A Bibliometric Review of Hybrid CNN-BiLSTM Deep Learning Frameworks for Fault Detection, Classification, and Location in Power Transmission Systems

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Abstract — This paper presents a bibliometric review of hybrid Convolutional Neural Network–Bidirectional Long Short-Term Memory (CNN-BiLSTM) models used for fault detection, fault classification, and fault localization in electrical power systems. A systematic literature search was conducted using the Scopus database following the PRISMA 2020 guidelines. After screening and eligibility assessment, 43 peer-reviewed journal articles and conference papers published between 2023 and 2026 were selected for analysis. The selected studies were examined based on publication trends, document and source distribution, keyword co-occurrence, citation analysis, and reported model performance. The review shows a significant increase in research on CNN-BiLSTM-based fault diagnosis since 2024. Keywords such as fault diagnosis, deep learning, and BiLSTM appeared most frequently, indicating the growing interest in hybrid deep learning techniques. Most studies reported diagnostic accuracies above 95%, demonstrating the effectiveness of CNN–BiLSTM models for power system fault diagnosis. However, the review also identifies several research gaps, including the limited availability of unified models for simultaneous fault detection, classification, and localization, the lack of standardized benchmark validation, and the need for robust real-time implementation under noisy operating conditions. These findings provide useful insights and highlight future research directions for developing intelligent fault diagnosis frameworks for power transmission systems.

Keywords: bibliometric analysis; CNN-BiLSTM; fault detection; deep learning; power transmission systems; PRISMA; IEEE 14-bus

I. Introduction

Reliable and timely detection of faults in electrical power transmission networks is fundamental to grid stability, equipment protection, and continuity of supply. Transmission lines are continually exposed to lightning strikes, insulation ageing, vegetation contact, and switching transients, all of which can precipitate single-line-to-ground (SLG), line-to-line (LLG), and three-phase (LLLG) faults. Conventional protection methods, such as distance relays, traveling-wave techniques, and rule-based expert systems, have been widely used in power systems. However, their performance may decrease under changing operating conditions, noisy PMU measurements, and when multiple tasks such as fault detection, classification, and location need to be performed simultaneously.

Deep learning has become a popular approach for overcoming these limitations. Convolutional Neural Networks (CNNs) are used to extract important features from voltage and current measurements, while Bidirectional Long Short-Term Memory (BiLSTM) networks learn the relationships in the data by processing it in both forward and backward directions. The combination of CNN and BiLSTM has been successfully applied to fault diagnosis in power systems, transformer protection, and condition monitoring of electrical machines. Many studies have reported classification accuracies of more than 95%, demonstrating the effectiveness of this hybrid approach.

As the number of studies on CNN–BiLSTM models continue to increase, a systematic review is needed to understand current research trends, identify important contributions, and highlight existing research gaps. In this paper, a bibliometric review was conducted following the PRISMA 2020 guidelines using publications retrieved from the Scopus database. The collected data were analysed using Python-based tools to examine publication trends, keyword relationships, and citation patterns. The findings of this review also provide the research background and motivation for developing a hybrid CNN–BiLSTM model for fault detection, fault classification, and fault localization in the IEEE 14-bus power transmission system. The remainder of this paper is organized as follows. Section II describes the search methodology, Section III presents the bibliometric analysis, Section IV summarizes the reviewed CNN–BiLSTM architectures, Section V discusses the identified research gaps, and Section VI concludes the paper.

II. Methodology

A. Search Strategy

The Scopus database was selected for this review because it provides extensive coverage of engineering and computer science publications along with reliable citation information. A Boolean search was performed using the Title, Abstract, and Keywords fields with the following search query:

("fault detection" OR "fault diagnosis" OR "fault classification" OR "fault location") AND ("CNN" OR "convolutional neural network") AND ("BiLSTM" OR "bidirectional long short-term memory") AND ("power system" OR "power transmission" OR "transmission line" OR "transformer" OR "power grid")

The search was limited to journal articles and conference papers published in English between January 2023 and April 2026. This time period was selected because it reflects the rapid growth in research on hybrid CNN–BiLSTM models for fault diagnosis in power systems.

B. PRISMA-Based Study Selection

The study selection process followed the four-stage PRISMA 2020 framework, as shown in Fig. 1. The initial Scopus search identified 187 records. After removing 9 duplicate and non-English records, 178 records remained for title and abstract screening. Based on this screening, 89 records were excluded because they were not relevant to the research topic. The remaining 89 studies were assessed in detail using the eligibility criteria listed in Table I. Of these, 46 studies were excluded because they did not use a hybrid CNN–BiLSTM model or did not have accessible full-text versions. As a result, 43 studies were selected for the final bibliometric analysis.

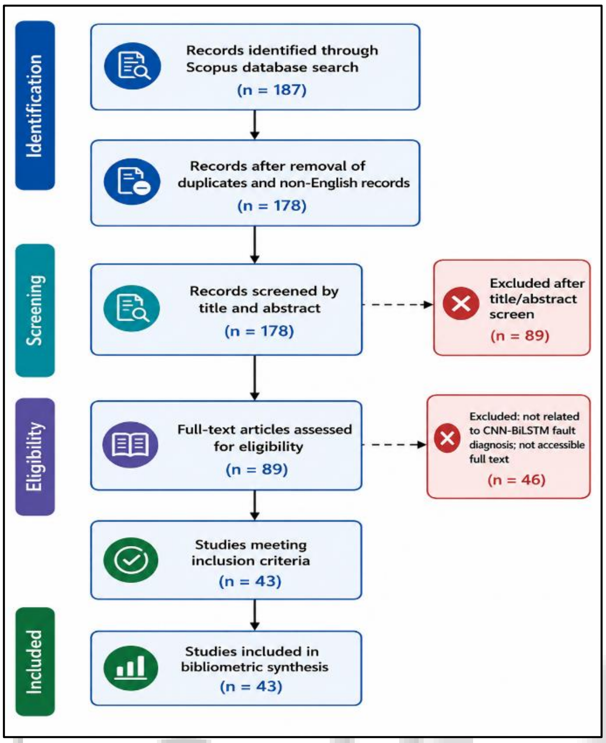

Fig. 1: PRISMA 2020 flow diagram of the literature selection process

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal articles and conference papers	Duplicate records retrieved across repeated search iterations
Published between January 2023 and April 2026	Non-English publications or inaccessible full text
Full text written in English	Studies not employing a CNN-BiLSTM hybrid (single-model CNN-only or LSTM-only works)
Explicitly involves a hybrid CNN-BiLSTM (or closely related CNN + BiLSTM) architecture	Application domains unrelated to power, energy, or electromechanical fault engineering
Application to fault detection, classification, diagnosis, prediction, or location in electrical / electromechanical systems	Editorials, posters, and non-peer-reviewed preprints

Table I: Inclusion and Exclusion Criteria

C. Data Extraction and Analysis Tools

The bibliographic information of the 43 selected studies, including authors, publication year, source, citations, abstract, and author keywords, was exported from the Scopus database in CSV format. The data were analysed using Python. The pandas library was used for data processing and descriptive analysis, while NetworkX and Matplotlib were used to generate and visualize keyword co-occurrence networks.

III. BIBLIOMETRIC RESULTS

A. Annual Scientific Production

Fig. 2 presents the yearly publication trend of the 43 selected studies. The number of publications increased from 6 in 2023 to 22 in 2025, showing growing research interest in CNN–BiLSTM-based fault diagnosis. The 7 publications already indexed for 2026 (partial year) indicate that this trend is likely to continue.

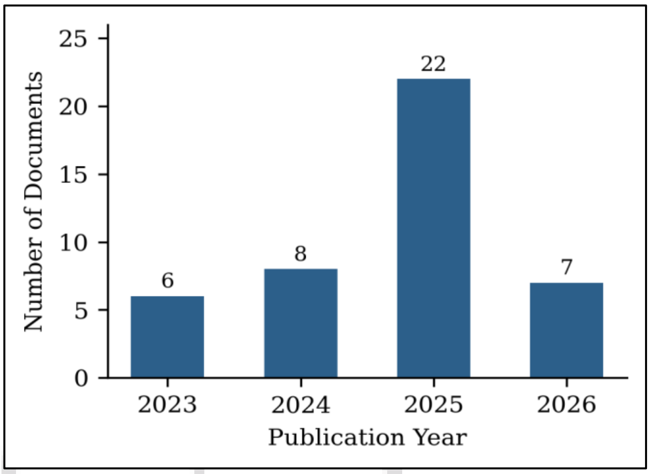

Fig. 2: Annual scientific production of the reviewed corpus (2023–2026)

B. Document Type and Source Distribution

The selected studies include 26 journal articles and 17 conference papers. Most publications are spread across different journals and conferences, with IEEE Access contributing the highest number of papers (3). This broad distribution reflects the growing interest in CNN–BiLSTM-based fault diagnosis across multiple research fields.

C. Keyword Co-occurrence Analysis

Fig. 3 shows the keyword co-occurrence network of the selected studies. The most frequently occurring keywords are fault diagnosis (12 occurrences), deep learning (9), and BiLSTM (6), indicating that these are the main research topics in the field. Other commonly connected keywords include fault classification, fault location, fault identification, and prediction, highlighting the focus on different fault diagnosis tasks. Keywords such as attention mechanism, metaheuristic algorithm, and feature extraction also appear, showing that recent studies are improving CNN–BiLSTM models by incorporating optimization techniques and enhanced feature learning.

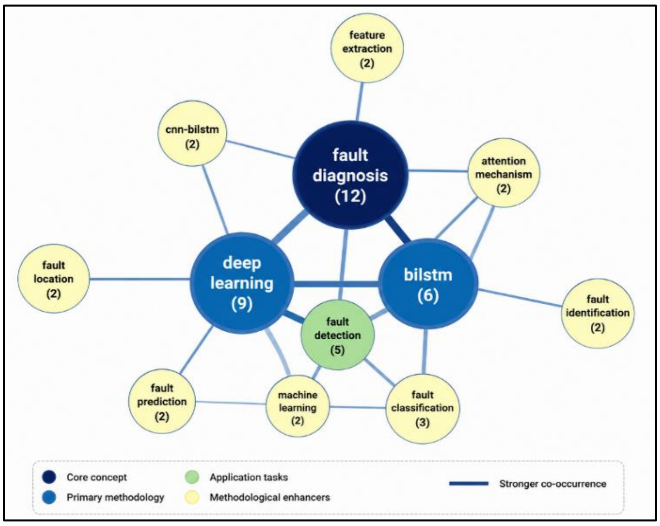

Fig. 3: Author-keyword co-occurrence network (minimum frequency = 2)

D. Citation Analysis

Table II lists the ten most-cited studies included in this review. The most-cited paper focuses on remaining useful life prediction of rolling bearings rather than fault diagnosis in power transmission systems. This indicates that CNN–BiLSTM research has received greater citation attention in mechanical and renewable energy applications. In comparison, studies on power transmission fault diagnosis are relatively new and have received fewer citations, although they make up a significant portion of the selected literature.

Study (First Author)	Year	Source	Cites
Bharatheedasan et al. [8]	2023	Sadhana – Acad. Proc. Eng. Sci.	24
Chen Y. et al. [41]	2025	Measurement	15
Zhao T. et al. [29]	2024	Int. J. Hydrogen Energy	14
Afsharisefat et al. [36]	2024	IET Gen., Transm. & Distrib.	9
Li Q. et al. [33]	2024	Scientific Reports	8
Zhang C.-L. et al. [34]	2025	Int. J. Hydrogen Energy	7
Ren Y. et al. [26]	2025	J. Franklin Institute	6
Ren C. et al. [32]	2024	Energies	5
Zhang D. et al. [20]	2024	Sensors	4
Lin J. et al. [11]	2025	Int. J. Elec. Power Energy Syst.	3

Table II: Top 10 Most-Cited Studies in The Reviewed Corpus

IV. Thematic Synthesis of Hybrid Architectures

Table III summarizes eight representative studies on CNN–BiLSTM-based fault diagnosis in power systems and related applications. Most studies use one of three approaches: a basic CNN–BiLSTM model, a CNN–BiLSTM model combined with signal processing techniques such as DWT or VMD, or an improved CNN–BiLSTM model with attention mechanisms or optimization algorithms. Most of these studies report classification accuracies above 95% and use large simulated datasets, often generated using MATLAB/MATPOWER. However, only a few studies perform fault detection, fault classification, and fault localization together in a single model. In addition, the IEEE 14-bus system is rarely used as a common benchmark, making it difficult to compare the performance of different methods.

Study	Hybrid Architecture	Application Domain	Reported Accuracy
Khalif et al. [2]	DWT + CNN-BiLSTM	Transmission line	99.86% / 93.75%
Omran et al. [4]	MLP-BiLSTM	PV DC arc fault	≈99%
Pan et al. [5]	VMD + Dilated CNN-BiLSTM	Electrical line anomaly	98.6%
Bharatheedasan et al. [8]	CNN-BiLSTM	Rolling bearing / RUL	99.8% / 98.3%
Feiyun et al. [14]	Multiscale petal pattern CNN-BiLSTM	Rolling bearing (acoustic)	98.44%
Afsharisefat et al. [36]	VMD + CNN-BiLSTM	Power transformer protection	99.8%
Zhang D. et al. [20]	TSO + CNN-BiLSTM	Hydraulic components	99.07%
Ibrahim Abo Elkheir et al. [35]	Hybrid deep learning	Microgrid fault management	99.72%

Table III: Comparative Synthesis of Representative CNN-Bilstm Studies

V. Research Gaps and Future Directions

The literature review identified four major research gaps. First, only a few studies provide a single model that can simultaneously perform fault detection, fault classification, and fault localization. Most existing studies focus on only one or two of these tasks. Second, standard IEEE test systems, such as the IEEE 14-bus and IEEE 30-bus systems, are used less frequently than custom simulation datasets, making it difficult to compare the performance of different methods. Third, the effects of PMU measurement noise, missing data, and real-time implementation are not thoroughly investigated in many studies. Finally, limited attention has been given to explaining how hybrid deep learning models make their decisions, which is important for increasing the confidence of power system operators. These research gaps provide the motivation for the present work, which develops a hybrid CNN–BiLSTM model for simultaneous fault detection, fault classification, and fault localization using the IEEE 14-bus power transmission system.

VI. Conclusion

This bibliometric review examined 43 Scopus-indexed studies on hybrid CNN–BiLSTM models for fault diagnosis in power systems using the PRISMA 2020 guidelines. The analysis showed a significant increase in research on CNN–BiLSTM models since 2023, with fault diagnosis, deep learning, and BiLSTM emerging as the most common research topics. Most studies reported classification accuracies above 95%, demonstrating the effectiveness of hybrid CNN–BiLSTM models. However, the review also found that only a few studies address fault detection, fault classification, and fault localization together in a single framework. In addition, standard IEEE test systems, such as the IEEE 14-bus system, are not widely used for model validation. These findings highlight the need for an integrated CNN–BiLSTM model that can simultaneously perform fault detection, classification, and localization using a standard power system benchmark such as the IEEE 14-bus system.

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