Devising a Vibration-Based Fault Detection System for Textile Machinery

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Abstract. The textile sector is the backbone of the economy of many developing countries in South Asia. Diverse machinery fault caused by intensive production schedules during operation is a major concern for industries in this sector. There exist several systems in the state-of-the-art literature for detecting textile machinery faults where faulty output is already produced before machine fault detection. In this study, we propose a vibration-based machinery fault detection system for the textile industry. We use a highly sensitive accelerometer to detect even the tiniest vibration changes. Using the accelerometer, we produce a data set by creating six artificial faults in the machine and measuring the vibration of the machine during those faults. Next, we perform Fast Fourier analysis to derive the machine frequency and statistical analysis to detect vibration variation during different faults. We find that there is a change in the machine frequency and vibration respectively during different faults. Then, we run eight different machine learning algorithms to detect the type of fault in the machine. We measure the precision, recall, and F1 score of our machine learning models through ten-fold cross-validation. We get the highest F1 score of 98.9% using the Decision Tree classifier. Finally, we construct a real device by implementing our trained machine learning model in Arduino to identify machine faults which demonstrate the utility of our proposed approach in real scenarios.

Keywords: machine-learning · vibration · FFT · textile-machinery

1 Introduction

The textile and clothing industries are the main source of foreign currency for developing south Asian countries. Bangladesh is the world's second-largest apparel garment exporter in the global textile market [14]. This sector contributes 80% of all exports [11] in this country. The textile industry consists of robust machinery like spinning, weaving, and finishing machinery and delicate machinery like knitting and dyeing machinery. Textile machinery consists of different mechanical components which contribute to the production of fabric.

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Damage or absence of any of these components can result in the production of faulty fabric [16]. Some of these components are tiny and it is difficult to detect if any fault occurs in them. This can result in a stoppage of machines and loss of production.

Vibration has always been a primary concern of the maintenance department of any textile factory. It is one of the significant reasons for machinery health degradation [18]. Typically there is a standard amount of vibration for every machine. The core concept of vibration-based fault detection is that any structural fault in a machine results in a change in the structural dynamics which changes the machine vibration [3]. Existing vibration-based fault detection systems [2,5,20] are trained with only a small amount of data set. Hence, they lack accuracy. Existing photoelectric-based fault detection approaches [29,30] are not suitable for the industry since they are expensive and difficult to implement. Moreover, there are approaches to detecting textile machine fault indirectly through detecting the fabric fault [10,12,15,17,28]. However, these approaches are not real-time and can not detect machine faults until the produced fabric is damaged.

In this paper, we use a sensitive accelerometer to measure the vibration of a machine on three different axes. Then, we create six different frequently occurring faults in the machine artificially. We measure the machine vibration during each fault. We store the data on a computer. We create a data set from the vibration data during different faults. First, we analyze if there is any difference in vibration due to machine fault. For this, we use Fast Fourier Analysis which gives us information about the machine frequency during each fault. We also perform statistical analysis to detect the difference in vibration during the faults. We find that there is a significant difference in machine frequency during the faults and also a difference in vibration value. Next, we use our data set to train eight different machine learning algorithms. Furthermore, we evaluate the accuracy of the trained models by calculating the precision, recall, and F1 score of each trained machine-learning model. Then we take the model with the best accuracy and use that to make an Arduino library. We install the library in Arduino to build a real device that can detect machine faults in real time by measuring machine vibration.

Based on our work, we make the following contributions:

– We measure the machinery vibration by a highly sensitive ADXL-345 accelerometer on three different axes such as X, Y, and Z. The sensor can measure the tiniest vibration which is important because our experimented machine has a very minimum amount of vibration.
– We prepare a machinery fault data set by creating six artificial faults in a real textile machine and measuring the vibration during those faulty conditions.
– We conduct a Fast Fourier analysis of the machinery vibration data, which separates the vibration signal wave into its components on different frequencies. From this analysis, we find the actual frequency of the machine. Besides, we find that the machine frequency changes during faulty conditions.
– We conduct the statistical analysis of the data which gives information on vibration variation during different faults. From both the Fast Fourier and

statistical analysis we find that there is a significant difference in vibration during different faults.
- We train different machine learning algorithms by our prepared data set and use ten-fold cross-validation to measure the precision, recall, and F1 score of our model. Here, we find that the Decision Tree classifier algorithm delivers a 98.9% F1 score while detecting different faults.
- We construct a real machine fault detection device by implementing our trained machine learning model in Arduino. This device can detect textile machinery faults in real-time in factory scenarios.

2 Background and Related Work

The textile industry runs on three shifts per day and each shift spans eight hours. Due to the long working hour of the machinery, most of the machinery becomes fatigued and personnel maintaining these machineries also become inattentive. As a result, different faults occur in the machinery and due to the busy schedule often maintenance team reaches the machine very late. This problem can be solved only when there is a proper fault detection system for the machinery. Among all the machinery in the textile industry, the knitting machine is the most delicate one. It has very tiny components. Hence, whenever a small fault occurs in the machinery, it is really difficult to identify it with the naked eye although its impact on fabric quality can be significantly harmful. Circular weft knitting machines typically have latch needles. The needle does the main function of the knitting action which is loop formation. The sinkers in the weft knitting machine hold down the old loop while the needle knocks over the new loop. This function is known as 'holding down' [1]. If there is any fault in these components the production of fabric will not occur properly and the produced fabric will become faulty. Moreover, if the production rate is high, a huge amount of knit fabric will be defective. So, it is necessary to identify the fault in these components as soon as possible. The purpose of our research is to develop a system that can detect even the tiniest of defects in the machinery just by measuring its vibration in real time.

2.1 Vibration-Based Fault Detection

Mohamad et al., proposed a diagnostic method using a combination of nonlinear dynamic analysis and computational intelligence techniques in a vibration-based fault diagnosis in nonlinear systems [20]. But the proposed system did not have real industry data for developing the system. Mainghai et al., proposed a system where a piezoelectric type accelerometer is used for diagnosing the faults on a hydraulic brake system of a light motor vehicle done on nine fault conditions and one good condition [2]. They also used the machine learning approach. However, only 55 data were used for testing every fault condition. Bhuiyan et al., proposed a wireless vibration-based machinery health monitoring system that used a simple vibration sensor for data collection [5]. However, no-fault analysis was done in the proposed system. Senapathy et al., proposed a vibration-based condition monitoring of rotating machinery [24]. However, the system can only detect if there is any fault in the machinery. It can not detect the type of fault. Han et al., proposed a real-time monitoring system of textile equipment based on MQTT [9]. However, this system requires a huge amount of storage for every machine which is quite inapplicable in the industry sector. 10 sets of 10000 ingots need 130GB per day; excessive data transmission will affect the read-write performance of MySQL, resulting in data loss. Patange et al., proposed a machine learning-based milling cutter condition monitoring system [22]. However, readings from various premade or known faulty conditions of the machine were not taken in this approach. Peeters et al., proposed envelope spectrum sparsity indicators for bearing and gear vibration-based condition monitoring [23]. However, this system can not detect the type of fault in the machinery. Mauricio et al., proposed a vibration-based condition monitoring system for wind turbine gearboxes [19]. However, the system is not tested on real experimentation. Rather it is evaluated based on publicly available data.

2.2 Photoelectric-Based Fault Detection

Zhang et al., proposed a photoelectric detector-based needle fault detection system in a circular knitting machine [29]. The proposed system uses a photoelectric detector that collects the laser signal reflected by the needle and a charge-coupled device camera takes a photo of the defective needle for identification. However, this approach to fault identification is quite expensive and difficult to implement. Furthermore, this device may create a hindrance in the swift workflow of the worker. Zhang et al., also proposed a machine vision-based needle fault detection that was very accurate [30]. But this system required a high-brightness linear supplementary lighting source. This makes the system unrealistic for application in a real-factory scenario. Iftikhar et al., proposed an intelligent automatic fault detection technique incorporating image processing and fuzzy logic [13]. However, the system can only detect machine faults that are visible from the outside.

2.3 Fabric Defect-Based Machine Fault Detection

Several researchers use fabric defect identification for identifying machine faults. A local neighborhood analysis window on the fabric image was used by Kure et al. [17]. He introduced the image variation coefficient that can identify fabric defects. Furthermore, it indirectly gives feedback on the stitch state. Hannay et al., [10] established a fabric defect image database. He performed a shearlet transformation on the fabric image so that he can obtain high-dimensional feature vectors that correspond to defects in the images. Jia et al., fabric defect inspection based on isotropic lattice segmentation [15]. Guanghua et al., proposed a fabric defect identification by a deep convolutional generative adversarial network (DCGAN) [12]. Zhang et al., proposed a fabric defect identification algorithm based on the Gabor filter that can identify machine fault by detecting fabric fault [28]. These approaches can identify machine faults by identifying a fabric fault. But these systems fail when there is a machine fault without occurring any fabric fault. Furthermore, these systems are not real-time. Fouda et al., proposed an online quality control system for a single jersey circular knitting machine [8]. However, this system can not detect machine faults if there is no laddering effect on the produced fabric.

2.4 Machine Learning-Based Fault Detection

Caggiano et al., proposed a machine learning-based image processing for online defect recognition in additive manufacturing [6]. The system detects machine faults by detecting a material defect. Sobie et al., proposed a system for machine learning-based bearing fault detection [25]. In the work, training data for the machine learning algorithm is generated by the information gained from the high-resolution simulation of roller bearings. No real experimentation with bearing was done here for fault detection. Delli et al., proposed an automated process monitoring system in 3D printing by supervised machine learning [7]. In this paper SVM (Support Vector Machine) algorithm was used to classify the parts into the 'good' or 'defective' categories. From identifying the defect, the machine defect was identified. Nasrabadi et al., proposed a CNN-based condition monitoring system for turbine blades [27]. However, this approach fails to detect the type of fault in the machinery. Nisha [21] et al., proposed a fabric defect detection system through image pre-processing, feature extraction, and defect detection and classification by the multi-SVM algorithm. It identifies the presence of any machine fault by identifying fabric faults like an oil stain, ink stain, soil stain, etc. Bandara et al., proposed an automatic fabric defect detection system which in terms indicates machine fault [4]. It detects fabric faults through image pre-processing and Neural Networks.

The major problem with these approaches is, that these systems can detect machine faults only after a defective output is generated. Furthermore, they do not give information on which machine part is defective. In contrast, our system can detect machine faults before the generation of faulty output because it directly detects the machine's fault.

3 Proposed Methodology

In this section, we discuss the construction and working algorithm of our system.

3.1 System Design

Our device consists of one ADXL345 accelerometer, one DS-3231 real-time clock, and an Arduino Uno R3 as a controller module. The block diagram of our device is shown in Fig. 1. The accelerometer senses the vibration data of the machine and gives outputs as acceleration on the X, Y, and Z-axis.

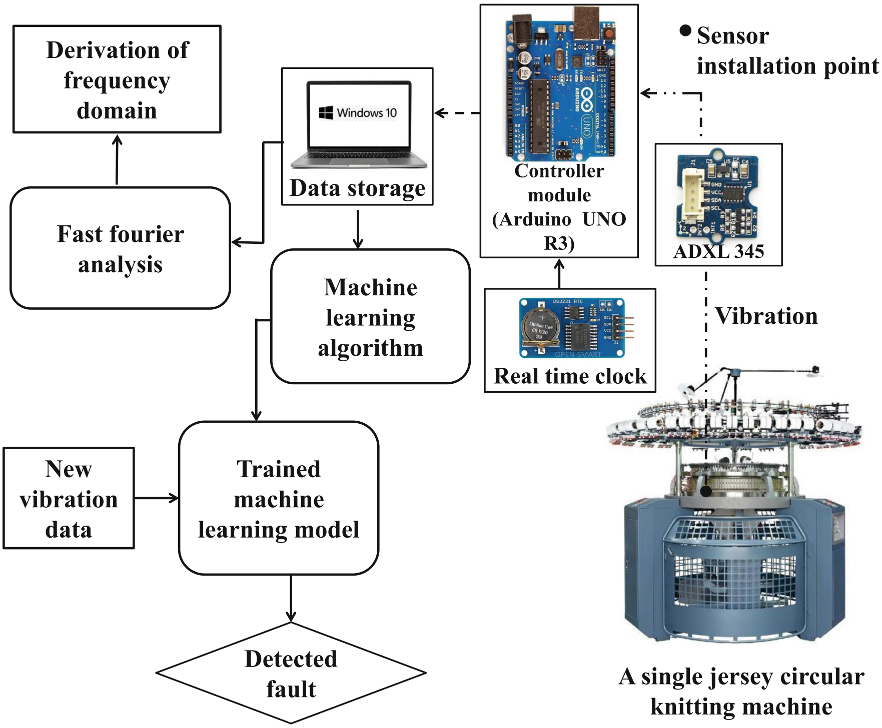


Fig. 1. Block diagram of our proposed system

Sensor. In our previous approach [5], we used the SW-420 vibration sensor. The problem regarding this sensor is, this sensor only gives numerical values indicating the intensity of vibration. It does not show any direction of vibration or any unit of vibration. In the case of the piezo sensor, they require an additional arrangement for measuring vibration, since the signal from the piezo sensor is very low. In order to get more meaningful vibration data, we use ADXL345 accelerometer in this approach. It is a three-axis acceleration measurement system and it has a choosable measurement range of either ± 2 g, ± 4 g, ± 8 g, or ± 16 g. It measures two types of acceleration. These are dynamic acceleration that results from motion or shock and static acceleration, such as gravity which broadens its application as a tilt sensor. The sensor itself is a poly silicon-surface-micro machined structure that is built on the top of a silicon wafer [26]. It consists of independent fixed plates and plates attached to the moving mass. When vibration occurs, the acceleration deflects the beam and unbalances the differential capacitor, which results in sensor output.

We use PuTTy software for data storage. It is a free and open-source terminal emulator. It can also be used as a serial console and network file transfer application. PuTTy software provides support for several network protocols, including

SCP, SSH, Telnet, login, and raw socket connection. For data collection from Arduino, the software has to be able to connect to the serial port. PuTTy software can connect to the Arduino serial port. The software shows the real-time data on the monitor and saves the data into a text, CSV file. Which can be later used to analyze the data.

Machine Learning. We use the stored raw accelerometer data to train the machine learning algorithms. For each condition 2000 sample data for each axis; in total 3 axes, 6000 sample data were stored for each condition (2000 data for each axis). In total, 42000 sample data was taken on the circular knitting machine under 7 conditions. The sampling rate was 50.

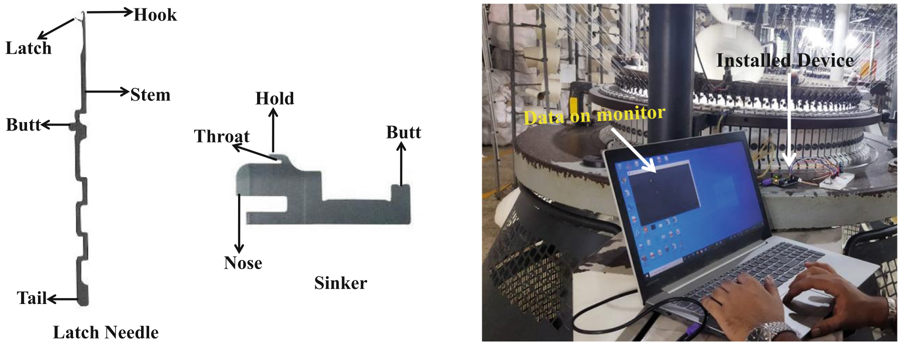
Data Labeling. First, we label the data according to the fault during which the vibration was measured. We use the following labels: Machine_ok, Needle_missing, Broken_hook, Broken_latch, Sinker_missing, Faulty_sinker, Broken_butt_sinker. For each fault, 6000 data points are given on 3 axes (on each axis 2000 data points).

Machine Learning Algorithm. We input the categorized labeled data in eight different machine learning algorithms.
Features: Vibration acceleration on X, Y, and Z axis as input. The type of fault as output.
The algorithms that are used are Decision Tree Classifier, Random Forest Classifier, Support Vector Machine, K Nearest Neighbors, Nearest Centroid, K Nearest Neighbors, Stochastic Gradient Descent, Gaussian Naive Bayes, and Gradient Boosting.

Evaluation of Machine Learning Models. We use ten-fold cross-validation to evaluate our machine learning algorithms by calculating precision, recall, and F1 score. First, the dataset is divided into ten folds. The cross-validation method takes a random fold as the test dataset and takes the remaining nine folds as the training dataset. It then fits a model on the training set and evaluates it based on the test set. Then it takes another fold as the test set and the remaining nine folds as the training set and so on. This process continues until all the folds are taken as a test set. Hence, it gives us ten evaluation results of the model. Finally, we find the mean precision, recall, and F1 scores of the ten test results of the cross-validation.

3.2 Algorithm

We implement our system on one of the most common machinery of the textile industry: the knitting machine. Firstly, we set the ADXL 345 accelerometer on the machine. Then we run the machine in a normal condition. We use PuTTy software for real-time monitoring and storing of the data. After saving



(a) Parts of needle and sinker

(b) Data collection on Saad Knitwear Limited

Fig. 2. Parts of the knitting machine's basic components and experimentation on the weft circular knitting machine

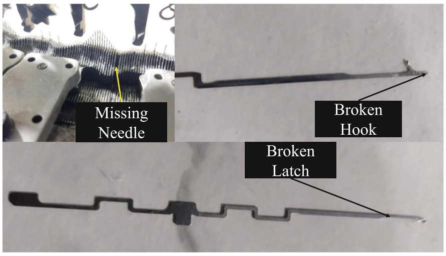
the data for almost 2 min, we stop the machine. We use a sampling rate of 50 samples/second. Then we open the upper cover of the cylinder and take out a needle. Then we start the machine again and monitor and store the vibration data in the same manner. We repeat this process for different conditions such as replacing a proper needle with a hook broken needle or a latch broken needle, replacing a sinker with a faulty sinker or butt broken sinker, and running the machine while a sinker is missing. Then we do a Fast Fourier analysis of the data to find out the frequency of the vibration measured under different conditions. We also do a statistical analysis to find the difference in vibration in different conditions. After that, we label the data according to the respective condition. We use the data set to train eight different machine-learning algorithms. We test the precision, recall, and F1 scores of these trained machine-learning models by ten-fold cross-validation.

4 Experimental Evaluation

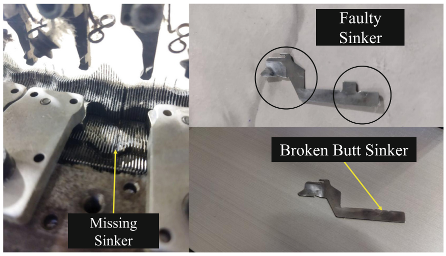
In this section, we discuss the experimentation and the analysis of experimented data.

4.1 Industrial Data Collection

We go to the Saad Knitwear Limited knit fabric production section. There we test our device on a circular knitting machine (Fig. 2b) for experimental evaluation and preparation of the data set. We artificially create six different faults in the needle and sinker (the faults are shown in Fig. 3) and measure the vibration during these conditions. The parts of the needle and sinker are shown in Fig. 2a. A significant change in vibration during any fault makes the fault detectable



(a) Artificially created needle faults



(b) Artificially created sinker faults

Fig. 3. Artificial faults created on needle and sinker for experimentation

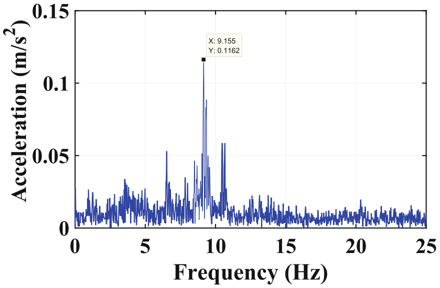
through monitoring of vibration data. The faults that were chosen for experimentation are missing needle, broken needle hook, Broken needle latch, missing sinker, faulty sinker, and butt broken sinker. The reason for choosing these faults is because these faults occur frequently in the knitting machine during normal operation. Furthermore, these faults can create defective fabric which results in a reduction in production efficiency.

Normal Condition. Firstly, we measure the vibration by our device in the normal condition of the circular knitting machine. Then we do the Fast Fourier Analysis of the vibration acceleration on the Z-axis. From the FFT, we plot the acceleration vs frequency graph (Fig. 4a). In this condition, the knitting machine will produce fabric without any fault.

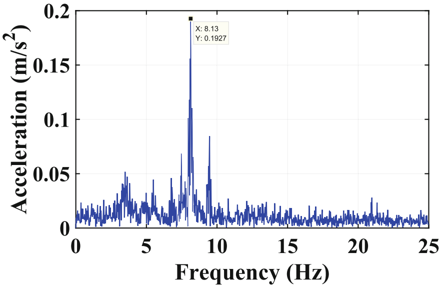
Missing Needle. Then we take a needle out of the machine cylinder. For that, we first remove the cam guiding the needle path. After that, we remove a needle and restart the machine. We measure the vibration and then do an fft on the sensor data (Fig. 4b). If a needle is missing in the knitting machine during production, it can cause an empty straight line on the fabric, resulting in defective fabric and production wastage.

Broken Needle Hook. A broken needle hook can cause severe problems in production by producing drop stitches in the knitted fabric. We replace a perfect needle with the hook broken needle, and then measure the machine's vibration. Then fft of the vibration is done (Fig. 4c).

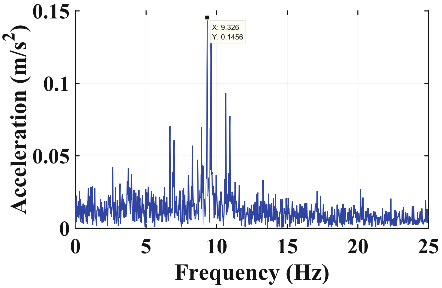
Broken Needle Latch. A needle latch is used for enclosing the hook during the loop formation of the knitting cycle. We break the latch of the needle and replace a perfect needle in the machine with this latch broken needle. The absence of a latch in the needle can result in absence of loop formation which can finally result in a drop stitch. We measure the machine vibration in this condition and do fft (Fig. 4d).



(a) FFT analysis of knitting machine's vibration data in normal condition



(b) FFT analysis of knitting machine's vibration data in needle missing condition



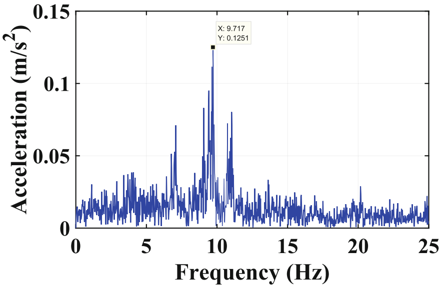
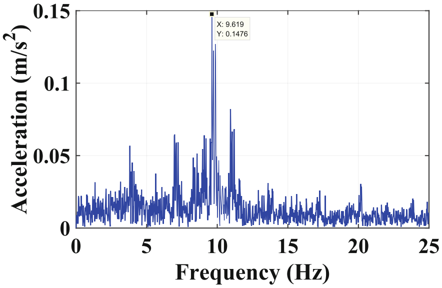


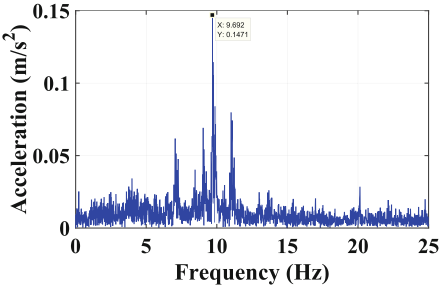
Fig. 4. FFT analysis of knitting machine's vibration data in normal condition and different needle faults

Missing Sinker. Sometimes due to workers' unawareness, sinkers can be found missing from the sinker ring of the circular knitting machine. Since sinkers perform the important function of 'holding down' in weft knitting machines, their absence can cause a heavy fault in the produced fabric. We deliberately take a sinker out of the sinker rail. Then we test and analyze the vibration by Fast Fourier transform (Fig. 5a).

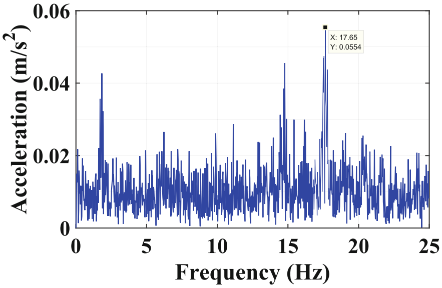
Faulty Sinker. A faulty sinker may fail to perform its function properly. Which will hamper the knitting cycle since it will not perform the holding-down function properly. As a result, defective fabric will be produced. We deliberately bend a sinker on two sides. After that, we replace a perfect sinker with this faulty sinker and restart the machine. Then we follow the same procedure as other conditions (Fig. 5b).



(a) FFT analysis of knitting machine's vibration data in sinker missing condition



(b) FFT analysis of knitting machine's vibration data in faulty sinker condition



(c) FFT analysis of knitting machine's vibration data in sinker's butt broken condition

Fig. 5. FFT analysis of knitting machine's vibration data in different sinker faults

Butt Broken Sinker. Due to misalignment, the sinkers' butt can be broken. When a sinker butt is broken, it fails to follow the cam track resulting in fault in the fabric. We intentionally break the butt of a sinker and replace that sinker with a perfect sinker for the machine. Finally, we measure the vibration to see if there is any change in total machine vibration due to this fault (shown in Fig. 5c)

4.2 Statistical Analysis

To further evaluate our data set, we perform statistical analysis on our data. We calculate different parameters of our data: mean, median, standard deviation, kurtosis, skewness, minimum and maximum value. Next, we check if there is a difference in these values during different faults.

Table 1. Vibration changes during different faults based on acceleration and frequency parameter

Condition	Acceleration (m/s^2)	Frequency (Hz)
Normal	0.1162	9.155
Missing needle	0.1927	8.13
Broken hook	0.1456	9.326
Broken latch	0.1251	9.717
Missing sinker	0.1476	9.619
Faulty sinker	0.1471	9.692
Broken butt sinker	0.0554	17.65

4.3 Findings

In this section, we discuss the significant findings that we got from the experimentation on Saad knitwear limited.

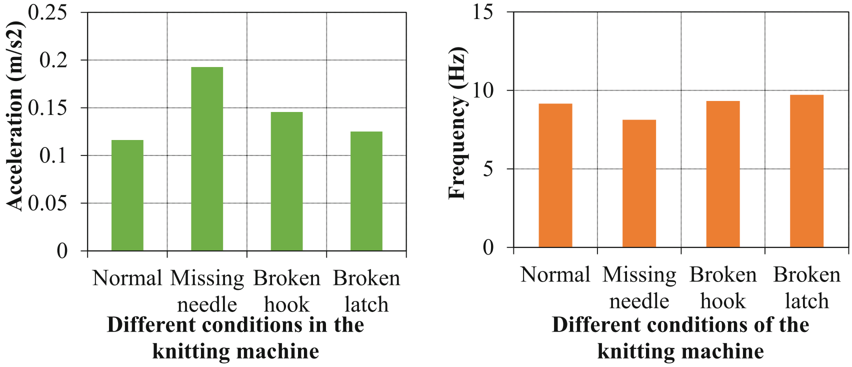
We find vibration data from the ADXL 345 accelerometer in the acceleration (m/s^2) unit. We then do the Fast Fourier Transform on the data and get the frequency component of the data.

The acceleration and frequency of the vibration during different faults are shown for clear understanding in Table 1.

Comparison Regarding Needle. Firstly we analyze the data from the acceleration values that are expressed in m/s^2. From the acceleration data, we see the strength of the occurring vibration. From Table 1, we plot Fig. 6a. There we see that the vibration measured in acceleration rises when we take out a needle from the cylinder. The acceleration falls a bit after the missing needle spot is replaced with a needle that has a broken hook. However, the vibration still stays higher than in normal condition. Finally, after we replace the hook broken needle with a latch broken needle, the vibration falls a bit more while still being higher than normal vibration. Overall, we see a clear distinction in the acceleration caused by vibration during different faults.

Then we analyze the data based on frequency values that are derived from Fast Fourier Analysis. The frequency values express the no of vibration cycles per second. In other words, it expressed the intensity of the machine vibration. We plot Fig. 6b from the data of Table 1. The vibration frequency drops significantly when we take out a needle from the cylinder. The frequency rises significantly again after we replace the empty needle spot with a hook broken needle. The frequency rises further when the hook broken needle is replaced with a latch broken needle.

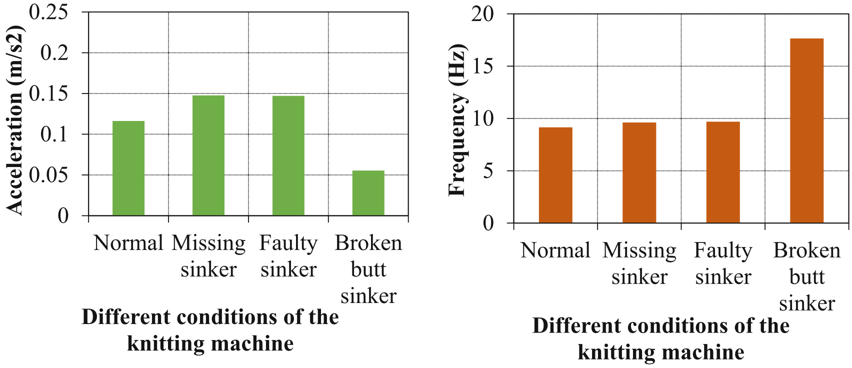
From the two graphs in Fig. 6 we can see that during a needle fault, while the acceleration increases the frequency of the vibration decreases, and when the acceleration decreases the frequency increases. We can detect the needle faults in a weft circular knitting machine by observing these changes in vibration acceleration and frequency.



(a) Comparison of acceleration due to vibration during different needle faults obtained from FFT

(b) Comparison of vibration frequency data during different needle faults obtained from FFT

Fig. 6. Comparison of vibration data during different needle faults obtained from Fast Fourier Analysis



(a) Comparison of acceleration due to vibration during different sinker faults obtained from FFT

(b) Comparison of vibration frequency data during different sinker faults obtained from FFT

Fig. 7. Comparison of vibration data during different sinker faults obtained from Fast Fourier Analysis

Comparison Regarding Sinker. We plot Fig. 7 from the data of Table 1. In the case of sinker faults, Fig. 7a shows that the acceleration due to vibration rises significantly when we take out a sinker from the sinker ring of the circular knitting machine. The acceleration falls on a very tiny amount after the sinker's missing spot is replaced with a faulty sinker. However, the vibration acceleration

Table 2. Statistical analysis of the vibration data during different faults

Axis	Mean	Median	Mode	S.D	Kurtosis	Skewness	Min	Max	Condition
X	−0.090	−0.08	−0.08	0.175	0.439	−0.402	−0.78	0.43	Machine ok
	−0.130	−0.12	−0.04	0.215	−0.602	−0.078	−0.75	0.47	Needle missing
	−0.084	−0.08	−0.04	0.194	−0.328	−0.287	−0.71	0.43	Broken hook
	−0.074	−0.08	−0.04	0.193	−0.291	−0.249	−0.67	0.47	Broken latch
	−0.072	−0.08	−0.08	0.184	−0.333	−0.235	−0.63	0.47	Sinker missing
	−0.067	−0.04	0	0.187	−0.169	−0.212	−0.71	0.47	Faulty sinker
	−0.064	−0.08	−0.04	0.266	0.036	−0.030	−1.22	0.82	Sinker butt broken
Y	−0.011	0	0	0.149	0.394	0.191	−0.51	0.55	Machine ok
	0.006	0	−0.04	0.157	−0.147	0.304	−0.39	0.59	Needle missing
	−0.011	0	−0.12	0.189	−0.486	0.194	−0.47	0.59	Broken hook
	−0.013	−0.04	−0.08	0.200	−0.478	0.117	−0.59	0.59	Broken latch
	−0.020	−0.04	−0.08	0.203	−0.507	0.041	−0.63	0.55	Sinker missing
	−0.013	−0.04	−0.04	0.210	−0.562	0.091	−0.55	0.55	Faulty sinker
	−0.399	−0.39	−0.12	0.407	−0.683	−0.005	−1.49	0.67	Sinker butt broken
Z	−0.001	0.010	0.05	0.332	−0.151	−0.162	−0.970	0.870	Machine ok
	0.000	−0.001	−0.2	0.423	−0.948	0.058	−1.021	0.979	Needle missing
	−0.001	0.017	0.24	0.405	−0.848	−0.016	−1.003	0.997	Broken hook
	0.001	0.030	0.3	0.427	−0.804	−0.031	−1.110	1.170	Broken latch
	0.001	−0.008	0.34	0.433	−0.963	−0.028	−1.108	1.172	Sinker missing
	0.005	−0.005	0.30	0.446	−0.927	−0.022	−1.305	1.135	Faulty sinker
	−0.001	−0.002	−0.04	0.281	0.008	−0.033	−1.022	1.058	Sinker butt broken

falls significantly when the faulty sinker is replaced with a butt broken sinker. Hence, we can detect any sinker fault in the machine by monitoring the vibration data.

Then we analyze the data based on the frequency of Fig. 7b. The frequency of the vibration rises slightly when a sinker is taken out of the machine. The frequency rises a very tiny amount when the sinker missing spot is replaced with a faulty sinker. The frequency rises significantly after the faulty sinker is replaced with a butt-broken sinker.

During the sinker faults, as the acceleration due to vibration increased the frequency or the intensity of the vibration decreased. And the frequency of the vibration increased when the acceleration due to vibration decreased. The faults of the sinker in a weft circular knitting machine can be detected by observing these changes in vibration data.

Result of Statistical Analysis. Table 2 shows some statistical analysis of our dataset. We see that, on three different axes, there is a significant change in the different parameters such as mean, median, kurtosis, skewness, etc. of the vibration data. As we artificially create a fault in the machine, the machine's vibration changes. Hence, feeding this data to any machine learning algorithm can help in detecting the machine fault by measuring its vibration.

Table 3. Evaluation of our machine learning models

ML Algorithm	Precision (%)	Recall (%)	F1 score (%)
DecisionTree Classifier	99.4	98.3	98.9
Gradient Boosting	100	39.5	56.5
Random Forest Classifier	48.3	28.6	36.8
K Nearest Neighbors	28.1	26.3	26.6
Gaussian Naive Bayes	24.0	26.0	24.0
Support Vector Machine	21.0	23.0	20.0
Stochastic Gradient Descent	12.3	22.1	13.9
Nearest Centroid	16.2	54.2	24.5

Accuracy of ML Models. Through cross-validation, we find the highest precision in the Gradient Boosting classifier and highest recall and F1 score in the Decision Tree Classifier algorithm, and the lowest in the Nearest Centroid algorithm. The precision, recall, and F1 scores of the machine learning model in different algorithms are shown in Table 3. The reason for finding the highest recall and F1 score and very high precision is the type of our data set. Our data set has discontinuous data which are very suitable for the Decision Tree Classifier algorithm. The recall and F1 scores in Random Forest Classifier were low because this algorithm works well with high dimensional data which has a large number of features. However, our data set has only 3 features. The number of estimators used was five. The support vector machine has low precision, recall, and F1 score for the same reason as the random forest algorithm. SVM also works well with high-dimensional data. Since our data is low dimensional, SVM has low accuracy. We use the linear kernel for SVM as it gives better accuracy than using other kernels. For the K Nearest Neighbor Classifier highest accuracy is found when the number of neighbors is one.

4.4 Fault Detection for Other Machinery

This methodology can be used to detect the fault in other machinery. The vibration is largely dependent on the unique structure of every machine. To implement this system, first, a fault data set have to be prepared by measuring the machine vibration during different fault. Then we have to train different machine learning algorithms using this data set and use those trained models to detect machine faults.

5 Real-Device Construction

To construct a device that can detect the machine's fault in real-time, we need to apply the machine learning algorithm in Arduino. We use the micromlgen library in python to get the raw code of different machine-learning algorithms according

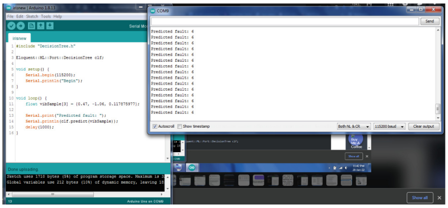


Fig. 8. Application of machine learning model in Arduino Uno

to our data set. We use that code to produce a header file that can be used to make an Arduino library. We use that library in Arduino. The Arduino then can detect machine faults on spot and show the machine fault in the serial monitor. This device only consists of an Arduino Uno and an accelerometer. Hence, by using this low-resource device, the maintenance personnel and machine operators can detect machine faults in real-time.

6 Conclusion

This paper presents a machine learning-based fault detection system for textile machinery. We prepare a machinery fault data set from real experimentation on textile machinery. Fast Fourier analysis of the data indicates that the machinery shows a change in vibration frequency when during the occurrence of any fault. Furthermore, we develop different machine learning models that can detect machinery faults by training eight different machine learning algorithms. Among the different machine learning algorithms, the Decision Tree Classifier algorithm shows 98.9% F1 score. We measure these parameters through ten-fold cross-validation. The maintenance department in the textile industry can detect machine faults automatically with the help of our fault detection system which can reduce the chances of faulty fabric production. This can result in improving the production efficiency and safety of machinery.

In the future, we will test the impact of different sampling frequencies on the accuracy of machine-learning models. Furthermore, we plan to produce a more effective data set by varying more parameters in a textile machine. We will test our device for real-time fault detection in industry scenarios.

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