¹Anjali Yeole ²Dashrath Mane ³Mahindra Gawali ⁴Manas Lalwani ⁵Mahindra Chetwani ⁶Parth Suryavanshi ⁷Harshita Anala

Predictive Maintenance of Server using Machine Learning and Deep Learning



Abstract: - Traditional IT maintenance often leads to wasted resources and downtime. This paper explores how predictive maintenance (PdM) with machine learning can revolutionize server management in Industry 4.0. By comparing various machine learning models for PdM, we analyze their effectiveness in predicting server failures. The paper emphasizes the critical role PdM plays in boosting server reliability and driving industry transformation, supported by statistics highlighting its growing importance. Furthermore, we bridge the theory-practice gap by proposing a web application specifically designed for server PdM, allowing for proactive maintenance and reduced downtime. Finally, we explore future research directions and emerging trends in server PdM, providing valuable insights for organizations seeking to optimize maintenance practices and achieve operational excellence in the digital age.

Keywords: Sever, Failure, Predictive Maintenance, Machine Learning

I. INTRODUCTION

In the current economic environment, which is characterized by intense globalization and markets that are becoming more demanding, industries are under pressure to increase the productivity and efficiency of their production lines in order to boost their competitiveness and please consumers. Industry 4.0, defined as connectedness, data, new devices, inventory reduction, customization, and controlled production, appears to be unstoppable today. This suggests that in order to integrate all of the new technologies and subsequently boost productivity, automation techniques must be used. Big Data and Internet of Things (IoT) technologies, along with the incorporation of AI techniques and cyber-physical systems (CPS) play a significant role in this context by bringing cognitive automation and, as a result, putting the idea of intelligent production into practice, resulting in intelligent products and services.

In the manufacturing industries, equipment downtime is the most critical problem. When equipment fails, there is a period of time during which it is not usable until maintenance is performed and it resumes its normal function. Under these conditions, the machine's productivity decreases. According to a common estimate, downtime costs nearly every industry between 5% and 20% of its productivity, and maintenance expenses can be exorbitant [2]. Production can come to a grinding halt due to machine failures, which can cost an industry millions of dollars. Reducing downtime can help in improving overall efficiency of the industry.

Machine learning techniques assist us by evaluating the equipment's historical data over a predetermined time period and creating some patterns regarding component degradation. As a result, we can foresee probable failures and plan maintenance before the system fails totally. As a result, there are less maintenance costs, productivity is preserved, and efficient use of the resources is guaranteed.

Our proposal involves creating a web application that utilizes machine sensor data to forecast the likelihood of machine downtime based on the historical data of its servers' components [4]. This is going to be carried out by

1. Carry out data cleaning on the data set that includes records of various parameters gathered by the server's sensors, and look for correlations to find patterns related to the server's downtime.

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¹ Corresponding author: Author 1 Anjali Yeole

² Author 2: Dashrath Mane

³ Author 3:Mahindra Gawali

⁴ Author 4:Manas Lalwani

⁵ Author 5: Mahindra Chetwani

⁶ Author 6:Parth Suryavanshi

⁷ Author 7:Harshita Anala

- Determine and train the best machine learning model that can predict system failure well in advance using the live data supplied to the corresponding model after analysing the data set and determining the correlation.
- 3. In terms of operations, the model will be highly helpful to the person operating the machine, as well as to their individual managers and other stakeholders. The project is expected to yield highly efficient results while also saving a significant amount of time. Profit and productivity as a whole have increased as a result.

Traditional server maintenance is unreliable and expensive due to unplanned downtime. Machine learning offers a proactive solution through predictive maintenance. By analyzing server data, it can predict failures and optimize maintenance schedules. This reduces downtime, costs, and improves service reliability.

II.APPROACHES AND KEY FEATURES

In response to the limitations of the traditional approach which results in downtime and loss for the business as well as economy, our ML based predictive model is a revolutionary solution designed to solve these problems and transform the landscape through its exceptional features. A more proactive and effective approach to maintenance is imperative given the increasing frequency of server failures and downtimes in contemporary IT infrastructures.

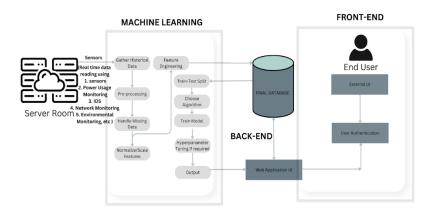


Fig 1 - System architecture

The growing complexity and size of server environments necessitate a more sophisticated approach, even though organizations may already use basic techniques for server monitoring and maintenance. Through the application of predictive maintenance methods that incorporate sophisticated analytics and machine learning algorithms, enterprises can shift from reactive to proactive maintenance approaches. With this change, possible problems can be identified early, maintenance plans can be optimized, and server uptime and reliability will eventually increase.

Corresponding to this, machine learning's decentralized architecture combined with advanced analytics are used in predictive maintenance of servers to address the fundamental problem of inconsistent server performance. Predictive maintenance reduces single points of failure by decentralizing the monitoring and maintenance procedures, which improves the security and robustness of server management systems. In addition to reducing the possibility of illegal access, this decentralized method guarantees the accuracy of server data, protecting it from future manipulation or tampering. The inherent vulnerabilities of traditional maintenance methods can be addressed by predictive maintenance systems by using machine learning's capabilities to maintain an accurate and transparent record of server health and performance metrics.

One of the key features of the model is its response to dynamic data received from the server room which is integrated on a regular basis. The predictive maintenance system's use of machine learning as an open, unchangeable digital ledger for tracking server health is a crucial component. The system guarantees the integrity and transparency of server maintenance activities by storing performance metrics, predictive models, and

maintenance logs as safe, immutable smart contracts on machine learning [16]. This method protects against unauthorized changes and gives IT teams the ability to monitor server health trends and status in real time. More accountability, transparency, and trust in the dependability of server operations are made possible by stakeholders having access to an extensive and reliable record of server maintenance activities thanks to blockchain's distributed ledger capabilities.

In the proposed system, the health of each server along with its component is displayed. Using which the server failure can be predicted. This machine learning approach eliminates central points of failure by giving a warning on prior. Later which can be corrected or looked into by the employees responsible. It guarantees a secure environment for details of server and its past records while protecting against unauthorized access.

Our model adopts a decentralized architecture and machine learning, the predictive maintenance system transforms server maintenance operations in a manner akin to this. The dashboard application, which is at the heart of the system, coordinates the generation and administration of predictive maintenance tasks, storage of maintenance logs, and the retrieval of historical performance data. This programme optimizes system performance to run with the least amount of latency possible while simultaneously guaranteeing the security and transparency of the maintenance ledger. Administrators, who manage system configuration and maintenance scheduling, and Maintenance Technicians, who carry out maintenance tasks and update the maintenance ledger with real-time data, are the two main roles involved in the proposed solution.

The power to integrate new Maintenance Technicians into the system belongs to the Administrator. They are able to assign roles and responsibilities, control user access permissions, and monitor how well the maintenance operations are running as a whole. Conversely, the Maintenance Technicians are outfitted with tools to track server health indicators, get alerts for preventive maintenance, and carry out planned maintenance duties. They can create reports on server performance and maintenance activities, update maintenance logs with real-time data, and show the status of maintenance tasks. This separation of duties permits administrators and technicians to carry out their individual duties with efficiency while guaranteeing efficient coordination and accountability in the upkeep of server infrastructure.

A centralised platform for managing and streamlining maintenance tasks throughout the server infrastructure is provided by the predictive maintenance dashboard for server management. Administrators and maintenance technicians can obtain comprehensive insights into server health and performance from the dashboard, which aggregates real-time data from multiple sources such as sensors, predictive analytics models, and server monitoring tools. Users can keep an eye on important performance metrics like CPU, memory, disc I/O, network traffic, and temperature variations with the help of easily navigable dashboards and intuitive visualizations. In order to prevent system failures and downtime, this enables the proactive identification of potential issues and anomalies and allows for timely intervention.

Administrators can define maintenance schedules, set threshold alerts, and allocate resources based on server priorities and workload demands thanks to the dashboard's advanced configuration and management features. They can also designate roles and permissions, oversee and onboard maintenance technicians, and monitor the real-time progress of maintenance tasks. In order to assess the efficacy of maintenance plans, spot trends and patterns in server performance, and make data-driven choices for better resource allocation and increased system reliability.

The dashboard is utilized by maintenance technicians to carry out designated duties, obtain notifications for predictive maintenance, and obtain comprehensive guidelines and records for carrying out maintenance operations. With the ability to update maintenance logs in real-time, they can document observations or interventions made during the process as well as the status of maintenance activities. The dashboard makes it easier for technicians and administrators to collaborate and communicate, which makes it easier to coordinate maintenance procedures and guarantees that servers will always be secure, dependable, and operational.

III. METHODOLOGY

1. DATASET COLLECTION - The dataset is extracted in real-time from a set of devices in the server room of the client company. These devices transmit daily sensor readings, which likely include various metrics such as temperature, humidity, power consumption, etc.

Columns: The dataset has 12 columns. The first two columns are "Date," and "Device ID," which records the date of the sensor readings and identifies the specific device from which the readings were taken. The third column is "Failure indicator," which likely indicates whether a failure occurred on that date, this is considered to be the target variable. The remaining 7 columns are metrics that are potentially affecting the failure. These include

temperature, humidity, voltage, power supply, utilization, fan speed and RAM. All these 7 metrics contribute to the failure prediction. The dataset used has 124,495 rows, each representing a set of sensor readings taken on a specific date from a specific device.

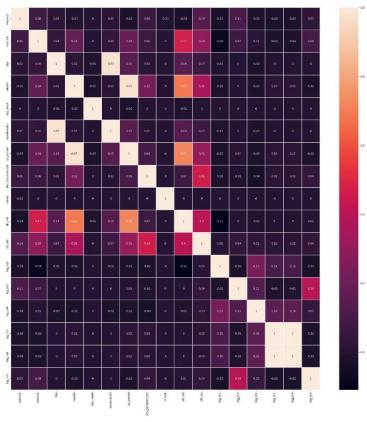


Fig 2 - Correlation Matrix

- **2. DATA PREPROCESSING** Extensive data preprocessing was carried out before the model was developed. During this phase, a number of crucial procedures had to be completed, such as the one-hot encoding of categorical variables to prepare them for modelling, the normalization of numerical features to achieve a uniform scale, and thorough data cleaning that involved addressing any missing values in the datasets and getting rid of duplicates. These preparation procedures were essential to guaranteeing the data's quality and applicability for machine learning.
- **3. DATASET SPLITTING** The dataset was divided into two separate subsets in order to evaluate model performance appropriately. The larger portion is designated as the training dataset. The machine learning models were trained using this selection as a basis. The testing dataset, which was kept apart to assess the models' performance, was allocated the remaining space. This distinct separation of testing and training data aids in reducing overfitting and providing a precise assessment of model generalization.
- **4. MODEL TRAINING** Five distinct machine learning models were employed such as Random Forest, Stratified K-fold, KNN (K-Nearest Neighbors), LSTM(Long Short Term Memory) and SVR(Support Vector Regression) for predicting server failures. Furthermore, Stratified K-fold and SVR are used for predicting the number of days remaining till failure. These models were trained on the training dataset, learning patterns and relationships within the data. During the training process, each model was fine-tuned and optimized to make accurate predictions based on the input features.

IV. RESULTS AND DISCUSSION

I. PERFORMANCE EVALUATION

All the models were extensively trained and compared, which yielded the following results-

Algorithm	Accuracy
Random Forest	0.93
Stratified K-fold	0.92
KNN	0.89
LSTM	0.86
SVR	0.65

Clearly, Random Forest and Stratified K-fold are better suited for the prediction task than other algorithms. On the other hand, LSTM comes out to be a poor choice for prediction as it yields significantly lower accuracy than other models. Hence, Random Forest was used to predict the number of days remaining till failure.



Fig 3 - Prediction Page

In Figure 3, the prediction is displayed within a text box, with an added server number. This prediction indicates the number of days until this specific server is anticipated to fail.

V. DISCUSSION AND INFERENCES

This predictive maintenance model revolutionizes server management by overcoming traditional limitations. It caters to diverse user groups - administrators, technicians, and even regular users - by offering functionalities that redefine the entire approach to server maintenance. The benefits are undeniable: significant reductions in downtime, cost savings through preventing unplanned repairs, improved asset management, and enhanced flexibility and scalability. Additionally, data-driven decision making becomes a reality. But this model goes beyond just functionality. Its emphasis on transparency, user engagement, and access controls fosters a secure and responsive environment for server management. These advancements underscore the critical role of proactive maintenance plans powered by machine learning and advanced analytics. By embracing such techniques, organizations can unlock the full potential of their server infrastructure, maximizing efficiency, dependability, and performance in today's demanding IT landscape.

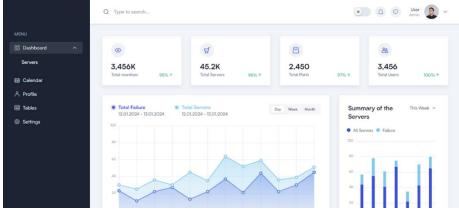


Fig 4 - Website Interface

VI. CONCLUSION

In conclusion, the application of predictive maintenance to servers is a noteworthy development in the optimization of IT infrastructure management. Through the utilization of machine learning algorithms, predictive analytics, and blockchain technology, entities can shift from reactive to proactive maintenance approaches, leading to decreased downtime, financial benefits, and enhanced asset administration. The findings show how predictive maintenance can improve server scalability, efficiency, and reliability while facilitating data-driven decision-making and future-proofing IT infrastructure. Predictive maintenance solutions could be further enhanced in the future by the ongoing advancement of technology, including edge computing and IoT integration. Organizations must adopt these innovations if they want to remain resilient and competitive in the quickly changing digital landscape.

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