Predictive Maintenance of Computerized Numerical Control Machine using IoT and Neural Networks

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Abstract. Failure in machines can result in a production halt in manufacturing industries, resulting in delayed customer orders. Regular and scheduled maintenance helps keep the machine's condition intact and increases its lifespan. However, failures can happen even before the scheduled maintenance date resulting in an unexpected breakdown and halt in production activities. Predictive maintenance is a way to continuously monitor the machine's condition and detect potential failures in advance. The idea is to predict the machine's failure, notify the staff in advance for timely maintenance, and prevent losses. The project aims to create a prototype that will allow employees to monitor the machine's health and predict any failure expected before the scheduled maintenance date.

Keywords: Machine Learning, Prediction, Analysis, Internet of Things, Neural Networks

1 Introduction

Computerized Numerical Control machines are programmable and widely utilized in manufacturing industries. For our prototype, we take the three parameters of a CNC machine as temperature, vibration, and current. As these machines will degrade over time, the company needs to increase the efficiency of its operations and lifespan.

Maintenance refers to the actions taken to keep a machine's performance and condition as good as when bought initially. Predictive maintenance, in theory, provides for the lowest feasible upkeep frequency to avoid any unforeseen repair while avoiding any apparent losses or expenses associated with performing an excessive amount of preventative maintenance.

Internet of Things (IoT) and multiple sensors are crucial in identifying the status of an asset in real-time for predictive maintenance. IoT allows various assets and systems to work together, attach and analyze, share, and action data.

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We may use the sensors to record real-time data and compare it to the threshold values to determine the part where failure is about to occur. All these devices are connected over the internet to detect, measure, and send data to the cloud.

2 IoT & Circuit Diagram

Real-time data from these sensors help in analyzing the difference between the expected and the actual values to predict failure, monitor levels, and increase efficiency. It assists in acquiring insights into the data regularly.

For prediction, the parameters (and their corresponding sensors) that majorly affect the life of the CNC machine are as follows -

1. Temperature (Thermistor)
2. Vibration (Vibration Sensor)
3. Current (ACS712 Current Sensor)

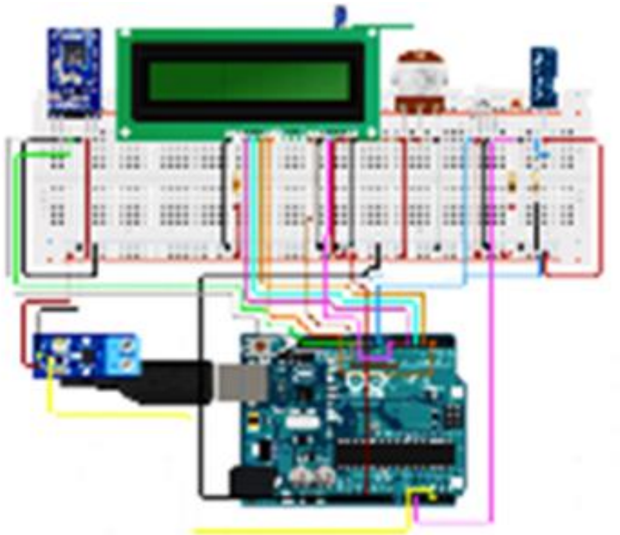

Fig. 1. Circuit diagram of Arduino UNO with multiple sensors.

The first step is to collect a large set of real-time sensor data from the CNC machine that represents a healthy or faulty operation. If the current value is equal to or less than the threshold, it is called a healthy operation. Arduino UNO helps in collecting data from these sensors in real-time and tabulated. This project uses a data set of 400 rows and 26 columns.

TEMP	VOLTAGE	CUT SPEED	VIBRATION	CURRENT	THICKNESS
25.6	112V	9144	232	30.2A	0.5
25.8	114V	8128	220	30.5A	0.8
26	115V	7000	218	30A	0.9
25.8	125V	3650	228.5	31.1A	1.5

Fig. 2. Screenshot of sample data set.

3 Data Acquisition

The data collected in real-time by IoT sensors are frequently unstructured. The data is analyzed and processed further in the cloud. The most crucial aspects of this type of data collection are Device Management and Event Processing. Device administration entails taking care of things like registering, upgrading, authenticating identity, and assigning roles to devices. It also refers to the interoperability of any IoT device with any IoT gateway that can access the device vendor's management service and follows specific protocols.

4 Pre-Process Data

After receiving the data, the next step is pre-processing and converting it for extracting condition indicators. The following steps are for converting data into a more acceptable format for data mining.

We can classify the pre-processing of data into two categories:

1. Filtering outlying data to choose qualities and data items for analysis
2. Adding/changing properties by normalizing available data or interpolating missing data

5 Selection & Implementation of Model

Following data processing, the next step is to select a model and an activation function. Several models developed by diverse researchers are available, and they are all tailored to the sort of data they use. Some models, for example, are primarily beneficial for data formats such as photos and videos, while others for tabular data in the form of text or digits.

5.1 Activation Function

The Rectified Linear Unit (ReLU) is a popular activation function in deep learning. The ReLU activation function translates the input value as the output value if positive and zero if the input value is negative.

Thus, the activation function can be given as

$$f(x) = \text{maximum}(0,\text{input value}) \quad (1)$$

The Convolution Neural Network is selected as it is the best to use with the ReLU activation function. ReLU is not costly in computational terms and doesn't involve complicated math. Hence, reducing the training and running time. Also, ReLU doesn't have any issues like the vanishing gradient problem with activation functions like tanh and sigmoid.

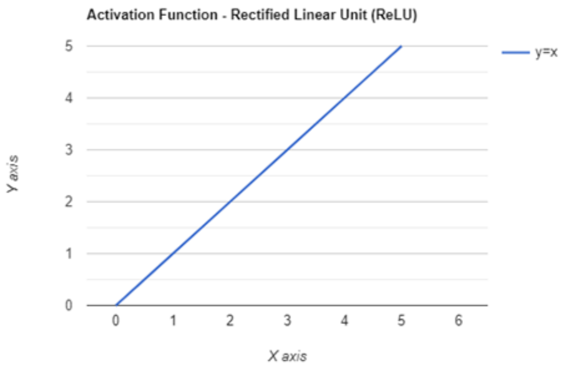

Fig. 3. Graph of Rectified Linear Unit (ReLU) Activation Function.

5.2 Identify Anomalies

When dealing with massive amounts of real-time data, there is always the possibility of anomalies. We can detect these anomalies by identifying the unusual collection of values that differ significantly from the rest of the values in the data set.

5.3 Classification of Data

Data classification is essential for analyzing data by categorizing it according to its features. Data classification classifies the data into two parts- features and targets.

5.4 Predict the transition from a Healthy State to a Failure

The model evaluates the relationship between the features and target values to estimate the time before any breakdown. Determining the relationship and predicting from the resulting data to identify the state from healthy to failure is essential in scheduling the maintenance of the machine.

6 Training of the Model

The complete data set is divided into two halves in a 4:1 ratio, with 80% of the data set was utilized for training and 20% for testing. The order of the data set values is modified randomly to increase the efficiency of the training process. The training data set is used to train the network and the test data set to evaluate the network's effectiveness after training.

Epochs are the number of times the network learns the training data set during the training phase. The weights are changed more frequently as the number of epochs grows, which improves performance.

Pre-processing, for example, reduced a 400-row sample data set to 250 rows. We used 80 percent of the data set for training and 20 percent for testing.

7 Result

After 250 epochs, the accuracy of the model was around 97 percent.

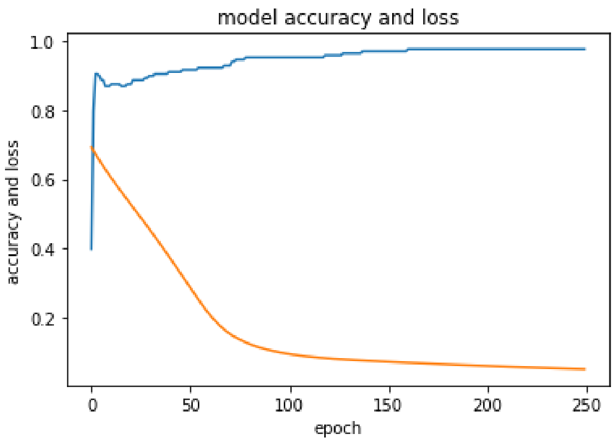

Fig. 4. Graph depicting the loss and accuracy of the model.

As a result, maintenance can be scheduled by evaluating the CNC machine's real-time behavior and utilizing the trained network to predict failure. In addition, the rate of error and difference between real-time and threshold values determined the reduction in the life of the CNC machine.

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