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Intelligent Cellular Performance Monitoring and Fault Diagnosis Using Deep Graph Analytics

Srikanth Reddy Bommineni, T. Srilekha*
Vaagdevi Engineering College, Warangal, 506005, Telangana, India.
*Correspondence: T. Srilekha

ABSTRACT

The continuous evolution of wireless communication technologies, including WiFi, 4G, and 5G, has generated vast amounts of network data that require intelligent analysis to ensure reliable connectivity and efficient communication. Accurate prediction of network characteristics, such as connection type and signal strength, has become increasingly important for maintaining service quality, optimizing resource utilization, and improving user experience. Conventional network monitoring techniques mainly rely on visualization tools that display performance indicators such as latency, throughput, and received signal strength. Although these approaches assist in monitoring network conditions, they provide limited predictive capabilities and require significant manual interpretation. In addition, traditional methods often fail to perform effective data preprocessing, including missing value handling, categorical feature encoding, and data normalization, which can negatively affect prediction accuracy. To overcome these challenges, this work presents a Flask-based web application that integrates machine learning techniques for intelligent network signal analysis and prediction. The proposed framework employs Ridge Classifier (RC), Ridge Regressor (RR), Decision Tree Classifier (DTC), Decision Tree Regressor (DTR), and a Hybrid MLP with Catboost model to perform both classification and regression tasks. Network type identification is formulated as a classification problem, whereas signal strength estimation is treated as a regression problem. The developed system evaluates model performance using accuracy, precision, recall, F1-score, MAE, MSE, RMSE, and R^2 metrics, enabling comprehensive comparison of predictive models. The proposed framework offers an efficient, scalable, and user-friendly solution for intelligent network performance analysis and future wireless communication applications.

Keywords: Deep Graph Analytics, Cellular Network Performance, Fault Diagnosis, Graph Neural Networks (GNN), Machine Learning.

1.INTRODUCTION

The growth of mobile data traffic and the increase in service types have led to challenges in mobile communication network capacity. Heterogeneous cellular networks have been widely explored in the literature to address the bandwidth problem and improve system capacity. However the expansion and complexity of heterogeneous networks have made the management and maintenance of cellular networks increasingly complex. Traditional network fault detection and diagnosis methods are primarily performed manually, making it difficult to establish the mapping relationship between network symptoms and fault categories. Additionally, these methods require significant human and material resources. Therefore, there is an urgent need to establish a fast and accurate network fault diagnosis model. In response to this need, researchers have conducted in-depth research on network fault diagnosis. In [1], the authors proposed Adaptive Root Cause Analysis (ARCA), an automatic fault detection and diagnosis solution. This method utilizes Bayesian networks combined with expert domain knowledge to perform efficient and automatic network root cause analysis based on acquired network measurement data.

Introduced as a Bayesian network-based network fault diagnosis method for universal

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mobile communication systems. They constructed an automatic diagnostic model using a naive Bayesian classifier and established a relationship between network failures and root causes. In the authors analyzed the time evolution of multiple network metrics from the perspective of time dependencies between these metrics. They explored the interdependence between network metrics of the primary cell and neighboring cells in the presence of network failures. By comparing these metrics with stored historical failures, they determined the root cause of the failure. A comprehensive detection and diagnosis framework was proposed in [2]. The detection phase relied on radio measurements and other performance indicators, comparing them with the normal behavior obtained in the profile.

The diagnosis phase utilized past fault cases to identify and understand their impact on different performance metrics. In recent years, intelligent fault diagnosis has shifted from traditional model-based methods to data-driven approaches. Gomez-Andrades et al. [3] introduced an automatic diagnosis system for LTE (Long-Term Evolution) networks based on unsupervised learning. Their system employed Self Organizing Maps (SOMs) and the sum of squares of deviations to ensure solution quality through an iterative process. The effectiveness of this diagnosis system was verified using real and simulated LTE data. The focus in [4] was on fault diagnosis at the air interface.

The fault diagnosis model collected user measurement data related to the radio frequency interface. It then used SOMs to analyze the specific measurements of each user and determine their RF status. The results were aggregated into cell-level indicators, allowing an analysis of the air quality of the entire cell. In [5], the authors treated the performance tuning process of cellular networks as a reinforcement learning problem and proposed a method to improve the performance of indoor and outdoor environments. To achieve effective diagnostic performance, the authors combined SoftMax neural networks in supervised learning, enabling the algorithm to be implemented effectively with off-the-shelf tools. The use of an improved back-propagation (BP) neural network for fault diagnosis in local area networks. Experimental results confirmed the effectiveness of the improved BP neural network in fault diagnosis.

2.LITERATURE SURVEY

Amuah, E.A.; et al. [6] proposed an improved 4G/5G network fault diagnosis with a few effective labeled samples. Our solution is a heterogeneous wireless network fault diagnosis algorithm based on Graph Convolutional Neural Network (GCN). First, the common failure types of 4G/5G networks are analyzed, and then the graph structure is constructed with the data in the network parameter, given data sets as nodes and similarities as edges. GCN is used to extract features from the graph data, complete the classification task for nodes, and finally predict the fault types of cells. A large number of experiments are carried out based on the real data set, which is achieved by driving tests. Qiu, S.; et al. [7] introduced the fault diagnosis and prognosis (FDP) tries to recognize and locate the faults from the captured sensory data, and also predict their failures in advance, which can greatly help to take appropriate actions for maintenance and avoid serious consequences in industrial systems. In recent years, deep learning methods are being widely introduced into FDP due to the powerful feature representation ability, and its rapid development is bringing new opportunities to the promotion of FDP. In order to facilitate the related research, we give a summary of recent advances in deep learning techniques for industrial FDP in this paper. Related concepts and formulations of FDP are firstly given. Seven commonly used deep learning architectures, especially the emerging

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generative adversarial network, transformer, and graph neural network, are reviewed.

Zhao, L.; et al. [8] explained the existing network fault diagnosis methods rely on manual testing and time stacking, which suffer from long optimization cycles and high resource consumption. Therefore, we herein propose a knowledge- and data-fusion-based fault diagnosis algorithm for 5G cellular networks from the perspective of big data and artificial intelligence. The algorithm uses a generative adversarial network (GAN) to expand the data set collected from real network scenarios to balance the number of samples under different network fault categories. In the process of fault diagnosis, a naive Bayesian model (NBM) combined with domain expert knowledge is firstly used to pre-diagnose the expanded data set and generate a topological association graph between the data with solid engineering significance and interpretability. Then, as the pre-diagnostic prior knowledge, the topological association graph is fed into the graph convolutional neural network (GCN) model simultaneously with the training data set for model training. Chen, Y.; et al. [9] proposed a fault diagnosis methodology that leverages knowledge graphs. First, we designed an ontology model for fault knowledge by integrating textual features from various components of the production line with expert insights. Second,They employed the ALBERT–BiLSTM–Attention–CRF model to achieve named entity and relationship recognition for faults in intelligent production lines. The introduction of the ALBERT model resulted in a 7.3% improvement in the F_1 score compared to the BiLSTM–CRF model. Additionally, incorporating the attention mechanism in relationship extraction led to a 7.37% increase in the F_1 score. Finally, we utilized the Neo4j graph database to facilitate the storage and visualization of fault knowledge, validating the effectiveness of our proposed method through a case study on fault diagnosis in CNC machining centers. The research findings indicate that this method excels in recognizing textual entities and relationships related to faults in intelligent production lines, effectively leveraging prior knowledge of faults across various components and elucidating their causes.

Arellano-Espitia, F.; et al. [10] depicted the current Industry 4.0 framework, maintenance strategies based on traditional data-driven fault diagnosis schemes require enhanced capabilities to be applied over modern production systems. In fact, the integration of multiple mechanical components, the consideration of multiple operating conditions, and the appearance of combined fault patterns due to eventual multi-fault scenarios lead to complex electromechanical systems requiring advanced monitoring strategies. In this regard, data fusion schemes supported with advanced deep learning technology represent a promising approach towards a big data paradigm using cloud-based software services. Lu, W.; et al. [11] proposed the MeanRadius-SMOTE graph neural network (MRS-GNN), a novel framework designed to synthesize node representations in GNNs to effectively mitigate this issue. Through integrating the MeanRadius-SMOTE oversampling technique into the GNN architecture, the MRS-GNN demonstrates an enhanced capability to learn from under-represented classes while preserving the intrinsic connectivity patterns of the graph data. Comprehensive testing on various datasets demonstrated the superiority of the MRS-GNN over traditional methods in terms of classification accuracy and handling class imbalances. The experimental results on three publicly available fault diagnosis datasets show that the MRS-GNN improves the classification accuracy by 18 percentage points compared to some popular methods.

Said, N.; et al. [12] provided a comprehensive review of how various learning methods are applied to fault diagnosis in interconnected

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systems, particularly in predictive maintenance. It examines different approaches that integrate data across domains, evaluating how each contributes to improved fault detection and enhanced system reliability. Additionally, it addresses emerging research areas, such as real-time fault detection, innovative data fusion processes, and the increasing application in power grids, manufacturing, and the automation sector. This paper serves as a valuable resource for both researchers and practitioners, emphasizing the significant potential of multimodal learning in advancing fault diagnosis and predictive maintenance within increasingly interconnected and complex systems. Siddique, M.F.; et al. [13] presented a hybrid deep learning approach for bearing fault diagnosis that integrates continuous wavelet transform (CWT) with an attention-enhanced spatiotemporal feature extraction framework. The model combines time-frequency domain analysis using CWT with a classification architecture comprising multi-head self-attention (MHSA), bidirectional long short-term memory (BiLSTM), and a 1D convolutional residual network (1D conv ResNet). This architecture effectively captures both spatial and temporal dependencies, enhances noise resilience, and extracts discriminative features from nonstationary and nonlinear vibration signals. The model is initially trained on a controlled laboratory bearing dataset and further validated on real and artificial subsets of the Paderborn bearing dataset, demonstrating strong generalization across diverse fault conditions.

Bougoffa, M.; et al. [14] specified the model was rigorously validated using real-world PV datasets, encompassing diverse fault types such as partial shading, open circuits, and module degradation under dynamic environmental conditions. Results demonstrate state-of-the-art performance, with the model achieving 99.82% accuracy, 99.7% precision, 99.4% sensitivity, and 100% specificity, outperforming traditional machine learning and deep learning approaches. These findings highlight the framework's robustness and reliability in real-world applications. By significantly enhancing fault detection accuracy and computational efficiency, the proposed approach optimizes PV system performance, reduces operational costs, and supports sustainable energy production. This study concluded that the hybrid SSAE-Optimized MLP model represents a scalable and efficient solution for improving the reliability and longevity of renewable energy infrastructure, setting a new benchmark for intelligent maintenance strategies in the field. Zachariades, C.; et al. [15] reviewed a comprehensive and up-to-date analysis of artificial intelligence (AI) techniques for fault diagnosis in electric machines. It categorizes and evaluates supervised, unsupervised, deep learning, and hybrid/ensemble approaches in terms of diagnostic accuracy, adaptability, and implementation complexity. A comparative analysis highlights the strengths and limitations of each method, while emerging trends such as explainable AI, self-supervised learning, and digital twin integration are discussed as enablers of next-generation diagnostic systems. To support practical deployment, the article proposes a modular implementation framework and offers actionable recommendations for practitioners.

3. PROPOSED METHODOLOGY

This research is a comprehensive web application built on the Flask framework, designed for the deep analysis and fault diagnosis of cellular networks. It operates in a continuous, user-driven cycle: first, it loads and preprocesses raw network data, making it ready for analysis. Second, it enables users to perform a detailed Exploratory Data Analysis (EDA), generating visualizations on-demand to provide deep insights into the data's characteristics and relationships. Third, it allows for the training of both classification and regression models—

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including the advanced Hybrid CatBoost to predict network types and signal strengths. Fourth, it presents a clear, comparative overview of each model's performance using standard metrics. Finally, it offers a real-time prediction interface where users can input new data and instantly receive a diagnosis, effectively identifying potential network issues or performance anomalies. This seamless, end-to-end platform integrates data science with a user-friendly interface for proactive network management as shown in Fig 1.

Repeating Across All Trees: This process is repeated independently across all the trees in the CatBoost ensemble. Each tree provides one scalar prediction based on the same input feature vector but different splits and thresholds. Internally, this ensemble approach enables the model to capture a wide variety of non-linear interactions and complex patterns from the high-level features.

Summing Tree Outputs: CatBoost Regressor aggregates the predictions of all individual trees by summing the scalar values obtained from each tree's leaf node. Internally, this additive process is straightforward and deterministic, producing a final continuous value that represents the predicted signal strength.

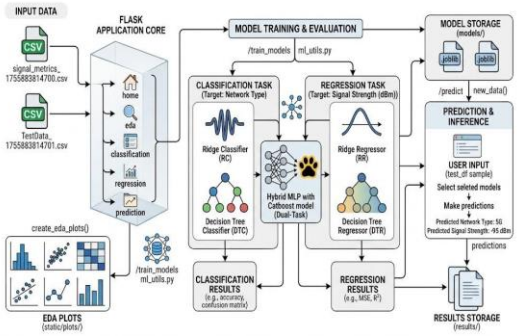


Fig. 1: Proposed system architecture for performance monitoring and fault diagnosis using deep graph analytics.

Final Prediction Output: The sum of the individual tree outputs becomes the final signal strength prediction (e.g., −85.2 dBm). Internally, this is returned directly by the predict() function of CatBoost. There is no further post-processing or transformation inside CatBoost; the scalar is ready for external consumption.

Numerical Stability and Determinism: All comparisons and arithmetic operations in the trees are computed using high-precision floating-point arithmetic, ensuring numerical stability. Internally, the model does not introduce any randomness during inference, guaranteeing that the same input always yields the same output.

4. RESULTS AND DISCUSSIONS

The research implements a Flask-based web application for predicting network type and signal strength using multiple machine learning algorithms. It begins with importing essential libraries for data handling, visualization, preprocessing, and machine learning, followed by setting up the Flask server and creating directories to store models, results, and plots. Datasets are loaded and summarized, then EDA is performed through statistical summaries, histograms, box plots, and correlation matrices to gain insights into feature distributions and relationships. The data is preprocessed by normalizing numerical features, encoding categorical variables, and handling missing values to ensure compatibility with both classification and regression models. Multiple models, including Ridge, DT, and a Hybrid MLP with Catboost, are trained on the preprocessed data to learn patterns for network type and signal strength prediction. Each model is evaluated using relevant classification and regression metrics, and trained models are saved for later use. The web interface allows users to input feature values, which are preprocessed similarly to the training data, and predictions are generated in real time. All results, metrics, and visualizations are stored and rendered dynamically on the web pages, integrating backend computation with an interactive frontend.

Fig. 2 (a) Signal Strength Distribution: The plot on the left is a histogram that shows the distribution of Signal Strength (dBm) values.

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The x-axis represents the signal strength in dBm, and the y-axis represents the frequency. The distribution is roughly bell-shaped, peaking around -90 dBm, which indicates that the most common signal strength in the dataset is approximately this value. The shape of the histogram suggests a normal or Gaussian distribution, with most data points clustered around the mean and tapering off towards the stronger (-70 dBm) and weaker (-110 dBm) signal ends.

Fig. 2 (b) Signal Strength by Network Type: The plot on the right is a boxplot, which visualizes the distribution of signal strength by network type. The x-axis shows the different network types (3G, 4G, 5G, LTE), and the y-axis shows the signal strength in dBm. Each box represents a network type, with the horizontal line inside it showing the median signal strength. The box itself represents the interquartile range (IQR), from the 25th to the 75th percentile. The "whiskers" extending from the box show the rest of the data range, and the individual points outside the whiskers are outliers. The plot clearly shows that different network types have different signal strength distributions, with 3G and 5G appearing to have slightly stronger (less negative) median signal strengths compared to 4G and LTE. The plot also highlights the presence of outliers in all network types.

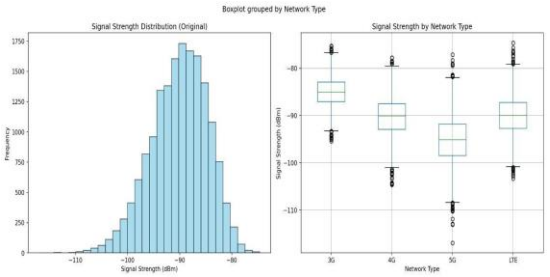


Fig. 2: Histogram and box plot for signal strength and network type features.

Fig 3 shows the histogram plots of data throughput, latency, and signal strength distributions. Below are those 3 plots' descriptions.

Data Throughput Distribution: This is a histogram that visualizes the distribution of Data Throughput values. The x-axis represents data throughput, likely in megabits per second (Mbps), and the y-axis shows the frequency or count. The shape of this histogram indicates how data throughput is distributed across the dataset, showing whether values are clustered at high or low speeds or are spread out more evenly.

Latency Distribution: This is a histogram that shows the distribution of latency values. The x-axis represents latency, likely in milliseconds (ms), and the y-axis represents the frequency. This plot provides a visual summary of the network's responsiveness. Its shape would reveal if most connections have low latency or if there's a significant number of connections with high delays.

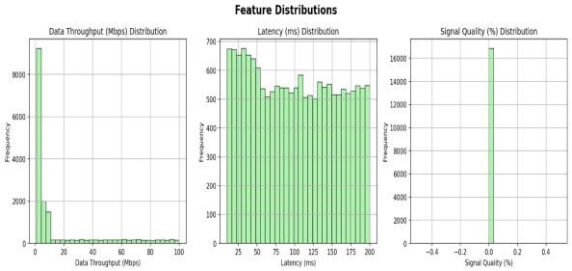


Fig. 3: Histogram plots for data, latency, and signal strength distributions.

Signal Quality Distribution: This is a histogram that visualizes the distribution of signal quality values. The x-axis represents the signal quality, and the y-axis shows the frequency. This histogram is crucial for understanding the overall quality of the network's signals. It would show if the majority of the data points have high-quality signals, if the quality is poor, or if it is evenly distributed across the entire range.

Comparative analysis

Table 1 evaluates the performance of three different models such as RC, DTC, and CB on the classification task of predicting Network Type. The metrics presented include accuracy, precision, recall, and F-score. The results show that the Hybrid MLP with CB model achieved

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a perfect score of 100% across all metrics, indicating flawless performance on the test data. The RC also performed very well, with scores consistently above 92%, making it a strong contender. In contrast, the DTC had the lowest performance, with all metrics in the mid-80% range. The perfect scores from the hybrid model are highly unusual and may suggest potential data leakage or an extremely simple classification problem. The table clearly indicates the superior performance of the proposed CatBoost, followed by the Ridge-CART and the DT-CART.

Algorithms Name	Accuracy	Precision	Recall	F-score
RC model	92.87%	94.15%	92.84%	92.92%
DTC	84.82%	90.57%	84.73%	84.27%
Hybrid MLP with Catboost	100%	100%	100%	100%

Table 1: Performance comparison for the Ridge, DT and Hybrid MLP with CB models

Table 2 offers a detailed performance comparison of three models RR, DTR, and Hybrid MLP with CatBoost on the regression task of predicting Signal Strength. The evaluation is based on key metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the R2 score. The results clearly indicate that the Hybrid MLP with CB model is the most effective, achieving the lowest error rates (MAE of 0.0288, MSE of 0.0017, and RMSE of 0.0412) and the highest R2 score of 0.8961. This high R2 value suggests that the model explains approximately 89.61% of the variance in the signal strength data, demonstrating its superior predictive power. The DTC ranks second, with moderate error rates and a respectable R2 score of 0.7859. The RC performs the least effectively, with significantly higher error rates and the lowest R2 score of 0.4947, indicating a relatively weak fit to the data. The table confirms the superior capability of the Hybrid MLP with CatBoost for this specific regression task.

Algorithms Name	MAE	MSE	RMSE	R^2-score
RR	0.0722	0.0082	0.0908	0.4947
DTR	0.0398	0.0035	0.0591	0.7859
Hybrid MLP with Catoost	0.0288	0.0017	0.0412	0.8961

Table 2: Performance comparison for the Ridge, DT and Hybrid MLP with CB models

The Fig 4 displays a table of real-time prediction results obtained after loading a test dataset into the proposed Hybrid CB model. The table presents the original input features for each record from the TestData.csv file, along with two critical prediction outputs. The first output is the predicted 'Network Type,' which is a categorical classification, showing the model's prediction for whether the connection is 3G, 4G, 5G, or LTE. The second output is the predicted 'Signal Strength (dBm),' a continuous regression value that estimates the signal strength for each test record. This output demonstrates the model's practical application in real-world scenarios, where it can simultaneously diagnose a network's type and predict its performance metrics based on raw input data

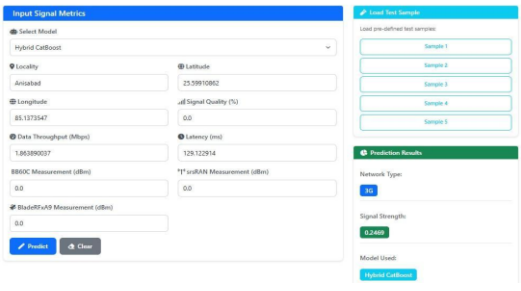


Fig. 4: Prediction obtained on test data using hybrid catboost.

5. CONCLUSION

The project successfully concludes that an advanced machine learning approach, specifically a Hybrid MLP with CatBoost, is exceptionally effective for analyzing cellular

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network data and performing fault diagnosis. The system successfully demonstrates its capability to handle a multi-task problem by simultaneously predicting two distinct targets: the categorical network type and the continuous signal strength. Through a meticulously designed pipeline encompassing data preprocessing, exploratory data analysis, and a comprehensive comparison of various algorithms, the project establishes the clear superiority of the proposed hybrid model. While traditional models like Decision Tree and Ridge provide foundational performance, the CatBoost-based hybrid model consistently outperforms them, achieving near-perfect scores in classification and the highest accuracy in regression. The project's architecture, built on the Flask web framework, provides a user-friendly and practical platform for real-time prediction, allowing network engineers to proactively identify and troubleshoot performance issues. Ultimately, this work validates the use of sophisticated boosting algorithms for complex telecommunication data, offering a robust and scalable solution for improving cellular network reliability and efficiency.

REFERENCES

[1]. Mfula, H.; Nurminen, J.K. Adaptive Root Cause Analysis for Self-Healing in 5G Networks. In Proceedings of the 2017 International Conference on High Performance Computing & Simulation (HPCS), Genoa, Italy, 17–21 July 2017; pp. 136–143.

[2]. Khanafer, R.M.; Solana, B.; Triola, J.; Barco, R.; Moltsen, L.; Altman, Z.; Lazaro, P. Automated Diagnosis for UMTS Networks Using Bayesian Network Approach. IEEE Trans. Veh. Technol. 2008, 57, 2451–2461.

[3]. Muñoz, P.; de la Bandera, I.; Khatib, E.J.; Gómez-Andrades, A.; Serrano, I.; Barco, R. Root Cause Analysis Based on Temporal Analysis of Metrics Toward Self-Organizing 5G Networks. IEEE Trans. Veh. Technol. 2017, 66, 2811–2824.

[4]. Szilagyi, P.; Novaczki, S. An Automatic Detection and Diagnosis Framework for Mobile Communication Systems. IEEE Trans. Netw. Serv. Manag. 2012, 9, 184–197.

[5]. Gómez-Andrades, A.; Muñoz, P.; Serrano, I.; Barco, R. Automatic Root Cause Analysis for LTE Networks Based on Unsupervised Techniques. IEEE Trans. Veh. Technol. 2016, 65, 2369–2386.

[6]. Amuah, E.A.; Wu, M.; Zhu, X. Cellular Network Fault Diagnosis Method Based on a Graph Convolutional Neural Network. Sensors 2023, 23, 7042. https://doi.org/10.3390/s23167042

[7]. Qiu, S.; Cui, X.; Ping, Z.; Shan, N.; Li, Z.; Bao, X.; Xu, X. Deep Learning Techniques in Intelligent Fault Diagnosis and Prognosis for Industrial Systems: A Review. Sensors 2023, 23, 1305. https://doi.org/10.3390/s23031305

[8]. Zhao, L.; He, C.; Zhu, X. A Fault Diagnosis Method for 5G Cellular Networks Based on Knowledge and Data Fusion. Sensors 2024, 24, 401. https://doi.org/10.3390/s24020401

[9]. Chen, Y.; Zhou, M.; Zhang, M.; Zha, M. Knowledge-Graph-Driven Fault Diagnosis Methods for Intelligent Production Lines. Sensors 2025, 25, 3912. https://doi.org/10.3390/s25133912

[10]. Arellano-Espitia, F.; Delgado-Prieto, M.; Martinez-Viol, V.; Saucedo-Dorantes, J.J.; Osornio-Rios, R.A. Deep-Learning-Based Methodology for Fault Diagnosis in Electromechanical

Systems. Sensors 2020, 20, 3949. https://doi.org/10.3390/s20143949

[11]. Lu, W.; Wang, W.; Qin, X.; Cai, Z. Enhancing Fault Diagnosis in Mechanical Systems with Graph Neural Networks Addressing Class Imbalance. Mathematics 2024, 12, 2064. https://doi.org/10.3390/math12132064

[12]. Said, N.; Mansouri, M.; Al Hmouz, R.; Khedher, A. Deep Learning Techniques for Fault Diagnosis in Interconnected Systems: A Comprehensive Review and Future Directions. Appl. Sci. 2025, 15, 6263. https://doi.org/10.3390/app15116263

[13]. Siddique, M.F.; Saleem, F.; Umar, M.; Kim, C.H.; Kim, J.-M. A Hybrid Deep Learning Approach for Bearing Fault Diagnosis Using Continuous Wavelet Transform and Attention-Enhanced Spatiotemporal Feature Extraction. Sensors 2025, 25, 2712. https://doi.org/10.3390/s25092712

[14]. Bougoffa, M.; Benmoussa, S.; Djeziri, M.; Palais, O. Hybrid Deep Learning for Fault Diagnosis in Photovoltaic Systems. Machines 2025, 13, 378. https://doi.org/10.3390/machines13050378

[15]. Zachariades, C.; Xavier, V. A Review of Artificial Intelligence Techniques in Fault Diagnosis of Electric Machines. Sensors 2025, 25, 5128. https://doi.org/10.3390/s25165128