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Investigation and Minimization of the Vibrations in High-Precision Manufacturing using Machine Learning

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Abstract: The work focuses on fault diagnosis and categorization of rotating equipment parts, using Machine Learning approaches based on the vibration signals pulled from the CWRU Bearing Data Centre at a sampling rate of 48000 samples/sec. The research uses multiple machine learning models, including Support Vector Machines (SVM), 1D Convolution Neural Networks (CNN), 2D CNN, and Long Short-Term Memory (LSTM) networks. In order to minimize overfitting and provide an accurate performance assessment, we used the concept of k-fold cross-validation. Our findings proved the resilience of Machine Learning models for predictive maintenance to detect and identify the faults in the bearings at an early stage. This results in cutting down the frequency of downtime, cost of maintenance, and extending the lifespan of the bearings, so demonstrating the applicability of using Machine Learning in enhancing functionality and monitoring future structures in High-Precision Manufacturing Industries.

Keywords: Machine Learning, Rotating Machinery, Fault Diagnosis, Vibration Data, High Precision Industries.

I. INTRODUCTION

The efficient functioning of rotating machinery is significant in high-precision manufacturing industries, where faults can lead to costly downtimes. Predictive maintenance, which utilizes real-time data and machine learning, predicts failures before they occur, thereby reducing maintenance costs and improving operational efficiency. This approach has evolved from reactive to preventive strategies, focusing on monitoring equipment conditions and predicting maintenance needs. Using deep learning, we are integrating machine learning with traditional diagnostic techniques; now, industries can gain a timely insight into machine health, regulating maintenance culture that enhances reliability, optimizes uptime, and resolves the risks associated with machinery failure.

Diagnosing faults relies on analyzing the complex vibration data to detect the fault before it occurs prior the traditional methods used to depend on human expertise and monitoring while experiencing the signal's noisy and non-linear nature. Different faults can show similar symptoms, thereby complicating diagnosis further. Machine learning models they offer an overall solution by analyzing multidimensional data and learn from historical patterns. However, their practical application requires machinery operations and advanced analytics expertise, which drives innovation in industrial maintenance.

This research utilizes available dataset from Case Western Reserve University Bearing Data Centre containing vibration data samples under various fault conditions and severity levels, making it ideal for developing and testing machine learning models. It includes detailed recordings of experimental setups, such as motor speeds and load conditions, such we can use standardized comparisons of diagnostic algorithms. The widespread use of the dataset is a reflection of the research community's cooperative efforts to improve diagnostic technologies, which will increase industrial machinery performance and reliability by implementing better fault detection and diagnosis procedures.

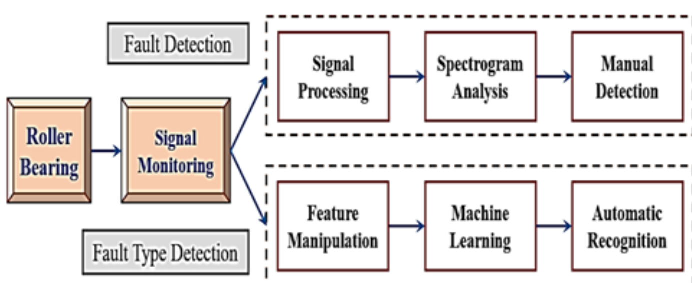

Figure 1: Fundamental Procedures for Diagnosing Roller Bearing Faults

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This research focuses on several machine learning techniques, namely Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks. Every one of these models offers unique advantages in processing time-series data. SVMs are effective in high-dimensional spaces, making them suitable for feature-rich datasets derived from vibration signals. CNNs, traditionally used in image processing, are adapted here to interpret time-series data as 2D images, taking advantage of their spatial hierarchy in data for feature extraction. LSTMs are adept at handling sequences of data with their memory cells, providing the ability to maintain information over time, which is crucial for time-series analysis like vibration data.

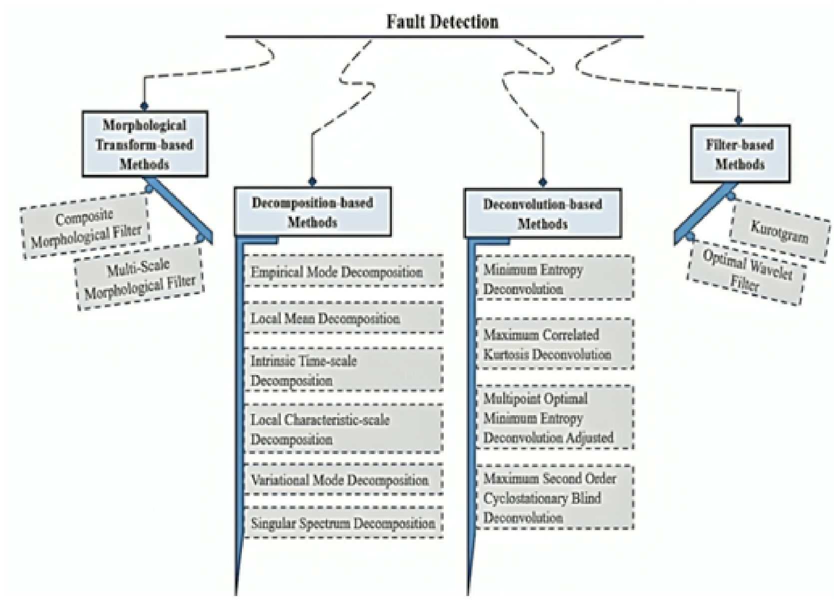

Figure 2: Diverse Methods for Roller Bearing Fault Detection

For high-dimensional data, such as vibration signals in equipment, Support Vector Machines (SVMs) are supervised learning techniques for classification, regression, and outlier detection. SVMs use kernel functions (such as RBF or polynomial) to manage non-linearity and choose the best hyperplane for class separation. When diagnosing faults with intricate vibration patterns, these convert data into higher dimensions for separability. By adjusting to minute, non-linear characteristics present in the behavior of machinery under faults, kernel selection and parameter tuning have a direct impact on accuracy. This guarantees reliable processing of complex vibration analysis datasets.

For Convolutional Neural Networks (CNNs), traditionally used in image processing, adapt to time-series data by treating it as 1D (temporal) or 2D (image-like) arrays, leveraging spatial hierarchy for feature extraction. In fault diagnosis, CNNs analyse time-frequency representations (e.g., spectrograms, scalograms) to capture temporal and spectral patterns. Their architecture—convolutional layers with nonlinear activations and pooling—reduces data dimensionality while preserving critical features, eliminating manual engineering. This automation efficiently identifies complex, subtle fault signatures (e.g., bearing defects), making CNNs powerful for vibration analysis tasks requiring nuanced pattern recognition in raw or transformed time-series data.

Recurrent neural network (RNN) variants known as Long Short-Term Memory networks (LSTMs) are excellent in processing sequential data, such as vibration signals from equipment.

By regulating information flow and maintaining long-term context, their architecture—memory cells and gating mechanisms—overcomes the short-term memory constraints of conventional RNNs. By simulating temporal relationships, LSTMs may detect fault patterns in vibrations over a range of time periods. They facilitate early defect detection in predictive maintenance by identifying long-term trends that indicate gradual degradation, which lowers downtime and costs through prompt intervention.

Practical machine learning in vibration analysis relies on meticulous preprocessing. Raw signals are segmented into fixed-size windows aligned with machinery rotations to capture behavioral dynamics. Preprocessing includes noise filtering, normalization, and segmentation to isolate meaningful operational states. Feature extraction derives time-domain metrics (mean, variance, kurtosis) and frequency-domain insights (peak frequency, amplitude) via the Fourier Transform. Dimensionality reduction techniques like PCA streamline inputs by retaining critical variance, enhancing model accuracy, and computational efficiency.

These steps ensure high-quality data representation, which is crucial for identifying fault patterns and enabling reliable predictive maintenance in rotating machinery.

To get the best results when training machine learning models on pre-processed and feature-extracted data, parameters must be carefully adjusted. This entails choosing the best neural network design and adjusting hyperparameters, like support vector machine (SVM) kernel functions. Whereas SVMs concentrate on optimizing the margin between classes, neural network training uses backpropagation to reduce prediction errors. Techniques for augmenting data, such as sampling with different stride lengths, are used to improve the generalizability and robustness of the model. Additionally, to avoid overfitting and guarantee that models can successfully generalize to new, unknown data, k-fold cross-validation is used during training.

Validation

K-fold cross-validation is one of the methods used to make sure the models function properly on both unseen and training data. By splitting the data into 'k' subgroups, this method iteratively uses one subset for testing and the others for training. The ability of the model to generalize is evaluated in this way, which is important for its application in practical situations. To increase the size of the training dataset, data augmentation techniques are also employed, such as changing the stride lengths in data sampling. Variations in the data are included, which enhances the model's generalizability and robustness and increases its capacity to handle actual operating data from machines.

II. RESEARCH METHODOLOGY

The analysis utilizes vibration data from the CWRU dataset, collected from a 2HP motor operating at 1750 RPM with a sampling frequency of 48 kHz. Given the bearing geometry, each rotational cycle corresponds to approximately 1670 samples. To fully encapsulate rotational characteristics, the data is divided into 1681-sample blocks (slightly exceeding one full rotation).

Overlapping windows with a 200-sample stride augment the dataset and improve feature representation across cycles.

Support Vector Machines (SVM): Input data is normalized to balance feature contributions, preventing bias toward high-magnitude variables. Training involves splitting data into training/test sets and using k-fold cross-validation to optimize hyperparameters and assess generalization. Decision boundaries are visualized in 2D (via principal components) to evaluate class separation, though the high-dimensional boundary may differ.

1D CNNs are particularly suited for time-series data like vibration signals from rotating machinery. They work by sliding convolutional filters over the data, capturing temporal patterns within the input features. This capability makes them ideal for analysing raw vibration signals where the temporal sequence and local features within the data are indicative of the machine's health.

2D CNNs for vibration data involves an innovative approach where the time-series data is converted into a 2D format, such as a spectrogram or a scalogram, which displays frequency components over time. This conversion allows the 2D CNN to treat the data similarly to an image, extracting features that are both temporally and frequency-wise important.

Long Short-Term Memory (LSTM**)** is a special kind of Recurrent Neural Network (RNN), are particularly designed to handle sequence prediction problems. Making them ideal for analysing time-series data, such as vibration signals from rotating machinery, which often contain sequential dependencies and long-term patterns that are critical for fault diagnosis.

III. RESULT

The experimental configuration comprises several components, including a 2-horsepower motor, a torque transducer, a dynamometer, control electronics, and fan and drive end bearings supported by the motor shaft. Vibration measurements were obtained by conducting tests using a two-horsepower Reliance Electric motor. Accelerometers were strategically placed near and far from the motor bearings to capture the vibration signals. Electro-discharge machining (EDM) introduced faults and modified the roller bearings at the inner and outer ring, resulting in fault diameters ranging from 0.007 to 0.004 inches. The faulty bearing was then reinstalled in the test motor, allowing vibration signal datasets to be obtained at motor speeds ranging from 1730 to 1767 RPM, along with loads varying from 0 to 3 horsepower.

The vibroacoustic waves are gathered with the help of an accelerometer installed on the bearing section at the motor's drive end. The accelerometer and dynamometer were also connected to an acceleration transducer to collect the data. Various operating conditions were recorded, encompassing regular operation, faults in the inner race, ball, faults in the outer race, at different motor speeds (1730, 1750, 1772, and 1797 rpm). The models were then trained, validated, and tested using a structured approach that included cross-validation techniques to prevent overfitting and to ensure that the findings are generalizable across different operational scenarios.

Performance metrics such as accuracy, precision, recall, and F1-score were computed to evaluate each model's effectiveness in fault classification.

Model	Training Accuracy (%)	Testing Accuracy (%)	Difference (%)
CNN-1D	99.8	95.5	4.3
CNN-2D	98.7	93.4	5.3
LSTM	96.2	91.8	4.4
SVM	95.0	92.0	3.0

Table 1: Overall Accuracy Comparison Across Models

Model	Precision (%)	Recall (%)
CNN-1D	95.2	94.8
CNN-2D	93.1	92.5
LSTM	91.5	91.2
SVM	92.3	92.1

Table 2: Precision and Recall Comparison in Testing

Model	F1-Score (%)
CNN-1D	95.0
CNN-2D	92.8
LSTM	91.3
SVM	92.2

Table 3: F1-Score Analysis for Testing Data

Model	Training Time (s)	Inference Time (ms)	Memory Usage (MB)
CNN-1D	120	20	1024
CNN-2D	180	35	2048
LSTM	300	50	1536
SVM	60	5	512

Table 4: Model Efficiency and Computational Load

The models were then trained, validated, and tested using a structured approach that included cross-validation techniques to prevent overfitting and to ensure that the findings are generalizable across different operational scenarios. Performance metrics such as accuracy, precision, recall, and F1-score were computed to evaluate each model's effectiveness in fault classification.

Overall Accuracy Comparison (Table 1) shows that while all models perform well, CNN1D achieves the highest accuracy, suggesting superior ability to handle complex feature patterns directly from raw data. The difference between training and testing accuracy highlights potential overfitting issues, particularly with the deep learning models.

Precision and Recall (Table 2) are critical in fault diagnosis to ensure that the models not only predict accurately but also minimize false positives and false negatives, which are costly in industrial settings. CNN-1D shows the best balance between precision and recall, indicating a reliable predictive performance.

F1-Score (Table 3) further solidifies the findings from precision and recall by providing a harmonic mean of the two, where CNN-1D again leads, confirming its effectiveness in a balanced performance across various fault types.

Model Efficiency and Computational Load (Table 4) highlight the trade-offs between computational efficiency and accuracy. While SVM offers the quickest inference time, its simplicity might limit performance on more complex datasets, whereas CNNs, despite their higher computational demand, offer better accuracy and feature handling.

The comprehensive evaluation of various machine learning models—1D CNN, 2D CNN, LSTM, and SVM—used for fault diagnosis in rotating machinery provides a rich set of insights into their performance and applicability in real-world industrial settings. The results analysed include a range of metrics such as accuracy, precision, recall, F1-score, and computational efficiency, captured through confusion matrices, accuracy comparisons, and other performance parameters.

IV. ANALYSIS

1) *Accuracy*: The 1D CNN demonstrated the highest overall accuracy in both training (99.8%) and testing phases (95.5%), suggesting its strong capability in capturing and classifying fault patterns from vibration data. The 2D CNN, while slightly less accurate than the 1D variant, still performed commendably, particularly in handling complex data transformations through its two-dimensional feature processing. LSTM showed robust sequential data processing capabilities but lagged slightly in accuracy (91.8% in testing), highlighting challenges in longterm dependency management. SVM, although the least complex model, showcased substantial robustness, achieving 92.0% accuracy in testing, indicative of its effectiveness in simpler fault classification scenarios.
2) *Precision and Recall*: The precision and recall metrics further reinforced the superior performance of CNN models, especially the 1D configuration, which effectively balanced both metrics leading to a high F1-score of 95.0%. These metrics are critical in fault diagnosis to minimize both false positives and false negatives, ensuring reliable maintenance triggers.
3) *F1-Score*: Reflecting on the harmonic mean of precision and recall, the F1-score provided an integrated view of model performance, with 1D CNN outperforming others. This score is particularly important in the industrial context where both types of classification errors (false positives and false negatives) carry significant cost implications.
4) *Computational Efficiency*: In terms of computational demands, SVM was the most efficient, with the lowest training and inference times. This efficiency makes SVM an attractive option for real-time fault diagnosis systems where computational resources are limited.
5) Conversely, CNN models, especially the 2D variant, required more substantial computational resources, which could be a trade-off for industries considering deployment at scale.
6) *Overfitting Analysis*: A key challenge identified across more complex models like CNNs and LSTM was overfitting, where models performed exceptionally well on training data but less so on unseen test data. This was evident from the accuracy discrepancies between training and testing datasets. Overfitting is a critical aspect to address, as it can lead to models that perform well in a controlled testing environment but fail to generalize in real operational settings.

V. CONCLUSION

This research systematically evaluated the performance of various machine learning models, including 1D and 2D Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTM), and Support Vector Machines (SVM), in diagnosing faults in rotating machinery based on vibration data. The findings from extensive testing and analysis reveal distinct capabilities and limitations of each model, providing critical insights that could inform their application in industrial settings.

1D CNN emerged as the most effective model in handling complex pattern recognition tasks, achieving the highest accuracy and F1-score among the tested models. This model excelled in extracting meaningful features from raw vibration data, demonstrating substantial robustness and reliability in fault classification. However, it also exhibited signs of overfitting, suggesting a need for improved training strategies or model adjustments to enhance its generalizability.

2D CNN while slightly less effective than its 1D counterpart in overall accuracy, offered advantages in processing data that could be represented in two-dimensional formats, such as spectrograms. This capability makes it particularly useful in scenarios where fault signatures are more discernible in the frequency domain.

LSTM provided valuable capabilities in handling data with temporal dependencies, showing promise in applications requiring analysis of sequential data or trends over time. Despite its potential, LSTM's performance was slightly lower in standard classification metrics, partly due to its complexity and the challenges associated with training recurrent networks.

SVM proved to be highly efficient, particularly in scenarios with limited computational resources. While it did not achieve the highest classification metrics, its speed and lower demand on computational resources make it suitable for real-time applications or as a preliminary fault screening tool.

In conclusion, this study demonstrates the potential of machine learning models to revolutionize fault diagnosis in rotating machinery, highlighting specific strengths and applications of different models.

By continuing to refine these technologies and address the challenges identified, there is a significant opportunity to enhance predictive maintenance strategies and achieve substantial improvements in industrial operations. The journey from experimental to practical application involves continuous improvement and adaptation, but the path is clear for these advanced diagnostic tools to become integral components of modern industrial systems.

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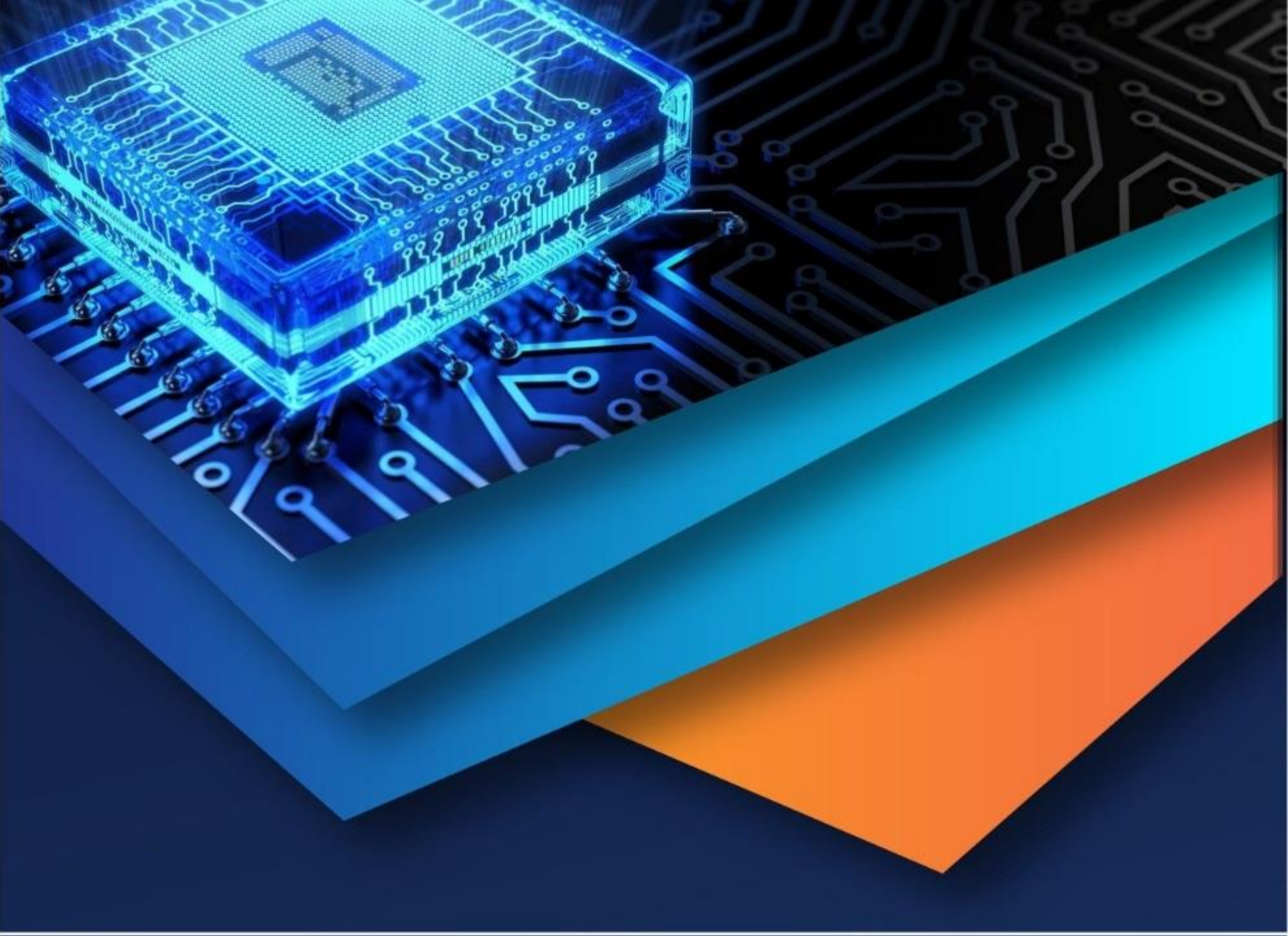

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