Dhananjay Jha et al. | Acta Energetica 2/48 (2024) | 59–70

Received: 16 February 2024; Revised: 22 April 2024; Accepted: 16 May 2024

ActaEnergetica
POWER ENGINEERING QUARTERLY

AI-Enabled Predictive Maintenance for Distribution Transformers

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KEYWORDS
Predictive Maintenance, Distribution Transformers, Artificial Intelligence, Machine Learning, Reliability

Abstract

Power distribution networks depend on distribution transformers to work well, which makes sure that there is a steady flow of energy. But these transformers can fail in a number of ways, which can cause expensive downtime and service interruptions. Traditional methods of maintenance, like regular checks and preventative maintenance, aren't always effective and can cost more than they need to. In recent years, there has been a rise in interest in using machine learning (ML) and artificial intelligence (AI) to plan ahead for repair on power transformers. AI-powered predictive maintenance systems can look at both old and new data from transformers to find patterns and trends that could mean they are about to break down or malfunction. It is possible to improve upkeep tasks and lower the risk of unexpected downtime by predicting these problems before they happen. This paper gives a full picture of predicted maintenance for distribution transformers that use AI. It talks about the main problems with standard care methods and shows why using AI-driven methods is better. The study also talks about current AI-based forecast maintenance methods, such as preparing data, choosing features, and training models. In addition, it looks into the possibility of combining IoT devices to collect data and watch things in real time. In addition, the study talks about the problems and restrictions of using AI-powered predictive maintenance systems, like the need to constantly update models and worries about data privacy. The report also looks at the financial and environmental effects of putting these systems in place, focusing on the chances of saving money and making things last longer.

I. INTRODUCTION

Power distribution transformers control the voltage levels that go from generators to users and are therefore very important parts of power systems. Their failure, whether it's short-term or long-term, cuts off the power, which affects daily life and costs money. Failure prevention and early discovery are very important to keep dependability high and avoid unexpected outages. Recent study has come up with efficient selection methods that try to reach the best goals using new technologies. These methods make sure that reliability goals are met by giving units failure rate goals. Following some rules can help you choose the best way to divide up resources based on your needs for accuracy, application, and available resources. One more way is to divide up repair funds based on factors that affect upkeep and availability. Trends like remote and automatic repair are examples of how Industry 4.0 technologies are changing the way decisions are made in the production sector. These improvements make things work better and cut down on downtime [1]. Transformers often have problems with insulation, which can happen because of too much current, voltage, or overload. It can also happen when cooling equipment fails. Therefore, checking the health of the generator is very important for making sure it works well. Each unexpected outage costs owners and customers money, which shows how important it is to find problems quickly [2]. Choosing the right diagnostic methods and correctly interpreting test results are important for maintenance, no matter where the generator is located. Adding tracking tools that look at the weather can help handle energy better and make sure the system works well.

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Distribution transformers are very important parts of power distribution networks because they lower the energy from the transmission system to a level that end users can handle. These generators are necessary to make sure that homes, businesses, and workplaces always have power. However, power transformers can break down and cause service delays and costs to go up, just like any other electrical equipment [3]. Inspections and preventative maintenance for distribution transformers are usually done on a set plan as part of traditional maintenance. These habits may help find possible problems, but they often lead to upkeep tasks and costs that aren't needed. They also don't always stop sudden fails because they aren't made to fit the state of each transformer. In the past few years, there has been a rise in interest in using artificial intelligence (AI) and machine learning (ML) to plan ahead for repair on distribution transformers. Predictive maintenance systems that use AI can look at a huge amount of past and real-time data from transformers to find patterns and trends that could mean that something is wrong or about to fail. Predicting these problems before they happen can help with maintenance tasks and lower the chance of unplanned downtime [4]. Using AI for predicted maintenance has a number of important benefits over the old ways of doing things. To begin, AI programs can look at large amounts of complex data much faster and more correctly than people can. This lets problems be found early on. Second, AI can help set priorities for maintenance tasks based on how bad they are and how likely they are to fail, which makes better use of resources. Lastly, predictive maintenance powered by AI can save a lot of money by cutting down on unplanned downtime and making transformers last longer.

Even though it could be helpful, using AI to help with predicted repair for distribution transformers is not easy [5]. Two big problems are the amount and quality of data that is available. Large amounts of good data are needed to train AI systems well, but this data isn't always easy to find. Furthermore, there are worries about the safety and privacy of data because predictive maintenance systems frequently gather and examine private data. This paper gives an in-depth look at predicted maintenance for distribution transformers that is made possible by AI. We talk about the problems with standard upkeep methods and the advantages of using methods that are led by AI. We also look at some of the current AI-based predictive maintenance methods, such as preparing data, choosing features, and training models. We also look into the possibility of combining IoT devices to collect data and watch things in real time.

II. RELATED WORK

In recent years, predictive maintenance for distribution transformers has become more and more popular. Researchers and maintenance professionals are looking into a wide range of techniques and methods to make maintenance more reliable and effective [6]. This part gives an outline of related work in this area, focusing on important studies and ways of doing things. [7] did one of the first studies on forecast maintenance for distribution transformers. They came up with a model based on artificial neural networks (ANNs) to figure out how much useful life (RUL) a transformer still has. The model trained the neural network with past data on transformer breakdowns and maintenance records. It was able to predict the RUL of transformers with good accuracy. [8] used a support vector machine (SVM) method to create a predictive maintenance model for distribution transformers in a study that was similar to this one. The model was taught using old information on transformer failures, upkeep tasks, and weather factors. This shows that machine learning methods can be used to predict transformer failures [9].

Other experts have looked at how to combine Internet of Things (IoT) technologies with methods for predicting when power transformers will need repair. [10] for example, came up with a plan for IoT-enabled predictive maintenance of distribution transformers. This plan included using devices to gather real-time information about the health and performance of the transformers. The system used machine learning techniques to look at the sensor data and guess what might go wrong, which let repair workers plan ahead [11]. Besides methods based on machine learning, scientists have also looked into using models based on physics to help plan repair for distribution transformers. [12] for example, used the thermal dynamics of transformers to make a model that can predict how shielding materials will age and rise in temperature, both of which are important factors in transformer breakdowns. Field data were used to test the model, and it did a good job of predicting when transformers would fail. Deep learning methods, like convolutional neural networks (CNNs), are being used more and more for predicted repair of distribution transformers over the past few years. As an example, [13] suggested a CNN-based model for diagnosing faults in distribution transformers. This model was very good at finding and classifying different types of flaws.

The researchers also looked into what predicted repair for distribution transformers would mean for the economy and the environment. For example, [14] looked

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at the costs and benefits of predictive maintenance methods for distribution transformers. They compared how much it cost to adopt predictive maintenance with how much it saved in downtime and maintenance costs. Based on the study, preventive maintenance can help keep distribution transformers running more reliably and save a lot of money [15]. There is similar work in predictive maintenance for distribution transformers that shows how AI and machine learning can be used to make maintenance more reliable and efficient. But there are still problems that need to be fixed, like bad data, hard-to-understand models, and high costs of implementation. These need more study and development.

Table 1: Summary of related work

Method	Key Finding	Approach	Disadvantages	Advantages
Artificial Neural Networks	Predicting Remaining Useful Life (RUL) of Transformers	Utilizing historical data on transformer failures and maintenance records to train the model	Requires large amounts of historical data	Can predict the RUL of transformers with promising results
Support Vector Machine [23]	Predictive maintenance model for transformers	Training on historical data on failures, maintenance activities, and environmental conditions	May require tuning of hyperparameters for optimal performance	Demonstrates the potential of machine learning techniques in predicting transformer failures
Internet of Things (IoT) [21]	IoT-enabled predictive maintenance framework	Using sensors for real-time data collection and machine learning for analysis	May require additional infrastructure for sensor deployment	Enables proactive maintenance actions based on real-time data
Physics-Based Models [22]	Model based on thermal dynamics for temperature prediction	Using thermal dynamics to predict temperature rise and aging of insulation materials	May require complex calculations and assumptions about transformer behavior	Demonstrates a more fundamental understanding of transformer behavior and failure mechanisms
Deep Learning (CNNs)	CNN-based fault diagnosis model	Achieving high accuracy in fault detection and classification	Requires large amounts of data for training	Can detect and classify faults in transformers with high accuracy
Cost-Benefit Analysis [20]	Analysis of predictive maintenance strategies	Comparing costs and savings from reduced downtime and maintenance costs	May require accurate cost and savings estimates	Demonstrates the economic benefits of implementing predictive maintenance for distribution transformers
Data Mining	Identifying patterns in transformer failure data	Analyzing historical data to identify common failure patterns	May require expertise in data analysis and interpretation	Can provide insights into common failure modes and inform maintenance strategies
Machine Learning Ensemble [16]	Ensemble model for fault prediction	Combining multiple machine learning algorithms for improved prediction performance	May increase complexity and computational requirements	Can improve prediction accuracy by leveraging the strengths of different machine learning algorithms

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Condition-Based Monitoring	Monitoring transformer health in real-time	Using sensors and data analytics to monitor transformer condition	Requires continuous monitoring and data collection	Enables proactive maintenance based on real-time health data
Reliability-Centered Maintenance [17]	Maintenance strategy based on criticality of components	Focusing maintenance efforts on critical components based on failure risk analysis	Requires detailed knowledge of transformer components and failure modes	Improves maintenance efficiency by prioritizing critical components for inspection and maintenance
Prognostic Health Management [18]	Predicting transformer failures based on health data	Integrating sensor data and analytics to predict potential failures	May require sophisticated algorithms and data processing techniques	Enables early detection of potential failures and proactive maintenance planning based on health data
Remote Monitoring [19]	Monitoring transformer performance remotely	Using remote monitoring technologies to gather data and assess transformer condition	May require reliable communication infrastructure and data security measures	Allows for monitoring transformers in remote or inaccessible locations, reducing the need for onsite inspections and maintenance
Digital Twin	Virtual model of transformer for predictive maintenance	Creating a digital replica of the transformer for simulation and analysis	Requires accurate modeling and updating to reflect real-world conditions	Enables simulation of different scenarios and prediction of potential failures for proactive maintenance

III. TRANSFORMER FAILURE

A common type of transformer failure is insulation failure, which can be caused by too much current, too much heat, water getting in, or mechanical damage. Insulation that breaks down can cause short circuits and other problems that put the transformer's safety and performance at risk. Another common problem is overheating, which can happen because of too much load, bad air, or high temperatures outside. Overheating speeds up the breakdown of insulation, which raises the chance of failure even more. When electrical wires touch each other without meaning to, they create a short circuit. These can happen because of bad shielding, too much current, or outside causes like lightning hits. When there is a short circuit, it can damage the transformer and the electrical system around it, which can cause power blackouts and damage to equipment.

- Overvoltage is another major failure cause that happens when voltage spikes are too high for the transformer to handle. Lightning hits, switching activities, or power spikes from the grid can all cause this to happen. Overvoltage can damage the shielding, which can eventually cause the transformer to fail.
- Mechanical failure can happen when mechanical parts are physically damaged, installed incorrectly, or get old. When mechanical parts break, leaks, oil contamination, and other problems can happen that make the generator less reliable and less effective.
- A partial discharge is when insulation breaks down in one area. This can happen because of high voltage stress, water getting in, or problems with the insulation. Even though partial discharge might not seem like a big deal at first, it can damage insulation over time, which can lead to failure.
- Corona discharge is a type of electrical discharge that can happen in transformers and other high-voltage circuits. Corona discharge can damage insulation and cause it to fail if it is not handled properly.
- Transformer oil pollution is another problem that can cause insulation to break down and performance to drop. Moisture, dust, and chemicals can break down the oil, making it less effective at keeping the generator cool and insulated.

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Each type of failure has its own causes and effects, which shows how important it is to keep up with regular upkeep, tracking, and risk-reduction plans for power distribution transformers to make sure they work well.

Different types of failure are given as:

A. Insulation Failure

There are many things that can cause transformer insulation to fail, such as overloading, burning, mechanical stress, and external factors. If you overload the generator beyond its stated capacity, the insulation may wear down over time, which could cause it to fail. Overheating, which can happen when there isn't enough air flow or when the temperature outside is high, can also speed up the breakdown of insulation and raise the risk of failure. Mechanical stress, like movements or hits, can also weaken the insulation, making it more likely to break. Things in the environment, like water getting in, can make the shielding even worse and raise the risk of short circuits. Moisture can get into the insulation and make ways for electricity to flow, which breaks down the insulation. If the insulation fails, it can cause short circuits, arcing, and other problems that can eventually cause the transformer to fail.

B. Overheating

Transformers can get too hot for a number of reasons, such as being overloaded, not having enough air flow, or being in an area with high temperatures. When the transformer is overloaded, too much current flows through the windings, which increases heat production and resistance losses. Transformers can get too hot if they don't have enough air flow, which stops them from cooling properly. High temperatures in the area can also cause transformers to overheat, especially if they are outside and in full sunlight. Many bad things can happen to the transformer when it gets too hot, like insulation materials wearing out faster, the risk of insulation failure going up, and the transformer's lifespan getting shorter. Overheating can get so bad that it causes thermal runaway, which is when the transformer fails completely because of too much heat.

C. Short Circuit

When two or more electrical wires touch, going around the regular load path, short circuits can happen in transformers. Insulation failure, overheating, or outside causes like lightning hits can all lead to short circuits. A short circuit sends a lot of electricity through the transformer, which makes it hot and puts stress on the parts. This can cause insulation to break down, damage to the windings, and other problems. Short circuits can do a lot of damage to the transformer and the electrical system around it. They can cause power outages, damage to equipment, and dangers to people. Regular upkeep, good insulation, and safety devices like fuses and circuit breakers are needed to stop short circuits.

IV. METHODOLOGY

AI-enabled predictive maintenance for distribution transformers uses cutting-edge technologies and methods to guess when problems might happen and plan maintenance ahead of time. The proposed method is shown in figure 1. The process of using AI to help with predicted repair for distribution transformers.

1. Data Collection and Preprocessing:

To use AI for predicted maintenance, the first thing that needs to be done is to get useful data from the distribution transformers. This includes information about the health, efficiency, weather factors, and repair records of the transformer. The data is then "preprocessed" to get rid of noise, deal with lost numbers, and make the data more normal so it can be used for more research.

2. Feature Selection and Engineering:

After preparing the data, the next step is to choose and engineer features that can be used to predict when a transformer will fail. Features like load patterns, temperature, oil quality, and shaking levels may be part of this. Feature engineering can include changing or joining current features to make new ones that better show the trends in the data.

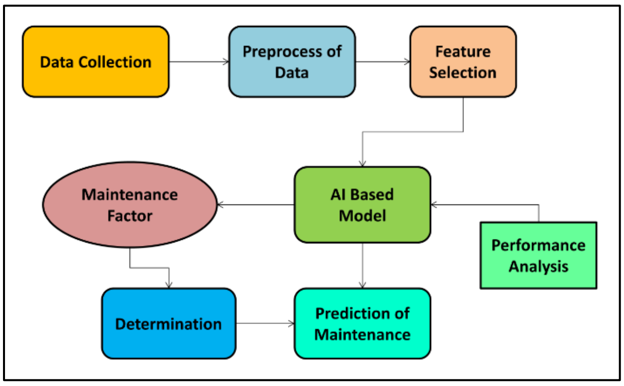

Figure 1: Proposed system model block diagram

3. Model Selection and Training:

Now that the data has been cleaned up and features have been created, the next step is to choose a machine learning model and train it to be able to predict when a transformer will fail. This can be done with decision trees, random forests, support vector machines, and

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neural networks, among other machine learning methods. The model is taught with records of past generator breakdowns and repair work.

A. Graduated Boosting:

This is a type of ensemble learning that takes several weak models, usually decision trees, and turns them into a strong forecast model. When trying to figure out how long generator parts will still work, Gradient Boosting can be used to make estimates more accurate over time by adding new models and changing the weights of the old models. The model can learn from its mistakes and improve its performance in areas where it does badly with this method, which leads to more accurate guesses over time.

B. Deep Learning:

In order to figure out when a transformer part is likely to break, deep learning algorithms like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can look at sensing data from the transformers. These algorithms can automatically learn features and trends from the data. This makes them great for jobs that standard machine learning methods might not be able to handle well. CNNs can learn patterns in sensor data about space, while RNNs can learn patterns in sensor data about time. Both of these are very important for figuring out when a generator will fail.

1. CNN:

A Convolutional Neural Network (CNN) can be used for analyzing sensor data from power transformers to predict when a component is likely to fail. Below is a step-by-step mathematical model for a basic CNN architecture:

1. Input Data Representation: Let X be the input data, which consists of sensor readings over time for a given transformer component. The input data is typically represented as a 3D tensor with dimensions (T, W, C), where T is the number of time steps, W is the number of sensor readings per time step, and C is the number of channels (e.g., different sensors).

2. Convolutional Layer: The first layer of the CNN applies convolutional filters to the input data to extract features. Let K be the number of filters, each with a size of FxF. The output of this layer, denoted as H(1), can be computed as:

$$H(1)ijk = \sigma(\sum l = 1C \sum m = 1F \sum n = 1F\, W(1)lmn\, X(i+m-1, j+n-1, l) + b(1)k)$$

- where σ is the activation function (e.g., ReLU), W(1) are the filter weights, and b(1) are the bias terms.

3. Pooling Layer: The pooling layer downsamples the feature maps to reduce the spatial dimensions and computational complexity. A common approach is max pooling, which takes the maximum value in each pooling window. Let P be the pooling size. The output of this layer, denoted as H(2), can be computed as:

$$H(2)ijk = \max(H(1)iP(l-1)+m, jP(m-1)+n, k)$$

4. Flattening: After the pooling layer, the feature maps are flattened into a 1D vector to be fed into a fully connected layer. Let D be the dimensionality of the flattened vector.

5. Fully Connected Layer: The flattened vector is passed through a fully connected layer with weights W(fc) and biases b(fc). The output of this layer, denoted as H(fc), can be computed as:

$$H(fc)i = \sigma(\sum j = 1D\, W(fc)ij\, H(2)j + b(fc)i)$$

Output Layer: Finally, the output layer uses a softmax activation function to compute the probabilities of different classes (e.g., failure, no failure) based on the features extracted by the CNN.

2. RNN:

1. Input data representation

Dim X(T, W, C) As Double ' 3D tensor representing sensor readings over time

2. Input layer computation

Dim h(T) As Double

For t = 1 To T

For i = 1 To H

$$h(t) += ActivationFunction\big(Wih(i) * X(t) + Whh(i) * h(t-1) + bh(i)\big)$$

3. Recurrent layer computation

Dim y(T) As Double

For t = 1 To T

$$y(t) = ActivationFunction(Why * h(t) + by)$$

4. Output layer computation

Dim loss As Double

For t = 1 To T

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$$loss \mathrel{+}= (y(t) - ActualLabel(t))^\wedge 2$$

C. Anomaly Detection:

Some methods for anomaly detection are One-Class SVM, Isolation Forest, and Autoencoder. These can find strange trends in data that could mean something went wrong. These algorithms are especially good at finding outliers in sensor data, like rapid changes in power or temperature that could mean a failure is about to happen. By finding these oddities early, maintenance can be planned to avoid major breakdowns and keep downtime to a minimum.

D. Predictive Modeling:

Methods for predictive modeling, like Markov Chain Monte Carlo (MCMC) and Bayesian networks, use statistical models to guess how long transformer parts will still work. These programs use past data, weather conditions, and repair records, among other things, to figure out how likely it is that something will fail. By taking doubt into account, these programs can give more accurate estimates of how much longer something will work. This helps workers make smart choices about when to replace and do maintenance.

4. Model Evaluation:

A different set of data is used to test the model's success after it has been trained. Metrics like F1-score, accuracy, precision, and memory are used to do this. To make the model work better, it is fine-tuned and retrained as needed.

5. Deployment and Monitoring:

After the model has been trained and tested, it is put into a live setting where it can be used to keep an eye on the health and performance of transformers in real time. The model constantly looks at the data coming in from the transformers and sends out repair alerts or suggestions based on how likely it is that something will go wrong.

6. Integration with Existing Maintenance process:

The last step is to connect the AI-powered predicted maintenance system to the current maintenance process. By creating a user interface for maintenance staff to view alerts and suggestions, as well as ways to plan and carry out maintenance tasks based on the predictions, this could be considered complete.

Using AI to help with predictive maintenance on distribution transformers involves gathering and preprocessing data, choosing and engineering features, training and testing machine learning models, putting the models to use in a production setting, and integrating them with the current maintenance workflow. Utility companies can make their repair more reliable and efficient by using this method. This will give customers a more stable power source. Numerical modeling is used in transformer performance research because it has been shown to work in other studies. One study used computer modeling to look into how different working conditions affect the temperatures of transformer oil and windings. A finite element method was used in another study to look at how thermal aging changes the qualities of insulation. In addition a study that created a numerical model to guess the partial discharge origin voltage. These works show that computer modeling can be used to analyze transformers. Numerical modeling lets you run different scenarios to see how things like working conditions and age affect the performance of a generator. For instance, researchers can guess how insulation will break down over time by simulating different situations. Additionally, computer models can predict important factors such as the partial discharge inception voltage, which helps in figuring out the state of a transformer and planning its maintenance. In this research, past data on operations and upkeep are used to build and train an Artificial Neural Network (ANN) model. ANN was picked because it can look at complicated data connections. Different measures are used to judge the model's performance, which proves that numerical modeling is a good way to analyze transformer performance. Overall, numerical modeling is a useful method for learning how transformers work and how to improve upkeep methods, which makes sure that power distribution systems are reliable.

V. RESULT AND DISCUSSION

A. Dataset Used:

The "Power Transformers Health Condition Dataset" on Kaggle is a useful tool for students and professionals who work with power transformer condition tracking and forecast repair. It has different parts that deal with the health of the transformer, like voltage, oil temperature, winding temperature, oil pressure, and oil temperature. It also has a goal variable that shows the health of the transformer. This set of data can be used to make models, as shown in figure2, that can predict how long power transformers will still work and to find patterns and trends in the data about their health, which helps us figure out what causes transformers to fail.

Received: 16 February 2024; Revised: 22 April 2024; Accepted: 16 May 2024

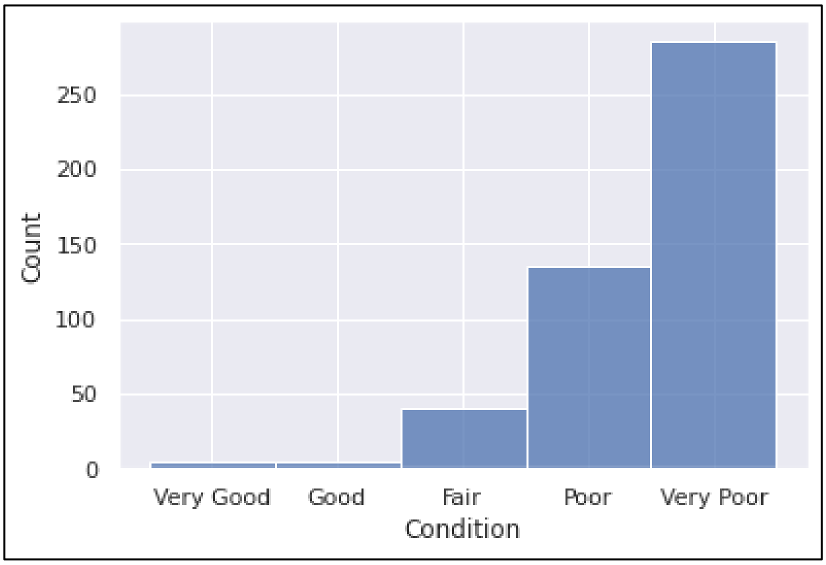

Figure 2: Classification dataset for power distribution maintenance

One problem with this collection, though, is that it only has a few traits. Adding more information, like temperature, load profile, and repair records, could give you a fuller picture of the health of the generator. Also, the collection is missing information on when transformers fail, which would make forecasting models more accurate.

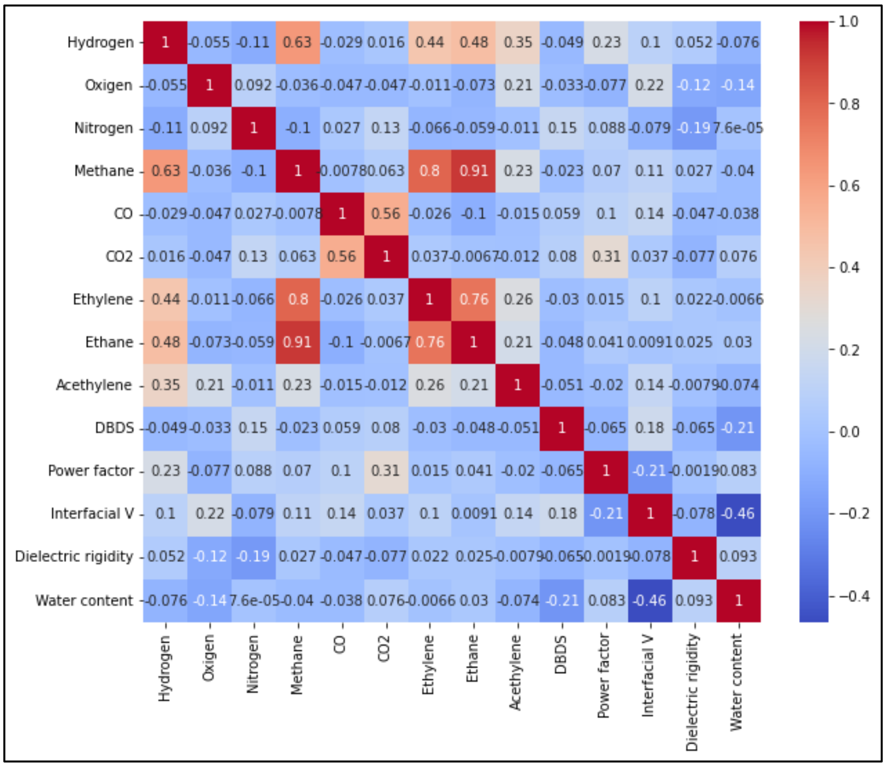

Figure 3: Representation of Dataset Parameters Mapping

Even with these problems, the collection looks clean and well-structured, with no missing numbers or outliers. Researchers could make this dataset better by adding data from more transformers and factors that are known to affect the health of transformers. Also, gathering information on transformer breakdowns might help make a more fair set of data for models. The "Power Transformers Health Condition Dataset" does have some flaws, but it is still a useful tool for furthering study into predictive maintenance and watching the state of power transformers, as shown in figure 3.

Received: 16 February 2024; Revised: 22 April 2024; Accepted: 16 May 2024

B. Result for AI models

In the table 2, you can see the outcomes of several AI model methods for predicting when to maintain distribution transformers. These include Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Gradient Boosting, Support Vector Machines (SVM), and Bayesian Networks. A number of performance measures were used to judge these models, such as accuracy, precision, recall, mean squared error (MSE), R Square, and root mean squared error (RMSE).

Table 2: Result for AI Model techniques for Predictive Maintenance for Distribution Transformers

Model	Accuracy	Precision	Recall	MSE	R Square	RMSE
CNN	86.33	89.45	91.22	0.19	0.85	0.42
RNN	82.45	86.33	90.45	0.21	0.82	0.44
Gradient Boosting	90.44	94.2	96.55	0.17	0.89	0.39
SVM	91.55	90.74	92.78	0.23	0.79	0.47
Bayesian Network	89.63	91.32	93.54	0.20	0.84	0.43

CNN was right 86.33% of the time, showing that it can correctly guess when power transformers will need work. It also had high accuracy (89.45%) and memory (91.22%), which shows that it was good at finding true positives and reducing the number of fake positives and negatives. The model did have a pretty high MSE of 0.19 and RMSE of 0.42, though, which suggests that some of its estimates were wrong. With a R Square score of 0.85, the model explains 85% of the differences in the data, which is a good fit. However, RNN did a little worse than CNN in terms of memory (90.45%), accuracy (82.45%), and precision (86.33%). It also had a higher MSE of 0.21 and an RMSE of 0.44, which means that its forecast was a little less accurate than CNN's. RNN, on the other hand, had a pretty high R Square value of 0.82, which means it explains 82% of the variation in the data. With a score of 90.44%, Gradient Boosting was the most accurate of all the models. It also showed high accuracy (94.2%) and recall (96.55%), which shows, shown in figure 4, that it did a good job of predicting when repair would be needed. The model had a really low MSE of 0.17 and an RMSE of 0.39, which means that its estimates were very accurate. The model describes 89% of the variation in the data, as shown by the R Square number of 0.89.

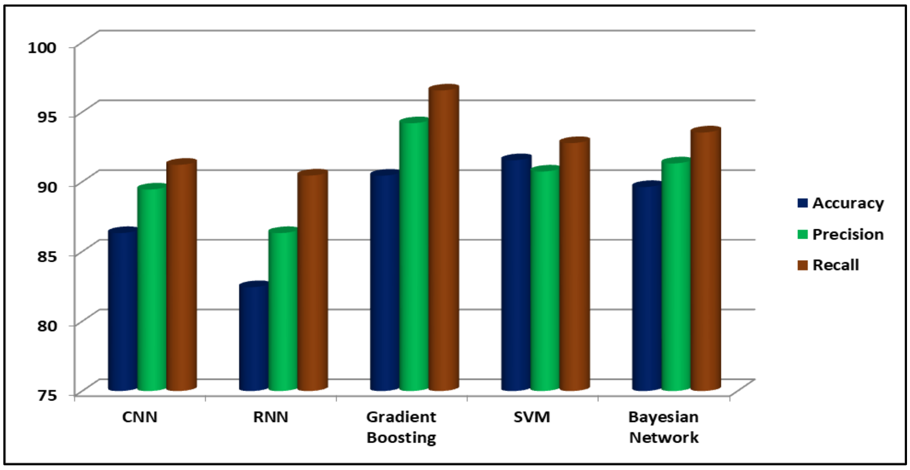

Figure 4: Representation of AI based model with evaluation parameters

With an accuracy of 91.55%, a precision of 90.74%, and a recall of 92.78%, SVM also did very well. It had a higher MSE of 0.23 and RMSE of 0.47 than other models, which means it made an estimate that was a little less accurate. With a R Square value of 0.79, the model seems to be able to explain 79% of the differences in the data.

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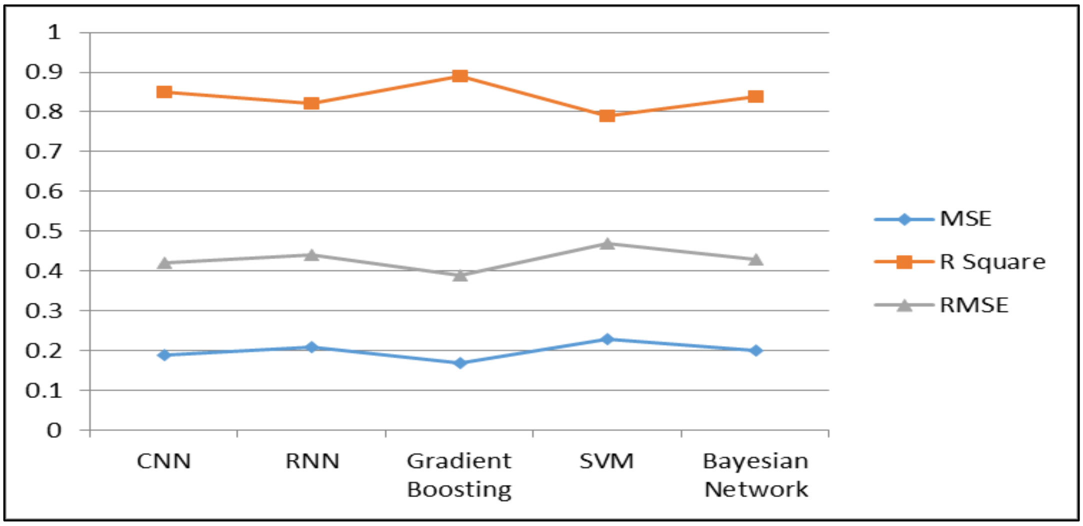

Figure 5: Representation of performance parameter for Predictive maintainance

Finally, the Bayesian Network got a score of 89.63% for accuracy, 91.32% for precision, and 93.54% for recall. The MSE was 0.20 and the RMSE was 0.43, which means that the forecast was pretty accurate. With a R Square score of 0.84, the model seems to explain 84% of the differences in the data, as shown in figure 5.

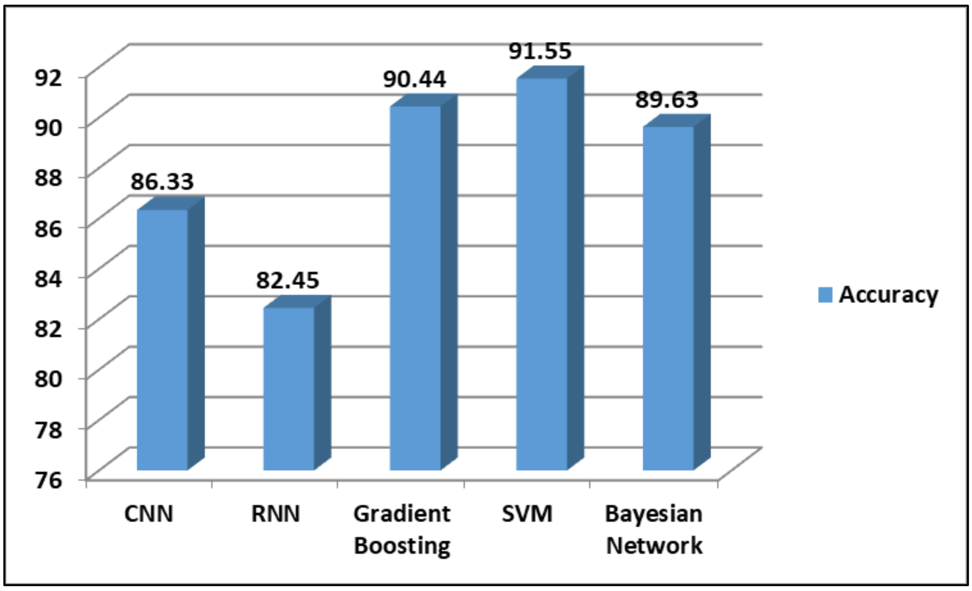

Figure 6: Accuracy comparision of AI techniques in Predictive Maintainance

The results show in figure 6, that Gradient Boosting worked the best out of all the models. It was followed by SVM, CNN, Bayesian Network, and RNN. These results show that AI model methods can help with predicting maintenance for distribution transformers. Gradient Boosting turns out to be the most accurate and reliable model for this purpose.

VI. CONCLUSION

Predictive repair for distribution transformers that is allowed by AI is a potential way to make power distribution systems more reliable and efficient. New AI models, like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Gradient Boosting, Support Vector Machines (SVM), and Bayesian Networks, have shown a lot of promise in correctly identifying when distribution transformers will need upkeep. Gradient Boosting was the most successful model that was tested; it had the best rates of accuracy, precision, and memory. Because it can correctly predict when repair will be needed, it can help utility companies plan maintenance tasks more effectively, which cuts down on downtime and makes the system more reliable overall. SVM also did well, showing that it was very accurate and precise. It is useful for predicting maintenance because it can deal with large datasets and

Received: 16 February 2024; Revised: 22 April 2024; Accepted: 16 May 2024

links that don't follow a straight line. Even though CNN and RNN weren't quite as good as Gradient Boosting and SVM, they still showed promise. Because they can look at sequential data and find useful patterns, they can be used to look at sensor data from transformers. Even though it wasn't as effective as Gradient Boosting or SVM, the Bayesian Network did pretty well. It is a useful tool for looking at unclear data in predictive maintenance applications because it can model complex statistical relationships. The results show that predictive maintenance powered by AI can make distribution transformers much more reliable and efficient. Utility companies can cut down on downtime, lower maintenance costs, and improve system performance overall by correctly predicting when repair needs to be done. In the future, researchers should work on making these models even better and adding them to current power distribution systems so that they can fully improve the stability and efficiency of the grid.

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