Early Failure Detection of Rapier Weaving Loom Using Sensors and Machine Learning Approach

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Abstract

The textile industry is the oldest and widespread across the world. This has high demand due to its impact on daily life. Textile production is not a simple task and hence textile industry uses many machines to meet daily production demands. Few of the common machineries used in textile industries are spinning machines, weaving looms, knitting machines, dyeing machines, and finishing machines. For weaving purpose, the terry and similar textile industries rely on high-speed rapier weaving looms. These machines are designed for longer operational time. The Terry and similar textile industries are frequently experienced breakdown in functioning of rapier looms due to involvement of complex electronic circuitry, sensors, and their failures. In a survey it is observed that, more faults related to electronics is the main cause of weaving loom stoppage as compared to faults related to mechanical reasons. The local working conditions in the industry are responsible for premature failure in electronic circuitry and sensor parts. Hence, the industry now experiencing higher faults in electronic circuits, sensors and power supply as compared to mechanical related faults. The main objective of this paper is to design an IoT framework for condition monitoring of rapier loom to generate data representing its current working condition. A classifier based on supervised learning is designed to distinguish between safe and unsafe working condition of rapier loom.

Keywords- Rapier loom, Internet of Things (IoT), condition monitoring (CM), heat-map, correlation matrix, confusion matrix, accuracy, F1 score.

I.INTRODUCTION

In the Industrial automation, sensors play vital role to make the production intellectual and exponentially automatic. Integration of sensory information and human knowledge is must to conduct task with or without human intervention. Rapier weaving looms in the textile industry (Fig-1) are intelligent machines deigned for seamless working. They utilize data from sensors for its smooth functioning. The rapier loom takes help of programmable logic controllers (PLCs) to ensure its smooth functioning. The PLC program considers type of loom desired output. Upon detection of operational fault in rapier loom PLC generates appropriate report. The policy of just reporting does not stop damage to the rapier loom and hence there shall be a system installed on the machine which will detect and report condition leading to potential failure in advance.

Condition monitoring (CM) of the rapier loom is the process of monitoring particular condition in machinery (such as vibration, temperature) to identify changes that could indicate a developing fault in the rapier loom. These conditional parameters corresponding to current working of rapier loom are sensed by the sensors deployed at various locations of the rapier loom. Sensor is a crucial feedback element in rapier loom for timely assessment of its health and to take appropriate measure to prevent any catastrophic conditions. The sensor system consists of sensing element, signal processing circuit and a power supply. Any event in which weaving machine fails to achieve its intended purpose or task is define as equipment failure. The equipment failure also produces equipment stoppage also called breakdown.

Fig-1 Textile rapier weaving loom

Fault detection is an essential process in the industry to maintain production rate. The advancement in the IoT and communication technology, attracts industry to deploy IoT in the fault-finding process. There is no specific defined standard for information exchange in the IoT platform, therefore service-oriented architecture-based approach in information communication is practiced (Fig-2). Service-oriented architecture (SOA) is a layered model architecture which allows applications to exchange their information across different platforms and languages.

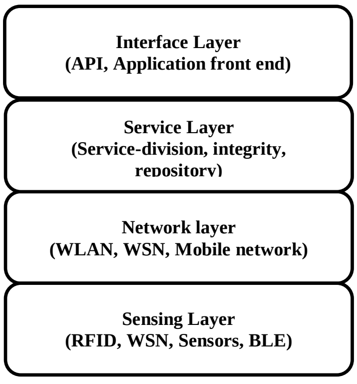

Fig-2 Service oriented architecture for IoT

The condition monitoring of rapier loom uses different sensors to capture both environmental parameters such as ambient temperature, pressure, temperature of the main motor, temperature nearby sensor and physical parameter such as vibration magnitude in three directions (x, y and z) in weaving loom. Electrical conditions such as supply voltage applied sensors working, signal conditioning circuit also affect rapier loom performance. Hence sensors measuring electrical parameters are also deployed and they are part of sensing layer, The data generated by these sensors is connected to processor in network layer using different protocol such as I2C, SPI communication protocols. Also, few sensors generate data in frame format e.g., MODBUS frame form. The data frame usually sent over two wire RS 485 network, which again into USB form to fed to controller in network layer. The service oriented IoT architecture is beneficial in gathering data of heterogeneous types into network layer.

II.RELATED WORK

The condition monitoring (CM) provides an effective interface to gather data from the equipment or machine under observation with help of IoT and communication protocols.

The bearing is critical component in induction motor [1] [4] [11] [14]. The vibration sensor was used to collect data related to vibration levels produced during motors functioning. An intelligent monitoring system is integrated with fault diagnostic system for diagnosis which classify the vibration levels as normal of abnormal. The FDD (fault detection and diagnosis) system is often useful in predictive maintenance of induction motors or similar rotation equipment.

Mechanical shock failure predictions [2] of a cantilever structure can be possible by deploying condition monitoring system which measures vibrations, strain produced in the structure under deformation. The data related to structure deformation and vibration level is processed using unsupervised learning method for prediction of structure failure.

The wind turbine bearing system [3] is prone to failure. Condition monitoring deploys sensors to monitor noise, vibration, temperature, and lubrication conditions of the bearing. A statistical approach for detection and separation of fault in turbine bearing is defined.

Reliability of sensors in the gas plant [5] is key factor for safe functioning of the gas plant. The data generated by sensor is validated first and based on current sample the sensor life predicted. Based on the data related to remaining life of sensor preventive maintenance can be performed to ensure safety of the gas plant.

The key role of a slitting machine [6] is to cut (slit) large rolls of papers, film, and foil materials into narrower rolls. The supervised machine learning models are used for process data collected during condition monitoring to ensure safe running of the machine with minimum maintenance cost without quality compromise.

An electrohydraulic servo valve system [7] is an electrically controlled valve used to regulate flow of hydraulic fluid in actuator. Servo valves are effective in controlling of heavy hydraulic cylinders with a low electrical actuating signal. A condition monitoring of EHSV utilize internal fluid leakage as a fault, here change in pressure level is recorded. The analysis of fluid pressure decides functionality of electrohydraulic valve along with its usability for required operation.

The conveyor belt system [8] finds its use in manufacturing industries to transport the job from one location to another. Textile industries and automotive industries deploy conveyor belt system to pass objects from one place to another. Series of operations are conducted, and quality of work is monitored with the help of bunch of sensors installed at various locations on conveyor belt. carry series of operations on the object, Different sensors are installed at various locations to monitor quality of operation performed. The reliability of the conveyor belt system is guaranteed by implementing highly accurate sensor failure prediction model so that quality is not compromised.

Mostly group of sensors [9] are deployed in the equipment to monitor its smoot functioning and quality of the product. A condition monitoring is useful to collect sensor data, to find relationship between sensor data, to detect sensor status transformation.

An image processing approach is used to judge faults in the woven fabric, the non-defective fabric is compared with defective fabric. The difference between designs patterns [13] is an indication of fault. By careful observation, the pattern mismatch is mapped to fault in the weaving loom. The sub-window system is used to compare part of image together to detect dissimilarities in defective and non-defective fabric.

In case our approach of condition monitoring of rapier loom, various sensors are deployed to capture physical, environmental, and electric parameters affecting machines working in time domain, frequency domain analysis and machine learning

III.EXPERIMENTAL SETUP AND DATA COLLECTION

The condition monitoring (CM) consists of multiple temperature sensors, pressure, humidity triaxial accelerometer, and voltage sensors (fig 3 and 3.1). Temperature of different location on the rapier loom is recorded.

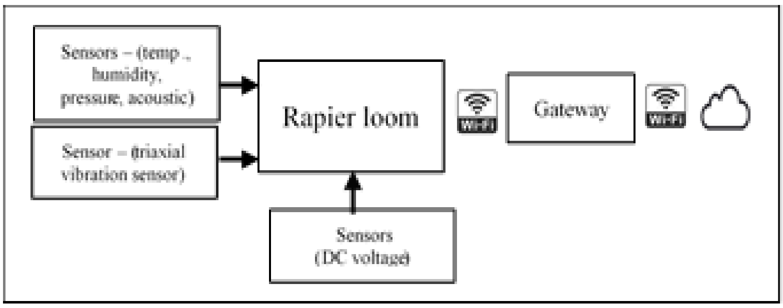

Fig-3 Block diagram of practical setup

Fig-3.1 Hardware implementation of practical setup

The data generated by different sensors is recorded both at local end (gateway) and over the cloud. The sampling duration for data recording is adjusted as per the parameter requirement. For recording of vibrations both instantaneous and RMS value of acceleration is considered. The raw data representing acceleration is especially useful in deciding limiting parameter to avoid mechanical damage to sensor installed on the rapier loom.

The data generated by condition monitoring system is recorded with the timestamp. This information is useful during time domain analysis, and regression. The data is stored in amazon cloud and database copy can be downloaded in .csv form. The following table shows captured data in table form.

date	time	dht_temp	bmp_pres	dht_humi	ds_temp	VELOCITY_	VELOCITY_	VELOCITY_	TEMPERA	AUDIO	volt_12	volt_5	fail
01-07-2021	9:00:00 AM	31.6	95782	65	65.44	15.346	12.7627	34.6929	33.875	133	12.45	5.36	0
01-07-2021	9:00:10 AM	31.6	95787	65	65.44	13.6609	12.0773	38.6843	33.837	132	12.26	5.2	0
01-07-2021	9:00:20 AM	31.6	95784	65	65.44	14.2548	11.6052	39.6929	33.7609	132	12.29	5.2	0
01-07-2021	9:00:30 AM	31.6	95780	65	65.44	14.6081	12.0001	42.1843	33.9328	131	12.29	5.2	0
01-07-2021	9:00:40 AM	31.6	95787	65	65.5	14.2453	11.6934	37.6843	33.9216	132	12.29	5.2	0
01-07-2021	9:00:50 AM	31.6	95788	65	65.5	17.7501	12.5731	40.6843	33.8887	133	12.29	5.2	0
01-07-2021	9:01:00 AM	31.6	95784	65	65.5	11.6795	11.9763	42.4258	33.966	133	12.45	5.36	0
01-07-2021	9:01:10 AM	31.6	95781	65	65.5	12.186	13.242	37.9343	33.7508	132	12.48	5.36	0
01-07-2021	9:01:20 AM	31.6	95773	65	65.5	15.9749	12.7244	39.9258	33.8395	132	12.26	5.2	0
01-07-2021	9:01:30 AM	31.6	95788	65	65.44	14.7655	12.7787	42.4343	33.8082	133	12.45	5.36	0
01-07-2021	9:01:40 AM	31.6	95779	65	65.44	15.404	13.4463	41.1843	33.8206	131	12.45	5.36	0
01-07-2021	9:01:50 AM	31.5	95782	65	65.44	17.4977	11.3005	38.1843	33.971	133	12.26	5.2	0
01-07-2021	9:02:00 AM	31.6	95783	65	65.44	17.5599	11.4862	39.6843	33.8303	133	12.26	5.2	0
01-07-2021	9:02:10 AM	31.6	95783	65	65.44	14.8049	12.0446	33.6929	33.9026	132	12.45	5.36	0
01-07-2021	9:02:20 AM	31.6	95780	65	65.44	11.7684	12.4094	36.4429	33.9062	132	12.26	5.2	0
01-07-2021	9:02:30 AM	31.6	95783	65	65.44	14.2467	11.9011	35.4429	33.8723	132	12.43	5.33	0
01-07-2021	9:02:40 AM	31.6	95786	65	65.44	13.2968	11.8889	37.2014	33.9691	132	12.26	5.2	0
01-07-2021	9:02:50 AM	31.6	95782	65	65.44	13.4195	12.2325	37.4514	33.9922	132	12.45	5.36	0
01-07-2021	9:03:00 AM	31.5	95784	65	65.44	13.9651	11.8287	37.9514	33.9104	131	12.45	5.36	0
01-07-2021	9:03:10 AM	31.5	95779	66	65.44	13.8901	11.4276	36.4599	33.8308	132	12.26	5.2	0
01-07-2021	9:03:20 AM	31.5	95784	66	65.44	12.6216	11.4677	39.4684	33.8091	133	12.26	5.2	0

Table-1 snapshot of data captured by the CM system in cloud

The data stored in the cloud is, analysed using Python tool and characteristics graphs of different performance related parameter are constructed using matplotlib library in Python.

i) The vibration signal produced in the rapier loom can be analysed using Python and matplotlib library.

matplotlib function is used to import pyplot as plt

df= pd.read_csv ('/test.csv')

df.columns

Graph plotting-

a=pd.DataFrame(df,columns=['time','VELOCITY_RMS_Z'])   a.plot()

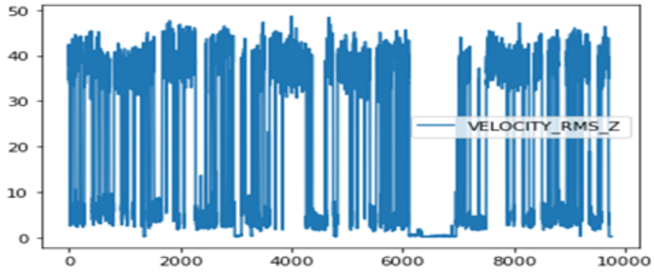

Fig: 4 Line graph for velocity in Z ditection

The above graph (Fig-4) is characterized using the following equation-

y (vibration z- directtion) = 0.0006 x +25.17

This statistical representation of vibration in the rapier loom is useful during analysis to define safe and unsafe operaing region to avoid ant physical damage due to mechanical looseness, if any available in the machine. In rapier loom, proximity sensors are mounted in a close vicinity of moving part, and are the strong candidate to get physically damaged.

Temperature sensors are deployed at different locations, such as over the main driving motor and another close to sensor on the rapier loom. Temperature contribute heavily in sensor and electronic circuit failure. Hence it is necessary to characterize variation in temperature of main motor, different location on the loom.

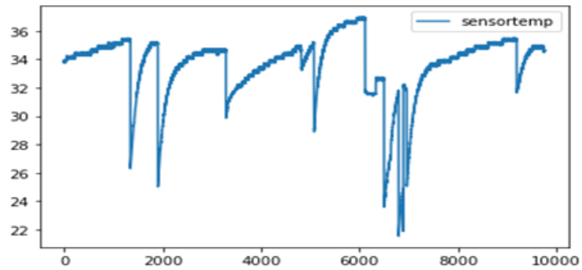

Fig:5 Line graph for temperature variation around sensor for long duration

The characteristics equation of sensor temperature variation (Fig-5) is expressed on the basic of long-term monitoring data is as given below-

Sensor temperature variation= y =3e^{-6} x +33.625

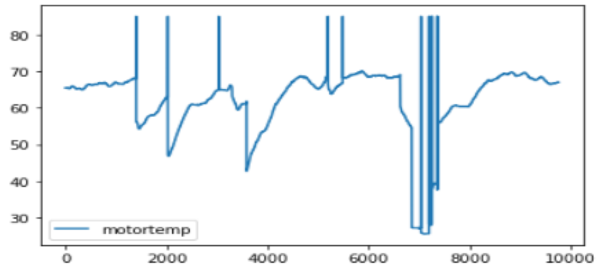

Fig:6 Line graph for main motor temp variation sensed for long duration

The characteristics equation for main drive motor temperature variation (Fig-6) based on long-term data monitoring expressed as given below-

$$\text{Motor Temperature variation} = y = 2e^{-5}\, x + 31.454$$

ii) In textile weaving process, wetness of the yarn is vital to get superior design and stiffness in the loops, especially in terry weaving industry. Hence manufacturers tend to install humidifier to control the moisture content in the environment. Sometimes this excessive moisture content become reason for electronic circuit failure and in turn sensor failure. Hence it is necessary to characterize the humidity variation in the plant.

IV. EXPERIMENTAL EVALUATION

Machine learning is useful in predicting future from historical data. Machine learning (ML) is a subset of artificial intelligence (AI) which allows controller to learn without being explicitly programmed.

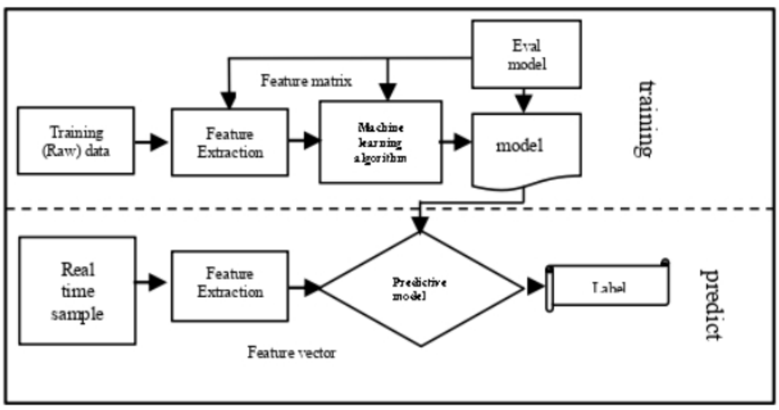

Fig:7 Flowchart showing supervised learning model

The methodology adopted for prediction using machine learning -

i) Real time data collection of various physical and electrical parameters of rapier loom with the help of deployed sensors.
ii) Supervised machine learning (Fig-7) rather than unsupervised learning approach adopted due to availability of labelled data representing ground truth.
iii) Classifier machine learning algorithm rather than regression machine learning algorithm are applied to classify machine operation into safe or potential unsafe operating mode.

iv) Divide the dataset into 80% $training$; 10% $validation\ and$ 10% $testing$.
v) Apply SMOTE to dataset. Hyper parameters used related SMOTE- sampling strategy, and k_neighbours
vi) Apply various algorithm in SKlearn, such as Naïve Bayes classifier, Decision Tree, SVM, random forest.
vii) Find out suitable algorithm with high accuracy-based performance parameters like-accuracy, recall, precision, and F1score
viii) Hyper parameter tuning for best performing algorithm – the hyper parameters used are n_estimators, max_features, max_depth, min_samples_split, and min_samples_leaf
ix) Improvement in prediction time (learning, validation, and prediction) with hyper parameters is 7.2 seconds from 27 seconds without hyper tuning.

Implementation of supervised machine learning algorithm for analysis of data collected in the cloud for learning provides useful outcome such as heatmap and corelation matrix. The Python tool is useful in feature extraction, training, and testing of dataset. In supervised learning approach, the dataset is divided into two classes namely training and testing dataset. The supervised learning algorithm maps input variable (x) with the output variable (y) to determine mapping function. Labelled training dataset is used for training purpose to define classification model. This classification model is useful in classification new input sample. After understanding the input sample, the model determines label to provide to new data based on pattern. Supervised learning further divided into two sub types of namely regression and classification.

In visualization of complex data, heatmap is advantages. Heatmap is two-dimensional representation which provides data summary in colourful manner. Following Python generates heatmap related to input dataset.

```
import matplotlib.pyplot as plt

import seaborn as sns

%matplotlib inline

import seaborn as sns

corrmat = df.corr()

top_corr_features = corrmat.index

plt.figure(figsize=(15,15))

g=sns.heatmap(df[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```

Fig:8 Snapshot of heatmap of dataset

```
]: corr = df.corr()
   corr.style.background_gradient(cmap='coolwarm')
```

]:

	dht_temp	bmp_pressure	dht_humidity	ds_temp	VELOCITY_RMS_X	VELOCITY_RMS_Y	VELOCITY_RMS_Z	TEMPERATURE	AUDIO	vo
dht_temp	1.000000	-0.200844	-0.898848	0.767579	0.102845	0.042719	0.038759	0.496657	0.053235	-0.0
bmp_pressure	-0.200844	1.000000	0.345433	0.100852	0.107642	0.173051	0.162926	-0.037175	0.177136	0.0
dht_humidity	-0.898848	0.345433	1.000000	-0.632002	-0.106517	-0.019660	-0.014582	-0.427434	-0.026152	0.0
ds_temp	0.767579	0.100852	-0.632002	1.000000	0.054570	0.004979	-0.010690	0.589139	0.008568	0.0
VELOCITY_RMS_X	0.102845	0.107642	-0.106517	0.054570	1.000000	0.938800	0.929332	0.040996	0.912303	0.0
VELOCITY_RMS_Y	0.042719	0.173051	-0.019660	0.004979	0.938800	1.000000	0.985359	-0.001239	0.973905	0.0
VELOCITY_RMS_Z	0.038759	0.162926	-0.014582	-0.010690	0.929332	0.985359	1.000000	-0.010288	0.976306	0.0
TEMPERATURE	0.496657	-0.037175	-0.427434	0.589139	0.040996	-0.001239	-0.010288	1.000000	0.002394	0.0
AUDIO	0.053235	0.177136	-0.026152	0.008568	0.912303	0.973905	0.976306	0.002394	1.000000	0.0
volt_12	-0.001804	0.002148	0.002233	0.000809	0.002264	0.000852	0.000548	0.001149	0.000081	1.0
volt_5	-0.048403	0.046225	0.042182	-0.031509	-0.013024	-0.007579	-0.005577	-0.059049	-0.010293	0.0
fail	-0.018349	0.003490	0.015526	0.051985	0.004906	0.005292	0.012225	0.037252	0.003899	0.0

Fig:9 Snapshot of co-relation matrix of dataset

Heatmap (Fig-8) and correlation matrix (Fig-9) is extremely useful to know dependency of one feature with another feature. The value quoted in the square of heatmap, and correlation matrix shows how strongly these features are bonded. In case of negative value in the matrix, which feature parameter can be excluded, as it is not showing much effect on the dependent parameter (output). In our dataset the feature parameter named pressure and acoustic exhibits negative value and hence these feature vectors are neglected during training phase of machine learning.

Handling imbalance dataset - Imbalance in dataset means there is a mismatch in majority and minority class data. In case of imbalance data set, machine learning algorithm shows high prediction accuracy even though the algorithm fails to detect false condition of dependent parameter. Hence it is necessary to form balance between majority and minority class data. This balance can be achieved by inserting synthetic data into minority class data so that minority class data become comparable with majority class data. The technique called SMOTE (Synthetic Minority Oversampling Technique) is used to provide balance in majority and minority class data. The SMOTE is frequently used in industries by repeating known false conditions in the dataset at several times. This repetition of false condition provides balance in dataset. The balanced dataset always provides better learning during training phase of machine learning. In SMOTE technique, few outlier samples (boundary cases) also considered as additional false conditions, the number of outliers to be considered is defined in program code. Following Python code is used to balance dataset using SMOTE-

```
from imblearn.over_sampling import SMOTE

oversample=SMOTE (sampling_strategy=0.5, k_neighbors =5, random_state = 42)

# transform the dataset

x, y = oversample.fit_resample (x, y)
```

Performance evaluation of different supervised learning algorithm- For perform evaluation of supervised algorithm confusion matrix is useful. A Confusion matrix is an N x N matrix shows performance of a classifier model, where N is the number of target classes. The matrix compares the actual values with predicted by the machine learning model. In our case binary classifier is used. Here target variables have two values namely positive and negative. In all four combinations are possible namely true positive (TP), true negative (TN), false positive (FP) and false negative (FN) Performance parameter such as accuracy, precision, recall and F1 score are considered to find its efficiency. The prediction accuracy of machine learning algorithm is calculated based on following formula-

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

Precision tells number of the correctly predicted cases found to be positive

$$Precision = \frac{(TP)}{(TP + FP)}$$

Recall tells number of the actual positive cases predicted correctly by the model

$$Recall = \frac{(TP)}{(TP + FN)}$$

F1-score is a harmonic mean of Precision and Recall.

$$F1\ score = \frac{2}{\frac{1}{Recall} + \frac{1}{Precision}}$$

The F1 score is an account of maximization of precision and recall. The high value of F1 score is preferrable, as it indicates that both accuracy and recall have highest value. Performance of machine learning algorithm is characterized by value of accuracy. But two or three exhibits same accuracy values, the choice of best performing algorithm is made based on F1 score.

1. Performance of Naïve Bayes Machine learning algorithm- The working logic of this classifier is based on assumption that the occurrence of a certain feature is independent of the occurrence of other features

```
Naive bayes accuracy: 0.9341616033372631
______________________________________
NB Confusion matrix:
 [[13192  1452]
 [    0  7410]]
______________________________________
NB Classification report:
               precision    recall  f1-score   support

           0       1.00      0.90      0.95     14644
           1       0.84      1.00      0.91      7410

    accuracy                           0.93     22054
   macro avg       0.92      0.95      0.93     22054
weighted avg       0.94      0.93      0.94     22054
```

Fig:9 Confusion matrix of Naïve Bayes algorithm

2. Logistic regression- Logistic regression estimates the probability of an event occurring, based on dataset of independent variables

```
logistic regression accuracy: 0.987167860705541
______________________________________
LR Confusion matrix:
 [[14459   185]
 [   98  7312]]
______________________________________
LR Classification report:
               precision    recall  f1-score   support

           0       0.99      0.99      0.99     14644
           1       0.98      0.99      0.98      7410

    accuracy                           0.99     22054
   macro avg       0.98      0.99      0.99     22054
weighted avg       0.99      0.99      0.99     22054
```

Fig:10 Confusion matrix of Naïve Bayes algorithm

3. Random forest algorithm- This algorithm is used for both classification and regression. Random Forest is a classifier uses multiple decision trees based on various subsets of the dataset and takes the average to improve the predictive accuracy of that dataset. This cluster-based approach is termed as ensemble learning.

The random forest algorithm uses bagging and booting techniques for learning.
For given training set $X = x_1, ..., x_n$ with responses

$Y = y_1, ..., y_n$, bagging repeatedly (B times) selects a random sample with replacement of the training set and fits trees to these samples-

For $b = 1, ..., B$:

1. $\hat{f}$ Sample, with replacement, n training examples from X, Y; call these X_b, Y_b.

2. Train a classification or regression tree f_b on X_b, Y_b.

As number of trees are formed during learning phase, accuracy of each tree is determined separately. The average of all accuracies is used for predictions of unseen samples

$$= \frac{1}{B}\sum_{b=1}^{B} fb(x')$$

or by considering majority vote in the case of classification trees. This bootstrapping process leads to better model performance due to reduction in the variance without increase in bias.

The estimate of the uncertainty of the prediction is standard deviation of all predictions from all the individual regression trees on x':

$$\sigma = \sqrt{\frac{\sum_{b=1}^{B}(f_b(x') - \hat{f})^2}{B-1}}.$$

The number of samples/trees, B, is a free parameter. Typically, few hundred to thousands of trees are used, depending on the size and nature of the training set.

```
Random forest accuracy: 0.9999093135032193
____________________________________________
RF Confusion matrix:
 [[14643     1]
 [    1  7409]]
____________________________________________
RF Classification report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     14644
           1       1.00      1.00      1.00      7410

    accuracy                           1.00     22054
   macro avg       1.00      1.00      1.00     22054
weighted avg       1.00      1.00      1.00     22054
```

Fig:11 Confusion matrix of Random Forest algorithm

Other supervised learning algorithm are also implemented to find various performance parameters such as accuracy.

The following table shows comparison of different performance parameters of supervised learning algorithm applied on dataset.

Sr. no	Machine learning Algorithm	Accuracy %	Precision %	Recall %	F1 score %
1	Random Forest	99.968260	99.919083	99.986505	99.952782
2	Decision Tree	99.882108	99.797680	99.851552	99.824609
3	SVM	98.544482	98.481740	97.165992	97.819442
4	Logistic Regression	97.401832	96.771104	95.452092	96.107072
5	Naive Bayes	94.123515	85.447588	99.446694	91.917176

Table-2 comparison of performance parameters of different supervised machine learning algorithm.

The Random Forest supervised learning model is showing best performance amongst all supervised learning algorithm. Hence it is chosen for prediction of early failure of sensor on the rapier loom. It is worth mentioning here, the time required for learning is minimal in case of Random Forest algorithm.

The prediction process for real time sample classification into safe or potential failure condition for sensor uses binary file corresponding to output function based on Random Forest model. The pickle module keeps track of the model which is already serialized ensuring faster execution time. The part of Python code to generate Pickle object is-

```
import pickle

with open('rf_mode_pickle.pkl','wb')as f:

   pickle.dump(rf,f)
```

The output Pickle module is used for real-time input sample representing rapier loom working condition. Following flowchart shows decision making process to classify sample corresponding to present working condition in the rapier is safe or condition prior to sensor failure.

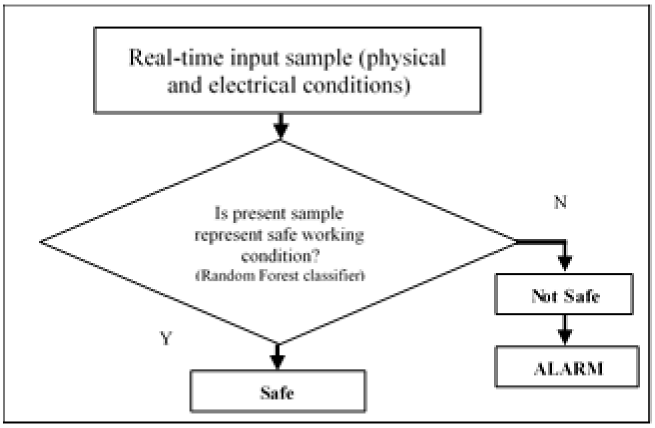

Fig:12 Flow chart showing early warning of sensor failure

V.CONCLUSION

Textile industry uses variety of weaving machines, amongst them rapier looms are popular due to their feature like higher operating speed and higher production rate. The rapier loom takes help of sensors and electronic circuits to ensure its smooth functioning. The rapier looms are prone to failure due to multiple physical and electrical parameters present at the location. Condition monitoring of rapier loom is an intelligent system designed for collection and monitoring of physical and electrical parameters present at the location of rapier loom. The service-oriented architecture is useful in IoT framework to extend sensor data to cloud for larger storage and further processing.

An efficient technique of data analysis is presented and implemented in this paper. The proposed method shows machine learning based approach for data balancing in case of asymmetricity in data and feature extraction, paradigms to facilitate building of decision-making system for rapier loom.

The implemented system has been subjected to extensive experimentation and testing of dataset. Different sensors are deployed to detect abnormalities in parameters like temperature, vibrations, humidity levels and electric voltage variations which are important part in decision making system. Furthermore, these experiments allowed to extend alert to loom attendant as well as technical expert over the mobile before actual failure takes place.

Monitoring of variety of parameter of rapier loom helps in avoiding early failure of sensors and associated electronic circuit. This predictive warning system also extend MTTR (mean time to repair) of the rapier loom, which reduces maintenance cost and enhance weaving looms operational uptime. The high accuracy provided by Random Forest machine learning algorithm also enhances reliability of rapier loom. The fast predictive early warning system protects sensor and associated circuitry.

VI. FUTURE WORK

The proof-of-concept (POC) system designed and developed during this work considers sensor and associated electronic circuitry for detection of probable failure conditions. It is also observed that issues related to yarn quality and strain on the warp and weft also leads to breakdown of rapier loom. These issues also can handle electronically to increase uptime of machine.

VII . REFERENCES

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