ARTIFICIAL INTELLIGENCE BASED FAULT DIAGNOSIS OF AUTOMOBILE GEARBOX

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Abstract - *The main component of an automobile is a gearbox as it plays a vital role in power transmission and speed regulation. Numerous factors are responsible for the proper functioning of the gearbox and it has to work under different operating conditions of load One such condition being working at different loads, which reduces the performance which leads to vibrations and sounds being generated in the gearbox. It is important to predict when such failures occur in a gearbox, thus a need arises for precise fault diagnosis of a gearbox. The Fault Diagnosis of a gearbox plays a vital role in the accuracy and safety of any rotating machine. Conventional fault diagnosis practice is usually manual extraction of the necessary characteristics from the raw sensor data before labelling them based on some pattern recognition models. Such methods require a lot of experience and domain knowledge, also this often leads to cause poor results which lead to poor flexibility of the model. As an upcoming domain in industrial applications and as an accurate solution for fault diagnosis, artificial intelligence (AI) techniques have been receiving a lot of attention from industries and researchers around the globe. With the advent of the 21st century, deep learning has developed at a rapid pace and a lot of discoveries have been made about image analysis and speech recognition. Despite such rapid growth, its applications in the field of fault diagnosis are yet to cross the preliminary stage. In recent years a slew of research has been conducted based on artificial intelligence methods for fault diagnosis using different machine learning and deep learning models. Research has shown that a combination of methods associated with machine learning (SVM, ANN, Decision tree, etc.) and deep learning (recurrent neural networks, deep neural networks, long short-term memory, etc.) can be used to fetch better results for fault classification. Even though a lot of research has been going on, there has been no effort to fully use artificial intelligence for fault diagnosis of an automobile gearbox, this project focuses on using different machine learning and deep learning algorithms to develop an accurate model for predicting gearbox failure. To tackle this issue models like Artificial neural networks, Decision tree, Multiclass logistic regression, K nearest neighbour, Random Forest, Support vector machine and deep learning techniques have been used for fault diagnosis in the automobile gearbox and the model that has higher accuracy is selected from the results. A web application for the SVM technique is developed using the Flask web framework.*

***Key Words*: Decision tree, SVM, ANN, DNN, Web application**

1.INTRODUCTION

Industrialization and a paradigm shift in the field of science and technology have led to the invention of new machines and also the up-gradation of existing mechanical equipment. The gearbox is one of the important pieces of rotating equipment used for power transmission. In recent years there has been an increase in demand for more accuracy of machines, so the accuracy of the gearbox is the most important factor [1]. Gears after running for some time are prone to errors such as misalignment, tooth cracks and backlash, which create vibrations in the machinery; it affects the functioning of rotating components like bearings and shafts [2]. These faults can be detected through vibration signals; these signals contain a plethora of information that determines the dynamic behaviour of the machine. Failure in such key components leads to higher maintenance costs and also may lead to casualties in some cases [3]. Therefore, it makes it imperative to detect failures in the gearbox.

The fault diagnostic of rotating machinery consists of three steps: determining the status of the machinery (if it is working properly), checking for the cause of the issue, and predicting the trend at which the fault is progressing [1]. This can be considered as a pattern identification problem for which a strong tool like Artificial Intelligence (AI) has gotten a lot of attention from academics and has proven to have a variety of industrial uses, one of which is fault diagnosis of rotating machinery. Finding the needed pattern for fault diagnosis in vibrating signals is difficult due to the vast amount of rich and complex information contained in them. As a result, any fault diagnosis system has two key steps. Data processing (feature extraction), followed by fault identification using the processed data [4]. Feature selection can be done using techniques like a Decision tree. For classifying the features, it can be done with the help of either machine learning or deep learning algorithms.

SVM is one such feature classification algorithm that has been proved to be more efficient over time when compared to other machine learning algorithms in terms of both accuracy and training time [5].

To experiment, data is gathered using an experimental setup consisting of a gearbox fitted with an accelerometer and microphone whichcollect the required vibration and sound signals respectively. This data is used for statistical feature extraction followedby feature selection using the decision tree. Post this the extracted featuresare classified based on different machine learning and deep learning models. Vibrating signalscontain a large quantity of rich and complex information, finding the required pattern for fault identification is difficult. As a result, each fault diagnosis system includes two critical processes. The first step is data processing (feature extraction), followed by fault detection by using the processed data with the help of different intelligent algorithm's. Feature selection canbe done using techniques like a Decision tree. For classifying the features, the features are classified with the help of either machinelearning or deep learning algorithms.

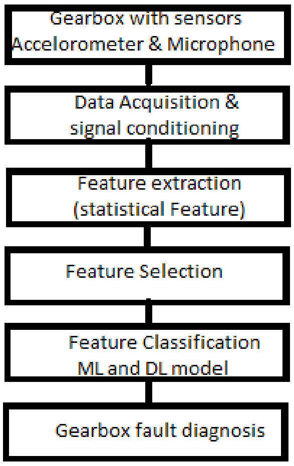

Fig 1 Methodology

The methodology of the project was divided into the following steps:

1. An experimental setup consisting of a gearbox fitted with sensors (accelerometer and microphone) was used to acquire the data.
2. Once data acquisition was completed the required statistical features such as mean, median, skewness, kurtosis, etc. were extracted.
3. After feature extraction, a decision tree algorithm was used to select the required features were selected using the decision tree algorithm.
4. Feature classification was done using both machine learning and deep learning algorithms, based on the classification accuracy that was achieved, the best algorithm for gearbox fault diagnosis was selected.

2. EXPERIMENTAL STUDIES

2.1. EXPERIMENTAL SETUP

A 0.5 hp variable speed Direct Current motor, synchronous speed gearbox with four sets of gears and four different speed ranges (500 rpm, 750 rpm, 1000 rpm), and an eddy current dynamometer make up the experimental setup. Motor power is used to give input for gearbox drive, with control panels that allow the motor speed to be varied from 0 to 1440 rpm. An eddy current dynamometer is linked on the gearbox output shaft to change the load on the gearbox to replicate gearbox loading situations. To reduce the impact of vibrations in the gearbox, a flexible coupling is used. To measure vibration, a Piezoelectric accelerometer and a Physical Acoustics AE Sensor are put on the flat surface of the gearbox with direct adhesive installation as well as AE signals Free field array G.R.A.S 40 PH for sound signal acquisition, a microphone is installed adjacent to the gearbox bearing housing. Figure 2 depicts the entire experimental setup

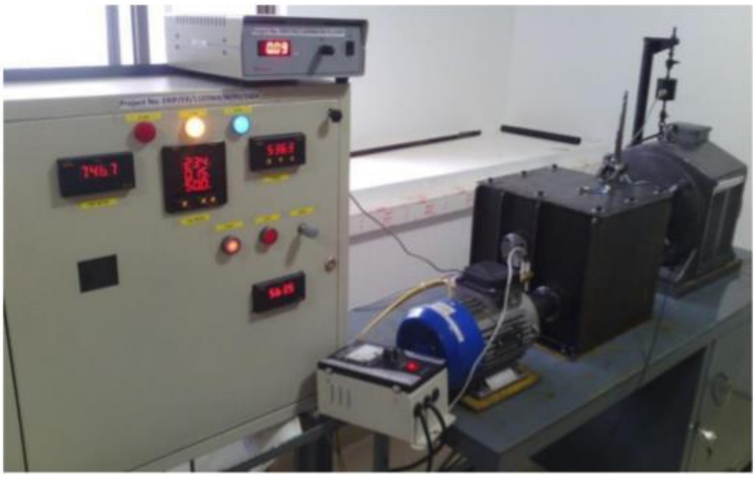

Fig 2 Experimental setup

2.2. PROCEDURE

The research was conducted using the following experimental settings: three input motor speeds, three loads, and two gear and bearing fault circumstances, totalling 36 test conditions (see Figure 3).

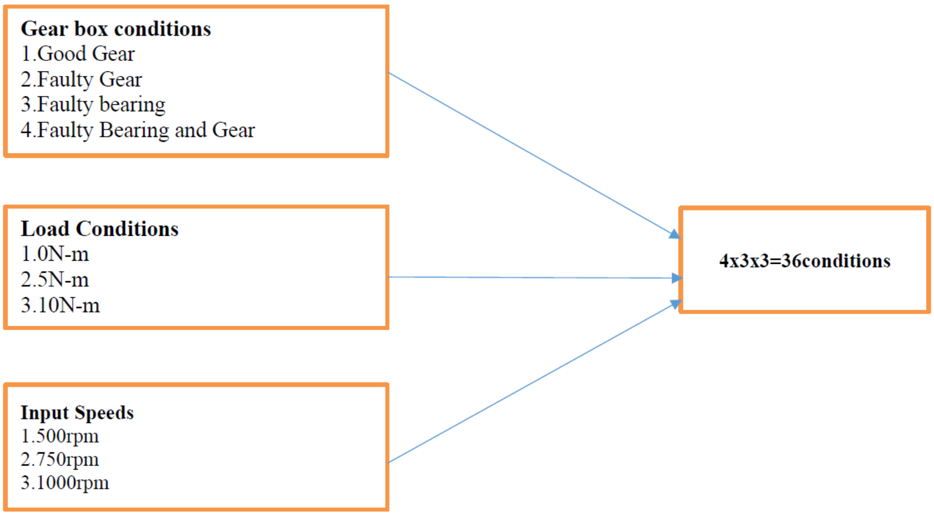

Fig 3 36 Test Conditions

A crack was produced in the bearing using the Electric Discharge Machining procedure to replicate faulty bearing conditions. A gear defect was simulated by chipping the tooth of the gear using a grinding operation to replicate faulty gear conditions. Two bearings and two gear sets were simulated, one with no defects and the other with outer race problems and chipped gear. First, all good gears are installed in the gearbox, and the test is run at 500rpm with a load of 0-Nm. To achieve a steady state, the setup is set to run for some time. The data from the accelerometer and microphone is acquired using the signal-conditioning unit after it has reached steady operating conditions. where the signal is transmitted through a charge amplifier and an Analogue to Digital Converter (ADC). Each experiment lasts 200 seconds, with 8192 samples were taken every second. Digital signals are fed into the computer through a USB connector. Signal recording in the computer's secondary memory and signal conditioning are done with the software SO analyzer. Using M+P data acquisition 8 channel the vibration and the sound data is collected separately [6].

3. FEATURE EXTRACTION AND FEATURE CLASSIFICATION

Now, from the raw data using statistical techniques in python, we will find the features like sum, variance, mean, minimum, maximum, skewness, kurtosis, the standard deviation for each column. The process is repeated for all gears at different speeds i.e. 500,750,1000 rpm. Using a decision tree we select the best 6 features out of 8 features. Using these features classification model has been developed for different algorithms i.e. Decision tree, Artificial neural network, Support vector machine, Deep neural network

4. MACHINE LEARNING

Machine learning is known as a subset of artificial intelligence (AI) that empowers systems to learn on their own and improve over time without having to be programmed. Machine Learning is used since traditional algorithms are incapable of performing complex jobs. The examination of enormous amounts of data has become easier thanks to machine learning. Machine learning algorithms used in this study are decision tree, SVM and ANN.

4.1. DECISION TREE

It's a graphical representation for finding all possible answers to a problem or making a decision based on a set of circumstances. A decision tree is a type of supervised learning technique that can be used to solve problems in classification and regression.

The split of the tree generally is based on the Gini index and entropy.

- Gini Index: Gini impurity is a metric for how often a randomly selected element from a set will be erroneously labelled if it is labelled according to the distribution of labels in the subset.

$$G = \sum_{i=1}^{C} p_i * (1 - p_i)$$

- Information Gain(Entropy): It's used to decide which feature to split on at each stage of the tree's construction. The more information gain you have, the better you can use that feature for splitting.

$$\sum_{i=1}^{C} -p_i * log_2 \, (p_i)$$

Internal nodes represent features, branches indicate decision roots, and leaf nodes indicate the outcome in this T-structure classifier. The decision node and the leaf node are the two nodes in a decision tree. The decision node is used to make any decision and has several branches, whilst the leaf nodes are the decisions' outputs. Classification accuracy is defined as the ratio of the number of correctly predicted values to all input values.

Steps involved in Machine Learning

1. Data gathering: Data was taken from the data logger in raw format after getting the data we will convert it into CSV format.
2. Exploratory Data Analysis: Here we performed both statistical and graphical data analysis. Here we get to know that there are no outliers in the given data and the distribution of the data is in Gaussian distribution.
3. Data Pre- Processing: It involves feature extraction, feature selection.
   i. Feature extraction: In this project, we used statistical features like mean, variance, standard error, kurtosis, skewness, median, root mean square, standard deviation, mode to extract these important features from the raw data.

   ii. Feature Selection: In this project, we used an extra tree classifier to know that which feature is contributing more to know the output.

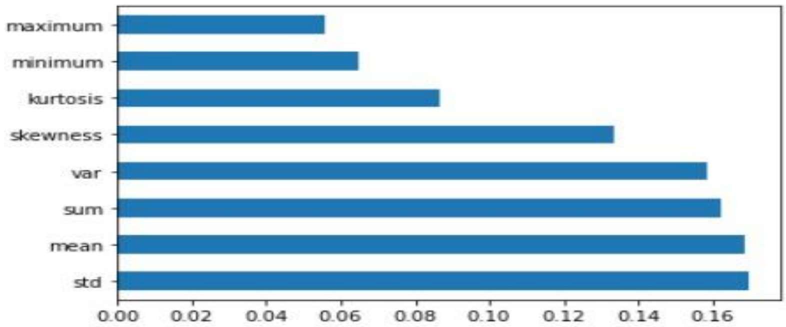

Fig 3 Feature selection using Decision Tree

4. Train and Test split of data: In this step, we divide the entire data into train size and test size using optimum parameters.

5. Model training: We trained the Model by fitting the input and output features in the decision tree algorithm. Then we find the accuracy of the model.

6. Hyperparameter tuning: It is the method used in Machine Learning to evaluate the model and increase its accuracy.

```
clf_GS = GridSearchCV(pipe, parameters)
clf_GS.fit(X, y)

GridSearchCV(estimator=Pipeline(steps=[('sc', StandardScaler()), ('pca', PCA
()),
                                       ('dec_tree', DecisionTreeClassifier
()))]),
             param_grid={'dec_tree__criterion': ['gini', 'entropy'],
                         'dec_tree__max_depth': [2, 4, 6, 8, 10, 12],
                         'pca__n_components': [1, 2, 3, 4, 5, 6, 7, 8]})
```

Fig 4 Hyperparameters used in Decision Tree

Classification Accuracy= (TP+TN)/(TP+FP+TN+FN)

Where,

TP and FP are truly positive and false positive respectively

TN and FN are truly negative and false negative respectively

Table 1 Confusion Matrix

N	Predicted-Yes	Predicted-No
Actual-Yes	TP	FN
Actual-No	FP	TN

Table 2 Classification Accuracy (DT)

Gear RPM	Classification Accuracy (%)
1_500	85
1_750	89.3
1_1000	78.1
2_500	88.12
2_750	86.80

2_1000	88.10
3_500	95
3_750	98.30
3_1000	100
4_500	96.6
4_750	97.5
4_1000	95
Mean	91.48

Table 2 depicts the classification accuracy which was found using a decision tree algorithm for different gears at different conditions and the mean accuracy is 91.48%

4.2. SUPPORT VECTOR MACHINE

One of the most widely used supervised learning algorithms for classification and regression problems. SVM selects the extreme points that assist in the formation of the hyperplane. The extreme points that assist in the formation of the hyperplane are called Support vectors, thus the algorithm associated is called support vector machine (Figure5).

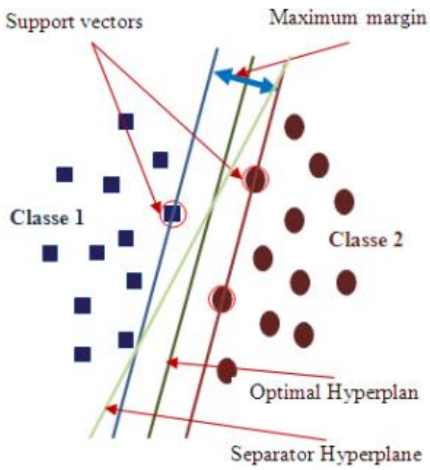

Fig 5 SVM illustration [Abdellatif Hajraoui et.al.]

The fundamental goal of the SVM algorithm is to divide the n-dimensional space into classes so that fresh data points can be readily placed in the correct category in the future by finding the optimal decision boundary with the help of a hyperplane as it is considered to be one of the best decision boundaries. Support vector machine uses three different types of Kernels

1. Linear **k (x, xi) =sum(x*xi)**
2. Polynomial **k (x, xi) =1+sum(x*xi) ^d**
3. Radial Basis Function (RBF) **k(x,xi)=exp(-gamma *sum(x-xi^2))**

Since this is a multiclass classification problem we used the RBF kernel

Steps involved in SVM:

1. Data gathering: Data was taken from the data logger in raw format after getting the data we will convert it into CSV format.
2. Exploratory Data Analysis: Here we performed both statistical and graphical data analysis. Here we get to know that there are no outliers in the given data and the distribution of the data is in gaussian distribution.
3. Data Pre-Processing: It involves feature extraction, feature selection.
   i. Feature extraction: In this project, we used statistical features like mean, variance, standard error, kurtosis, skewness, median, root mean square, standard deviation, mode to extract these important features from the raw data.

ii. Feature Selection: In this project, we used an extra tree classifier to know that which feature is contributing more to know the output.

4. Train and Test split of data: In this step, we divide the entire data into train size and test size using optimum parameters.

5. Model training: The model is trained by fitting the input and output features in the Support Vector Machine classifier then we found the best parameters using hyperparameter tuning to find the best accuracy.

6. RBF kernel was used in this project because it is best suited for classification problems.

```
tuned_svm_clf.fit(train_data_scaled, train_data['Class'])

GridSearchCV(cv=10, estimator=SVC(), n_jobs=-1,
             param_grid={'C': [1, 10, 50, 100, 300, 500],
                         'gamma': [0.01, 0.05, 0.1, 0.5, 1, 5],
                         'kernel': ['rbf']})
```

Fig 6 Hyperparameter tuning for SVM

Table 3 Classification Accuracy (SVM)

Gear RPM	Classification Accuracy (%)
1_500	89
1_750	89.3
1_1000	80.25
2_500	93.08
2_750	88
2_1000	89.2
3_500	95.3
3_750	98
3_1000	99
4_500	98
4_750	99
4_1000	93.6
Mean	92.64

Table 3 depicts the classification accuracy which was found using a support vector machine algorithm (RBF kernel) for different gears at different conditions and the mean accuracy is 92.64%

GG 0 Nm	GG 5 Nm	GG 10 Nm	GG 15 Nm	FB 0 Nm	FB 5 Nm	FB 10 Nm	FB 15 Nm	FG 0 Nm	FG 5 Nm	FG 10 Nm	FG 15 Nm	FGFB 0 Nm	FGFB 5 Nm	FGFB 10 Nm	FGFB 15 Nm	classified as
90	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	GG 0 Nm
13	84	3	0	0	0	0	0	0	0	0	0	0	0	0	0	GG 5 Nm
0	2	53	45	0	0	0	0	0	0	0	0	0	0	0	0	GG 10 Nm
0	2	27	69	0	0	0	0	0	0	0	2	0	0	0	0	GG 15 Nm
0	0	0	0	90	10	0	0	0	0	0	0	0	0	0	0	FB 0 Nm
0	0	0	0	15	71	14	0	0	0	0	0	0	0	0	0	FB 5 Nm
0	0	0	0	0	7	91	0	0	0	0	0	1	1	0	0	FB 10 Nm
0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0	FB 15 Nm
0	0	0	0	0	0	0	0	100	0	0	0	0	0	0	0	FG 0 Nm
0	0	0	0	0	0	0	0	1	99	0	0	0	0	0	0	FG 5 Nm
0	0	0	0	0	0	0	0	0	1	87	12	0	0	0	0	FG 10 Nm
0	0	0	0	0	0	0	0	0	0	8	92	0	0	0	0	FG 15 Nm
0	0	0	0	0	0	0	0	0	0	0	0	96	4	0	0	FGFB 0 Nm
0	0	0	0	0	0	0	0	0	0	0	0	5	72	18	5	FGFB 5 Nm
0	0	0	0	0	0	0	1	0	0	0	0	0	25	51	23	FGFB 10 Nm
0	0	0	0	0	0	0	2	0	0	0	0	0	5	18	75	FGFB 15 Nm

Fig 7 Confusion Matrix

Figure 7 depicts the confusion matrix for the SVM algorithm, where all the diagonal elements represent the correctly classified data. The result of feature classification is obtained in the form of a confusion matrix. An Mx M matrix is used to evaluate the performance of a classification model, where M is the number of target classes is known as a confusion matrix. The matrix compares the actual values to the machine learning model's predicted values. Each column representsprojected fault classes, whereas each row represents actual fault classes. The number of datapoints categorized as faulty bearing (FB) in the first row of the firstcolumn shows the number of data points accurately categorized as faulty bearing (FB) by the model. The second element in the first-row second column represents the numberof datapoints belonging to the faulty bearing (FB) class but are misclassified by the model as faulty gear (FB).

4.3. ARTIFICIAL NEURAL NETWORK(ANN)

The adjective "neural" refers to a neuron, while "network" refers to a graph-like structure. Neural nets are another name for an artificial neural network. These are programs that attempt to act like a typical human nervous system to solve any problem. In general, neural networks are made up of three layers. The layers are the input layer, output layer and one hidden layer.

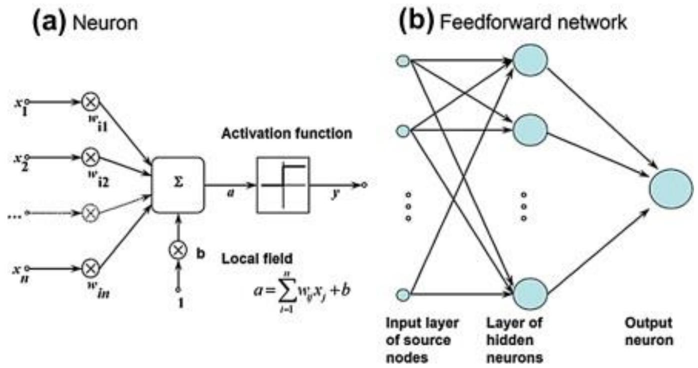

Fig 8 Artificial Neural Network [N.J.Sairamya et. al.]

Learning in an ANN refers to the process of changing the weights of the connections between nodes in a network. The learning ability of a neural network is determined by the architectural and computational methods used to train it. In feedforward network (Figure 8) takes each feature as input and assigns some weights to it and then it goes to the hidden layer.

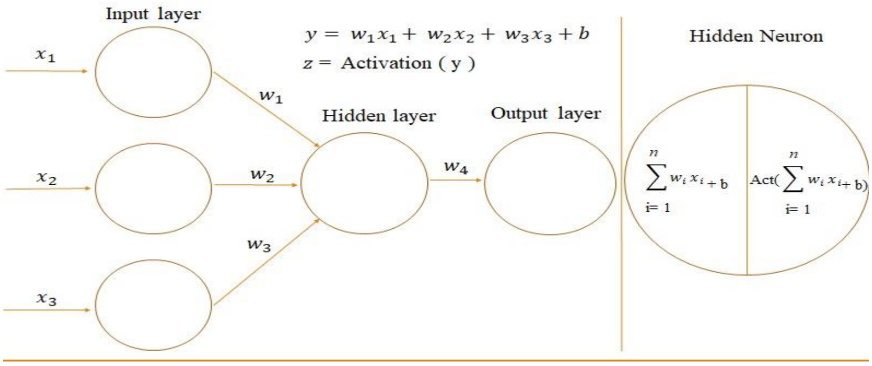

Fig 9 Learning process of a neural network

$$y = \sum_{i=1}^{n} wixi + b$$

In the hidden layer, the output feature=Summation of all features to weights and adding bias to it. Then activation function is applied to the y value.

z=Activation(y)

Then it passes to the output layer with some assigned weights. This is a forward propagation process or feedforward network.

Evaluating the model: It tells us about the difference between the original value(y) and the predicted value ($\hat{y}$). If the loss is very high then the model will perform backpropagation and adjust weights. This process will continue till we achieve minimal loss.

Table 4 Classification Accuracy (ANN)

Gear RPM	Classification Accuracy (%)
1_500	81.7
1_750	81.5
1_1000	74.2
2_500	84
2_750	81.7
2_1000	82.3
3_500	88
3_750	94.2
3_1000	99.2
4_500	92.2
4_750	93.1
4_1000	91.1
Mean	86.93

Table 4 depicts the classification accuracy which was found using an artificial neural network for different gears at different conditions and the mean accuracy is 86.93%

5. DEEP LEARNING

Deep learning is a branch of machine learning that employs numerous layers to extract higher-level features from raw data.

5.1. DEEP NEURAL NETWORKS

It is a type of Artificial Neural Network where there are numerous hidden layers between the input and output layers. Here the data is passed from the input layer to the output layer without looping back.

5.2. ACTIVATION FUNCTION

An activation function aids in determining a neural network's output. This sort of function is tied to each neuron in the network and assesses whether the network should be engaged or not based on the relevance of each neuron's input to the model's prediction.

5.3. ACTIVATION FUNCTIONS USED IN THE STUDY:

5.3.1. SIGMOID ACTIVATION FUNCTION: The output of a sigmoid function is in the range of (0,1). If the value is less than 0.5, it is classified as zero; otherwise, it is classified as one. As a result, it is the most widely used binary classification function.

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

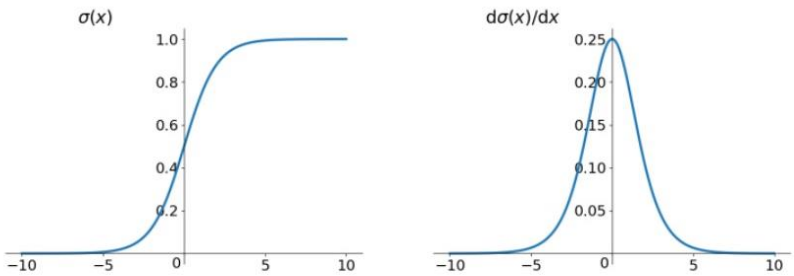

Fig 10 Sigmoid Function

5.3.2.TANH FUNCTION: It is a hyperbolic tangent function. The tanh function's curves are slightly different from the sigmoid function's. The key distinction between the two functions is that tanh is from -1 to 1, whereas sigmoid is from 0 to 1.

$$tanhx = \frac{e^{x} - e^{-x}}{e^{x} + e^{x}}$$

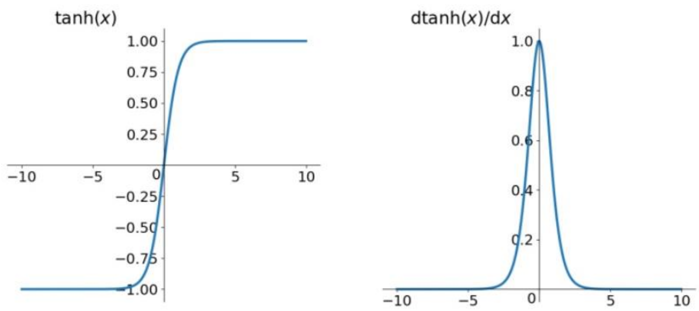

Fig 11 Tanh Function

5.3.3. RECTIFIED LINEAR UNIT FUNCTION (ReLU): When compared to Sigmoid and Tanh functions, it is currently the most popular because of the following benefits.

When the input is positive there is no gradient saturation problem. The calculation speed is much faster because it has only a linear relationship. It outperforms sigmoid and tanh functions in both forward and backward propagation (exponent needs to be calculated by sigmoid and tanh, which will take longer).

ReLU=max(0,x)

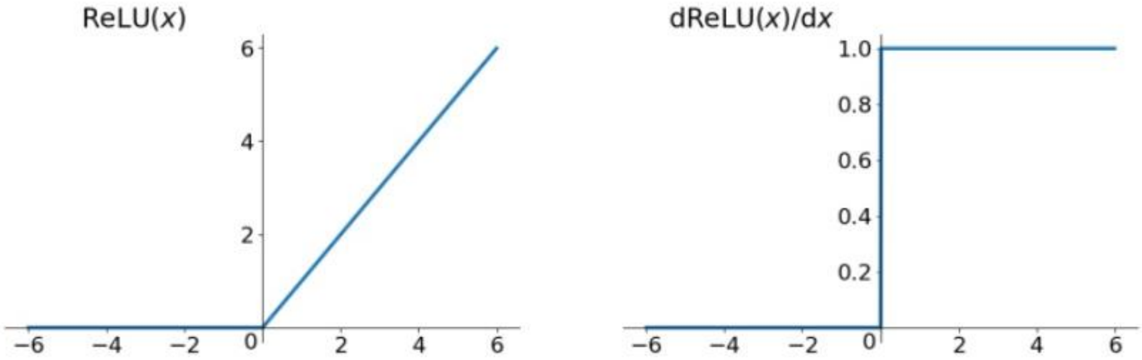

Fig 12 ReLU Function

5.3.4. SOFTMAX FUNCTION: It is generally used in the output layer for Multi-class classification problems.

$$S(x_j) = \frac{e^{x_j}}{\sum_{k=1}^{K} e^{x_k}}, j = 1,2, \dots, K$$

```
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                448

dense_1 (Dense)              (None, 64)                4160

dense_2 (Dense)              (None, 64)                4160

dense_3 (Dense)              (None, 64)                4160

dense_4 (Dense)              (None, 16)                1040
=================================================================
Total params: 13,968
Trainable params: 13,968
Non-trainable params: 0
```

Fig 13 Deep Neural Network Model

Table 5 Classification Accuracy (DNN-using ReLU)

Gear RPM	Classification Accuracy (%)
1_500	84.5
1_750	85.5
1_1000	78.5
2_500	92
2_750	83.5

2_1000	89.5
3_500	94
3_750	95.5
3_1000	99
4_500	97
4_750	100
4_1000	96
Mean	91.2

Table 5 depicts the classification accuracy which was found using a deep neural network (ReLU Activation function) for different gears at different conditions and the mean accuracy is 91.2%

6. WEB APPLICATION

6.1. INTRODUCTION

Based on the research done so far, there has been no attempt to fully automate the fault classification process. Automatic fault classification techniques will have a lot of demand soon as this will help in detecting faults efficiently so that the health of the machine is maintained [9]. A model has been created to identify the faults using machine learning.

6.2. PROCEDURE FOR CREATING THE WEB APPLICATION

Build a . Html file. Create an SVM model using sci-kit learn, pandas and NumPy libraries and save it as a .py file. Convert the .py file to a pickle file (.pkl). Create a web application using the FLASK framework and save it as app.py. Open. pkl file in app.py file using flask libraries by importing request, flask and render the template. Run the app.py file on the Local Host. Deploy the model on the HEROKU cloud platform.

Click the link https://ml-based-fault-diagnosis.herokuapp.com/. The below page will appear on the screen (figure 7)

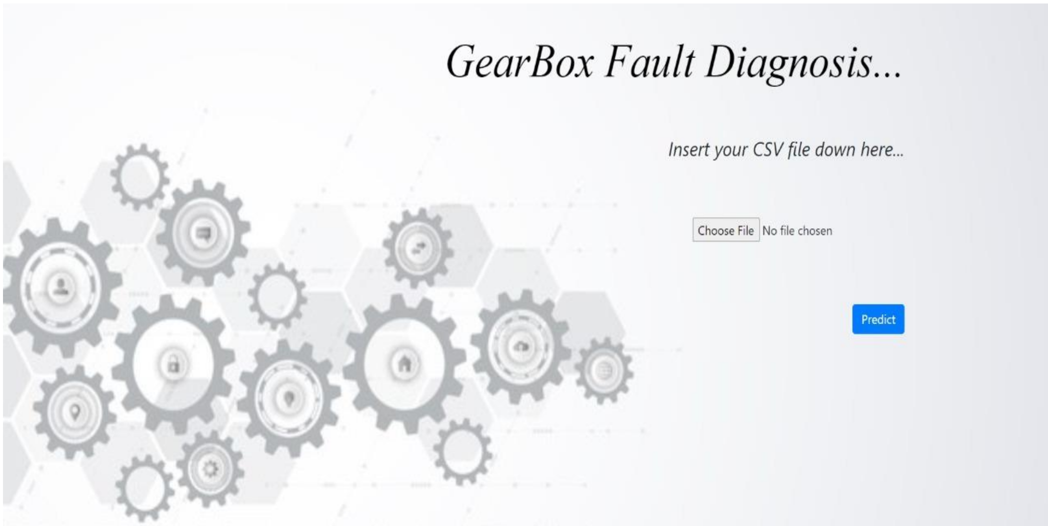

Fig 14 Web Application Page of the machine learning model

6.3. WORKING ON THE WEB APPLICATION

A data file (.csv format) is given as an input to the model as shown in figure 8. When the predict option is clicked, the SVM model will predict the faults for the given data and store it in a data frame. Using the value_counts function will show the number of different faults and also will show how frequently each fault has occurred. If the fault has occurred more than 80% in the given data, then the model will show the corresponding fault on the web page as shown in figure 9.

A1 f_x 1.518303416

	A	B	C	D	E	F
1	1.518303	1.522977	0.161775	-0.03332	-0.39789	0.162591
2	1.536903	1.543256	0.131123	-0.06077	-0.47142	0.105492
3	1.531341	1.52375	0.158258	-0.03655	-0.70879	0.534889
4	1.428268	1.439676	0.167973	-0.0279	-0.42949	-0.01272
5	1.508001	1.518703	0.16881	-0.02707	-0.09558	0.20288
6	1.539593	1.539482	0.17484	-0.0217	-0.55125	0.173682
7	1.586776	1.588772	0.1802	-0.01681	-0.73164	0.278022
8	1.558922	1.571039	0.182545	-0.01462	-0.67254	0.097592
9	1.577203	1.577086	0.131123	-0.06072	-0.68231	0.447013
10	1.536584	1.53589	0.11722	-0.07308	-0.5243	0.217763
11	1.480876	1.493149	0.118895	-0.07156	-0.21695	-0.16588
12	1.565304	1.577723	0.165293	-0.03025	-0.66056	0.069469
13	1.470026	1.47005	0.151725	-0.04236	-0.53281	0.424546
14	1.467975	1.469141	0.150888	-0.04309	-0.52217	0.205597
15	1.469342	1.473688	0.121408	-0.06942	-0.80367	0.316794
16	1.521631	1.532844	0.155578	-0.03889	-0.42792	-0.08022
17	1.531387	1.528661	0.145193	-0.04827	-0.49025	0.196718
18	1.475223	1.472824	0.158258	-0.03655	-0.59783	0.20724
19	1.479463	1.488147	0.166465	-0.02917	-0.54495	0.179244
20	1.540869	1.545121	0.16211	-0.03313	-0.6842	0.509894
21	1.596258	1.595456	0.109181	-0.08011	-0.44565	0.242947
22	1.478186	1.480372	0.152898	-0.04138	-0.68593	0.203796
23	1.446913	1.455636	0.117555	-0.07279	-0.43438	0.083278
24	1.478779	1.491785	0.187403	-0.01032	-0.45676	0.070828
25	1.459815	1.450452	0.207	0.007557	-0.06753	0.249772
26	1.503852	1.497105	0.153065	-0.04119	-0.81234	0.486227
27	1.497196	1.495013	0.151223	-0.0428	-0.83787	0.449635
28	1.593432	1.593501	0.167973	-0.02785	-0.74394	0.357872

Fig 15 Vibration data in .csv format from gearbox

Fig 16 Predicted result for vibration data at 10 Nm condition

7. RESULTS

The accelerometer and microphone put on the gearbox were used to collect time-domain data at various speeds (500, 750, and 1000 rpm) and loading conditions (0 N, 5 N, 10N, 15N). The obtained data was translated into statistical features using freely available statistical methods in Python to simplify the fault diagnosis procedure. It's a 16-class problem with four fault circumstances (Faulty Gear(FG), (Good Gear(GG), Faulty Gear and Faulty Bearing(FGFB), Faulty Bearing(FB)), with four loading situations. An extra tree classifier is utilized for feature selection due to its robustness. Using this classifier the best 6 features out of 8 features were selected as they contribute towards the best classification model for vibration and microphone data.

The selected 6 features for the vibration and microphone data were given as an input to the four models such as Decision Tree, Support Vector Machine, Artificial Neural Network and Deep Neural Network. For the classification process, a supervised method of training was utilised, and the classification accuracy attained is shown in Tables 6 and 7.

Motor speed (in RPM)	Gear	Algorithm					
		Decision Tree	Support Vector Machine	Artificial Neural Network	Deep Neural Network		
					Relu	tanh	sigmoid
500	1	85%	89%	81.70%	84.50%	85%	84%
	2	88.12%	93.08%	84%	92%	88.50%	92%
	3	95%	95.30%	88%	94.00%	93.00%	93%
	4	96.60%	98.00%	92.20%	97.00%	94.50%	97%
750	1	89.30%	89.30%	81.50%	85.50%	81.50%	90.50%
	2	86.80%	88%	81.70%	83.50%	82%	80.50%
	3	98.30%	98%	94.20%	95.50%	97%	96%
	4	97.50%	99%	93.10%	100.00%	97.50%	98.50%
1000	1	78.10%	80.25%	74.20%	78.50%	78%	81%
	2	88.10%	89.20%	82.30%	89.50%	86%	86.50%
	3	100%	99.00%	99.20%	99.00%	99.00%	99%
	4	95%	93.60%	91.10%	96%	94%	98%

Fig 17 Vibration data classification accuracy

Figure 17 compares the classification accuracy which was found using different machine learning and deep learning algorithms for vibration data of different gears at different conditions. It shows SVM performs better than other algorithms.

Motor speed (in RPM)	Gear	Algorithm					
		Decision Tree	Artificial Neural Network	Support Vector Machine	Deep Neural Network		
					Relu	tanh	Sigmoid
500		71.80%	70.80%	73.70%	74.50%	74%	70%
		68.10%	60.20%	73.40%	64.20%	57%	68.40%
		72%	76.30%	81.80%	79.80%	80.03%	65.20%
		68.30%	73.50%	75%	68.20%	67.30%	73.70%
750		58.75%	62.90%	74.00%	74.40%	74.20%	50.80%
		82.50%	84.10%	90.30%	83.70%	87.70%	87.10%
		89.10%	89.40%	87.30%	80.00%	88.60%	50%
		78.30%	82.10%	83.50%	75%	75.30%	76.30%
1000		70.60%	75.90%	76.80%	67.20%	69.50%	73.50%
		77.50%	74.40%	80.00%	72.50%	72.20%	79.50%
		80.80%	82.30%	86.10%	79.80%	82.80%	78.80%
		80%	77.30%	81.06%	71%	74.70%	75.30%

Fig 18 Sound data classification accuracy

Figure 18 compares the classification accuracy which was found using different machine learning and deep learning algorithms for vibration data of different gears at different conditions. It shows SVM performs better than other algorithms.

8. CONCLUSIONS

One of the key research areas in the field of condition monitoring is the diagnosis of gearbox faults using machine learning algorithms. Statistical data for 16 different classes were retrieved from the obtained signals. Using the extra tree classifier technique, the best six features are chosen from an initial set of eight. The selected features are fed into the system, which is subsequently trained and categorized using Decision Tree, ANN, SVM, and DNN.

Based on the different algorithms performed on given data Support Vector Machine isperforming better than other algorithms. As SVM is performing better than other algorithms, a web application using the Flask framework was created, which will take the data in comma-separated value format (.csv) and automatically predict the output for the given data (in .csv format).

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