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Experimental investigation of centrifugal pump machine and its faults through different type of DAQ system and selecting one based on statistical approach

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ABSTRACT

Owing to the continuous usage of centrifugal pump machines (CPM), health-monitoring systems are important for improving the hydraulic machine industry. While operating the CPM, supervision is carried out by either the operator or the online health-monitoring system. The Health Monitoring System (HMS) helps to understand the conditions of the pump and maintenance prospectus. For breakdown and accidents in the CPM industry, the prime reasons are impeller failure, bearing failure, cavitation, and shaft misalignment; therefore, it is necessary to supervise the parameters to provide a better life to the plant and enhance its efficiency using Data Acquisition (DAQ). The independent features and dependent features are selected and experimentally investigated to examine the characteristics of the CPM plant. The feature selection and extraction process should be compatible with the DAQ system which will help to reduce the curse of data biases and data preparation. Based on that three different DAQ systems based on Arduino, Raspberry Pi, and Dewsoft FFT are used in the experiments and compared based on 5-Point summary, Standard Deviation, cost analysis, flexibility, and maintenance. This paper presents the various techniques and procedures for acquiring the data from CPM using all three DAQ systems and selecting one of them through a statistical approach.

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dependent features

SUBJECTS

Manufacturing Engineering;
Mechanical Engineering;
Mechanical Engineering
Design

1. Introduction

A centrifugal pump machine (CPM) health monitoring system is a predictive maintenance system used for hydraulic systems or fluid applications that monitors the health and condition of pumps (Chen et al., 2022). The monitoring parameters for pumps are bearing fault, impeller fault, misalignment, cavitation, current, pressure, and temperature, which are to be extracted by various sensors (Al Tobi et al., 2022). The Enhanced and adaptable health monitoring system should be flexible and should help reduce the downtime of CPM (Abdel Fatah et al., 2019; Kulkarni et al., 2019). Owing to the modern-day health monitoring system of CPM, the productivity of supporting industries has increased (Duan et al., 2020). Health Monitoring systems also focus on implementing an

optimized sensor-based extraction method to monitor and record the conditions to prevent losses in CPM industries (Irfan et al., 2021; Xiao et al., 2021; Mousmoulis et al., 2019). To maintain good health conditions in plants, the production and quality of powerful products and smart monitoring systems are required (Karami & Madlener, 2019; Abd-Elaal et al., 2019; Rapur & Tiwari, 2019). In a Health Monitoring System (HMS), different sensors are used to extract data such as vibration, flow, pressure, surface roughness, and current (Ahmad et al., 2021; Chen et al., 2021; Ahmad et al., 2020; Yang et al., 2021; Wang et al., 2019). A data Extraction technique was used to extract the raw signal using different sensors (Giro et al., 2021; Li et al., 2020; Quintero et al., 2019). Machine Learning and Artificial Intelligence

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methodologies use the extracted data to monitor the health of CPM machines (Surucu et al., 2023; Dutta et al., 2022; Liu et al., 2018). Comparing the training data and testing data among all the models, in the end, the best model is selected, which defines the overall accuracy of HMS (Surucu et al., 2023; Chen et al., 2021; Hachem et al., 2021; Rapur & Tiwari, 2018). This paper presents an experimental investigation of the faults, a comparison between Data acquisition (DAQ) systems, and a selection of the best DAQ system based on a statistical approach (Irfan et al., 2021; Xiao et al., 2021; Quintero et al., 2019; Farokhzad, 2013).

2. Detailed Information on independent variables and sensors

Eleven independent variables were recorded using seven different types of sensors. Detailed information on the variables, unit, formula, and sensors, and their characteristics are shown in Table 1

The total 11 independent variables recorded by sensors are:

- Casing Vibration
- Casing Temperature
- Bearing Vibration
- Bearing Temperature
- Impeller Vibration
- Impeller Temperature
- Flow
- Pressure
- Surface Roughness
- Current
- Voltage

3. The dependent variables and fault considered

The total four independent variables were considered:

- Good Health Condition (GHC)
- Impeller Fault (IF)
- Impeller & Bearing Fault (IBF)
- Misalignment of Shaft (MA)

3.1. Fault detected at the teeth of impeller

The left image in Figure 1 shows the good condition of the impeller, and the right image indicates the two missing teeth, that is, the faulty impeller of the CPM.

The left figure of the impeller indicates the Good Health Condition (GHC) -dependent variable, while the right image indicates the Impeller Fault (IF) -dependent variable. The sensor that was used to record the data is MPU6050. The Faulty impeller is also considered to be part of the Impeller & Bearing Fault (IBF) and misalignment of the shaft (MA) dependent variables. The image was captured after disassembly of the centrifugal pump machine (CPM).

3.2. Fault detected on bearing of shaft

The left image in Figure 2 shows the good condition of the bearing, and the right image of the bearing indicates 2-ball damage i.e., a faulty bearing.

The left image of the bearing indicates the Good Health Condition (GHC) -dependent variable, whereas the right image indicates the bearing fault - Independent variable. The sensor that was used to record the data is MPU6050. The faulty bearing is also considered to be part of the Impeller & Bearing Fault (IBF) and misalignment of the shaft (MA) dependent variables. The image was captured after disassembly of the centrifugal pump machine (CPM).

3.3. Cavitation formation on impeller casing

The left image in Figure 3 shows the good condition of the impeller casing with no cavity, and the right image shows the formation of the cavity.

The left image of the impeller casing indicates a Good Health Condition (GHC) -dependent variable, whereas the right image indicates impeller casing cavitation.

The gauge used to record the data was the Surface Roughness Gauge SJ-210, as shown in Figure 4. Cavitation is considered to be part of the Miss Alignment of the shaft (MA) dependent variables; however, it generally occurs after Impeller Failure (IF). Images and readings were taken after the disassembly of the centrifugal pump machine (CPM). Calibration was performed at the delivery casing and outlet valve position. Cavitation is generally a slow aging process, but due to particles from impeller failure, it might occur before aging.

3.4. Misalignment of Shaft

The left image in Figure 5 shows the good condition of the shaft, and the right image of the shaft indicates a fault, that is, Misalignment of Shaft (MA).

The left image of the shaft indicates the Good Health Condition (GHC) -dependent variable, whereas the right image of the shaft indicates the Misalignment

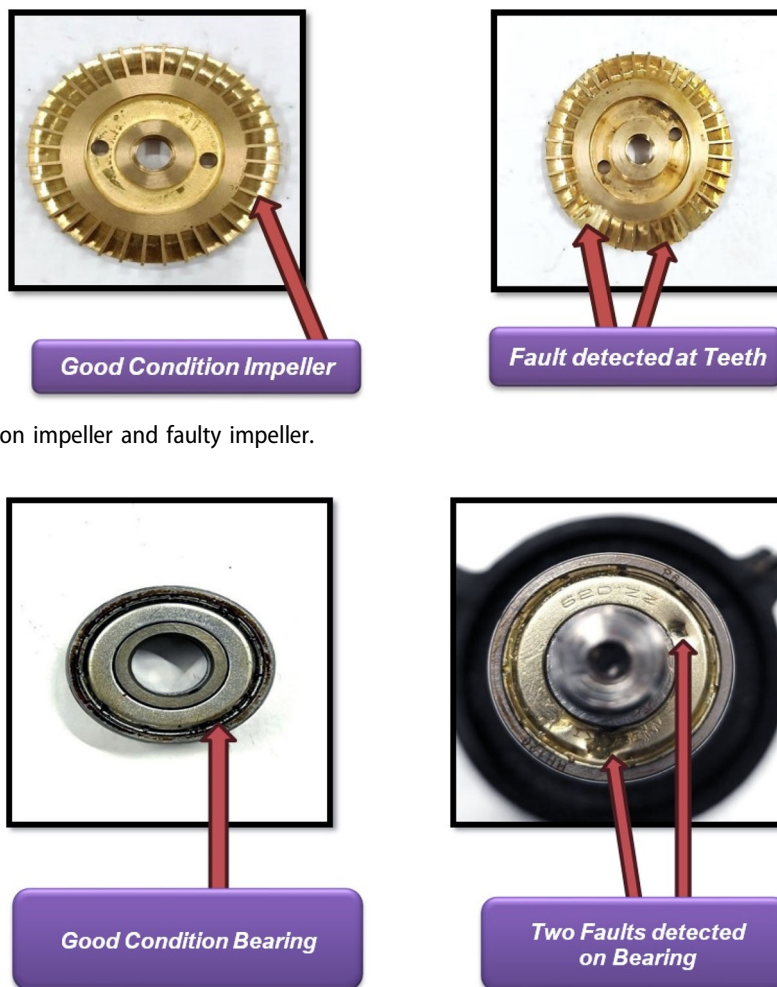
Table 1. Detailed information of independent variables and sensors used.

Sr. No	Variables	Unit	Formula	Sensors/ Devices used	Characteristics
1.	Casing, bearing and impeller vibration	G	$G = 9.8 \frac{m}{s^2}$		Accelerometers are devices that measure acceleration, which is the rate of change in the velocity of an object. A single G-force for us here on planet Earth is equivalent to $9.8 \frac{m}{s^2}$.
2.	Temperature of casing, bearing and impeller temperature	°C	–	ADXL335 MPU6050 	Temperature is measured with a thermocouple. It reflects the kinetic energy of the vibrating and colliding atoms making up a substance.
3.	Flow	L/Min	$Q = \frac{volume}{time}$	Digital Clamp Meter 	Flow rate refers to the volume of fluid passing the context of centrifugal pumps, it represents the amount of fluid being discharged by the pump in a given time period.
4.	Pressure	KPa	$P = \frac{H.p.g}{y}$	Flow sensor YF-G1 	Pressure in a centrifugal pump is the force generated by the pump to move fluid through a system. It is created by the impeller's rotation.
5.	Roughness (DC_RA)	μm		Pressure Sensor 	RA refers to the presence of irregularities or damage on the interior surface of the casing. This can be caused by the abrasive action of particles or debris suspended in the pumped fluid, resulting in wear and erosion.
6.	Current	Ampere	$I = \frac{V}{R}$	Surface Roughness Gauge SJ-210 	Current refers to the flow of electric charge (measured in amperes) within the electrical circuit, which powers the pump motor.

(continued)

Table 1. Continued.

Sr. No	Variables	Unit	Formula	Sensors/ Devices used	Characteristics
7.	Voltage	Volt	$V = IR$		Voltage is the electrical potential difference applied to a centrifugal pump. It provides the energy required to drive the pump motor.

**Figure 1.** Good condition impeller and faulty impeller.**Figure 2.** Good condition bearing and faulty bearing.

of Shaft (MA) -dependent variable. The 3x sensor used to record the data was an MPU6050. The fault is considered to be part of the Miss Alignment of the shaft (MA) - dependent variable only.

The image was captured after disassembly of the centrifugal pump machine (CPM). The Misalignment of Shaft is the final stage, which can lead to plant downtime or accidents. The MA includes impeller faults, bearing faults, cavitation, and bending of the shaft.

4. Experimental investigation of DAQ systems

4.1. Data acquisition system (DAQ) using Arduino

The Arduino-based DAQ system is a simple and cost-effective solution commonly used for data acquisition tasks. It operates on an open-source microcontroller platform, which can be easily

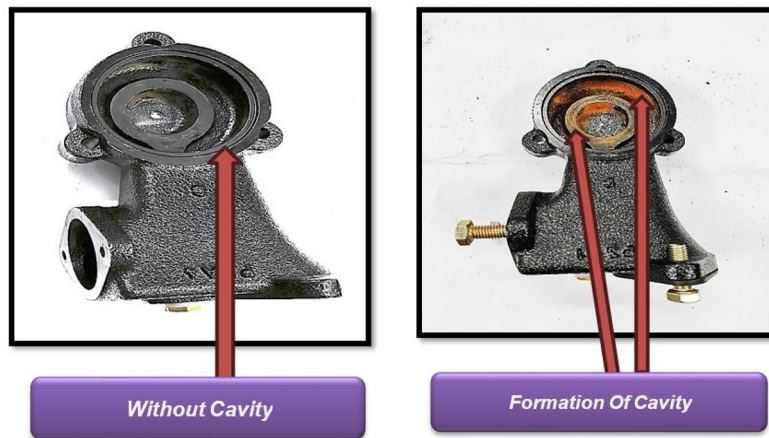


Figure 3. Good condition impeller casing and cavitated impeller casing.



Figure 4. Calibrating: Good condition impeller casing and cavitated impeller casing.

programmed using the Arduino IDE. Key characteristics include an ATmega328P microcontroller that is used, and capable of handling analog and digital inputs. The sampling rate is limited to about 10 kHz, which is suitable for low-frequency signals. The system is highly flexible due to the availability of various shields and modules, allowing it to interface with a wide range of sensors.

The availability of the system in Figure 6 shows the real-time system designed for the centrifugal pump, which contains CPM, Motor, Water tank,

Waterflow Sensor, Pressure sensor, three accelerometers, DAQ-Arduino-based, and a laptop with all the required software.

The standard deviation of impeller, casing and bearing readings was conducted which is 9.96 Arduino.

4.2. Data acquisition system (DAQ) using Raspberry Pi

The Raspberry Pi-based DAQ system offers a more powerful alternative to the Arduino, with its ability to

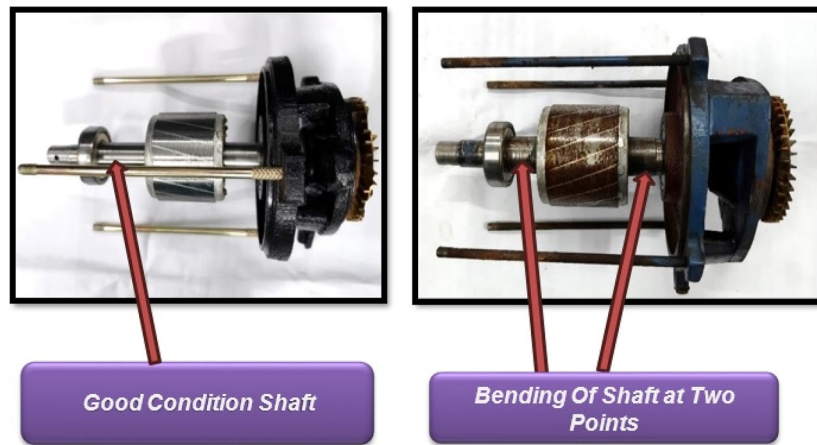


Figure 5. Good condition of shaft and misalignment of shaft.

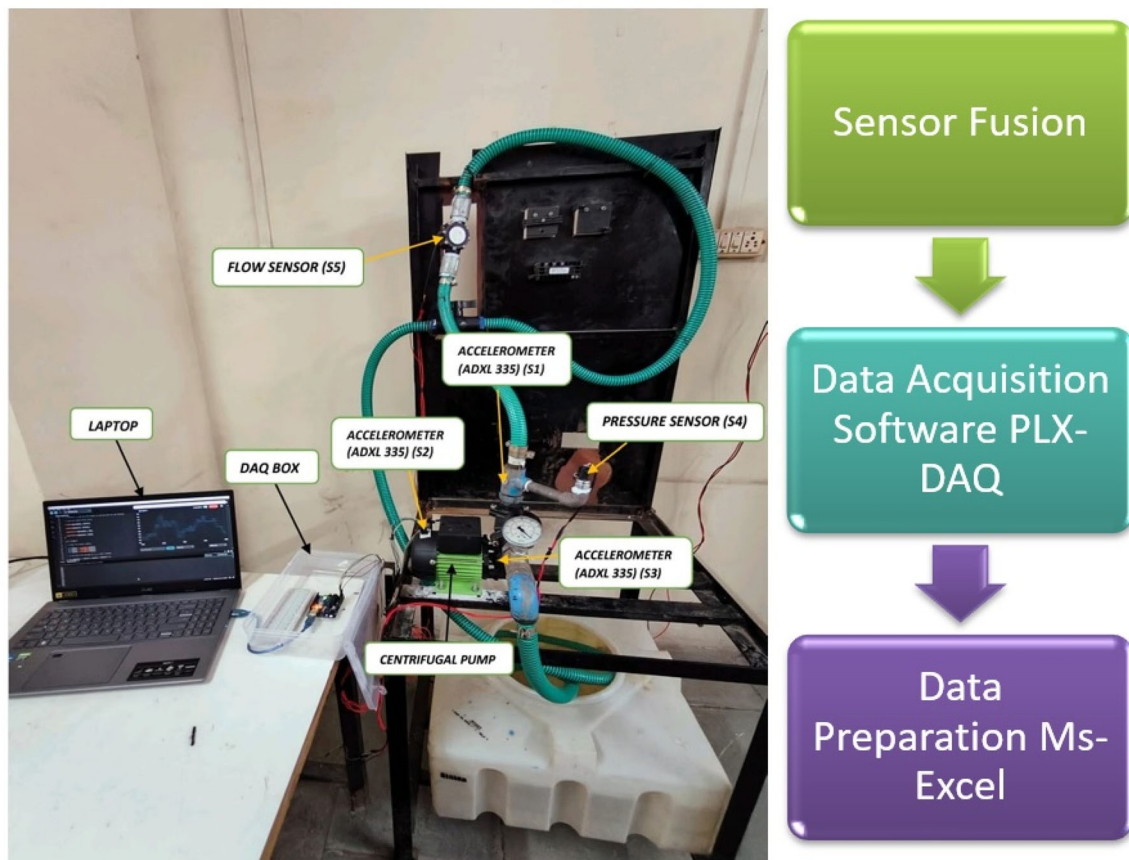


Figure 6. DAQ system using Arduino.

run a full Linux operating system and interface with a variety of hardware components. The Key characteristics include a processor powered by a multi-core ARM processor, providing more computational power than Arduino. Raspberry Pi is higher than Arduino, with the ability to achieve sampling rates up to 100 kHz depending on the configuration. Offers extensive GPIO pins and the ability to use various programming

languages like Python, making it versatile for complex projects. Moderately priced, offering a balance between performance and affordability. While more powerful, the Raspberry Pi may still face challenges with real-time processing and high-speed data acquisition tasks compared to dedicated DAQ systems.

The standard deviations of the impeller, casing, and bearing readings were 4.26 G. Figure 7 shows

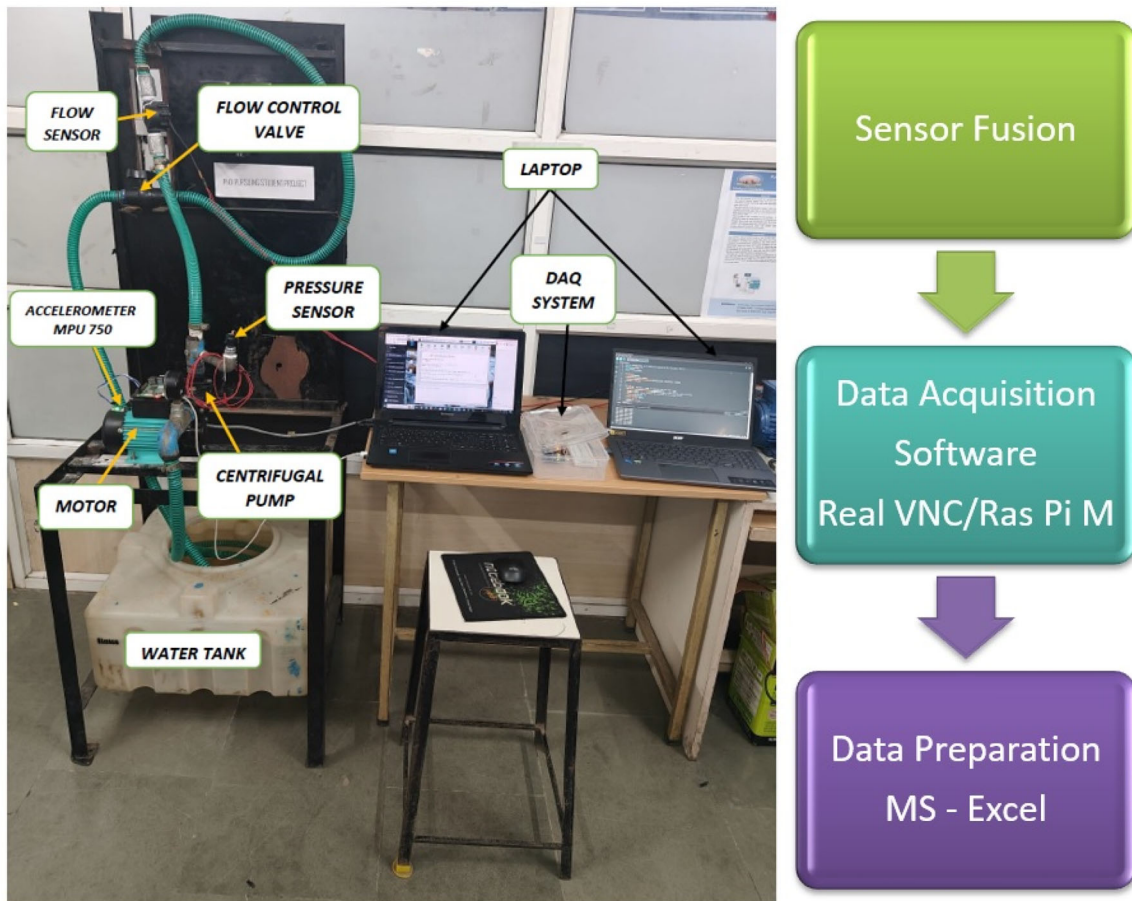


Figure 7. DAQ system using Raspberry Pi.

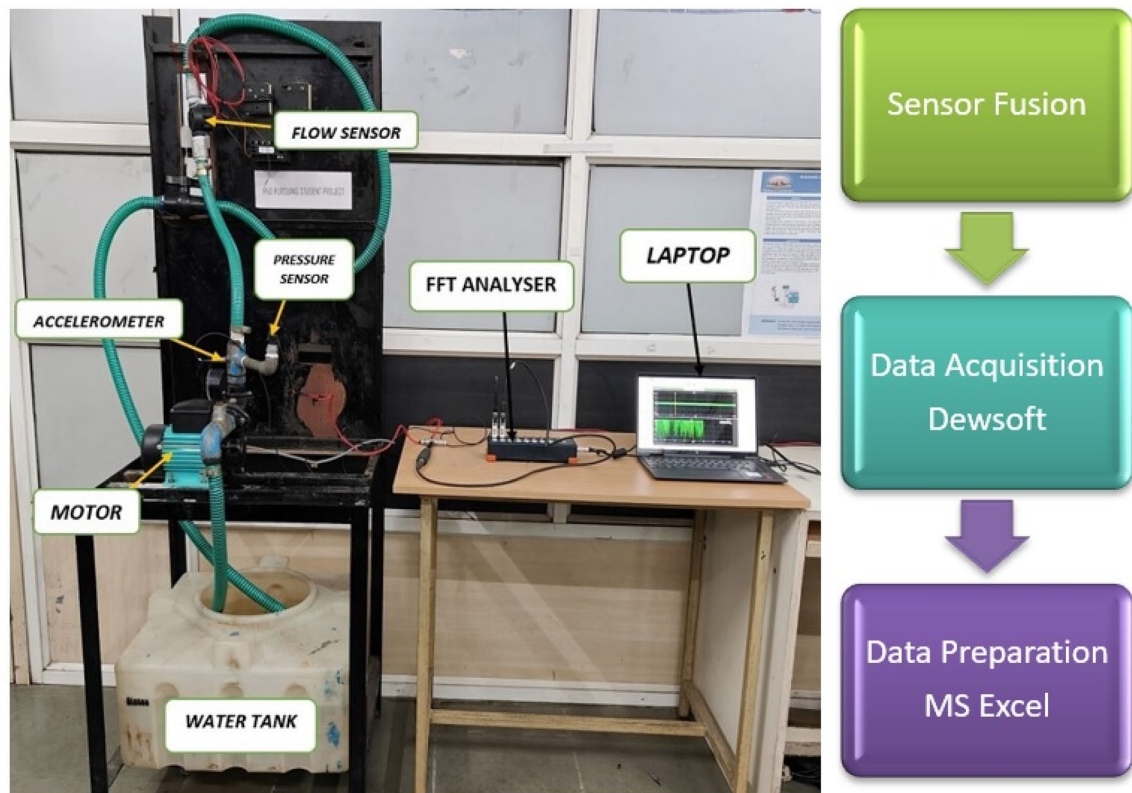


Figure 8. DAQ system using FFT.

the real-time system designed for the Centrifugal Pump, which contains CPM, Motor, Water tank, Waterflow Sensor, Pressure sensor, and three accelerometers, DAQ-Raspberry Pi-based, and laptop with all the required software.

4.3. Data acquisition system (DAQ) using Dewsoft FFT

The FFT Dewesoft DAQ system is a professional-grade solution designed for high-performance data acquisition tasks. It is commonly used in industrial and research applications due to its advanced features. The key characteristics include high-speed processors and specialized hardware for signal processing. The FFT is Capable of very high sampling rates, often exceeding 1 MHz, making it suitable for capturing high-frequency signals. Flexibility. It is highly flexible with a wide range of input modules and software support for various data analysis tasks, including FFT (Fast Fourier Transform) for frequency domain analysis. Significantly higher than Arduino and Raspberry Pi, reflecting its advanced capabilities. The main limitation is the cost, expandability and complexity, which might be overkill for simple data acquisition tasks.

Figure 8 shows the real-time system designed for the Centrifugal Pump, which contains CPM, Motor, Water tank, Waterflow Sensor, Pressure sensor, three

Table 2. Comparison of DAQ system cost-benefit analysis.

DaQ system	Flexibility	Cost (\$)	Life (Years)	Maintenance
Arduino	Moderate	59.61	5	Low
Raspberry Pi	High	119.22	10	Low
Dewsoft FFT	High	11921.69	25	High

accelerometers, DAQ-FFT-based, and laptop with all the required software. The standard deviations of the impeller, casing, and bearing readings were 4.190 G.

5. Statistical analysis

The standard deviation (SD) is a measure of the amount of variation or dispersion in a set of values.

SD is widely used in research to describe the spread or variability within a data set. A smaller SD indicates that the data points tend to be close to the mean, while a larger SD suggests that the data points are spread out over a wider range of values. The SD was calculated for each data set to assess the variability in measurements.

Mathematical Expression of SD:

$$SD = \frac{\sqrt{\sum (x_i - \mu)^2}}{n - 1}$$

where SD = sample average

x_i = Individual population value

μ = The mean of x_i

n = Total no of samples

The Arduino-based DAQ system is cheaper, but its SD is double that of the Raspberry Pi and DewSoft FFT. The SD of DAQ-RPi and DAQ-FFT- DS is on the lower side with 4.26 & 4.190 respectively. The cost of DAQ-FFT-DS is 5x the cost of Raspberry Pi as shown

Table 3. 5 Point summary of CPM data for GHC.

Statistical Features	Bearing	Casing	Impeller	Flow	Pressure
Mean	491.33	491.48	490.52	157.50	28.97
Median	492	492	491	158.4	29.3
Mode	491	493	491	158.4	29.3
Standard Deviation	4.31	4.91	4.32	1.86	0.78
MIN	480	479	480	153.6	28.1
MAX	500	500	500	158.4	30.5

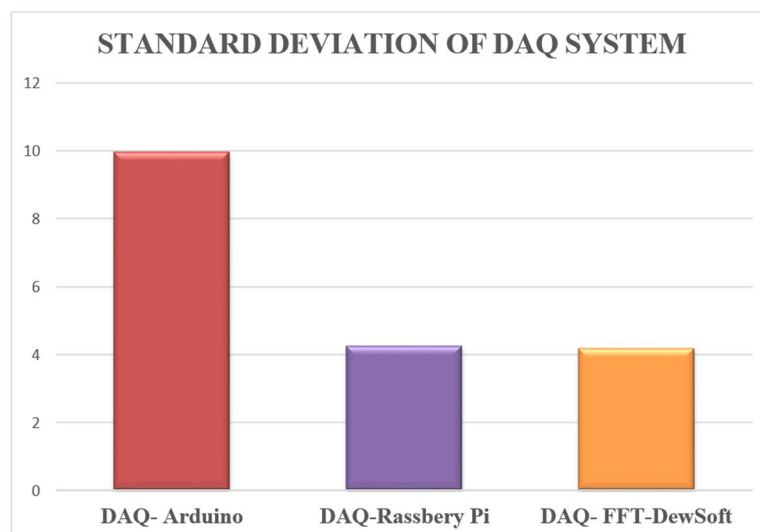


Figure 9. Comparison of DAQ system through SD.

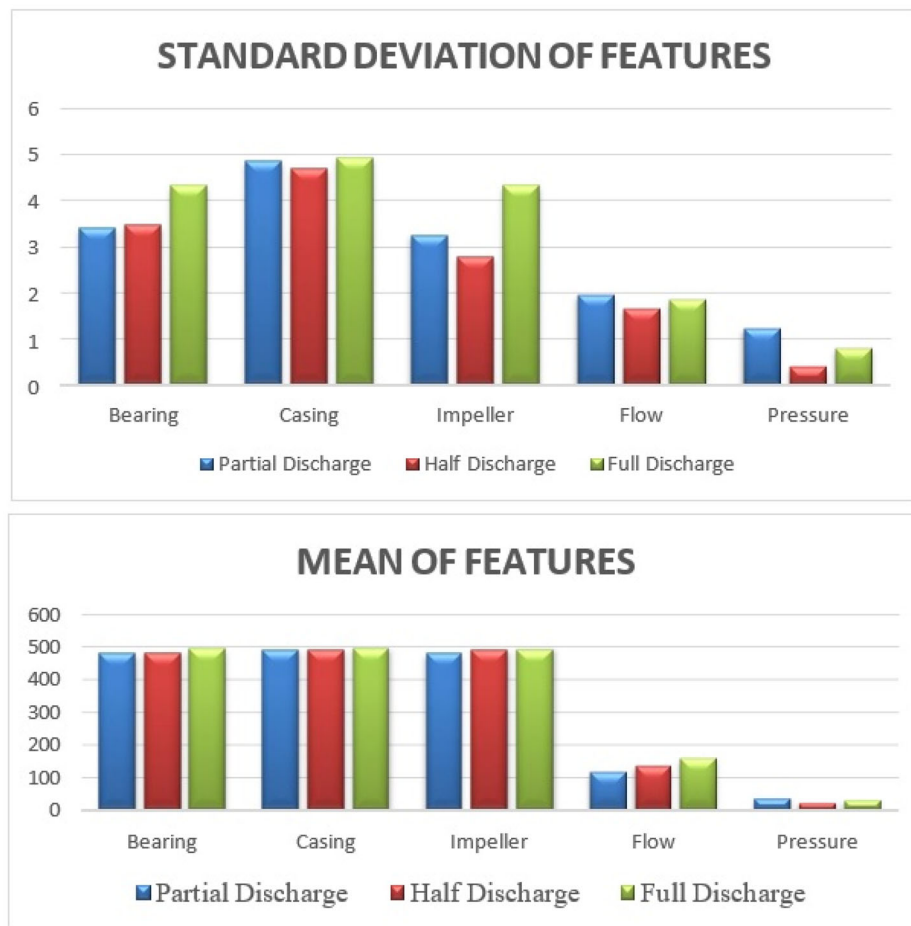


Figure 10. Comparison of features with mean and SD for good health condition.

in Table 2. As the ML/DL model will be applied for model processing, the SD of 4.26 is the optimal performance because DAQ-RPi is more flexible than other DAQ systems.

As a result, using a statistical technique, Raspberry Pi is chosen due to its lower Standard Deviation, as demonstrated in Figure 9, as well as the added benefits of flexibility, maintenance, and cost, as compared in Table 2.

A low SD in this study suggests high precision in the measurements, whereas a high SD might indicate underlying factors contributing to variability, warranting further investigation. The low SD observed across the trials suggests a high level of precision in the experimental measurements, reducing the likelihood of outliers influencing the overall results.

A total of 5000 data points were collected for the Good Health Condition (GHC) of the CPM through DAQ-RPi. Table 3 shows the detailed 5-point summary of data for GHC:

The standard deviation of features including the bearing, casing, impeller, flow and pressure is taken

with respect to three different discharge flow rates, as shown in Figure 10.

The standard deviation of casing feature was higher than that at the outer free side of the CPM with no defects. The Bearing feature was lower than that of the casing, followed by the impeller feature. The SD of Flow varies based on the valve-opening position. The Pressure was higher when the discharge was partially open. The SD of the bearing, casing, and impeller features have a positive correlation with the Discharge Flow position. The meanings of the bearing, casing and impeller features are almost identical for the GHC. The Flow rate and pressure exhibit an inverse relationship (Figure 11a–c).

Figure 11a–c shows the GHC has a vibration of around 500 G while the vibration is dropping for IF and IBF Feature to 200 G. The MA feature has maximum vibration of around 700 G due to the complete misalignment of shaft. The bar plot shows the difference in the vibration characteristic that is been recorded by the Data Acquisition system for all four conditions of CPM.

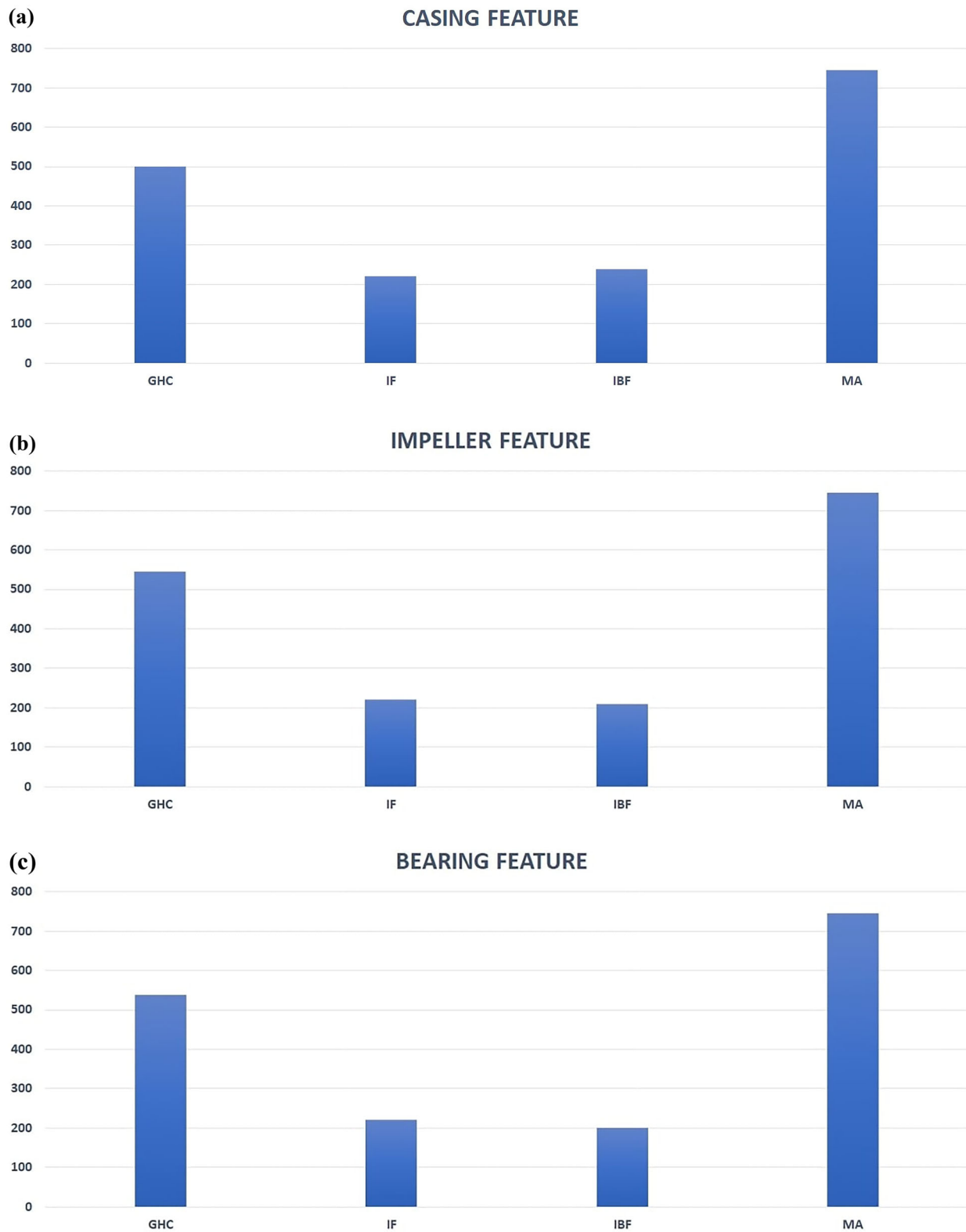


Figure 11. (a) Comparison of casing vibration feature vs independent features. (b) Comparison of impeller vibration feature vs independent features. (c) Comparison of bearing vibration features vs independent features.

6. Conclusion

The feature selection and extraction process depend on the high compatibility of the DAQ System for the

CPM plant. The DAQ system should be designed like a special-purpose machine after deeply analyzing the characteristics of the plant that can be deployed

in real-time. The following are the outcomes of the research:

- The eleven independent variables and four dependent variables were selected and recorded using seven different types of sensors and three different DAQ Systems.
- The dependent features and faults were identified and experimentally investigated while taking the readings.
- Three different DAQ systems, based on Arduino, Raspberry Pi, and FFT, were experimentally used and compared to investigate the quality of the recorded data.
- The Five-point summary of data recorded for three different discharge rates shows the statistical behavior of the Good Health Condition (GHC) of CPM. Comparison of Dependent Vibration Features vs Independent Vibration Features was analyzed to examine the variables.
- The results show that the selection of the Raspberry Pi-based DAQ owing to the lower Standard Deviation parameter of 4.26 is made with the additional benefit of flexibility and cost factor. The experiment will help to reduce the curse of data biases and will reduce the time for data preparation.
- Future work should be carried out to make the DAQ more embedded based on the Industrial Internet of Things (IIOT) and cloud-based interaction systems. This will help the current DAQ system used in industry for health monitoring to transform with respect to Industrial 5.0 revolution. The IIOT cloud-based solution will help to achieve the live interaction demography dashboard of machines and plants that will reduce accidents and downtime in the industry.

In addition, the transfer learning strategy should be employed for models that can learn and adapt to new future data and self-tune the hyperparameters, which helps to increase the model's life.

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Authors' contribution

G. S. Dave: Conceptualization, methodology, validation, formal analysis, investigation, data curation, writing the original draft, writing—review and editing, and visualization.

A. P. Pandhare: Conceptualization, validation, investigation, and writing—review and editing.

A. P. Kulkarni: Conceptualization, methodology, validation, formal analysis, investigation, data curation, writing—review and editing, supervision.

D.V. Khankal: Methodology, validation, data curation, writing—review and editing.

Masuk Abdullah: Writing—review and editing, project administration, supervision, funding acquisition.

Disclosure statement

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Data availability statement

The authors confirm that the data supporting the findings of this study are available in the article and its supplementary materials. The corresponding author, G. S. Dave, agrees to share the data upon reasonable request.

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