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A K-NN Algorithm-Based ML Model for Predictive Maintenance in Aircraft Engines

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Abstract:- Engine maintenance is a vital cog in the airworthiness of an airplane that ensures the safety of passengers. Therefore, effective forecasting of the Remaining Useful Life (RUL) of aircraft's engine components is critical for ensuring the safety and reliability of aircraft operations. Since small defects can lead to catastrophic consequences, precise RUL predictions are indispensable in aviation maintenance practices. This research paper aims to establish the efficacy of Machine Learning (ML) methods in the context of Predictive Maintenance (PdM) of aircraft engines. Several factors influence the RUL of an engine component that can only be considered into account when real-time data analytics is used for the prognosis of a machine's state and PdM. The proposed method employs batch processing and real-time stream data to facilitate health monitoring and predictive analysis of RUL of engine components. It is found to enhance maintenance prediction and optimize the overall service aircraft operators provide. Ultimately, this research has employed various ML algorithms for effective prediction of RUL and it is established that in the field of PdM, the technique of the K-Nearest Neighbours (K-NN) algorithm performs better than other ML algorithms.

Keywords*: Predictive Maintenance (PdM), RUL Predictions, K-NN algorithm.*

1. Introduction

Aircraft safety has always been one of the hotly discussed topics due to the lives involved and the investment made by service operators. Engine maintenance is one such vital cog that dictates the success of each mission flown by the operators [1]. A typical modern jet engine comprises about 45,000 individual components that need to be in perfect condition for the smooth functioning of the engine. Since this is an onerous task, human intervention is not advisable in all instances of the maintenance check process, as it is time-consuming and increases the operation cost of an aircraft. Automation of maintenance checks has revolutionized the industry by allowing some sensitive components to be checked under a controlled environment [2]. Even though automation reduced the time taken for maintenance checks, it did not consider the condition of the component under operating conditions [2,3]. Sensor fusion and real-time data acquisition enabled the storage of various real-time parameters of components during the operation of an aircraft for detailed analysis [4]. Even though sensor fusion is an effective solution, there was room for error as the statistical life span of each component was not considered in the analysis [5]. As more people have started using air travel, the operators are having less time between each run of the aircraft. In this scenario, the time taken for maintenance check has become a major bottleneck that need to be addressed. PdM technology offers promising advances in the field of maintenance checks. It considers the entire lifespan of a component including the parameters when the engine is in operation. The forecasting of Remaining Useful Life (RUL), has evolved by incorporating various technologies such as fuzzy logic, neural network, data mining, etc., [6, 7, 8]. Further, the adoption of Machine Learning (ML) models has led to substantial advancements in RUL prediction, particularly in the domain of aircraft engines. Aircraft operators have recognized the significance of maintenance factors in predicting machine conditions PdM, [9,10] a crucial technique relying on real-time data, plays a vital role in detecting aircraft engine failures and forecasting the RUL, where safety concerns are paramount due to the significant costs involved and human lives at stake. The proposed work aims to develop a system capable of generating reliable and timely alerts for technicians and specialists responsible for managing the major airline industry. Additionally, real-time streaming for health monitoring and general aviation forecasting will be explored to enhance maintenance prediction and optimize aircraft performance. By examining these aspects, this research seeks to contribute to the advancement of PdM practices and ensure the safety and efficiency of aircraft operations.

2. Objectives

The integration of Machine Learning (ML) methods in Predictive Maintenance (PdM) has gained significant attention in various industries, showcasing its potential to revolutionize maintenance strategies and improve operational efficiency. In the context of aircraft engines, the application of ML for PdM has emerged as a promising approach to predict and prevent failures, ensuring the safety of aviation operations. One of the primary factors driving the adoption of ML in PdM is its capability to process real-time data and historical performance records to forecast the Remaining Useful Life (RUL) of critical components. This enables proactive maintenance interventions, reducing downtime, and optimizing maintenance schedules. Extensive investigations have been conducted to explore and validate the effectiveness of ML algorithms for PdM in different domains, including manufacturing, power generation, and transportation, with promising results [13 – 16].

Deep learning algorithms were applied for engine fault diagnosis, achieving superior accuracy compared to traditional methods [13]. Similarly, ensembles of ML models were used for RUL prediction in aircraft engines, yielding improved maintenance decision-making and resource allocation [14 - 16].

Comparative analyses between international aircraft operators regarding the adoption and efficacy of ML in PdM are limited. However, insights from studies conducted in the broader context of PdM can still provide valuable implications for the aviation industry. For instance, comprehensive survey of PdM [17,18] techniques, highlighting the advantages and limitations of various ML algorithms in industrial applications, which can serve as a basis for similar investigations in the aviation domain.

Furthermore, the importance of timely alerts and predictive insights for engineers and fleet specialists managing large aircraft fleets cannot be understated. Studies have explored real-time data streaming [19 - 21] and health monitoring for fault detection and maintenance optimization in aviation. Such research contributes to the development of reliable alert systems and informed decision-making. In conclusion, the objective of this research work is to assess the impact of K-NN ML method in predicting the RUL of components in aircraft engines.

3. Methods

Machine learning (ML) is a subset of artificial intelligence (AI) that empowers software applications to deliver more accurate and inconspicuous results. Among the various engine failures, approximately 17% can be attributed to issues with connecting cables, cranks, valves, or camshafts. As the propulsion system of an airplane, aircraft engines stand as the cornerstone of advanced aviation, responsible for emissions from airborne flights, significantly contributing to global warming over centuries. The high emissions from aircraft have the potential to exert a considerable impact on the atmosphere, leading to planet-warming effects. In light of these environmental concerns, machine learning prediction models have emerged as valuable tools for businesses to make accurate predictions based on historical data. By leveraging these models, companies can address fuel problems like leaks and mismanagement, thereby mitigating pollution and environmental impacts.

Moreover, machine learning has transformed the global business landscape, with data becoming the most valuable asset in any organization. Companies harness data-driven insights to gain a competitive advantage, and the prevalence of data analytics driven by machine learning is witnessing rapid growth across industries. This shift is ushering in automated systems that support decision-making processes, driving the quest for enhanced efficiency and innovation. Within this context, this project delves into the utilization of machine learning for the design and optimization of aircraft engines. By harnessing the power of ML techniques, we aim to explore new possibilities for enhancing engine performance, minimizing emissions, and ultimately contributing to a more sustainable and environmentally conscious aviation industry. Figure 1 gives the data flow diagram of the proposed predictive model of PdM.

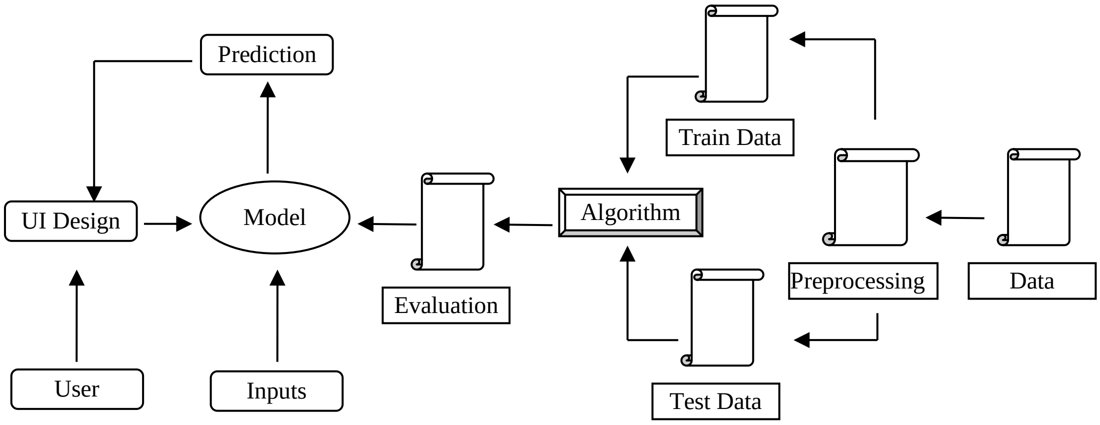

Fig.1. Data flow Diagram of K-NN based PdM model

4. Results

The function of the proposed system begins with the placement of order of a component of the engine for new replacement. A typical order begins with filling of a registration form that comprises of the details of component, date of purchase and the engine for which the spare part is purchased. The registration form shown in figure 2 functions as a repository of fields where users input their information, which is subsequently transmitted to the database. Companies utilize registration forms to enroll customers in subscriptions, services, or other activities, encompassing documents like driver's licenses, registration certificates, and temporary or non-temporary passports.

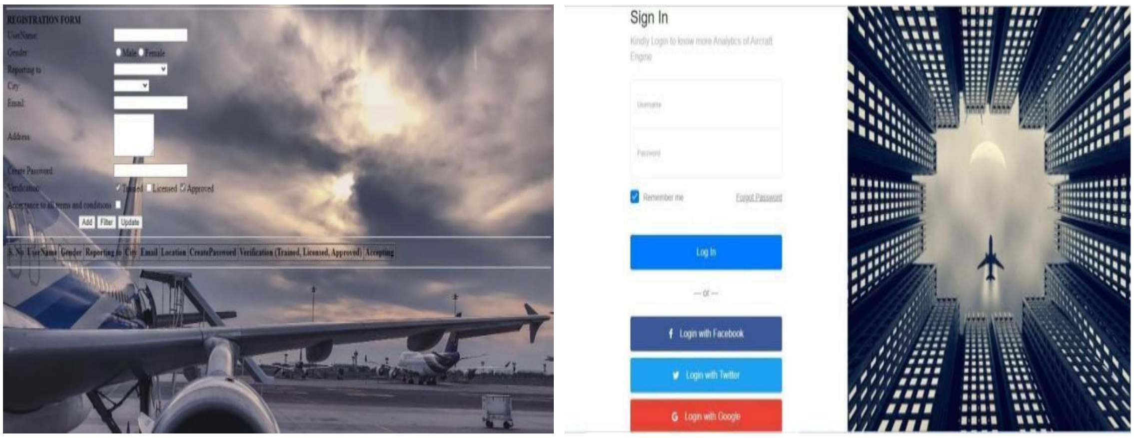

Fig.2. Screenshot of Registration for User and Login Details

Each field is associated with a control (input) and its corresponding text. The majority of websites and applications incorporate a login form, serving as a means to authenticate users' credentials for login validation. Typically, the login form involves a username or email and a password, with additional fields augmenting site security. Login credentials authenticate users when accessing their online accounts, with biometric details occasionally required. The webpage dashboard application materializes as shown in Figure 3, opens as a popup window displaying the login page contents, providing users with the ability to close it. This feature is particularly useful for new memberships or additional approvals, with events like on Success, on Error, and on close customizable to tailor login behavior.

Fig.3. Webpage Dashboard Application

After collection of databases, the next aim is to present the test coverage concisely and feed pre-processed data to the Machine Learning-based predictive analytics for aircraft engine RUL prediction during the release to User Acceptance Testing. The test result will be rendered as shown in Figure 4 and 5. The VB. Net application necessitates the creation of a server object instance and the establishment of a connection to the SQL Server instance, with the SQL connection object facilitating communication between the application and the SQL Server database. The connection string contains essential parameters for server connection, encompassing server instance, database name, authentication details, and communication settings. Microsoft ActiveX Data Objects.Net (ADONET), integral to the .Net framework, enables efficient data storage, access, and manipulation from datasets or data sources, including Oracle and OLE DB. The paper also explores various data providers catering to different sources, such as ODBC and Oracle, alongside the Entity client provider facilitating data access through Entity Data Model applications.

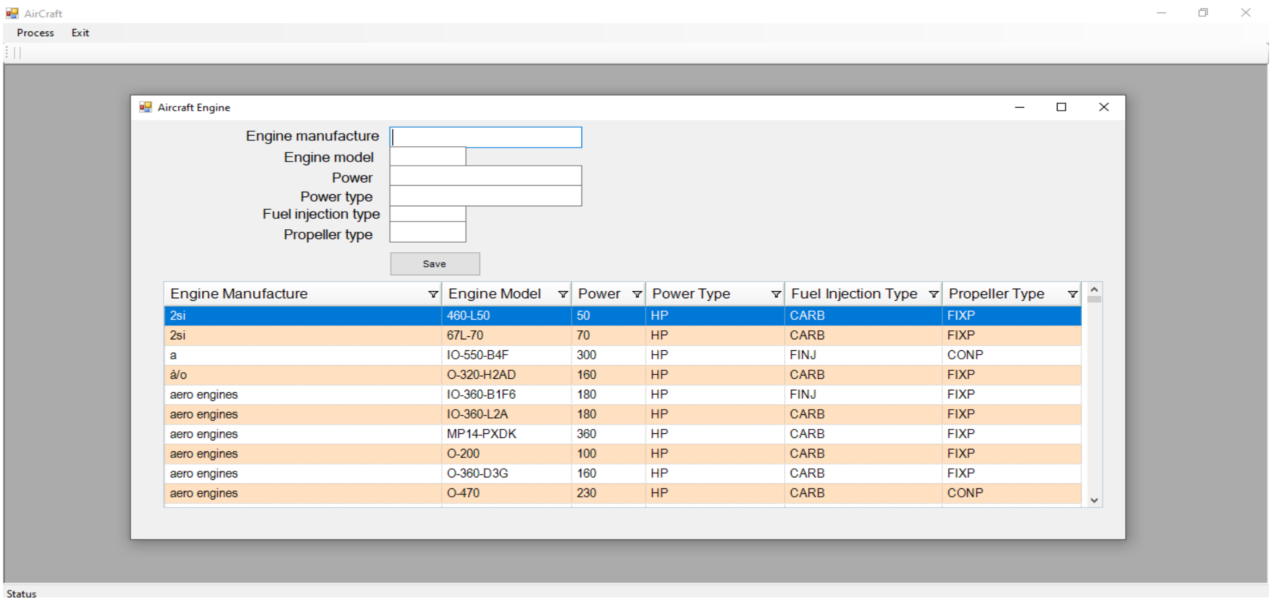

Fig.4. Training data for Engine PdM

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Engine Manufacture	Engine Model	Power	Power Type	Fuel Injection Type	Propeller Type
aero engines	IO-360-B1F6	180	HP	FINJ	FIXP
aero engines	IO-360-B1F6	180	HP	FINJ	FIXP
aero engines	IO-360-L2A	180	HP	CARB	FIXP
aero engines	IO-360-L2A	180	HP	CARB	FIXP
aero engines	MP14-PXDK	360	HP	CARB	FIXP
aero engines	MP14-PXDK	360	HP	CARB	FIXP
aero engines	O-200	100	HP	CARB	FIXP
aero engines	O-200	100	HP	CARB	FIXP
aero engines	O-360-D3G	160	HP	CARB	FIXP
aero engines	O-360-D3G	160	HP	CARB	FIXP

Fig.5. Real-time data feed for End Test Case

The PdM model developed for prediction of aircraft engine maintenance uses K-Nearest Neighbour (K-NN) algorithm for the classification of various parts based on their RUL. The K-NN is chosen over other algorithms as it stores all the dataset fed to it and classification is performed based on the constraint placed on the classifier. Considering other ML algorithms, the K-NN shows an accuracy of 80 pergentage in the PdM model as shown in figure 6.

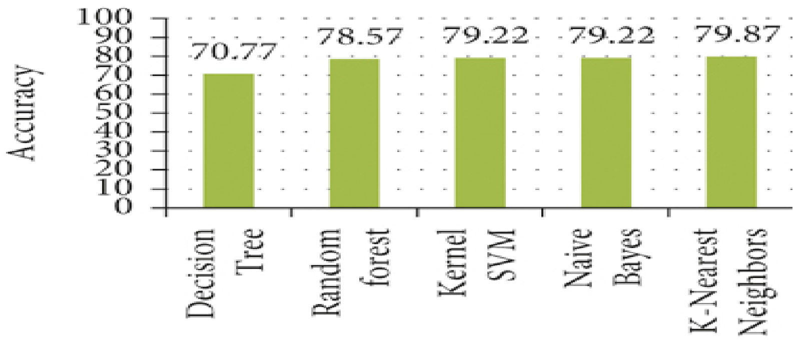

Fig.6. Comparision of various ML in proposed PdM model

In conclusion, predictive maintenance stands as a transformative approach that leverages technology to assess equipment condition and forecast maintenance needs, thereby mitigating failures and preventing unscheduled repairs. By harnessing performance data and information from repair facilities, this approach reduces maintenance efforts and associated costs compared to traditional preventive maintenance practices. As the demand for more powerful turbine engines grows, advanced engine control technologies are being researched to replace existing systems. The pursuit of innovative solutions aims to enhance energy efficiency and operational effectiveness, paving the way for a more sustainable aviation industry. Active component control methods, such as active combustion control and active flow control, coupled with the adoption of distributed engine control architecture, are pivotal in the pursuit of reduced aircraft engine emissions.

Integration of access control and engine technology plays a crucial role in achieving security and performance goals for high-speed operations, while intelligent propulsion control and diagnosis ensure reliable launch site operations. The dedication of numerous teams and individuals in advancing the engine management system exemplifies the commitment to continuous improvement and technological advancement in the field of aircraft maintenance and propulsion. In summary, predictive maintenance, coupled with advancements in engine control technologies, holds the potential to revolutionize aircraft maintenance practices and pave the way for a more efficient and environmentally conscious aviation industry.

5. Discussion

The primary objective of this project is to enhance the accuracy of TSFC's (Thrust Specific Fuel Consumption) forecasts by expanding the dataset. The results demonstrate that machine learning-based prediction, coupled with website analytics, proves to be a powerful tool for exploring engine design during the concept phase. This approach leverages big data and advanced machine learning algorithms, enabling a comprehensive evaluation of various engine designs, ultimately aiding in the selection of the most optimal design. During flight, the pressure difference caused by the varying airspeed above and below the wing results in lift. Engine compression is a key factor in increasing horsepower and power output. The predictive model's outcomes highlight the effectiveness of machine learning in aircraft engine design exploration. Electric motors and reciprocating engines, along with turboprops and turbojet engines, are employed to generate thrust for aircraft propulsion. The engine serves as the powerhouse of the aircraft, generating the necessary power for flight. The majority of aircraft engines are either lightweight piston engines or gas turbines. Engines with higher fuel and cooling capacities can better handle thermal stress, ensuring optimal engine performance and reliability. Engine performance is influenced by various factors, such as emissions, fuel consumption, and noise levels, particularly during high-load operations. This comprehensive understanding of engine behavior aids in optimizing engine performance for efficient and effective flight operations.

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