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IOT SIMULATION FOR PREDICTIVE MAINTENANCE: BRIDGING THE GAP BETWEEN AI AND OPERATIONS

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Abstract:

This project combines Deep Learning (DL) for accurate prediction with SimPy for realistic simulation to address predictive maintenance in industrial IoT. Our main goal was to develop a reliable system by first building a highly accurate model to predict robot failures and then testing its performance under real-world conditions. We created a Deep Neural Network (DNN) that reached 1.0000 accuracy in classifying robot status. Next, we used this model in a SimPy environment to simulate maintenance queue management. The simulation showed that even with perfect prediction, the system still faced bottlenecks, leading to an average robot waiting time of 9.47 time units. This result shows that the main challenge is not prediction, but resource management.

Keywords **—IoT, predictive maintenance, deep learning, simulation, resource management.**

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I. INTRODUCTION

In today's manufacturing environments, robot downtime can quickly lead to significant financial losses. Relying on reactive maintenance is no longer sufficient, as unexpected failures interrupt workflows and reduce productivity. Predictive Maintenance (PdM) aims to anticipate failures before they occur, helping industries avoid costly interruptions. However, accurate prediction alone does not guarantee efficient operations. This project moves beyond simple forecasting. It presents an integrated approach that combines Deep Learning for highly accurate failure prediction with SimPy simulation to evaluate the real operational impact of those predictions. By first perfecting the diagnostic stage and then analyzing maintenance flow dynamics, we address a critical question: If we know exactly when a robot will fail, how efficiently can the maintenance team handle the resulting workload?

II. BACKGROUND

A. Data Preparation and Feature Integrity

The dataset included ten numerical sensor readings and a key categorical feature. To ensure feature integrity and consistency during training, we employed a Column Transformer pipeline. This included using StandardScaler to normalize numerical values for stable model training, and OneHotEncoder to convert the source feature into a machine-readable format. This preprocessing ensured consistent feature structures, minimizing the risk of mismatches during inference.

B. Deep Learning for Diagnostic Precision

A three-layer Deep Neural Network (DNN) was created to classify the robot's condition into five predefined status categories (0 to 4). Despite its simple architecture, the model effectively mapped complex sensor patterns to the correct diagnostic class, providing a solid foundation for the simulation stage.

C. SimPy: Modeling Operational Reality

We utilized the SimPy framework to simulate robot flow through the maintenance system, which introduced key elements. First, "Waiting Chairs" (The Resource) were modeled as a single maintenance technician reflecting limited repair capacity. Second, "Time" was used as the metric for calculating arrival, service, and waiting times. This framework allows examination of how prediction accuracy interacts with operational bottlenecks.

III. EXPERIMENT DISCUSSION

A. Model Training and Performance

The DNN was trained on the fully processed dataset, and its classifications were pivotal during simulation. When a robot entered the simulated environment, its sensor data was instantly processed by the model. If the model indicated a status of 2, 3, or 4 (maintenance required), the robot was directed to the technician queue. This integration provided a realistic decision-making pipeline, where predictive insights shaped maintenance workflows.

B. Integrated Logic Flow

The simulation followed a DL-driven operational loop, as illustrated in Fig. 1. First, a robot arrives with an arrival time generated using an exponential distribution. Second, the robot's features are assessed by the deep learning model. Third, a decision is made: if the status is Normal, the robot exits the system. If Maintenance is Needed, it requests technician access. If the technician is busy, the robot enters a waiting queue. The primary metric collected was average waiting time.

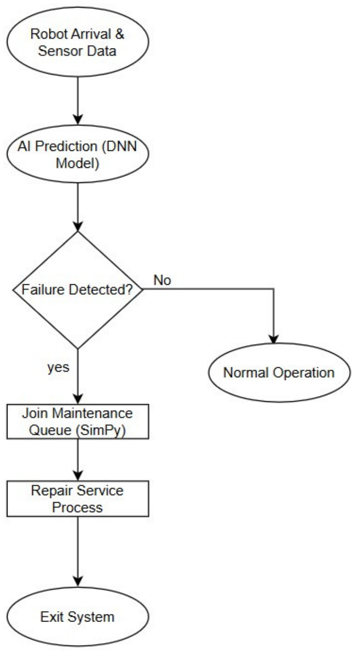

Fig. 1. Overview of the simulation model structure showing the flow of operations and service stations.

IV. FINDINGS / RESULTS ANALYSIS

A. Predictive Performance

The Deep Neural Network achieved perfect classification performance, with a confusion matrix showing zero misclassifications across all five robot status categories. This 1.0000 accuracy is reasonable here due to the clarity and consistency of the dataset and the strong preprocessing pipeline. With prediction no longer a limiting factor, this perfect accuracy shifts attention to the operational challenges revealed in the simulation stage.

B. Simulation Outcomes

After integrating the trained model into the SimPy environment, the simulation made it clear that accurate prediction alone does not eliminate delays. Even with perfect diagnostic output, the system experienced noticeable slowdowns due to the limited availability of the maintenance technician. Robots often had to wait before being serviced, resulting in an average waiting time of 9.47 time units. This outcome demonstrates that the real bottleneck

Lies not in prediction accuracy, but in managing maintenance capacity and resource allocation.

V. CONCLUSION

This project successfully met all academic objectives by developing an integrated framework that combines highly accurate Deep Learning predictions with a realistic SimPy-based operational model.

The deep learning model achieved 1.0000 accuracy, confirming its reliability in diagnosing robot status. However, the simulation quantified the impact of limited maintenance capacity, showing an average robot waiting time of 9.47 time units.

The main conclusion is that predictive maintenance is only one part of the equation. Accurate diagnostics alone cannot ensure smooth operations if the system lacks sufficient maintenance resources. The simulation provides clear evidence that increasing the capacity of the resources—such as assigning an additional technician—would significantly reduce waiting time and improve overall robot uptime.

