BALKAN JOURNAL OF ELECTRICAL & COMPUTER ENGINEERING, Vol. 11, No. 4, October 2023
Research Article

Different Induction Motor Faults by New Proposed Random Forest Method

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***Abstract*—Induction motors (IM) are widely used in industry. Failures in asynchronous motors cause disruptions and interruptions in production processes. Due to this situation, economic losses are experienced. Monitoring the induction motor status and monitoring the symptoms before the failure occurs is a matter of great importance in the industry. In this study, 8 different situations that may occur in the motor were monitored through the acceleration and sound data obtained from the induction motor. The feature vector was created with the Short-Term Fourier Transform (STFT) method on the acceleration and sound data obtained from the engine. The feature vectors were classified using the Random Forest (RF) method. The feature vectors created from the acceleration and sound data were also analyzed separately and the classification performance was examined. In addition, a new RF algorithm based on weight values using the Gini algorithm has been proposed. With this algorithm, the traditional RF algorithm has been developed and the success rates have been increased. In classical RF classification based on acceleration and sound data, 89.9% accuracy was achieved. The success rate of the proposed model was 95.7%. This shows that the proposed model successfully detects all types of faults in asynchronous motors. In addition, when we compared in terms of time, it was observed that the proposed model produced faster and more accurate results both in fault detection and in the production maintenance phase.**

Index Terms—**Random Forest, the Short-Term Fourier Transform, Induction motors, feature vector,**

I. INTRODUCTION

Asynchronous motors are more widely used among electric motors, especially in industry. Simple working principles, low production costs, maintenance and repair conveniences of induction motors increase their preference. At the same time, the ease of speed control provides an advantage for different production process needs.

Asynchronous motors basically consist of 4 components. These are the stator, rotor and shaft components. The general structure of the induction motor is given in our study. In these motors, the stator copper cable windings work on the principle that the rotor placed in the stator rotates and the shaft connected to the rotor rotates by creating a magnetic field at AC voltage.

In asynchronous motors, different malfunctions may occur due to working principles, usage conditions, electrical network conditions and environmental conditions. When the causes of these failures were examined by conducting a research on 7500 engines by IEEE and EPRI, it was seen that they were gathered under 4 main headings. The proportional distributions of failure types are shown in Figure 1 [1]. The schematic variety of faults is shown in Figure 2.

Various data obtained from the engine are used to detect faults [2]. These are basically voltage, current, acceleration, vibration, temperature, sound, air flow and thermal image data. The electrical faults that occur can cause significant changes in the mechanical behavior and warming up due to the working principle of the asynchronous motor, especially in the current. Similarly, changes in current values may occur in mechanical faults.

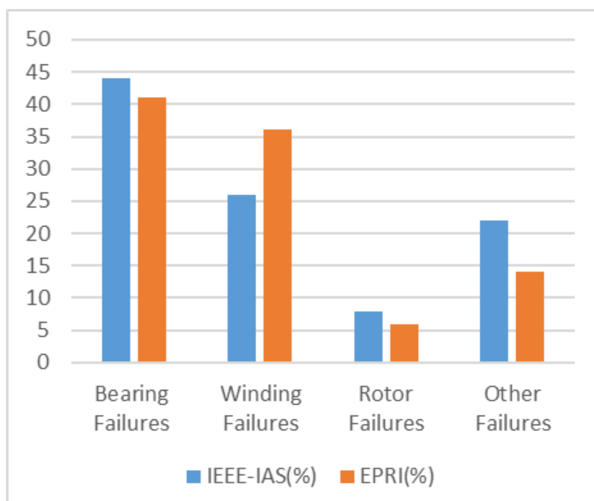

Fig.1. Proportional distribution of asynchronous motor failures

An AC powered induction motor with a single phase AC voltage of 230 V 50 Hz is generated by obtaining measurements to start and run the motor using a motor capacitor on a condition monitor screen. The motor has a removable fan guard. The original fan is replaced with modified 3D printed fans that look like the original fan but have missing fan blades. The motor is connected to the air

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Manuscript received Apr 14, 2023; accepted Aug 11, 2023.
DOI: 10.17694/bajece.1283336

compressor using a metal shaft with an attached 3D-printed apparatus that allows a screw to be tightened to create a state of unbalance. The aluminum profiles holding the motor and compressor are separated from each other and the main body by polymer springs. An LSM9DS1 sensor is mounted in the motor profile. The sensor is used to measure 3-axis accelerations with 400 Hz sampling. The sensor is connected to an ESP32 microcontroller that reads measurements at a sampling time of <= 3 ms.

8 different conditions monitored for the engine are given in Table 1. Each condition is labeled with an ID and an abbreviated tag and a short description is given. Acceleration data were collected in 10 seconds with the LSM9DS1 sensor for each condition. The data is presented as raw data in the form of 'time series data'. Acceleration values are represented in mg (=10^(-3) g). In addition to the acceleration data, audio data can be obtained with the microphone. Microphone data can be generated at 48000 Hz and 16-bit resolution [3].

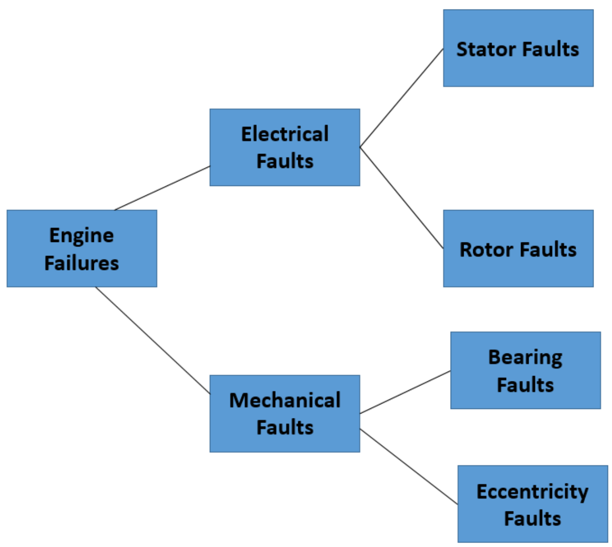

Fig.2. Types of asynchronous motor faults

TABLE I
CONDITIONS OF THE ENGINE

ID	Label	Explanation
1	off	The engine will not start.
2	on	The engine is running.
3	cap	Motor capacitor is disabled.
4	out	Compressor outlet valve is compressed.
5	unb	A grub screw is placed on one side of the shaft to create unbalance.
6	c25	By attaching a cover to the fan housing, the air passage is reduced by 25%.
7	c75	By attaching a cover to the fan housing, the air passage is reduced by 75%.
8	vnt	The fan was replaced with a defective fan with 3 fan blades missing.

It is recommended to use the frequency attributes in the 'Frequency Attributes' folder to train a condition monitoring classifier. These features are obtained by Short-Time Fourier Transform using a 200 ms rectangular window on both the acceleration and sound data. The windows were overlapped by 80% to obtain more observations. Acceleration data is converted to frequency amplitude values of 10, 15, …, 120 Hz (23 units) and audio data to 25, 50, …, 2500 Hz (100 units). These values are the amplitude values corresponding to the relevant frequency band [4].

In this way, a total of 169 frequency attributes are obtained, each of which is 3 x 23 = 69 acceleration and 100 sound sources. For a recording time of 10 seconds, 250 observations are formed with a 200 ms window and 80% overlap. The resulting attribute dataset, consisting of 8 x 250 = 2000 observations with 250 observations per condition, is labeled with corresponding IDs and tags. In addition, the timestamp when the STFT window started is also given in the data set. While creating the attribute names, the first character axis (x,y,z), the next 3 characters are the data type (Acc, snd), the next 4 characters are the STFT frequency (Acc 10-120, snd 25-2500), and the last two characters are fixed " It means “Hz”. Examples are xAcc0085Hz, zAcc0015Hz, snd0075Hz, snd1225Hz. All attributes are of floating point data type.

WEKA software was used to classify the feature vector with RF method based on machine learning. WEKA is the abbreviated name of the software platform developed at the University of Waikato for use in machine learning processes and formed from the initials of the words "Waikato Environment for Knowledge Analysis". It offers many currently widely used machine learning algorithms and methods to users [5].

One of the research subjects studied is the classification of faults through engine data, which contains important clues about faults. Measurement instruments, microphones and thermal cameras are used together with sensors to collect data. Working on raw data is both difficult and requires high microprocessor power. Therefore, size reduction is preferred by processing with signal processing methods rather than using raw data directly. Signal processing methods are effective in obtaining meaningful results by transforming the data obtained in the time-amplitude axis into different planes. This process is commonly referred to as feature extraction. Among the signal processing methods, Fourier Transform and Wavelet Transform are frequently preferred methods [6].

The feature vector obtained by feature extraction is classified using machine learning methods. Machine learning methods are evaluated in two groups as supervised and unsupervised. While class value is assigned to feature vector columns in supervised learning, class value is not assigned in unsupervised learning. Among the frequently preferred methods in machine learning and classification applications are decision tree, support vector machine, artificial neural networks, random forest method.

II. Related Works

Some of the previous studies on the classification of asynchronous motor failures are given below.

In the study, asynchronous motor condition monitoring data set, which was collected and presented by the data collection mechanism created by Matzka et al., was tried to be classified by random forest method [7].

Yang et al., proposed a hybrid method combined with genetic algorithm to explore the possibilities of applying RF method in machine fault diagnosis and to improve classification accuracy [8]. The proposed method is illustrated by a case study on diagnosing asynchronous motor failures. Experimental results show that RF method has higher overall performance than ART-KNN, SVM and CART methods. In addition, it is seen that the proposed hybrid method (RFOGA) reaches 98.89% success.

Dos Santos et al., proposed an approach based on Random Forest and Park Vector to detect stator winding short-circuit faults in squirrel cage induction motors [9]. It is accomplished by scoring the Park Vector for both current and voltage as well as imbalance in current and voltage waveforms. The proposed strategy was tested experimentally on a custom 400-V, 50-Hz, 4-pole, 2.2-kW asynchronous motor and it was possible to simulate reconfigurable stator windings with different types of inter-turn short circuits. Even when only 1 kHz sampling frequency is used to obtain current and voltage waveforms in three phases and the use of Fast Fourier Transform is avoided, the results are quite promising. The developed solution can be used to monitor engine condition and implement advanced predictive maintenance strategies.

Vamsi et al., used an RF classifier to perform real-time fault monitoring for a squirrel cage induction motor [10]. The advantage of the proposed method is shown in the fact that it has a graphical user interface with all its functions running in the background to ultimately display the accuracy of the estimation and the status of the machine.

Sonje et al., proposed a newly developed classification model for multi-class diagnostics in an induction motor [11]. The basis of this model is RF. The stator currents were obtained using different criteria from the induction motor. Fourteen time features were determined for each current signal within the preprocessing steps on the dataset they used. These current signals form the input of the model. In addition, rotor, stator and different faults form the classes of the dataset. The obtained results were compared with the Multilayer Perceptual Neural Network (MLPNN) with various performance measures. The results are more successful than the MLPNN classification.

Saberi et al., presented a diagnostic scheme for asynchronous motors using SVM and RF [12]. First, a set of time-domain and frequency-domain characteristics are extracted from vibration and current signals under different operating conditions of the motor. Then, these features are combined and accepted as the input of the SVM-based classification model. To avoid overfitting, RF was used to identify the most dominant features that contributed to correct classification. It has been proven that the proposed method can obtain highly accurate diagnostic results for broken rotor bar and eccentricity faults and can properly handle high dimensionality of aggregated data.

Quiroz et al., proposed a new analysis-based approach for broken rotor bar failure in the engine starting state [13]. For the detection of engine failure, data were obtained using intact and broken engines. 13 different time features were created from the current signals and the dataset was trained with RF. In addition, the 2 most important features were determined by feature selection. 98.8% success was achieved with the proposed model. The results were compared with different classification algorithms such as regression and SVM.

Harach et al., proposed a model for the EU25 inspection station to detect emission measurements [14]. In this model, different vehicle samples were tried to be determined with 9 static test points, constant engine load and engine speed using machine learning algorithms. In addition, a different platform was used for the engine condition coefficient and function coefficient. Detection of motor defects was calculated by regression method.

Elhaija et al., tried to detect broken motor rods failure and correct functioning of induction motor in asynchronous motors with optimizable neural networks [15]. Different approaches have been developed to improve existing signals. The simulation-based approach has achieved considerable success in detecting broken engine failure. In addition, they made error detection with the developed method. With the error detection based on the deep learning approach, both the error rate was tried to be reduced and the time for error detection was determined in time.

Reyes-Malanche et al., performed electric current phasor analysis for short-circuit fault diagnosis in asynchronous motors [16]. By using fuzzy logic, they tried to detect faults in asynchronous motors during the production process and to prevent possible interruptions. Online monitoring of induction motors is very important nowadays. They have developed new different approaches for this online monitoring in asynchronous motors. They have developed a non-invasive method that will reduce the timeout of induction motors and detect short-circuit faults in the stator windings of the induction motor. This method relies on phasor analysis and RMS values of line currents, followed by a small simple if-then rule to perform diagnosis and identification of stator winding faults. Results from different experimental tests on a rewound induction motor stator to induce short-circuit faults show that the proposed approach is capable of detecting and finding with high efficiency the initial and forward deficiencies in the insulation of the windings.

III. PROPOSED RF MODEL

The Random Forest method is an ensemble learning method built on decision trees (DT). Community learning methods are popular in the field of machine learning. It can be used for classification and regression operations. As a basic principle, ensemble learning methods decide on the solution of a classification problem depending on the decisions of more than one classifier. In decision making, the highest vote (majority) or the lowest error (minimized error) approaches can be preferred.

In the RF method, there is a forest structure consisting of individual decision trees for the same problem [17]. The decision of each tree in the forest is independent of the decisions of other trees. The randomness in the method is due to the selection of variables in the creation of a decision tree.

The traditional decision tree consists of root, twig (brunch) and leaves (leaf). While the root and branch structures are determined according to the variables that will determine the classification result, the leaves show the class decisions. The information gain of the variable is calculated in the selection of the variable for the roots and branches in the traditional decision tree. One of the most used calculation methods is the GINI index. Information gain is the effect of the variable on the class decision. The higher this effect, the higher the effect of the variable on the outcome. The root of the decision tree is established with the variable with the highest information gain and the branches are completed according to the gain order of the variables. In the RF method, variable selections are made randomly while creating each tree. This randomness is useful in preventing overfitting. At the same time, the samples to be selected for each tree created are selected as a subset of the whole sample with the bootstrap technique with a random approach.

The RF method was developed by Breiman [18]. Breiman, who previously developed the CART (Classification and Regression Trees) method, developed the RF technique by first developing Bagging- Bootstrap Aggregating and then Random Subspace methods and combining these methods because the CART method, which has a very good learning ability, is prone to excessive learning.

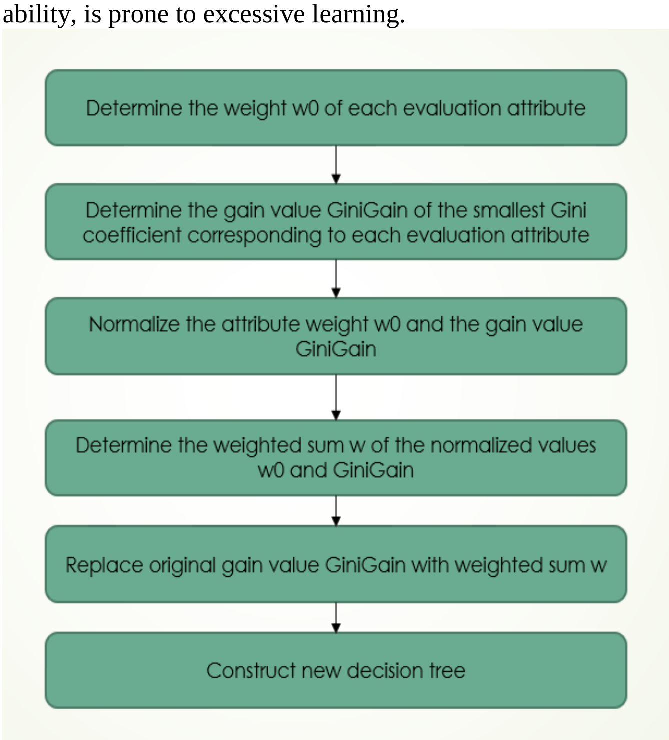

Fig.3. Proposed RF flow chart

In the RF method, 2/3 of the data set is used as training data and 1/3 is used as test data. The bagging method can be applied to many different tree methods. In a data set containing m samples, n samples (n<m) are selected with the bootstrap sampling method, and new models are created with K trees. K prediction values produced by K decision tree models are combined.

In the Random Subspace method, if there are P variables in the data set, less than P random variables are selected. For each tree created in the Bagging method, it is ensured that the branches are made over these selected random variables. As a result, randomness is obtained through the variables.

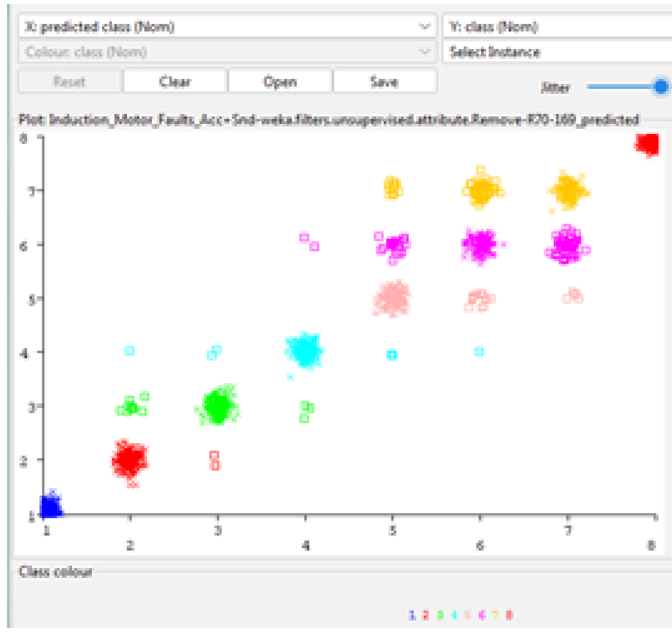

Fig.4. Graphical view of the traditional RF classification model

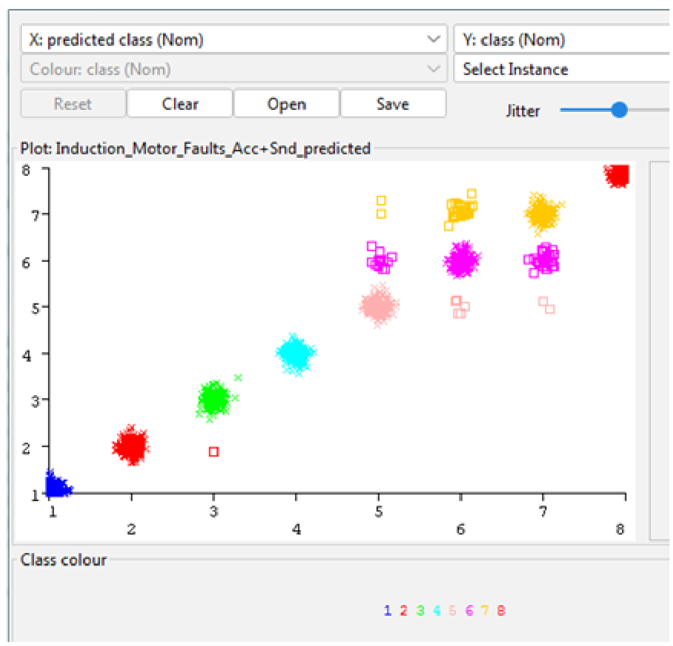

Fig.5. Graphical view of the proposed RF classification model

In the proposed RF method, the Gini algorithm is used to obtain the weights of the features and the value of the smallest Gini coefficient corresponding to the feature is taken and all the resulting values are added. The optimum weight value is calculated by constantly changing the weighted total with the original weight value. Thus, a new decision tree is created with the CART node split criterion. All weight values are normalized. The normalized value is constantly replaced by the original weight value. The flow chart of the proposed RF method is given in Figure 3 [19].

In our proposed model, unlike the traditional RF classification model, CART (trees with a weight determination algorithm based on decision making, trial and evaluation) is used to obtain the weights of the features based on regression. The gain value of the Gini coefficient is calculated with the Gini algorithm, which determines the feature weight. The gain value of the smallest Gini coefficient is weighted by the same attribute and summed. The weighted sum is then used to replace the original gain value. This value rule is used as a new CART node split criterion to create a new decision tree, thus creating a new random forest, C-RF.

IV. Experimental Study

The performance criteria reached as a result of the traditional RF classification process by using all the features created from the acceleration and sound data are given in Table-2. Table 3 shows the confusion matrix. Figure 4 shows the graphical view of correct and incorrect classifications. When the results are examined, it is seen that an accuracy of 89.9% was obtained for all classes.

The performance criteria reached as a result of the traditional RF classification process by using all the features created from the acceleration and sound data are given in Table-4. Table 5 shows the confusion matrix. Figure 5 gives a graphical view of the correct and incorrect classifications. When the results are examined, it is seen that 95.7% accuracy was obtained for all classes.

When the classification results are evaluated in general, it is concluded that when the features obtained from the acceleration and sound data are used together, a higher accuracy classification performance is achieved when they are used separately. It is seen that class 1 of the classes is classified exactly correctly in each approach. It is seen that classes 6 and 7 are classified correctly with the lowest accuracy in each approach. In addition, it has been observed that the proposed model gives more successful results in all types of failures compared to the traditional RF model.

For the induction motor monitoring system, it is considered that the features extracted from the acceleration and sound data with STFT and the classification performed using the RF classifier have achieved acceptable results, but it would be appropriate to obtain the features with different methods and to conduct a comparative study with different machine learning algorithms. In addition, it should be taken into account that there is a need for closer studies to real-world applications where engine failures can coexist in different combinations.

TABLE II
TRADITIONAL RF RESULTS USING ALL DATA FEATURE

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
1	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
2	0.992	0.006	0.958	0.992	0.974	0.971	1.000	0.998
3	0.952	0.002	0.983	0.952	0.967	0.963	1.000	0.998
4	0.972	0.003	0.980	0.972	0.976	0.972	0.999	0.996
5	0.928	0.021	0.862	0.928	0.894	0.879	0.994	0.949
6	0.664	0.046	0.672	0.664	0.668	0.621	0.954	0.723
7	0.684	0.037	0.728	0.684	0.705	0.665	0.965	0.732
8	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
Weighted Avg.	0.899	0.014	0.898	0.899	0.898	0.884	0.989	0.925

TABLE III
CONFUSION MATRIX RESULTS FOR TRADITIONAL RF

classified as -->	a	b	c	d	E	f	g	h
a = 1	250	0	0	0	0	0	0	0
b = 2	0	248	2	0	0	0	0	0
c = 3	0	9	238	3	0	0	0	0
d = 4	0	2	2	243	2	1	0	0
e = 5	0	0	0	0	232	13	5	0
f = 6	0	0	0	2	23	166	59	0
g = 7	0	0	0	0	12	67	171	0
h = 8	0	0	0	0	0	0	0	250

TABLE IV
PROPOSED RF RESULTS USING ALL DATA FEATURE

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
1	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
2	0.996	0.000	1.000	0.996	0.998	0.998	1.000	1.000
3	1.000	0.001	0.996	1.000	0.998	0.998	1.000	1.000
4	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
5	0.972	0.010	0.935	0.972	0.953	0.946	0.998	0.985
6	0.812	0.020	0.853	0.812	0.832	0.809	0.982	0.895
7	0.872	0.019	0.865	0.872	0.869	0.850	0.987	0.912
8	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
Weighted Avg.	0.957	0.006	0.956	0.957	0.956	0.950	0.996	0.974

TABLE V
CONFUSION MATRIX RESULTS FOR PROPOSED RF

classified as -->	a	b	c	d	e	f	g	h
a = 1	250	0	0	0	0	0	0	0
b = 2	0	249	1	0	0	0	0	0
c = 3	0	0	250	0	0	0	0	0
d = 4	0	0	0	250	0	0	0	0
e = 5	0	0	0	0	243	5	2	0
f = 6	0	0	0	0	15	203	32	0
g = 7	0	0	0	0	2	30	218	0
h = 8	0	0	0	0	0	0	0	250

V. CONCLUSION

Asynchronous motors have a very important place in industry and industry. However, the use of asynchronous motors brings with it many risks in daily life. At the beginning of these risks, many failures such as broken motor and bearing, maintenance of asynchronous motors, and short-circuit isolation are the most common types. In order to solve these problems, it is necessary to determine the malfunctions and other problems that may occur at the beginning. In our study, a classification method has been developed that can detect these problems in the first place and automatically detect the faults. With this model, it has given very successful results in detecting all the errors that may occur in asynchronous motors. In addition, our work is important in terms of determining the industrial maintenance phase and the detection of errors in the shortest possible time in terms of time. In this way, all major industrial failures can be detected without creating future problems and financial losses that may occur are tried to be prevented. Errors are minimized by automatic diagnosis. Our work may be a step forward for industrial applications in the future.

Our proposed RF model offers the advantages of the integrated learning method in the processing and classification of unbalanced data. Also, performing the features with CART to find the feature weight helps to include subjectivity and other qualitative assessment information to those performing fault detection in asynchronous motors. The feature weight and the gain value of the smallest Gini coefficient corresponding to the same attribute can now be weighted and summed proportionally, and the weighted sum is used to replace the original gain value as the new CART node split criterion to create the new RF. With this model, it alleviates the shortcomings of the traditional RF model's original division criterion of classification and reduces the preference for multi-valued features. Thus, the traditional RF model was developed.

Although the RF model we propose successfully detects the faults of all asynchronous motors, there are also some shortcomings. In the future, the study will be expanded by considering some deficiencies such as data instability, scarcity or unknown malfunctions.

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