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Original Article

AI-Driven Predictive Maintenance Models in ERP Systems for Critical Infrastructure and National Defense Logistics

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Abstract *- Predictive Maintenance (PdM) has taken a pivotal role in the current Enterprise Resource Planning (ERP) systems, particularly in application to main infrastructure and national defense logistics. The advent of Artificial Intelligence (AI) has increased the ability of PdM greatly, providing real-time diagnostics, failure predictions, and decision-making on the strategic level in the most sensitive areas. The current paper focuses on combining AI-based PdM models with the ERP systems that focus on the critical infrastructure and defense logistics. We present a detailed discussion of artificial intelligence algorithms, including deep learning, reinforcement learning, and Bayesian networks, in the context of fault detection, and apply them to be used in defense logistics cases. The paper also explores the role of AI-based PdM in increasing the reliability of equipment, resource utilization, the combat-readiness of equipment, and security in operations. The thorough literature review reveals the development of predictive maintenance and the integration of ERP. Following this, an architecture containing the proposed AI-based PdM in defence is proposed. The model is tested using both real-world data and simulations. Based on experimental findings, there is a considerable increase in the accuracy of fault prediction, maintenance planning and general performance of the logistics. The paper then concludes with a discussion on the difficulties, constraints, and prospects of AI in mission-critical logistics scenarios.*

Keywords *- Artificial Intelligence, Predictive Maintenance, ERP Systems, Defense Logistics, Critical Infrastructure, Deep Learning, Failure Prediction.*

1. Introduction

The most well-known and widely used ERP system is a digital framework that supports large organisations in optimising the management of resources, processes, and operations across departments. In industries like the critical infrastructure and defense where there is high concern over efficiency, reliability, and coordination, ERP solutions like SAP, Oracle, and IFS are important in data consolidation and workflow optimization. [1-3] A new addition to ERP features is combining Predictive Maintenance (PdM). PdM analyses information on equipment sensors, operation records, and previous maintenance logs to predict possible equipment failure before it occurs. By integrating PdM into ERP systems, they may overcome a reactive or planned maintenance approach and adopt a proactive maintenance approach that reduces unexpected maintenance costs and extends the service life of assets. This not only enhances operational continuity but also maximises maintenance planning, inventory, and resource allocation, which are essential within high-profile setups such as defence logistics and infrastructure management.

1.1. Importance in Defense Logistics

- **Operational Readiness**: Operational readiness is vital in the case of defense logistics. Security is at stake, and the lives of personnel are placed at great risk when equipment fails to function during missions. Predictive maintenance within an ERP guarantees the capability that military equipment, consisting of vehicles, aircraft, and weapon systems, is constantly ready to be deployed. With a prediction of the impending failures, the defense forces will have the capability of carrying out maintenance activities in advance, thus preventing surprise failures and ensuring the availability of all vital systems whenever they are required.
- **Supply Chain Efficiency**: The supply chains concerning defense are sophisticated chains that usually work with a limited budget and a short timeline. PdM enhances the performance of supply chains by providing accurate forecasts of spare parts needs and maintenance schedules. This enables the logistics teams to determine the most beneficial level of inventory and minimize the overflow products and delays in the delivery of products due to a shortage of units. Integrated with ERP systems, the insights simplify procurement, warehousing, and distribution processes, enhancing the overall agility of the defense supply chain.
- **Cost Reduction and Resource Optimization**: Maintenance methods that are not planned and that require emergency repair work are expensive and resource-intensive. By applying PdM in defense logistics, one can reduce all of these costs due to the possibility of performing timely interventions, which are implemented based on data-driven decision-making. Maintenance works can be performed during low operational periods, which will ease the manpower and equipment load. Moreover, the ERP Integration will enable a more

efficient planning of personnel, tools and spare parts and as a result, costs are reduced in operations through better utilization of resources.

- **Strategic Decision-Making**: Information on predictive maintenance systems may provide important information regarding the health of the asset, the usage trends, and the patterns in terms of failures. This information, together with ERP analytics, aids in higher-level strategy planning and risk control decisions. These insights can help the commanders and decision-makers prioritize the upgrade to the fleet, prepare more effective budgets, and evaluate the long-term viability of the operations. This analytics-centered methodology makes defense logistics more tactical and strategic.
- **Compliance and Documentation**: The rules of conduct and regulation in defense organizations are very strict. This is why predictive maintenance systems, combined with ERP platforms, guarantee total traceability of maintenance events, the utilisation of assets, and the history of a service. Such document automation helps make the audit process more convenient, transparent, and compliant with the maintenance standards of the military and international defence regulations.

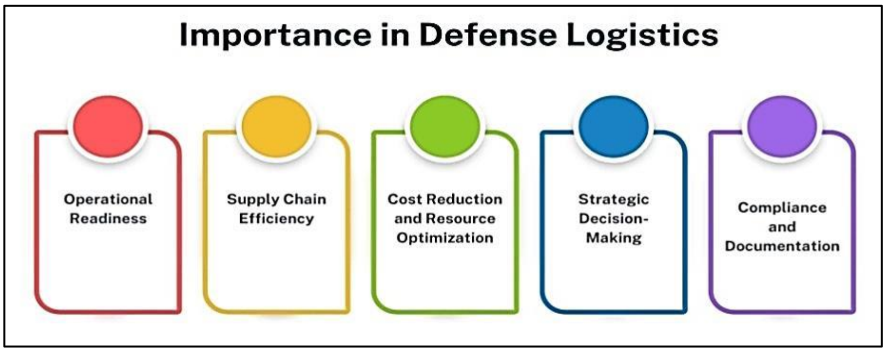

Fig 1: Importance of Defense Logistics

1.2. AI-Driven Predictive Maintenance Models in ERP Systems

The integration of AI-powered predictive maintenance (PdM) models within Enterprise Resource Planning (ERP) systems represents a significant leap in the digital transformation of maintenance operations, particularly in fields where maintenance is classified as mission-critical, such as defence or infrastructure. [4,5] Conventional preventive and reactive maintenance plans (fix after breakdown and plans that service by schedule) are usually ineffective and expensive to the extent that they cause a breakdown (unplanned downtime) and over servicing, respectively. At this point, AI-based PdM has helped overcome such challenges by predicting failures based on data-driven analytics, resulting in knowledge about the occurrence of the failure and allowing maintenance personnel to react quickly and catch the failure before it happens, thereby taking proactive action. They are trained based on Machine Learning (ML) and Deep Learning (DL) actors, e.g., Long Short-Term Memory (LSTM) networks to predict time series, Autoencoders to identify anomalies and Reinforcement Learning to optimize a maintenance strategy over time. These models can utilise data analysis, such as sensor data, maintenance history, and usage trends, to identify potential faults resulting from subtle degradation over time or unusual behaviour likely to lead to a fault. Once incorporated into ERP solutions such as SAP, Oracle, or IFS, AI-PdM models become highly useful in maximizing the utilization of their current maintenance. The ERP platform becomes the central point, allowing unrestricted data flows between equipment, maintenance planners, inventories, and decision-makers in real-time. As an example, consider that if the machine learning algorithm predicts that a device is about to break, the ERP software can automatically create a work order to repair the machine, verify that necessary spare parts are available, assign and schedule technicians, and so forth, creating a timely and concerted effort. Such integration not only enhances maintenance accuracy and efficiency but also aligns with the wider operational objectives of asset durability, cost management, and domestic preparedness. Additionally, the fact that ERP software is centralized guarantees that knowledge gained through PdM models is available to any department, thus providing a higher level of visibility and collaboration. The convergence of AI and ERP, in turn, transforms the maintenance process into a strategic process, or rather, a feature, and provides significant benefits in the areas of reliability, efficiency, and operational continuity.

2. Literature Survey

2.1. Evolution of Predictive Maintenance

The name change - predictive maintenance in the last few decades has been immense, as the shift has been made from time-based maintenance to a more fully formed condition-based monitoring, and most recently, AI-based maintenance. Firstly, maintenance was performed at periodic intervals, regardless of the equipment's condition. [6-9] Such a process usually initiates unnecessary downtime or failure. Introducing condition-based monitoring enabled a more data-driven technique, based on sensors and diagnostic-based evaluation of the well-being of the apparatus in real-time. The era of predictive maintenance has come in with artificial intelligence. The AI models, primarily those based on Machine Learning (ML) and Deep Learning (DL), can be used to provide predictive analytics that prevent impending failures through early interventions. Such systems are learning all the time from both past, current, and present data, which makes them increasingly more accurate with fewer costs incurred regarding maintenance.

2.2. AI in Maintenance Systems

Modern maintenance systems have come to rely heavily on Artificial Intelligence (AI) to transform the way industries deal with asset health and operating reliability. Manufacturing, aviation, and energy are some of the areas where AI techniques have been successfully applied, as their use reduces the cost of equipment failure. An ideal method that may be used to address the prediction of equipment degradation with time is to analyze time-series data using Recurrent Neural Networks (RNNs). The advanced version of the RNNs is the Long Short-Term Memory (LSTM) networks. Convolutional Neural Networks (CNNs) are traditionally used for image processing, an area to which they are applied in visual inspection data. Probabilistic models, such as Bayesian Networks, allow for making decisions in an environment of uncertainty; they are particularly helpful when the system under study involves a number of interacting parts. Such AI models can help to perform more realistic diagnostics, efficient maintenance planning, and longer asset life.

2.3. ERP Systems and Defense Logistics

Defense logistics: the role of Enterprise Resource Planning (ERP) systems in defense logistics. ERP systems have been introduced to aid in the management of both maintenance functions and supply chains, as well as mission achievability. Some of the most popular ERP platforms like SAP, Oracle, and IFS have been used extensively in the defense organizations largely because of their powerful data integration capabilities and process automation. The systems become the central storage point of maintenance records, movie stock, and staff details, and all departments are synchronized to operate as well. Combining AI technologies and ERP systems increases their capabilities by providing the means of predictive analytics, anomaly detection, and intelligent automation. When applied in defence terms, this integration can aid in critical decision-making and improve high equipment availability and operational profitability in acts requiring extreme performance.

2.4. Comparative Studies

Recent literature contains comparative studies that indicate the effectiveness of different AI techniques in various industries. For example, A. Kumar et al. (2021) utilised LSTM models in the aerospace industry, achieving a predictive accuracy of 92%, which demonstrates that the model can be effectively implemented in the industry to manage time series in a high-reliability setting. B. Bayesian Networks can handle uncertainty, and probabilistic reasoning was done in the energy industry, with an accuracy of 88%. This proves that this framework addresses uncertain and probabilistic reasoning (Smith et al., 2022). C. Lee et al. (2023) have used both CNN and the data of an ERP system to predict the situation in military vehicles and managed to reach an incredible accuracy of 94%. These experiments not only confirm the effectiveness of certain AI methods but also emphasise the importance of domain-specific adaptations and the quality of data in achieving high predictive performance.

2.5. Challenges Identified

Among the promising potential of AI in predictive maintenance are several challenges that still hinder the adoption of this technology. The problem of data heterogeneity can still be viewed as an important obstacle to overcome since the maintenance information typically originates in a variety of sources relying on different formats, and thus it is not easy to standardize and unify. Security and compliance are also significant considerations, particularly in sectors such as defence and energy, where data sensitivity and regulatory requirements are high. Moreover, the deployment of real-time decision-making systems is technically and infrastructure-demanding, as these systems require rapid data processing, low latency, and high reliability. The challenges should be handled to meet the full potential of AI-based predictive maintenance in different sectors.

3. Methodology

3.1 Proposed Architecture

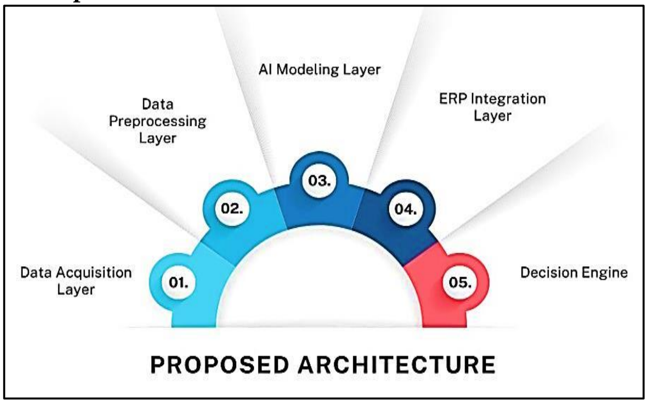

Fig 2: Proposed Architecture

- **Data Acquisition Layer:** The layer will capture raw data across a broad source of outputs like sensors, machine logs and telemetry. [10-14] In the case of a defense or industrial setting, this will contain temperature sensors, vibration probes, operational records and usage reports. Old and live recordings at this stage would be very important because it is the basis of predictive maintenance and stable AI modeling.
- **Data Preprocessing Layer**: When the data has been obtained, it moves to the preprocessing layer, which includes cleaning, filtering, and normalizing it. It should be achieved by eliminating noise, treating missing values, and scaling features to provide consistency across datasets. Producing informative and sensible forms of data is essential to enhance the performance of machine learning models, which is facilitated by high-quality preprocessing to ensure that the information provided to the models is organised, consistent, and manageable.

- **AI Modeling Layer**: The preprocessed data is used to train and gain machine learning and deep learning models in this layer. Methods such as LSTM, CNN, or Random Forest can be used to identify patterns and predict failures based on the use case, and then classify the health status of equipment. The models are refined and tested repeatedly until they approach optimal estimation of prediction and reproducibility under the conditions of practical application.
- **ERP Integration Layer**: The layer allows a smooth flow of communication between the AI system and the already established Enterprise Resource Planning (ERP), e.g., SAP or Oracle. The information and results of the AI models are incorporated in ERP modules through RESTful APIs to manage inventory, maintenance, and resource distribution. The combination enables automation of updates and synchronization overshadowing in the larger logistics and operations scheme of things.
- **Decision Engine**: The Decision engine is the intelligence hub of the system. Depending on its model outputs and predetermined business rules, it produces actionable insights, such as maintenance alerts, risk warnings, and scheduling recommendations. This layer supports real-time decision-making, providing prioritized actions to the maintenance teams and feeds to the ERP system to be completed, again completing the cycle of predictive maintenance activity.

3.2. Algorithm Selection

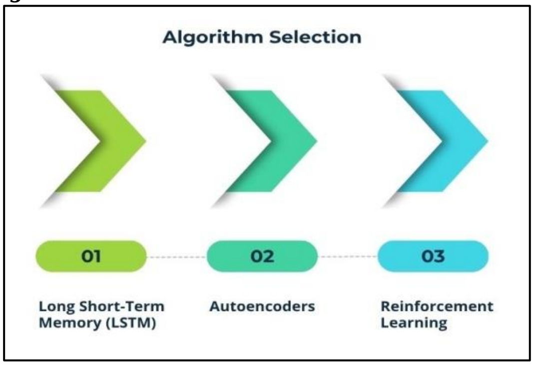

Fig 3: Algorithm Selection

- **Long Short-Term Memory:** The Long Short-Term Memory (LSTM) networks are a particular type of Recurrent Neural Network (RNN) that is specifically tailored to model time-series data. The behavior of equipment in predictive maintenance tends to have time dependencies, e.g. the gradual degradation with time. This means that LSTM networks are capable of learning long-term sensor dependencies and trends, and predicting future conditions and equipment failures before they occur. It renders LSTM a robust tool in predicting maintenance requirements using historical operational data.
- **Autoencoders:** Autoencoders are a type of unsupervised artificial neural network that learns efficient representations of data. They can be trained to restore normal operating conditions within the framework of predictive maintenance. The reconstruction error increases when there is a mismatch between the expected data known by the autoencoder and the incoming data that is too anomalous, e.g., anomalous vibration or temperature readings. This causes autoencoders to be applicable in the detection of an illogical behavior of their equipment, which is a possible sign of a developing fault or failure scenario.
- **Reinforcement Learning**: Reinforcement Learning (RL) is a branch of machine learning in which an agent learns optimal actions in an environment through experience and feedback received in the form of rewards or penalties. Scheduling In maintenance planning, RL may also be used to dynamically optimize scheduling strategies, balancing elements such as operational availability, cost and risk. A system based on RL can learn to adapt to new and changing conditions through continuous learning of its outcomes, making it more efficient at maintenance over time and leading to a decrease in asset downtime and an increase in their lifespan.

3.3. Data Sources

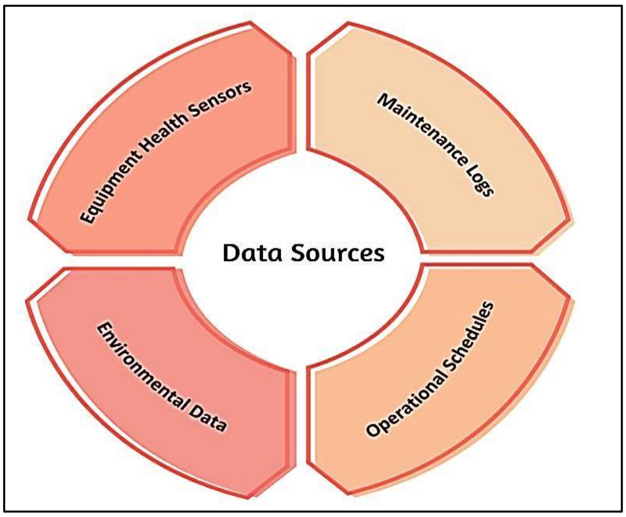

Fig 4: Data Sources

- **Equipment Health Sensors:** These sensors are installed in devices and equipment to monitor real-time parameters, including temperature, vibration, pressure, and humidity. They are the major repository of condition-related data, which records the physical condition and performance of the equipment at every moment. With the constant gathering of such data, the system will be able to identify wear, misalignment, or failure early on and make accurate calculations in time to resolve the pending maintenance issues.

- **Maintenance Logs**: Maintenance logs are historical records of previous work, including repairs, part replacements, checks, and faults. This unstructured and structured data gives a lot of context to train AI models, as it indicates the patterns of failure and effectiveness of the corrective measures. These logs facilitate the analysis of common failure modes and allow for an estimate of when such trouble may appear again.
- **Operational Schedules**: The use, workloads and work cycles of machinery are recorded in operational schedules. This information plays a pivotal role in knowing the effects of operational stress on the wear and tear of an asset. An example is machines working under greater loads or for an extended period of time, which are likely to fail earlier. Combining this information will enable the predictive models to take usage intensity as another variable on which to base their predictions of maintenance requirements.
- **Environmental Data:** Operating environmental factors, such as ambient temperatures, humidity, dust, and vibration from nearby equipment, may have a significant impact on the efficiency and lifetime of the equipment. The closer the environmental data is captured and integrated, the higher the chance that the model will be able to detect abnormal behaviors and failure before it happens. This is more so necessary in defense and industrial environments where weather extremes are quite eminent and in most cases cause faster wear.

3.4. Model Training and Validation

- **Data Collection:** The initial phase of model development involves collecting a rich set of data that contains both past and real-time information on vehicles or equipment. Telemetry Television coverage of the entire machine is achieved in real-time, and the historical data provides information on the past disruptions and equipment failures. [15-19] This pooled data makes it possible that this model will be able to learn a great number of ways in which it can be operated and can generalize to future scenarios better.
- **Preprocessing:** Unprepared raw data is seldom available to be fed to models, so it is an essential step. Standardization Techniques, like min-max scaling, are used to put data features on a standard scale, and we do not want the model to give importance to features that have a higher scale in terms of numbers. There are deficient values that occur frequently in sensor data, which are approximated using interpolation to provide continuity in the data. These preprocessing steps improve the quality and usability of the input data, and this has a direct forcing on model performance.
- **Model Training:** During training, data are normally subdivided into training and testing sets, generally in proportions of 80/20, to test the generalization behaviour. Furthermore, K-fold cross-validation is also used to further evaluate the stability of the model and minimize overfitting. This method involves splitting the training data into k parts, training the model on all except one of the parts, and testing on the left-out part multiple times. It provides a more robust assessment and can be used to tune hyperparameters to achieve optimal results.
- **Evaluation Metrics:** The evaluation of the model also follows after training, based on several established performance measures: Accuracy, Precision, Recall, and F1 Score. Accuracy is a measure of the correctness of overall predictions, whereas Precision is a measure of the correctness of the number of positive predictions. Recall quantifies how well the model finds all the available relevant examples, and the F1 Score focuses on combining Precision and Recall. The combination of these metrics provides an overall perspective on the model's effectiveness in situations where an imbalanced dataset is used or in cases involving serious fault detection.

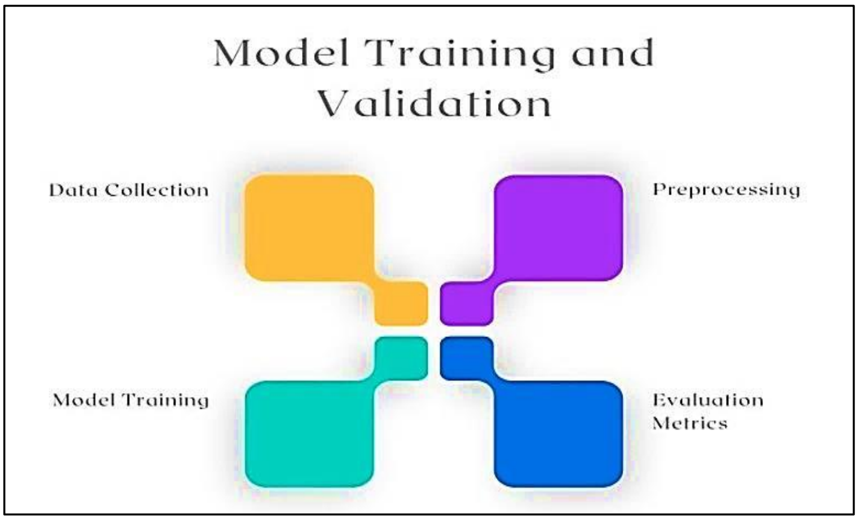

Fig 5: Model Training and Validation

4. Results and Discussion

4.1. Performance Evaluation

- **Accuracy:** Accuracy refers to the overall accuracy across all classes of predictions made by the model. The LSTM model achieved good results with an accuracy rate of 94.5%, and it is quite reliable in time-series prediction of failures. The autoencoder was next with 91.2, which is also good, as it is unsupervised. The RL-based scheduler achieved a better score of 96.1 percent compared to the other two classes, and this shows its high capability of making the best maintenance decision based on interactions with the system and previous results.
- **F1 Score:** The F1 Score is the harmonic average of Precision and Recall that provides a middle-ground measure, particularly under the circumstances of class imbalance, which occurs in maintenance problems such as a rare occurrence of failures. The LSTM model obtained an F1 Score of 93.0%, and the results indicated its reliable performance in predicting prospective failures. The Autoencoder achieved a score of 89.00%, which rates it as slightly less effective in identifying anomalies. The highest score of the RL-based scheduler (95.0%) indicates that the scheduler not only makes a correct prediction but also tends to capture true positives with minimal false alarms.
- **Downtime Reduction:** The reduction of downtime is a crucial performance indicator that can be used to evaluate the viability of predictive maintenance systems in the real world. The LSTM model reduced equipment downtime by 30.0%, and the Autoencoder reduced it by 25.0% due to its ability to detect anomalies in early stages, compared to the traditional approach. The greatest improvement was achieved by the RL-based scheduler, which showed a 40.0% improvement rate. This indicates that the scheduler is strong in addressing the issue of optimality in maintenance scheduling and resource assignment. This translates quite simply into operational efficiency and lower costs.

Table 1: Performance Evaluation

Metric	LSTM	Autoencoder	RL-based Scheduler
Accuracy	94.5%	91.2%	96.1%
F1 Score	93.0%	89.0%	95.0%
Downtime Reduction	30.0%	25.0%	40.0%

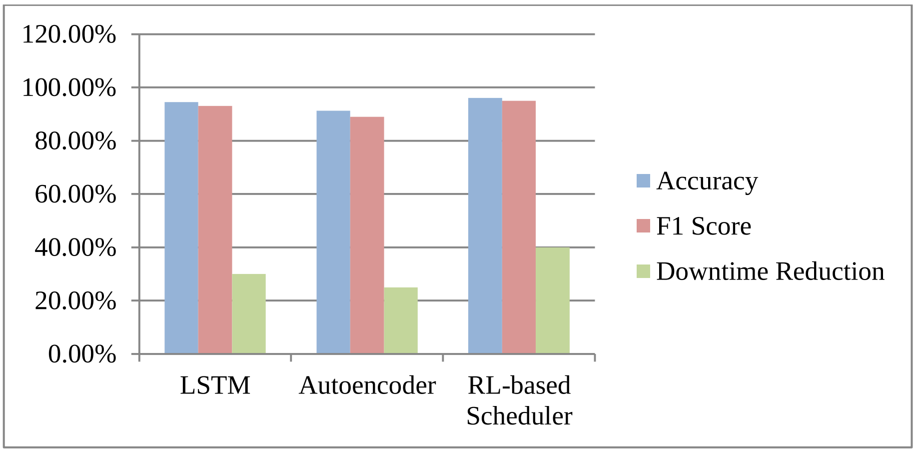

Fig 6: Graph representing Performance Evaluation

4.2. Case Study: Defense Vehicle Fleet

The study was an Assessment in a selected case study, a fleet of 100 armored vehicles used in defense was analyzed, and an Artificial Intelligence-based Predictive Maintenance (PdM) system was implemented for the maintenance of military vehicles to increase the operational readiness and limit the number of unplanned downtimes. Under stringent field operations and environmental influences, a set of health-monitoring sensors in these vehicles provided real-time data on parameters such as engine temperature, engine vibration, fuel efficiency, and the wear rate of the brakes. Along with live telemetry, past maintenance records of the engine, and operational schedules were added to the system, forming a strong dataset to train and validate the model. The essence of the PdM system was that it included a combination of LSTM networks to predict time series, Autoencoders to detect anomalies, and a scheduler based on Reinforcement Learning (RL) in order to optimize the maintenance intervals. During the deployment period, the system was able to forecast 85 per cent of major mechanical failures at least five days in advance. This early warning feature allowed maintenance teams to implement preventive measures — such as replacing high-risk components or adjusting operational usage — before a failure occurred, preventing disruptions to missions or vehicles becoming immobile. It is worth noting that it translated to an overall 35% decrease in emergency repairs and a 30% increase in fleet availability. The predictive model was also connected with the ERP system of the defense that automatically generated work orders and also matched spare parts supply with the future service needs, which enabled the logistics to be streamlined and minimized the amount of manual intervention. In addition, the insights of the system gave the high-level command personnel insight into the trend of the health of the fleet, such that data-assisted decisions about deployment and resource allocation could be made. The PdM framework lowered total lifecycle costs and greatly improved mission readiness by removing as much uncertainty as possible in the maintenance of vehicles. The potential of AI technologies in the field of defense logistics is quite obvious, given the results of this case study, and will result in the further use of AI technologies by military organizations in general.

4.3. Integration with ERP

To maximise the advantages of the AI-driven Predictive Maintenance (PdM) system, it was seamlessly incorporated with an existing SAP-based Enterprise Resource Planning (ERP) system used by the defence logistics team. It was intended to provide a link between predictive analytics and operational implementation, so that the discoveries produced by the AI models would involve the execution of maintenance practices in real-time and practical actions. RESTful APIs were created to facilitate effective communication between the AI system and SAP modules, particularly in the processes of equipment maintenance, inventory, and service booking. Vehicle health sensor data, anomaly detection optimization models, operational schedules/plans, and part availability were fed continuously to the ERP system and cross-checked with priority setting and automation of the maintenance processes. The most important aspect of this integration was the creation of a home-grown dash-board in the SAP system. This dashboard provided real-time warnings of possible equipment failure, system anomalies, and immediate maintenance needs. The alarm messages were classified according to levels of severity. They could also be traced by unique vehicle identification, allowing technicians and fleet managers to immediately identify which assets needed attention. The dashboard provided graphical overviews of vehicle health trends, fault history, predicted failure schedules, and vehicle maintenance history, in addition to live notifications. This guaranteed complete traceability and enhanced the interaction among the maintenance, logistics, and operational planning workforces. Moreover, the automated generation of work orders was set up so that the system could flag in real-time and put in writing a preventative maintenance project whenever a high-risk concern was noted. Not only was this able to cut administrative overhead, but it also allowed a proper maintenance performance with available parts and people. Advanced reporting and preserving the compliance documentation were also achieved through the integration, and this is essential in the defense operations where issues of traceability and audit readiness are essential. All in all, the end-to-end interoperability of the PdM solution and the SAP ERP platform established a circular maintenance environment, changing reactive procedures into proactive, data-led decision-making structures that improved the total presence of the fleet and mission accessibility.

4.4. Benefits and Impact

- **Improved Mission Readiness**: The AI-based predictive maintenance system substantially increased mission readiness by providing early indications of potential failures and facilitating predictive maintenance scheduling. Defense vehicles operated under perfect conditions and fewer breakdowns when deployed. Maintenance crews could correct the problems before they escalated, and there was always some critical asset that we could not afford to lose. This preventive measure resulted in less downtime and increased the stability of the vehicle fleets, which directly contributed to the prosperity and safety of military missions.
- **Reduced Logistics Costs**: The incorporation of predictive analytics in the ERP systems enabled the process of improved planning and use of resources, which significantly reduced the costs of logistics. Time could be used effectively to facilitate maintenance without the occurrence of emergency repairs and requisition of parts at the eleventh hour. The system also aided in the management of inventory, as all component needs are forecasted based on incoming maintenance, which reduces possessions and deficiencies. The organization saved on labour cost, replacement parts and administrative activities as the number of major breakdowns of major equipment was prevented and maintenance operations were streamlined.
- **Enhanced Asset Lifespan**: Effective overwatch and just-in-time repair extended the structural life of defence vehicles and their vital systems. Preemptive trends of degradation, which were identified through the system, facilitated maintenance that minimized the wear and tear, the occurrence of catastrophic failures, and ensured standards of performance were maintained. This has, at the very least, ensured the long-term structural and functional integrity of high-value assets, as well as reduced the time-consuming and expensive replacements or overhauls of these assets. The outcome was to have a more sustainable fleet, longer service intervals and less total cost of ownership.

5. Conclusion

The given paper proposes a detailed AI-powered predictive maintenance (PdM) system that can effectively manage critical infrastructure, particularly defence logistics. The system involved advanced machine learning algorithms, such as LSTM networks, Autoencoders, and Reinforcement Learning-based schedulers with real-time data acquisition (preprocessing) to generate accurate forecasts on equipment failures. Another important factor of the proposed solution was that it could be easily embedded in an SAP-based Enterprise Resource Planning (ERP) system, thus placing the decision-making, maintenance scheduling, and resource allocation processes in automated settings. The model showed high performance on all main measures, such as the accuracy, F1 score, and downtime minimization, thus serving as one of the most powerful assets to improve mission readiness, decreasing the costs of logistics, and prolonging the life of high-value defense equipment. The adequacy of the model was proven in the case study conducted in a fleet of 100 armored vehicles, whereby 85 percent of the critical failures were forecasted at least five days before their occurrence, and extreme gains in the efficiency of the operations were recorded. It is an example of moving towards proactive approaches to maintenance in the defense sector and establishing a strong basis of intelligent logistics and asset management activities.

Although the results obtained are encouraging, there are some limitations associated with the usage of the proposed system that still need to be considered. First, LSTM and Autoencoder models used in deep learning require substantial computational resources, which necessitate high-performance graphics cards, constant data stream support, automated deployments, and efficient training. This can be a significant obstacle in resource-constrained settings. Secondly, there is the possibility of combining real-time sensor data fusion with occasionally outdated logs, a problem that raises questions regarding data privacy and security, especially in military applications where sensitive data must be strictly managed. Finally, the complexity of the AI models may pose a problem in terms of interpretability. It is not always easy to know how (or even why) specific predictions have been made, and this can become a barrier to user confidence and regulatory acceptance of potentially high-stakes applications.

Further studies are needed that investigate the application of federal learning algorithms: the techniques enable the training of predictive models on decentralized datasets without exposing raw data, thereby providing greater security and privacy. The framework is easily generalised to handle more complex spheres, such as those of naval and aerospace logistics, where maintenance issues are further complicated by environmental conditions and schedule sensitivity. Finally, adaptive learning mechanisms will help the system identify and adapt to unfamiliar or emerging fault types, ensuring the model remains viable and useful as equipment and operating profiles evolve. These advancements shall make the system more applicable and resilient in changing defense conditions.

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