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SOA BASED IOT FRAMEWORK FOR EARLY DETECTION OF SENSOR FAILURE

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ABSTRACT: Industry tend to use advanced equipment's for the reason of improvement in performance and quality of production. These advanced machineries require optimal maintenance policy for long term efficiency. 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, ESD and variations in input supply voltages, present at working place are responsible to early failure of sensor. The objective of this paper is to collect ground truth using supervised learning and using appropriate machine learning algorithm that analyses data for classification and providing alarm for early detection sensor failure.

KEYWORDS— 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 labours leads downtime. Hence manufacturers are adopting new ways of optimising 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 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 regular maintenance. In this exercise, machine data from different sensors is collected for an appropriate period, and then this data is analyzed and validated using different machine learning algorithms such as regression, classification and validation. Many predictive maintenance schemes are available, which has main components such as data capturing, data filtering, feature extraction and selection [3], possible fault detection and time to failure (TTF) probability. The predictive sensor failure mechanism of can implemented with the use of different machine learning algorithms such as supervised, unsupervised and reinforcement learning. Supervised and unsupervised learning methods are the most suitable methods for finding probable failure of sensor. Supervised learning approach is more accurate when the dependent or independent variable are known.

II. RELATED WORK

It became increasingly difficult have control over inventory, line breakdown, process synchronization, and standstill labour 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.

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Due to advancement in sensing and communication technology, data related to present condition of sensor and output from any part of machine can be sensed and communicated, the condition- based maintenance provides services like fault prediction, type of fault and time to fail. The condition-based monitoring provides information collected from different sensors, this gathered data provides solid base for predictive maintenance policy. 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 fault finding along with its class, the combination of Gaussian Clustering and K-means algorithm is suggested [10]. Analysis of incident-based monitoring of complex systems for predictive maintenance (PdM) involves phases such as data collection, pre-processing, model induction and model evaluation. This method classifies sensors behavior in normal and abnormal class [11]. The use of image processing in process monitoring is an alternate mechanism of capturing industrial parameters like temperature, humidity, pressure level. All the sensor output values are submitted over the cloud for further processing. The data is analyzed with the help of platforms like Hadoop and so [12]. The support vector machine (SVM), ANN [14], Kohonen Feature Mapping [15], fuzzy logic [16], self-organizing map [17], hierarchical clustering [19] and k- means [18] are few popular fault classification algorithms.

FEATURE PARAMETERS

Temperature is foremost parameter in industrial measurement. The temperature affects right from common functions such as monitoring of parameters to demanding measurements such as controlling of parameters. The temperature at times changes output of sensor, this output change is so pronounced that the sensor is considered as faulty sensor. The excess temperature heats the sensor protective shield and at times this heating of the sensor burns the sensing arrangement inside the sensor.

The humidity is one more parameter, which shows its effect on sensing distance in case of inductive proximity sensors. In number of industrial machineries, the inductive proximity sensor is used for applications like distance sensing, measurement of speed of drive.

The moving parts and rotating drive in the machine create vibrations in many parts. These vibrations are damped by proper foundation. However even after proper foundation, vibrations are producing effect on measured quantity. The common effect is change in sensors position which results in improper measurement. Also, it is evident that enhanced vibrations create adverse effect of different parts of machine and various sensors mounted.

The power supplied to the sensor and signal conditioning circuit is another point of worry, any variation beyond threshold leads to faulty output. It is vital to keep dc voltage constant. There is another issue with the dc voltage supplied to the circuit, the surge voltage also called electrostatic discharge (ESD). It is very common in the industry, to experience electric surge superimposed over dc power supply. These surges many times become reason for sensor failure. Hence surge voltage measurement is important

The proper earthing in the industrial environment is essential to avoid electric shock hazards. Many times improper earthing creates some current to flow in ground terminals, causing ground volage. This ground voltage even changes the potential difference supplied to sensor and its signal conditioning circuits.

All above mentioned parameters produce effect on sensors working and present conditions which leads to sensor's early failure.

SERVICE ORIENTED ARCHITECTURE (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- sensing layer, networking layer, service layer and interface layer. This architecture is providing communication stack to collect data. The table-1 shows functions supported in different SOA layer.

Data collection: For collecting data from the surroundings of sensor under test, different sensors and opensource IoT hardware (ESP 8266/NodeMCU) is used. For mobility and expansion purpose one NodeMCU is used for each sensor.

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Table-1- Functions handled in different SOA layers

Layers	Description
Sensing layer	Sensors and associated signal conditioning circuits are main contributors. This hardware can be mobile nodes. Data sensing and acquisition protocols are main components.
Networking layer	Supports for data forwarding using basic wired or wireless support. Different techniques such as Wi-Fi, Bluetooth, 6lowpan etc.
Service layer	This layer provides solutions to satisfy users need. This layer is responsible to create messages to fulfil users' requirements
Interface layer	Interaction between users and related applications

Different independent parameters such as temperature, humidity, atmospheric pressure, vibrations of the equipment's, input supply voltage variations, electrostatic discharge (ESD) 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.

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 model development-

Assumption 1: It is assumed that the equipment is working in practical condition (industrial environment) where, voltage, current, machine temperature, environmental pressure, vibrations of machine and ESD are significant parameters.

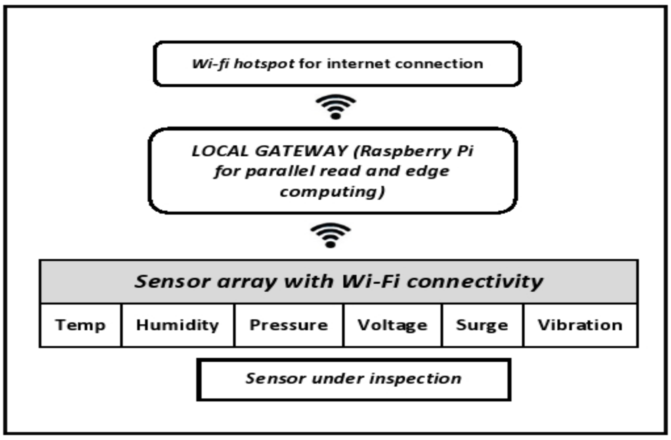

Figure-2 -Practical setup

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Fig- 3 Setup mounted over Terry weaving machine

Assumption 2: All above defined attributes are significant for sensor installed in the machine
Assumption 3: the probabilistic model uses data generated by sensors installed nearby sensor in the terry weaving machines.
In supervised learning, the expected output is a function that represents labelled data used during training phase. The training data consist of independent input vectors, such as temperature, vibration etc. and output vector is again a labeled parameter specifying sensors present working condition. The labelled output is the proof of its respective input vector. The labelled input and output vectors represent training data. Regression and classification are two major algorithms popularly used in supervised learning

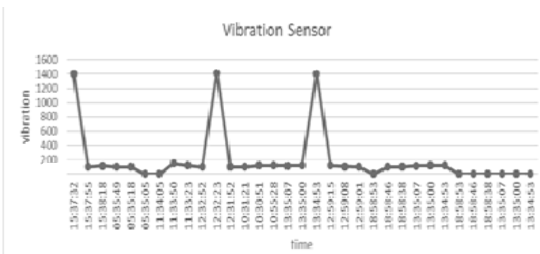

Fig- 4 Graph showing output of vibration sensor

The vibrations generated by the machine has certain frequency and direction. To estimate direction, a three-axis accelerometer is used. The output on x, y and z direction are measured and recorded. The peak values of vibrations are found at regular intervals using fast Fourier transfer (FFT). It is evident that for regular vibrations, the output of accelerometer follows certain pattern.
The temperature changes are recorded, the output of temperature sensor vital information of actual temperature present at the actual point of interest. The wireless nodes allow mounting of sensor at the location of interest. It is very helpful to study combined effect of vibration and temperature on the failure of the sensor.

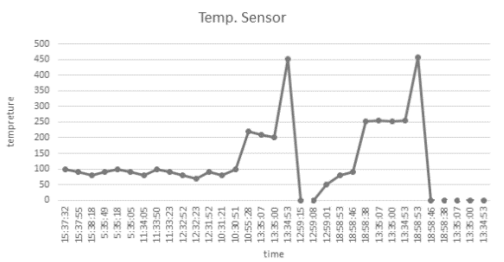

Fig- 5 Graph showing output of temperature sensor

VALIDATION AND EVALUATION

From training data set, a performance function, which fits perfectly, is decided and function representing performance of the equipment is identified. To avoid overfitting, labelled data is divided into two parts: training data and testing data A training set is used to define the model and testing set is utilized to validate the defined model.

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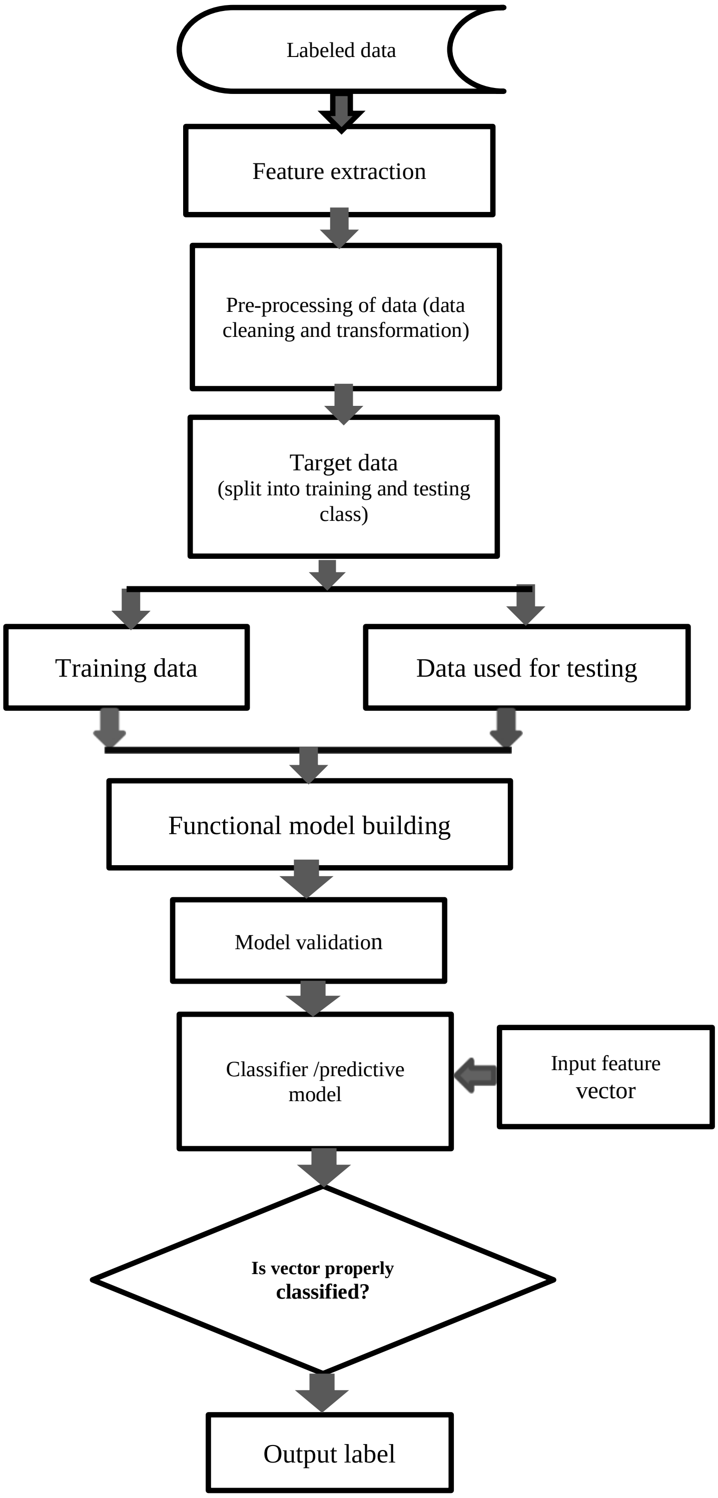

Fig-6 System flowchart

Support Vector Machine (SVM) is popular supervised machine learning algorithm used for both classification and for finding statistical relation between one dependent variable and many independent parameters. In our case SVM is used for classification. Here different feature parameters, such as temperature, pressure, vibrations are plotted in the n-dimensional space. The classifier function is a hyper plane, that separates two classes clearly.

The real time input vector is classified and appropriate label is allocated, here working properly or improper.

Part of code-Using SVM

```
instances. set Class Index (2);
        try (FileReader fr=new FileReader ("datasett.csv");
                BufferedReader br=new Buffered Reader(fr))
        {
            String header=br.readLine();
            String line;
            while((line=br.readLine())!=null)
            {
                String []tokens=line.split(",");
                Instance instance=new Dense Instance (3);
                instance.set Dataset(instances);
Double.parseDouble(tokens[6]);
instance.setValue (1, Double.parseDouble(tokens[7])
Double.parseDouble (tokens[5])==0?("FAILED":"NORMAL");
instances.add (instance);
attributes.add (new Attribute("VS"));
```

III. RESULTS

Run:
Correct:570.0 Incorrect:53.0
% Correct :87.48277688603532
% Incorrect :12.5172231
% Unclassified :0.0

Confusion Matrix of fault prediction using SVM

Table-2 Confusion matrix for SVM

		Predicted	
		Positive	Negative
Actual	True	492	45
	False	35	20

Accuracy = $\frac{(TP+FN)}{(TP+TN+FP+FN)} = \frac{512}{80} = 86.486$ %

A decision tree is another supervised machine learning algorithm used for both classification and regression problems. Some times single tree structure doesn't provide expected results. Then by combining multiple decision trees expect result can be drawn. The combined decision tree is

known as random forest algorithm. This algorithm is used for regression and decision making, as classifier. The result of SVM is also compared with the random forest algorithm. The following table shows that support vector machine performs better than random forest for our case of predictions.

Table-3 Comparison of accuracy with SVM and random forest classifier

Supervised Model	***Prediction Accuracy (%)***
Support Vector Machine	86.486
Random forest	78.243

IV. CONCLUSION

Using labelled data generated during supervised learning can effectively be used to develop a predictive model regarding prediction of early failure of sensor. Here prediction model for proximity sensor mounted on terry weaving machine based on different feature parameters is proposed. The predictive model uses historical data to predict failure as well as type of failure. The implementation provides prediction accuracy of more than 85%. The comparison between random forest and SVM shows, support vector machine provides better accuracy of prediction for vector under test. This study provides combined effects of parameters like temperature, vibrations. The suggested methodology can be installed on the machine which is already in use, ensuring reusability of old machine. The IoT based framework confirms recycling of old machineries added with smart solutions like industry 4.0 and predictive maintenance (PdM).

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V. FUTURE SCOPE OF WORK

The present work is to be extended to cover more physical parameters responsible for sensors failure. The future work targets parameters like supply voltage variations, humidity, ground currents due to faulty earthing and electrostatic discharge (ESD). This study allows correlation between above mentioned independent parameters and probability of sensors failure. This correlation provides valuable information regarding prominent parameter responsible for sensors failure. An alarm system can be implemented to provide alerts before actual damage occurs, saving cost of damage.

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