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Framework for Early Failure Detection of Sensor

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***Abstract*—Industry are adopting modern machinery to fulfil their expectations of production. The advancement in the technology uses complex design and multiple sensors. These machines need optimal maintenance policy to keep them properly functioning. Maintenance is systematic activity done for keeping an equipment in proper services. The condition-based maintenance relies on sensor data to establish a baseline of prediction. The sensor supplying data is assumed to be providing true data based on present condition. The sensor installed in the equipment may become faulty and not able to complete its specified lifetime. Various independent parameters, such as temperature, vibrations, EMI and variations in input supply voltages, present in the working place are responsible to early failure of sensor. The objective of this paper is to collect ground truth using supervised learning and using support vector machines model that analyses data for classification and regression analysis for providing early detection sensor failure.**

***Index Terms*— Supervised learning, support vector machines (SVM), regression analysis, sensor failure.**

I. INTRODUCTION

Automation is an impulse behind manufacturing to pace the industrial revolution. Advancement in technology and new inventions have provided eminence, so that processes have only become sophisticated. Industry is facing problems like decline in sales, machine start-up cost, premium priced components and idle skilled labors leads downtime. Hence manufacturers are adopting new ways of optimizing productivity by minimizing or getting zero downtime culture.

Preventative maintenance and condition monitoring [1] procedures are adopted to avoid major breakdowns and are becoming popular due to its data accuracy. Advances in sensing techniques, make it possible to provide data from any part of ongoing process. Also, due to enhanced wireless technology that allows real time communication. New hardware is available at low cost that connects data from sensors to cloud. This is backbone of industrial IoT. The IIoT prefers SOA (Service oriented Architecture) to provide services needed in condition monitoring.

Gathering machine data over time helps to plan and forecast downtime more accurately, allowing operations managers to predict probable failures before they occur, so as to plan maintenance and component replacements during machines off time. During condition monitoring parameters like vibrations, thermal

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output, input voltage variations, electromagnetic interference and other environmental parameters [2], which help determine maintenance schedules and reactive measures expected to ensure machines optimal functioning. Recent advancements like cloud storage for wireless data, 24-hour manufacturing facility, sensing-measurement- processing have raised zero-time culture in the industry

Predictive maintenance is suitable for zero downtime for a machine, which is opposite to conventional maintenance. In this process, various parameters related to different sections related to process is collected for a suitable period, and then this data is tested and validated using machine learning algorithms which includes regression analysis, classification and validation. Many predictive maintenance architectures are available, which has main components such as data collection, data filtration, feature extraction and selection [3], fault and Time to Failure (TTF) prediction. The implementation of predictive failure of sensor can be performed using different learning approaches such as supervised, unsupervised and reinforcement learning. Supervised and unsupervised learning methods are preferred in predictive maintenance. Supervised learning approach is more accurate when the dependent variable or independent variable is known.

II. Related Work

It became increasingly difficult have control over inventory, line breakdown, process synchronization, and standstill labor due to equipment failure [5] and sensors performance issues. The right-on-time maintenance strategy provides many advantages such as reduction in maintenance cost, quality enhancement and reliability. Due to advancement in sensing and communication technology, data related to present condition of any part of machine can be captured and communicated. The condition monitoring is the base of condition-based maintenance, which provides services like fault prediction, type of fault and time to fail. The predictive maintenance policy for sensors uses their own collected data to predict possible failure of the sensor. Different stages like feature extraction, status classification, time series modelling and anomaly detection using encoders [6]. Effective reliability and types of sensor failure modes is observed in practice and reported for corrective action [7]. Using collected data from sensors and using of Autoregressive Integrated Moving Average (ARIMA) it is possible to predict the failures and quality defects. Data generated from the machine is collected in cloud and using supervised learning, data analysis early faults can be detected [8]. A general model for measurement of uncertainties in sensor measurement is defined. Applying available data and analyzing sensor performance against parameters like temperature and pressure, sensor failure prediction is possible [9]. Unsupervised learning model is adopted to define uncertainties in sensor output. For rapid implementation strategy for fault prediction along with its class, clustering of Gaussian Mixture Model and K-means algorithm are suggested [10]. An event-based monitoring of complex process for predictive maintenance involves phase like acquisition, pre-processing, model induction and model evaluation. This method classifies sensors behavior in normal and abnormal class [11]. The image processing techniques are used to monitor the industrial parameters like temperature, humidity level, pressure level, supply voltage variations etc. All parameter values captured by sensor are updated in the cloud. The data is analyzed with the help of Hadoop [12]. Algorithm like support vector machine (SVM), ANN [14], self-organizing map [17], hierarchical clustering [19] and k- means [18] are commonly used for fault classification.

III. SOA FOR IOT AND DATA COLLECTION

For data collection IoT is used, which provides layered architecture for connecting data of heterogeneous type and from heterogeneous networks. SOA is layered architecture, having four layers, namely i) sensing layer ii) networking layer iii) service layer and iv) interface layer. This architecture is providing communication stack to collect data. The table-1 shows functions supported in different SOA layers.

TABLE I. FUNCTIONS HANDLED IN DIFFERENT LAYERS IN SOA

Layer	Description
Sensing layer	This layer is consisting of sensors and associated hardware. This hardware can be mobile nodes. Data sensing and acquisition protocols.
Networking layer	Basic networking support for data transfer over wired or wireless network is provided by this slayer
Service layer	Various services are handled by this layer by providing appropriate messages to users' needs requirements
Interface layer	Interaction between users and applications

Data collection: For collecting data from the surroundings of sensor under test, different sensors and open source IoT hardware (ESP 8266/NodeMCU) is used. For mobility and expansion purpose one NodeMCU is used for each sensor. Different independent parameters such as temperature, humidity, atmospheric pressure, vibrations, input supply voltage variations, electromagnetic interference (EMI) affecting sensors output are considered. The sensors are chosen according to the standards and specifications. The figure-2 shows practical setup for data collection. This practical setup is installed on terry weaving machine figure-3. For collecting data related to present condition around sensor, level 4 IoT architecture is preferred. This allows data manipulation at cloud level.

IV. SUPERVISED LEARNING AND MODEL BUILDING

A model using linear regression and support vector machines approach is developed feature extraction, learning, testing and validation. This model is further used to detect conditions those could make the sensor faulty or malfunctioning. Following are the assumptions used for development of model-

Assumption 1: The system is in practically working condition (industrial environment), where supply voltage, different currents, temperature at certain part of the machine, absolute barometric pressure, vibration, ESD / EMI are major factors.

Assumption 2: All above defined attributes are significant for machine

Assumption 3: the probabilistic model uses data generated by sensors installed over terry weaving machines.

In supervised learning, the outcome is to conclude a system function from labelled data. The training data consist of input vector and output vector with label X & Y respectively. A label from vector Y is the output of its respective input vector X. The above data is utilized for training of the model which includes regression and Classification.

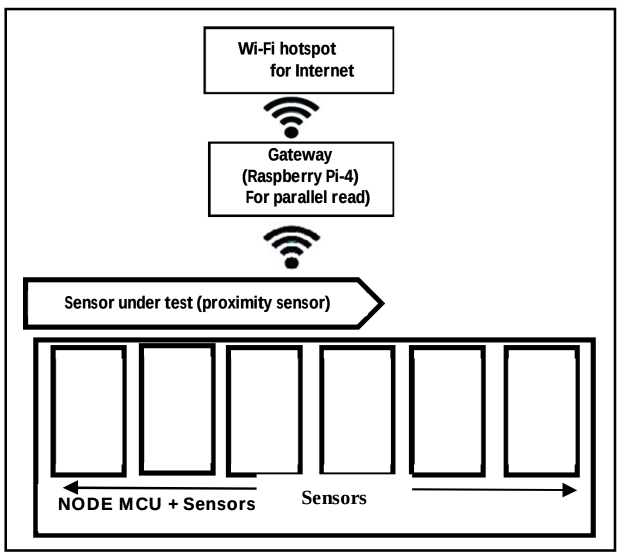

Figure-2 -Practical setup

A. Validation and Evaluation

The collected data, representing machine's present condition, is carefully chosen for training the model and validation. From training data set, a performance function which fits perfectly with data is identified and decided. The overfitting is detected through cross validation, which estimates how well the determined function fits new observations. Techniques like partitioning of the data is used to assess the function's performance.

Fig- 3 Terry weaving machine

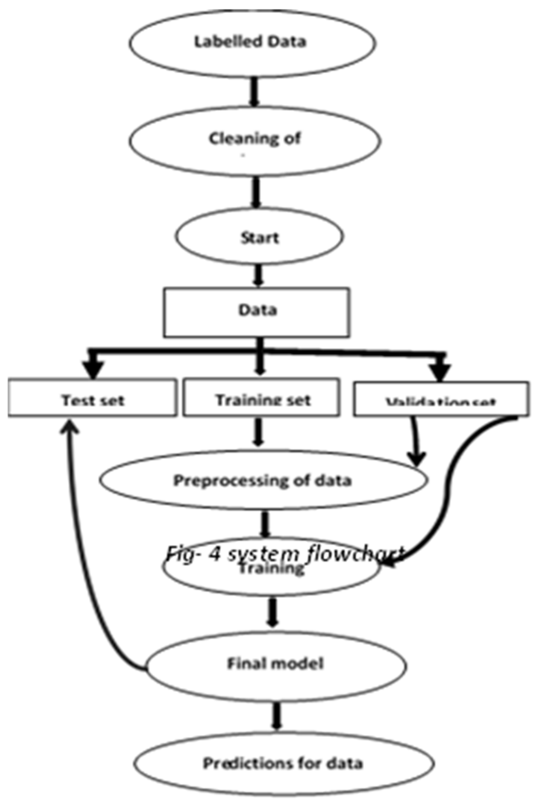

Fig- 4 system flowchart

V. DATA ANALYSIS USING MACHINE LEARNING ALGORITHM

Part of code-Using Support Vector Machines-

```
import java.io.BufferedReader;
import java.io.FileReader;
import weka.core.Attribute;
import java.util.ArrayList;
import java.util.Arrays;
import weka.classifiers.Evaluation;
import eka.classifiers.evaluation.EvaluationUtils;
import weka.classifiers.functions.SMO;
```

```
import weka.core.DenseInstance;
import weka.core.Instance;
import weka.core.Instances;
import weka.experiment.ClassifierSplitEvaluator;
public class Sensor
{
  public static void main(String[] args) throws Exception
   {
       ArrayList<Attribute> attributes=new ArrayList<>();
//       attributes.add(new Attribute("USS"));
       attributes.add(new Attribute("VS"));
```

VI. GRAPHS AND RESULT

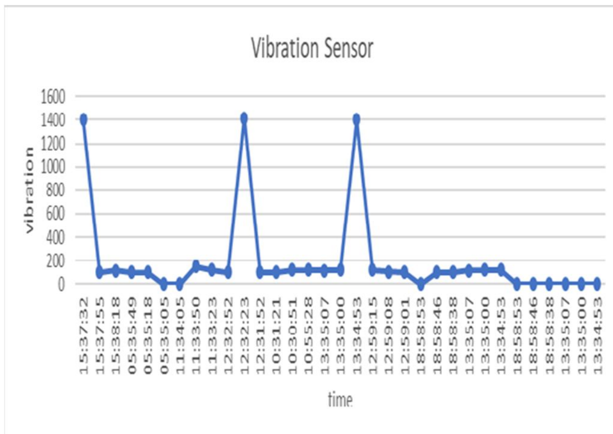

Fig- 5 Graph showing output of vibration sensor

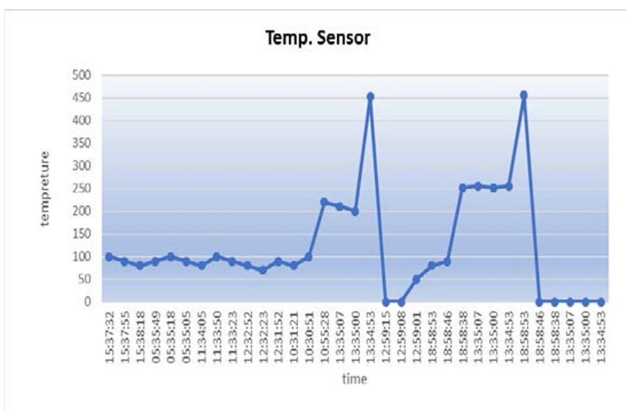

Fig-6 Graph showing output of temp sensor

Results:

```
run:
Correct:    570.0
Incorrect:   53.0
% Correct :91.49277688603532
% Incorrect :8.507223113964686
% Unclassified :0.0
```

Confusion Matrix of fault prediction using SVM:

	Predicted	
Actual		***Positive***	***Negative***
	Positive	528	10
	False	43	42

$$\text{Accuracy} = \frac{TP+FN}{TP+TN+FP+FN} * 100 = 91.429\ \%$$

V. Conclusion

Using labelled data generated during supervised learning can be used to develop a predictive model for prediction of early failure of sensor. The predictive model uses historical data to predict failure as well as type of failure. The implementation provides prediction accuracy of more than 90%. The comparison between random forest and SVM shows, support vector machine provides better model for system under test.

Future Scope

The present work is extended further to cover more physical parameters responsible for sensors failure. The future work targets parameters like supply voltage variations, atmospheric pressure, humidity and electrostatic discharge (ESD) / electromagnetic interference (EMI). This study allows correlation between above mentioned independent parameters and probability of failure. This correlation provides valuable information regarding prominent.

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