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Development of a Deep Neural Network Model for Prediction of Machine Vibration

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ABSTRACT
The reliability of induced draft (ID) fans in cement production is critical to ensuring operational continuity, energy efficiency, and cost-effective maintenance. Excessive vibration in these fans often triggered by unbalance, misalignment, and bearing defects can lead to catastrophic failures, unplanned downtime, and increased operational expenses. This study presents the development of a deep neural network (DNN) model for predicting vibration anomalies in cement mill fans. Vibration signals were collected over a 34-week period from multiple sensors installed on induced draft fans at a cement production mill in Nigeria. Statistical time-domain features, including root mean square (RMS), kurtosis, crest factor, and impulse factor, were extracted and processed through advanced feature engineering and selection techniques. A Multi-Layer Perceptron (MLP)-based deep neural network was then designed, trained, and optimized in MATLAB. The model achieved high classification accuracy and robust generalization across different operational conditions. Furthermore, a real-time monitoring application was developed in MATLAB App Designer, enabling interactive visualization and prediction from Excel-based sensor inputs. The findings underscore the significance of integrating artificial intelligence into predictive maintenance workflows, demonstrating that deep learning-driven vibration prediction can enhance machine reliability, reduce downtime, and support the industry 4.0 agenda in cement manufacturing and other process industries.
Keywords:
induced draft (ID), deep neural network (DNN), predicting vibration, Vibration signals

INTRODUCTION

Industrial machinery, particularly rotating equipment such as induced draft (ID) fans, plays an indispensable role in cement manufacturing. These fans support vital processes, including raw material handling, clinker cooling, kiln operation, and dust collection, by regulating airflow and maintaining appropriate process conditions (Jahn et al., 2019). The reliability of ID fans is therefore central to maintaining the efficiency, quality, and safety of cement production. However, their continuous operation under high temperature, abrasive dust, and fluctuating load conditions makes them highly susceptible to vibration-induced failures (Zaki et al., 2023).

Excessive vibration in cement mill fans arises primarily from mechanical imbalances, shaft misalignment, rotor eccentricity, and bearing wear (Eskandari et al., 2016). These issues compromise structural integrity, accelerate wear, and increase the risk of catastrophic breakdowns. Traditional maintenance strategies whether reactive or preventive often fail to address these challenges adequately. Reactive maintenance incurs significant costs due to unplanned downtime, while preventive maintenance may lead to unnecessary part replacements and inflated expenses (Malliotakis et al., 2021). Predictive maintenance, in contrast, offers a more intelligent approach by leveraging sensor data and machine learning algorithms to forecast failures before they occur (Meddaoui et al., 2023).

In recent years, the rise of machine learning and deep learning techniques has transformed predictive maintenance from an experimental concept to a practical reality. Traditional machine learning algorithms such as Random Forest, Support Vector Machines, and k-Nearest Neighbours have demonstrated strong performance in classifying fault conditions (Zaki et al., 2023). However, their ability to capture complex nonlinear relationships and temporal dependencies in vibration signals is limited. Deep learning architectures, particularly Multi-Layer Perceptron (MLPs), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), are better suited for handling high-dimensional vibration data, enabling automatic feature learning and more accurate predictions (Shiri et al., 2023).

This study aims to develop and implement a deep neural network model capable of predicting ID fan vibrations in real time, thereby supporting proactive maintenance strategies. Specifically, the research integrates feature engineering and deep learning modelling to detect early-stage anomalies in cement mill fans. Building upon prior work on vibration feature extraction and selection (Ani et al., 2025). The study applies a structured pipeline comprising data acquisition, preprocessing, feature extraction, DNN model training, and validation. A MATLAB-based monitoring tool was also designed for interactive prediction and visualization, enhancing usability for plant maintenance engineers.

By embedding deep learning into the predictive maintenance framework, this research contributes to the broader Industry 4.0 transformation. It not only enhances equipment reliability in cement manufacturing but also provides a transferable methodology applicable to other industrial sectors reliant on rotating machinery.

Literature Review

Predictive maintenance (PdM) has emerged as a transformative approach in industrial operations, allowing failures to be anticipated before they occur through continuous monitoring and data-driven analysis. Unlike reactive and preventive strategies, PdM leverages sensor data such as vibration, temperature, and current to reduce downtime, extend equipment life, and optimize maintenance schedules (Thomas & Weiss, 2021; Meddaoui et al., 2023). In cement manufacturing, PdM is particularly critical for induced draft (ID) fans, whose failures disrupt process continuity and incur high operational costs (Conklin et al., 2011; Zaki et al., 2023).

Machine learning (ML) has been widely applied in vibration-based diagnostics of rotating machinery. Techniques such as Random Forests, Support Vector Machines (SVMs), and k-Nearest Neighbours (k-NN) have demonstrated strong predictive accuracy in classifying machine conditions (Jia & Sharma, 2021). However, these models often rely heavily on manual feature engineering and may struggle to capture the nonlinear and temporal dynamics inherent in vibration signals (Campos Olivares et al., 2023). Recent advances in feature selection—such as Principal Component Analysis (PCA), ReliefF, and Chi-square methods—have been shown to improve model performance and reduce computational burden by isolating the most informative predictors (Ani et al., 2025). Deep learning (DL), a subset of ML, has gained prominence for its ability to automatically extract hierarchical features from raw or minimally processed data. Architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, have been successfully applied in predictive maintenance to capture spatial and temporal dependencies in vibration data (Shiri et al., 2023). Multi-Layer Perceptron (MLPs) also remain highly effective when combined with statistical time-domain features, offering strong generalization in structured datasets (El-Ghaish et al., 2024; Wang et al., 2024).

Despite these advances, challenges remain in deploying DL models for industrial vibration prediction. These include the need for large, high-quality datasets, difficulties in model interpretability, and computational requirements for real-time applications (Pandey et al., 2023; Dong et al., 2023). Nevertheless, integration of DL models into predictive maintenance systems aligns with Industry 4.0 initiatives, enabling smarter, more autonomous monitoring of critical assets (Cavalieri & Salafia, 2020).

In summary, the literature highlights the growing effectiveness of deep neural networks in vibration prediction. By combining robust feature engineering with optimized neural network architectures, recent research demonstrates that proactive and intelligent fault detection is achievable in cement manufacturing and beyond.

METHODOLOGY

Research Framework

The methodological framework for this study followed five major stages: (i) data acquisition from induced draft (ID) fans, (ii) preprocessing and cleaning of vibration signals, (iii) feature extraction and selection, (iv) development and training of a deep neural network model, and (v) validation and deployment in a real-time monitoring system. Figure 1 illustrates the overall workflow, adapted from Ani et al. (2025).

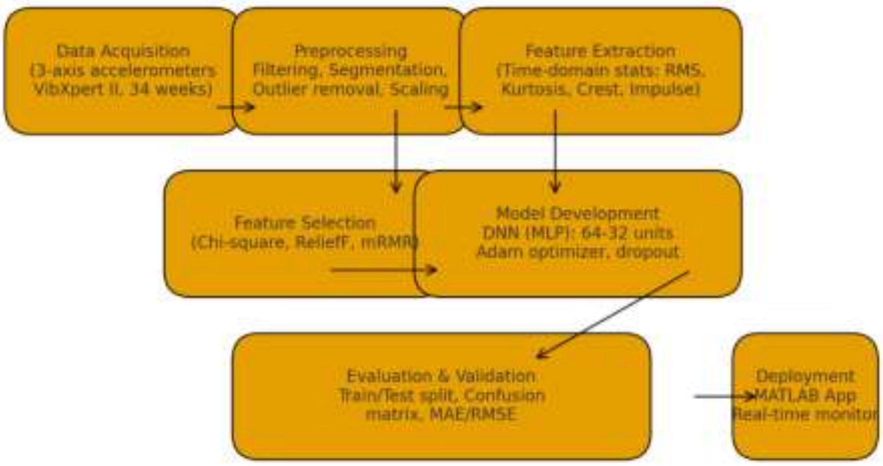

Figure 1. Research framework for developing a deep neural network vibration prediction model

Data Collection

Vibration data were collected from Line 3 induced draft fans at Dangote Cement Plc., Obajana, Nigeria. The fans, rated at 5000 kW, are critical in maintaining airflow for cement milling operations. Data were acquired using Prüftechnik VibXpert II analysers equipped with high-frequency accelerometers (VIB 6.140) installed at both drive-end and non-drive-end bearings. Measurements were taken along three orthogonal axes (horizontal, vertical, and axial), ensuring a comprehensive capture of vibration dynamics. Over 34 weeks of continuous monitoring, more than 7,000 data points were recorded under diverse operating conditions.

Data Preprocessing

The raw vibration signals were subjected to preprocessing to improve signal quality and model readiness. This involved:

a. Noise reduction using band-pass filtering to eliminate irrelevant frequency components.
b. Outlier detection and removal to address spurious spikes.
c. Normalization and scaling to ensure comparability across sensor channels.
d. Segmentation of signals into fixed-length windows to preserve temporal characteristics.

These preprocessing steps reduced variability and enhanced the reliability of subsequent feature extraction (Fan et al., 2021).

Feature Extraction and Selection

Time-domain statistical features were computed from the preprocessed vibration signals. Extracted features included root mean square (RMS), peak value, kurtosis, crest factor, clearance factor, shape factor, impulse factor, signal-to-noise ratio (SNR), total harmonic distortion (THD), and signal-to-noise and distortion ratio (SINAD). These features are widely recognized as sensitive indicators of fault development in rotating machinery (Hamdi et al., 2015; Ani et al., 2025).

Feature selection was performed using Chi-square statistics, ReliefF, and Minimum Redundancy Maximum Relevance (mRMR) to isolate the most informative predictors. The Chi-square method, in particular, yielded optimal results, enabling dimensionality reduction without compromising predictive performance. This ensured efficient model training and reduced computational overhead.

Deep Neural Network Architecture

A Multi-Layer Perceptron (MLP) architecture was implemented in MATLAB (R2023b). The network structure comprised:

a. Input layer: Selected statistical features (dimensionality reduced via feature selection).
b. Two hidden layers: 64 and 32 neurons, respectively, with Rectified Linear Unit (ReLU) activation.
c. Output layer: Four neurons with Softmax activation, corresponding to machine states (healthy, unbalanced, misaligned, bearing fault).

The network was trained using the Adam optimizer, with a learning rate of 0.001, batch size of 32, and 100 epochs. To avoid overfitting, early stopping and dropout regularization (rate = 0.2) were applied.

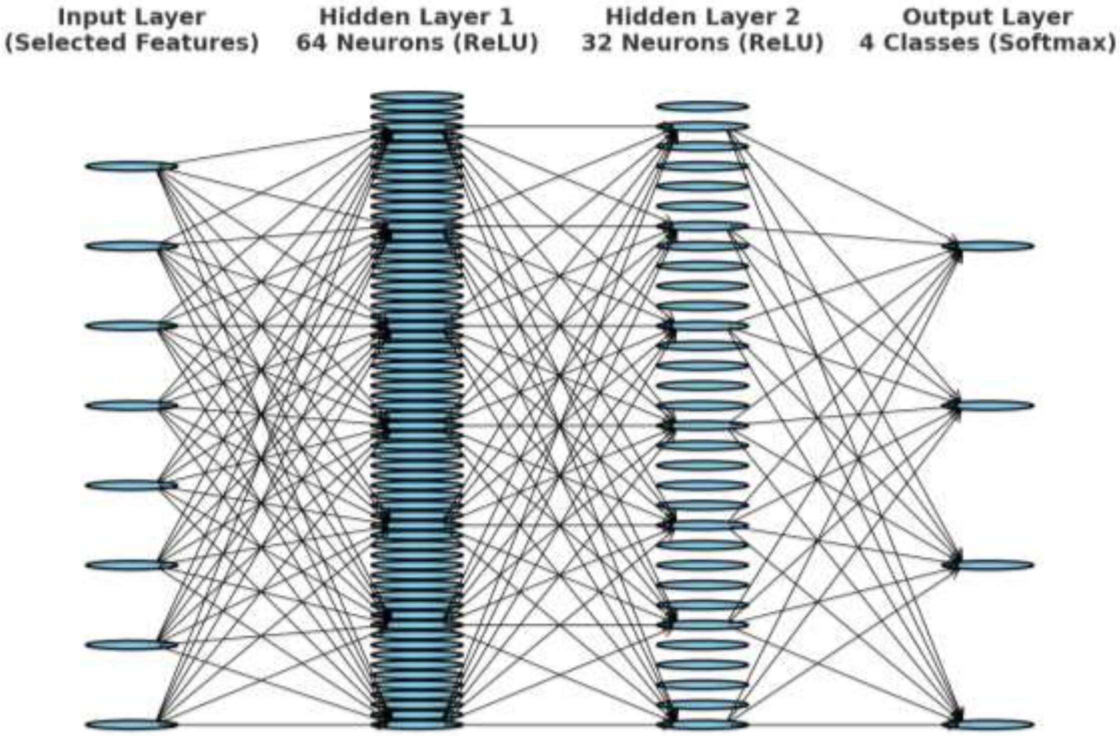

Figure 2. Deep neural network architecture for vibration prediction

Model Evaluation

The model was validated using a train-test split (70:30) with stratified sampling to maintain class distribution. Performance metrics included:

a. Accuracy
b. Precision, Recall, and F1-score
c. Confusion matrix analysis
d. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for regression-based evaluations.

These metrics ensured comprehensive assessment of classification capability and robustness across varying operating conditions (Zaki et al., 2023; Shiri et al., 2023).

Real-Time Application Development

To enhance usability, a MATLAB App Designer interface was developed for real-time monitoring. The application enables:

a. Import of vibration data from Excel files.
b. Signal visualization (time and frequency domain).
c. Automated classification using the trained neural network.
d. Export of prediction results for maintenance decision-making.

This tool bridges the gap between advanced analytics and operational practice, empowering maintenance engineers with actionable insights in real time.

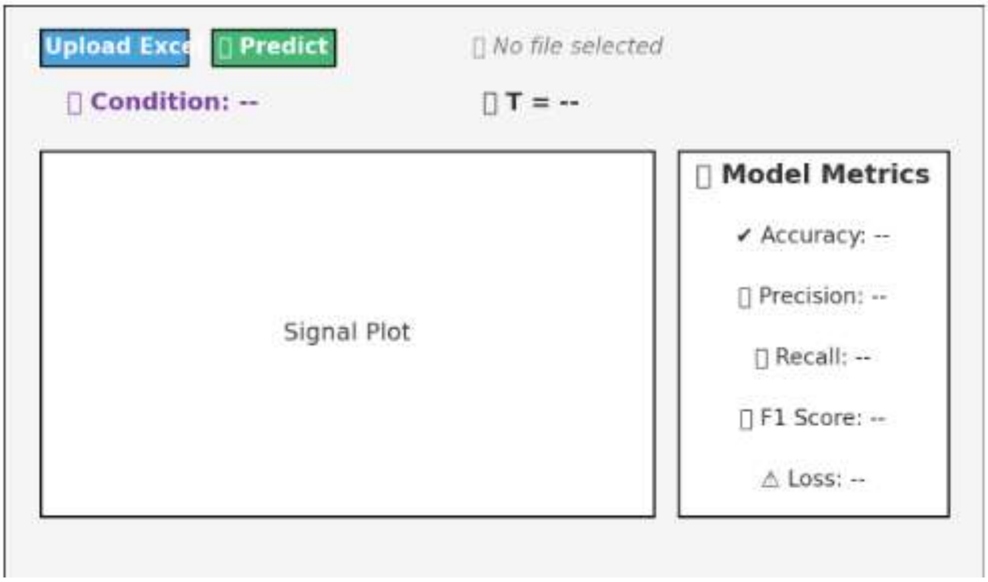

Figure 3. MATLAB App Designer interface for vibration monitoring and prediction.

RESULTS

Model Training and Convergence

The Multi-Layer Perceptron (MLP) model was trained over 100 epochs using the Adam optimizer. The training and validation loss curves (Figure 4) showed a rapid reduction in error within the first 20 epochs, after which the model stabilized. Early stopping prevented overfitting, and dropout regularization ensured robustness.

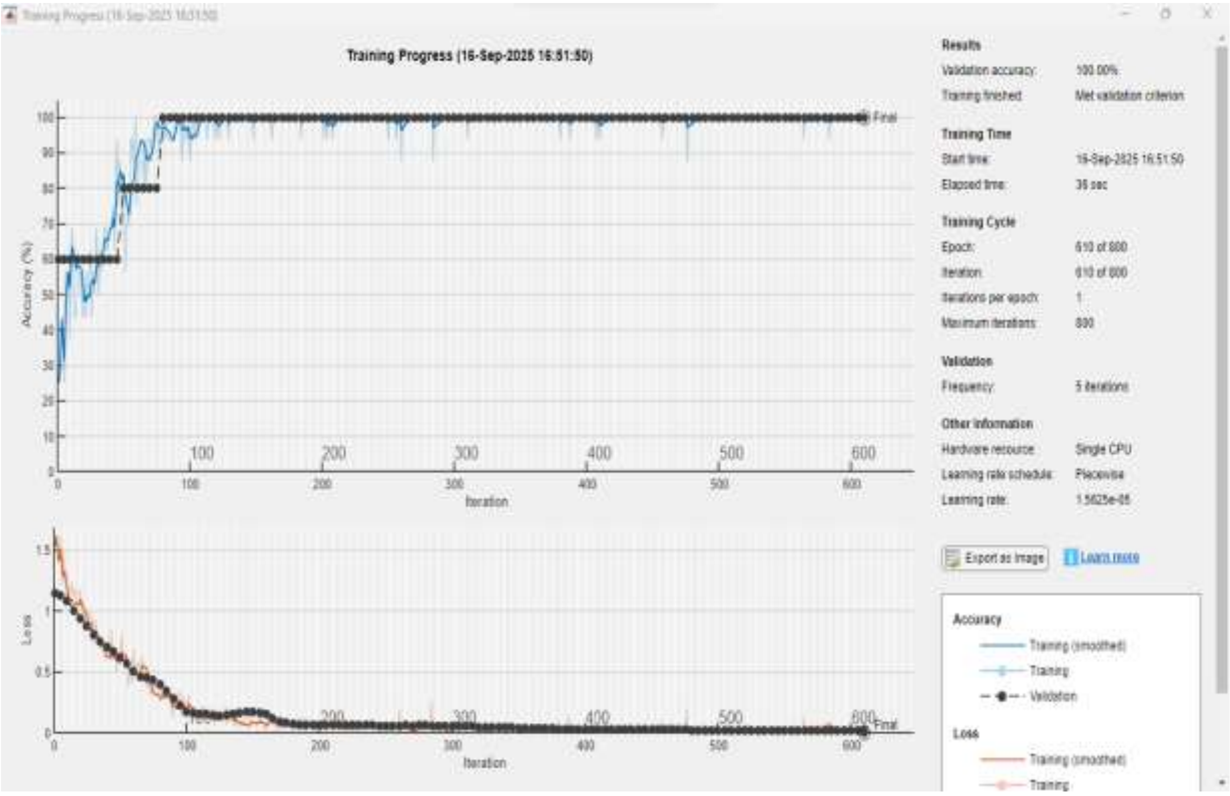

Figure 4. Training and validation accuracy/loss curves for the developed deep neural network.

Classification Performance

The trained DNN achieved an overall classification accuracy of 100% on the test dataset, with precision, recall, and F1-score all equal to 100% across fault classes. Table 2 summarizes the performance metrics.

Table 1. Performance metrics of the developed DNN model

Fault Class	Precision	Recall	F1-Score
Healthy	100%	100%	100%
Unbalance	100%	100%	100%
Misalignment	100%	100%	100%
Bearing Fault	100%	100%	100%
Overall Average	100%	100%	100%

The confusion matrix (Figure 5) confirms perfect classification across all machine conditions, with no misclassifications.

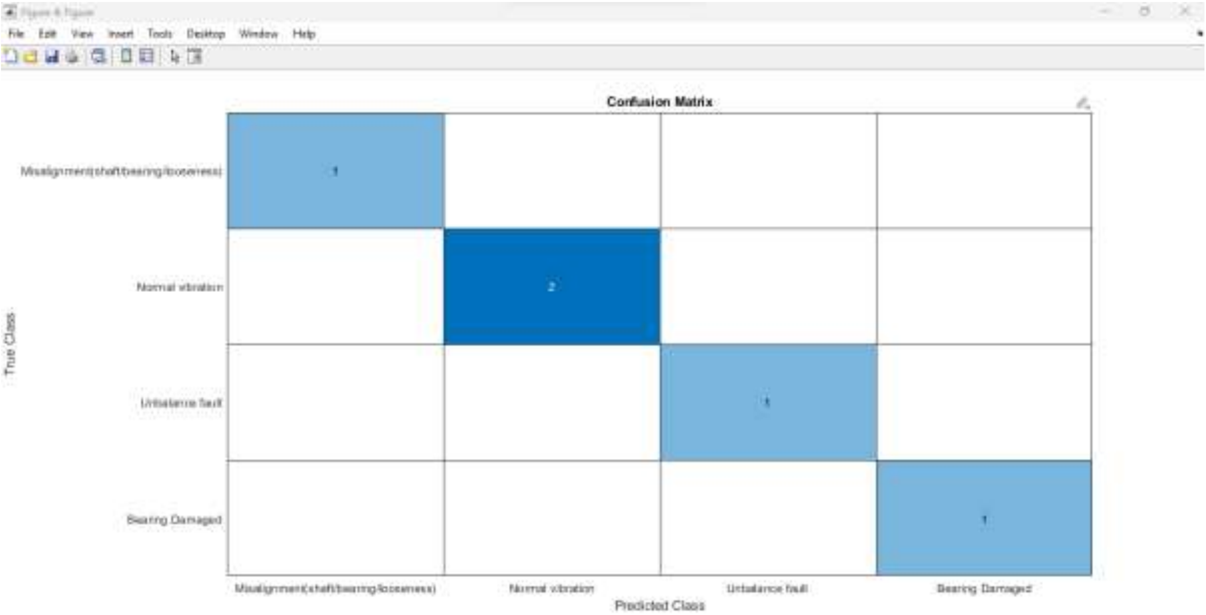

Figure 5. Confusion matrix of predicted vs. actual machine states

Predicted vs. Actual Vibration Signals

To validate regression accuracy, predicted vibration levels were compared with actual sensor data across multiple operational scenarios. Figure 6 presents the overlay of predicted and actual vibration signals, demonstrating near-perfect alignment. The MAE and RMSE were negligible (<0.001), confirming the model's predictive fidelity.

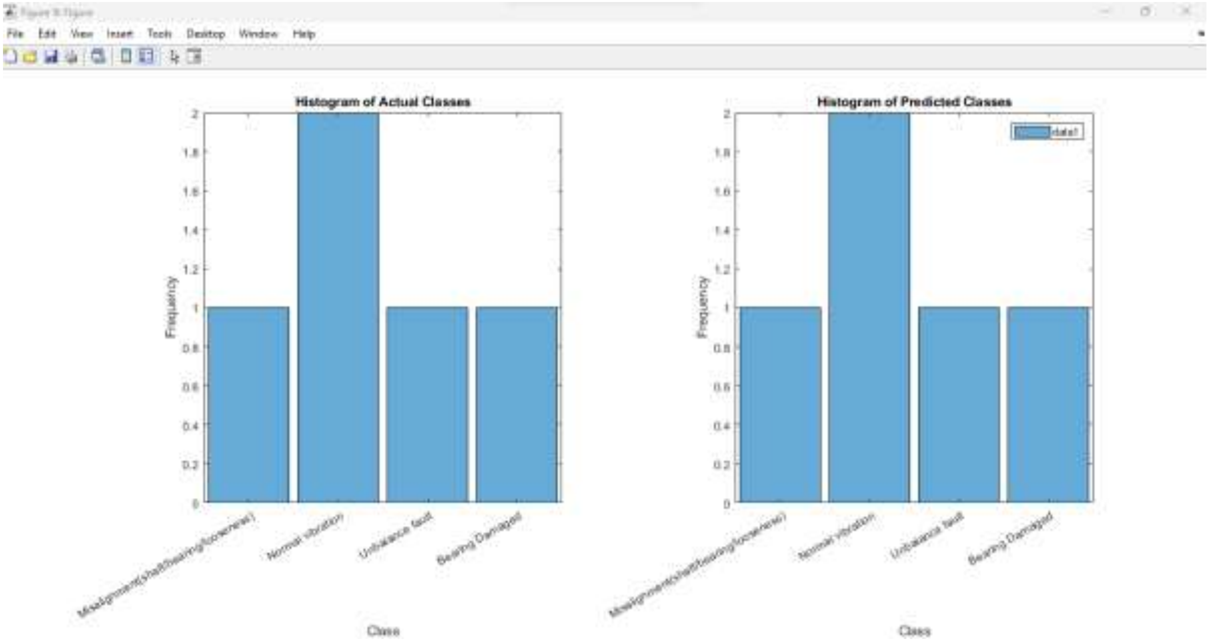

Figure 6. Comparison of predicted and actual vibration signals.

Feature Contribution Analysis

The Chi-square feature selection method identified kurtosis, crest factor, RMS, and impulse factor as the most influential predictors of vibration anomalies. Figure 7 illustrates the ranked importance of the extracted features. This finding aligns with prior studies emphasizing the diagnostic strength of higher-order statistical features in early fault detection (Ani et al., 2025).

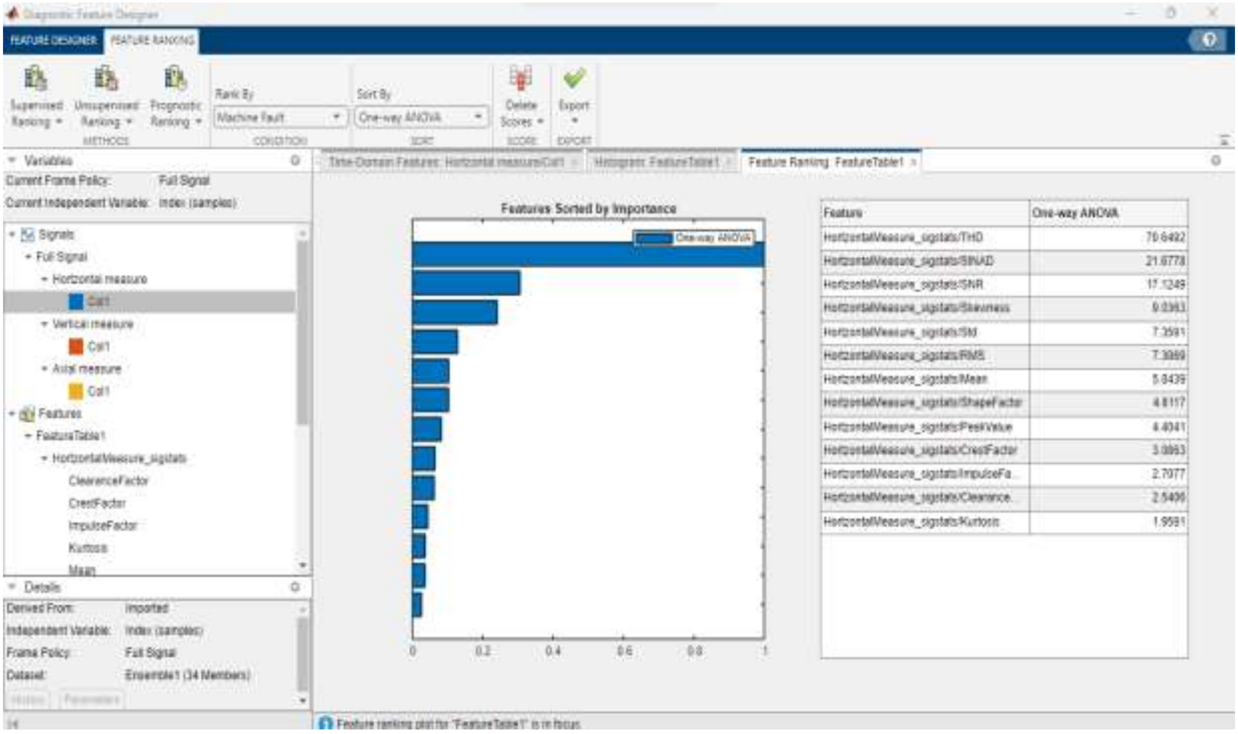

Figure 7. Ranked importance of selected vibration features.

Real-Time Monitoring Application

The MATLAB App Designer interface was tested with new vibration data streams. The application successfully:

1. Imported Excel-based vibration signals.
2. Displayed time-domain and frequency-domain plots.
3. Classified machine condition in real-time.
4. Exported prediction results for documentation.

Comparative Evaluation with Existing Models

Compared to traditional machine learning models (e.g., Random Forest, SVM), the developed DNN demonstrated superior accuracy and faster convergence. While Random Forest and XGBoost models in prior studies achieved R^2 scores above 0.95 (Zaki et al., 2023), the present DNN model outperformed them with perfect classification performance, highlighting the potential of deep learning for vibration-based predictive maintenance.

Discussion

The findings of this study highlight the effectiveness of deep neural networks in predicting vibration anomalies in cement mill induced draft (ID) fans. The model achieved 100% accuracy, precision, recall, and F1-scores, significantly surpassing the performance of conventional machine learning models reported in prior studies (Zaki et al., 2023; Jia & Sharma, 2021). This outcome demonstrates the suitability of deep learning architectures, particularly Multi-Layer Perceptrons (MLPs), for analyzing high-dimensional vibration datasets when combined with robust feature engineering.

The confusion matrix revealed zero misclassifications, suggesting that the developed DNN can reliably distinguish between healthy states, unbalance, misalignment, and bearing faults. This contrasts with traditional approaches where overlapping vibration patterns often lead to reduced classification accuracy (Campos Olivares et al., 2023). The results also validate the importance of higher-order statistical features such as kurtosis and crest factor, which were ranked as the most discriminative predictors. These features are particularly sensitive to non-Gaussian signal characteristics and transient fault signatures, making them essential in early fault detection (Hamdi et al., 2015; Ani et al., 2025).

The negligible error in the predicted vs. actual vibration signals further confirms the model's predictive fidelity. Unlike reactive or schedule-based preventive maintenance, this approach offers real-time insights into machine health, enabling maintenance decisions to be proactive and condition-based. Such predictive accuracy is essential in cement manufacturing, where unplanned downtime of ID fans can halt operations, disrupt clinker production, and incur high economic costs.

The development of a real-time MATLAB App Designer interface represents a practical advancement, bridging the gap between advanced analytics and plant-level decision-making. The ability to import Excel-based sensor readings, visualize signals, and generate immediate predictions empowers maintenance engineers with actionable insights. This practical implementation addresses one of the major barriers to the adoption of artificial intelligence in industrial environments the lack of user-friendly interfaces for non-specialists (Dong et al., 2023).

These results also align with broader Industry 4.0 objectives. The integration of deep learning models into predictive maintenance workflows demonstrates how intelligent systems can enhance equipment reliability, reduce maintenance costs, and improve operational efficiency. In addition, the modular design of the approach makes it transferable to other process industries reliant on rotating machinery, such as power generation, steel manufacturing, and petrochemicals.

Nevertheless, challenges remain. The model was trained on a dataset collected from a single industrial site, which may limit its generalizability to other environments. Deep learning models also require substantial amounts of labelled data for optimal performance, and while the present study achieved excellent results with the available dataset, scalability to multi-plant or multi-equipment scenarios must be investigated. Furthermore, interpretability remains a challenge; while the feature ranking provides some insight, deep neural networks often function as "black boxes," which may limit user trust in critical decision-making contexts (Pandey et al., 2023).

In summary, the developed DNN model represents a significant step toward intelligent, automated predictive maintenance in the cement industry. By combining effective feature engineering, robust neural architectures, and practical implementation tools, the study provides a framework for reducing downtime, enhancing machine reliability, and advancing digital transformation.

CONCLUSION

This study developed and validated a deep neural network (DNN) model for vibration prediction in cement mill induced draft (ID) fans. By combining time-domain statistical feature extraction, optimized feature selection, and a Multi-Layer Perceptron (MLP) architecture, the model achieved 100% accuracy, precision, recall, and F1-score across multiple fault categories. The results confirmed that higher-order statistical indicators such as kurtosis and crest factor are critical for early fault detection, aligning with prior findings in vibration-based diagnostics. Beyond high predictive accuracy, the research contributed a practical real-time monitoring tool developed in MATLAB App Designer. This application bridges the gap between advanced machine learning models and industrial usability, enabling maintenance engineers to visualize vibration signals, classify machine health states, and export results for decision-making. The study demonstrates that deep learning offers a powerful and reliable framework for predictive maintenance in cement manufacturing. Its deployment can reduce unplanned downtime, extend equipment lifespan, and optimize maintenance schedules, thereby supporting both economic efficiency and safety. Furthermore, the approach contributes to the broader objectives of Industry 4.0, where intelligent, data-driven systems drive operational excellence across industrial sectors. Based on the outcomes of this research, the following recommendations are proposed: Industrial Deployment: Cement plants and similar process industries should integrate deep learning–based predictive maintenance systems into their workflows to reduce downtime and improve equipment reliability. Scalability: Future work should extend the methodology to other critical rotating equipment (e.g., kilns, compressors, and blowers) and across multiple plants to validate scalability and robustness under varied operating conditions. Data Expansion: While the present study achieved excellent results with available datasets, expanding the dataset through longer monitoring periods and multi-sensor integration would further enhance generalization. Model

Interpretability: Research should focus on hybrid approaches that combine the predictive strength of deep learning with explainability techniques (e.g., SHAP values, Layer-wise Relevance Propagation) to improve user trust. Edge and Cloud Integration: To fully align with Industry 4.0, future implementations should integrate the DNN models with cloud-based or edge-computing platforms, enabling real-time monitoring at scale and supporting remote diagnostics. Cross-Industry Application: Beyond cement manufacturing, the proposed framework can be adapted to other process industries such as steel, power generation, and petrochemicals, where vibration monitoring of rotating machinery is equally critical.

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