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Original Article

Fault Prediction of Induction Motor using Machine Learning Algorithm

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Abstract **-** *Induction motor fault identification prior to the occurrence of total shut-down is critical for industries. The identification of faults based on condition monitoring techniques and the use of machine learning has enormous potential. Machine learning's power may be harnessed and properly applied for motor defect detection. To avoid losses, the issue, particularly in induction motors, must be repaired at the appropriate time. Machine learning algorithm applications in the sphere of defect detection give a dependable and effective preventative maintenance solution. In this paper, an algorithm-based machine learning approach is developed to learn features from the frequency distribution of vibration signals with the goal of characterizing the working status of induction motors such as current, voltage, and temperature, and it is also updated in the IoT-based application. It combines feature extraction and classification tasks to enable automated and intelligent problem diagnosis.*

Keywords - *Induction Motor, Machine, Fault Prediction.*

I. INTRODUCTION

Induction motors are the most thoroughly used electrical motors because of their ease of construction, sturdiness, and low cost. Induction motors are used in more than 90% of industries, mostly as electrical drives due to their ability to be configured for a broad variety of power ratings. Despite their flexibility and robustness, they are prone to numerous catastrophic failures. Identifying and correcting these flaws early on is critical since they may lead to significant production and financial losses. Pre-fault identification and isolation of healthy components also minimize fault development and failure of other more critical components. Because industries require a huge number of motors. As a result, several attempts at automated maintenance have been attempted. Previously, conditional monitoring of electrical machinery was used, and electromechanical relays were used to do this. However, because of the mechanical elements involved, these relays are sluggish to operate and cause significant power losses [6]. As a result, they cannot be employed in important applications that need fast reaction times. Solid-state relays, which require extremely little power and are relatively quick, eventually superseded electromechanical relays. With the introduction of microprocessors, attempts were made to conditionally monitor machines by downloading pre-written programs into the microprocessor chips. However, because they cannot address catastrophic failures, the aforementioned solutions cannot ensure optimum safety and dependability. With the advent of machine learning, the computer revolution caught the attention of scientists, who began to consider how these approaches could be used to monitor and safeguard machines. To intelligently monitor and manage the defined system tasks, machine learning models assume the position of humans [4]. Artificial neural networks are highly useful in this area since they can manage large amounts of data, have a short reaction time, and can successfully handle non-linearity (which is an inherent aspect of electromechanical systems most of the time). The goal of this study is to avoid fault progression and preserve critical components of the power system by utilizing an artificial neural network to identify electrical faults in three-phase induction motors early. We handled seven types of induction motor electrical issues.

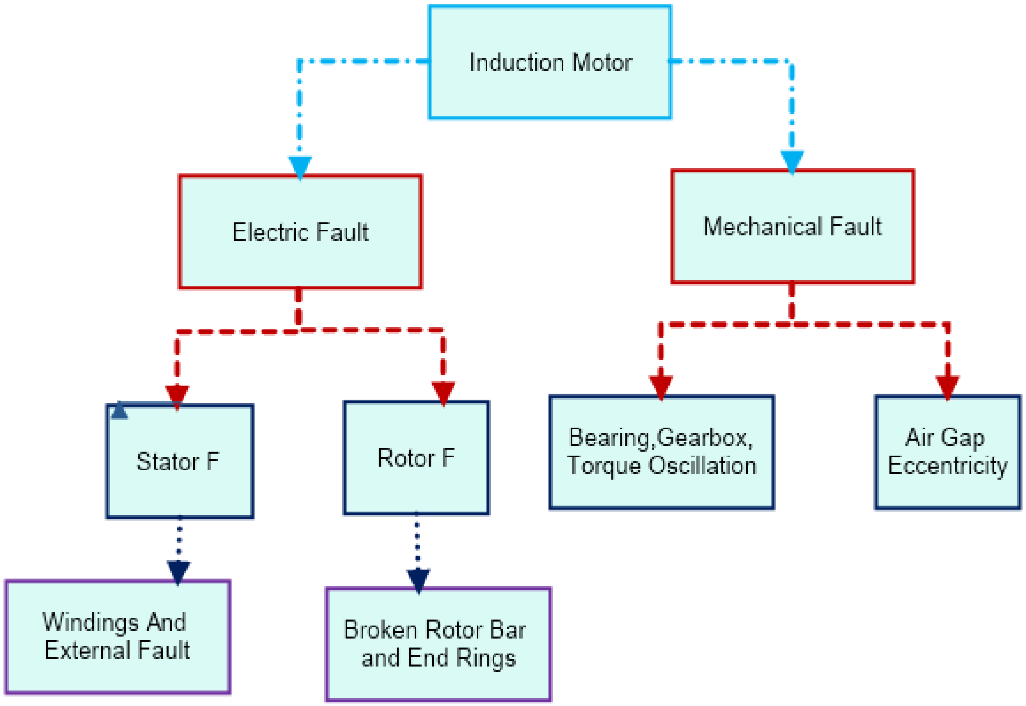


Fig. 1 Types of faults in induction motor

II. ARTIFICIAL NEURAL NETWORK (ANN)

ANN is thought to be a replica of the human brain, comprised of a network of linked nodes known as neurons. The most common type of ANN is composed of three layers, each of which has a number of processing nodes. Figure 1 depicts the fundamental structure of an ANN, which consists of neurons, connection weights, and biases. The neuron is represented here by circular nodes, and the connection weights are represented by arrows linking distinct nodes between the input, hidden, and output layers. The most widely used multi-layered feed-forward ANN that uses the backpropagation technique for training is FFBPNN. When the number of hidden layer neurons is increased, the ANN performs best with backpropagation learning. ANN is thought to be a replica of the human brain, comprised of a network of linked nodes known as neurons. The most common type of ANN is composed of three layers, each of which has a number of processing nodes. Figure 1 depicts the fundamental structure of an ANN, which consists of neurons, connection weights, and biases. The neuron is represented here by circular nodes, and the connection weights are represented by arrows linking distinct nodes between the input, hidden, and output layers. The most widely used multi-layered feed-forward ANN that uses the backpropagation technique for training is FFBPNN. When the number of hidden layer neurons is increased, the ANN performs best with backpropagation learning. In the case of conjugate gradient-based training techniques, the search is conducted in conjugate directions, which typically results in faster convergence than the steepest descent path. The step size for conjugate gradient algorithms is changed for each iteration. In this case, the search is carried out in the conjugate gradient direction in order to find the step size for which the performance function is minimized for a given search path. Trains cg is a backpropagation training technique that uses the Scaled Conjugate Gradient (SCG) algorithm to update network weights and biases. Moller [21] proposed it to avoid time-consuming line searches by combining the model-trust region method (used in trainlm) with a scaled conjugate gradient approach. The trainlm method is the fastest for training networks of modest size. Despite requiring more memory than other training algorithms, trainlm is the most generally suggested and utilized training technique for improving classification accuracy. It is based on the Levenberg-Marquardt (LM) backpropagation algorithm, which is regarded as one of the quickest backpropagation algorithms for neural network training.

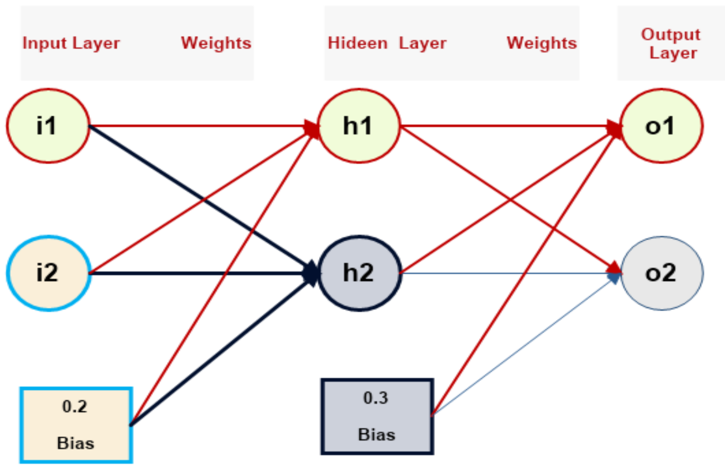


Fig. 2 Structure of Machine Learning algorithm

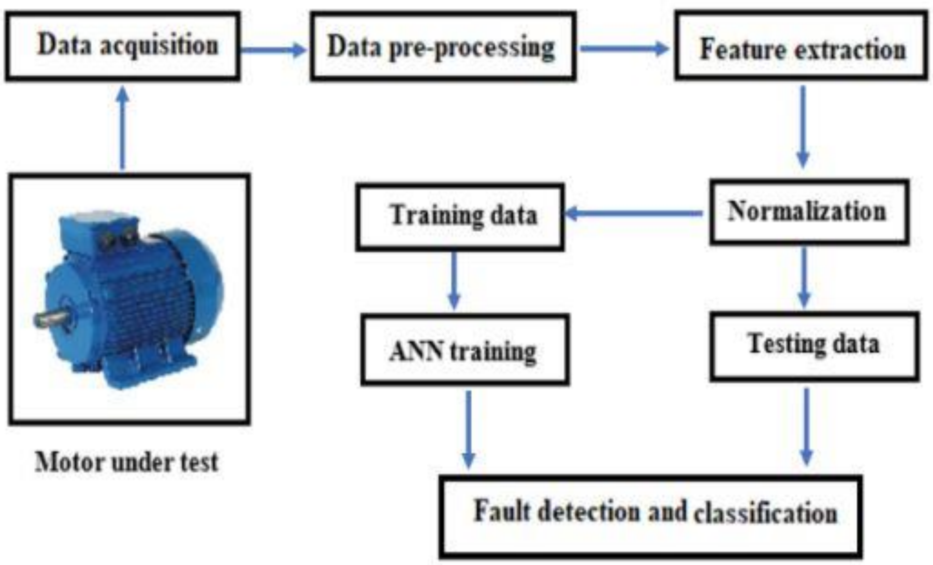


Fig. 3 General Structure of ANN vased Induction motor

III. EXPERIMENTAL SETUP AND DATA COLLECTION

Experimentation is carried out utilizing a machine fault simulator, as shown in Figure 3, to assess the suggested technique for defect diagnostics of induction motors. It replicates six various operating circumstances for motors, and vibration signals corresponding to different functioning states are monitored. Table 1 lists the descriptions of the various operation situations. These vibration signals are utilized to put the DBN-based fault diagnostic system through its paces. These vibration signals are separated into training and testing datasets, which are then randomized before being employed in the DBN model. A three-phase, four-pole, 0.5-hp inverter was used in the experiment. The experimental setup included a three-phase, four-pole, 0.5-hp induction motor connected to the mechanical load through a belt pulley system. A Direct-On-Line (D-O-L) starter was used to link the motor terminals to a three-phase power supply. The experimental setup for data collecting and condition monitoring of a three-phase induction motor is shown in Fig. 3.

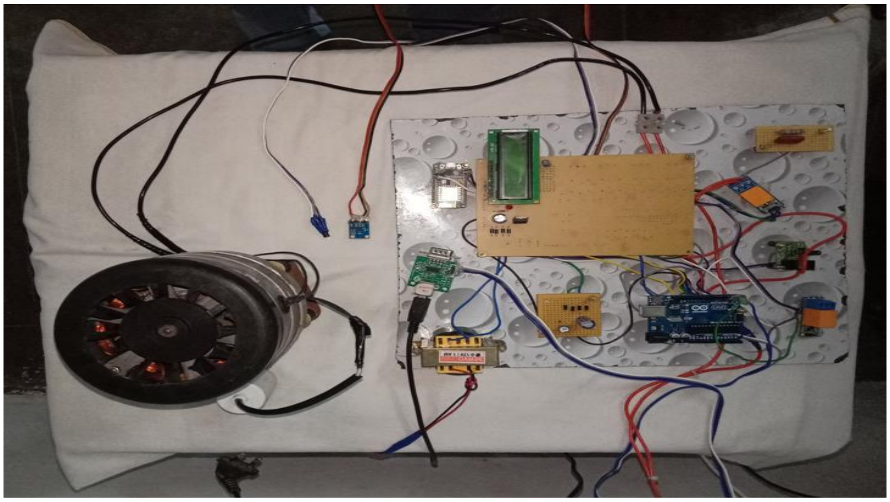
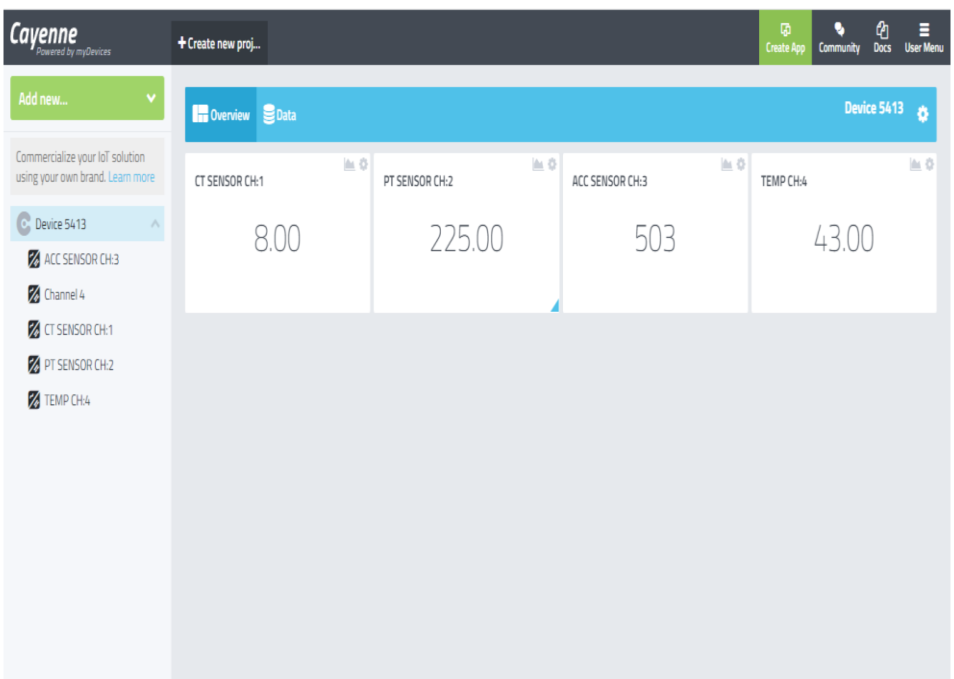


Fig. 4 Experimental setup for fault detection of induction motor

IV. RESULTS AND DISCUSSION

The image above depicts induction motor fault prediction in action. The vibration and temperature monitoring system for the induction motor. If the temperature and vibration values are abnormal, the induction motor will trip automatically, and the load will not be harmed. The current transformer, potential transformer, accelerometer sensor, and temperature sensor values are updated on the Cayenne dashboard. All of the parameters' values have been changed on the Cayenne homepage.

- The current transformer, potential transformer, accelerometer sensor, and temperature sensor values are updated on the Cayenne dashboard.
- In addition, we will make every effort to reduce the time delay.
- In the future, we will strive to improve performance and dependability.



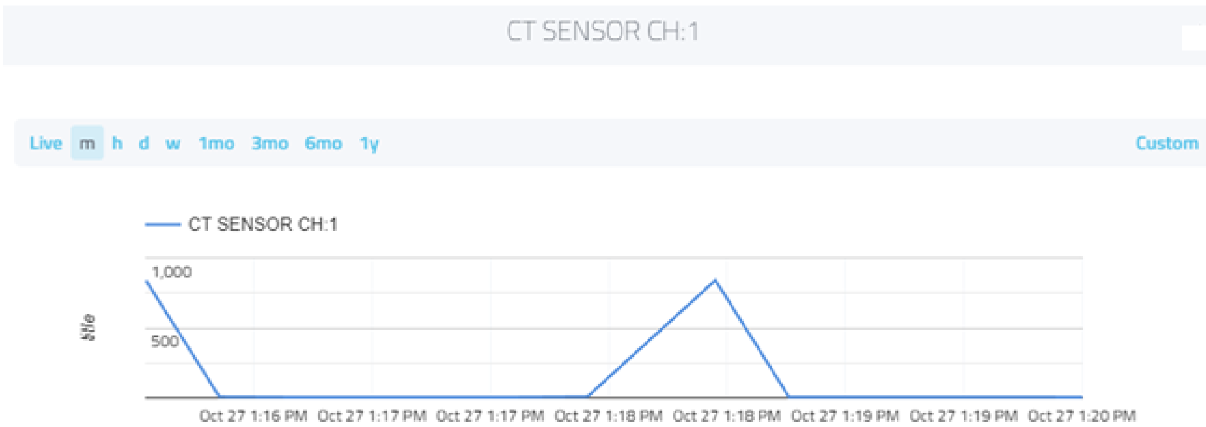


Fig. 5 Current Transformer output

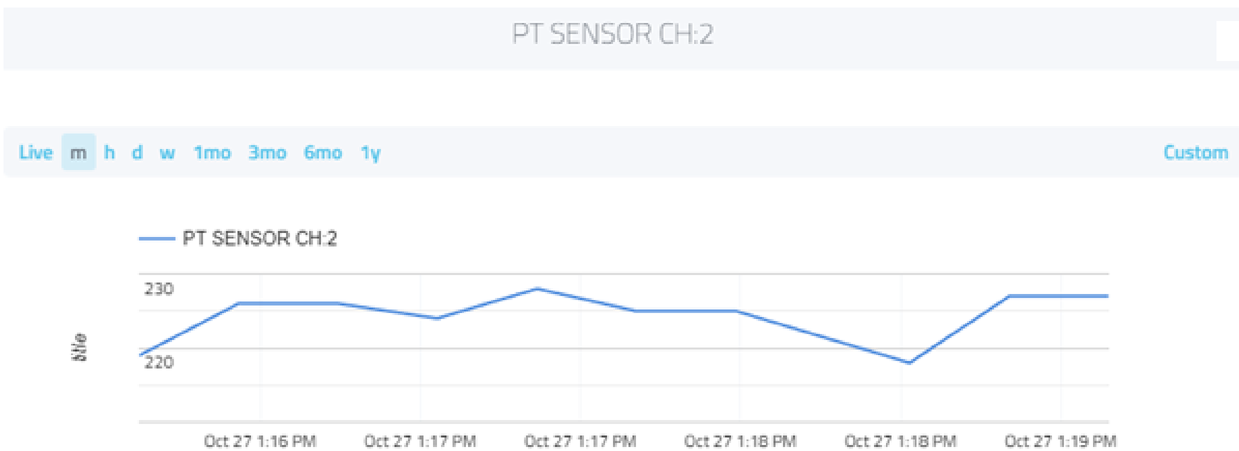


Fig. 6 Potential Transformer output

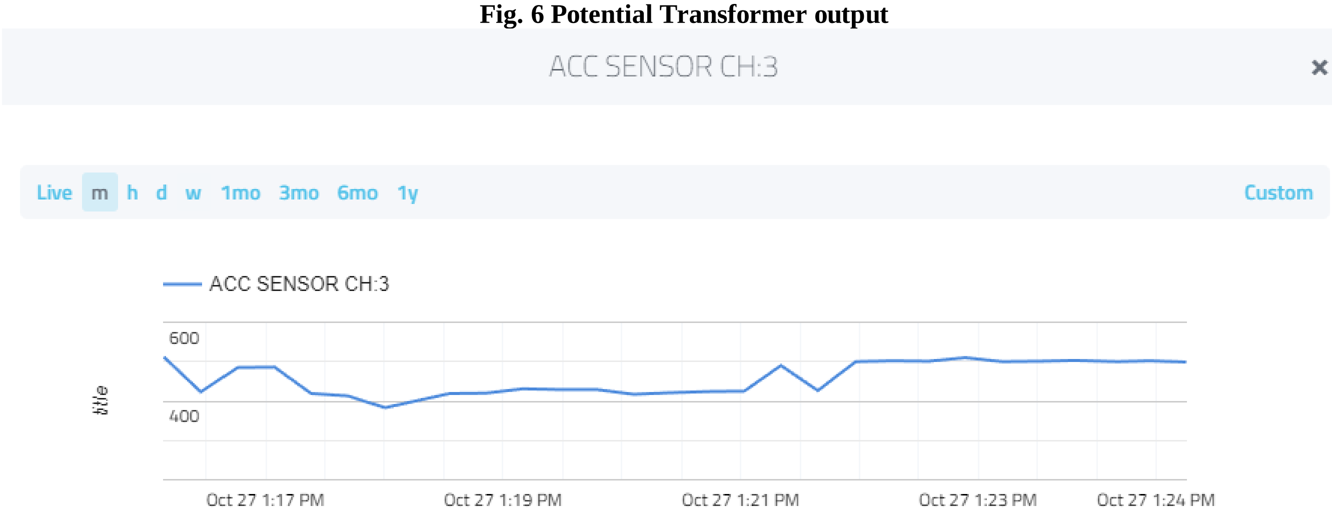


Fig. 7 Accelerometer sensor output

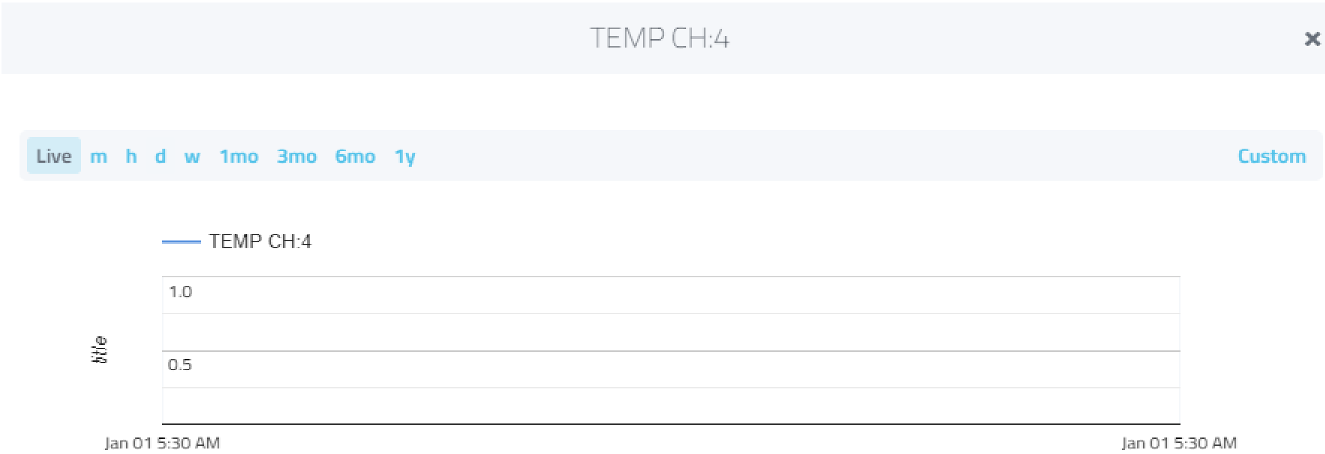


Fig. 8 Temperature Sensor output

V. CONCLUSION

Because induction motors are used in crucial industrial processes, effectively detecting different electrical or mechanical problems in induction motors is critical to avoiding production downtime and substantial financial losses. This study proposes, develops, and validates a machine learning-based fault diagnostic approach for single- and multi-fault induction motors using experimental data. The performance of several fault-tolerant single-phase induction drives has been re-examined in this work, taking into consideration the influence of both current and voltage constraints post-fault equations for a single-phase induction motor with two active phases are derived from first principles, and it is demonstrated that the post-fault phase voltage need is a function of the healthy phase voltages and the stator branch voltage of the faulty phase.

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