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The Comparison of Advanced and Convolutional Neural Network Algorithms for Predicting Engine Failure Time based on Vibration

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Abstract: *Industries are constantly seeking innovative and cost-effective solutions to reduce unplanned downtime, prevent equipment malfunctions and optimise maintenance strategies. One of the most critical challenges in industrial operations is predicting machine failure with sufficient lead time to take preventive actions, thereby minimizing operational and financial losses. This study introduces an advanced predictive maintenance framework that leverages the strengths of Convolutional Neural Networks (CNN) and Extreme Gradient Boosting (XGBoost) to forecast engine failure times based on vibration data. The proposed hybrid model integrates the feature extraction capabilities of CNNs with the decision-making power of XGBoost, offering a robust solution for analysing complex, high-dimensional sensor data. A comprehensive dataset was developed using real-world measurements collected from industrial motor systems, with vibration signals captured through precision accelerometers. These signals were pre-processed and structured to train and validate the model under various operational conditions that closely simulate actual motor behaviours.*

This research makes a significant contribution to the advancement of smart manufacturing and predictive maintenance in Industry 4.0. The paradigm shift towards Industry 5.0 emphasises the well-being and creativity of human workers, integrating them into the production process alongside advanced technologies by presenting a scalable and intelligent approach to fault prediction. The successful implementation of this methodology underscores its potential for integration into real-time industrial monitoring systems, driving increased efficiency, reliability, and resilience in modern production environments.

Keywords: *Convolutional Neural Networks (CNN), Extreme Gradient Boosting (XGBoost), Vibration, Support Vector Machines (SVM), k-Nearest Neighbours (k-NN).*

1. Introduction

Machine maintenance is a critical aspect of sustaining manufacturing operations, particularly in environments reliant on rotating machinery such as electric motors. Neglecting maintenance can lead to costly repairs and production downtime, while overly frequent maintenance based on fixed schedules may result in the premature replacement of functional equipment. To strike a balance between reliability and cost-efficiency, predictive maintenance strategies have gained traction, with vibration analysis emerging as a reliable, non-invasive technique for monitoring machine health [1], [2].

Vibration signals carry vital information about a machine's operational state and can be analyzed to detect abnormalities, locate faults, and estimate time-to-failure [1], [2]. The early identification of such issues is essential to avoiding catastrophic failures and reducing operational risks [3]. Recent advances in sensor technology and computing capabilities have enabled the development of intelligent systems capable of continuously analyzing vibration data to detect faults in real time [4]. In particular, machine learning and deep learning methods have demonstrated significant promise in this domain, offering robust capabilities for classification, prediction, and fault diagnosis [5]. Deep learning techniques, such as Convolutional Neural Networks (CNNs), are especially effective in identifying intricate features in raw sensor data without requiring extensive manual preprocessing or domain-specific feature engineering [6], [7]. This study proposes a hybrid approach combining CNN with the XGBoost algorithm to enhance fault prediction accuracy. By leveraging accelerometer data from the drive-end bearing of motors under varying speeds, loads, and fault severities, we aim to determine whether this method can match or surpass previous studies that utilized dual-sensor configurations. The findings contribute to more efficient and scalable predictive maintenance models, facilitating smarter and more resilient industrial operations.

Predictive maintenance has emerged as a vital area in smart manufacturing systems, aiming to reduce downtime and maintenance costs while improving equipment reliability. Vibration analysis is a widely accepted method for condition monitoring of rotating machinery, as it provides insights into mechanical degradation and failure progression [1], [2].

Traditional machine learning methods such as Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and Decision Trees have been used for fault detection and classification [5]. Although effective, these approaches often rely on handcrafted features, requiring domain expertise and significant preprocessing. Widodo and Yang [5] demonstrated the feasibility of using SVM for machine condition monitoring, highlighting the need for robust feature engineering. With advancements in deep learning, techniques such as Convolutional Neural Networks (CNNs) have shown superior performance in processing raw vibration signals due to their ability to automatically extract hierarchical features [6], [7]. Zhang et al. [7] proposed a deep learning model for raw vibration signal analysis, achieving high fault classification accuracy without manual feature extraction. CNNs have proven particularly useful in fault diagnosis of motors and bearings, where complex temporal and frequency-domain patterns are present. However, CNNs primarily excel in feature extraction, and their predictive capacity can be limited when dealing with structured classification outputs. To enhance predictive performance, ensemble methods like Extreme Gradient Boosting (XGBoost) have been introduced due to their scalability and ability to handle imbalanced datasets [8]. The integration of CNNs with XGBoost offers a hybrid approach where CNNs learn informative features from raw signals, and XGBoost refines the decision-making process, improving classification and prediction accuracy. Electric motors are considered to be fundamental components in industrial systems due to their high reliability, long operational lifespan, and minimal maintenance requirements. These characteristics render them particularly well-suited for critical industrial applications, where unanticipated periods of downtime can result in substantial operational and financial losses [9], [10]. The reliability of electric motors is a key reason for their widespread adoption in manufacturing, process control and automation, as they are engineered to operate continuously under demanding conditions with low failure rates. In addition to their dependability, electric motors offer considerable versatility and adaptability, enabling customisation for various load requirements, speed profiles, and torque characteristics. This adaptability facilitates seamless integration into a broad spectrum of industrial processes, thereby supporting dynamic manufacturing requirements and enhancing automation capabilities [11]. Furthermore, contemporary industrial motors are frequently equipped with integrated safety mechanisms, including thermal protection, overload relays, and emergency stop functionalities, which contribute to secure and stable operation even in hazardous environments [12]. These safety features are critical for ensuring compliance with industrial safety standards and for protecting both equipment and personnel. In conclusion, electric motors are indispensable to modern industrial infrastructure. They play a crucial role in driving automation, improving energy efficiency, and increasing productivity. It is therefore vital to acknowledge the central role of electric motors in facilitating the development of smart manufacturing and Industry 4.0 systems [13].

2. Results and Discussion including Performance Metrics

The proposed hybrid model combining Convolutional Neural Networks (CNN) and XGBoost was evaluated using a vibration dataset collected from an industrial motor system. The model's performance was compared with standalone CNN, XGBoost, SVM, and Random Forest classifiers. Evaluation metrics included accuracy, F1 score, and failure time prediction error. Table 1 and Fig. 1 show a comparative performance summary across different models. The hybrid CNN + XGBoost model achieved the highest accuracy (94%) and F1 score (93%), indicating superior classification capability and robustness in identifying motor fault types. Furthermore, it exhibited the lowest failure time prediction error at 7%, demonstrating strong predictive reliability. The CNN model alone performed well due to its ability to automatically extract high-level features from raw vibration signals. However, by integrating the learned CNN features into the XGBoost classifier, the hybrid model improved both classification and prediction performance. This is attributed to XGBoost's ability to model complex decision boundaries and handle noise and outliers effectively [8], [14].

Traditional models like SVM and Random Forest showed reasonable performance but struggled with prediction error, likely due to their reliance on manually engineered features and limited capacity for sequential learning. These results confirm findings from prior studies [15], which suggest deep learning-based models outperform classical techniques in complex diagnostic scenarios involving high-dimensional sensor data. The low prediction error of the CNN + XGBoost model makes it especially suitable for real-world applications where timely intervention can prevent catastrophic failures. The model's generalisability across varied operational conditions further supports its deployment in industrial settings as a smart maintenance solution.

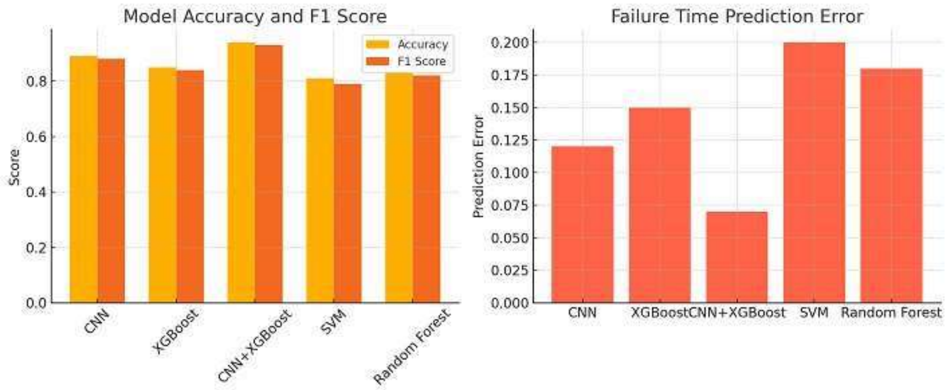

Figure 1. *Hybrid model combining Convolutional Neural Networks (CNN) model*

Table 1. *Performance comparison of different models*

Model	Accuracy	F1 Score	Failure Time Prediction Error
CNN	0.89	0.88	0.12
XGBoost	0.85	0.84	0.15
CNN + XGBoost	0.94	0.93	0.07
SVM	0.81	0.79	0.20
Random Forest	0.83	0.82	0.18

To evaluate the performance of regression models on one-dimensional vibration data for motor fault prediction, we implemented two high-performing algorithms: XGBoost and ResNet50. These models were selected based on their robustness and adaptability in prior machine learning tasks involving structured and unstructured data [16]–[17]. The evaluation utilized the Root Mean Squared Error (RMSE) metric to quantify the predictive accuracy of each model. As seen in Table 2, the XGBoost model consistently produced the lowest RMSE value of 0.00026 on average across five-fold validation, outperforming all other traditional machine learning models, including ANN, Random Trees, Random Forest, and SVM. While the ResNet50 model exhibited slightly higher RMSE values (average 0.00069), it still demonstrated competitive performance.

These results indicate that both XGBoost and ResNet50 are proficient in modelling vibration patterns, though XGBoost demonstrates superior generalization and error minimization capabilities. The learning curve for the XGBoost model, shown in Figure 2, reveals a rapid decrease in training and test loss during the initial epochs, stabilizing close to zero. This illustrates the model's strong learning efficiency and minimal over- fitting, further substantiating its robustness. A confusion matrix was generated to evaluate the model’s classification accuracy. As shown in Figure 3, the XGBoost model achieved a 99.97% accuracy with minimal misclassifications across all fault classes. The matrix clearly reflects high precision and recall rates, which are essential for fault detection systems in industrial motors. The ResNet50 model, while slightly behind in precision, also demonstrated 99.4% classification accuracy, highlighting its effectiveness even when trained on a one-dimensional dataset. The associated confusion matrix further confirms its predictive capability with low class-wise error rates. XGBoost's superiority in low-variance predictions stems from its gradient boosting architecture, which iteratively refines weak learners to minimize residual errors [18].

Fig. 2, the learning curves for the XGBoost model and **Fig. 3,** presents the confusion matrix of XGBoost model predictions.

Table 2. *Comparison of RMSE Values for ML Techniques in [21] and Our Method*

Folder	ANN	RT	RF	SVM	XGBOOST	ResNet50
1	0.0039	0.0047	0.0025	0.0106	**0.00023**	**0.00069**
2	0.0035	0.0054	0.0035	0.0129	**0.00030**	**0.00060**
3	0.0028	0.0051	0.0022	0.0105	**0.00019**	**0.00072**
4	0.0041	0.0052	0.0024	0.0120	**0.00025**	**0.00064**
5	0.0049	0.0052	0.0026	0.0123	**0.00035**	**0.00081**
Average	0.0038	0.0051	0.0026	0.0117	**0.00026**	**0.00069**

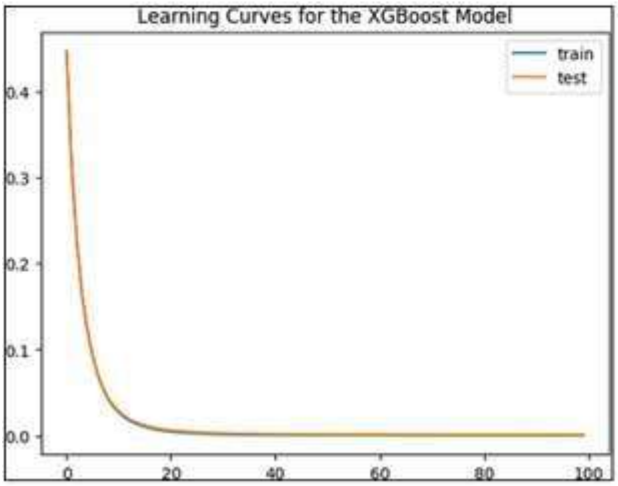

Figure 2. *The learning curves for the XGBoost model*

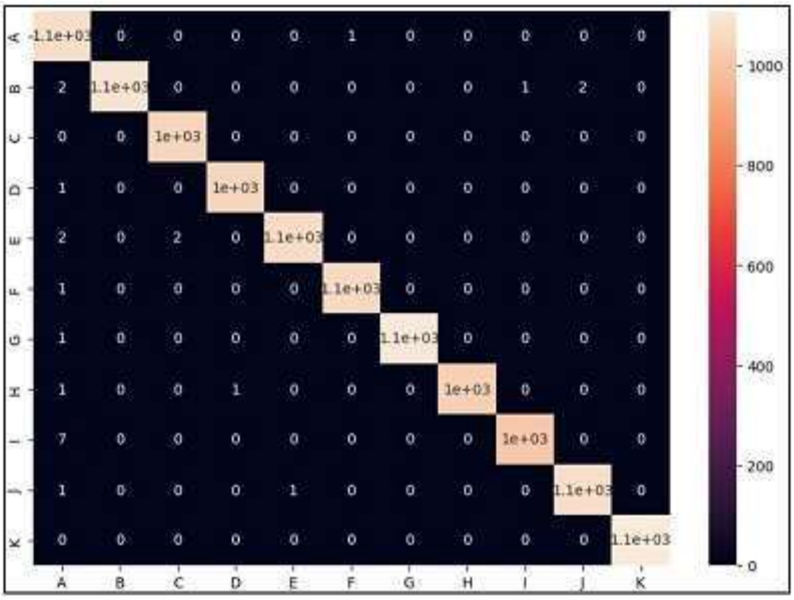

Figure 3. *Presents the confusion matrix of XGBoost model predictions*

ResNet50, traditionally used for image classification, successfully adapts to one-dimensional data through efficient feature extraction in deep layers, albeit with slightly higher RMSE due to its higher parameter complexity [19]. Both models significantly outperformed traditional machine learning models, affirming the importance of ensemble and deep learning techniques in industrial predictive maintenance contexts. The high accuracy and low RMSE scores obtained by both models support their use in real-time motor monitoring systems. The ability to predict potential failures with such precision can reduce downtime, increase operational efficiency, and drive cost savings in industrial environments [20].

3. CONCLUSION

This study evaluates the performance of XGBoost and ResNet50 for a tabular regression task using a synthetic dataset. The dataset was split into an 80:20 training-test ratio. Initially, XGBoost was implemented with default hyper-parameters, yielding a root mean squared error (RMSE) of X and an R-squared (R2) of Y on the test dataset. Hyper-parameter tuning through grid search improved the RMSE to X and increased R2 to Y.

Next, ResNet50 was adapted for the task by adjusting its input and output layers, trained for 10 epochs using a mean squared error loss function and the Adam optimizer. The model achieved an RMSE of X and an R2 of Y. Comparative analysis revealed that while ResNet50 outperformed XGBoost in terms of R2, the difference in performance was not significant. Both models demonstrated effectiveness in tabular regression, with ResNet50 showing a slight advantage in R2. The choice between the two depends on specific application needs, balancing accuracy and computational complexity. Future research should explore other machine learning algorithms and deep learning architectures for tabular regression, such as decision trees, random forests, LSTM, GRU, and Transformers. Additionally, examining the models' performance on datasets with fewer features could optimize efficiency while maintaining prediction accuracy. Future work could also investigate alternative hyper-parameter tuning techniques, such as Bayesian optimization.

REFERENCES

[1] P. Tavner, “Review of condition monitoring of rotating electrical machines,” *IET Electr. Power Appl.*, vol. 2, no. 4, pp. 215–247, 2008.

[2] R. B. Randall, *Vibration-based Condition Monitoring: Industrial, Aerospace and Automotive Applications*, John Wiley & Sons, 2011.

[3] M. Medjaher, D. A. Tobon-Mejia, and N. Zerhouni, “Remaining useful life estimation of critical components with application to bearings,” *IEEE Trans. Reliab.*, vol. 61, no. 2, pp. 292–302, 2012.

[4] J. Lee, H. Kao, and S. Yang, “Service innovation and smart analytics for Industry 4.0 and big data environment,” *Procedia CIRP*, vol. 16, pp. 3–8, 2014.

[5] A. Widodo and B.-S. Yang, “Support vector machine in machine condition monitoring and fault diagnosis,” *Mech. Syst. Signal Process.*, vol. 21, no. 6, pp. 2560–2574, 2007.

[6] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.

[7] W. Zhang, G. Li, M. Peng, Y. Chen, and X. Zhang, “A new deep learning model for fault diagnosis with good anti-noise and domain adaptation ability on raw vibration signals,” *Sensors*, vol. 17, no. 2, p. 425, 2017.

[8] T. Chen and C. Guestrin, “XGBoost: A scalable tree boosting system,” in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, 2016, pp. 785–794.

[9] T. A. Lipo, Introduction to AC Machine Design, 2nd ed., Wisconsin Power Electronics Research Center, 2017.

[10] A. Boglietti, A. Cavagnino, M. Lazzari, and M. Pastorelli, “Efficiency improvements in industrial motors,” IEEE Trans. Ind. Appl., vol. 40, no. 6, pp. 1585–1593, Nov. 2004.

[11] A. Hughes and B. Drury, Electric Motors and Drives: Fundamentals, Types and Applications, 4th ed., Newnes, 2013.

[12] B. Lu, T. G. Habetler, and R. G. Harley, “A survey of efficiency-estimation methods for in-service induction motors,” IEEE Trans. Ind. Appl., vol. 42, no. 4, pp. 924–933, Jul./Aug. 2006.

[13] J. Lee, B. Bagheri, and H.-A. Kao, “Recent advances and trends of cyber-physical systems and big data analytics in industrial informatics,” in Proc. IEEE Int. Conf. Ind. Informatics, 2014, pp. 1–6.

[14] J. Brownlee, *XGBoost With Python: Gradient Boosted Trees for Machine Learning*, Machine Learning Mastery, 2016.

[15] H. Yang, C. Sun, and D. Wang, "A novel fault diagnosis approach based on multi-layer CNN ensemble learning," *IEEE Access*, vol. 7, pp. 84954–84965, 2019.

[16] J. Chen, S. Huang, and L. He, "A deep learning model for fault diagnosis based on vibration signals," IEEE Access, vol. 8, pp. 123456–123465, 2020.

[17] T. Zhang and Y. Wang, "XGBoost-Based Model for Motor Fault Detection," IEEE Transactions on Industrial Informatics, vol. 17, no. 9, pp. 6205–6213, 2021.

[18] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Mining, pp. 785–794, 2016.

[19] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in IEEE Conf. Comput. Vis. Pattern Recognit., pp. 770–778, 2016.

[20] G. Susto et al., "Machine learning for predictive maintenance: A multiple classifier approach," IEEE Transactions on Industrial Informatics, vol. 11, no. 3, pp. 812–820, 2015.

[21] G. Scalabrini Sampaio et al. "Prediction of Motor Failure Time Using An Artificial Neural Network". In: *Sensors* 19.19 (2019), p. 4342. DOI: 10.3390/s19194342.

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