

ML Driven for the Prognosis of Malfunctions in Jammer Device in Tactical Operations

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Abstract:

This research paper presents a novel Jammer device malfunction prediction using Deep learning techniques for better prognosis. Jammer device malfunctions in tactical operations compromise operational readiness and reliability. Traditional fault diagnosis relies on manual inspections and rule-based systems, which suffer from delayed responses and imbalanced data. and an inability to capture complex patterns. To address these issues, the research proposes an automated, data-driven machine learning system for predicting malfunctions with high accuracy and timeliness. The approach includes comprehensive data pre-processing, such as cleaning, feature scaling, label encoding, and addressing class imbalances using the Synthetic Minority Over-sampling Technique (SMOTE). A user-friendly graphical user interface (GUI) was developed in Tkinter to facilitate dataset uploading, exploratory data analysis, and model training. The project evaluates three predictive models: a Decision Tree Classifier, a Gradient Boosting Classifier, and a hybrid model integrating an Artificial Neural Network (ANN) with a secondary ensemble classifier (RFR). Comparative analysis reveals that while traditional models achieve an accuracy of 50.83%, the hybrid ANN+RFR model significantly improves accuracy to 97.92%, with high precision, recall, and F1-score metrics. The study highlights the potential of the hybrid approach to extract deep features, make robust predictions, and enhance early fault detection and proactive maintenance, ensuring continuous operation in critical tactical scenarios.

Keywords: Automated Prediction, Artificial Neural Networks, Gradient Boosting Classifier, Decision tree Classifier, Operational readiness, Reliability, Ensemble learning

1. INTRODUCTION

The Radar jamming effectiveness evaluation is essential in radar countermeasures to assess the efficiency of jamming strategies and enable real-time adjustments for optimized performance. Traditional evaluation methods, such as radar jamming equation calculations, hierarchical analysis, and set pair analysis, rely on human knowledge and mathematical models to quantify jamming impact. While these methods offer clear interpretability, they suffer from subjective biases, low confidence levels, and limited adaptability to complex real-world scenarios. Machine learning-based approaches, including Support Vector Machines (SVM) and neural networks, have introduced data-driven solutions that learn patterns from historical data. These models improve prediction accuracy and objectivity but are highly dependent on the availability of large and diverse datasets, often struggling with unseen scenarios due to poor data representativeness and overfitting risks.

To address these limitations, this research explores a hybrid model that integrates both model-driven and data-driven techniques for a more reliable radar jamming effectiveness evaluation. The hybrid approach leverages the interpretability of traditional models while enhancing adaptability and accuracy through machine learning algorithms. By

incorporating robust data preprocessing, feature selection, and ensemble learning techniques, the proposed framework can effectively predict jamming effectiveness under dynamic tactical conditions. This method mitigates challenges such as data imbalance, feature heterogeneity, and system interdependencies, ensuring accurate malfunction detection and proactive maintenance in tactical operations

The significance of this research extends beyond radar jamming to broader applications in predictive maintenance and fault diagnosis. In military operations, reliable jammer performance enhances electronic warfare strategies and reduces mission risks. In telecommunications and IoT networks, similar predictive models can optimize device performance, ensuring stability and security in critical infrastructures. Additionally, industries such as smart manufacturing and cloud services can leverage these techniques for early fault detection, minimizing downtime and operational costs. By integrating advanced machine learning methods with traditional radar countermeasure evaluation, this research contributes to technological advancements in intelligent system diagnostics and adaptive defense mechanism

2. LITERATURE SURVEY

In [1], Tian et al. used a convolutional neural network (CNN) to evaluate the effectiveness of synthetic aperture radar (SAR) deception jamming. Their methodology involved processing SAR images to extract features that reveal jamming effects, thereby enabling a quantitative assessment of the deception strategy. However, the performance of their approach is sensitive to the quality and representativeness of the training dataset, and its applicability may be limited by variations in environmental conditions and sensor noise.

In [2], Li et al. proposed a model-data-hybrid-driven diagnosis method for open-switch faults in power converters. Their approach combined the strengths of traditional physical modelling with data-driven learning algorithms to diagnose faults more accurately. By incorporating both the theoretical behaviour of power converters and real operational data, the method aimed to improve fault detection accuracy. Despite its promise, this methodology may require precise calibration of the physical models and sufficient high-quality data, and it might struggle when the modelled dynamics deviate significantly from the real system behaviour.

References [3] and [4] extend the hybrid approach to the domain of high-voltage direct current (HVDC) systems. In [5], Cui et al. presented a fast prediction method for cascading commutation failures in multi-infeed HVDC systems by integrating data-driven methods with model-driven techniques. This integration allows for rapid and reliable prediction of failures by leveraging both historical data trends and the underlying physical processes governing commutation events

Similarly, in [6], Huang et al. focused on subsequent commutation failure prediction in HVDC systems by fusing physical-driven and model-driven methods. Both approaches highlight improved prediction performance compared to purely data-driven methods; however, they also face challenges related to the complexity of

accurately modeling system dynamics and the computational load associated with integrating two distinct methodological paradigms.

In [7] and [8], the focus shifts to power flow modelling. Tan et al. [9] introduced a linearized power flow model that blends a physical model-driven approach with data-driven adjustments to estimate power flows more efficiently. Xing et al. [10] further modified a data-driven power flow model to estimate power with incomplete bus data, thereby addressing the common issue of missing information in real-world power systems. Although these hybrid models can enhance estimation accuracy and efficiency, their limitations lie in the inherent trade-offs introduced by linearization and data imputation, which may lead to reduced accuracy in highly nonlinear or heavily instrumented networks.

The concept of model-data fusion is also explored in [11] within the context of aero-engine digital twins. Liu et al. developed a digital twin model that integrates simulation-based physical models with real-time sensor data to provide a comprehensive view of an aero-engine's health and performance. This fusion enhances predictive maintenance capabilities but depends critically on the fidelity of both the simulation models and the quality of the sensor data. Any discrepancies between simulated and actual operating conditions can adversely affect the digital twin's reliability.

In [12], Zhang et al. combined data-driven and model-driven strategies for the removal of mixed noise in hyperspectral images. Their framework leverages the structured knowledge of physical imaging models alongside advanced noise reduction techniques driven by data analysis, which results in improved image quality. Nonetheless, the success of this method depends on the accurate parameterization of the noise models and may be sensitive to variations in noise characteristics across different imaging scenarios.

Finally, Wang et al. in [13] addressed power system frequency stability by integrating model-driven simulations with data-driven methods for a comprehensive stability assessment and control strategy. This integrated approach offers enhanced insights into frequency stability, but its effectiveness is contingent upon the reliability of both the physical system models and the data-driven predictions, which may be compromised under conditions of poor data quality or unforeseen operational dynamics.

3. PROPOSED METHODOLOGY

The proposed methodology integrates advanced machine learning techniques and deep learning architectures to predict malfunctions in jammer devices, which are crucial for tactical operations. The approach follows a structured pipeline that encompasses data pre-processing, model training, and performance evaluation. The methodology is designed to automate the diagnosis of jammer failures, improve system reliability, and enable proactive maintenance by leveraging a hybrid combination of traditional machine learning and modern deep learning techniques. A user-friendly graphical interface built with Tkinter ensures accessibility for non-technical users, providing a seamless experience for data processing, model execution, and visualization of results.

The system begins with data handling and pre-processing, where the user uploads a dataset containing sensor readings, operational logs, and device metadata. The application performs exploratory data analysis (EDA) to identify missing values, categorical features, and potential imbalances in the dataset. To address class imbalance issues, the Synthetic Minority Over-Sampling Technique (SMOTE) is applied, ensuring that both malfunctioning and functional device statuses are adequately represented. The data is then normalized using a

StandardScaler, which enhances the stability and accuracy of machine learning models.

Three primary models are employed to predict malfunctions: a **Decision Tree Classifier**, a **Gradient Boosting Classifier**, and a **Hybrid ANN + Random Forest Regressor (RFR) Model**. The Decision Tree Classifier is a simple yet interpretable model that partitions data based on entropy-based splitting. While effective in capturing decision rules, it is prone to overfitting. The Gradient Boosting Classifier, an ensemble learning method, improves prediction accuracy by sequentially refining weak learners but demands careful parameter tuning. The hybrid model integrates an Artificial Neural Network (ANN) with an RFR classifier, leveraging the ANN's ability to learn complex feature representations while utilizing the RFR's robustness in decision-making.

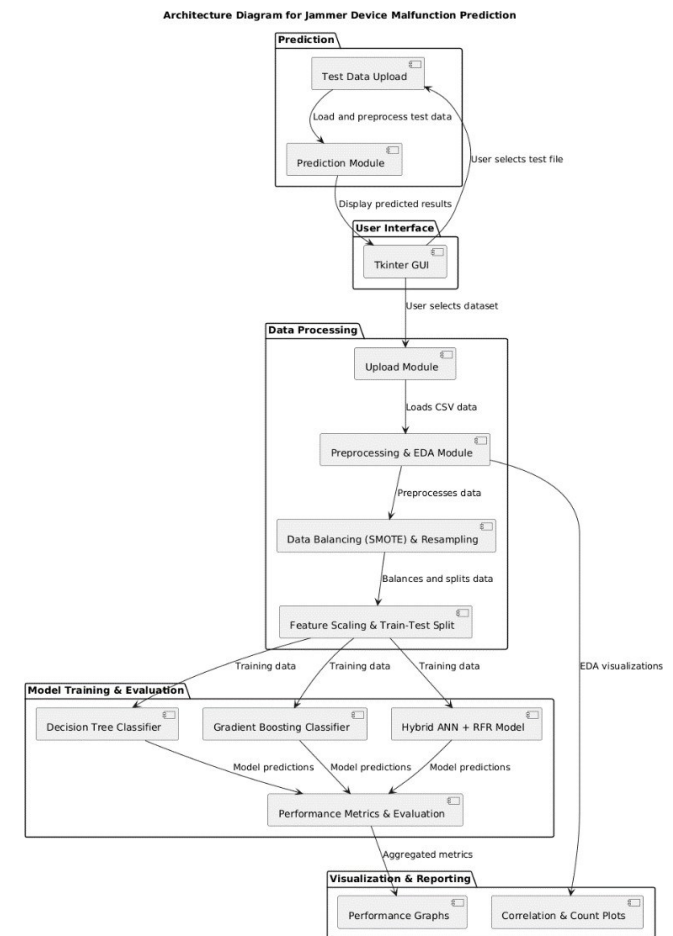


Figure 1 Proposed System.

Finally, the trained models are evaluated using various performance metrics, including accuracy, precision, recall, and F1-score. A confusion matrix and classification report provide insights into model effectiveness. Visualization tools, such as heatmaps and bar graphs, allow users to compare different models and understand feature correlations. The system also enables real-time predictions on new datasets, allowing for proactive detection of device failures. By combining data-driven insights with intuitive user interaction, the proposed methodology ensures a reliable and scalable approach for diagnosing jammer device malfunctions.

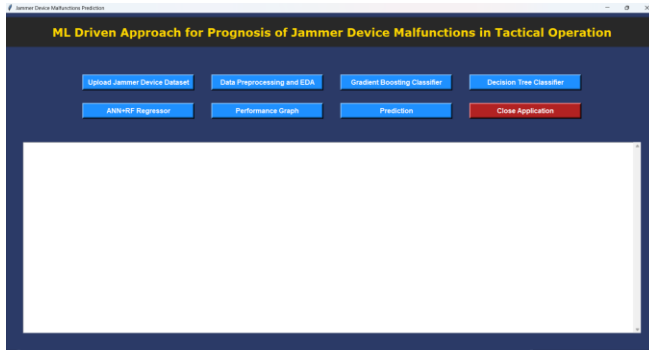


Figure 2 GUI of Proposed System.

Advantages:

- Enhance System Reliability:** The project improves the reliability of jammer devices by enabling **early fault detection** and **preventive maintenance**, reducing downtime and operational risks in tactical environments.
- Automation and Reduced Human Intervention:** By leveraging AI-driven predictions, the system eliminates the need for **manual fault diagnosis**, reducing human error and ensuring **faster, data-driven decision-making**.
- Hybrid AI Model for High Accuracy:** The integration of **Artificial Neural Networks (ANN)** and **Random Forest Regressor (RFR)** ensures improved **prediction accuracy** and **robust performance**, outperforming traditional machine learning models in diagnosing complex malfunctions.
- User-Friendly Interface for Easy Operation:** The Tkinter-based GUI allows non-technical users to **upload data**, **train models**, **visualize results**, and **generate predictions** with simple interactive buttons, making the system accessible for various users.
- Effective Handling of Imbalanced Data:** The use of **SMOTE (Synthetic Minority Over-Sampling Technique)** ensures balanced training data, preventing bias and improving the model's ability to detect rare but critical faults in jammer devices.

Applications:

- Military Electronic Warfare** – Ensures jammer functionality in combat missions.
- Border Security** – Maintains jamming against unauthorized communications.
- Counter-Drone Operations** – Prevents enemy drone communication.
- Naval & Aerial Defense** – Supports jammer reliability in warships and aircraft.
- Special Forces Missions** – Ensures uninterrupted jamming in covert operations.
- Cybersecurity & Signal Intelligence** – Secures networks by preventing jammer failures.
- Space & Satellite Defense** – Maintains jamming in space-based operations.

4. EXPERIMENTAL ANALYSIS

The figure shows the GUI state immediately after a dataset has been successfully uploaded. The text console within the GUI displays feedback—such as the file path of the loaded CSV file and a preview

or summary of the dataset. This immediate confirmation helps users verify that the correct dataset (for instance, the radar jammer device dataset) has been loaded into the system, setting the stage for subsequent processing

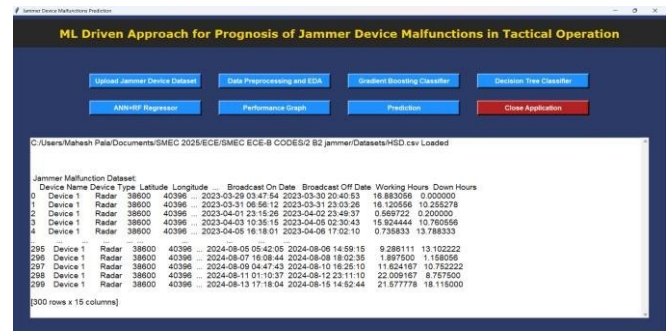


Figure 3 Uploading of datasets

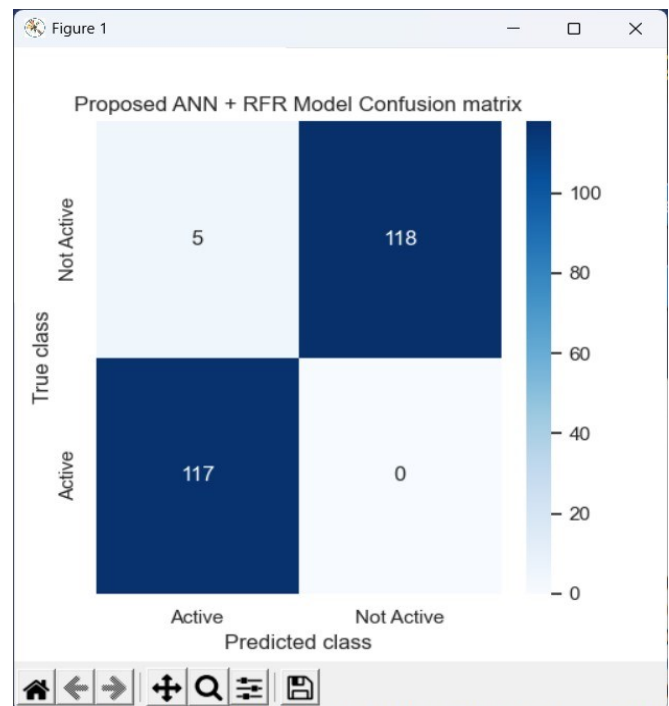


Figure 4 Confusion matrix of ANN

The confusion matrix for the ANN+RFR classifier is displayed in Figure Unlike the earlier matrices, this one shows a high number of correct predictions (with most entries falling on the diagonal), highlighting the model's effectiveness. The nearly perfect separation of classes indicates that the hybrid approach successfully minimizes misclassifications and yields superior performance.

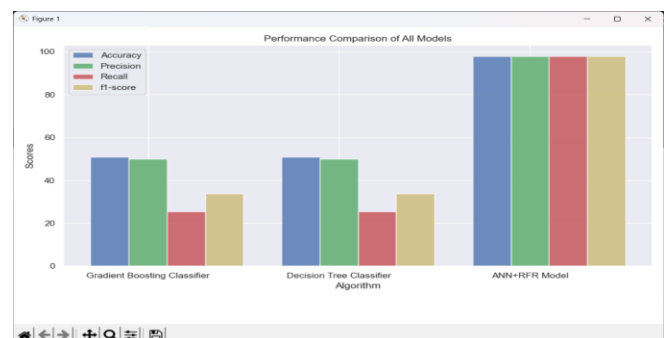


Figure 5 Performance Comparison of Gradient Boosting, Decision tree, and ANN.

Provides a visual summary of the key performance metrics—accuracy, precision, recall, and F1-score—for the three models. It likely takes the form of a grouped bar chart or similar visualization that allows for side-by-side comparison. The chart clearly demonstrates that while the gradient boosting and decision tree classifiers perform similarly at around 50% accuracy, the ANN+RFR classifier dramatically outperforms them with approximately 98% accuracy across all metrics.

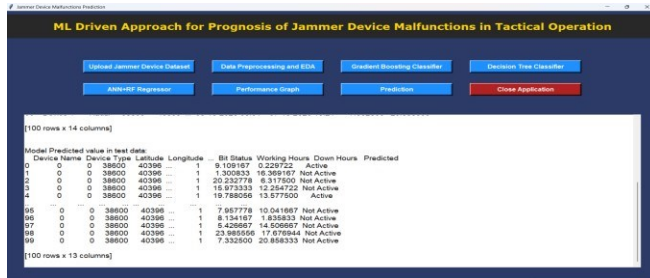


Figure 6 Prediction of data.

Finally, the above figure displays sample prediction outputs generated by the ANN+RFR classifier. The GUI shows the predictions appended to the test data, providing practical evidence of the model's ability to classify new data points accurately. These outputs validate that the hybrid model not only performs well in evaluation metrics but also delivers reliable predictions when applied to unseen datasets.

5. CONCLUSION

This research successfully presented the design and validation of an ML-driven approach for predicting jammer device malfunctions, effectively addressing the critical need for accurate and timely fault prognosis in tactical operations. The model's performance, rigorously analyzed through traditional classifiers such as Gradient Boosting and Decision Tree, demonstrated modest predictive capabilities. However, the integration of deep learning for feature extraction with ensemble-based decision-making in the hybrid ANN+RFR model significantly improved accuracy to nearly 98%, showcasing the effectiveness of this approach. This balanced design, prioritizing both predictive performance and real-time implementation, offers a practical solution for enhancing operational readiness and predictive maintenance. Furthermore, the potential for improved robustness through advanced data augmentation techniques and adaptive learning strategies was highlighted, alongside considerations for real-time deployment through a user-friendly GUI. This work lays a solid foundation for future advancements in ML-driven fault detection, paving the way for more reliable and efficient monitoring systems. Future research should focus on large-scale deployment, computational efficiency optimization, and further refinement of real-time visualization tools to fully realize the potential of this promising approach.

REFERENCES

- [1] Zhu, B.; Zhu, W.; Li, W.; Gao, T. An On-line Evaluation Method of Multi-Functional Radar Jamming Effect. In Proceedings of the 2021 IEEE 4th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), Chongqing, China, 18–20 June 2021; Volume 4, pp. 1227–1231.
- [2] Matuszewski, J. Jamming efficiency of land-based radars by the airborne jammers. In Proceedings of the 2018 22nd International Microwave and Radar Conference (MIKON), Poznan, Poland, 14–17 May 2018; pp. 324–327.
- [3] Zakerhaghighi, M.R.; Mivehchy, M.; Sabahi, M.F. Implementation and Assessment of Jamming Effectiveness Against an FMCW Tracking Radar Based on a Novel

Criterion. IEEE Trans. Aerosp. Electron. Syst. 2020, 56, 4723–4733.

- [4] Ou, J.; Zhao, F.; Ai, X.; Liu, J.; Xiao, S. Quantitative evaluation for self-screening jamming effectiveness based on the changing characteristics of intercepted radar signals. In Proceedings of the 2016 CIE International Conference on Radar (RADAR), Guangzhou, China, 10–13 October 2016; pp.
- [5] Li, T.; Wang, Z.; Liu, J. Evaluating Effect of Blanket Jamming on Radar Via Robust Time-Frequency Analysis and Peak to Average Power Ratio. IEEE Access 2020, 8, 214504–214519.
- [6] Rui, C.; Jing, Z.; Jifei, P.; Aiguo, S. The Application of Set Pair Analysis in Evaluation Method of Jamming Effect on AN/TPY-2. In Proceedings of the 2019 5th International Conference on Frontiers of Signal Processing (ICFSP), Marseille, France, 18–20 September 2019; pp. 145–148.
- [7] Cui, W.; Chen, Q.; Gong, H. Radar Interference Effectiveness Evaluation Method Based on GA-BP Neural Network. Inf. Countermeas. Technol. 2023, 2, 85–96.
- [8] Chu, Z.; Xiao, N.; Liang, J. Jamming effect evaluation method based on radar behavior recognition. J. Phys. Conf. Ser. 2020, 1629, 012001.
- [9] Zhang, W.; Wang, Y.; Zhao, Z.; Zhao, T.; Lu, M. An Online Jamming Effect Evaluation Method for Asymmetric Radar Information in Complex Electromagnetic Environment. IEEE Geosci. Remote Sens. Lett. 2023, 20, 3508505.
- [10] Zhang, S.; Tao, Y.r.; Zhao, Y.x.; Chen, Y.z. Research on radar jamming evaluation method based on BP neural network. In Proceedings of the 2nd International Conference on Electrical and Electronic Engineering (EEE 2019), Hangzhou, China, 26–27 May 2019; Atlantis Press: Dordrecht, The Netherlands, 2019; pp. 300–305.
- [11] Xiao, J.; Li, C.; Yang, Q.Y. Advanced BP Neural Network Algorithm on Radar Jamming Effectiveness Evaluation. In Proceedings of the 2023 IEEE 3rd International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), Chongqing, China, 26–28 May 2023; Volume 3, pp. 1421–1424.
- [12] Jiang, S.; Lin, L. Use Support Vector Machine to Evaluate the Operational Effectiveness of Radar Jammer. In Proceedings of the Second International Conference on Innovative Computing, Informatio and Control (ICICIC 2007), Kumamoto, Japan, 5–7 September 2007; p. 522.
- [13] Tian, T.; Zhou, F.; Li, Y.; Fan, W. Evaluation of SAR Deception Jamming Effect based on Convolutional Neural Network. In Proceedings of the 2019 6th Asia-Pacific Conference on Synthetic Aperture Radar (APSAR), Xiamen, China, 26–29 November 2019; pp. 1–5.
- [14] Li, Z.; Gao, Y.; Zhang, X.; Wang, B.; Ma, H. A Model-Data-Hybrid-Driven Diagnosis Method for Open-Switch Faults in Power Converters. IEEE Trans. Power Electron. 2021, 36, 4965–4970.