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ORIGINAL RESEARCH PAPER

Deep learning base faults diagnosis of centrifugal pumps

Amar P. Pandhare[1], Vishal Naranje[1], Vinod Shukla[2], Gábor Balogh[3], Atul Kulkarni[4], Gaurav S. Dave[5], Dhananjay V. Khankal[6], Komal Garse[6] and Timotei István Erdei[7]*

[1] Department of Mechanical Engineering, School of Engineering, Architecture and Interior Design, Amity University Dubai, UAE

[2] Department of Information Technology, School of Engineering, Architecture and Interior Design, Amity University Dubai, UAE

[3] Department of Mechanical Engineering, Faculty of Engineering, University of Debrecen, Debrecen, Hungary

[4] Department of Mechanical Engineering, Vishwakarma Institute of Information Technology, Pune, India

[5] Department of Mechanical Engineering, Smt. Kashibai Navale College of Engineering, Pune, India

[6] Department of Mechanical Engineering, Sinhgad College of Engineering, Pune, India

[7] Department of Vehicles Engineering, Faculty of Engineering, University of Debrecen, Debrecen, Hungary

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ABSTRACT

Centrifugal pumps are critical components in industrial systems, where early fault detection is essential to reduce downtime and maintenance costs. This study proposes a deep learning based framework for intelligent health monitoring of centrifugal pumps using time series vibration signals. Recurrent neural networks, long short term memory networks, and hybrid convolutional neural network long short term memory models are evaluated for operating condition classification and fault detection. The vibration data are preprocessed and normalized to capture temporal characteristics effectively. Experimental results based on accuracy, precision recall metrics, and confusion matrices show that the convolutional neural network long short term memory model achieves superior performance and generalization, making it suitable for fault diagnosis of rotating machinery.

KEYWORDS

centrifugal pump, deep learning, long short-term memory, convolutional neural network, recurrent neural networks, fault diagnosis, predictive maintenance

1. INTRODUCTION

Centrifugal pumps are extensively employed across various industrial domains, including chemical manufacturing, water purification, petroleum exploration, and energy production, where continuous operation is crucial for ensuring process consistency and operational efficiency [1]. Nonetheless, these pumps are susceptible to a decline in performance and mechanical failures as a result of ongoing wear and exposure to adverse operational circumstances [2]. Traditional fault detection methods often fail to consider the complex and nonlinear nature of pump dynamics, especially under varying load and speed conditions [3]. The swift progression of artificial intelligence, especially in the realm of deep learning, has

*Corresponding author.
E-mail: timoteierdei@eng.unideb.hu

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introduced formidable instruments for autonomous feature extraction and intelligent condition monitoring [4]. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly adept at modeling sequential data and have demonstrated considerable promise in elucidating temporal dependencies within machine vibration signals [5]. Furthermore, hybrid architectures including Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) have been utilized to concurrently extract spatial and temporal features, facilitating enhanced accuracy in fault classification [6]. The study focuses on utilizing deep learning techniques to evaluate centrifugal pump performance using the Centrifugal Pump Machine (CPM) dataset. The analysis of LSTM, RNN, and CNN-LSTM models on labeled datasets illustrating normal and defective conditions establishes a scalable framework for real-time fault detection [7]. This investigation addresses a significant demand within Industry 4.0 applications [8], wherein predictive maintenance and intelligent diagnostic systems are instrumental in attaining operational excellence and minimizing unforeseen downtimes [8]. Notwithstanding the encouraging outcomes, the models employed in this study are constrained by their reliance on extensive, labeled datasets, which may not consistently be accessible within industrial contexts [9]. The risk of overfitting increases with model complexity, especially with small datasets. Furthermore, the models' performance in unpredictable real-world conditions, marked by noise, sensor drift, or data absence, requires further validation.

Future investigations may concentrate on the integration of sensor fusion methodologies with Industrial Internet Of Things (IOT) diagnostic precision [10, 11]. The implementation of transformer-based architectures, which have exhibited superior performance in CPM data analyses, also represents a compelling avenue for exploration. Moreover, the real-time deployment of edge Artificial Intelligence (AI) systems and adaptive learning strategies that dynamically update the model could render the solution genuinely industrial-grade and scalable across a variety of pump types and operational scenarios [4, 12].

2. DATA STRUCTURE OF CPM RECORDED

The assembled dataset, as it is depicted in Table 1, comprises a total of 132,047 instances, each characterized by 10 distinct attributes, which encompass timestamp data, vibration metrics, flow, and pressure indicators, electrical properties, as well as the fault status associated with the centrifugal pump. To increase the robustness and efficacy of machine learning models, it is imperative to conduct data preprocessing and cleansing, prior to the commencement of classifier training [13]. This approach includes the management of missing values with data pre- processing, the standardization of sensor readings and the identification of any anomalies present within the dataset using deep learning techniques [14–16].

The dataset comprises eight quantitative features in conjunction with one categorical feature, designated as condition, which specifies the nature of the fault identified.

Table 1. CPM features recorded and its data-type

Sr No	Features recorded	Non-null count	Data type
1	Timestamp	132,047	float64
2	Casing Vibration	132,047	float64
3	Bearing Vibration	132,047	float64
4	Impeller Vibration	132,047	float64
5	Flow Sensors	132,047	float64
6	Pressure	132,047	float64
7	Pump Load Variation (PGV)	132,047	float64
8	Current	132,047	float64
9	Voltage	132,047	int64
10	Condition	132,047	object

Each recorded instance includes a Timestamp (float64), which denotes the precise moment at which the data was acquired. The casing vibration metric quantifies the vibrational activity occurring at the pump casing, thereby facilitating the detection of mechanical imbalances, cavitation events, or alignment discrepancies. Similarly, bearing vibration captures the oscillatory movements within the bearing assembly, which are pivotal for identifying wear or lubrication failures. The impeller vibration evaluates the dynamics of the impeller, providing critical insights into potential malfunctions related to the impeller. Moreover, the flow densor (L min^{-1}) quantifies the fluid flow rate passing through the pump, which assists in the detection of blockages or cavitation phenomena. The pressure (kPa) measurement records variations that may indicate systemic inefficiencies, occurrences of leakage, or cavitation. The load current variation reflects fluctuations in current under varying operational loads, signaling possible electrical and mechanical anomalies. Additionally, the dataset includes current (A) and voltage (V) metrics, which monitor the overall electrical power consumption of the pump. The condition column serves as the target variable, encompassing four distinct fault categories: No Fault (NF), indicative of standard operational conditions; Bearing Fault (BF), attributed to excessive vibrations and wear within the bearings; Impeller and Bearing Fault (IBF), triggered by issues associated with the impeller leading to abnormal vibrations, and MisAlignment (MA), resulting from improper shaft alignment, culminating in excessive vibrational activity.

3. CPM DEEP LEARNING ARCHITECTURE

CPM, the deep learning architecture as it can be seen in Fig. 1, focuses on developing an intelligent fault detection system for centrifugal pumps using advanced deep learning

Fig. 1. CPM as deep learning architecture

techniques [17, 18]. The approach begins with comprehensive data analysis collected through vibration sensors placed on the pump housing [19–21]. The raw, noisy data is cleaned using deep learning to reduce noise, remove outliers, and handle missing values [22–24]. The use of deep learning methods for these preprocessing tasks ensures a high level of automation and consistency, minimizing the need for manual intervention [25, 26].

Once cleaned, the data is standardized to bring all input features to a common scale, which is critical for stable and efficient training of neural networks [27]. Standardization improves convergence and allows the models to better identify underlying fault patterns across different samples and operating conditions [17, 28]. Unlike traditional machine learning techniques that require manual feature extraction and selection, deep learning architectures can learn discriminative features directly from the data, capturing both spatial and temporal dependencies in pump behavior [29–31].

Various deep learning architectures, such as RNN, LSTM, and hybrid CNN–LSTM, have been utilized to analyze centrifugal pump vibration signals. These models are utilized for the classification of various fault conditions, including imbalance, misalignment, impeller faults, and normal operation. Analysis via confusion matrices reveals that all architectures exhibit high classification accuracy, with LSTM and CNN–LSTM exhibiting the least misclassification rates [32–34].

This end-to-end deep learning pipeline provides a robust and scalable framework for predictive maintenance of rotating machinery [30, 35–37]. It reduces downtime, improves reliability, and extends the operational life of centrifugal pumps [10, 38]. As the model adapts to new data patterns over time, it evolves into a self-learning diagnostic tool, paving the way for fully automated Industry 4.0-ready monitoring systems [39, 40].

4. DEEP LEARNING MODELING

Deep learning has emerged as a revolutionary paradigm in contemporary data-centric diagnostic methodologies, particularly within the realm of condition monitoring for industrial machinery, exemplified by centrifugal pumps [41]. This technique facilitates the automated extraction of features and the attainment of high-level abstractions from intricate datasets, thereby enabling precise and resilient classification of fault conditions [42, 43]. In this investigation, a variety of deep learning architectures are utilized and assessed, encompassing the Keras-based Artificial Neural Network (ANN), Multi-Layer Perceptron (MLP), RNN, 1-Dimensional Convolutional Neural Network (1D-CNN), LSTM, and a hybrid CNN-LSTM model [44, 45]. Each model undergoes training with a standardized and meticulously pre-processed dataset consisting of signals from different sensors procured under diverse fault scenarios [46–48]. This section delineates the design, execution, and performance metrics of these models, underscoring their capacity to capture temporal dependencies, spatial characteristics, and sequential patterns inherent in sensor data derived from centrifugal pumps. The aim is to ascertain the model that is both the most accurate and computationally efficient, thereby rendering it suitable for real-time fault classification.

4.1. Keras-based artificial neural network

The Keras-Artificial Neural Network (K-ANN) model serves as a foundational deep learning methodology for the classification of faults in centrifugal pumps. The output layer employs a SoftMax activation function to categorize the data into one of four distinct fault classifications: impeller and bearing fault, impeller fault, misalignment, and no fault [49].

Upon completion of the training and evaluation process, the Keras neural network model attained a test accuracy of 99.81%, thereby exhibiting exceptional generalization capabilities on previously un-encountered data as it can be seen in Fig. 2. Among a total of 35,708 test samples, a mere 66 instances were inaccurately classified, which included 16 instances of Impeller Fault (IF), samples erroneously predicted as IBF, alongside 50 instances of IBF samples misclassified as IF. The confusion matrix substantiates this finding, revealing impeccable classification performance for the MA and NF categories. The classification report corroborates this result, exhibiting nearly flawless precision, recall, and F1-scores across all four fault categories. These findings affirm the Keras-based artificial neural network as a dependable and effective model for the detection and classification of faults within centrifugal pump systems.

The misclassification between Impeller Fault (IF) and Impeller Bearing Fault (IBF) likely arises from the observation that impeller malfunctions generally manifest prior to the onset of bearing issues in centrifugal pumps, with bearing deterioration typically following the progressive degradation of the impeller. Given that bearing defects are invariably associated with pre-existing impeller

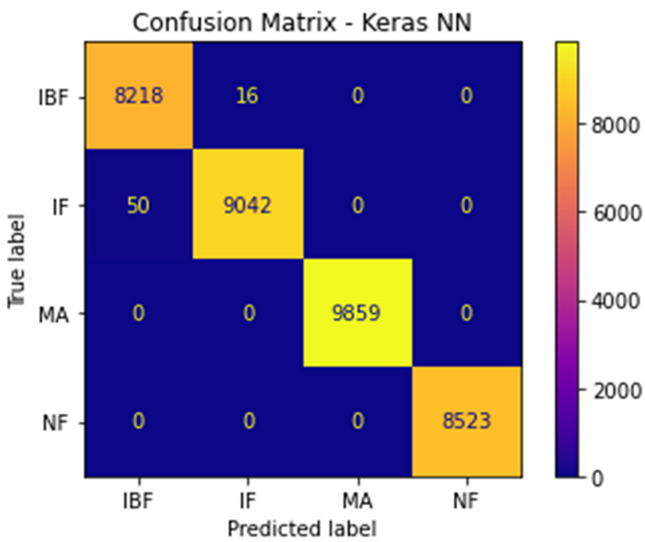

Fig. 2. Keras neural network confusion matrix

malfunctions, both fault conditions exhibit predominant vibration signatures related to the impeller, thereby rendering the signals associated with IBF strikingly analogous to those of IF and consequently complicating the process of differentiation.

4.2. Multilayer perceptron

The MLP constitutes a traditional framework of feed-forward artificial neural networks that effectively associates input data sets with corresponding output categories [50–53].

In the present investigation, the MLP model was executed utilizing deep feed-forward architecture. The input dataset, which underwent standardization via Z-score normalization, was transmitted through several densely interconnected hidden layers. The initial hidden layer comprised 256 neurons employing Rectified Linear Unit (ReLU) activation, subsequently followed by batch normalization and dropout regularization (with a dropout rate of 0.3). This was succeeded by a secondary hidden layer containing 128 neurons, along with analogous regularization strategies. The terminal output layer employed SoftMax activation to categorize the data into four discrete conditions: IBF, IF, MA, and NF.

The MLP model, as it can be seen in Fig. 3, exhibited remarkable classification efficacy, attaining a testing accuracy of 99.85%. The model successfully predicted a significant proportion of fault conditions across all four designated categories. Nevertheless, a total of 53 misclassifications were documented from a dataset comprising 35,708 samples. Specifically, the model erroneously categorized 10 instances of IBF as IF, 42 instances of IF as IBF, and 1 instance of NF as IF. No instances of misclassification were detected within the MA category, thereby underscoring the model's robust discriminative ability for that particular fault class. The confusion matrix illustrates a highly dependable performance in real-time classification contexts, rendering MLP a reliable model for diagnosing centrifugal pump faults in industrial settings.

4.3. Recurrent neural network

RNNs represent a category of deep learning architectures explicitly formulated to encapsulate sequential dependencies inherent in datasets. In contrast to feed-forward neural networks, RNNs preserve a "memory" of antecedent inputs by transmitting the hidden state from one time step to the subsequent one [54, 55].

As it is shown in Fig. 4 RNN model demonstrated a test accuracy of 99.49%, thereby illustrating remarkable generalization capabilities across diverse categories. Among the total samples analyzed, 183 instances were inaccurately classified - predominantly between the IBF and IF categories. In particular, 181 samples originating from the IBF category were erroneously identified as IF, whereas merely 2 samples from the IF category were misclassified as IBF. No misclassifications were noted within the MA and NF categories, thereby substantiating the model's resilience in accurately identifying these conditions. The conclusive confusion matrix corroborates this assessment, affirming the RNN model's proficient sequential learning characteristics for intricate signal-based classification endeavors.

4.4. Convolution neural network - 1D

A 1D-CNN constitutes a specialized architecture within deep learning paradigms, specifically designed for the analysis of one-dimensional sequential data, rendering it particularly suited for domains including signal classification, vibration analysis, and time-series forecasting [15, 56–58]. In contrast to conventional 2-Dimensional Convolutional Neural Networks (2D-CNNs) employed for image processing, the 1D-CNN executes convolutional operations along a singular temporal or spatial dimension to elucidate significant local patterns.

The trained 1D CNN model, as it can be seen in Fig. 5, has accomplished an exceptional testing accuracy of 99.82%, thereby illustrating its enhanced classification proficiency

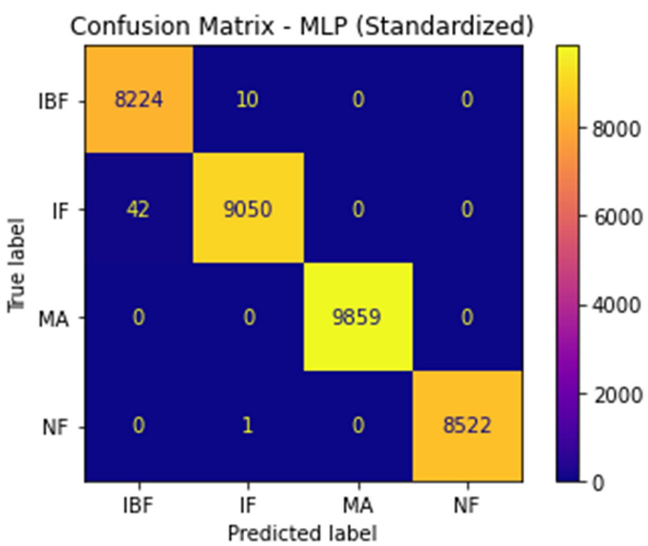

Fig. 3. Multilayer perceptron confusion matrix

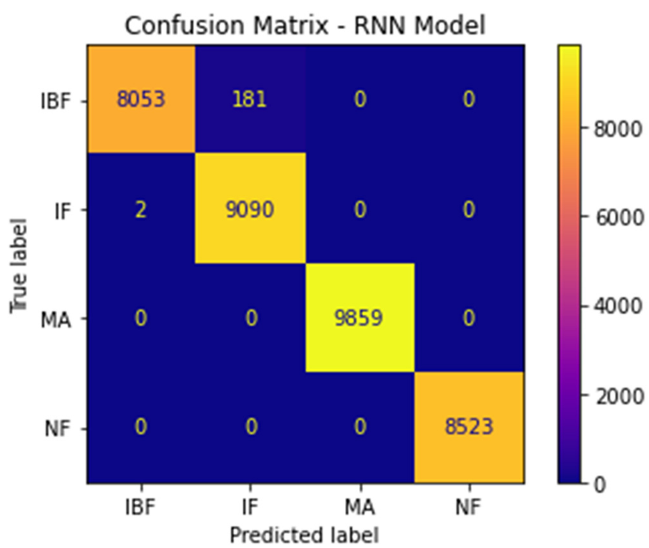

Fig. 4. Recurrent neural network confusion matrix

across the four distinct fault conditions. The confusion matrix corroborates this performance, revealing a minimal number of misclassifications. Specifically, only 50 samples from the IBF class were inaccurately classified as IF, while 16 IF samples were misidentified as IBF. No misclassifications were recorded for the MA and NF classes, as all test instances were accurately recognized. This elevated accuracy level and the negligible confusion between classes substantiate the efficacy of the 1D CNN in assimilating the temporal and spectral features inherent in the vibration signal data.

4.5. Long short-term memory model

LSTM networks represent a sophisticated variant of RNNs (Fig. 6) that are specifically engineered to proficiently capture long-term dependencies inherent in sequential datasets [59, 60].

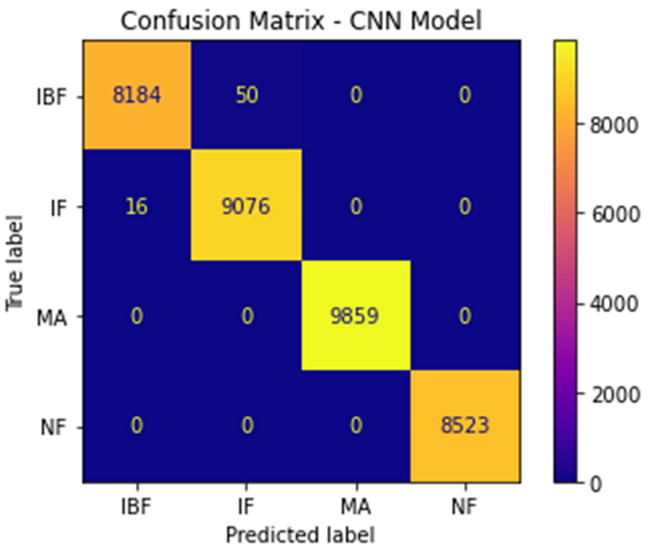

Fig. 5. Convolution neural network - 1D confusion matrix

The LSTM model achieved a high test accuracy of 99.84%, reflecting its strong capability to capture temporal dependencies in vibration signals. The confusion matrix showed negligible misclassification, highlighting the model's robustness and reliable generalization in distinguishing closely related fault conditions.

4.6. CNN + LSTM hybrid model

The hybrid architecture of CNNs and LSTM networks amalgamates the advantages inherent to both paradigms to facilitate local feature extraction alongside temporal sequence learning, thus rendering it exceptionally competent for signal-based classification endeavors [61]. This architectural configuration proves particularly advantageous when addressing intricate datasets wherein patterns are intricately woven into both spatial and temporal dimensions [62]. The primary task of convolution layers is to extract spatial features from the input signal and produce feature maps of shape that includes batch size & sequence length. These feature maps are then reshaped to each time step that contains a feature vector derived from the CNN filters. This sequence of feature vectors is connected with the LSTM layer, that model integrates with the temporal dependencies across the sequence. In this method, the CNN acts as a feature extractor and the LSTM captures sequential patterns in the extracted features.

Figure 7 demonstrates outstanding classification performance with a test accuracy of 99.89%. The confusion matrix indicates near-perfect classification across all four fault conditions, with only negligible misclassifications between the IBF and IF classes, confirming the model's ability to effectively capture both spatial and temporal characteristics of vibration signals and its suitability for high-accuracy fault diagnosis in hydraulic rotating machinery systems.

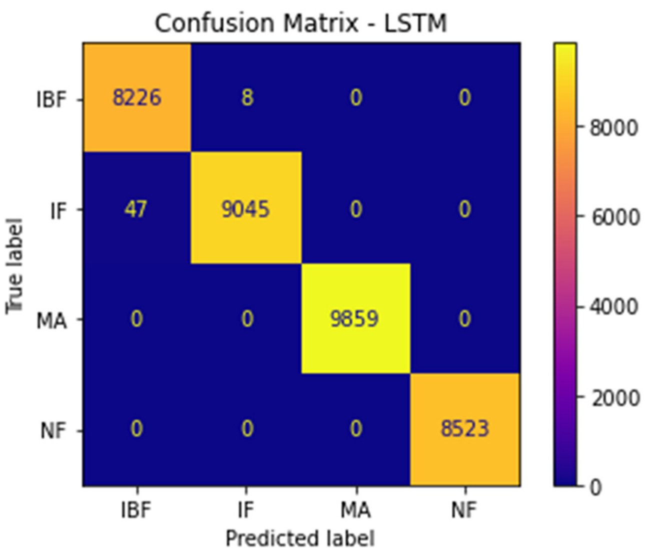

Fig. 6. Long short-term memory confusion matrix

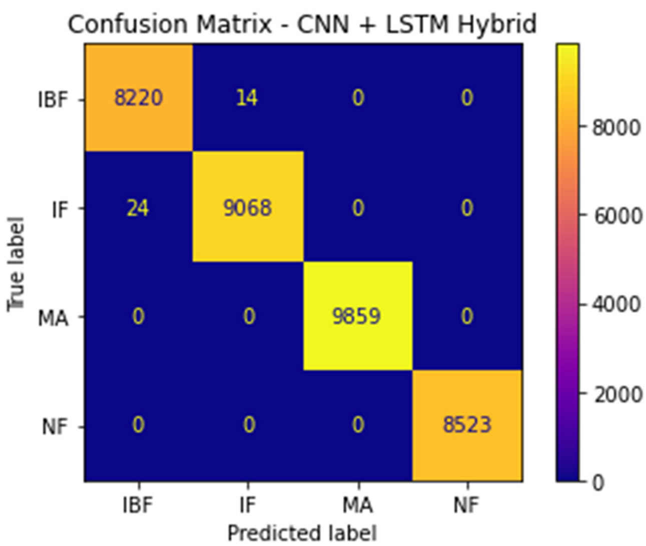

Fig. 7. CNN + LSTM hybrid model

5. RESULTS AND DISCUSSION

The validation accuracy graph as seen in compares all six models across 50 epochs:

- ANN starts lower but improves steadily with 99.81% accuracy;
- MLP with 99.85% shows a slight improvement over ANN;
- RNN performed with 99.49% slightly lesser than both MLP and ANN;
- CNN demonstrates stronger performance with 99.82% accuracy;
- LSTM surpasses CNN with consistent accuracy gains and achieved 99.84%;
- CNN + LSTM achieve the highest validation accuracy, nearing 99.89%.

6. CONCLUSION

In this investigation, various deep learning frameworks - including Keras-based ANN, MLP, RNN, 1D-CNN) LSTM, and a composite CNN-LSTM architecture - were meticulously designed and assessed for the classification of centrifugal pump faults utilizing standardized vibration signal datasets acquired under four distinct operational conditions (IBF, IF, MA, and NF). All methodologies exhibited a significant generalization capacity, attaining testing accuracies exceeding 99%, thereby substantiating the efficacy of deep learning techniques for automated feature extraction and reliable fault identification in rotating machinery.

Among the assessed models, the CNN-LSTM hybrid architecture attained the highest test accuracy of 99.89%, accompanied by the fewest misclassifications. An analysis of the confusion matrix indicated that classification errors were predominantly confined to the IBF and IF categories, whereas the MA and NF categories were accurately identified with either perfect or nearly perfect precision across all models. The observed confusion between IBF and IF is physically warranted, as impeller faults generally precede bearing damage in centrifugal pumps; thus, IBF conditions inherently encompass dominant vibration components related to the impeller, resulting in highly analogous signal characteristics to those of IF. The enhanced performance of the hybrid model substantiates that the integration of convolutional layers for the extraction of local spatial features, in conjunction with LSTM layers for the learning of temporal dependencies, yields a more holistic representation of vibration signals. Consequently, the CNN–LSTM model emerges as the most precise and computationally dependable architecture for the real-time diagnosis of centrifugal pump faults and its practical application in industrial settings.

7. LIMITATION

Although the CNN-LSTM hybrid architecture demonstrated strong performance, the study is subject to certain limitations. The model's accuracy is highly dependent on the quality and volume of the training data, and issues such as data imbalance or noise can negatively affect the results. Additionally, the computational complexity of deep hybrid architectures is often associated with improving flow efficiency and analyzing losses caused by friction [63]. Water management and the economical use of drinking water are also important areas [64]. Nevertheless, it should be noted that, in the spirit of green transition, other studies discussing energy development [65] and structural change [66] also served as a basis for the dissertation, and substantial training time and resources, which may limit their suitability for real-time applications.

8. FUTURE WORK

To overcome the identified limitations and further improve model performance, future research may focus on incorporating advanced data augmentation techniques to reduce over-fitting and improve generalization, as well as adopting more systematic hyper-parameter optimization strategies to refine the model architecture for enhanced accuracy and computational efficiency. Overall, this study highlights the promising potential of hybrid deep learning architectures for fault diagnosis using CPM data and provides a solid foundation for future research and methodological advancements.

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