Enhancing Metro Rail Efficiency: A Predictive Maintenance Approach Leveraging Machine Learning and Deep Learning Technologies

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Abstract

This paper looks into the modeling and implementation of a predictive maintenance system of an air production unit for a metro rail designed to suit the challenges detailed by the industrial sector. Using modern machine learning, deep learning, and AI techniques, the system identifies the faulty equipment well in advance when applied to the huge volume of sensor data. One of the major functionalities of the system is an interface designed to alert users, whereby the instant alerts are made to the maintenance personnel for faster intervention, minimization of the possible downtime. The basis of the study is on the application of the predictive maintenance system within the unit of air production. It indicates great efficacy toward the prediction of a failure. A wide variety of ML and deep learning models were experimented with and fine-tuned carefully by training and evaluation over the training set and also over the testing set to ensure predictive accuracies. For example, from the above comparative model analysis, the most suitable predictive approach was indicated through the use of accuracy. Deep Learning Models, including LSTM, RNN, and BiLSTM, have been exceedingly good, with all the above models giving an accuracy of above 99.7 percent. Notably, Adaboost, a Boosting technique also has performed well. The culmination of this project highlights the pivotal role of AI and ML technologies in advancing predictive maintenance strategies within the industrial sector. The findings illustrate the potential of these technologies to transform maintenance practices, optimize operational processes, and contribute to the overall sustainability of industrial operations. This paper contributes valuable insights into the feasibility and effectiveness of AI-driven predictive maintenance systems.

Keywords: Long Short Term Memory, Networks, Predictive maintenance, Failure Detection

1 Introduction

The advancement of predictive maintenance systems marks a transformative era in industrial operations, equipping the sector with the unprecedented ability to predict equipment failures and enhance operational reliability. This research paper delves into the development of a predictive maintenance framework, wherein various techniques of ML, DL and boosting were implemented and their accuracies were compared to identify the best among them. Predictive maintenance is a pivotal strategy in the contemporary industrial landscape, where the constant pursuit of greater efficiency and reliability is given the highest priority. The system being proposed sees the implementation and comparison of various ML and DL approaches, which together, bring a more proactive approach to the challenge of predicting when equipment can malfunction. In addition to a significant reduction in unplanned downtime — and the resulting costs and safety hazards — the aim is to create a new set of tools and standards for AI-driven analytics, which can be put to use far beyond the current system. The end goal is a predictive maintenance system that will not only benefit the bottom line by enabling operational staff to act quickly and reduce their workload, but one that can also be easily used and adapted by non-expert maintainers when applying them to different industrial settings.

One of the most effective, dependable, and green modes of mass transit, the backbone in the framework of urban transport, is the metro rail systems. Their worth goes far beyond simple transportation. They are a massive aid to city decongestion, reduction of travel times, and environmental health from cutting carbon emissions that are generally high with road transport. These track systems provide a vigorous, energy-smart competitor for automobiles and buses that contribute to clogging our streets, hence increasing the quality of urban living. It also supports economic development through increasing access to jobs, educational facilities, and services, which allows denser agglomerations and reduces the sprawl of urban areas. Metro rail ensures mobility for the entire population, including inclusivity, especially those sections who have no option related to private transport. This, above all, means the towering urbanization and environmental issues: towering investment and broadening of metro rail infrastructures are fundamentally essential in nurturing cities that are more sustainable and inclined toward economic dynamism and inclusiveness.

Metro rails come under critical urban transportation infrastructures that demand the best reliability and efficiency, even in classes. The air production unit, which is of most importance to maintain the quality and comfort of the air inside the metro car, is an excellent example of a component that can yield good benefits with the help of predictive maintenance. This is far more improved than the traditional kind of reactive maintenance that follows in the aftermath of system failure, enabling the metro rail operator to now carry out:

1. Anticipate Failures: This system is able to perform proactive predictions before failures can occur and are based on sensor data that monitors the conditions of the air production units.

2. Optimize Maintenance Schedules: For the city's metro system, this meant AI and ML insights could schedule maintenance activities during the night or non-peak hours to minimize the effect on the disruption of metro services and, in turn, maximize passenger satisfaction.

3. Extend Equipment Lifespan: Proactive detection and remediation would save more money by going beyond minimizing maintenance expenditures: avoiding catastrophic failures hence lengthening the life of the equipment, which leads to lesser long-term capital expenditure.

4. Reduce Maintenance Costs: In this way, the operator will have reduced the general maintenance expenses that are associated with the air production units, since the units will have been taken off the cycle of emergency repair and exposed to scheduled preventive maintenance.

5. Enhance Safety and Reliability: The process of predictive maintenance shall ensure continued operational integrity of the air production units, and the result is the improvement of air quality and comfort to passengers, strengthening safety and reliability of metro rail services.

Predictive maintenance is superior not only in reducing downtime but also, with respect to optimized resource allocation and operational efficiency, in every way compared to traditional reactive approaches. This paper tries to dig out the exact impacts of the transformation of a predictive maintenance system designed specifically for the application of maintaining air production units in metro rail systems. This study, therefore, attempts to make evident—through meticulous analyses of system architecture, operational mechanism, and practical implementations—what tangible benefits can be reaped through integrating advanced AI, DL, and ML technologies into maintenance practice. In a nutshell, this paper proposes a framework of predictive maintenance signaling both a leap toward increasingly sustainable and efficient industrial operations and a benchmark solution scalable to the unique challenges of different industrial environments. It takes innovation in this area to a new level of benchmark.

2 Related Work

Davari et al. [1] proposed an anomaly detection framework in air production units of railway industries using deep learning. The work proposes a sparse autoencoder network that, by aggregating data from various sensors, detects failures in advance to increase the efficiency of maintenance and reduce downtime in the operation of trains at Metro do Porto. Wang et al. [2] developed an enhanced LSTM model for time-series anomaly detection tailored to rail transit systems. It overcomes the challenges of diversified data distributions and lack of labeled anomaly data facing rail transit operations by the employment of IoT and cloud technologies. The proposed model, in addition, defines thresholds on a dynamic basis and includes an error-pruning algorithm for the least number of false positives. This approach has been tested in a real metro environment, where it gave an even better model of performance than existing ones in a proper identification of device-related anomaly detection for different rail transits. Davari et al. [3] explores the integration of ML and DL technologies into predictive maintenance in the railway sector. This review identifies ML and DL techniques as pivotal in advancing the analysis of industrial equipment for predictive maintenance purposes. Despite significant strides, the field faces challenges in data handling, method selection, and application performance. The authors highlight the growing research attention towards data-driven PdM in railways, emphasizing its critical role in enhancing system efficiency, safety, and cost-effectiveness. Veloso et al. [4] introduced the MetroPT dataset, a comprehensive collection of data from Porto's metro public transportation service, designed to support the analysis of AI methods for failure prediction. This dataset encompasses a set of analog sensor readings (e.g., temperature, pressure), digital readings (control and discrete signals), and location data, offering a rich resource for predictive maintenance (PdM) research. Aimed at reducing operational disruptions and transitioning from reactive to predictive maintenance approaches, the MetroPT dataset presents real-world anomalies confirmed by maintenance reports, making it an ideal benchmark for PdM models. Zhao et al. [5] suggested a hybrid model that integrates time series decomposition with "deep learning for short-term passenger flow prediction in urban railway systems". By STL to categorize passenger flow into seasonal, trend, and residual components, the study enhances prediction accuracy by addressing varied characteristics of passenger flows. The methodology combines Holt-Winters (HW) method for predictable components and LSTM networks for residuals, demonstrating superior prediction performance over traditional models. Li et al. [6] explored deep learning applications in failure detection, categorizing anomalies into abnormal time points, intervals, and series. They highlight Long Short-Term Memory (LSTM) and autoencoders as prevalent techniques for identifying abnormal points and intervals, with dynamic graphs employed to reveal relational features among time series. Despite advancements, the field grapples with explainability limitations, noting a gap in understanding the underlying causes of anomalies. Addressing this gap, enhancing anomaly explainability emerges as a critical future research direction. Berroukham et al. [7] talks about "deep learning-based methods for anomaly detection in video surveillance". It highlights the improvement from selected features to deep learning models, emphasizing their efficacy in learning complex representations of normal and abnormal events. The paper surveys various datasets, evaluates methods through standard metrics like AUC and EER, and discusses challenges like explainability and real-time processing. It suggests potential research directions, including the application of vision transformers for improving anomaly detection accuracy and computational efficiency. Alamr et al. [8] introduced an transformer based architecture for failure detection in ECG signals, showcasing its effectiveness in identifying irregular patterns within electrocardiogram data. The model employs a transformer encoder to analyze time series ECG data from two prominent datasets, "ECG5000 and MIT-BIH Arrhythmia", achieving notable results. We substantiate that the proposed approach exhibits improved performance in considered performance metrics over several state-of-the-art deep learning models and generalizes anomaly detection across healthcare data, holding the potential to be a strong tool for the early detection of cardiac irregularities. Luo et al. [9] investigate data-supported decision help in the control of rail traffic and find the place of the predictive model in improving the reliability of the transportation system. Zeng et al. confirm only how burdensome it is to deal with the rail traffic and what potential the predictive analysis has in its turn to polish the operational strategies. It proposes a new hybrid prediction model that uses optimized synthetic minority oversampling techniques with a deep forest ensemble learning model. It was tested against actual high-speed railway data and found to improve the decision-making capability of rail traffic controllers. It offers a vast improvement in controlling the dynamic rail traffic conditions. Girish et al. [10] proposed an AI-based model using Stjson file that achieves over 93 percent accuracy in the OpenStack cloud environment in order for it to be capable of detecting anomalies. In this approach, they significantly improved upon the conventional manual way of using advanced machine-learning techniques for the preemptive detection of anomalies. Among the big contributors to the security of the IoT, Abusitta et al. [11] came up with a new deep learning model for the detection of anomalous behavior which performs well in light of the diversity of data and disturbances to the system. They used a denoising autoencoder so that only clean, non-malicious data populates the IoT systems. The remarkable superior performance of our model in real-life IoT datasets testifies very truly that our model really has robust feature extraction capability, setting new standards in this domain for IoT-based anomaly detection. Cerdà-Alabern et al. [12] focus on machine learning in fault detection for wireless community networks. Its actual area of research is not that vast, since there are no shared datasets available. Their study shows such potential of ML by implementing four unsupervised machine learning techniques on real network data. This result, therefore, recommends feature selection and model tuning to show clear performance differences between ML approaches used. Pan et al. [13] address the anomaly detection in SHM for civil infrastructures through transfer learning based methods. Their approach works by exploiting pattern similarity that occurs across several different bridges, dealing with sensor faults and environmental noise. Their approach outperforms in classification capability, proven to outperform in the assigned task of new bridges having the smallest target data by building up a multivariate database and using a CNN for the classification of an anomaly. The results of two long-span bridges show that transfer learning is effective in improving detection performance with very few labeled data, much better than classical methods. In one of the first works on the topic, Sousa Tomé et al. [14] developed an online, data-driven predictive maintenance framework for railway switches, an essential element within the railway infrastructure. Their approach uses real-time data logging from the railway's interlocking system to predict maintenance needs, aiming to improve maintenance efficiency and railway switch reliability. The methodology, which includes anomaly detection and remaining useful life prediction phases, was tested using seven months of data from the Metro do Porto. This study represents a significant stride towards optimizing railway switch operations through advanced data-driven methods.

3 Dataset Description

The time period of the dataset [15] is from February to August 2020 and comprises more than 15 million data points, labeled for one of fifteen different attributes. These are drawn from a combination of 7 analog and 8 digital sensors mounted on an APU compressor, effectively picking a variety of signals that include temperature, pressure, current, and signals from sensors. The dataset includes various attributes collected via a range of analog and digital sensor sensors.

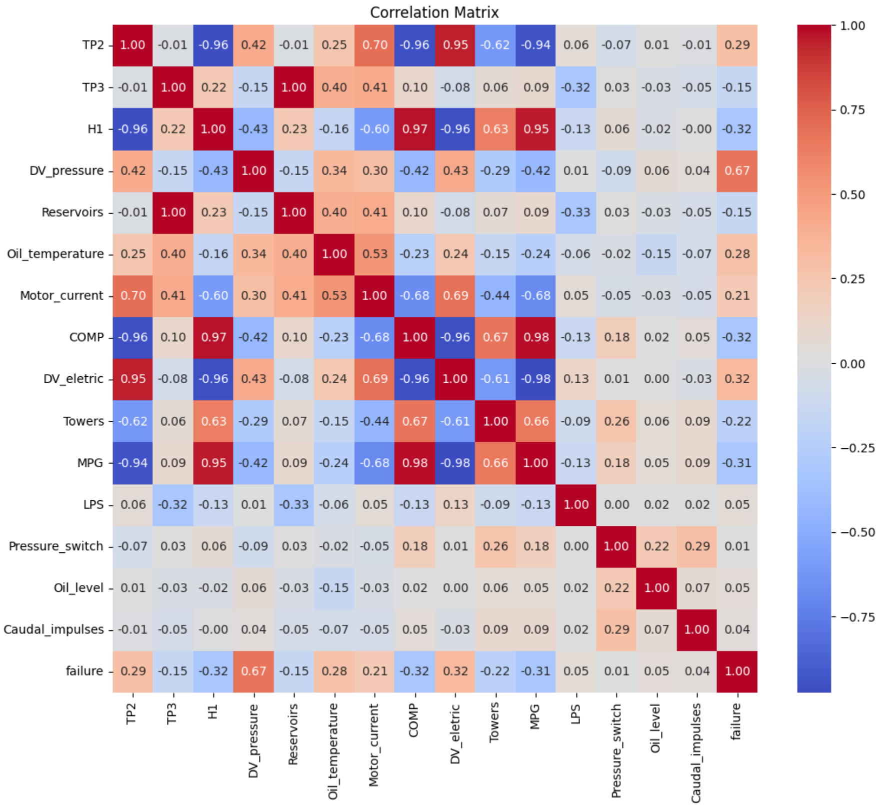

Fig. 1 The Heat Map depicting the correlation of the dataset.

The analog sensors (attributes 1-7) include measurements such as TP2 and TP3, which record the pressure within the compressor and at the pneumatic panel, respectively, and H1, which measures pressure drops indicative of cyclonic separator filter discharge. DV pressure and Reservoirs bar readings provide insight into the operational load and reservoir pressure dynamics, while Motor Current and Oil Temperature offer critical information on motor phase activity and system temperature. The digital sensors (attributes 8-15) focus on the compressor's operational state (COMP), the condition of the outlet valve (DV electric), and the status of air-drying towers

(TOWERS), alongside signals that initiate compressor load operations (MPG), detect low-pressure scenarios (LPS), monitor air-drying discharge (Pressure Switch), gauge oil levels (Oil Level), and quantify airflow (Caudal Impulse).

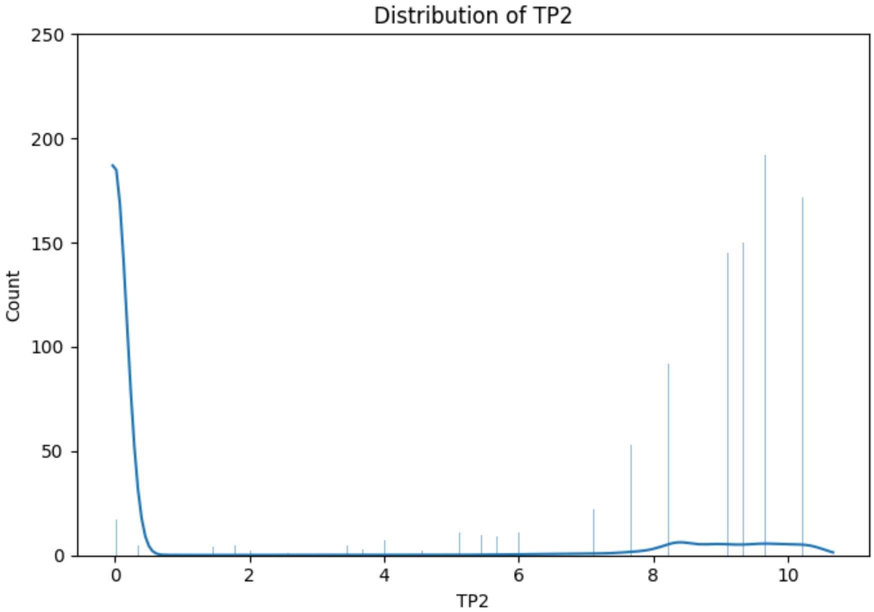

Fig. 2 The Histogram plot of the attribute T2.

4 Methodology

To perform predictive analysis on the dataset for the given problem, various approaches of ML and DL were employed. Supervised algorithms like Naive Bayes and Logistic Regression were implemented. Boosting techniques like Adaboost have been used. Deep learning and neural networks were an integral part of the implementation. Algorithms like LSTM, BiLSTM, ANN, SimpleRNN, a hybrid model of LSTM and random forest and a custom neural network architecture have been implemented and the results have been discussed in the later sections of this paper.

4.1 *Naive Bayes*

Naïve Bayes is a probabilistic model of machine learning that depends on Bayes' Theorem with an extra assumption that assumes independence among the predictors. The method is widely used with simplicity, efficiency, and gaining effectiveness from use in classification. Although both of its simplifying assumptions are not true, Naive Bayes can lead to remarkably good and fast classification results on relatively large data, which is a rich tool for a binary or even multiclass classification problem.

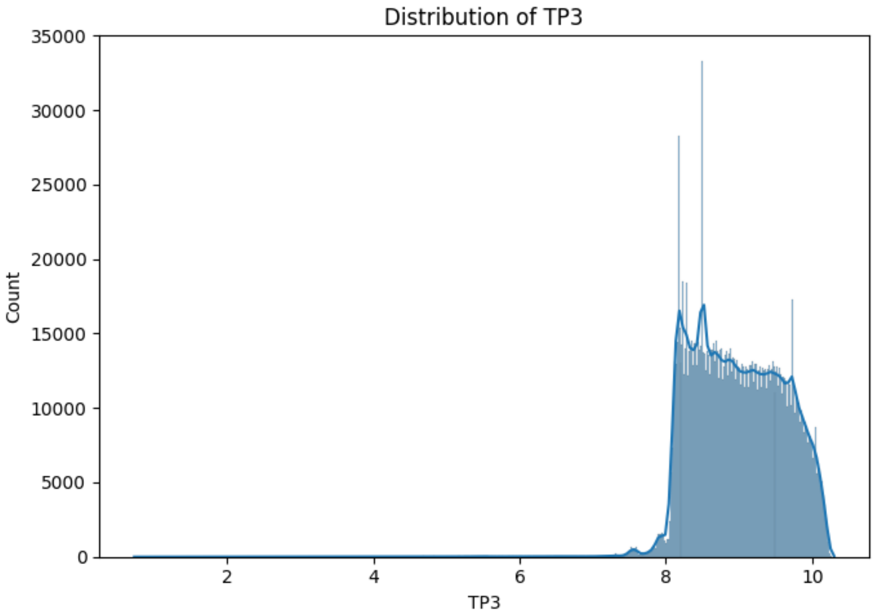

Fig. 3 The Histogram plot of the attribute T3.

$$P(A \mid B) = \frac{P(B \mid A) * P(A)}{P(B)} \tag{1}$$

4.2 *Logistic Regression*

Logistic Regression is a statistical technique and machine learning classifier used for modeling the probability of a given input, hence classifying it into a particular category. It does so by applying the logistic function to a linear combination of the input features, producing outputs between 0 and 1 that represent probabilities.

$$P = \frac{e^{a+bX}}{1 + e^{a+bX}} \tag{2}$$

4.3 *Random Forest*

It is a estimator that uses averaging in order to increase prediction accuracy while at the same time controlling overfitting, achieved by fitting many classification decision trees on different subsamples of the dataset.

4.4 *Adaptive boosting*

AdaBoost refers to a learning technique in ensemble learning. It tends to work with most classifiers, making them perform in the most appropriate manner possible. Sample weights are adjusted successively by weak classifiers that are misclassified, so that

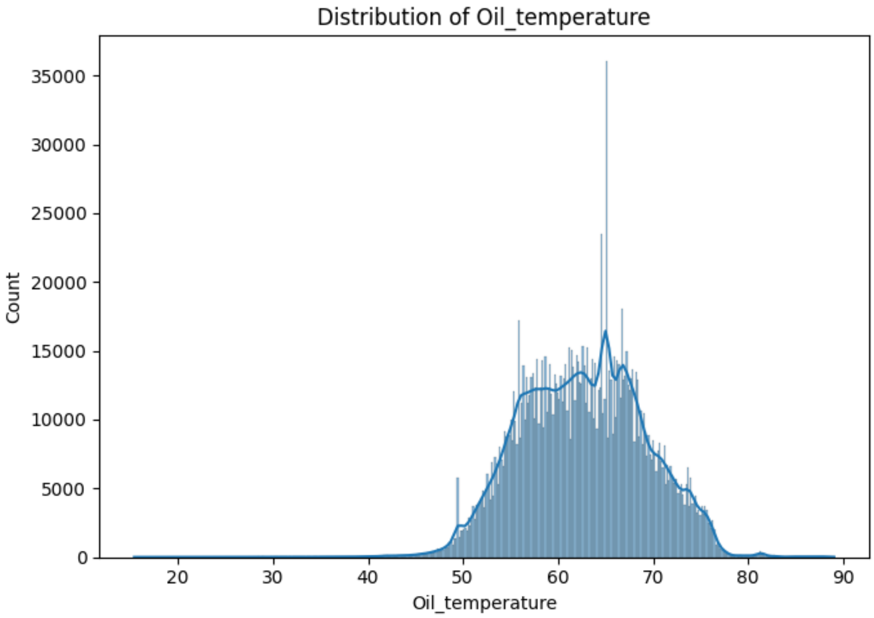

Fig. 4 The Histogram plot of the attribute Oil temperature.

more attention will be paid to hard cases by the next classifier. It further improves the generalization of the model in predicting a wide range of data sets. AdaBoost is best applied in binary classification problems, and it is said to have an easy approach, easy to implement, and provides significant improvements in classification performance.

4.5 *Artificial Neural Networks*

Artificial Neural Networks are computational models with a structure that simulates human brain patterns in decision-making. They are multi-layered networks of linked nodes that learn from the data by adjusting synaptic weights. ANNs are so designed that they can perform a lot of tasks in the domain of artificial intelligence and machine learning, including tasks like classification, regression, and even data generation. The output from an individual neuron to an ANN can be represented as:

$$y = f\left(\sum_{i=1}^{n} w_i * x_i + b\right) \tag{3}$$

4.6 *SimpleRNN*

Basically, it is only another type of neural network: the Simple Recurrent Neural Network adds a feedback loop to its neurons in order to process sequences of data. It is able to memorize through the use of its output as part of the input for the next processing, hence applicable for many tasks involving sequential information, like time series prediction or natural language processing. However, some of these SimpleRNNs

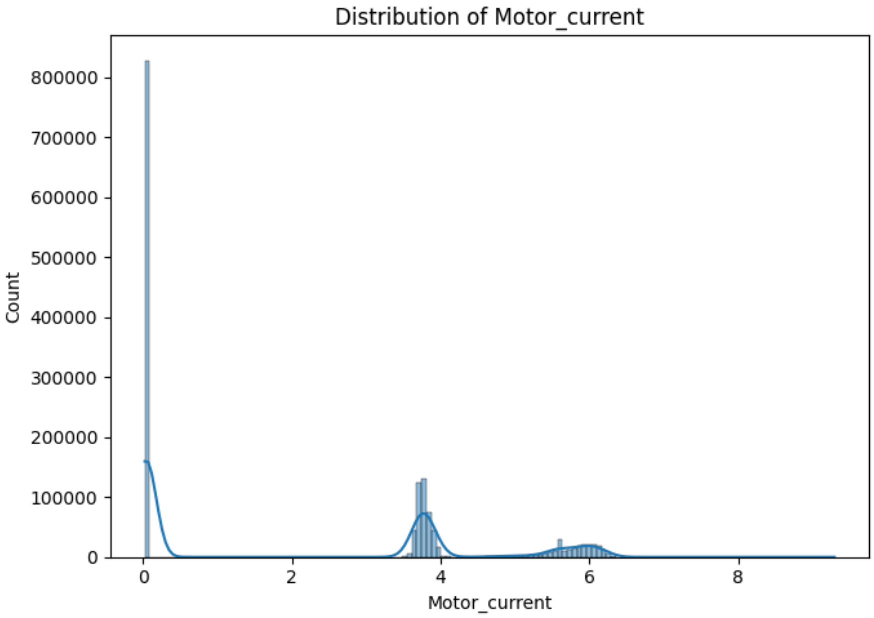

Fig. 5 The Histogram plot of the attribute Motor current.

have been observed to suffer from long-term dependencies due to challenges such as vanishing gradients. The simple Rjson equation for the hidden state at time t(ht) is given by:

$$h_t = f\left(W \cdot h_{t-1} + U \cdot x_t + b\right) \tag{4}$$

4.7 *Long Short-Term Memory*

LSTM networks are a kind of Recurrent Neural Network with an architecture aimed at solving the vanishing gradient problem in conventional RNNs. Long Short-Term Memory cells contain special memory cells and gate mechanisms in them: input, forget, and output gates. Hence, they enable the RNNs to learn the long-time dependencies presented in sequence data. These give LSTM the ability to hold information above long sequences and are very successful in tasks such as time series analysis, processing of natural language, and speech recognition.

$$\begin{aligned} f_t &= \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \\ i_t &= \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \end{aligned} \tag{5}$$

4.8 *Bidirectional Long Short-Term Memory*

BiLSTM extends LSTMs in such a way that it processes data in a forward and backward manner, hence captures context from both past and future states. It is these two-way characteristics in processing that make BiLSTMs very suitable for the kind of application in which information extraction from the complete sequence is

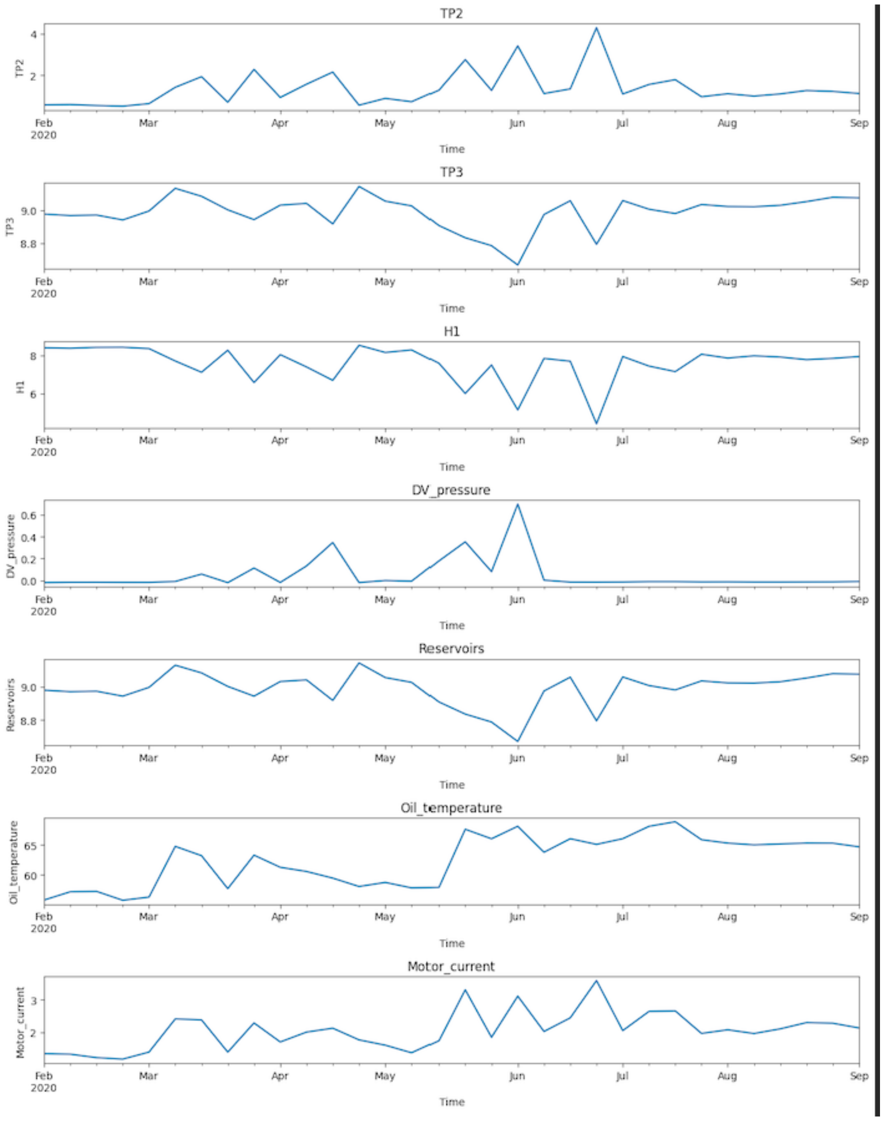

Fig. 6 The Time-series plot of few attributes in the dataset.

needed—e.g., understanding natural language, phoneme classification in the context of speech recognition, or even text generation from end to start. In this way, BiLSTMs can pool information from both directions in such a manner that they get some kind of global understanding of sequence data, often leading to better performance over a majority of sequential modeling tasks.

4.9 *Hybrid model of LSTM and Random Forest*

A combined approach that should strengthen the good qualities of both the deep learning methods and the ensemble learning method in predictive analytics: LSTM networks combined with random forest. The LSTM part is best for capturing long-term dependencies in sequential data, hence able to model sequential input features. After sequential data has been run through the LSTM and processed, the features that the LSTM has learned can be thrown into a Random Forest model. The LSTM model results in high-quality feature representation, which Random Forest benefits from. Thereby, the gain in accuracy and robustness occurs due to predictions aggregated from many decision trees to handle non-linear relationships of features and their interaction. There naturally arises an almost powerful combination that deals with tasks best supported by temporally dynamic modeling of the relationships within a data space, providing for improved generalization and robustness over using either model alone.

4.10 *Custom Neural Network Model*

A deep learning custom model developed for a binary class task, which consists of multiple linear layers from 2048 neurons to one output neuron with a neural network architecture. The model makes use of ReLU activation functions for the nonlinear transformation across its intermediate layers and gives a single output without any activation for compatibility to the criterion of BCEWithLogitsLoss, which merges a sigmoid layer with the binary cross-entropy loss in one single class. This included clipping the gradient to prevent it from exploding, early stopping on validation accuracy for avoiding overfitting, and an Adam optimizer to help in effectively training the network. This configuration shows that the model learns sophisticated patterns from complex datasets in such a way that high predictive accuracy might be achieved, but without making the computation inefficient.

5 Proposed work

This paper undertakes the work of fault identification in the air production units (APU) with a provided dataset that covers 15 different attributes of the analog and digital sensors. Time intervals when APU was also found to be faulty were assessed. These time intervals play a very important role because they give a window into the conditions that led to malfunction incidents and are directly associated with them. This gives a clear difference in data points, referring to faulty operation. Thus, we added the class value to the dataset following a binary classification criterion. The failure periods identified were, therefore, classified as '1', and the other records of data were classified as '0'.This binary labeling transformed our initially unstructured data into a structured format, primed for analytical scrutiny. Leveraging this structured dataset, our proposed work revolves around the development and assessment of various machine learning and deep learning models. These models are designed to predict potential failures in air production units, thereby enabling preemptive maintenance actions. Performance evaluation of these models is a critical component of our methodology. The metrics gives a proper view of model performance, ensuring that our models are not only accurate but also reliable in predicting failures.

Table 1 Time intervals of failures in the APU

S. No	Start time	End time	Failure
1	4/18/2020 0:00	4/18/2020 23:59	Air Leak
2	5/29/2020 23:30	5/30/2020 6:00	Air Leak
3	6/5/2020 10:00	6/7/2020 14:30	Air Leak
4	7/15/2020 14:30	7/15/2020 19:00	Air Leak

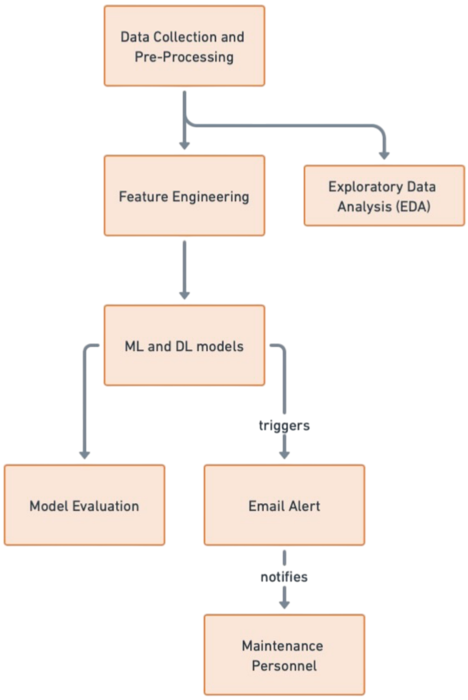

Fig. 7 Proposed Work Architecture

In addition to these, an automated email alert system has also been developed. Therefore, this system is programmed in such a way that it brings the relevant notifications to the involved personnel in situations where new testing data has been introduced into the system, with immediate insights being made on the operational status of the APU, whether it is performing well or likely to have developed a fault. This is poised to improve operational efficiency and reduce possible disturbances through timely maintenance and intervention strategies, using a proactive alert mechanism.

6 Evaluation metrics

6.1 *Accuracy*

Accuracy is the overall correctness of the model in a classification task. It is the ratio of the number of correct predictions to the total number of predictions made.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

6.2 *Precision*

Precision is the ratio of true positives (correctly predicted positive observations) to the total predicted positives. Precision is highly important in cases where the cost of a false positive is high.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{7}$$

6.3 *Recall*

Recall tells a model's capability to identify all required instances, it is the ratio of the number of true positives to the sum of true positives and false negatives. It's crucial in scenarios where missing positives is costly, aiming to minimize false negatives. Higher recall indicates more comprehensive positive case identification.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{8}$$

7 Results and Discussion

A comprehensive comparative analysis has been carried out, evaluating the performance of the models for the metro rail air production unit. Due to the critical importance of maintaining continuous operation in urban transport networks, the selected models were subjected to rigorous training and testing phases to ensure their predictive accuracy. This section elaborates on the implications of such results with respect to predictive maintenance, detailing the application results for all the different algorithms used. Our evaluation framework encompassed a range of supervised algorithms, including Naive Bayes, Logistic Regression, and Adaptive Boosting, alongside advanced DL techniques such as ANNs, SimpleRNN, LSTM, BiLSTM networks, and a novel hybrid model combining LSTM with Random Forest. A custom neural network architecture was also developed to specifically address the binary classification task inherent to predictive maintenance—distinguishing between normal and faulty operational states of the air production unit based on sensor data. Each model's general predictive capabilities were assessed using an extensive suite of metrics to provide a comprehensive prediction. The results of the various approaches implemented in our study are mentioned below.

Table 2 Evaluation Metrics of the Models

Model	Accuracy	Precision	Recall
Naive Bayes	90.93	17.8	99.32
Logistic Regression	98.62	64.28	70.29
Random Forest	99.4	98.2	98.7
Adaptive Boosting	99.6	93.13	95.37
ANN	99.7	94.82	96.36
SimpleRNN	99.77	94.13	94.52
LSTM	99.83	95.08	96.37
BiLSTM	99.80	95.03	95.22
Hybrid (LSTM + Random Forest)	99.7	57.8	91.43

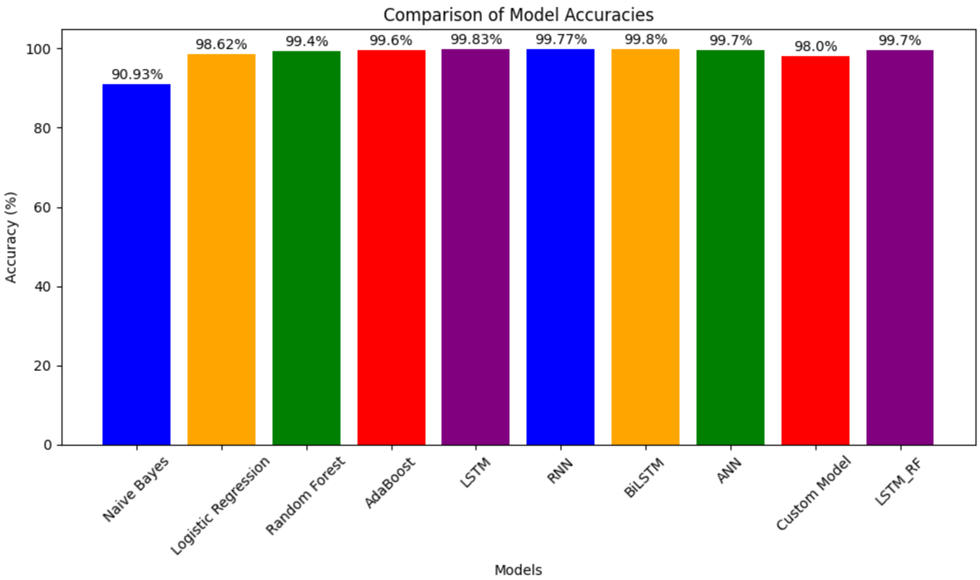

Fig. 8 Comparision of accuracies of the Models.

The result of this work gives very strong pieces of evidence regarding the usage of modern DL and ML techniques in the domain of predictive maintenance. For example, the superior performance of LSTM, BiLSTM, and the hybrid model, in a way, is indicative of adding value during the incorporation of temporal dynamics and sequence learning in the predictive models, reflecting the complex nature of equipment failure mechanisms. Worth noting is that even though the deep learning models have substantially surpassed the performance exhibited by their machine learning counterparts, the continued success of AdaBoost sends a message of continued relevance and appropriateness in ensembles, both in general and more specifically where interpretability and computational efficiency matter most. The custom model which has been implemented had an accuracy of 98% on the testing data. The practical implications of these findings are profound. The proposed predictive maintenance system will enable significant enhancement, hence allowing an extremely accurate prediction

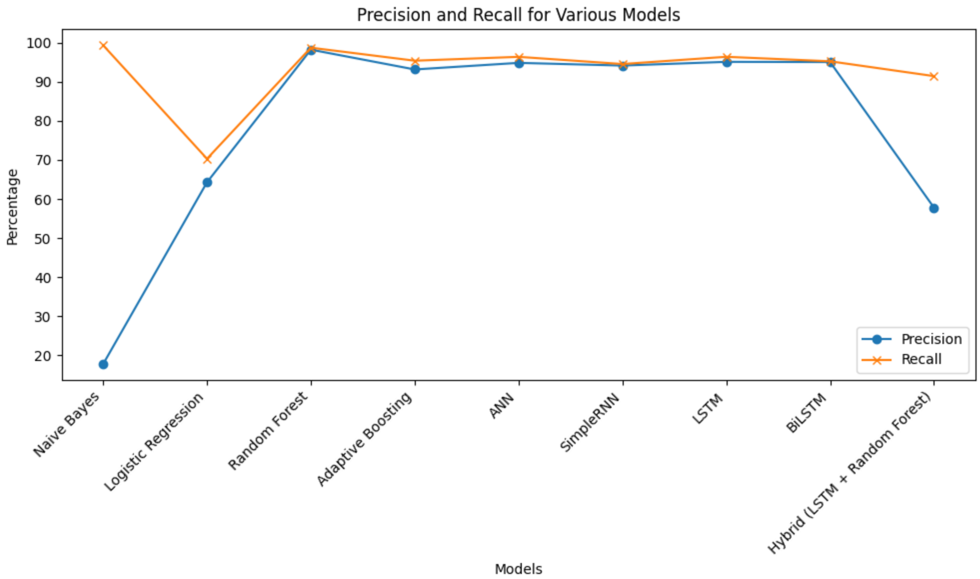

Fig. 9 Comparision of Precision and Recall across Models.

of failure of equipment, reliability, and efficiency of operations of the metro rail. This definitely reduces maintenance costs while enhancing the safety and comfort of passengers. Further, it will go a long way in realization of operational excellence where timely information to act on is issued to maintenance personnel.

8 Conclusion And Future Work

This work embarked on the ambitious goal of revolutionizing predictive maintenance within the metro rail's air production units implementing advanced AI techniques. The rigorous comparative analysis of various ML and DL models has not only demonstrated the profound capabilities of these technologies in forecasting equipment failures but also highlighted their immense potential in enhancing the efficiency of metro railway systems. The standout performance of LSTM, BiLSTM, and hybrid models, in particular, underscores the importance of incorporating sequence learning and temporal dynamics into predictive maintenance systems to accurately model and predict complex failure mechanisms.

The table compares various machine learning models based on their precision and recall values in a specific task. Among these, LSTM networks and BiLSTM demonstrate the highest performance, where both have a precision of slightly above 95% and recall around 96%, portraying vividly their being supreme in overall performance. On the other hand, the Hybrid of LSTM and Random Forest had markedly lower Precision of 57.80%, though it showed high Recall of 91.43%. It would suggest that this model may have more False Positives compared to pure Deep Learning models.

The work can be further extended by adding more data with additional attributes, usage of adaptive learning models can be done where the models continuously learn with the addition of new data. As AI and ML models become more complex, the importance of interpretability grows. Explainable AI approaches can be implemented so that the predictions of DL models more transparent and understandable to maintenance personnel. Another possible future work is the usage of GANs to improve the training using data augmentation.

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