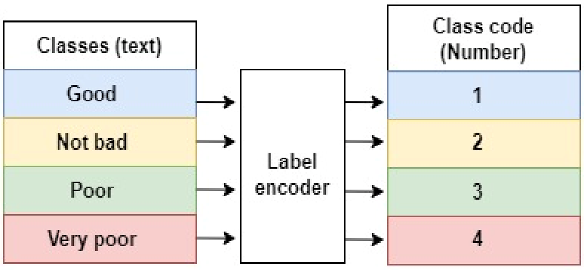

Figure. 5 The label encoding used in classification systems

where Q1 and Q3 represent the first and third quartiles of the data, respectively [17]. Determine quartiles (IQR) by Eq. (2).

$$IQR = Q3 - Q1 \quad (2)$$

(IQR): Values that partition an array of numbers into quarters, specifically between the first and third quartiles.

Determine lowest and upper ranges by Eqs. (3) and (4)

$$Lower\ range = Q1 - (1.5 * IQR) \quad (3)$$

$$Upper\ range = Q3 + (1.5 * IQR) \quad (4)$$

Update the values in the dataset so that the new value is equal to the lower range if the value is less than the lower range. The new value is equal to the higher range if the value is greater than the upper range.

E. Feature Normalization:

Machine learning and deep learning-based classification algorithms are sensitive to variations in feature scales, which could impair the suggested system's performance. The proposed model uses the "Min-Max" scaling technique to normalize the data. Where all values lie between 0 and 1 by applying the following Eq. (5) [17].

$$Z' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (5)$$

Where Z' is the normalized value, x is the original feature value, $\max(x)$ and $\min(x)$ are the maximum and minimum feature values.

3.3 Classification model stage

During this stage, the suggested system will divide the dataset into three parts: 70% for training, 20% for validation, and 10% for testing. The testing set evaluates the system's performance on unlabelled data, while the training set trains the model. The validation data set examines the model's performance during the training phase. It is utilized to improve the model's parameters and select the most efficient model. The suggested system employed two approaches to classify the condition of the transformer oil, categorizing it as either Good, Not bad, Poor, or Very poor. Machine learning algorithms and deep learning algorithms.

- **Classification Model based on ML approaches**
- **Random Forest**

RF is an ensemble approach based on many decision trees and bagging (also known as Bootstrap aggregation) techniques. Bagging demands training each decision tree on a part of the whole dataset. Each tree gets its classification, and finally, it is done using majority voting on the decision tree results. The random forest has two critical parameters: n-estimators, which define the number of trees in the forest, and training data. In this work, there were 150 trees in the forest. The random forest is constructed in two steps. First, the algorithm randomly chooses “k” features from a total of m features. Then, the test features and the rules of each randomly generated decision tree are used to predict the outcome, making predictions using the trained random forest method. After storing the projected outcome, computing the votes for each predicted target. Finally, the RF algorithm’s ultimate forecast should be the highly-voted predicted target [18].

- **Gaussian Naïve Bayes**

This classifier is predicated on the premise that the variables associated with the predictor are conditionally independent with respect to the category of the data sample being considered. It is necessary to compute both the predictor prior probability and the class prior probability to ascertain the likelihood of the predictor variable about the class. The posterior probability calculated to be the highest across all classes is utilized to classify the samples [18].

- **Classification Model based on DL approaches**
- **1D-CNN**

Fig. 6 Shows that the proposed algorithm consists of five layers, showing the number and size of filters, the Activation function used, the number of units in the dense layer and, other details.

- **CNN-LSTM**

Fig. 7 Shows that the proposed algorithm consists of five layers, showing the number and size of filters, the Activation function used, the number of units in the dense layer and, other details.

In 1D-CNN and CNN-LSTM algorithms compiling the model using the (CE) loss function, “Adam” optimizer to provide improved optimization for noisy data. The selected initial learning rate is 0.001. Training the models approach with 100 epochs on the “training” and “validation” partitions (70% and 20% respectively of the dataset). Testing the approaches on the “testing” partition (10% remaining dataset) and achieving the needed results concerning many metrics of evaluation (“accuracy”, “precision”, “recall”, and “F-score”). These results will help us evaluate the performance of the model.

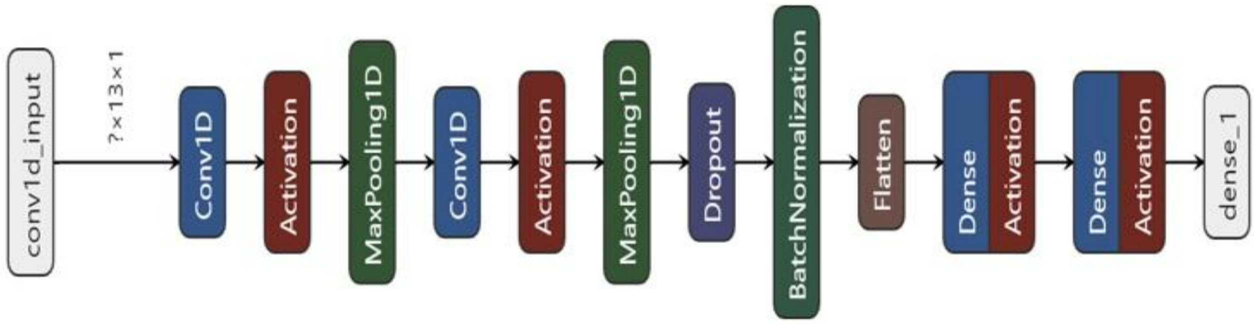

Figure. 6 The architecture of the1D- CNN

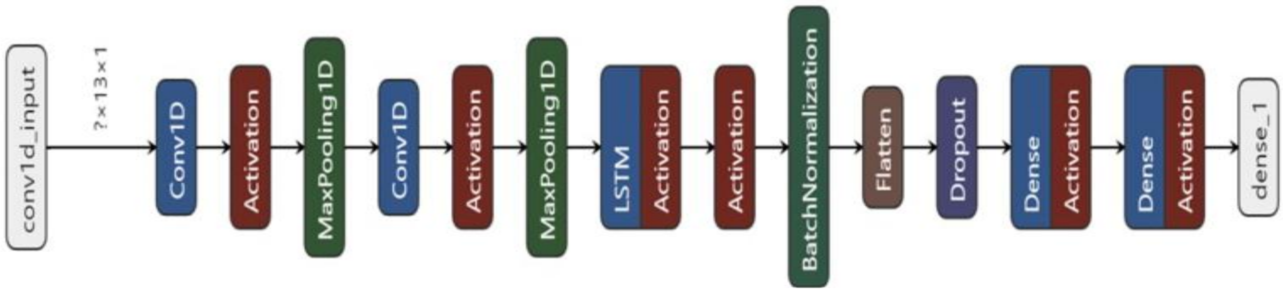

Figure. 7 The architecture of the CNN-LSTM

4. Experimental results

4.1 Results of dataset collection

The dataset comprises 805 records and 13 attributes (Temperature, Centroid Wavelength, Peak Wavelength, Peak Level, FWHM, Peak Position, Offset Peak Position, Wavelength, Offset Wavelength, Level, Offset Level, Noise, and OSNR). Figs. 8 and 9 illustrates some feature with its frequency, with the X-axis representing the feature and the Y-axis denoting its frequency within the database. Table 1 shows three samples in the dataset.

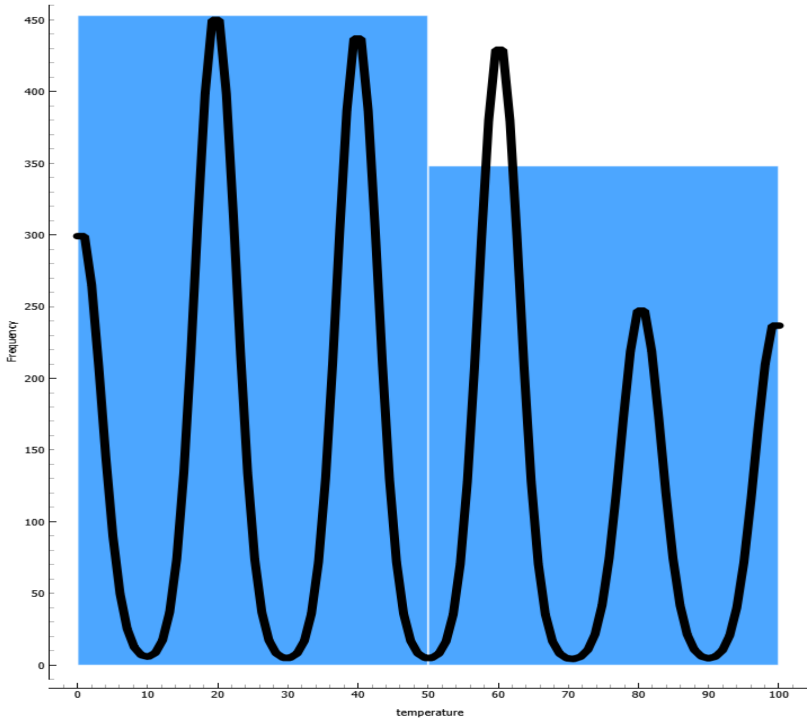

Figure. 8 Temperature and Frequencies with dataset

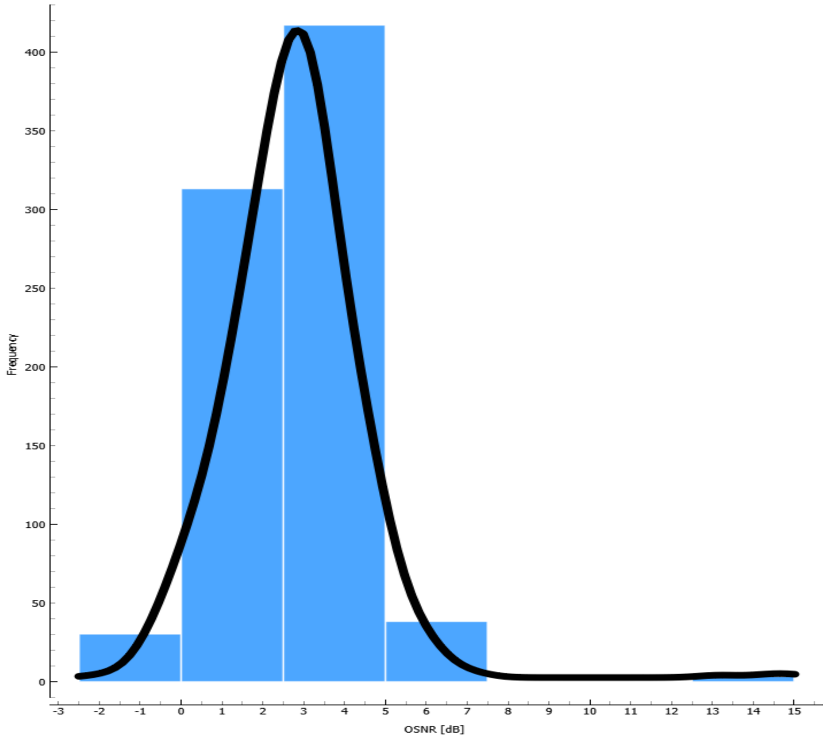

Figure. 9 OSNR and Frequencies with dataset

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Table 1. Samples of Dataset

OSNR [dB]	3.53309035301208	3.63274908065796	0.709992229938507
Noise [dBm]	-75.0206680297852	-75.8684844970703	-76.5626983642578
Offset Level [dB]	1.16278076171875	0.705162048339844	-2.29535675048828
Level [dBm]	-72.3006362915039	-72.7860717773438	-76.3928298950195
Offset Wavelength [nm (air)]	0.639206213425723	0.811473802464207	28.7389434906679
Wavelength [nm (air)]	1455.17521150117	1455.3318616663	1483.2750239796
Offset Peak Position [nm (air)]	0.6221923828125	0.8297119140625	28.8553466796875
Peak Position [nm (air)]	0.6221923828125	0.311279296875	0.646484375
FWHM [pm (air)]	142.688495126549	104.057762936918	300.38168828878
Peak Level [nW]	0.0588757664843342	0.052649340887001	0.037900960592196
Peak Wavelength [nm (air)]	1455.22338867188	1455.32836914063	1483.35546875
Centroid Wavelength [nm (air)]	1455.17521150117	1455.3318616663	1483.2750239796
Temperature	20	40	60
No. record	1	2	3

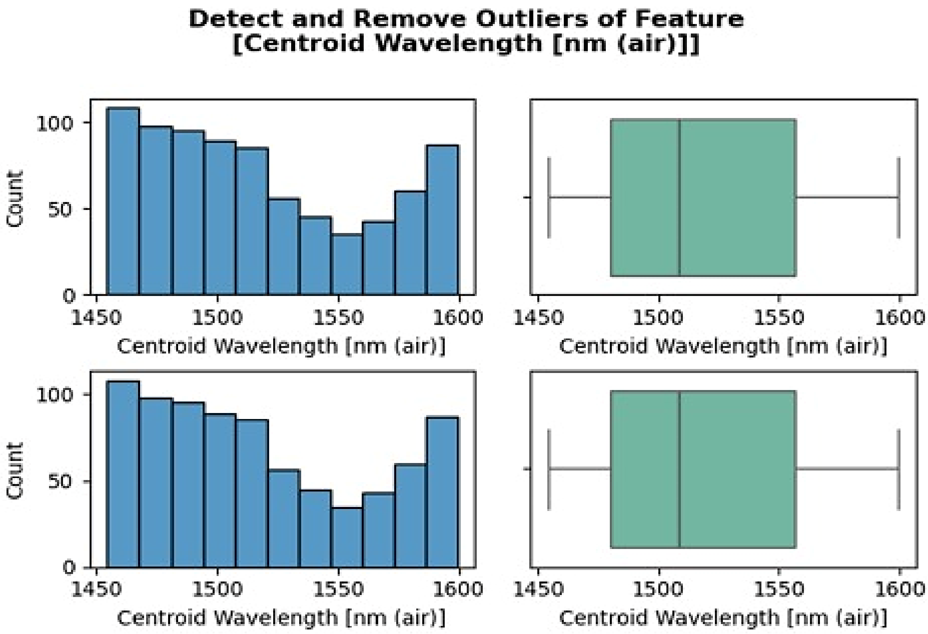

Figure. 10 Detect and Remove Outliers in the dataset

4.2 Results of dataset pre-processing

The dataset initially had four entries with missing values, which resulted in a total of 805 records. After using the Data cleaning procedure, the total number of records decreased to 801.

The dataset initially consists of 13 attributes. After applying the Sieve Diagram operation, one additional class attribute is included, resulting in 14 attributes. The classification attribute was done with four samples (Good, Not Bad, Poor, and Very Poor).

Following the addition of the attribute "class" to the database in the previous phase, these classes were encoded as 1 refers to the class labeled as "Good", 2 refers to the class labeled as "Not Bad", 3 corresponds to the class labeled as "Poor", and 4 refers to the class labeled as "Very Poor".

The proposed model utilized Exploratory Data Analysis (EDA) to identify and eliminate outliers in the dataset. The procedure for identifying and eliminating outliers from the dataset for features is shown in Fig. 10. It shows a series of plots showing the distribution of the feature's outlier detection procedure. Two plots in the upper section show the data before the outliers were eliminated. Conversely, the data is depicted in the lower part's charts after eliminating the outliers. (in the upper left corner) Shows the histogram distribution of the feature (Centroid Wavelength [nm (air)]], where the x-axis represents the centroid wavelength and the y-axis shows the frequency of the data points. We notice an uneven distribution with a relatively higher concentration at the edges, while Box plot (in the upper right corner) summarizes the feature's

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distribution by showing the median, quartiles, and possible outliers. The line inside the box refers the median, the box represents the (IQR), and the whiskers extend to 1.5 times the IQR. Now that the outliers have been removed, graphs (in the lower left corner) and (in the lower right corner) show that there is a slight decrease in the number of data points, especially in the tails, indicating a more balanced distribution of the data, which appears more central and less skewed.

4.3 Results of classification system

The proposed method for categorizing the conditions of transformer oil employs (ML) and (DL) algorithms. The outcomes of each model are individually displayed in the following:

- **Results Based on Machine Learning:**

The first approach to classifying transformer oil condition is ML based on (Random Forest and Gaussian NB) algorithms. Tables 2 and 3 show the values of accuracy, precision ‹recall, F1, and Specificity measures used as metrics to evaluate the performance of the methods implemented.

These metrics depend on four important Factors: True Negatives “TN”, True Positives “TP”, False Negatives “FN”, and False Positives “FP” for training and testing to classify transformer oil conditions.

Figs. 11 and 12 demonstrate the confusion matrices concerning testing sets in Random Forest and Gaussian NB algorithms.

Table 2. Results of ML algorithms for Training set

Random Forest Classifier									
Class Name	"TP"	"TN"	"FP"	"FN"	“Accuracy”	“precision”	“Recall”	“F1-score”	“Specificity”
Class1	195	365	0	0	1	1	1	1	1
Class2	122	438	0	0	1	1	1	1	1
Class3	116	444	0	0	1	1	1	1	1
Class4	127	433	0	0	1	1	1	1	1
Average	140	420	0	0	1	1	1	1	1
Gaussian NB Classifier									
Class Name	"TP"	"TN"	"FP"	"FN"	“Accuracy”	“precision”	“Recall”	“F1-score”	“Specificity”
Class1	195	362	3	0	0.99464285	0.984848	1	0.992366	1
Class2	121	438	0	1	0.99821428	1	0.991803	0.995885	0.991803
Class3	115	444	0	1	0.99821428	1	0.991379	0.995671	0.991379
Class4	126	433	0	1	0.99821428	1	0.992126	0.996047	0.992126
Average	139.2	419.2	0.75	0.75	0.99732142	0.996212	0.993827	0.994992	0.993827

Table 3. Results of ML algorithms for Testing set

Random Forest Classifier									
Class Name	"TP"	"TN"	"FP"	"FN"	“Accuracy”	“precision”	“Recall”	“F1-score”	“Specificity”
Class1	91	150	0	0	1	1	1	1	1
Class2	45	196	0	0	1	1	1	1	1
Class3	48	193	0	0	1	1	1	1	1
Class4	57	184	0	0	1	1	1	1	1
Average	60.25	180.75	0	0	1	1	1	1	1
Gaussian NB Classifier									
Class Name	"TP"	"TN"	"FP"	"FN"	“Accuracy”	“precision”	“Recall”	“F1-score”	“Specificity”
Class1	91	150	0	0	1	1	1	1	1
Class2	45	196	0	0	1	1	1	1	1
Class3	48	193	0	0	1	1	1	1	1
Class4	57	184	0	0	1	1	1	1	1
Average	60.25	180.75	0	0	1	1	1	1	1

Figure. 11 The confusion matrixes of the implemented Random Forest

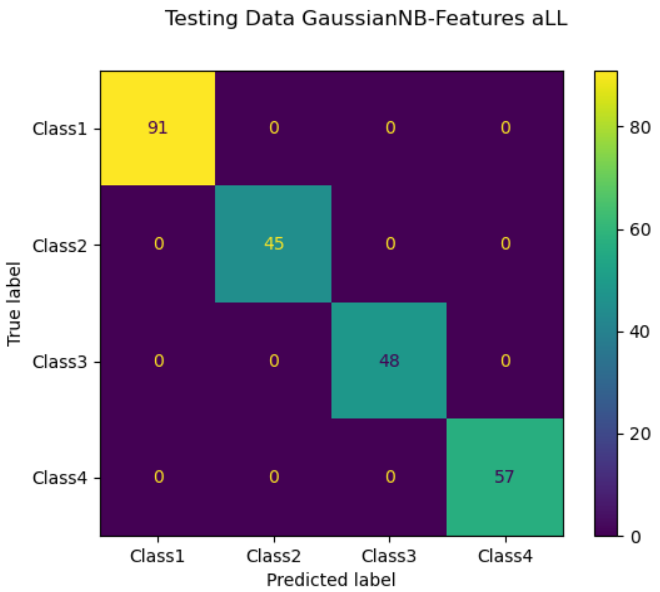

Figure. 12 The confusion matrixes of the implemented Gaussian NB

- **Results Based on Deep Learning:**

The second approach to classifying transformer oil conditions is DL based on (1D-CNN and hybrid CNN-LSTM) algorithms. Figs. 13 to 16 display the accuracy and loss of the implemented (1D-CNN) and (CNN-LSTM) models on the training and validation of the dataset for each epoch. The loss function descends to the down, while the accuracy goes from the down to the up.

Within 1D-CNN with 100 epochs, the training accuracy score attains approximately 0.99, and the validation accuracy score reaches 1.00, as illustrated in Fig. 13. This implies that during the training and validation process, the CNN classified the data in an efficient and accurate manner. Fig. 14 shows that the validation loss is 0.00084, and the training loss value is around 0. 01315.shows how effectively the model generalises and keeps its error level low when used with unknown data. As shown in Fig. 15, the training accuracy score in CNN-LSTM with 100 epochs is roughly 1.00, whereas the validation accuracy score is 0.99. This suggests that the model accurately and efficiently classified the data during the training and validation phases.

According to Fig. 16, the training loss value is approximately 0.00023, and the validation loss is

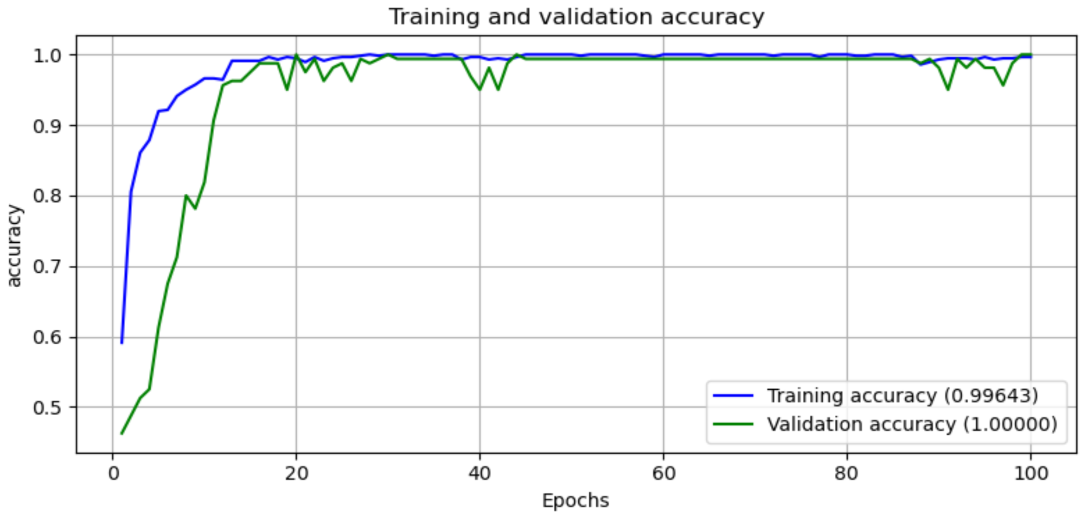

Figure. 13 The accuracy of the implemented 1D-CNN models on the training and validation dataset for each epoch

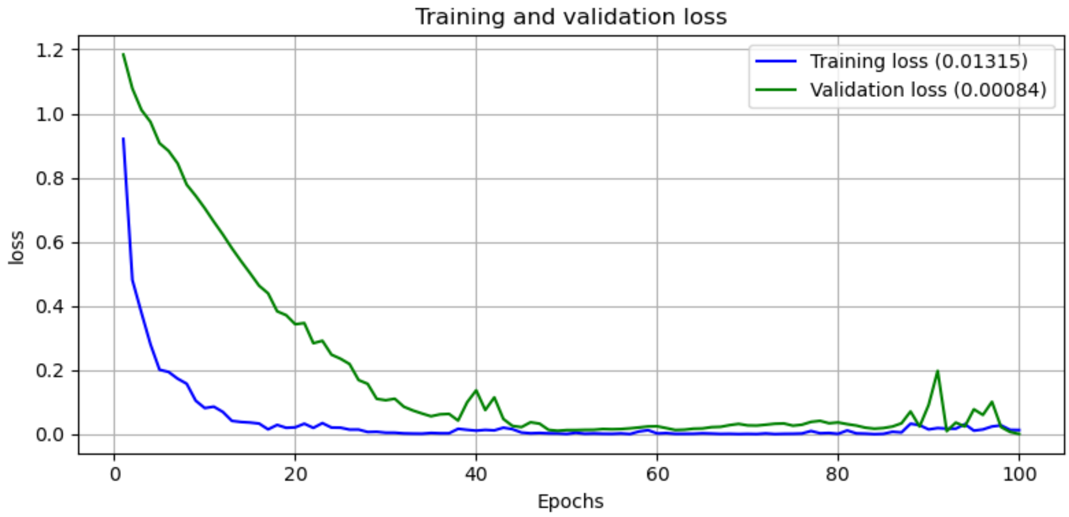

Figure. 14 The loss of the implemented 1D-CNN models on the training and validation dataset for each epoch

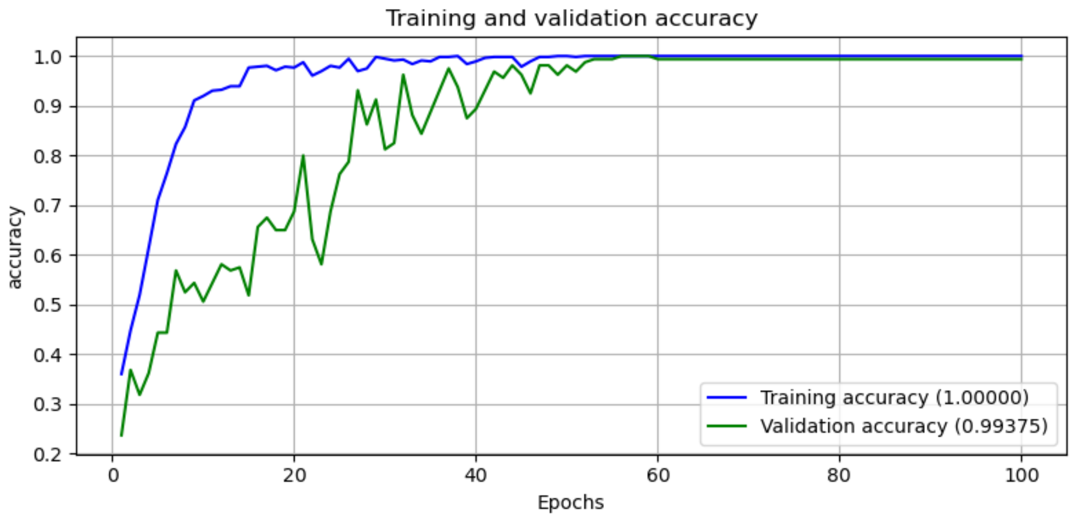

Figure. 15 The accuracy of the implemented CNN-LSTM models on the training and validation dataset for each epoch

Figure. 16 The loss of the implemented CNN-LSTM models on the training and validation dataset for each epoch

0.01174. Demonstrates how well the model generalises and maintains a low error level when applied to unknown data.

These curves illustrate the system's capability to generalize to new data compared to the training data set.

Tables 4 and 5 show the values of accuracy, precision ‹recall, F1, and Specificity measures used as metrics to evaluate the performance of the methods implemented depending on values: True Negatives "TN", True Positives "TP", False Negatives "FN", and False Positives "FP" for training and testing based on 1D-CNN and CNN-LSTM algorithms performed on the dataset to classify transformer oil condition.

Figs. 17 and 18 demonstrate the confusion matrix concerning the testing sets in CNN and CNN-LSTM algorithms.

From the previous tables, the proposed classification methods achieved ideal results in "accuracy", "precision", "recall," and "F1 score" measures during the training and testing phases. The machine learning and deep learning algorithms achieved ideal results of up to 100%, except for the Gaussian NB algorithm, which achieved (0.997, 0.996, 0.993,0.994, and 0.993) results, respectively, in the accuracy measures in the training set. The algorithm's performance improved to reach 100% in the testing process.

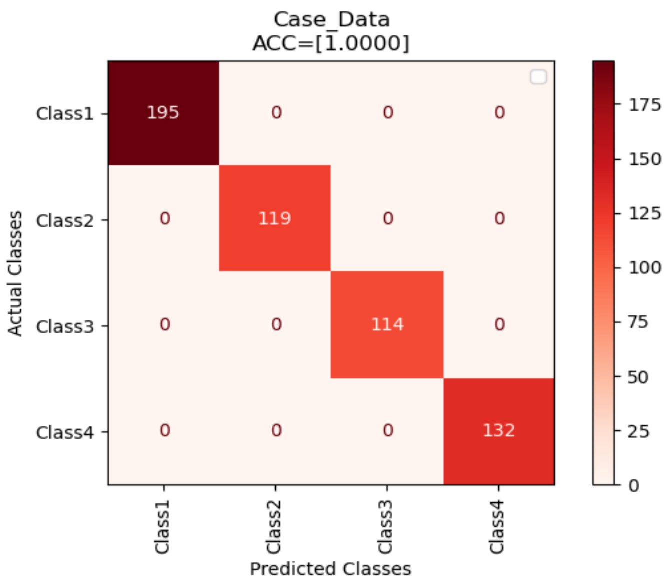

Figure. 17 The confusion matrixes of the implemented 1D-CNN

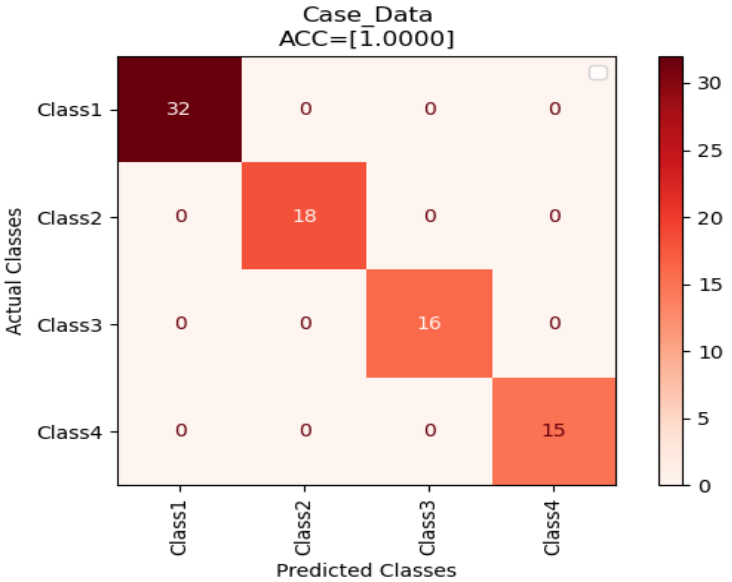

Figure. 18 The confusion matrixes of the implemented CNN-LSTM

Table 4. Results of DL algorithms for Training set

1D-CNN									
Class Name	"TP"	"TN"	"FP"	"FN"	"Accuracy"	"precision"	"Recall"	"F1-score"	"Specificity"
Class1	204	356	0	0	1	1	1	1	1
Class2	116	444	0	0	1	1	1	1	1
Class3	106	454	0	0	1	1	1	1	1
Class4	134	426	0	0	1	1	1	1	1
Average	140	420	0	0	1	1	1	1	1
CNN-LSTM									
Class Name	"TP"	"TN"	"FP"	"FN"	"Accuracy"	"precision"	"Recall"	"F1-score"	"Specificity"
Class1	195	365	0	0	1	1	1	1	1
Class2	119	441	0	0	1	1	1	1	1
Class3	114	446	0	0	1	1	1	1	1
Class4	132	428	0	0	1	1	1	1	1
Average	140	420	0	0	1	1	1	1	1

Table 5. Results of DL algorithms for Testing set

1D-CNN									
Class Name	"TP"	"TN"	"FP"	"FN"	"Accuracy"	"precision"	"Recall"	"F1-score"	"Specificity"
Class1	29	52	0	0	1	1	1	1	1
Class2	9	72	0	0	1	1	1	1	1
Class3	18	63	0	0	1	1	1	1	1
Class4	25	56	0	0	1	1	1	1	1
Average	20.25	60.75	0	0	1	1	1	1	1
CNN-LSTM									
Class Name	"TP"	"TN"	"FP"	"FN"	"Accuracy"	"precision"	"Recall"	"F1-score"	"Specificity"
Class1	32	49	0	0	1	1	1	1	1
Class2	18	63	0	0	1	1	1	1	1
Class3	16	65	0	0	1	1	1	1	1
Class4	15	66	0	0	1	1	1	1	1
Average	20.25	60.75	0	0	1	1	1	1	1

Table 6. A comparison between the suggested approach and earlier research using transformer oil as a database

Year	Ref.	Classify Method	Monitoring technique (Transformer oil analysis)	Accuracy
2020	[13]	Gaussian NB	Spectroscopy technique	92%
2021	[8]	Decision tree	DGA	99.9%
2021	[14]	Random Forest (RF)	Oil color and acidity.	89%
2022	[15]	LSTM	CT	97%
2024	**Our study**	RF, Gaussian NB, 1D-CNN, CNN-LSTM	FPI	100%

The machine learning and deep learning algorithms achieved 100% accuracy metrics in the testing set, which indicates the effectiveness of the proposed system in accurately classifying transformer oil conditions and implementing suitable measures for each condition. This ultimately prolongs the lifespan of transformers, reduces failures, and saves time, effort, and cost. Many research studies have focused on classifying transformer oil using different methods and techniques in the past years. The comparison is based on qualitative measures, such as transformer oil laboratory analysis technique, classification methods and accuracy value. The comparison is shown in Table 6.

Table 6 compares the efficacy of machine learning and deep learning algorithms from prior studies with the proposed approach. This comparison relies on the outcomes derived from each method. This investigation aims to identify the method for analysing transformer oil and the algorithm that yielded the most accurate classification results for differentiating various oil ageing processes. The FPI approach employed for analyzing oil qualities, despite its simplicity and low cost, demonstrated exceptional performance in oil classification methods using machine learning (RF and Gaussian NB) and deep learning (1D-CNN and CNN-LSTM) algorithms, achieving an accuracy value of 100%. Consequently, the suggested model is deemed the most appropriate and efficient for identifying transformer oil degradation and forecasting failures.

Before their manifestation in a real-world setting, thereby conserving effort, time, and resources.

5. Conclusion

Power transformers are typically essential and costly in power transmission and distribution networks. The annual failure rate of power transformers, at 3% per unit, incurs substantial financial losses. Failures are chiefly ascribed to substantial insulating oil spills, leading to significant supply disruptions.

The research initiative aims to create a precise and cost-effective model for oil safety evaluation in power transformers, utilising defect monitoring and transformer oil quality assessment via the FPI technique. This method is characterised by low cost and rapid response, analysing the oil's properties based on temperature and light reflection spectrum through the insulating oil, with a maximum temperature of 70 °C. The proposed model initially analysed the input data, then preprocessed the raw data to optimise the efficacy of the proposed algorithms. The preprocessing involved several steps: cleansing data by removing null values, applying unsupervised learning via Sieve Diagram, employing supervised learning with labelled data, utilising Exploratory Data Analysis (EDA) techniques, and eliminating outliers. Ultimately, this data is utilised in Machine Learning techniques (Random Forest and Gaussian Naive Bayes) and deep learning methodologies (1D-CNN and CNN-LSTM) to classify transformer oil as Good, Not Bad, Poor, or Very Poor. This preprocessing had the most significant effect on the classification and identification of oil ageing. The proposed ML (RF and Gaussian NB) and DL (1D-CNN and CNN-LSTM) models were assessed and attained a classification accuracy of 100%, surpassing other established approaches. Future study will concentrate on the strategy and execution of sophisticated, dependable, and secure IoT architecture utilising AI for the online monitoring and regulation of oil conditions in transformers employed in distribution.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Faraqid Q. Mohammed and Yassine AYDI; methodology, Faraqid Q. Mohammed; software, Faraqid Q. Mohammed; validation, Yassine AYDI, and Mohamed Abid; formal analysis, Faraqid Q. Mohammed;

investigation, Mohamed Abid; resources, Faraqid Q. Mohammed; data curation, Yassine AYDI; writing—original draft preparation, Yassine AYDI and Mohamed Abid; writing—review and editing, Faraqid Q. Mohammed; visualization, Faraqid Q. Mohammed and Mohamed Abid; supervision, Faraqid Q. Mohammed; project administration, Faraqid Q. Mohammed; funding acquisition, Yassine AYDI.

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