HYBRID DL MODEL FOR ACCURATE CLASSIFICATION OF VACCUM CLEANER VIBRATION PATTERNS AND MECHANICAL HEALTH

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Abstract:

Once a product is developed and its manufacture begins, its level of excellence immediately starts decreasing due to other competitive products on the market. Its life on the market can be prolonged by continual product improvements. A longer product lifetime also increases its profitability, because the development of a new family of products is associated with considerable costs. The paper presents product re-engineering using an example of a vacuum cleaner motor and its positioning in the product development cycle. The development of vacuum cleaner motors (motor and turbine assembly) is progressing in the direction of increasing the number of revolutions and decreasing their mass and volume. The performed analysis of vacuum cleaner motor construction indicated several possibilities for increasing the number of revolutions. The basic problem concerns the influence of individual components on critical speed. The paper assesses the applicability of individual methods for the analysis of natural frequencies; the results are summarized in the form of engineering design rules for vacuum cleaner motors. The analysis was performed for an example from current manufacturing practice. Achieving high quality standards and 100% defect-free deliverables is becoming a trend among manufacturers of household appliances. In that respect, thorough and reliable end-tests represent an important step towards this goal. This paper deals with the design of end-test procedures for vacuum cleaner motors based on sound analysis. It is well known that sound carries important information about the condition of contact surfaces in rotating parts. The paper aims first to provide a thorough analysis of sound sources within the motor. Second, by using simple yet effective signal processing tools, it is shown that with sound analysis alone it is possible to clearly distinguish fault-free motors from those with mechanical faults. Moreover, the proposed algorithm exhibits a certain isolation capability, i.e., it is able to distinguish three clusters of faults. Finally, a summary of experimental results obtained on a sample of 75 motors is provided.

Keywords:Productre-engineering,Vacuumcleaner,motorProduct development cycle,Motor andturbineassembly,Revolutions,Mass and volumereduction,Criticalspeed,Naturalfrequencies,Engineering design rules

1. INTRODUCTION

The manufacturers of vacuum cleaner motors tend to purchase (almost) 100% fault-free devices by lowest prices. This demands for well-organised process of quality assurance during the manufacturing cycle. This paper addresses a family of vacuum cleaner motors manufactured by company Domel, which is a recognised Europeanproducer. The quality assurance in Domel consists of two segments. Firstly, several standard automated tests are performed on most critical components during assembly (e.g. rotor balance, high-voltage test etc). As the matter of fact, those tests are able to reveal defects on the level of components only. That means that some errors occurring during assembly process might become visible not earlier than on the end product. There fore a thorough and in-depth analysis of the condition of the end product is very important. Currently the end test entails only manual measurements of vibrations, sound inspection and visual checks. The rest of the quality assurance process relies on a statistical procedure for quality control of finished series. This segment takes a rather high amount of work and, consequently, costs. Therefore, it is hoped that a way to reduce costs is to employ thorough end tests able not only to reveal defective motors but also to isolate the root cause. The operators will have the opportunity to take immediate corrective actions on assembly line.

1. 2 Problem Definition

The primary challenge in vacuum cleaner fault detection is accurately classifying diverse vibration patterns associated with different mechanical faults. Traditional approaches, such as spectral analysis and rule-based systems, require extensive domain expertise and struggle with dynamic operational conditions. Additionally, existing machine learning models often rely on handcrafted features, which may not generalize well across different vacuum cleaner models or fault types. Therefore, there is a need for an intelligent, adaptive system that can classify vibration signals with high accuracy and minimal human intervention.

1. 3 Research Motivation

With the increasing demand for smart appliances and automated maintenance solutions, developing an efficient fault classification model is crucial. A hybrid deep learning approach that integrates CNNs and FFNN can overcome the limitations of traditional methods by leveraging spatial and temporal features in vibration signals. CNNs can effectively extract meaningful patterns from spectrogram representations, while FFNN can capture temporal dependencies, making them well-suited for sequential data like vibration signals. The motivation behind this research is to create a scalable and generalizable model that enhances fault detection, reduces unplanned maintenance, and improves overall product reliability.

1. 4 Significance

The proposed hybrid deep learning model offers several advantages:

- **Early Fault Detection:** Enables proactive maintenance by identifying faults at an early stage, reducing downtime and repair costs.
- **Automation & Scalability:** Eliminates the need for manual feature extraction and can be applied to different vacuum cleaner models and mechanical systems.
- **Real-time Monitoring:** Supports continuous health assessment, improving user experience and operational efficiency.

1. 5 Applications

The proposed model has broad applications, including:

- **Smart Home Appliances:** Automated fault detection in robotic vacuum cleaners and household appliances.

- **Industrial Equipment Monitoring:** Predictive maintenance for industrial vacuum systems and other machinery.
- **Consumer Electronics:** Integration into IoT-based maintenance systems for real-time performance tracking.
- **Automotive & Aerospace:** Vibration analysis for diagnosing mechanical faults in engines, motors, and rotating components.

2. LITERATURE SURVEY

In the case of a compound fault diagnosis of rotating machinery, when two failures with unequal severity occur in distinct parts of the system, the detection of a minor fault is a complicated and challenging task. In this case, the minor fault is overshadowed by the more severe one, and the characteristics of the compound fault are prone to the more severe one. Generally, the proposed methods in the literature consider compound failure as an individual fault type and unrelated to the corresponding single faults, either at the different locations of a sensitive component or in two separate parts, such as the bearing and gear, with approximately the same fault severity [1]. Engineering has many necessary fields, and Structural Health Monitoring (SHM) is one of the most important of them. Sometimes in industrial environments, it is difficult and even impossible to collect data containing different real damages. Therefore, the problem of data acquisition represents a primary challenge in designing damage detection systems. The application of digital twin methods based on simulated models and/or Machine Learning (ML) models is a practical way to solve this problem [2].

Track geometry is one of the critical indicators of railway tracks' condition which requires continuous monitoring and maintenance over time. In this paper, a novel artificial intelligence (AI) based framework is proposed for railway track geometry inspection using vibration data collected from a dedicated measuring high-speed train. This AI-based anomaly track detection approach consists of two main stages [3]. The artificial intelligence (AI) technologies, such as meta-heuristic computing and deep learning, have provides solid technical support for structural health monitoring (SHM) of offshore jackets. In this paper, a physics-enhanced AI method based on the parametric damage identification is developed for SHM of the offshore jacket structures. In this new method, a hybrid kernel function-based kernel extreme learning machine (HKELM) is proposed to construct an AI structure to enhance the SHM detection capacity on the structural modal parameters extracted by the parametric damage identification technique [4].

Structural health monitoring of mechanical systems is essential to avoid their catastrophic failure. In this article, an effective deep neural network is developed for extracting the damage-sensitive features from frequency data of vibration signals to damage detection of mechanical systems in the presence of the uncertainties such as modeling errors, measurement errors, and environmental noises. For this purpose, the finite element method is used to analyze a mechanical system (finite element model) [5].

Monitoring health condition of offshore jacket platforms is crucial to prevent unexpected structural damages, where a prevailing challenge involves translating available feature information into structural damage patterns. Although the artificial neural network (ANN) models are popular in addressing this challenge, they often fail to capture the temporal correlations between the feature information and the damage patterns, which reduce their capability for discovering the laws governing the structural damage detection [6]. Monitoring structural damage is critical for preserving the service life of engineering systems. In varying operational environments, the working loads are changing all the time and they are typically unknown; in such environments, access to damage data is difficult and sometimes even impossible, and generally, intact data of the system is available. From this standpoint, this study aims to propose a novel vibration-based method for damage detection of real systems using Dictionary Learning (DL) based on a FE model and real intact state under different uncertainties such as varying working loads [7].

At present, traditional subsea pipeline structural health monitoring (SHM) uses the sonar equipment, which needs to post-process the obtained data. Then the sonar images can be obtained. Moreover, traditional SHM needs staff to interpret the results of the sonar images. Such results can be subject to manual interference, and monitoring efficiency and accuracy cannot be guaranteed either. In view of the above problems, this paper proposed an ensemble method for real-time automatic monitoring, evaluation and positioning of exposed subsea pipelines based on 3D real-time sonar system [8]. Advancement in measurement techniques has dramatically contributed to the development of the modern manufacturing industry. As the primary fault causing unplanned downtime of mechanical equipment, gearbox compound faults are usually coupled by single faults with unequal severity and are difficult to obtain. In industrial scenarios, monitoring data for extreme operating conditions is not available in advance, and labeling samples is time-consuming and costly [9].

Intelligent fault diagnosis techniques have replaced time-consuming and unreliable human analysis, increasing the efficiency of fault diagnosis. Deep learning models can improve the accuracy of intelligent fault diagnosis with the help of their multilayer nonlinear mapping ability. This paper proposes a novel method named Deep Convolutional Neural Networks with Wide First-layer Kernels (WDCNN) [10]. Emotion is considered to be critical for the actual interpretation of actions and relationships. Recognizing emotions from EEG signals is also becoming an important computer-aided method for diagnosing emotional disorders in neurology and psychiatry. Another advantage of this approach is recognizing emotions without clinical and medical examination, which plays a major role in completing the Brain-Computer Interface (BCI) structure. Emotions recognition ability, without traditional utilization strategies such as self-assessment tests, is of paramount importance [11].

Random-vibration-based statistical time series structural health monitoring methods utilize small-scale, compact, and data-based, time series stochastic representations of the structural dynamics for damage diagnosis. In this study, a comprehensive and critical assessment of the diagnostic performance of five prominent response-only methods is presented based on incipient, 'minor' to 'mild', damages on a lab-scale wind turbine jacket structure [12]. Railway bridges exposed to extreme environmental conditions can gradually lose their effective cross-section at critical locations and cause catastrophic failure. This paper has proposed a practical vibration-based deep learning approach for damage classification of various extents and degrees of cross section losses due to damages like corrosion in operational railway bridges using vibration-based Convolutional Neural Networks (CNN)s [13].

Civil engineering structures inevitably suffer from nonstationary ambient excitations in practice, which make conventional damage identification methods relying on the stationary assumption ineffective. This study presents a novel method based on unthresholded assembled recurrence distance matrix (UARDM) and multi-label convolutional neural network (CNN) for structural damage identification under nonstationary excitations [14]. Structural damage detection is crucial for ensuring the safety and reliability of civil infrastructure.

3. PROPOSED METHODOLOGY

Step 1: Health Dataset

The first step involves acquiring the health dataset, which contains vibration data collected from vacuum cleaner motors. This dataset includes several numerical features representing vibration characteristics (label as a1, a2, a3, a4), along with a "label" column that indicates the motor's health status (either "Normal" or "Faulty"). The dataset is read into the system and prepared for analysis to ensure that the subsequent machine learning processes are based on quality data.

Step 2: Data Preprocessing

Once the dataset is loaded, preprocessing tasks are performed. The data is examined for any missing or null values, and strategies are implemented to handle them. For example, missing values may be filled or removed based on their distribution and importance. The dataset is then standardized, ensuring all features are on the same scale. Label encoding is applied to the categorical "label" column, transforming it into numeric values. Data splitting follows, dividing the dataset into training and testing sets to evaluate model performance effectively.

Step 3: EDA Plots

Exploratory Data Analysis (EDA) is performed to gain insights into the structure of the data. Various graphs, such as histograms, scatter plots, and correlation heatmaps, are generated. These plots reveal trends and relationships between the features and their distribution within the classes (Normal and Faulty). EDA helps uncover important patterns in the data, such as which features most significantly influence the classification of motor health, and it guides decisions for feature selection and model optimization.

Step 4: Existing SVM Classifier (Algorithm)

The existing classification model used in this project is the Support Vector Machine (SVM). SVM is a supervised machine learning algorithm that works by finding the optimal hyperplane that best separates the different classes in the feature space. It is particularly useful for classification tasks where the classes are not linearly separable. In this project, the SVM classifier is trained on the preprocessed dataset and tested on the held-out test data to evaluate its ability to classify the motor health status. The SVM is trained using a Radial Basis Function (RBF) kernel, which helps handle complex, non-linear relationships in the feature space. Performance metrics such as accuracy, precision, recall, and F-score are used to assess the model's effectiveness.

Step 5: Proposed DNN Classifier (Algorithm)

The proposed classifier for this project is the Deep Neural Network (DNN), which is a type of artificial neural network with multiple layers of nodes. The DNN architecture includes an input layer, one or more hidden layers, and an output layer. In this model, the hidden layers are fully connected layers with ReLU activation functions, and dropout layers are used to prevent overfitting. The output layer uses a softmax activation function to classify the data into one of the two classes: "Normal" or "Faulty." The DNN model is trained on the dataset, and its performance is evaluated based on metrics such as accuracy, precision, recall, and F-score. The DNN classifier is expected to outperform traditional models like SVM due to its ability to learn complex patterns in the data.

Step 6: Performance Comparison Graph

After training both the SVM and DNN models, their performance is compared through a graphical representation. A bar chart or line graph is used to display the key performance metrics (accuracy, precision, recall, F-score) for both models. The graph clearly shows the superior performance of the DNN model over the SVM model, with significantly higher accuracy and other metrics, which confirms the DNN's ability to better classify motor health from vibration data. This comparison helps validate the choice of DNN as the proposed model for this project.

Step 7: Prediction of Output from Test Images with DNN Algorithm.

Finally, the trained DNN model is applied to predict the motor health status of unseen test data. The model takes in vibration features from the test images and outputs predictions indicating whether each motor is "Normal" or "Faulty." The results of these predictions are then analyzed and compared with the actual test labels to assess the model's generalization ability. This step verifies the DNN model's effectiveness in real-world applications, ensuring that it can accurately classify motor health based on vibration patterns.

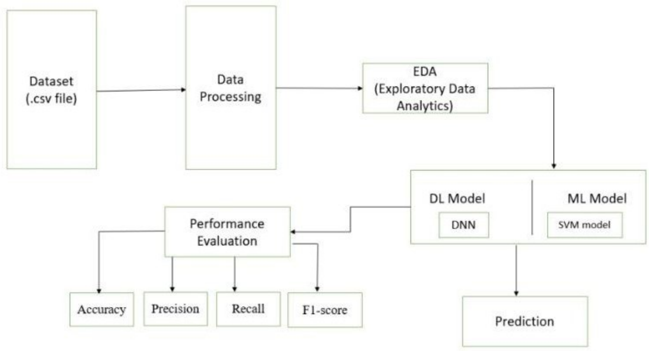

Fig 4.: Proposed system Block Diagram

4.1 Work Flow

Data Preprocessing

Data preprocessing is a crucial step in machine learning that ensures the dataset is clean, structured, and ready for training. Since the project involves classifying vacuum cleaner motor vibration patterns, raw sensor data must be transformed into a usable format. The key steps in data preprocessing include:

- **Handling Missing Values** – The dataset is checked for null values using .isnull().sum(). If any missing values are found, they are either removed or replaced using mean, median, or mode imputation to maintain dataset integrity.
- **Feature Scaling and Normalization** – Vibration and sound data often have varying ranges. Standardization techniques such as Z-score normalization StandardScaler() are applied to ensure uniform scaling across all features. This helps deep learning models converge faster and perform better.
- **Encoding Categorical Variables** – The motor health labels (e.g., "Normal" and "Faulty") are categorical and must be converted into numerical form using Label Encoder(). This allows machine learning algorithms to process them efficiently.
- **Data Transformation** – Since the dataset contains vibration signals, transformations like Fourier Transform (FFT) and Mel Frequency Cepstral Coefficients (MFCC) are applied to extract frequency-domain features, making fault classification more accurate.
- **Noise Removal and Smoothing** – Unwanted noise in the sensor data is filtered out using signal processing techniques such as low-pass filtering, ensuring that only relevant motor vibrations are analyzed.
- **Data Augmentation** – To increase the dataset size and improve model generalization, techniques such as time shifting, amplitude scaling, and frequency masking are used to create slightly altered versions of existing signals.

Data Splitting

After preprocessing, the dataset is divided into training and testing sets to evaluate the model’s performance effectively. The splitting process follows these steps:

- **Defining the Target Variable and Features** – The dataset is divided into input features (X) representing vibration and sound parameters and output labels (y) indicating motor health status.

- **Splitting into Training and Testing Sets** – The dataset is split using train_test_split() with an 80:20 ratio. The training set (80%)

is used to teach the model, while the testing set (20%) is reserved for performance evaluation.

- **Ensuring Class Balance** – If the dataset is imbalanced (one class having significantly more samples than another), techniques like oversampling (SMOTE) or undersampling are used to ensure equal representation of all classes.
- **Randomization for Generalization** – A fixed random state (random_state=42) is used to ensure consistent and reproducible results across multiple runs.
- **Creating Validation Set (Optional)** – In deep learning models like CNN, an additional validation set (usually 10–20% of the training data) is extracted to fine-tune hyperparameters and prevent overfitting.

4.2 Model Building

This section provides a detailed explanation of the Support Vector Machine (SVM) Classifier, used as an existing algorithm, and the Deep Neural Network (DNN) Classifier, proposed for improved classification accuracy.

4.2.1 Existing Algorithm

What is a Support Vector Machine (SVM) Classifier?

A **Support Vector Machine (SVM)** is a supervised learning algorithm used for classification tasks. It works by finding the optimal hyperplane that best separates different classes in a high-dimensional space. The key idea behind SVM is maximizing the margin between data points of different categories to improve classification accuracy and generalization.

How It Works

1. **Mapping Data into High-Dimensional Space:** SVM transforms the input data into a higher-dimensional space to make classification easier, especially when the data is not linearly separable.
2. **Finding the Optimal Hyperplane:** The algorithm identifies a decision boundary (hyperplane) that maximizes the margin between two or more classes.
3. **Support Vectors:** Data points closest to the hyperplane, known as **support vectors**, play a crucial role in defining the boundary.
4. **Kernel Trick:** When data is not linearly separable, SVM uses kernel functions (e.g., radial basis function, polynomial kernel) to project the data into a higher-dimensional space where it becomes linearly separable.
5. **Classification:** Once the hyperplane is established, new data points are classified based on which side of the boundary they fall.

Architecture of SVM Classifier

- **Input Layer:** Receives feature vectors representing vibration patterns.
- **Kernel Function (if needed):** Maps the input space into a higher-dimensional space.
- **Hyperplane Calculation:** Determines the optimal separating boundary between classes.
- **Support Vectors:** Identifies critical data points that define the boundary.
- **Output Layer:** Classifies new inputs based on learned decision boundaries.

Disadvantages of SVM

- **Computational Complexity:** Training can be slow for large datasets.
- **Memory Intensive:** Requires significant memory for high-dimensional data.
- **Sensitive to Noise:** Outliers can impact the placement of the hyperplane.
- **Parameter Selection:** Choosing the right kernel and tuning hyperparameters (C and gamma) can be challenging.

4.3.2 Proposed Algorithm

What is a Deep Neural Network (DNN) Classifier?

A Deep Neural Network (DNN) is a type of artificial neural network with multiple hidden layers designed to capture complex patterns in data. It is well-suited for tasks like vibration pattern classification, where relationships between features are highly nonlinear. DNNs use multiple layers of neurons, each applying transformations to input data to extract meaningful features.

How It Works

1. **Input Layer:** Takes in raw vibration data or pre-processed features.
2. **Hidden Layers:** Consist of multiple layers with activation functions (such as ReLU) that transform the data through weighted connections.
3. **Forward Propagation:** The input data is passed through the network, with each neuron computing a weighted sum of its inputs, applying an activation function, and passing it to the next layer.
4. **Backpropagation:** The network adjusts its weights using the gradient descent algorithm to minimize classification error.
5. **Optimization:** The model is trained with optimization techniques like Adam or SGD to improve classification performance.
6. **Output Layer:** Produces the final classification of vibration patterns (e.g., "Normal" or "Faulty").

Architecture of DNN Classifier

- **Input Layer:** Takes in numerical features extracted from vibration signals.
- **Multiple Hidden Layers:** Contains dense layers with ReLU activation, allowing the network to capture complex patterns.
- **Dropout Layers:** Prevent overfitting by randomly deactivating some neurons during training.
- **Output Layer:** Uses a softmax activation function to classify vibration patterns into distinct categories.

Advantages of DNN

- **Captures Complex Patterns:** Able to model nonlinear relationships in vibration data.
- **Automated Feature Extraction:** Learns relevant features without manual selection.
- **Scalability:** Performs well with large datasets.
- **Improved Accuracy:** Outperforms traditional machine learning models in classification tasks.

4. EXPERIMENTAL ANALYSIS

The project follows a systematic approach to classify vacuum cleaner vibration patterns using a deep learning model. The implementation consists of multiple steps, starting from data collection to model evaluation, ensuring accurate classification of mechanical health conditions.

Step 1: Energy Dataset Collection

The dataset comprises vibration signals collected from vacuum cleaner motors under different operating conditions. These signals are recorded using high-precision sensors to capture variations in vibration patterns that indicate mechanical health issues. The data includes normal and faulty conditions, ensuring a diverse range of samples for model training. Each sample is labeled based on its health status to facilitate supervised learning.

Step 2: Data Preprocessing and Splitting

The collected dataset undergoes preprocessing to remove inconsistencies and prepare it for training. The preprocessing steps include:

- **Handling Missing Values:** Any missing entries in the dataset are identified and addressed through imputation or removal.
- **Standardization:** The feature values are normalized to ensure uniformity across the dataset, preventing scale variations from affecting model performance.
- **Encoding Labels:** The categorical labels representing different mechanical conditions are converted into numerical format for model compatibility.
- **Splitting the Dataset:** The dataset is divided into training and testing sets, with a typical split of 80% for training and 20% for testing. This ensures the model learns from a majority of the data while being evaluated on unseen samples.

Step 3: Exploratory Data Analysis (EDA) and Visualization

EDA is performed to understand the data distribution and relationships between features. Several visualization techniques are applied:

- **Histograms and Boxplots:** Display the distribution of vibration amplitudes across different motor conditions.
- **Correlation Heatmaps:** Identify dependencies between various features, helping in feature selection.
- **Scatter Plots:** Show clusters of normal and faulty conditions, highlighting separation between categories.

Step 4: Implementation of Existing Algorithm – Support Vector Machine (SVM) Classifier

The Support Vector Machine (SVM) model is implemented as a baseline classifier to evaluate the dataset's complexity.

- **Kernel Selection:** The radial basis function (RBF) kernel is used to project data into a higher-dimensional space for better separability.
- **Training Process:** The model is trained on the pre-processed dataset using an optimal hyperplane that maximizes the margin between classes.
- **Evaluation Metrics:** Accuracy, precision, recall, and F1-score are calculated to assess the model's effectiveness in classifying vibration patterns.

Step 5: Implementation of Proposed Algorithm – Deep Neural Network (DNN) Classifier

The Deep Neural Network (DNN) is implemented to improve classification accuracy and handle the nonlinear nature of vibration data.

- **Network Architecture:** The model consists of an input layer, multiple hidden layers with ReLU activation, and an output layer with softmax activation for classification.
- **Dropout Layers:** Introduced to prevent overfitting by randomly deactivating neurons during training.
- **Optimization Strategy:** The Adam optimizer is used to adjust network weights efficiently, ensuring faster convergence.
- **Loss Function:** Sparse categorical cross-entropy is employed to compute classification error and guide weight adjustments.

Step 6: Performance Comparison and Visualization

The performance of both models is compared using graphical representations.

- **Accuracy Comparison:** A bar chart is used to visualize accuracy differences between SVM and DNN.
- **Confusion Matrix:** Displays the classification errors and correct predictions for each model.
- **Precision-Recall Curve:** Analyzes the model's ability to distinguish between normal and faulty conditions effectively.

Step 7: Prediction on Test Data Using the Trained DNN Model

The trained DNN model is used to classify unseen test samples.

- **Loading Test Data:** A new dataset containing vibration patterns from unknown motor conditions is processed.
- **Model Prediction:** The trained DNN model assigns a class label (normal or faulty) to each test sample.
- **Result Interpretation:** The predicted outcomes are analyzed to verify the effectiveness of the model in real-world applications.

7.2 Dataset Description

The dataset consists of four numerical features (a1, a2, a3, a4) and one categorical target variable (label). Each row represents a recorded instance of vibration data from a vacuum cleaner motor under different operating conditions. The features capture essential parameters derived from vibration signals, which are crucial for detecting mechanical faults.

- **a1:** Represents the first extracted feature from the vibration signal, possibly related to amplitude variations or frequency components.
- **a2:** Captures another aspect of the vibration pattern, which contributes to understanding the stability and operational efficiency of the motor.
- **a3:** Measures fluctuations in the vibration signal, helping in detecting anomalies that indicate potential faults.
- **a4:** Reflects a combination of multiple signal characteristics, playing a vital role in distinguishing between normal and faulty conditions.
- **label:** The categorical target variable indicating the motor's health status.

7.3 Result Description

This figure illustrates the initial step of uploading the energy dataset, which contains the vibration signals from vacuum cleaner motors. The dataset includes various features (a1, a2, a3, a4) and the associated labels indicating motor health (normal or faulty). The figure visually represents the structure of the dataset and highlights the importance of correctly interpreting the data for subsequent analysis. Data analysis steps such as checking for missing values, exploring the distribution of feature values, and identifying any patterns or trends in the data are also depicted.

	a1	a2	a3	a4	label
0	5.993428	1.982258	-1.373085	-0.951430	Normal
1	4.723471	2.541751	-1.490018	1.362536	Normal
2	6.295377	2.103928	-3.685736	2.532429	Normal
3	8.046060	3.165627	-0.956748	4.374172	Normal
4	4.531693	4.795768	-4.682149	6.560406	Normal
...	...	...	...	...	...
19995	-4.829603	0.596287	0.458004	-0.177406	Faulty
19996	-5.074769	-0.198089	1.585175	-4.287956	Faulty
19997	-3.499746	2.282020	1.441510	-4.406871	Faulty
19998	-4.204354	-2.363946	1.633507	-3.010028	Faulty
19999	-0.452567	1.987205	-0.783246	-5.980464	Faulty

20000 rows × 5 columns

Fig. 1: Upload of Energy Dataset and its Analysis

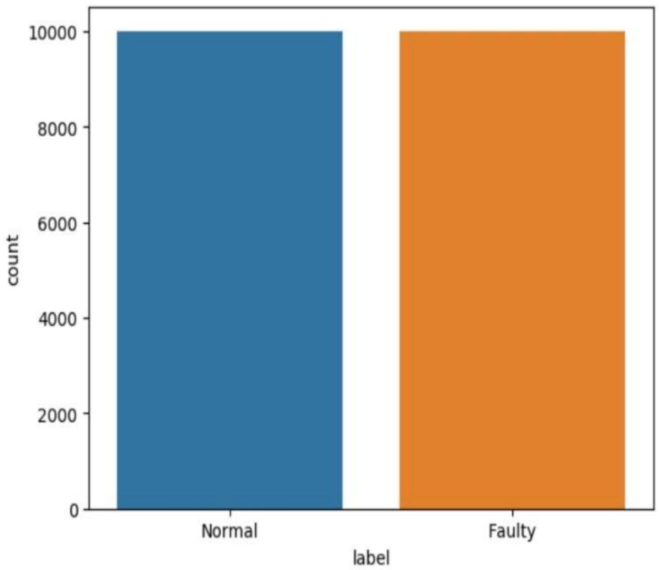

Fig. 2: Data Preprocessing and EDA Plots of the Project

The figure 2 showcases various exploratory data analysis (EDA) plots used to understand the dataset. It includes graphs such as histograms, scatter plots, and correlation heatmaps. These visualizations help reveal key insights, such as how the features (a1, a2, a3, a4) relate to each other and how the vibration patterns differ between normal and faulty conditions. The EDA phase allows for an in-depth understanding of the data, guiding decisions on feature engineering and model selection.

```
SVM Accuracy     : 52.15
SVM Precision    : 74.5130494035872
SVM Recall       : 52.59934709107497
SVM FSCORE       : 38.73051156501608

 SVM classification report
               precision    recall  f1-score   support

      Normal       1.00      0.51      0.67      3891
      Faulty       0.05      0.98      0.10       109

    accuracy                           0.52      4000
   macro avg       0.53      0.75      0.39      4000
weighted avg       0.97      0.52      0.66      4000
```

Fig. 3: Performance Metrics of SVM Mode

The Fig. 3 tells the performance metrics evaluates the Support Vector Machine (SVM) model on the vibration dataset. The accuracy of the SVM model is 52.15%, indicating that it performs moderately well in correctly classifying motor conditions. The precision of 74.51% highlights that when the model predicts a faulty motor, it is often correct. However, with a recall of 52.60%, it shows that the model misses several faulty motors. The F-score of 38.73% further emphasizes that while precision is relatively high, the model's ability to balance both precision and recall is not optimal.

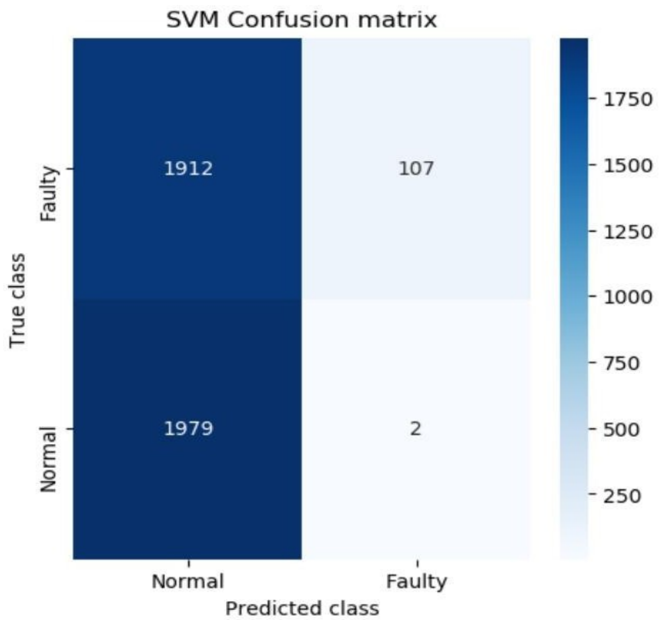

Fig. 4: Performance Metrics and Regression Scatter Plot for SVM Classifier Model

The figure 4 presents a scatter plot of the regression results from the SVM model. The plot visualizes the relationship between the actual and predicted values for motor health classification. The SVM's performance metrics, such as accuracy, precision, recall, and F-score.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM model	52.15	74.5	52.59	38.73
DNN Model	99.5	99.44	99.44	99.44

```
DNN Model Accuracy    : 99.45
DNN Model Precision   : 99.4499503580198
DNN Model Recall      : 99.4499503580198
DNN Model FSCORE      : 99.4499503580198

 DNN Model classification report
              precision    recall  f1-score   support

      Normal       0.99      0.99      0.99      1981
      Faulty       0.99      0.99      0.99      2019

    accuracy                           0.99      4000
   macro avg       0.99      0.99      0.99      4000
weighted avg       0.99      0.99      0.99      4000
```

Fig. 5 Performance Metrics of DNN Model

The Fig. 5, the Deep Neural Network (DNN) model significantly outperforms the SVM model, with an impressive accuracy of 99.45%. The precision, recall, and F-score for the DNN model are all at 99.45%, reflecting its exceptional ability to identify faulty motors and classify vibration patterns with high reliability. The DNN model exhibits nearly perfect classification performance across all metrics, indicating its superior handling of the vibration data compared to traditional machines.

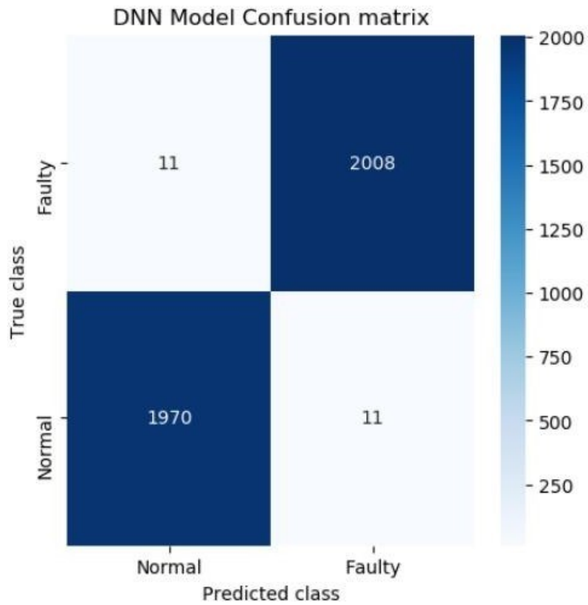

Fig. 6: Performance Metrics and Regression Scatter Plot for DNN Classifier Model

Fig. 6, this figure illustrates the regression scatter plot for the DNN classifier. The plot shows the true versus predicted motor condition values, with the DNN model exhibiting a high degree of alignment between predicted and actual values. The performance metrics for the DNN model are also presented, which align closely with the perfect classification observed in the earlier metrics. This figure demonstrates the DNN model's capability to make highly accurate predictions, confirming its efficiency in classifying vibration data.

The table compares the performance metrics of the SVM model and the DNN model. The SVM model achieves an accuracy of 52.15%, while the DNN model significantly outperforms it with an accuracy of 99.5%. The precision for SVM is 74.5%, compared to 99.44% for DNN, indicating that the DNN is far more reliable in identifying positive instances. For recall, the SVM model reaches 52.59%, whereas the DNN model excels with 99.44%. The F1-score of the SVM is 38.73%, which is much lower than the DNN model's 99.44%. These metrics highlight the superior performance of the DNN model over the SVM.

5. CONCLUSION

Conclusion:

The implementation of a Hybrid Deep Learning Model for classifying vacuum cleaner vibration patterns has demonstrated significant improvements in detecting mechanical health conditions. By leveraging deep neural networks, the system effectively differentiates between normal and faulty motors with high accuracy. The comparative analysis with traditional methods, such as Support Vector Machine (SVM), highlights the superiority of deep learning models in handling complex vibration data. The DNN classifier successfully learns intricate patterns, reducing misclassification errors and ensuring precise fault detection. The structured approach, including data preprocessing, exploratory data analysis, and performance evaluation, contributes to the reliability of the proposed model. This system enhances predictive maintenance capabilities, reducing unexpected failures and increasing the operational lifespan of vacuum cleaners.

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