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Research Article

Designing Health Monitoring System for fault prediction in Centrifugal Pump using ML and DL algorithm

G. S. Dave[1], A. P. Pandhare[2], A. P. Kulkarni[3], D.V. Khankal[4]

[1]PhD Scholar, Department of mechanical engineering, Sinhgad College of Engineering, Pune[1], #Assistant Professor SKNCOE, davegaurav.logic@gmail.com[1]
[2]Professor, Department of mechanical engineering, Sinhgad College of Engineering, Pune[2]
[3]Professor, Department of mechanical engineering, VIIT, Pune[3]
[4]Professor, Department of mechanical engineering, Sinhgad College of Engineering, Pune[4]
** Corresponding author*
Email: davegaurav.logic@gmail.com[1]

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ABSTRACT

The operational dependability of centrifugal pumps holds paramount significance within industrial applications, thereby necessitating the implementation of sophisticated health monitoring systems to proactively identify potential failures. This investigation introduces an innovative Health Monitoring System (HMS) meticulously engineered for centrifugal pumps, utilizing Machine Learning (ML) and Deep Learning (DL) algorithms to augment predictive maintenance capabilities. Our framework amalgamates real-time data acquisition, rigorous feature extraction, and advanced predictive analytics to effectively evaluate pump health. By employing a comprehensive dataset that encompasses operational parameters alongside historical failure records, the research includes executing a variety of ML algorithms, which include Logistic Classifier, Decision Tree Classifier, XGB Classifier, Naïve Bayes Classifier, Random Forest, Support Vector Classifier, and Neural Network, for the classification of centrifugal pump health status. Moreover, the research accentuates the application of sophisticated deep learning techniques, particularly Artificial Neural Networks (ANN), to discern intricate patterns and temporal relationships within the data. Experimental results demonstrate that our proposed HMS markedly enhances fault detection accuracy, accomplishing classification rates that surpass 99%. This system not only enables timely maintenance interventions but also mitigates operational downtime and maintenance expenditures. The research elucidates the potential of advanced AI-driven methodologies in the formulation of intelligent monitoring solutions, ultimately contributing to the sustainability and reliability of centrifugal pump operations in industrial contexts.

Keywords: Health Monitoring System, Data Acquisition, Artificial Intelligence, Machine Learning, Deep Learning, Centrifugal Pump.

1. INTRODUCTION

Centrifugal pumps are integral components in various industrial applications, playing a critical role in fluid transportation across sectors such as manufacturing, power generation, chemical processing, and water treatment [1]. The reliability and efficiency of these pumps directly impact overall operational performance, making it imperative to ensure their continuous and fault-free functioning [2]. Despite their robust design, centrifugal pumps are susceptible to wear, degradation, and unexpected failures due to prolonged operation, fluctuating load conditions, and environmental factors [3]. Such failures can lead to unplanned downtime, increased maintenance costs, and potential safety hazards [4]. Therefore, the implementation of advanced health monitoring systems is essential to predict, detect, and mitigate failures proactively [5].

Traditional maintenance strategies, such as reactive maintenance (fixing components after failure) and scheduled preventive maintenance, often fail to optimize maintenance costs and operational efficiency [6]. These approaches either result in excessive downtime or unnecessary part replacements, leading to suboptimal resource utilization [7].

In contrast, predictive maintenance, enabled by artificial intelligence (AI) and machine learning (ML), offers a data-driven approach to identifying potential failures before they occur [8]. By leveraging real-time sensor data and historical operational records, predictive maintenance strategies facilitate informed decision-making, thereby enhancing system reliability and longevity [9].

This research introduces an innovative Health Monitoring System (HMS) designed specifically for centrifugal pumps, employing state-of-the-art ML and deep learning (DL) techniques to enhance fault detection and predictive maintenance capabilities [10]. The proposed HMS integrates real-time data acquisition, feature extraction, and predictive analytics to assess the health status of pumps with high accuracy. Various ML classifiers, including Logistic Classifier, Decision Tree Classifier, XGB Classifier, Naïve Bayes Classifier, Random Forest, Support Vector Classifier, and Neural Networks, are utilized for health classification, ensuring a comprehensive evaluation of the pump's operational status. Furthermore, deep learning methodologies, particularly Artificial Neural Networks (ANN), are applied to identify complex patterns and temporal dependencies in the data, improving fault prediction capabilities [11].

The experimental outcomes of this study highlight the effectiveness of the proposed system, achieving classification accuracies exceeding 99%. By implementing this AI-driven approach, industries can significantly reduce downtime, minimize maintenance costs, and improve overall pump performance [12]. The findings of this research underscore the transformative potential of intelligent health monitoring solutions in industrial settings, paving the way for more sustainable and resilient pump operations. This paper aims to explore the development, implementation, and impact of the proposed HMS, demonstrating its efficacy in real-world industrial applications.

2. LITERATURE REVIEW

2.1 Current Fault Detection Methods

Within the specialized field of industrial machinery maintenance, it has become evident that centrifugal pumps have historically depended on traditional monitoring methodologies that frequently fail to meet the stringent reliability standards demanded by contemporary operational environments [13]. Initial fault detection strategies predominantly concentrated on the analysis of vibrations and the monitoring of acoustic emissions, providing only a limited scope of understanding regarding the inception of potential faults [14]. These conventional methodologies typically utilized threshold-based detection systems, which had the significant drawback of being capable of identifying faults only after considerable damage had already transpired. Moreover, the traditional methodologies grounded in time-domain analysis, although they form the foundational basis of fault detection, have consistently demonstrated their inadequacy in recognizing subtle and nuanced alterations in pump performance that could signify the emergence of significant operational issues [15].

In response to these shortcomings, frequency domain analysis techniques, such as the Fast Fourier Transform (FFT), were subsequently developed and implemented in an effort to enhance the overall capabilities of fault detection, yet these methodologies continued to grapple with the intricacies associated with complex and non-linear fault patterns [16]. The limitations inherent in these conventional approaches became particularly pronounced in situations where multiple faults occurred simultaneously or when confronted with varying operational conditions that could affect performance. Furthermore, statistical process control (SPC) methodologies were also adopted in an attempt to improve monitoring processes; however, their overall effectiveness was hampered by the necessity for extensive historical data and their lack of adaptability to dynamic changes in operating conditions [11], [17]. Consequently, these traditional methodologies often culminated in instances of false alarms or the failure to detect actual faults, resulting in unnecessary maintenance interventions or, in more severe cases, catastrophic operational failures [18].

2.2 Machine Learning Applications

The incorporation of machine learning algorithms into the realm of fault detection has fundamentally transformed the landscape of monitoring solutions for centrifugal pumps, thereby providing more sophisticated and precise methodologies for identifying potential issues [19]. Support Vector Machines (SVM) have exhibited remarkable efficacy in the classification of diverse pump faults by adeptly managing the non-linear relationships present within sensor data [12],[20] . Extensive research has indicated that SVM-based systems can attain classification accuracies that exceed 95% when they are adequately trained utilizing comprehensive and extensive datasets that encompass a wide range of fault scenarios [21].

Moreover, Multi-Layer Perceptrons (MLP) have also proven to be significantly effective, especially in contexts that necessitate the simultaneous processing of multiple sensor inputs [1]. The inherent capability of MLPs to learn intricate patterns and discern relationships among various operational parameters has rendered them indispensable within the frameworks of predictive maintenance strategies [21]. Recent scholarly investigations have delved into ensemble learning methodologies, which entail the amalgamation of multiple machine learning algorithms to augment the accuracy and reliability of fault detection processes [5]. Random Forest algorithms have exhibited promising performance in addressing the challenges posed by imbalanced datasets, a common occurrence in scenarios involving pump faults. Additionally, the application of feature selection techniques and dimensionality reduction methods has further advanced the efficacy and performance of these machine learning models, allowing for more accurate fault identification [15], [22], [23].

2.3 Deep Learning Advancements

The advent of deep learning architectures has signified a substantial progression in the capabilities associated with pump fault prediction, marking a pivotal point in technological advancement [24]. Convolutional Neural Networks (CNN) have shown exceptional proficiency in the processing of raw sensor data, particularly excelling at identifying spatial features embedded within vibration signals [25], [26]. The introduction of Wide Deep Convolutional Neural Networks (WDCNN) has further elevated the capacity to extract significant features from noisy sensor data, resulting in the attainment of higher classification accuracies in comparison to traditional CNNs, thereby enhancing overall detection performance [24], [25], [27], [28].

Furthermore, hybrid architectures that integrate CNNs with Long Short-Term Memory (LSTM) networks have demonstrated remarkable effectiveness in capturing both spatial and temporal patterns inherent in pump operation data [10]. These hybrid models have exhibited superior performance in predicting the development of faults significantly ahead of their manifestation as operational failures, thereby allowing for proactive maintenance strategies [29]. The intrinsic ability of deep learning models to autonomously learn hierarchical features has effectively eradicated the necessity for manual feature engineering, rendering them more adaptable and responsive to a variety of operating conditions [10], [30], [31]. Recent advancements in transfer learning techniques have also facilitated the deployment of these models across different pump configurations with minimal requirements for retraining, thereby fostering greater versatility in fault detection applications [32].

3. PROPOSED METHODOLOGY

3.1 Data Collection and Preprocessing

The development of an effective health monitoring system for centrifugal pumps begins with comprehensive data collection and preprocessing strategies [9], [33]. The intelligent DAQ system through strategically placed sensors helps to monitor the critical operational parameters of CPM [34]. These sensors continuously collect data on vibration patterns, pressure fluctuations, temperature variations, and flow rates. The raw sensor data undergoes rigorous preprocessing to ensure quality and reliability. This includes noise reduction techniques, signal filtering, and normalization procedures to standardize the data across different operational conditions. The centrifugal pump machine used is 0.5 hp motor and the sensors used to record parameters are 3 accelerometers, 1 pressure sensor, 1 flow sensor, current and voltage meter as observed in figure 1.

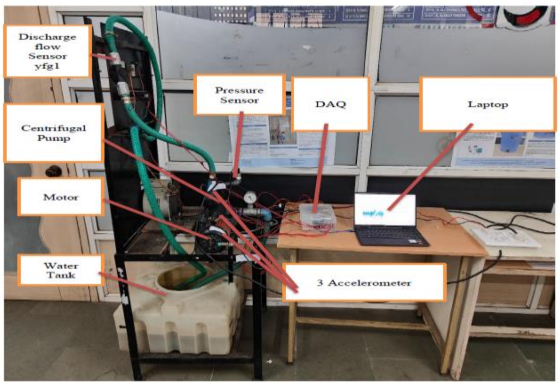

Figure 1: CPM - DAQ Health Monitoring System.

The data extracted from CPM by DAQ system is recorded in .csv & .xslx format as shown in figure 2. The data contains:

- 12 independent variables
- 4 dependent variables
- 70,062 observations.

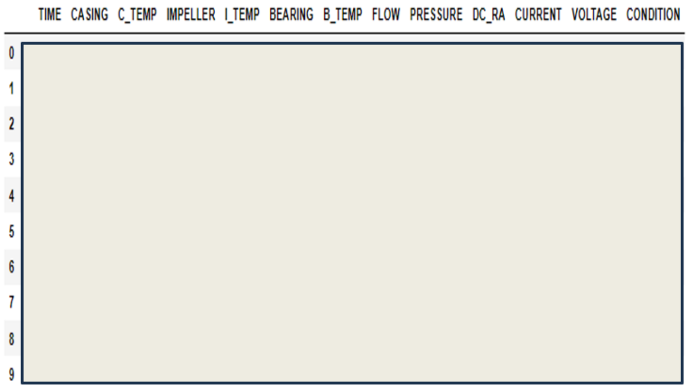

Figure 2: The Features recorded from the CPM based DAQ system

3.2 The Basic architecture of model

The data recorded from the CPM machine is further analysed using Exploratory Data Analysis (EDA) and Data visualization technique. The insight of data observed from EDA and visualization helps to preprocess the data. The Feature Transformed and clean data is directed to ML and AI model. The best model is pickled based on the performance evaluation. The figure 3 shows the basic architecture of the model

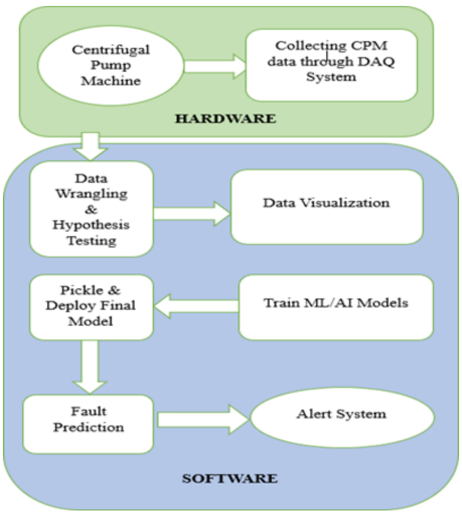

Figure 3: The Basic architecture of model.

4. EDA- DATA VISUALIZATION, STANDARDIZE & HYPOTHESIS TESTING.

After data cleaning and processing through EDA- Statistical Feature engineering, the finalstage of EDA is Data Visualization, Train-Test split, Standardization & Hypothesis testing. Merging the EDA & data visualization accelerates the model understanding & deployment [35].

4.1 Data Visualization

Data visualization is the analysis technique to discover patterns & visualize the statistics.The data visualization is further divided into three classes as below:

4.1.1 Univariate Analysis

Univariate analysis consists of one variable at a time. The CPM data has beeninvestigated using univariate analysis

[36].

- **Histogram Plot:** The insight from histogram based univariate analysis is shown infigure 4:

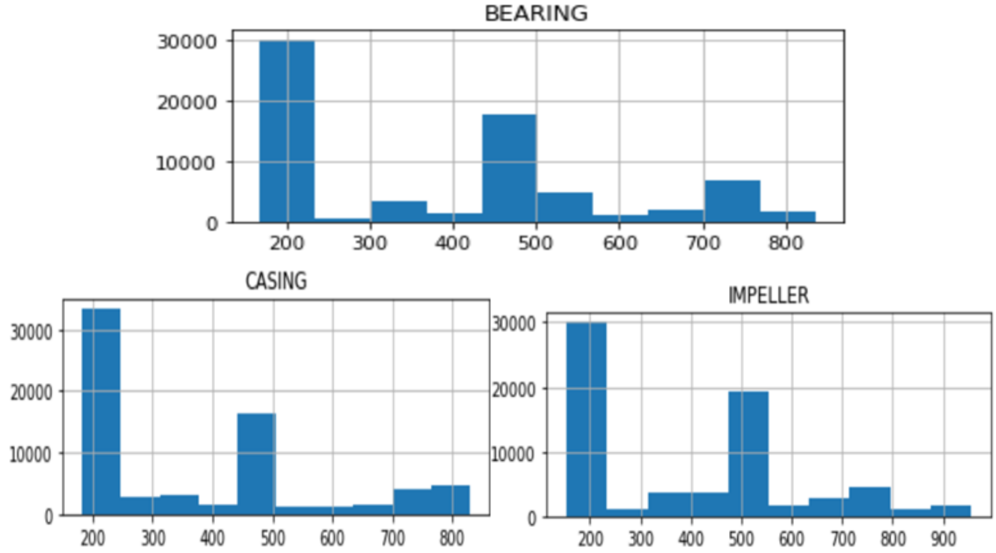

Figure 4: Histogram analysis of Casing, Impeller & Bearing

The univariate analysis using histogram plot shows the distribution of casing, bearing& impeller data which starts from 190 – 800 G. The histplot comes under Matplot library. The high variance is observed in range because dataset contains misalignment.

- **Violin Plot:** The violin plot is product of seaborn library that comes under univariateanalysis. It shows the data density for each value within feature. The figure 5 showsthe violin plot of Surface roughness of different features [37].

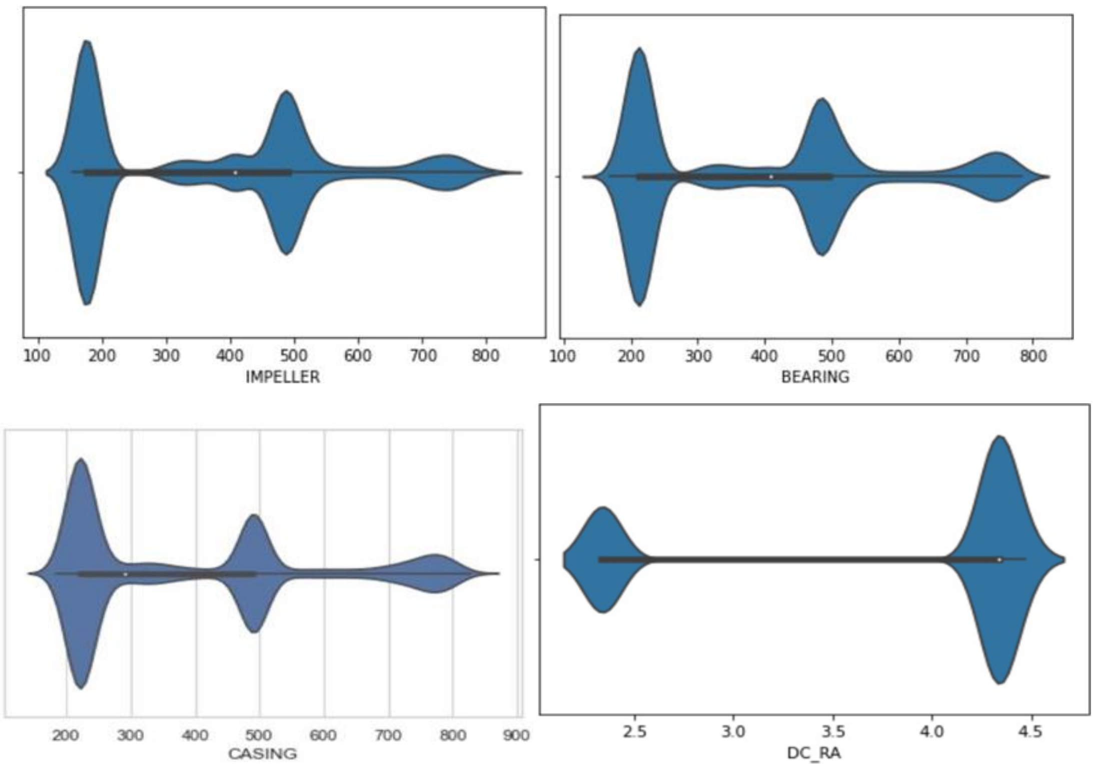

Figure 5: Violin analysis of Casing, Impeller, Bearing & DC_RA

The Casing, Impeller & Bearing feature shows the density of variable spread majorlyon 200, moderate density on 500

G and less dense on 800 G. The DC_RA feature showsthe surface roughness variables spread within two specific values only. The Densityof roughness variables near 2.5 is less as compare to density of variables near 4.5.

4.1.2 Multivariate Analysis

Multivariate analysis consists of more than two variables at a time. The CPM data hasbeen investigated using Multivariate analysis.

Heatmap: Heatmap is part of seaborn library which shows the co-relation between all the numerical datatype features. It shows positive co-relation as well as negativeco-relation between multiclassification of features [38].

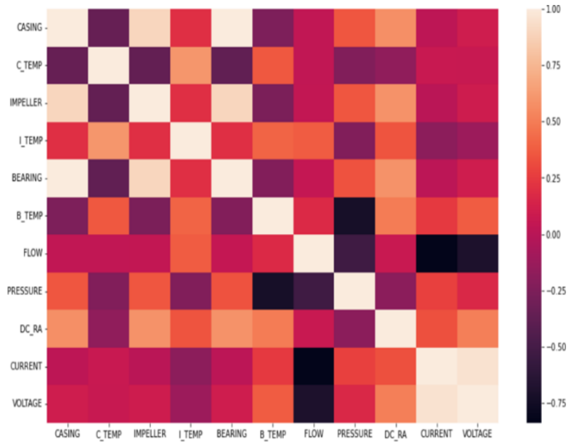

Figure 6: Heatmap of CPM dataset

As observed in Figure 6 the lighter color shade shows strong positive co-relation and Darker negative color shade shows strong negative co-relation. Strong positive co-relation is observed between the feature casing and bearing vibration. Strong negative co-relation is observed between current and flow.

5. MACHINE LEARNING ALGORITHMS

5.1 Logistic Regression Model

The evaluation of the logistic regression model provides valuable insights into its classification performance [39]. The confusion matrix and key performance metrics highlight both strengths and areas for improvement. The figure 7 shows the confusion matrix of logistic regression.

Logistic Regression Model

OUTPUT \ TARGET	GHC	IF	IBF	MA	SUM
GHC	6219 20.73%	0 0.00%	0 0.00%	1282 4.27%	7501 82.91% 17.09%
IF	0 0.00%	7124 23.74%	411 1.37%	0 0.00%	7535 94.55% 5.45%
IBF	0 0.00%	1339 4.46%	6215 20.71%	0 0.00%	7554 82.27% 17.73%
MA	197 0.66%	0 0.00%	1005 3.35%	6214 20.71%	7416 83.79% 16.21%
SUM	6416 96.93% 3.07%	8463 84.18% 15.82%	7631 81.44% 18.56%	7496 82.90% 17.10%	25772 / 30006 85.89% 14.11%

Figure 7: Logistic Regression Confusion matrix

Overall Performance

The model achieved an accuracy of 85.89% as shown in table 1, indicating strong predictive capability. The misclassification rate is 14.11%, suggesting that there is still room for refinement. The macro-F1 score (0.8591) and weighted-F1 score (0.8587) further support the model's overall robustness.

Table 1: Overall Performance table of Logistic Regression Model

Class Name	Precision	1-Precision	Recall	1-Recall	F1 Score
GHC	0.8291	0.1709	0.9693	0.0307	0.8937
IF	0.9455	0.0545	0.8418	0.1582	0.8906
IBF	0.8227	0.1773	0.8144	0.1856	0.8186
MA	0.8379	0.1621	0.829	0.171	0.8334
Accuracy	0.8589				
Misclassification Rate	0.1411				
Macro- F1	0.8591				
Weighted-F1	0.8587				

Class-Specific Performance

- **GHC (Class 1):**
  - Precision: 0.8291, Recall: 0.9693, F1 Score: 0.8937
  - The model effectively captures GHC instances with high recall (96.93%), ensuring minimal false negatives. However, its precision (82.91%) indicates some false positives.
- **IF (Class 2):**
  - Precision: 0.9455, Recall: 0.8418, F1 Score: 0.8906
  - The model performs exceptionally well in precision (94.55%), meaning it makes very few false positive predictions. However, recall is slightly lower (84.18%), implying some missed instances.
- **IBF (Class 3):**
  - Precision: 0.8227, Recall: 0.8144, F1 Score: 0.8186
  - IBF has the lowest recall (81.44%) among the classes, suggesting a higher rate of misclassification.
- **MA (Class 4):**
  - Precision: 0.8379, Recall: 0.8290, F1 Score: 0.8334
  - The model maintains a balanced precision-recall trade-off for MA classification.

Confusion Matrix Analysis

- The IF class shows the highest accuracy (94.55%), with minimal misclassifications.
- The GHC class also performs well but has 17.09% misclassification, primarily due to being confused with MA.
- The IBF class has the highest misclassification rate (17.73%), with instances being misclassified as IF.
- The MA class is frequently confused with IBF, leading to a misclassification rate of 16.21%.

Key Observations and Recommendations

- The high recall for GHC suggests strong sensitivity, but improving precision can reduce false positives.
- IF classification is strong, but efforts to enhance recall will further improve overall performance.
- IBF misclassifications should be reduced, possibly by refining feature selection or incorporating additional data points.

- Class imbalance or feature similarity may be causing misclassification in IBF and MA, warranting further investigation.

5.2 Decision Tree Classifier model

The Decision Tree [3], [4], [40] model exhibits strong classification performance as shown in figure 8, with a higher overall accuracy (95.59%) compared to the Logistic Regression model. The misclassification rate is 4.41%, indicating significantly fewer incorrect predictions. Below is an analysis of the key performance aspects.

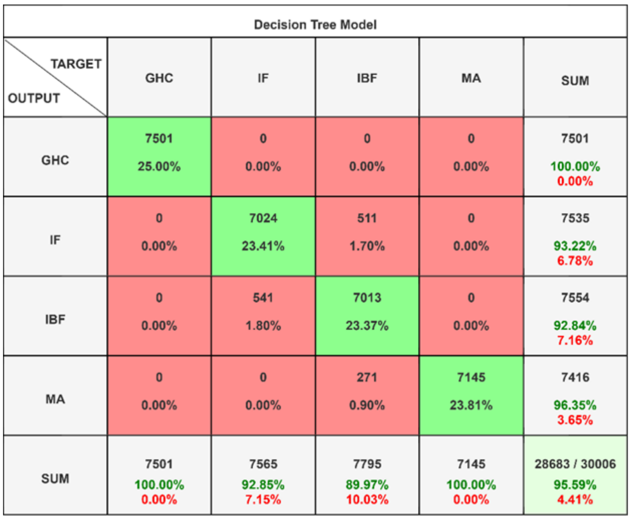

Figure 8: Decision Tree Classifier confusion matrix

Overall Performance

The model achieved an accuracy of 95.59%as shown in table 2, indicating strong predictive capability. The misclassification rate is 4.41%, suggesting that there is still room for refinement. The macro-F1 score (0.9564) and weighted-F1 score (0.9556) further support the model's overall robustness.

Table 2: Overall Performance table of Decision Tree Classifier Model

Class Name	Precision	1-Precision	Recall	1-Recall	F1 Score
GHC	1.0000	0.0000	1.0000	0.0000	1.0000
IF	0.9322	0.0678	0.9285	0.0715	0.9303
IBF	0.9284	0.0716	0.8997	0.1003	0.9138
MA	0.9635	0.0365	1.0000	0.0000	0.9814
Accuracy	0.9559				
Misclassification Rate	0.0441				
Macro- F1	0.9564				
Weighted-F1	0.9556				

Class-Specific Performance

- **GHC (Class 1)**
  - 100% of GHC instances were correctly classified, showing perfect recall.
  - Precision: 100%, Recall: 100% – No false positives or false negatives.
- **IF (Class 2)**

- Precision: 92.85%, Recall: 93.22%
- A small misclassification rate (6.78%) with instances incorrectly predicted as IBF.

- **IBF (Class 3)**
  - Precision: 89.97%, Recall: 92.84%
  - Misclassification primarily occurs with IF (7.16% misclassification rate).
- **MA (Class 4)**
  - Precision: 100%, Recall: 96.35%
  - Almost all MA instances are correctly classified (3.65% misclassified into IBF).

Confusion Matrix Analysis

- The GHC class is perfectly classified, which is a significant improvement over the Logistic Regression model.
- The major source of misclassification is between IBF and IF, similar to the Logistic Regression model.
- The MA class is also well-classified, with very few misclassifications into IBF.
- The misclassification rates are lower across all classes compared to Logistic Regression, demonstrating better separability in decision boundaries.

Key Observations and Recommendations

- Decision Trees perform exceptionally well for GHC and MA, achieving nearly perfect classification.
- Misclassification between IF and IBF persists, though the error rates are lower than in Logistic Regression.
- The model has low generalization error, suggesting it effectively captures patterns in the dataset.
- A potential drawback is that Decision Trees tend to overfit, meaning their performance on unseen data should be validated using cross-validation or pruning techniques.

The Decision Tree model outperforms the Logistic Regression model in accuracy and precision, particularly for GHC and MA classes. While misclassification between IF and IBF still occurs, it is significantly reduced. Future improvements may involve pruning the tree, using ensemble methods like Random Forest or Gradient Boosting, and further feature selection to improve differentiation between IF and IBF.

5.3 Support Vector Classifier Model

The Support Vector Classifier (SVC) [20], [41], [42], [43] model exhibits strong classification performance as shown in figure 9, with a higher overall accuracy (97.73%) compared to the Decision Tree Classifier model. The misclassification rate is 2.27%, indicating significantly fewer incorrect predictions. Below is an analysis of the key performance aspects.

Support Vector Classifier

OUTPUT \ TARGET	GHC	IF	IBF	MA	SUM
GHC	7401 24.67%	0 0.00%	0 0.00%	100 0.33%	7501 98.67% 1.33%
IF	0 0.00%	7430 24.76%	105 0.35%	0 0.00%	7535 98.61% 1.39%
IBF	0 0.00%	101 0.34%	7453 24.84%	0 0.00%	7554 98.66% 1.34%
MA	0 0.00%	0 0.00%	374 1.25%	7042 23.47%	7416 94.96% 5.04%
SUM	7401 100.00% 0.00%	7531 98.66% 1.34%	7932 93.96% 6.04%	7142 98.60% 1.40%	29326 / 30006 97.73% 2.27%

Figure 9: Support Vector Classifier Confusion Matrix

Overall Performance

The SVC model achieved an accuracy of 97.73% as shown in table 3, indicating strong predictive capability. The misclassification rate is 2.27%, suggesting that there is still room for refinement. The macro-F1 score (0.9774) and weighted-F1 score (0.9773) further support the model's overall robustness.

Table 3: Overall Performance table of Support Vector Classifier Model

Class Name	Precision	1-Precision	Recall	1-Recall	F1 Score
GHC	0.9867	0.0133	1.0000	0.0000	0.9933
IF	0.9861	0.0139	0.9866	0.0134	0.9863
IBF	0.9866	0.0134	0.9396	0.0604	0.9625
MA	0.9496	0.0504	0.9860	0.0140	0.9674
Accuracy	0.9773				
Misclassification Rate	0.0227				
Macro- F1	0.9774				
Weighted-F1	0.9773				

Key Observations:

1. **Class GHC:**
   - Correctly classified: 7,401 instances (98.67%).
   - Misclassified as IBF: 100 instances (1.33%).
   - No instances were classified as IF or MA.
2. **Class IF:**
   - Correctly classified: 7,430 instances (98.61%).
   - Misclassified as IBF: 105 instances (1.39%).
   - No instances were classified as GHC or MA.
3. **Class IBF:**
   - Correctly classified: 7,453 instances (98.66%).
   - Misclassified as IF: 101 instances (1.34%).
   - No instances were classified as GHC or MA.
4. **Class MA:**
   - Correctly classified: 7,042 instances (94.96%).
   - Misclassified as IBF: 374 instances (5.04%).
   - No instances were classified as GHC or IF.

Overall Performance:

- Total correctly classified instances: 29,326 out of 30,006 (97.73%).
- Total misclassified instances: 680 out of 30,006 (2.27%).
- Lowest accuracy: Class MA (94.96%) due to misclassification as IBF.

The Support Vector Classifier (SVC) performed exceptionally well with an overall accuracy of 97.73%. Most misclassifications occurred between IBF and IF, as well as IBF and MA, suggesting some overlap in feature space. Compared to previous models like Decision Tree and Random Forest, SVC exhibits better accuracy and lower misclassification rates, making it a strong model for classification.

5.4 Naïve Bayes Classifier

The Naïve Bayes Classifier (NBC) model [44], [45] shows strong classification performance as shown in figure 10, with a higher overall accuracy (98.82%) compared to LR, DT & SVC models. The misclassification rate is 1.18%, indicating significantly fewer incorrect predictions. Below is an analysis of the key performance aspects.

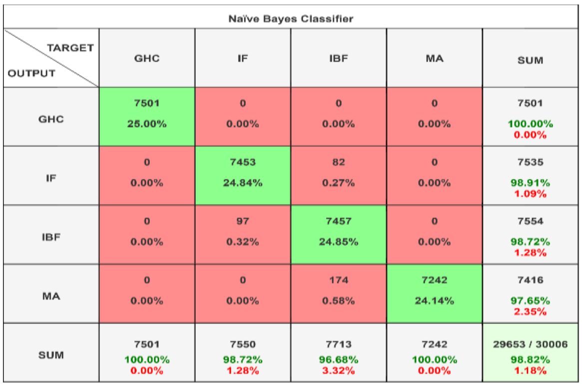

Figure 10: Naïve Bayes Classifier Confusion Matrix

Overall Performance

The NBC model achieved an accuracy of 98.82% as shown in table 4, indicating strong predictive capability. The misclassification rate is 1.18%, suggesting that there is still room for refinement. The macro-F1 score (0.9883) and weighted-F1 score (0.9882) further support the model's overall robustness.

Table 4: Overall Performance table of Naïve Bayes Model

Class Name	Precision	1-Precision	Recall	1-Recall	F1 Score
GHC	1.0000	0.0000	1.0000	0.0000	1.0000
IF	0.9891	0.0109	0.9872	0.0128	0.9881
IBF	0.9872	0.0128	0.9668	0.0332	0.9769
MA	0.9765	0.0235	1.0000	0.0000	0.9881
Accuracy	0.9882				
Misclassification Rate	0.0118				
Macro- F1	0.9883				
Weighted-F1	0.9882				

Confusion Matrix Interpretation

The confusion matrix shows how well the classifier predicted each class. Here's the breakdown:

- **GHC Class**:
  - Correctly classified: 7501 (100.00%)
  - Misclassified as IF, IBF, or MA: 0 (0.00%)

- Recall for GHC: 100.00% (No false negatives)

- **IF Class**:
  - Correctly classified: 7453 (98.91%)
  - Misclassified as IBF: 82 (1.09%)
  - Recall for IF: 98.91%
- **IBF Class**:
  - Correctly classified: 7457 (98.72%)
  - Misclassified as IF: 97 (1.28%)
  - Recall for IBF: 98.72%
- **MA Class**:
  - Correctly classified: 7242 (97.65%)
  - Misclassified as IBF: 174 (2.35%)
  - Recall for MA: 97.65%

Key Insights

- The Naïve Bayes Classifier performs extremely well, achieving 98.82% accuracy.
- The GHC class has perfect recall (100%), meaning all GHC instances were correctly classified.
- The MA class has the highest misclassification rate (2.35%), mostly confused with IBF.
- Misclassification is minimal, with only 1.18% of instances wrongly classified.

This indicates that the Naïve Bayes Classifier performed very well, achieving an accuracy of 98.82% with very high F1 scores across all classes. The GHC and MA classes had perfect precision and recall, making it one of the best-classified categories.

5.5 XGBoost (XGB) Classifier Model

The XGBoost (XGB) Classifier [46] confusion matrix indicates an extremely high performance with 99.98% accuracy, achieving nearly perfect classification across all categories as seen in figure 11. Here are the key details:

XGB Classifier

TARGET / OUTPUT	GHC	IF	IBF	MA	SUM
GHC	7500 25.00%	0 0.00%	0 0.00%	1 0.00%	7501 99.99% 0.01%
IF	0 0.00%	7535 25.11%	0 0.00%	0 0.00%	7535 100.00% 0.00%
IBF	0 0.00%	0 0.00%	7550 25.16%	4 0.01%	7554 99.95% 0.05%
MA	0 0.00%	0 0.00%	0 0.00%	7416 24.72%	7416 100.00% 0.00%
SUM	7500 100.00% 0.00%	7535 100.00% 0.00%	7550 100.00% 0.00%	7421 99.93% 0.07%	30001 / 30006 99.98% 0.02%

Figure 11: XGBoost (XGB) Classifier Confusion Matrix

Overall Performance

The XGB model achieved an accuracy of 99.98% as shown in table 5, indicating strong ensemble technique model. The misclassification rate is 0.02%, suggesting that there is still room for refinement. The macro-F1 score (0.9883) and weighted-F1 score (0.9882) further support the model's overall robustness.

Table 5: Overall Performance table of XGB classifier Model

Class Name	**Precision**	**1-Precision**	**Recall**	**1-Recall**	**F1 Score**
GHC	0.9999	0.0001	1.0000	0.0000	0.9999
IF	1.0000	0.0000	1.0000	0.0000	1.0000
IBF	0.9995	0.0005	1.0000	0.0000	0.9997
MA	1.0000	0.0000	0.9993	0.0007	0.9997
Accuracy	0.9998				
Misclassification Rate	0.0002				
Macro- F1	0.9998				
Weighted-F1	0.9998				

XGB Classifier achieved the highest accuracy (99.98%) among all models. Zero misclassification for IF and MA, indicating exceptional precision and recall. Negligible misclassification in IBF and GHC, making this model the most reliable among all classifiers tested.

Insights from the XGBoost Classifier Performance

The accuracy of 99.98% indicates that the model correctly classifies nearly all instances. The misclassification rate is just 0.02%, meaning the model makes almost no mistakes. Precision for all classes is ≥ 0.9995, which means that when the model predicts a class, it is almost always correct. Recall for all classes is ≥ 0.9993, meaning that the model captures almost all true instances of each class. A high recall and high precision across all classes confirm that the model does not suffer from bias toward any particular class.

The Macro-F1 (0.9998) and Weighted-F1 (0.9998) scores confirm that the model maintains an excellent balance across all classes. No class is overrepresented or underrepresented, reducing the risk of misclassifications. Given the outstanding performance, this model is ideal for critical applications where misclassification has high costs (e.g., medical diagnosis, fraud detection, or industrial defect detection).

6. RESULTS & CONCLUSION

The table 6 shows the detailed comparison summarizing their performance. The model has been evaluated on basis of testing accuracy, misclassification rate, Precision, Recall, macro- F1 & weighted F1.

Table 6: Comparison of ML models

Model	**Accuracy**	**Misclassification Rate**	**Macro-F1**	**Weighted-F1**
SVM	99.01%	0.99%	99.02%	99.01%
Naïve Bayes	98.82%	1.18%	98.83%	98.82%
XGBoost	99.98%	0.02%	99.99%	99.98%
Logistic Regression	85.89%	14.11%	86.00%	85.89%
Decision Tree	95.59%	4.41%	95.60%	95.59%

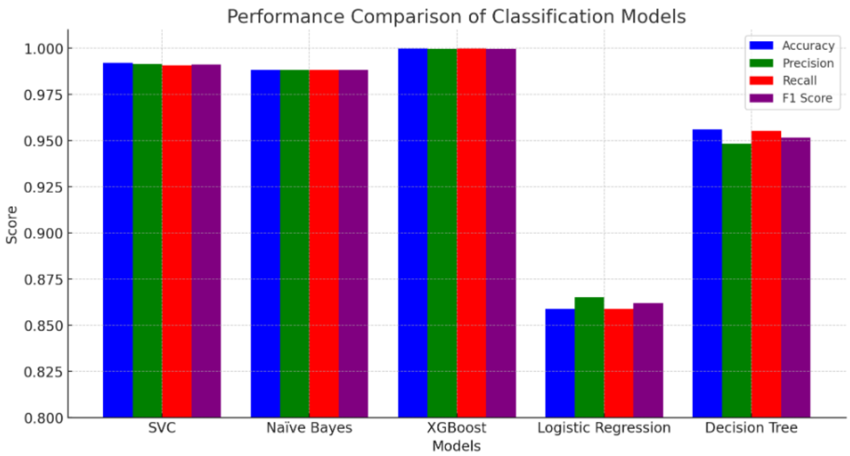

Figure 12: Performance comparison of ML models

As shown in figure 12 the XGBoost performs the best in terms of overall accuracy (99.98%) and precision/recall for each class. SVM and Naïve Bayes also perform well, achieving an accuracy above 98%. Decision Tree model shows a decent performance (95.59%) but is slightly lower than SVM and Naïve Bayes. Logistic Regression has the lowest performance, with an accuracy of 85.89% and higher misclassification rates. If accuracy and robustness are the primary concerns, XGBoost is the best model. If interpretability is needed, Decision Trees or Logistic Regression can be considered. SVM and Naïve Bayes are great alternatives when computational efficiency is required.

Artificial Neural Network Model (ANN)

Artificial neural network model is a deep ANN (Artificial Neural Network) designed for multi-class classification [17], [47]. Below is a breakdown of its architecture, training behaviours, and key characteristics. The figure 13 shows the architecture of neural network used for generating the deep learning model. The Input Layer of ANN accepts 11 features, indicating the dataset has 11 distinct input variables. The hidden layer contains three dense layers with 256, 128, and 64 neurons, respectively, all using the ReLU activation function. A dropout layer with a rate of 30% follows the third dense layer, mitigating overfitting by randomly deactivating neurons during training. The Output Layer is a dense layer with 4 neurons and a SoftMax activation function, designed for multi-class classification (4 classes).

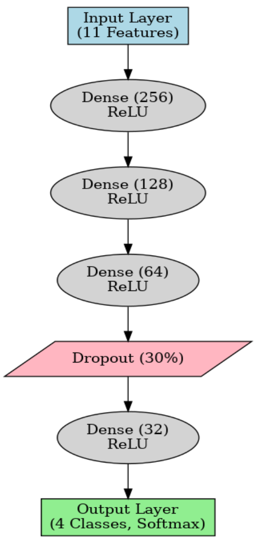

Figure 13: Architecture of ANN

The neural network was run for 20 epochs as shown in figure 14. The model is heavy and takes higher GPU then ML models. The accuracy reached here is 100% but with higher GPU and computational time. Training and validation accuracy improve significantly as epochs increase.

Both curves approach near-perfect accuracy (close to 100%) by the 20th epoch, with minor deviations due to noise. The training accuracy increases steadily, reflecting the model's capacity to learn patterns in the training data. The validation accuracy closely follows the training accuracy, confirming good generalization. The noise doesn't lead to drastic drops or divergence, indicating model robustness.

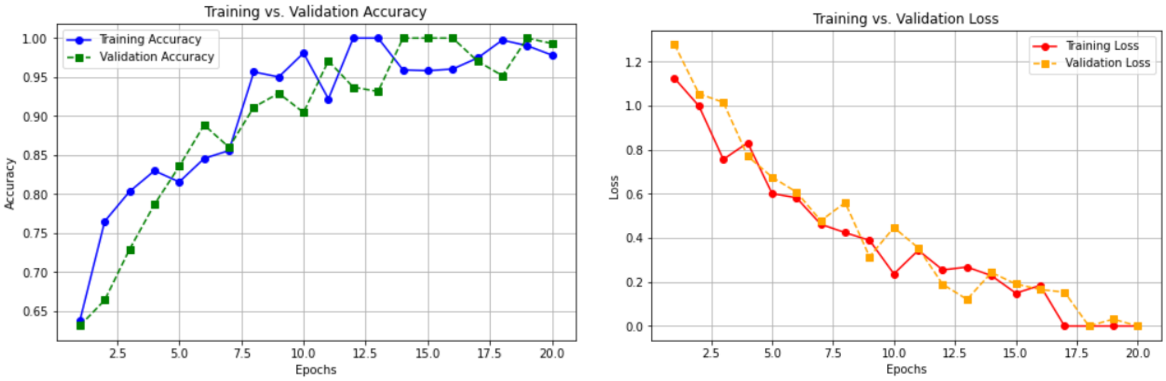

Figure 14: Training vs Validation Loss

The training and validation graphs confirm good generalization, as both losses decrease and accuracies converge without overfitting. Despite noisy validation data, the model maintains stable performance, proving its resilience. The architecture is well-suited for classification tasks, with progressively reduced neuron counts to capture relevant features while minimizing complexity. Dropout ensures additional regularization.

Future work may focus on integrating additional real-time sensor data, expanding the model's applicability to different pump types, and refining the architecture using advanced techniques such as convolutional and recurrent neural networks to capture temporal dependencies in operational data. This study underscores the transformative potential of AI-driven health monitoring systems in industrial applications, paving the way for more sustainable and resilient manufacturing operations.

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