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Original Article

WeaveSense: IoT Infrastructure for Rapier Loom Condition Monitoring and Analysis

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Abstract *- Various machines and equipment are involved at different stages of the textile manufacturing process. The rapier looms are used to produce high-quality fabrics and other traditional textiles. The rapier looms are exposed to mechanical and frequently occurring electronic problems, which disrupts their operation and production efficiency. The condition monitoring of the rapier loom is helpful to ensure optimal performance. The IoT infrastructure for condition monitoring is designed and implemented at the industrial level, and ground truth data is captured. Weavesense targets temporal analysis of Service-Oriented Architecture (SOA) based on an IoT framework implemented for condition monitoring of rapier loom. The study of captured streaming data involves pre-processing, feature extraction and behaviour pattern recognition. The supervised machine learning approach permits correlating extracted features and captured data. The application scenario of the rapier loom and sequence of observations clearly show the consequences on the performance of the rapier loom.*

Keywords *- Rapier loom, Augmented framework, Filtering, Feature extraction, Data validation, Supervised learning, Correlation.*

1. Introduction

The oldest and most significant industry in the world is the textile industry. Globalization has a significant impact on the textile industry. The textile and apparel business is a crucial area of the economy, which accounts for substantial global exports that generate revenue and employment. Since creating fabrics is complex, the textile industry needs a lot of machinery to meet regular manufacturing demands.

The working conditions inside textile industries vary widely based on factors like the facility's size, location, and compliance with labour and regulatory authorities. However, it's important to note that the textile industry faces significant challenges due to long working hours, on-site working conditions and semi-skilled technical staff.

Different stages of fabric manufacturing use other machines for spinning, weaving, knitting, dyeing, finishing, printing, cutting, and sewing to acquire the desired output. The weaving machine adopts a complex weaving process to produce fabric, which decides the quality and efficiency of production. Dobby (Figure 1) and Jacquard looms are advanced weaving machines used in the textile industry to create intricate fabric patterns and designs. They also cater to the high manufacturing demand of fabric production by providing finely crafted, aesthetically pleasing fabrics as an output. The choice between Dobby and Jacquard looms depends on the complexity of the desired patterns, the type of fabric being produced, and the level of craftsmanship required.

Rapier looms also experience mechanical problems that can affect their performance and efficiency like any other machinery. Here are some common mechanical problems in rapier looms: yarn breaks, faulty selvedges, rapier head issues, faulty grippers, worn-out parts, oil and lubrication, timing, synchronization, vibration, and alignment. Regular maintenance, timely replacements of worn-out parts, proper lubrication, and operator training are essential to prevent and address mechanical problems in rapier looms.

The rapier loom uses old warp and weft weaving methods to produce fabric. There is not much medication in the basic weaving process in the rapier loom. The only advancement is in the weft insertion mechanism, and this significant advancement in the rapier loom is in the form of its automation. Electronic problems in rapier looms can disrupt their operation and affect production efficiency. These issues relate to the electronic components and control systems used in the looms. Sensor malfunctions, faulty control panels, power supply problems, communication errors, software glitches, electric motor problems, electronic board failures, encoder failures, and wiring and cable problems are regular problems in rapier looms.

To prevent electronic problems in rapier looms, regular maintenance, timely software updates, proper operator training, and ensuring a stable power supply are essential. Additionally, having skilled technicians who can diagnose and repair electronic issues promptly is crucial to minimizing downtime and maintaining production efficiency in the textile industry.

Different types of maintenance schemes include corrective, predetermined, and reactive maintenance. Most enterprises adopt reactive maintenance, also popularly known as breakdown maintenance. Moreover, breakdown maintenance is carried out by technicians, who are usually semi-skilled and tackle the problem based on their experience or based on their limited knowledge.

In most cases, the problem escalates, making the situation worse. It was also observed that breakdown maintenance couldn't prevent damage to the machine. The machine repair ensures double economic loss due to no stoppage in production and idle labour. The terry chaddar industries often encounter thread breakage issues due to warp and weft made by waste cotton. The rapier looms are typically designed to operate at 300 rpm, but it is observed that the industry prefers to run them at 190 to 200 rpm to avoid potential breakdown due to higher speed. Condition monitoring of rapier looms is helpful to ensure optimal performance, minimize downtime, and extend operational lifespan. Implementing manufacturers to detect issues early, perform timely maintenance, and prevent costly breakdowns.

The Internet of Things (IoT) plays a vital role in the condition monitoring of machines by enabling real-time data collection, analysis, and remote management of equipment [1, 2]. Condition monitoring is an intelligent monitoring system often preferred to characterize the accurate tile functioning of the machine. Table 1 shows a few condition-monitoring themes.

2. Experimental Setup for SOA-Based IoT Infrastructure and Discussion

Service Oriented Architecture (SOA) based IoT infrastructure provides a flexible and scalable approach for building Internet of Things (IoT) infrastructure for application. SOA allows different services and devices to communicate and interact with each other, fostering interoperability, reusability, and modularity. An SOA-based IoT framework is typically structured as shown in Figure 2, and the IoT infrastructure for the rapier loom is shown in Figure 3.

Table 1. A few condition-monitoring themes

Theme	Purpose of Condition Monitoring	Sensors Used
A condition monitoring strategy of looms based on DSmT theory and genetic multi-objective optimization improves the rough set method [21]	Characteristic description of the vibration signal of the loom spindle	Piezoelectric-accelerometers
Low-cost vibration sensor for condition-based monitoring manufactured from polyurethane foam [22]	Determination of bearing condition	Piezoelectric sensor and MEMS
Wind turbine gearbox condition monitoring vibration [23]	Vibration monitoring of motor	Liner accelerometer

Fig. 1 Dobby rapier weaving loom

The rapier loom is equipped with several sensors to ensure its normal functioning. The condition monitoring system is over and above the observatory system for the functioning of rapier loom.

The experimental setup is implemented by installing additional sensors, other than rapier loom sensors (Figure 3), to observe its routine functioning. Different physical parameters of the rapier are finalized [3, 4] to monitor. These features are- motor temperature, sensor temperature, the temperature of the control panel, barometric pressure, humidity in the surroundings, vibrating velocity experienced by the sensor in x, y and z direction, acoustics, output voltage of regulated power supply (5, 12-volts). Table 2 shows some of the sensors used in condition monitoring and their purpose of use.

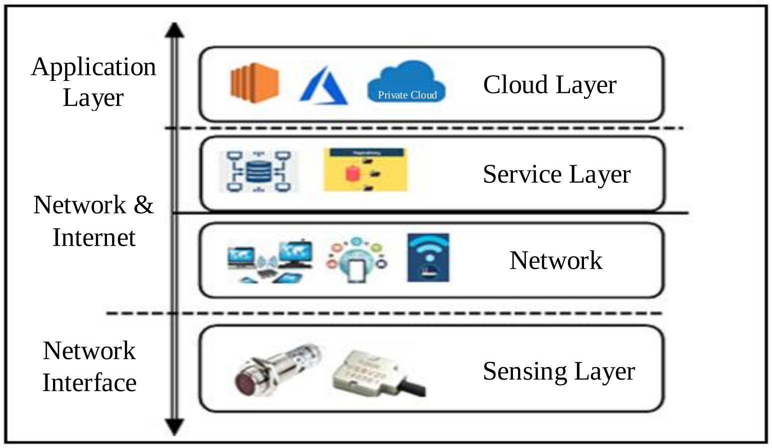

Fig. 2 Service Oriented Architecture (SOA)

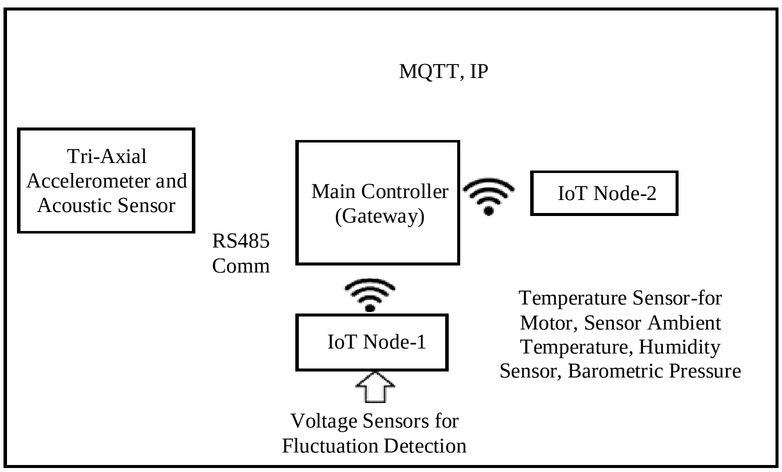

Fig. 3 SOA oriented IoT infrastructure

Table 2. A few of the sensors used for condition monitoring

Sensor	Purpose
Temperature of main motor	To capture temperature to co-relate it with another feature parameter
Temperature of sensor [14]	
Humidity sensor	Effect of humidity on the functioning of electronic circuit
Vibration sensor [14]	Determination of frequency and placement of the sensor
Voltage sensor	Monitor regulated power supply.

The vibration sensor is installed beside a rapier loom sensor whose vibrating frequency will be monitored. Humidity sensor to monitor ambient humidity level. The voltage sensors are installed in the regulated power supply output to detect and record voltage fluctuation. The pressure and acoustic sensors are installed over the rapier loom. Figure 4 shows the hardware implementation of condition monitoring IoT infrastructure for the rapier loom.

The condition monitoring system is designed for the rapier loom, and data related to local conditions and rapier loom functioning is captured (Figure 5). Data of more than eight months' duration is captured and utilized for time series data analysis.

Fig. 4 SOA oriented IoT infrastructure hardware implementation

Fig. 5 IoT condition monitoring implemented on rapier loom

3. Augmented SOA-Based Framework for a Rapier Loom for Supervised Time Series Analysis

Figure 6 shows the combined methodology data collection mechanism and data processing approach. The data login circuit provides diverse data and follows different communication protocols, formats, and technology. In addition to diversity, the data tends to vary due to the tolerance of low-quality sensors. The machine learning algorithms are applied to detect irregularity [6, 7, 9] classification [7], prediction [9, 15]. This article focuses on systematically implementing IoT temporal data analysis to optimise rapier loom performance using supervised machine learning methods.

Figure 6 shows the combined methodology data collection mechanism and data processing approach. The data login circuit provides diverse data and follows communication protocols, data format, and technology.

In addition to diversity, the data tends to vary due to the tolerance of low-quality sensors. Several approaches in time series modelling and analysis are adopted [12, 13, 20]. A few of the techniques are listed in Table 3.

Validation of IoT infrastructure: The modular design of the data login circuit makes it scalable and flexible.

Verification of data integrity and accuracy [5]: The data related to local conditions in the workplace is stored at the local server and compared periodically with data stored on the cloud to ensure data integrity. The data generated by infrastructure is validated with the help of a validation algorithm. Figure 7 shows the basic approach utilized to validate temperature data.

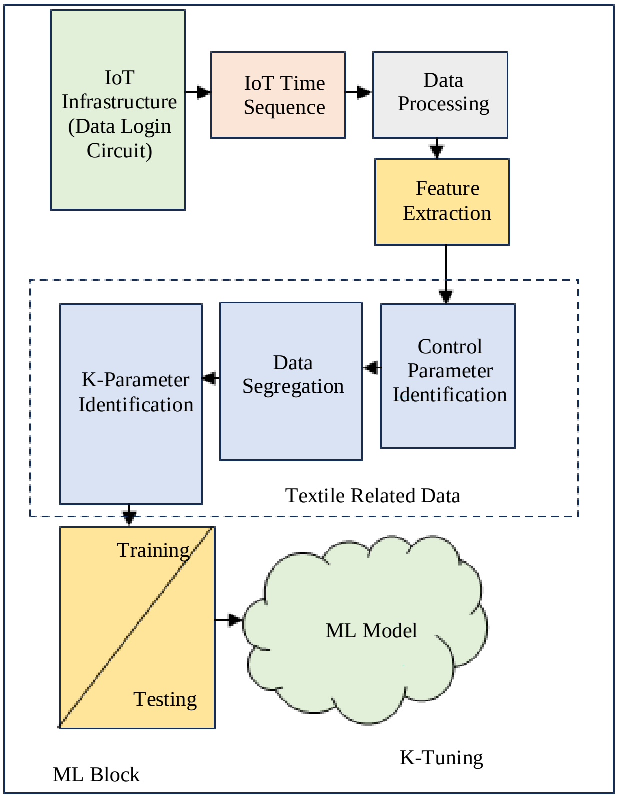

Fig. 6 Augmented SOA-based framework for a rapier loom for supervised time series analysis

Table 3. Different approaches in time series modelling

Approach	Purpose
Outlier Detection Techniques for Temporal Data (10)	To Detect Irregularity
Graph Theory-Based AnomalyDetection in Time Series Data (10)	Framework to Detect Fault in General AccessMethod
Iot Anomaly Detection Methods and Applications: A Survey (9)	Detecting Irregularityin Case of Shortage of Ground Truth Data
Statistical and ML Methods for Univariate Time Series Data Analysis (11)	Detection and Forecasting Anomaly

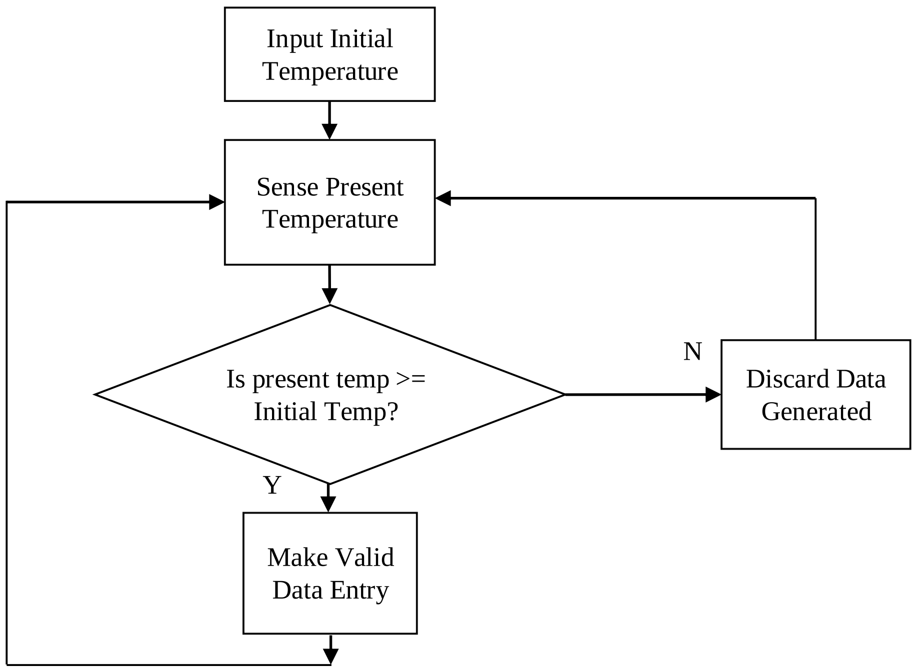

Fig. 7 Flowchart for temp data validation

4. Data Collected from Augmented SOA-Based Framework for Rapier Loom and Its Analysis

The data collected from the condition monitoring infrastructure is stored in table form at the local level and in the cloud. Table 4 shows data collected at the cloud level.

- Pre-processing of captured time series data: Raw data from different sensors in a condition monitoring system defines a multi-variate time series dataset. The co-relation between captured data is defined as Gaussian distribution. The drift in IoT time-based data is handled by mathematical transformation of the input data using Fourier transforms. The vibration data is dealt with using Fourier transforms to determine the vibrating frequency of sensor mounting.
- Feature extraction: Several sensors are capturing data from different locations of the rapier loom. Identifying captured data impacting rapier loom functioning is called feature extraction [10, 11]. Feature extraction helps to summarize low-dimensional data from higher-dimensional data [11, 17]. For feature extraction, the embedded method is used. Data of fifteen independent features is reduced to lower dimensional data which affects the functionality of rapier loom.
- Pattern recognition: Identification of behavior patterns is found using SVM, Randon Forest or similar machine learning algorithms. Table 5 shows the standard scalar for the input dataset.

The data generated by condition monitoring sensors is stored at local servers and in the cloud to facilitate long-term monitoring of the rapier loom.

Standardization of a dataset is necessary for machine learning estimators; otherwise, they may behave poorly as collected data does not follow standard distribution (e.g., Gaussian with 0 mean and unit variance).

The standardised scalar for independent features can be achieved by removing the mean and scaling it to unit variance. The standard score of an independent feature x is calculated as z = (x - u) / s, where u is the mean, and s is the standard deviation of samples. The supervised Learning algorithm uses labelled data for its learning. After learning, the algorithm decides which label should be assigned to new data based on the pattern and associates the patterns with the unlabeled new data. Figure 8 shows a heatmap demonstrating the correlation and proportion of dependency. The correlation matrix shows the balance of inter-dependency between monitored parameters, which is essential in deciding feature extraction [17]. Here, eleven sensor parameter vectors are minimized to smaller dimensional vectors.

Table 4. Data collected using IoT infrastructure

dht_ temp	bmp_ pressure	dht_ humidity	ds_ temp	velocity_ RMS_X	velocity_ RMS_Y	velocity_ RMS_Z	Temp	Audio	Volt_12	Volt_5
31.6	95782	65	65.44	15.346	12.7627	34.6929	33.875	133	12.45	5.36
31.6	95787	65	65.44	13.6609	12.0773	38.6843	33.837	132	12.26	5.2
31.6	95784	65	65.44	14.2548	11.6052	39.6929	33.7609	132	12.29	5.2
31.6	95780	65	65.44	14.6081	12.0001	42.1843	33.9328	131	12.29	5.2
31.6	95787	65	65.5	14.2453	11.6934	37.6843	33.9216	132	12.29	5.2
31.6	95788	65	65.5	17.7501	12.5731	40.6843	33.8887	133	12.29	5.2
31.6	95784	65	65.5	11.6795	11.9763	42.4258	33.966	133	12.45	5.36
31.6	95781	65	65.5	12.186	13.242	37.9343	33.7508	132	12.48	5.36
31.6	95773	65	65.5	15.9749	12.7244	39.9258	33.8395	132	12.26	5.2
31.6	95788	65	65.44	14.7655	12.7787	42.4343	33.8082	133	12.45	5.36
31.6	95779	65	65.44	15.404	13.4463	41.1843	33.8206	131	12.45	5.36
31.5	95782	65	65.44	17.4977	11.3005	38.1843	33.971	133	12.26	5.2

Table 5. Standard scaler of independent variables

dht_humidity	ds_temp	Velocity_RMS_Z	Temp	Volt_12
-0.173247	0.382987	0.578405	-0.057822	-0.261009
-0.173247	0.382987	0.814391	-0.078999	-0.347202
-0.173247	0.382987	0.874024	-0.121409	-0.333593
-0.173247	0.382987	1.02124	-0.225611	-0.333593
-0.173247	0.389683	0.755268	-0.031852	-0.333593

dht_temp	bmp_pressure	dht_humidity	ds_temp	VELOCITY_RMS_X	VELOCITY_RMS_Y	VELOCITY_RMS_Z
dht_temp	1.000000	-0.200844	-0.898848	0.767579	0.102845	0.042719
bmp_pressure	-0.200844	1.000000	0.345433	0.100852	0.107642	0.173051
dht_humidity	-0.89884	0.345433	1.000000	-0.632002	-0.106517	-0.019660
ds_temp	0.767579	0.100852	-0.632002	1.000000	0.054570	0.004979
VELOCITY_RMS_X	0.102845	0.107642	-0.106517	0.054570	1.000000	0.938800
VELOCITY_RMS_Y	0.042719	0.173051	-0.019660	0.004979	0.938800	1.000000
VELOCITY_RMS_Z	0.038759	0.162926	-0.014582	-0.010690	0.929332	0.985359
TEMPERATURE	0.496657	-0.037175	-0.427434	0.589139	0.040996	-0.001239
AUDIO	0.053235	0.177136	-0.026152	0.008568	0.912303	0.973905

Fig. 8 Correlation matrix of dataset

5. Model-Based Machine Learning

In this approach, a custom solution is described for each parameter. This approach evolved due to combining feature parameter graphs, updating uncertainty models, and probabilistic programming [9, 15].

5.1. Vibration Analysis

The triaxial sensor is placed in line with the proximity sensor of the rapier loom. It is observed that the vibrating velocity generated by the rapier loom is in all x, y and z directions. However, the z-axis component of vibrating velocity is dominant. At the same time, vibrations in the x and y-axis direction exert lesser impact [14] on performance analysis.

The graph in Figure 9 is velocity per second in the z-direction. Table 6 shows observed vibration amplitudes in the z-direction. The resultant data related to vibrations create a fixed pattern.

The camshaft in the rapier loom is rotating part to ensure its proper functioning. The proximity sensor is mounted very close to the camshaft to sense its rotation. The machine's vibrating velocity often loosens the proximity sensor's placement, hampering sensing distance. This disturbance in the position of proximity sensors results in the stoppage of the rapier loom.

The improper fitment of the mechanical assembly leads to the loosening of the camshaft, creating abnormal rotation. This abnormal rotation often damages proximity sensors physically. Hence, the vibrating velocity is monitored and related to the functioning of the rapier loom.

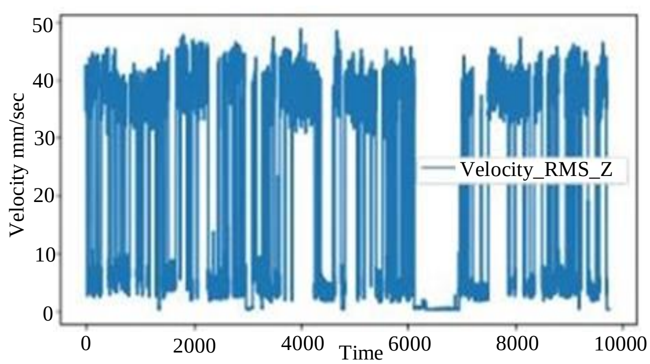

Fig. 9 Line graph of vibrations in z direction

Table 6. Vibration data analysis

S. No.	Vibration Velocity (mm/sec)	Data Generated (%)
1	35-38	70
2	40-45	25
3	≥48	10

5.2. Temperature Analysis of Main Drive and Control Panel

The temperature sensor ds18b20 is mounted on 3ϕ induction. Figure 10 shows the main motor temperature changes. The main drive uses class A insulation, and it's observed that the drive temperature rose to 850°C while it was working. Winding coils lead to short circuits in motor winding, which results in motor burning. The burning of the motor could be avoided by controlling the heating of motor windings. Induction motors with class A insulation withstand temperatures below 1000°C (International standard IEC-60076-11).

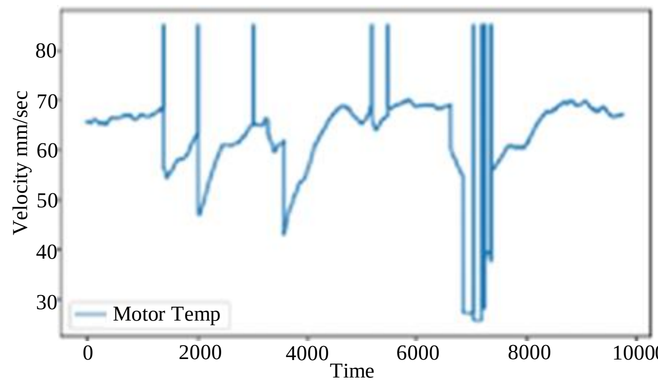

Fig. 10 Motor temperature graph

The textile industry works in shifts throughout the week. It is noticed that the usual working temperature of the motor is 850°C, which can be easily raised to a safe temperature rating of 1000°C. It was also observed that motor heating is due to improper motor placement and ventilation.

The long-term working of rapier loom also tends to produce heating of electronic components and PCB. Usually, PCBs are designed to handle working temperatures ranging between 850°C to 1000°C. The electronic control cards have a central controller, signal conditioning circuits of sensors, and other switching parts. The malfunctioning of electronic components and thermal runaway are the main reasons for PCB heating, which permanently damages PCB. Hence, the temperature connected to electronic cards is monitored.

The SMPS in the rapier loom is a failure candidate due to temperature. The faulty components tolerance in value quality of components often tends to vary the output voltage of regulated power supply. It is observed that excess temperature results in the bulging of the capacitor, creating fluctuations in the output voltage. These fluctuations damaged the electronic circuits, resulting in the breakdown of the rapier loom.

5.3. Acoustic Analysis

The data related to the sound generated by the rapier loom is captured with the help of a microphone, and Figure 11 shows typical sound levels.

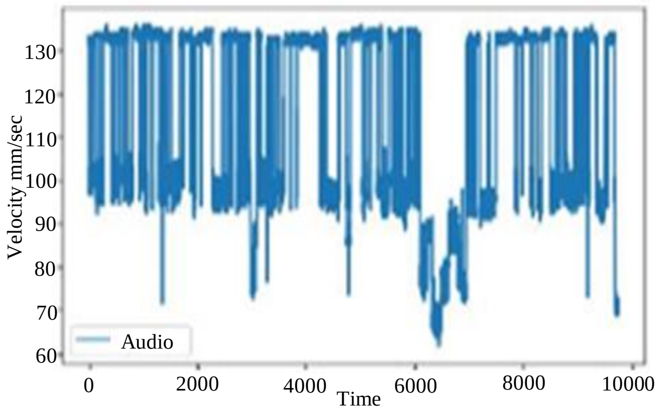

Fig. 11 Acoustic monitoring

5.4. Effect of Humidity

In the case of terry towels and other fabric production, it is necessary to maintain relative humidity close to 70 percent. The collective effect of temperature and humidity creates rusting of contacts and joints.

The excessive moisture between soldered terminals results in short circuit conditions, creating permanent damage in electronic circuits and producing a breakdown of the rapier loom. The data captured by the IoT infrastructure is analysed over a period of time, and safe threshold values are determined.

These obtained threshold values are utilized for generating alerts upon finding potential failure of the rapier loom.The data analysis confirms the following rapier loom's safe working profile for four dominant feature parameters as a secure working profile. Those parameters are listed in Table 7 below.

Table 7. Safe working profile for rapier loom

S. No.	Particular	Safe Value
1	Main Drive Temperature	< 90ºC
2	Sensor Temperature	< 75ºC
3	Vibrating Velocity	< 50mm/sec
4	Humidity	< 80%

The data analysis of time series data from the augmented framework shows the impact of feature parameters on the functioning of rapier looms. This study attempts to correlate captured parameters from the actual workplace- ground truth data- with the functioning of the rapier loom. The sequence of observations confirms that even the individual parameters are within the threshold limits, but their combined effect results in a working situation leading to the failure of the rapier loom [9, 18, 19]. Finally, the augmented SOA-based framework and its data analysis result in a condition-monitoring IoT infrastructure capable of real-time monitoring of the rapier loom.

Based on trends in variation in data related to feature parameters, the rapier loom can be stopped well before the actual damage happens. This defines the predictive maintenance scheme along with the information on the feature parameter responsible for the potential failure of the rapier loom [20]. The condition monitoring IoT infrastructure is reduced to a system consisting of a microcontroller, temperature sensors, humidity sensor, single-axis vibration sensor, voltage sensor, and Wi-Fi communication support (Figure 12). The data collected from SoA oriented IoT infrastructure is analysed for early detection of rapier loom failure; the following table (Table 8) shows the machine learning algorithm used for analysis and their performance accuracy.

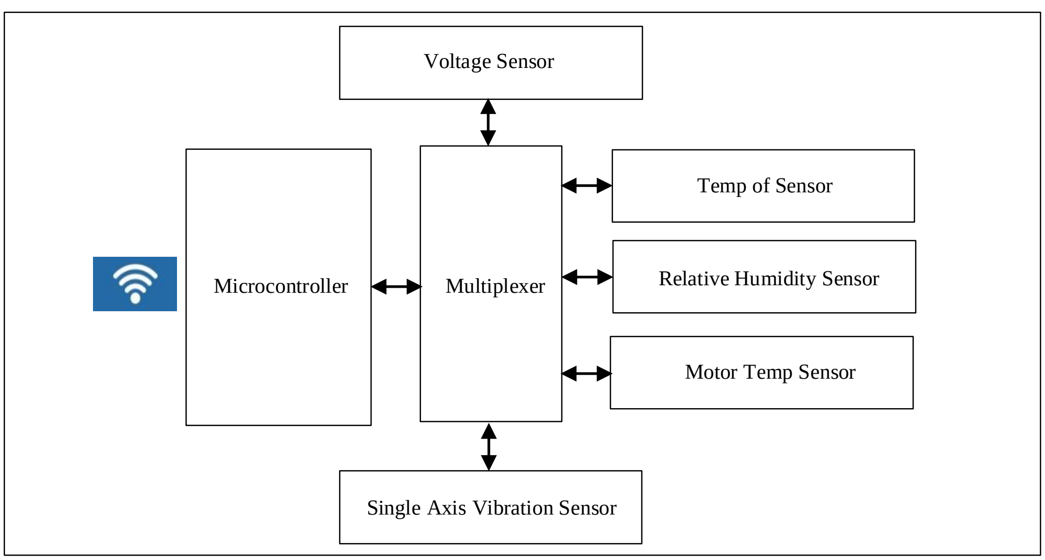

Fig. 12 Reduced condition monitoring IoT infrastructure for rapier loom

Table 8. Comparison of performance parameters of different supervised machine learning algorithms

S. No.	ML Algorithm	Accuracy %	Precision %	F1 Score %
1	SVM	98.544482	98.481740	97.819442
2	Logistic Regression	97.401832	96.771104	96.107072
3	NaiveBayes	94.123515	85.447588	91.917176

6. Conclusion

The real-time functioning parameters of the rapier loom can be monitored with the help of condition monitoring IoT infrastructure. The temporal analysis of data generated defines the safe working profile of the rapier loom. The condition monitoring infrastructure helps reduce damages to rapier loom by stopping them before they occur. The condition monitoring allows the rapier loom to operate close to its suggested speed compared to 190rpm. This increase in working speed ensures a rise in the production efficiency of rapier loom. In all, a 20% minimum enhancement in production efficiency is observed. Long-term condition monitoring allows predictive maintenance, making it economically advantageous.

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Author Contributions

All authors contribute equally to the conceptualization, methodology, validation, original draft preparation, and review for this research work.

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