

Comparative Analysis of Decision Tree (DT) & Deep Neural Network (DNN) Techniques to Diagnose the Stator Winding Fault in the Permanent Magnet Synchronous Motor (PMSM)

Prakhar Singh Bhadoria¹, Raghavendra Sharma²

¹Department Electronics & Communication Engineering

Amity University

Gwalior, India

Prakhar.singh5@student.amity.edu

²Department Electronics & Communication Engineering

Amity University

Gwalior, India

Rsharma3@gwa.amity.edu

Rahul Dubey³

³Department of Electronics Engineering

MITS

Gwalior, India

rahul@mitsgwalior.in

Abstract— Every industry is moving towards automation, and Electrical motors like DC and AC play a significant role in the overall automation scheme. Electrical motors, however, are prone to multiple manufacturing defects, and untimed wear and tear. Automated detection of faults, while the motor is in operations, can prevent automation breakdowns, and unforeseen accidents. The majority of faults in electrical motors are because of overheating of windings, bearing misalignment, shaft mismatch, vibrations, noise, etc. A few hours of Electric Motor running can generate a lot of sensor data measuring temperature, torque etc.. Manual analysis of such data can be extremely time consuming. Machine Learning can be used to perform automated analysis of data and real-time fault detection as suggested by many experts. In this research, we have used a few machine learning techniques to train the model on top of sensor data and use the model to diagnose the electric motor faults, occurring because of heat in the stator winding part of the permanent magnet synchronous motor (pmsm). We have specifically compared Decision Tree (DT) and Deep Neural Network (DNN) techniques on real-life datasets, and compared their accuracy. As per the final results, Decision Tree (DT) and Deep Neural Network (DNN) have 93.82% & 97% accuracy respectively.

Keywords- Stator fault, Machine learning, Decision Tree, Deep Neural Network.

I. INTRODUCTION

In the growing production in industries, technologies play a challenging role in the present time [1] [2]. Machines are going advanced day by day. Many industries can only run using rotary machines [3]. Industries like cement, textile, paper mills, automobile sector, medical sector, etc., below show the chart for using rotary machines as a main application.

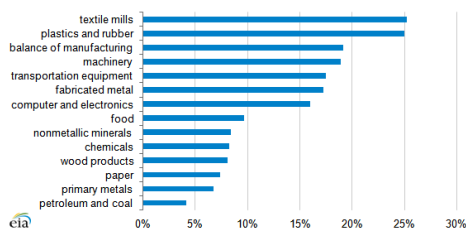


Fig. 1 Use of rotary machines in various sectors

So rotary machines like electrical motors, mills, gearboxes, mechanical rotaries, and compressors play a very important role in these industries. Due to the continuous running of these rotary machines, there are large chances of faults occurring in the various parts of the rotary machines [4]. If we take the example of bearing faults, various factors can damage the bearing, like bad assembly, inadequate lubrication, material lassitude, and others [5]. The below chart shows the percentage of fault that occurs in various parts of an electrical motor.

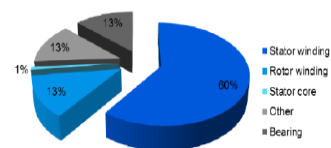


Fig. 2 Percentage of faults that occurs in an electric motor

In this, we are researching to diagnose the faults which mainly occur in electric motors since 80% of manufacturing industries use an electric motor. Since all electric motors mainly comprise stators, rotors, bearings, conductors, shafts, etc. [6].

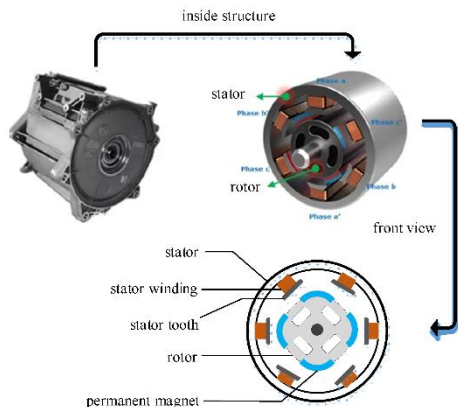


Fig.3 Major parts of an electrical motor

Machine learning (ML) which makes the computation of multi-layer neural network feasible” [9]. It helps solve complex problems with a more accurate prediction with self-learning without human interference.

So basically DNN method mainly consists of three-layer, i.e. input layer, the hidden layer or middle layer, and the output layer. We fed our input to the system through the input layer. In the hidden layers, the system learns the patterns of the input to identify the exact output required. Therefore the number of hidden layers may vary depending on the complexity of the data. At last, the output layer predicts the accurate required output from its learning [10].

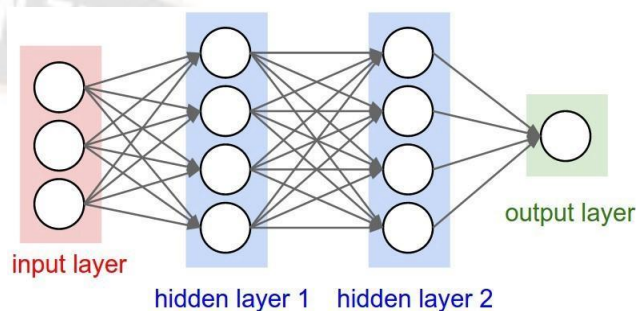


Fig. 5 Basic work functioning of Neural Network

So our focus is to diagnose the fault in the stationary part of the machine, i.e. stator winding. Since 60% of faults mainly occur in the stator part of the electric motor [7].

We have applied machine learning techniques due to inherent properties like the Able to generalize, be Robust, Reliable, Learn the model of high quality, be Scalable and efficient, Explicative and Determinist [8]. The two machine learning techniques are Decision Tree (DT) & Deep Neural Network (DNN).

Decision Tree: A decision tree (DT) is a supervised learning technique in machine learning that solves both classifications and regression types of problems. Mostly it is used to solve classification problems. It consists of two nodes, a decision node, and a terminal node or leaf node. By the name given, decision nodes are those responsible for taking further decisions, and the terminal or leaf node is the output of the network through which output is predicted.

II. MATERIALS & METHODS

For this, permanent magnet synchronous motor (PMSM) is considered for which stator fault is to be diagnosed. The real-time data is measured in a 0.2 hp pmsm motor run for 140 hours to measure data for various changing parameters. This data is taken from the Kaggle website. In the data, input parameters are considered to be voltage-current along the d and q axis, coolant temperature, ambient temperature, motor surface temperature, stator yoke temperature, stator tooth temperature, speed and torque of the motor and output as the stator winding temperature for which prediction is to be done.

TABLE 1: PARAMETERS CONSIDERED FOR THE TESTING

S.No	ambient	coolant	u_d	u_q	motor_sptorque	i_d	i_q	pm	stator_yol	stator_toc	stator_wip	profile_id	
1	-0.75214	-1.11845	0.327935	-1.29786	-1.22243	-0.25018	1.029572	-0.24586	-2.52207	-1.83142	-2.06614	-2.01803	4
2	-0.77126	-1.11702	0.329665	-1.29769	-1.22243	-0.24913	1.029505	-0.24583	-2.52242	-1.83097	-2.06486	-2.01763	4
3	-0.78289	-1.11668	0.332772	-1.30182	-1.22243	-0.24943	1.029448	-0.24582	-2.52267	-1.8304	-2.06407	-2.01734	4
4	-0.78094	-1.11676	0.3337	-1.30185	-1.22243	-0.24864	1.032845	-0.24695	-2.52164	-1.83033	-2.06314	-2.01763	4
5	-0.77404	-1.11678	0.335206	-1.30312	-1.22243	-0.2487	1.031807	-0.24661	-2.5219	-1.8305	-2.06279	-2.01814	4

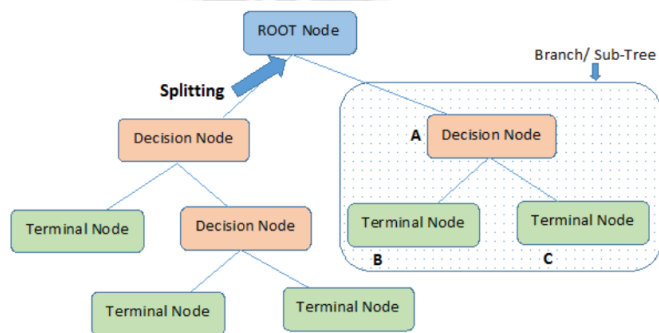


Fig.4 Decision tree flow chart

Deep Neural Network (DNN): Deep Neural Network (DNN) method is implemented, which is basically “A subset of

In the above data, u_d and u_q are voltages across the d and q axis, and i_d and i_q are the currents across the d and q axis. So, these parameters are considered input fed to the input layer of the system, and with the help of these input patterns, the system predicts the output temperature at various changes, which helps in predicting the fault at the output end.

A. Decision tree (DT) method:

The workflow of the decision tree algorithm can be done in given following way:

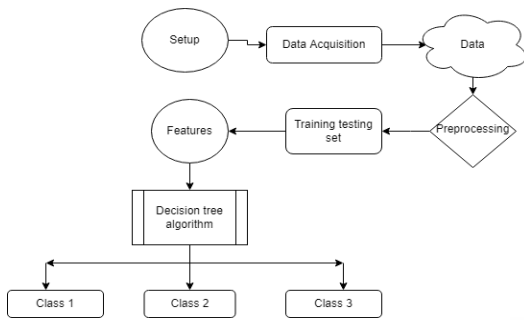


Fig. 6 Flow chart of the research work

So, data is collected from the pmsm motor, which is preprocessed so that the data is arranged and useful for the network. This data is divided into training and testing purposes. Approx. 80% data is taken for the training purpose, and 20% data is taken for testing. Training data is trained to extract useful information further to extract the fault features in which, with the help of the decision tree algorithm, the final fault prediction is done.

This raw data is imported into the python software. The raw data is viewed in 2D and 3D model using binning also termed as KBinsDiscretizer, which transform the continuous linear model into the discrete form in space by implementing one hot coding and then plotting the data in a scattered color bar. It helps in studying the data in an easy way which helps in improving the accuracy of the output.

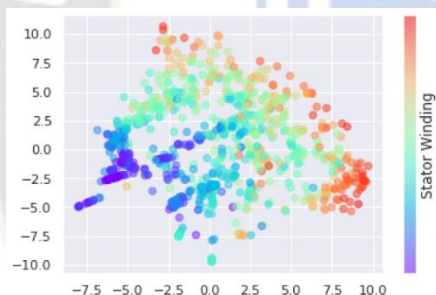


Fig. 7 Scattered plot for dataset

Now, this data set is fed to Principal Component Analysis (PCA), which helps in reducing the dimensionality of the data, which increases interpretability, yet, at the same time, it minimizes information loss. It helps find the most significant features in a dataset to predict the output results. It also helps in improving the accuracy of the output.

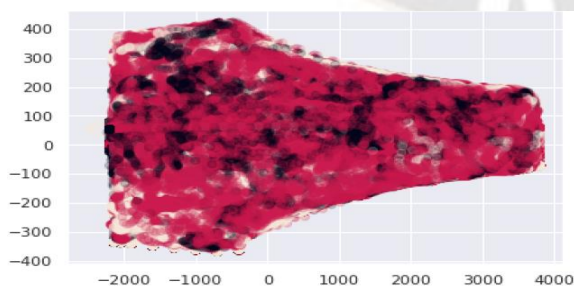


Fig. 8 Data plot after Implementing PCA

This final data, which is obtained, will split as trained and test data, and trained data is fed to the decision tree network for

further classification, which helps obtain the confusion matrix. We repeat this classification process till it reaches its accurate value.

B. Deep Neural Network (DNN) method:

In a deep neural network, the raw data is imported into the network. The inputs like voltage across the d & q axis, current across the d & q axis, speed of the motor, the torque of the motor, the surface temperature of the motor, ambient temperature, coolant, etc. are taken in the input layer of the neural network to achieve the stator winding temperature of the pmsm motor at the output layer. Hidden layers of the neural network will execute the calculation to obtain the best accurate output for the network.

Below given the layout of the working of the deep neural network:

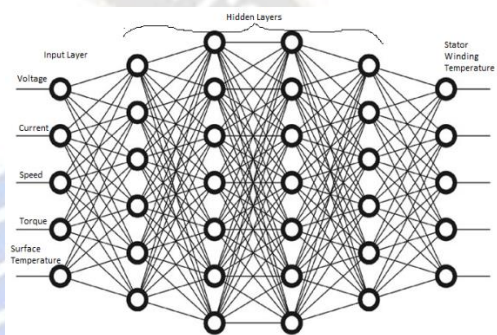


Fig. 9 Working of the neural network in the system

In the above network, considered the inputs in the input layers as voltage as X1, current as X2, speed as X3, torque as X4, Surface Temperature as X5, and so on, and the output from the input layers can be considered as weights W1, W2, W3, W4, W5 and so on respectively.

So the linear function for the above system can be written as:

$$Z = X1*W1 + X2*W2 + X3*W3 + X4*W4 + X5*W5..... (i)$$

This is a linear function, so to get the final output, various activation functions like the sigmoid function, Tanh or hyperbolic tangent function, rectified linear unit (ReLU) and Leaky ReLU are used. These activation functions help in mapping the results in the range between 0 to 1 or -1 to 1.

In this research, we have used the ReLU activation function to get the final output from the system. The ReLU activation function is the most common function used worldwide for the deep neural network. In this, the function returns 0 if it receives any negative input, but for any positive value of z, it returns that value back. So this function can be written as:

$$f(z) = \max(0, z)$$

$$\text{ReLU}(z) = z \quad (z > 0)$$

$$= 0 \quad (z \leq 0)$$

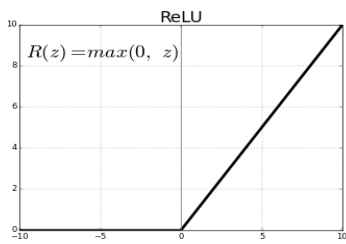


Fig. 10 Condition plot or ReLU activation function

It is seen from the above graph that, for the ReLU activation function, $f(z)$ is zero when z is less than zero, and $f(z)$ is equal to z when z is above or equal to zero.

III. RESULTS

After the calculation in the decision tree algorithm, we get the final output of the network in the form of a confusion matrix which can be calculated with the help of the formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where, TP – True Positive values,
 TN – True Negative values,
 FP – False Positive values &
 FN – False Negative values.

The confusion matrix thus obtained will be given as:

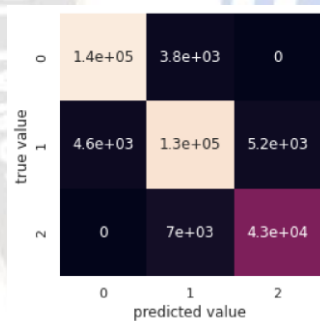


Fig. 11 Confusion matrix for the given dataset

So, it is calculated from the above matrix taking diagonals values as true positive values, the accuracy is calculated to be **93.82 %** by the given confusion matrix formula. Also Area under ROC (AUC) – Receiver Operating Characteristic (ROC) curve, the value is achieved near 1 which is better for any network. The plot is given as:

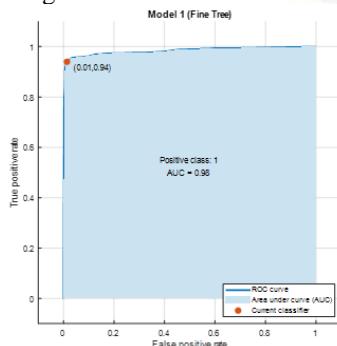


Fig. 12 AUC-ROC curve

In the Deep Neural Network, with the given data, after applying the DNN algorithm we have received a comparison graph between the various parameters like voltage v/s current, voltage v/s speed, voltage v/s torque, current v/s speed, current v/s torque, and so on. The comparison graph is shown below:

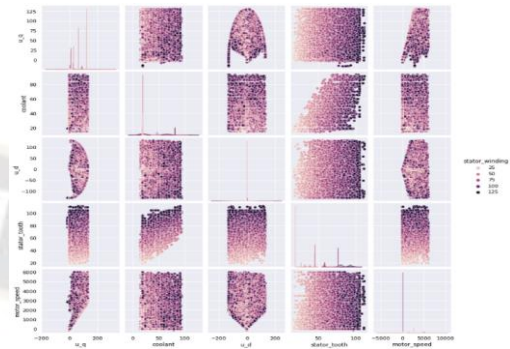


Fig. 13 comparison plots for various electrical parameters

So with the above graphs, we can see that, there are relations between the various parameters w.r.t to stator winding temperatures. Some curves are denser, some show linear relationships, some are elliptical and some are normal with different colors which shows the temperature range in comparing the two parameters. For example, if we compare u_q and motor speed since stator winding temperature is directly connected to speed and voltage, so, the stator winding temperature will be more in this area (125 range particles are more in the graph). Similarly, other parameters are also compared w.r.t to the stator winding temperature.

Now we come to the final output which is predicted in the system. The prediction output is shown below:

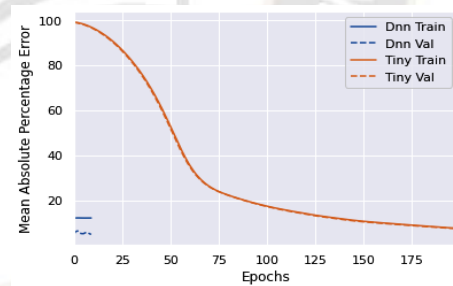


Fig. 14 Plot between mean absolute error v/s epochs

From the above plot 14, it can be predicted that the more epochs, the less mean absolute percentage error will be since the number of iterations will increase, which will improve the accuracy of the prediction. So we can see clearly that, means the percentage error is less than 10 % with the increase in the epochs.

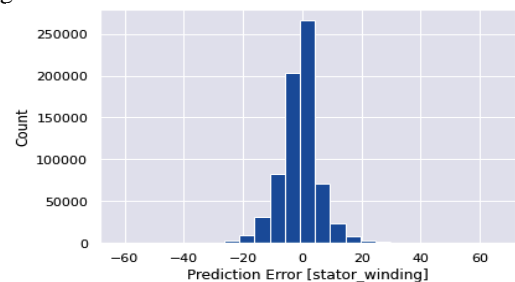


Fig. 15 Result plot between numbers of counts v/s prediction error

So above plot shows the prediction error for stator winding done by the system based on input data. Y-axis shows the count i.e the number of samples or data considered by the system to predict the output. It is seen that the more the number of samples, the more will the accuracy of the system. In the graph, prediction error lies between 0 to 5% for more than 2 lakh samples and error is more for less number of samples. So from the above plot, it can be said that the prediction accuracy is nearly about **97 %**.

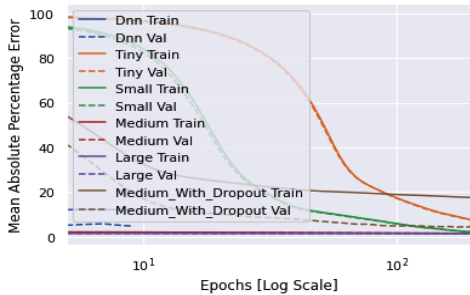


Fig. 16 comparative plots for various data sizes

The above graph is plotted between the epochs and mean absolute error for various sizes of data like tiny, small, medium, large, and medium with dropout. We can see from the above that, the mean absolute will be more for small-size data shown by indigo, orange, and green color graph, and mean the absolute error will be less for large-size data and medium with dropout. The error will be very less for the dropout case since repetition of neurons waste the machine resource since repetition tends to overfitting. So, in the dropout case, the machine randomly shutdown some fraction of a layer's neurons at each training step by zeroing out the neuron's values. We are improving the overfitting, thus improving the accuracy of the prediction.

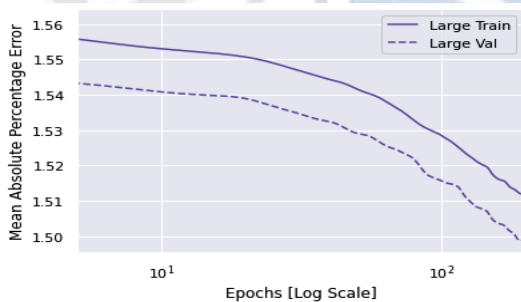


Fig. 17 plot between mean absolute error v/s epochs for large data size

The above graph is plotted for large training and testing values which lie nearly to mean absolute error of 1 to 1.5 % with a large number of epochs of approx. 10^2 .

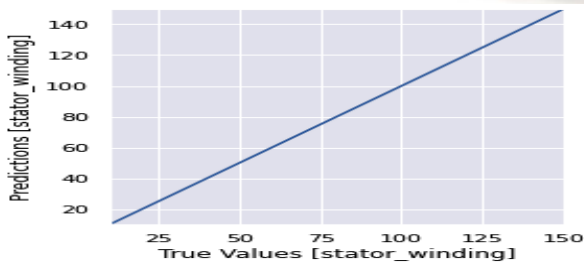


Fig. 18 plot between prediction values and the true values

The graph in the above fig. is a plot between the prediction value and the true values. It is seen that the graph is a straight line, which means that with the increase in the true values of the system, the prediction will be more accurate i.e prediction is directly proportional to the true values of the system.

IV. CONCLUSIONS

So from the above work and results it can be concluded that output results from the Deep Neural Network (DNN) algorithm are predicted to be **97 %** accurate whereas, from the Decision tree (DT) method, the output is predicted to be **93.82 %** accurate. So, both results achieved a very high accuracy percentage. We can conclude that for large numbers datasets Deep Neural Network (DNN) method is more suitable for better accuracy as compared to Decision Tree (DT) method. Also, several samples will increase the accuracy of the prediction and minimize the mean absolute error. Since DNN uses several layers so due to the epochs and iteration, it helps the system to learn the data pattern in a very easy way which helps the system to learn the data easily for accurate prediction.

REFERENCES

- [1] Yang R, Huang M, Lu Q, Zhong M, "Rotating Machinery Fault Diagnosis Using Long-short-term Memory Recurrent Neural Network," ScienceDirect (International Federation of Automatic Control, IFAC), 2018, 51-24, 481-485.
- [2] Muszynska A, "Vibration Diagnostic of Rotary Machinery Malfunction", International Journal of Rotary Machinery", 1995, 1(3), 237-266.
- [3] Joshi A, Nagmoti N. S, Khot M. M, "Condition Monitoring and Fault Diagnosis of a Rotary Machine using Fast Fourier Transform (FFT) Analysis", Journal of Emerging Technologies and Innovative Research (JETIR), 2021, 8(6), 557-563.
- [4] Shen C, Wang D, Kong F, Tse P. W, "Fault Diagnosis of Rotating Machinery based on the Statistical Parameters of Wavelet Packet Paving and a Generic Support Vector Regressive Classifier", Elsevier (Measurement), 2013, 46, 1551-1564.
- [5] Verstraete D, Ferrada A, Droguett E. L, Meruane V, Modarres M, "Deep Learning Enabled Fault Diagnosis Using Time-Frequency Image Analysis of Rolling Element Bearings", Hindwai (Shock and Vibration), 2017, 1-17.
- [6] Nourse D. E, "Electric Motor Failure – Comparative Study of Its Causes", IEEE Journal, 1968, 68C-EI-85, 142-143.
- [7] Hosselni S. M, Hosselni F, Abedi M, "Stator Fault Diagnosis of a BLDC Motor based on Discrete Wavelet Analysis using ADAMS Simulation", Springer Nature Journal, 2019, 1:1406.
- [8] Jimenez D. G, Olmo J. D, Poza J, Garramiola F, Sarasola I, "Machine Learning-Based Fault Detection and Diagnosis of Faulty Power Connections of Induction Machines", MDPI (Energies), 2021, 14, 4886, 1-21.
- [9] Guo H, Ding Q, Song Y, Tang H, Likun W, Zhao J, "Predicting Temperature of Permanent Magnet Synchronous Motor Based on Deep Neural Network", MDPI (Energies), 2020, 13, 4782, 1-14.
- [10] Neelavathi G, Ravikumar M, "Clustering of Data Points in Medical Datasets using Deep Neural Networks", International Journal of Computer Engineering and Technology (IJCET), 2019, 10(6), 133-138.