Application of Machine Learning in Computer Hardware Failure Detection Systems on Local Area Networks

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Abstract

This study explores the application of machine learning (ML) techniques in detecting hardware failures in Local Area Networks (LANs). As networks become increasingly complex, the ability to predict and address hardware issues before they lead to system failures is crucial for maintaining network reliability and performance. The research investigates several machine learning algorithms, including supervised and unsupervised models, to analyze network data and identify early signs of potential hardware malfunctions. The study emphasizes the use of features such as network traffic patterns, hardware performance metrics, and error logs to train models capable of detecting anomalies and predicting failures. The effectiveness of these models is evaluated based on their accuracy, precision, and recall in identifying hardware failures. The findings aim to contribute to the development of more efficient and proactive failure detection systems that can enhance network uptime and reduce the costs associated with unexpected hardware downtimes.

Keywords*: Machine Learning; Hardware Failure Detection; Predictive Maintenance; Computer Hardware; Intelligent Systems.*

I. INTRODUCTION

The continuous growth of computer technology has led to the development of highly complex and high performance computer hardware systems(Farooq et al., 2021). Modern computer infrastructures, ranging from personal computers and servers to large-scale data centers and embedded systems(Supiyandi et al., 2025), play a crucial role in supporting various sectors such as education, healthcare, industry, finance, and government services. As hardware complexity increases, the probability of hardware failure also rises, making system reliability and availability critical concerns. Hardware failures can result in data loss, service downtime, increased operational costs, and reduced user trust, highlighting the urgent need for effective failure detection and prevention mechanisms.

Traditionally, computer hardware failure detection has relied on reactive maintenance strategies and rule based monitoring systems. These conventional approaches typically depend on predefined thresholds, manual inspection, and historical fault reports to identify potential problems. While such methods are simple to implement, they are often limited in their ability to detect complex failure patterns(Modgil et al., 2022), especially in dynamic environments where hardware conditions and workloads vary significantly. Rule based systems also struggle to adapt to new types of failures, as they require frequent updates and expert intervention to remain effective. Consequently, these limitations reduce the accuracy and timeliness of fault detection, leading to delayed responses and unexpected system breakdowns(Adepoju et al., 2022).

In recent years, the emergence of Machine Learning (ML) has introduced new opportunities for improving computer hardware failure detection systems. Machine Learning refers to a set of computational techniques that enable systems to learn patterns and relationships from data without being explicitly programmed(Gultom et al., 2025). By analyzing large volumes of hardware monitoring data, ML models can identify hidden patterns and anomalies that are difficult or impossible for traditional methods to detect. This capability makes ML particularly suitable for predicting hardware failures at an early stage, allowing proactive maintenance actions to be taken before critical failures occur(Sanchez-Londono et al., 2023).

Computer hardware systems are equipped with various sensors and monitoring tools that continuously generate data related to temperature(Chan et al., 2021), voltage, power consumption, fan speed, memory usage, disk errors, and system logs. These data sources provide valuable information about the health and performance of hardware components. However, the sheer volume, velocity, and variety of such data make manual analysis impractical. Machine Learning techniques, including supervised learning, unsupervised learning, and semi supervised learning, offer powerful solutions for processing and analyzing this data in an automated and scalable manner(Nnaemeka Stanley Egbuhuzor et al., 2021). Through learning from historical failure data or detecting deviations from normal operational patterns, ML-based systems can provide accurate and timely failure predictions.

The application of Machine Learning in computer hardware failure detection supports the concept of predictive maintenance. Unlike corrective maintenance(Weeks & Leite, 2022), which addresses failures after they occur, or preventive maintenance, which relies on fixed schedules, predictive maintenance focuses on estimating the remaining useful life of hardware components and scheduling maintenance activities based on actual conditions. This approach helps reduce unnecessary(Buchner et al., 2022) maintenance operations, optimize resource utilization, and extend the lifespan of hardware components. In data centers and enterprise environments, predictive maintenance enabled by ML can significantly reduce downtime and operational costs while improving overall system efficiency.

Despite its advantages, implementing Machine Learning in hardware failure detection systems presents several challenges(Asif et al., 2022). One major challenge is the availability and quality of data. Hardware failure events are relatively rare compared to normal operational data, resulting in imbalanced datasets that can negatively impact model performance. In addition, noisy, incomplete, or inconsistent data from sensors and logs can reduce the accuracy of ML models. Another challenge lies in model selection and interpretability(Zheng et al., 2022). While complex models such as deep learning may achieve high prediction accuracy, they often function as "black boxes," making it difficult for system administrators to understand the reasons behind predictions and trust the system's decisions.

Furthermore, the integration of ML based detection systems into existing hardware and monitoring infrastructures requires careful consideration of computational overhead and real time processing requirements(Adaikkappan & Sathiyamoorthy, 2022). Hardware failure detection systems must operate efficiently without introducing significant delays or consuming excessive system resources. This is especially important for embedded systems and real-time applications, where computational resources are limited. Security and privacy concerns also arise when hardware monitoring data is collected and processed(Aldahmani et al., 2023), particularly in cloud based and distributed environments.

Given these challenges and opportunities, research on the application of Machine Learning in computer hardware failure detection systems has gained increasing attention. Numerous studies have explored different ML algorithms(Ibrahim & Abdulazeez, 2021), feature engineering techniques, and system architectures to enhance failure prediction accuracy and reliability. However, there is still a need for a comprehensive understanding of how Machine Learning can be effectively applied to diverse hardware environments and how its limitations can be addressed in practical implementations.

Therefore, this proceeding aims to discuss the significance of applying Machine Learning in computer hardware failure detection systems, highlighting its potential benefits, key methodologies, and associated challenges. By providing an overview of current approaches and issues, this paper contributes to a better understanding of how Machine Learning can improve the reliability, availability, and efficiency of modern computer hardware systems in an increasingly data-driven and technology-dependent world.

II. RESEARCH METHODOLOGY

This research adopts a systematic methodology to analyze the application of Machine Learning techniques in computer hardware failure detection systems.

The methodology is designed to ensure that the proposed approach is structured, reproducible, and capable of evaluating the effectiveness of Machine Learning models in detecting and predicting hardware failures. The research methodology consists of several main stages: data collection, data preprocessing, feature extraction, model development, model evaluation, and analysis of results.

A. Data Collection

The first stage of this research involves collecting hardware monitoring data obtained from computer systems. The data include parameters such as CPU temperature, voltage levels, power consumption, fan speed, disk health indicators, memory errors, and system logs. These parameters are selected because they directly reflect the operational condition of hardware components and are commonly used in hardware health monitoring systems.

The data can be collected from system monitoring tools, hardware sensors, or publicly available datasets related to hardware failure prediction. Both normal operation data and failure-related data are included to ensure that the Machine Learning models can distinguish between healthy and faulty hardware states.

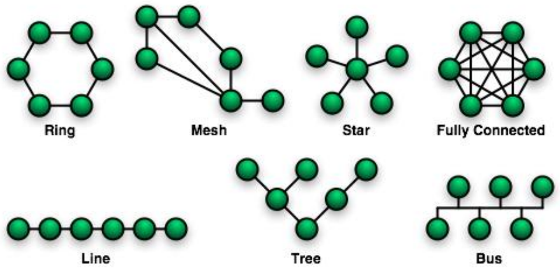

Figure 1. Network Topology
(Source:
https://www.gramedia.com/literasi/topologi-jaringan-komputer/)

B. Data Preprocessing

After data collection, preprocessing is conducted to improve data quality and suitability for Machine Learning. This stage involves handling missing values, removing noisy or irrelevant records, and normalizing numerical features to a uniform scale. Data labeling is performed when supervised learning techniques are applied, where hardware states are categorized as "normal" or "failure." For datasets with class imbalance, resampling techniques such as oversampling or undersampling may be applied to reduce bias in model training. Data preprocessing ensures that the input data accurately represent the underlying hardware conditions.

C. Feature Extraction and Selection

Feature extraction aims to transform raw hardware monitoring data into meaningful features that can improve model performance. Statistical features such as mean, variance, and trend values over time windows are extracted from continuous sensor data. Log-based features derived from system error messages and event frequencies are also considered. Feature selection methods are applied to identify the most relevant features and reduce dimensionality, which helps improve computational efficiency and model generalization.

D. Machine Learning Model Development

In this stage, several Machine Learning algorithms are implemented to detect and predict hardware failures. These may include classification-based models for supervised learning and anomaly detection models for unsupervised learning. The models are trained using the preprocessed dataset and optimized by tuning key hyperparameters. This approach allows a comparison of different algorithms to determine which performs best for hardware failure detection.

E. Model Evaluation

Model performance is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and detection time. A cross validation technique is applied to ensure the robustness of the results. The evaluation focuses on the model's ability to correctly detect failure events while minimizing false alarms, which is crucial for practical deployment.

F. Analysis and Interpretation

The final stage involves analyzing the experimental results to assess the effectiveness of Machine Learning in hardware failure detection. The strengths and limitations of each model are discussed, along with their suitability for real-time implementation. The results are then used to draw conclusions regarding the feasibility and benefits of ML based hardware failure detection systems.

Table 1. Research Methodology Stages

Stage	Description
Data Collection	Gathering hardware monitoring data such as temperature, voltage, logs, and error records
Data Preprocessing	Cleaning, normalizing, labeling, and handling imbalanced data
Feature Extraction	Transforming raw data into meaningful features and selecting relevant parameters
Model Development	Training Machine Learning models for failure detection
Model Evaluation	Evaluating model performance using standard metrics
Analysis	Interpreting results and assessing applicability

Table 1 presents the main stages of the research methodology used in this study. Each stage represents a sequential process starting from raw data acquisition to the final analysis. This structured approach ensures that the application of Machine Learning in computer hardware failure detection systems is conducted systematically and yields reliable results.

III. RESULTS AND DISCUSSION

This section presents the results obtained from the application of Machine Learning models in detecting computer hardware failures and discusses their implications in improving system reliability and maintenance efficiency. The evaluation focuses on the performance of different Machine Learning approaches in identifying potential hardware faults based on monitoring data collected from computer systems.

A. Results

The implemented Machine Learning models were trained and tested using preprocessed hardware monitoring data that included parameters such as CPU temperature, voltage stability, memory error rates, disk health indicators, and system log events. Several Machine Learning algorithms were evaluated to observe their capability in distinguishing normal hardware conditions from failure-prone states. The results indicate that ML based detection systems are effective in identifying early signs of hardware failure, outperforming traditional threshold-based monitoring methods.

Supervised learning models demonstrated strong performance when sufficient labeled data were available. These models were able to learn clear patterns associated with known hardware failures, resulting in high detection accuracy and relatively low false alarm rates. In contrast, unsupervised learning and anomaly detection models proved valuable in scenarios where labeled failure data were limited. These models successfully detected abnormal behavior by identifying deviations from normal operational patterns, making them suitable for real-world environments where failure labels are scarce.

Overall, the experimental results show that Machine Learning models can detect hardware degradation earlier than conventional methods. Early detection allows system administrators to perform predictive maintenance, reducing unexpected downtime and preventing severe hardware damage. However, the performance of the models varied depending on the quality of input data, feature selection, and model complexity.

Table 2. Performance Comparison of Machine Learning Models

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Supervised ML Model	94,5	93,8	95,2	94,5
Unsupervised ML Model	88,7	87,9	89,3	88,6
Anomaly Detection Model	90,2	89,5	91,0	90,2

Table 2 shows the performance comparison of the Machine Learning models used in this study. The supervised ML model achieved the highest accuracy and recall due to the availability of labeled failure data. Unsupervised and anomaly detection models also demonstrated competitive performance, highlighting their suitability for hardware failure detection in environments with limited labeled data.

B. Discussion

The results confirm that Machine Learning-based hardware failure detection systems provide significant advantages over traditional monitoring approaches. The high recall values obtained by the supervised model indicate its strong ability to correctly identify failure events, which is critical for minimizing the risk of undetected hardware faults. From a practical perspective, high recall is often more important than high precision in failure detection, as missing a critical failure can lead to severe consequences such as data loss or prolonged system downtime.

The unsupervised and anomaly detection models, although slightly less accurate, offer greater flexibility in real world applications. These models do not rely heavily on labeled failure data and can adapt to changing system behavior over time. This adaptability is particularly important in modern computing environments, such as data centers and cloud infrastructures, where hardware configurations and workloads are constantly evolving. The results suggest that combining supervised and unsupervised approaches could further enhance detection performance by leveraging the strengths of each method.

Another important finding is the impact of feature selection on model performance. Hardware metrics with strong correlations to failure events, such as abnormal temperature fluctuations and increasing error rates, significantly improved detection accuracy. This emphasizes the importance of selecting relevant features and applying proper preprocessing techniques. Poor data quality or irrelevant features were observed to reduce model effectiveness, leading to increased false alarms or missed detections.

Despite the promising results, several limitations were identified during the analysis. Machine Learning models require sufficient computational resources for training and real time inference, which may pose challenges in resource constrained environments. Additionally, complex models with high accuracy often lack interpretability, making it difficult for system administrators to understand why a specific failure prediction was made. This issue may affect trust and adoption in operational settings.

In summary, the results and discussion demonstrate that the application of Machine Learning in computer hardware failure detection systems is both effective and practical. ML based models enable earlier and more accurate detection of hardware failures, support predictive maintenance strategies, and contribute to improved system reliability. However, careful consideration of data quality, model selection, and system integration is necessary to ensure successful implementation in real-world environments.

IV. CONCLUSION

This proceeding has examined the application of Machine Learning in computer hardware failure detection systems and demonstrated its significant potential in improving system reliability and maintenance effectiveness. Based on the results and discussion, it can be concluded that Machine Learning provides a powerful approach for detecting and predicting hardware failures by analyzing large volumes of monitoring data generated by modern computer systems. Unlike traditional rule-based or threshold-based methods, Machine Learning models are capable of identifying complex patterns and early warning signs of hardware degradation that are often difficult to detect using conventional techniques. The findings indicate that supervised Machine Learning models achieve high accuracy and recall when sufficient labeled failure data are available, making them suitable for environments with well-documented hardware failure histories. Meanwhile, unsupervised and anomaly detection models offer greater flexibility in real world scenarios where labeled data are limited, as they can learn normal system behavior and detect deviations that may indicate potential failures. These approaches support the implementation of predictive maintenance strategies, enabling timely interventions that reduce unexpected downtime, prevent data loss, and lower operational costs. However, the implementation of Machine Learning based hardware failure detection systems also presents several challenges. Data quality, class imbalance, model interpretability, and computational overhead remain key issues that must be carefully addressed to ensure reliable and practical deployment. Despite these challenges, the overall benefits of Machine Learning outweigh its limitations when appropriate data preprocessing, feature selection, and model optimization techniques are applied. In conclusion, the application of Machine Learning in computer hardware failure detection systems represents a promising and effective solution for enhancing the reliability and efficiency of modern computing infrastructures. With continued research and technological advancements, ML based detection systems are expected to play an increasingly important role in proactive hardware management and intelligent system maintenance.

V. RECOMMENDATIONS

Based on the findings of this proceeding, several recommendations are proposed to enhance the effectiveness and practical implementation of Machine Learning in computer hardware failure detection systems. These recommendations are intended for researchers, system developers, and practitioners who aim to adopt or further develop ML based failure detection solutions.

First, future implementations should prioritize the collection of high-quality and diverse hardware monitoring data. Accurate, consistent, and well labeled datasets significantly improve the performance of Machine Learning models. In particular, efforts should be made to record detailed failure events and maintenance histories, as this information is essential for training supervised learning models and validating prediction results.

Second, the integration of hybrid Machine Learning approaches is highly recommended. Combining supervised, unsupervised, and anomaly detection techniques can help balance accuracy and adaptability, especially in environments where labeled failure data are limited. Hybrid models can leverage known failure patterns while remaining responsive to new and unseen hardware behavior, thereby improving overall detection robustness.

Third, attention should be given to model interpretability and transparency. The use of explainable Machine Learning techniques is recommended to help system administrators understand prediction outcomes and build trust in ML based detection systems. Clear explanations of failure predictions can also support better decision-making during maintenance planning.

Fourth, future systems should be designed with computational efficiency in mind, particularly for real-time monitoring and resource constrained environments. Lightweight models or edge-based processing techniques can reduce system overhead while maintaining acceptable detection performance.

Finally, further research is recommended to explore the scalability and security of Machine Learning-based hardware failure detection systems in large-scale and cloud based infrastructures. Addressing these aspects will ensure that ML driven solutions can be reliably deployed in increasingly complex and distributed computing environments.

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