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Evaluation of Bearing Fault Detection on Different _K-Folds using Deep Learning Ensemble Models

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Abstract—One of the most crucial parts of contemporary machinery and industrial equipment is the induction motor. Therefore, it is essential to create a fault diagnosis system that can identify induction motor problems and operating circumstances before they become serious. In this study, an induction motor's defect diagnosis is carried out in three different states, including normal, rotor fault, and bearing fault. The suggested fault diagnostic system is also described, along with a GUI. The experimental findings support the suitability of the suggested approach for rotor and bearing defects in induction motor diagnosis. A GUI for defect diagnostics was also created and used in a real-world setting. We have used Chi-Square method for high score attributes values. For the normal, rotor fault, and bearing fault states of induction motors identified by DBN, CNN, SNN, SVM and RF respectively, the fault detection system's accuracy in the actual world. In the experiment, we find Algorithms model-II, K-Folds (5, 10 & 15) , Accuracy (%), Training loss, Validation loss value for RF-SVM-CNN are 89.2, 0.260013, 0.304936 for k fold 5, 98.4, 0.155960, 0.154133 for k-fold 10 and 98.3, 0.155759, 0.144127 for k- fold 15 respectively.

Keywords-Bearing fault; Chi-Square method; Deep Belief Network model; Convolution Neural network model and Shallow Neural Network model; Support Vector Classifier; Random Forest Classifier; fault diagnosis system; induction motor; rotor fault.

I. INTRODUCTION

One of the most crucial parts for powering electrical device motors machinery is the induction motor. However, unanticipated induction motor fault-related plant shutdowns result in large financial losses. This problem can identify induction motor problems and operating conditions before they become serious [1]. The process of fault diagnosis entails locating and categorizing systemic flaws. Structure approaches and non-model-based methods are two major categories for fault diagnostic techniques. In non_structure approaches, system flaws are identified; however, due to the nonlinearity of the system, it is difficult to construct an accurate mathematical model. In addition to thresholding, expert system approaches, and neural networks, non-model-based methods for defect identification also include those that rely on measurements [2]. The principal motor signals used to identify induction motor faults are vibration signals, motor currents [3–9], auditory signals [10], and thermal imaging [11]. The vibration signal-based approach measures the vibration signals produced by an induction motor, and defect diagnosis is carried out using frequency analysis of the recorded signals. A fixed magnetic current is acquired using the motor current approach, and defect finding is done using frequency analysis of the recorded signals. Thermal pictures of an induction motor are obtained using this technique, and problem diagnostics is carried out using characteristics deduced from the images. In addition, a GUI is put into place to allow users to quickly and easily detect induction motor issues. Through an experiment and a simulation, the performance of the suggested defect diagnostic approach is confirmed.

Three three-phase induction motors were used to create the simulator for the purpose of diagnosing faults in induction motors. We used a vibration sensor to collect vibration data from these induction motors. Three different induction motors were employed, yet their specs are identical.

II. RELATED WORK

Artificial intelligence has a high degree of precision and dependability and may be used to monitor conditions in real time. The previous study comparison shows machine learning and deep learning defect detection techniques. Various algorithms may produce high accuracy in the categorization of machine condition monitoring because to its excellent generalization capability. Speech recognition and image

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processing have both long used deep neural networks (DNN). Over the past years, DNN's interest in fault detection systems has dramatically increased. The main goal of these publications is to analyze induction motor deterioration. Mechanical vibrations,stator currents, and less frequently voltages are monitored in the majority of DNN-based systems.

The bearing fault identification technique presents a superior option in this research for exhibiting a notable difference between healthy and defective curves. More variety in the representation of fault improves the accuracy. This enables maintenance staff to notice or identify the issue. The findings show that the problem may be identified when a little deviation starts to progress towards a known fault curve that has been predetermined and stored in our database. From the table I it is clear that each researcher organized various proposed models with features extraction techniques to enhanced classification accuracy.

TABLE I:PREVIOUS WORK STUDY FROM VARIOUS RESEARCHERS AND THEIR LIMITATIONS

Reference	**No. Hidden Layers**	**Training Sample(%)**	**Average Accuracy(%)**	**Limitations Feature Extraction Algorithms Classifier Characteristics**
X. Guo, L. Chen et al [2016][12]	03	50(100)	97.9(100)	Authors used Adaptive CNN for fault size only on 50% sample.
C. Lu, Z. Wang et al [2017][13]	04	90(100)	92.6(100)	Authors used CNN for Noise-resilient only on 90% sample.
M. Xia, T. Li, et al[2018][14]	04	70(100)	99.4(100)	Researchers used CNN for Sensor fusion only on 70% sample.
L. Wen, X. Li et al [2018][15]	08	83(100)	99.8(100)	Experiment conducted using CNN based on different layer with 83% sample only.
W. Zhang, F. Zhang, et al [2018][16]	08	78(100)	99.2(100)	Results have done by CNN only use 78% sample size.
Z. Zhuang, Q. Wei et al [2018][17]	09	90(100)	98.6(100)	Results have conducted by Multi-scale CNN for Reduce training time using only 90 % sample size.
W. Zhang, C. Li, et al [2018][18]	13	96(100)	95.5(100)	Authors have done experiment only with CNN.
S. Li, G. Liu, et al [2017][19]	03	80(100)	98.9(100)	Researchers used only 80% sample for CNN.
J. Pan, Y. Zi, et al [2018][20]	06	50(100)	99.6(100)	Authors used CNN and FC layer to find speed change on very less sample size.
S. Guo, T. Yang, et al[2018][21]	09	67(100)	99.2(100)	Authors did work with frequency of bearing but they did not cover frequency signal of bearing fault from sensor.
W. Qian, S. Li, et al [2018][22]	04	05(100)	99.2(100)	Researchers used CNN raw vibration signals with less hidden layers.
H. Shao, H. Jiang, et al [2018][23]	03	67(100)	99.2(100)	Authors used ensemble model in deep learning for pool the input of different sizes from a fixed size. They did not covered polling from dynamic size.
J. Sun, C. Yan et al [2018][24]	02	N/A(100)	97.5(100)	Authors have used stack sparse and data compression which covered limited capacity on complex relationships in irregular signal.
H. Jiang, X. Li, H et al [2018][25]	03	60(100)	94.8(100)	Authors used Deep RNN and calculated less accuracy.
Y. Xie, T. Zhang [2018][26]	08	96(100)	86.3(100)	Researchers used SVM for data augmentation and calculated less accuracy compare to previous study.
H. Liu, J. Zhou, et al [2018][27]	11	91(100)	90.7(100)	Authors used Softmax method with 11 layer but did not calculate high accuracy compare to previous study.

III. MATERIAL AND METHODS

A. *Dataset Descripions*

The dataset represents the motor bearing performance. With the use of machine learning algorithms, we identify significant traits, rank them according to importance using correlation and chi-square, and evaluate the practicality of each method. All feature sets and ranking feature sets have been categorized using the defined classification methods. The outcomes are evaluated using accuracy. The outcomes are also compared to those of earlier techniques for the same dataset.

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	Specs	Score
7	crest factor	650.01
2	mean	217.82
8	form factor	130.47
4	RMS	110.72
0	maximum	81.43
3	standard deviation	45.97
1	minimum	24.37
6	kurtosis	9.74
5	skewness	1.48

Figure 1. Feature rankings with Chi-Square method.

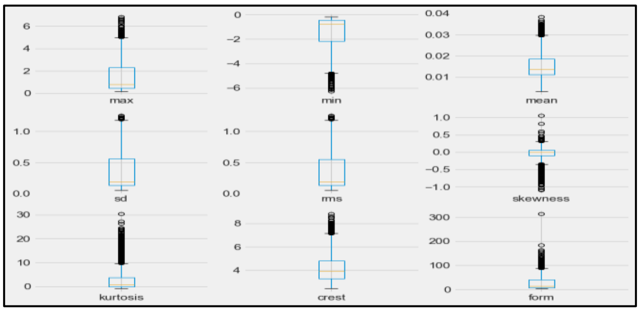

Figure 2. Representation of motors bearing fault attributes.

There aren't many datasets in the subject of mechanical engineering that are dedicated to employing machine learning in an industrial context. The test bearings hold up the motor shaft. Any defect that exists in the bearing's ball, inner race, or outer race has a time series. The maximum, minimum, mean, standard deviation, RMS, skewness, kurtosis, crest factor, and form factor must all be determined in order to carry out the fault detection prediction. Each feature is computed across a time range of 2048 points (0.04 seconds at the accelerometer sampling rate of 48 kHz). Figure 2 illustrates this dataset, which is publicly accessible due to Case Western Reserve University](https://case.edu/).

B. Algorithms Description

In this experiment we have used features selection techniques and some neural network methods as:The chi-square approach is a technique for data analysis that uses an average of k independent samples, each of which contains a number of classes or categories, to evaluate comparison hypotheses. This study's contribution is to identify the locations of tourist attractions with influencing elements by utilizing the chi-square approach to identify dominating features and exclude insignificant ones.The Chi-Square test is beneficial for machine learning and how it differs from other tests. When there are many features in line, choosing the best ones to use in the model building process is a significant difficulty in machine learning. By examining the relationships between the features, the chi-square test aids in feature selection issue resolution. The chi-square test in statistics is used to evaluate if two occurrences are independent. From the data of two variables, we may get the observed count O and the anticipated count E. The difference between the expected count E and the actual count O is calculated using the Chi-Square formula [28].

The Formula for Chi Square Is

$$\chi_c^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

where:

$c =$ degrees of freedom

$O =$ observed value(s)

$E =$ expected value(s)

Support vector machine was first developed as a binary classification method that supported both linear and nonlinearclassifications. Additionally, it developed to support various categorization issues. A support vector machine's learning method is to maximize the interval, which is identical to the regularized hinge loss function minimization issue and may be formalized as a convex quadratic programming problem. Support vector machines (SVMs), a type of deep learning system, employ supervised learning to categories or forecast the behavior of groups of data. AI and machine learning supervised learning systems provide input and desired output data that are marked for classification.

The SVM method seeks a hyperplane that effectively separates data points from one class from those from another. The terms plus and minus are used to convey the notion of "best" hyperplane, which is the hyperplane with the largest margin between the two classes [29].

Due to its excellent accuracy, resilience, feature significance, adaptability, and scalability, Random Forest is a well-known machine learning technique used for classification and regression problems. By averaging many decision trees,

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Random Forest lessens over fitting and is less susceptible to noise and outliers in the data. The biggest drawback of random forest is that it might be too sluggish and inefficient for real-time forecasts when there are a lot of trees. These algorithms are often quick to train but take a long time to make predictions after training. Because we create a forest of decision trees (many trees) using random selections of data and characteristics, it is known as a Random Forest. As we employ several subsets of data in each model to provide predictions, Random Forest is another well-known illustration of a bagging strategy [30].

Although they are not the same, deep belief networks are a type of machine learning method that resemble deep neural networks. These neural networks are feedforward and have a deep architecture, or numerous hidden layers. DBN uses hidden layers effectively (increasing layers yields a better performance improvement than does multilayer perceptron). DBN is very strong in classifying objects based on their size, location, colour, and rotation and view angle. The same neural network methodology used in DBN may be used to a variety of applications and data formats [31].

For deep learning algorithms, a CNN is a specific kind of network design that is used for tasks like image recognition and pixel data processing. CNNs are the ideal network architecture for recognising and detecting objects in deep learning, even if there are other types of neural networks available. Convolutional neural networks, often known as CNNs or ConvNets, are a type of deep learning network that learns directly from input. By searching for patterns in the pictures, CNNs are highly useful for identifying items, classes, and categories in photographs. They could be very helpful for classifying audio, time-series, and signal data. CNNs are capable of identifying important features without human supervision. They excel in classifying and identifying visual content. In comparison to a standard neural network, convolutional neural networks also reduce computation [32].

An artificial recurrent neural network (RNN) is the foundation of the deep learning architecture known as long short-term memory (LSTM). For situations requiring sequences and time series, LSTMs provide a practical solution. LSTMs have a lot of benefits over conventional RNNs. They excel at managing long-term dependencies, to start. This is a result of their propensityfor long-term memory retention. Second, the vanishing gradient issue is significantly less likely to affect LSTMs [33].

Voting ensembles are an ensemble approach that is used to train many machine learning models before combining the output of each model's predictions. In contrast to voting ensembles, approaches like bagging and boosting employ the same algorithm as their underlying models. Voting classifiers are machine learning models that anticipate an output (class) based on the class that has the best chance of becoming the output [34].

IV. PROPOSED MODEL

In this experiment we have used motors bearing faults dataset and evaluate import features by Chi-square and use some machine learning basic classifiers with baseline neural works as baseline classifiers RF, SVM and neural network basic classifiers as DBN, CNN and SNN. We have generated two different models for and test on different k-folds parameter. Each model performs or calculated different values on different parameter. Finally test all the values by voting ensemble algorithms and find higher score between algorithms experiment. In order to compare suggested and similar approaches, we present Area Under Curve (AUC) as the assessment statistic.

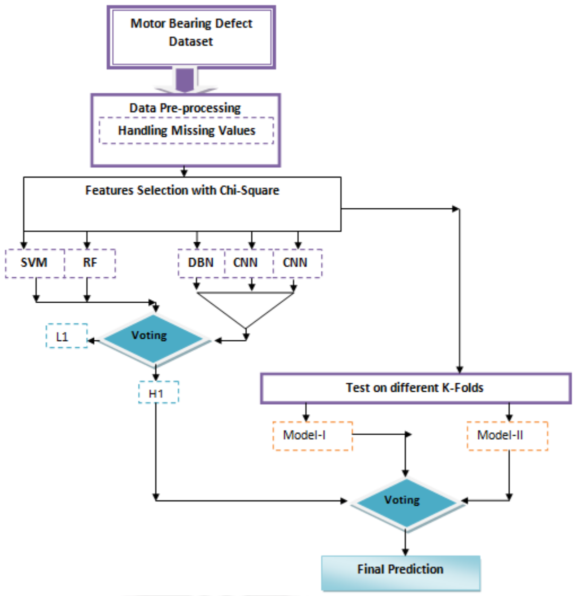

Figure 3. Proposed methods and implementation details

We categorize the methods in our main experiments into four groups:

1. Baseline machine learning algorithms which are popularly used in the bearing engineering domain: Support Vector Machine (SVM), Random Forest (RF).
2. Deep Belief Network (DBN) Convolution Neural network (CNN) and Shallow Neural Network (SNN).
3. Model-I, SVM-DBN, , SVM-CNN, , SVM-LSTM, , RF-DBN, , RF-CNN and , RF-LSTM.
4. Model-II, RF-SVM-DBN, RF-SVM-CNN and RF-SVM-LSTM.

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V. RESULTS AND DISCUSSION

The prediction performance comparison of the models is shown in Table II. We note that the classification tasks are for both models I and II, and the deep models outperform baselines from ordinary machine learning.

TABLE II.REPRESENTS AREA UNDER CURVE (AUC) RESULTS CLASSIFICATION

Method	Algorithms	AUC(K=5)	AUC(K=10)	AUC(k=15)
Baseline	SVM	0.64	0.70	0.72
	RF	0.69	0.72	0.76
NN-based	DBN	0.73	0.74	0.72
	CNN	0.73	0.75	0.78
	LSTM	0.77	0.76	0.77
Model-I	SVM-DBN	0.73	0.74	0.78
	SVM-CNN	0.75	0.77	0.78
	SVM-LSTM	0.77	0.76	0.77
	RF-DBN	0.76	0.76	0.78
	RF-CNN	0.77	0.70	0.74
	RF-LSTM	0.74	0.76	0.72
Model-II	RF-SVM-DBN	0.77	0.78	0.80
	RF-SVM-CNN	0.78	0.83	0.84
	RF-SVM-LSTM	0.76	0.81	0.78

TABLE III. REPRESENTS ACCURACY, TRAINING LOSS AND VALIDATION LOSS ON DIFFERENT K-FOLDS

Algorithms	K-Folds	Accuracy (%)	Training loss	Validation loss
RF-SVM-DBN	5	87.3	0.190015	0.284939
RF-SVM-CNN		89.2	0.260013	0.304936
RF-SVM-LSTM		86.7	0.360017	0.354938
RF-SVM-DBN	10	94.8	0.175961	0.164139
RF-SVM-CNN		98.4	0.155960	0.154133
RF-SVM-LSTM		95.3	0.165962	0.174131
RF-SVM-DBN	15	95.1	0.121600	0.110991
RF-SVM-CNN		98.3	0.155759	0.144127
RF-SVM-LSTM		95.5	0.165341	0.172171

On the bearing dataset, we used three-fold classification models with Chi-Square and other classifiers to assess ROC performance. The experimental graphic shows ROC value comparisons in table II.

We carefully followed the experiment's progression and discovered that model-II computed high accuracy training loss and validation loss values using features selection procedures with 5 fold, 10 fold, and 15 fold cross validation. The accuracy values in the current work are 89.2, 98.4, and 98.3 in table III.

A dataset test's performance may be evaluated using the ROC performance measure. It has enough details to make sense of it and boost the effectiveness of any machine learning system. On 10 & 15_Fold cross validation, the classifier achieves great results, as shown in figure. The Chi-Square features selection methodology was utilized to determine the 78% ROC value.

Additionally, it is shown when the enhanced Random Forest method is used to precisely classify bearing faults in a multi-class bearing defect dataset. According to the findings, classification accuracy rises in relation to cross validation values. The accuracy scores for K=5, 10, and 15 are 89.2, 98.4, and 98.3, respectively. The ROC score continues to rise, with model-II (RF-SVM-CNN) scoring 0.78, 0.83, and 0.84 for K=5, 10, and 15 correspondingly. In the experiment, we discover that the RF-SVM-CNN's Algorithms model-II, K-Folds (5, 10 & 15), Accuracy (%), Training loss, and Validation loss values are 89.2, 0.260013, 0.304936, 98.4, 0.155960, 0.154133, and 98.3, respectively, for K-Folds 10 and 15.

VI. CONCLUSION

The study looks at ROC values for datasets with many classes of bearing defects as well as models I and II that use CNN to increase classification accuracy. The results of the experiment confirm that the recommended technique is appropriate for rotor and bearing faults in induction motor diagnostics. Additionally, a GUI for defect diagnostics was developed and put to use in a real-world situation. The accuracy of the fault detection system in the real world was 89.2, 98.4, and 98.3 for the normal, rotor fault, and bearing fault states of induction motors recognized by DBN, CNN, SNN, SVM, and RF, respectively. To train interpretable features and prediction rules, we have suggested the model-I and model-II approaches as deep networks using baseline classifiers in this research. Our early experimental findings indicate comparable or perhaps superior performance. In the experiment, accuracy (%), training loss, and validation loss values for RF-SVM-CNN are found to be 98.3, 0.155759, and 0.144127 for k-fold 15, respectively.

In our upcoming study, we intend to extract more beneficial data from approaches for improved engineering in mechanical development, such as decision rules or tree node attributes.

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