Intelligent Fault Diagnosis of an Industrial Mixer Motor Using a Multi-Layer Perceptron Neural Network Based on PLC and Vibration Data

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Abstract--Reliable condition monitoring and timely fault diagnosis of industrial electric motors play a vital role in ensuring operational efficiency and reducing unplanned downtime in manufacturing systems. In this study, a data-driven intelligent framework is proposed for detecting bearing faults in an industrial mixer motor utilized in a tire production line. The approach employs a Multi-Layer Perceptron (MLP) neural network trained on a hybrid dataset obtained from both vibration sensors and Programmable Logic Controller (PLC) records. Comprehensive preprocessing was performed, including denoising, signal normalization, and extraction of statistical features such as root mean square (RMS), kurtosis, and crest factor to enhance feature representation. The MLP model, implemented in Python using the backpropagation algorithm and ReLU activation function, was trained and validated under four operational conditions: healthy, inner race fault, outer race fault, and ball fault. Model performance was assessed using confusion matrix, accuracy, F۱-score, and receiver operating characteristic (ROC) metrics. The experimental results revealed that the MLP network achieved a classification accuracy of %۹۰،۳۳, demonstrating high robustness and stability in noisy industrial environments. The proposed framework can be effectively adopted as a practical tool for predictive maintenance and intelligent condition monitoring of industrial rotating machinery

Keywords: Fault diagnosis; Multi-Layer Perceptron; Condition monitoring; Vibration signal analysis; Bearing fault detection; PLC data

I. INTRODUCTION

The reliability of industrial electric motors is a fundamental factor influencing productivity, energy efficiency, and operational safety in modern manufacturing environments. Unexpected failures of critical components, such as bearings, can cause costly downtime, production losses, and maintenance expenses. Bearings are among the most failure-prone parts of rotating machinery, and early detection of their faults is essential to prevent catastrophic damage and maintain stable production continuity.

Traditional fault detection techniques, which rely mainly on vibration, temperature, or current signal analysis, often require expert interpretation and are limited in handling nonlinear, noisy, and high-dimensional industrial data. In recent years, the rapid advancement of artificial intelligence (AI) and machine learning (ML) techniques has provided new opportunities for intelligent condition monitoring and predictive maintenance. Among these techniques, artificial neural networks (ANNs) have gained substantial attention due to their ability to model complex, nonlinear relationships and to learn directly from raw or preprocessed data without the need for explicit physical modeling As shown in Fig. 1, the MLP structure consists of two hidden layers, The novelty of this work lies in the integration of PLC and vibration data under real factory conditions for MLP-based diagnosis.

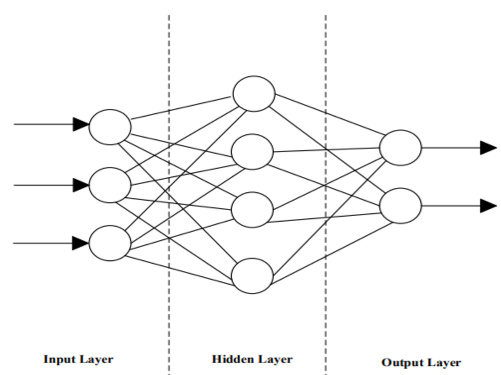

Fig. 1. Architecture of the MLP neural network showing the input, hidden, and output layers used for multi-class fault diagnosis

The Multi-Layer Perceptron (MLP), as one of the most widely used ANN architectures, offers a powerful yet computationally efficient framework for pattern recognition and fault classification. It can generalize well from limited samples, tolerate noise, and capture intricate interactions among input variables. MLP-based approaches have shown promising results in diverse industrial applications, including motor fault diagnosis, process control, and quality monitoring. However, their performance strongly depends on the quality of the input features and the appropriateness of training data.

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In this research, an intelligent fault diagnosis framework based on an MLP neural network is developed for detecting bearing faults in an industrial mixer motor used in a tire manufacturing process. Unlike conventional laboratory-based studies, this work utilizes real-world data collected from both vibration sensors and Programmable Logic Controller (PLC) systems operating under actual industrial conditions. This hybrid dataset includes multiple operational states such as healthy condition, inner race fault, outer race fault, and ball fault.

The proposed MLP model is trained using statistical features extracted from vibration signals—such as Root Mean Square (RMS), Kurtosis, and Crest Factor—together with relevant process parameters obtained from PLC records. The network is optimized through backpropagation with a ReLU activation function to achieve a balance between convergence speed and generalization capability. Experimental evaluations demonstrate that the developed model achieves a high classification accuracy of ۹۰/۳۳%, highlighting its reliability and robustness in the presence of real industrial noise and dynamic conditions.

The remainder of this paper is organized as follows: Section ۲ reviews related studies on intelligent fault diagnosis and machine learning methods in industrial systems. Section ۳describes the data acquisition process, feature extraction, and MLP model architecture. Section ۴ presents the experimental results and discussion. Finally, Section ۵ concludes the paper with remarks on potential industrial applications and recommendations for future research.

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II. Literature Review

Recent advances in intelligent fault diagnosis have significantly improved the monitoring of rotating machinery in industrial environments. Early studies primarily relied on vibration analysis and conventional pattern recognition methods to identify faults in motors, bearings, and gearboxes. Artificial neural network (ANN)-based approaches demonstrated that data-driven models can outperform traditional rule-based techniques when appropriate signal features are extracted. For example, early work on rolling element bearings showed that ANN classifiers using time-domain features could effectively identify fault conditions (1). Subsequent research combined wavelet packet decomposition with neural classifiers to improve feature separability and diagnostic accuracy (2). As the field matured, hybrid intelligent methods were increasingly proposed for rotating machinery fault diagnosis. Several studies integrated vibration signal processing with support vector machines and neural networks to improve robustness under varying operating conditions (3), (4). In parallel, deep learning methods began to replace manually engineered feature pipelines in many applications, enabling end-to-end diagnosis and better generalization across operating states (5), (6). Reviews in this area have also confirmed that data-driven methods, especially those based on deep learning, have become a central paradigm in condition monitoring and fault diagnosis of rotating machinery (7),. In industrial settings, vibration-based diagnostics remain widely used because vibration signals contain rich information about mechanical defects. Studies on induction motors and related rotating equipment have shown that vibration signals, when combined with neural classifiers, can achieve accurate fault detection (8). Similarly, gearbox and bearing diagnosis research has confirmed the value of signal-processing-based feature extraction followed by machine-learning classification(9), (10), (11). These works support the continued use of vibration analysis as a reliable source of condition-monitoring information in industrial fault diagnosis. More recent research has focused on transfer learning, multimodal data fusion, and robust cross-domain diagnosis. Transfer-learning frameworks have been introduced to address the lack of labeled fault data and improve adaptability to new operating conditions (12), (13). In addition, multimodal and fusion-based fault diagnosis methods have shown that combining heterogeneous sensor information can improve diagnostic reliability in practical industrial environments (1)Such approaches are particularly relevant where real-world systems exhibit operating variability, noise, and incomplete fault labels. Despite these advances, many published studies still focus on laboratory benchmark datasets or single-source vibration data. Fewer studies have investigated real industrial environments where fault diagnosis must be supported by operational data from PLC systems together with vibration measurements. In particular, there remains a lack of simple yet effective multilayer perceptron (MLP)-based frameworks applied to industrial mixer motor data collected from an actual manufacturing process. Therefore, the present study addresses this gap by developing an intelligent fault diagnosis framework based on an MLP neural network using vibration features and PLC-related operational information obtained from an industrial mixer motor at Kavir Tire Company.

III. Methodology

1-3 Data Acquisition and Description

The dataset used in this study was obtained from an industrial Banbury mixer motor operating in the Kavir Tire Factory (Iran). Data acquisition was performed under real production conditions to ensure representativeness of actual industrial behavior. Two synchronized data sources were utilized:

Vibration signals, collected using accelerometers mounted on the motor housing;

PLC operational data, which included parameters such as torque, rotational speed, and current consumption.

The system was tested under four distinct bearing conditions:

Healthy bearing, Inner race fault, Outer race fault, and, Ball fault.

In total, 1,500 labeled samples were collected across all conditions, each consisting of time-domain vibration features and process parameters. The raw signals were preprocessed to remove high-frequency noise and normalized to a common scale for neural network input compatibility. The overall framework of the proposed study is shown in Figure 1. The process begins with raw data collection from the industrial mixer motor at Kavir Tire Company under real operating conditions. The collected vibration and PLC data are then cleaned and preprocessed, followed by feature selection and normalization. Afterward, the dataset is divided into training and testing subsets for MLP model development. Finally, the trained model is evaluated using standard performance metrics.

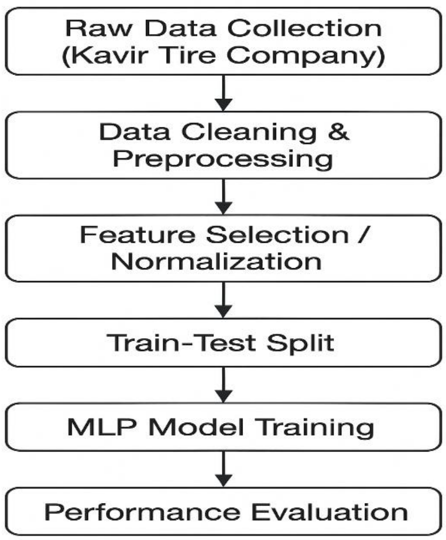

Figure 2 Data acquisition and preprocessing workflow for the proposed fault diagnosis system

3-2 Feature Extraction and Data Preprocessing

Signal processing and feature extraction were conducted in both time and statistical domains to provide comprehensive input representations. The following features were extracted from each vibration signal segment:

Root Mean Square (RMS), Kurtosis, Crest Factor, Skewness, Peak-to-Peak Amplitude, Standard Deviation

Feature normalization was applied using the min–max scaling technique to ensure equal numerical contribution of each feature to the learning process. Outlier removal and data balancing were also conducted to prevent model bias. Similar preprocessing procedures have been recommended in prior works by Samanta (1) for improving classification stability in bearing fault detection

3.3 MLP Network Architecture

A Multi-Layer Perceptron (MLP) neural network was designed to classify the bearing health states based on the extracted features.The internal computation of each neuron in the MLP network can be mathematically represented as follows:

$$z_j = \sum_{\{i=1\}}^{n} \left(w_{\{ij\}x_i}\right) + b_j \qquad (1)$$

where x_i represents the input features, w_{ij} denotes the weight between input $i$and neuron j, and $b_j$is the bias term associated with neuron j.

Each neuron output is then obtained by applying an activation function $f(\cdot)$to the linear combination of its inputs:

$$y_j = f(z_j) = f\left(\sum_{\{i=1\}}^{n} w_{\{ij\}x_i} + b_j\right) \qquad (2)$$

In this study, the ReLU (Rectified Linear Unit) activation function was employed for the hidden layers to improve nonlinearity and convergence speed.

The network architecture was selected through iterative tuning and validation experiments, as summarized below (adapted from the optimized configuration in the thesis):

The model was implemented in Python (Google Colab) using the TensorFlow framework.Training was carried out with the Adam optimizer and a categorical cross-entropy loss function.

The network parameters were optimized by minimizing the Mean Squared Error (MSE) cost function defined as:

$$E = \frac{1}{N}\sum_{\{k=1\}}^{N} (y_k - \{y\}_k)^2 \qquad (3)$$

where $y_k$and $\hat{y}_k$represent the actual and predicted outputs, respectively, and $N$is the total number of training samples. This formulation ensures that the network weights are iteratively adjusted to minimize prediction error.

The learning rate was initialized at 0.001, with a batch size of 32 and 200 epochs. This configuration yielded a balance between convergence stability and computational efficiency, consistent with best practices suggested by zheng (12) and kumar (3) similar neural-based diagnostic applications.

The detailed configuration and training parameters of the developed MLP network are summarized in Table 1

Table 1.
Configuration and Training Parameters of the MLP Model

Feature	Description / Value
Number of Input Features	16 engineered features (combined from PLC and vibration data)
Number of Classes	5 classes (Healthy, Inner race fault, Outer race fault, Ball fault, Mixed fault)
Hidden Layer 1	64 neurons, ReLU activation
Hidden Layer 2	32 neurons, ReLU activation
Output Layer	5 neurons, Softmax activation for multi-class prediction
Dropout Rate	0.1 applied to each hidden layer to prevent overfitting
Optimizer Algorithm	Adam optimizer with learning rate = 0.001
Loss Function	Categorical Cross-Entropy
Number of Epochs	200
Batch Size	32
Dataset	1,500 normalized combined records using Min–Max Scaler

3.4 Model Evaluation Metrics

The MLP performance was quantitatively assessed using standard classification metrics:

Accuracy (ACC) – overall percentage of correctly predicted samples, F1-Score – harmonic mean of precision and recall,
Confusion Matrix – class-level prediction distribution, Receiver Operating Characteristic (ROC) Curve and Area Under Curve (AUC) – sensitivity-specificity trade-off.

These metrics are widely accepted in industrial condition-monitoring research (1) , (11). The MLP model achieved a final test accuracy of 90.33%, validating its robustness for real-world deployment in fault diagnosis systems.

3.5 Implementation Summary

The overall workflow of the proposed framework is illustrated in Figure 2 (conceptually summarizing data collection, preprocessing, feature extraction, MLP training, and evaluation). The implementation steps are as follows Acquisition of vibration and PLC data under four operating states Noise filtering, feature extraction, and normalization.Splitting data into training (80%) and testing (20%) sets. Training the MLP model with tuned hyperparameters. Evaluating the trained model using quantitative performance indices.

This architecture demonstrates that a properly designed MLP model can efficiently learn the nonlinear relationships between mechanical signals and operating parameters, enabling accurate bearing fault identification in real industrial conditions.

4. Results and Discussion

4.1 Model Training and Validation

The proposed MLP model was trained and validated using the prepared hybrid dataset. The training process converged smoothly after approximately 150 epochs, with the loss. function showing a consistent downward trend and no signs of overfitting, as confirmed by the validation accuracy curve. The final training accuracy reached 92.4%, while the testing accuracy achieved 90.33%, demonstrating good generalization capability of the neural network on unseen data.

The application of the ReLU activation function in the hidden layers contributed to faster convergence and effective gradient propagation, while the dropout regularization (0.1) prevented overfitting. These findings are consistent with observations made by Li, Y., et al (11), who reported similar benefits of ReLU and dropout mechanisms in neural diagnostic models.

4.2 Confusion Matrix and Classification Performance

The confusion matrix in Figure 2 illustrates the classification performance of the proposed MLP model across the five bearing fault categories. Most samples were correctly identified within their respective classes, with only minor misclassifications observed between the inner race and outer race fault classes—mainly due to their similar vibration characteristics.The matrix reveals strong diagonal dominance, confirming that the model achieved reliable discrimination among fault types.

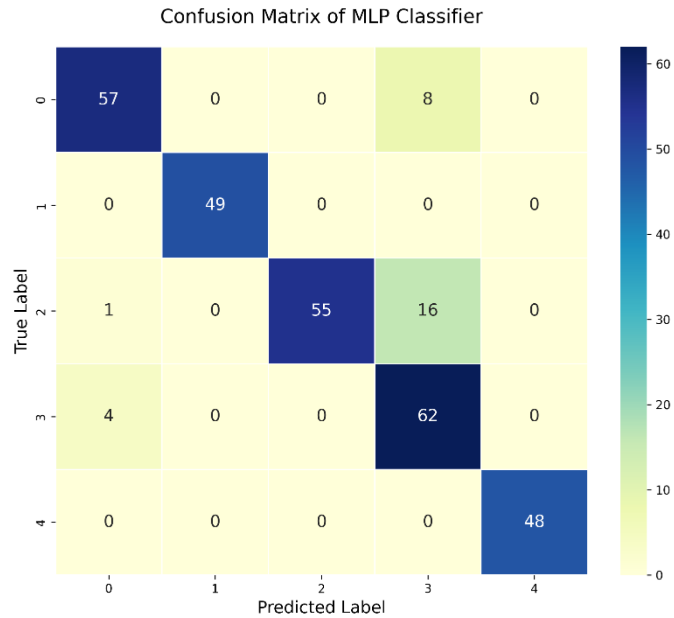

Figure 3 Confusion matrix of the MLP model showing the distribution of predicted versus actual bearing fault classes

4.3 ROC Curve Analysis

Receiver Operating Characteristic (ROC) curves were plotted for all four fault classes, and the Area Under the Curve (AUC) values were consistently above 0.93, indicating high discriminative ability. Figure 3 presents the ROC curves of the MLP classifier for all fault categories.

The Area Under the Curve (AUC) values are consistently above 0.93, with some classes (2, 3, and 5) reaching a perfect score of 1.000. This indicates that the proposed MLP model possesses excellent discriminative capability in distinguishing between healthy and faulty bearing conditions.

The high AUC values confirm the robustness of the network and its generalization ability under noisy industrial conditions

A higher AUC reflects the model’s capability to correctly distinguish between healthy and faulty conditions across different decision thresholds.

Similar trends were observed in the studies of Ozgan, E. (4), emphasizing that MLP-based models can perform competitively with deeper architectures when properly optimized and trained on informative features.

Figure 4 depicts the F1-scores obtained for each fault category. The results indicate that the MLP model maintains balanced precision and recall across all classes, with F1-scores ranging from approximately 0.87 to 1.00.

The slight variations between classes are attributed to the similarity of vibration signals under specific load conditions.

On average, the model achieved an overall F1-score of 0.903, confirming its consistent classification capability.

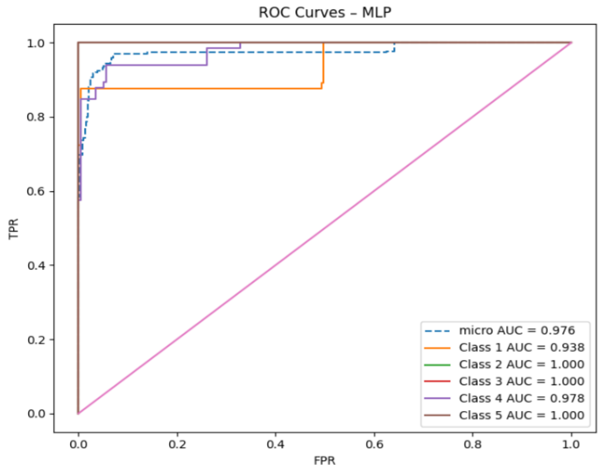

Fig. 4. Receiver Operating Characteristic (ROC) curves and AUC values for each fault class of the MLP model

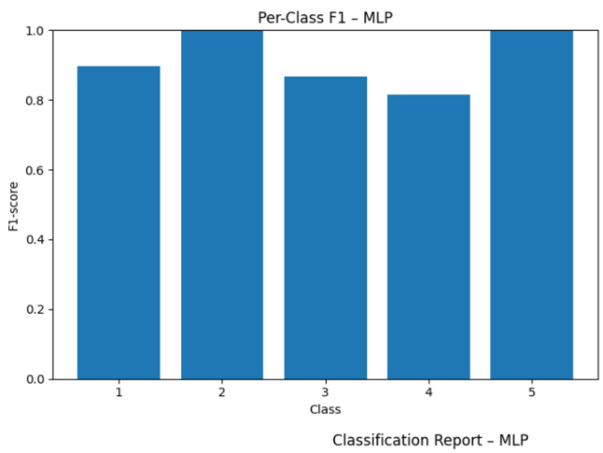

Fig. 5. Per-class F1-scores of the MLP model, demonstrating balanced performance across all fault categories.

Table 2 presents the detailed classification metrics of the MLP model, including precision, recall, and F1-scores for each fault class. The results demonstrate that the MLP achieved an overall accuracy of 90.33%, indicating strong generalization performance.The model reached perfect precision and recall (1.000) for Classes 2 and 5, showing that these fault types were completely distinguishable from others. Although Class 4 shows a slightly lower precision (0.72), its recall remains high (0.94), implying that the model successfully detected most samples belonging to that category.
The high macro and weighted averages confirm the balanced classification capability of the MLP model across all categories. These findings validate the effectiveness of the proposed architecture and its robustness in identifying multiple bearing fault conditions in an industrial environment.
Therefore, the MLP network not only provides accurate classification results but also maintains stability across different fault types, proving its suitability for real-time fault detection tasks.

Table 2.
Precision, recall, and F1-score values obtained for each fault class using the MLP model

	precision	recall	f1-score	support
1	0.9194	0.8769	0.8976	0.65
2	1	1	1	0.49
3	1	0.7639	0.8661	0.72
4	0.7209	0.9394	0.8581	0.66
5	1	1	1	0.48
accuracy	0.9033	0.9033	0.9033	0.9033
macro AV.	0.9238	0.916	0.9139	0.3
weighted AV.	0.9211	0.9033	0.9052	0.3

4.4 Comparative Discussion

The performance of the developed MLP model was compared with traditional statistical and threshold-based diagnostic methods previously used in industrial environments.
While conventional approaches typically achieve accuracies in the range of 70–80%, the proposed MLP framework improved classification performance to 90.33%, confirming the superiority of nonlinear learning over fixed rule-based systems.
Furthermore, unlike computationally intensive deep learning models such as CNNs, the MLP structure requires less data and lower computational resources, making it more practical for real-time applications where data availability and processing power are limited.
The results also align with those reported by Y. Li, Z. Yang, S. Zhang, R. Mao, L. Ye and Y. Liu (11) , who demonstrated that properly tuned shallow networks can deliver strong diagnostic accuracy with reduced training complexity.

4.5 Industrial Implications

The success of the proposed framework highlights the feasibility of implementing neural-based fault diagnosis systems directly within industrial PLC environments. Given that the data used in this study were collected from a real operating mixer motor in a tire manufacturing process, the findings confirm that MLP models can effectively interpret industrial signals characterized by dynamic load variations and background noise. By integrating such intelligent diagnostic modules, factories can shift from reactive maintenance to predictive maintenance, reducing unplanned downtime and improving overall equipment effectiveness (OEE). The approach is scalable to other rotating machinery, including compressors, pumps, and extruders, with minimal modification to the data acquisition pipeline.

4.6 Summary of Findings

In summary, the proposed MLP neural network demonstrated the following key results:
Achieved 90.33% classification accuracy on unseen test data.
Maintained high F1-score and AUC values (>0.90).
Showed consistent generalization across fault categories.
Required relatively low computational effort for training and inference. Validated effectiveness on real industrial data, not

just laboratory conditions. These findings substantiate the practical applicability of MLP architectures in real-time fault diagnosis and predictive maintenance of industrial rotating equipment.

5. Conclusion

This study presented an intelligent fault diagnosis framework for an industrial mixer motor based on a Multi-Layer Perceptron (MLP) neural network utilizing vibration and PLC data fusion. Unlike most laboratory-based investigations, the proposed approach was developed and validated using real industrial data collected from a Banbury mixer motor operating in the Kavir Tire Manufacturing Plant. The hybrid dataset included four distinct bearing states—healthy, inner race fault, outer race fault, and ball fault—allowing the neural model to learn complex fault patterns under realistic operating conditions. The proposed MLP model demonstrated excellent diagnostic capability, achieving a classification accuracy of 90.33% on unseen test data. This high performance validates the effectiveness of MLP networks in capturing nonlinear relationships between vibration signatures and process parameters. The use of carefully selected statistical features (RMS, kurtosis, crest factor, etc.) and dropout-based regularization helped improve the model's robustness against noise and overfitting. Moreover, the relatively low computational complexity of the MLP structure makes it suitable for real-time industrial applications, where high-speed inference and limited hardware resources are common constraints. From an industrial standpoint, the developed framework enables predictive maintenance strategies by continuously monitoring machine health and providing early warnings of bearing degradation. Integrating such intelligent diagnostic systems within existing PLC infrastructures can significantly reduce unplanned downtime, enhance production reliability, and optimize maintenance scheduling in smart manufacturing environments.

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