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Predicting the Maintenance of Aircraft Engines using LSTM

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ABSTRACT

What if apart of aircraft could let you know when the aircraft component needed to be replaced or repaired? It can be done with continuous data collection, monitoring, and advanced analytics. In the aviation industry, predictive maintenance promises increased reliability as well as improved supply chain and operational performance. The main goal is to ensure that the engines work correctly under all conditions and there is no risk of failure. If an effective method for predicting failures is applied, maintenance may be improved. The main source of data regarding the health of the engines is measured during the flights. Several variables are calculated, including fan speed, core speed, quantity and oil pressure and, environmental variables such as outside temperature, aircraft speed, altitude, and so on.

Sensor data obtained in real time can be used to model component deterioration. To predict the maintenance of an aircraft engine, LSTM networks is used in this paper. A sequential input file is dealt with by the LSTM model. The training of LSTM networks was carried out on a high-performance large-scale processing engine. Machines, data, ideas, and people must all be brought together to understand the importance of predictive maintenance and achieve business results that matter.

KEYWORDS: *Aircraft Engine Maintenance, Predictive Maintenance, Neural Networks, Aircraft Engines, LSTM*

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INTRODUCTION

One of the core concepts of the aeronautic industry is the safe and efficient operation of engines[1, 2].A basic necessity is to keep aircraft engines in working order and to identify potential faults as soon as possible. Companies can track the health of engine components and built structures by collecting signals from sensors, thanks to the rapid advancement of Internet of Things technology. Companies can develop systems to predict component conditions based on the performance of IoT sensors. In order to fulfil their assigned mission, the components must be preserved or replaced before they reach the end of their useful life. For industries that want to develop in a fast-paced technological setting, predicting the life state of a component is critical. Recent predictive maintenance studies have aided industries in generating an alarm before components are compromised.

Companies can maintain their operations effectively while reducing maintenance costs by replacing components ahead of time thanks to component failure prediction. Since maintenance directly affects manufacturing capacity and service quality, optimizing maintenance is a critical problem for businesses looking to generate additional revenue and remain competitive in an increasingly industrialized world.

Components may be taken out of active operation until a failure happens with the help of a well-designed prediction method for understanding the current state of an engine. Efficient maintenance, with the aid of inspection, extends component life, increases equipment availability, and maintains components in good working order while lowering costs.

By predicting the state of the system and performing anomaly detection, Prognostic and Health Management (PHM) improves system reliability and protection[3-6].Because of the widespread use of sensors, obtaining a large number of equipment monitoring data is relatively simple, making the aircraft engine maintenance prediction process feasible[7, 8].Applying analytics to those data sources to detect patterns and trends that can guide maintenance strategies—delivering the right information at the right time in the right context to avoid failures—is the key to predictive maintenance. The data can also be used to make recommendations for potential product design improvements.

For determining, preparing, and executing effective maintenance actions for specific capital assets, a number of strategies are available [9]. Corrective and preventive maintenance are the two most common choices, according to Tinga [10].The two most common solutions are corrective and preventive maintenance. Corrective maintenance has a number of advantages, including maximizing asset lifespan, but it also has a number of drawbacks in terms of device protection and availability, including high spare parts inventory costs, high component latencyhigh overtime labor costs, and poor production availability[11].Preventive maintenance, on the other hand, provides for efficient preparation of maintenance operations to ensure readiness and has clear safety advantages. Assets, on the other hand, are often replaced for safety considerations until they reach the end of their useful lives, which is inefficient economically.

There is an opportunity to step away from conventional preventative maintenance and toward predictive maintenance as the industry becomes more comfortable with intelligently tracking and evaluating equipment to assess the need for repair or replacement. Large reductions in unplanned downtime will save millions of dollars, keep planes going, and keep consumers happy.

The main contributions of this paper are as follows:

- A LSTM model is built for predicting the maintenance of aircraft engines, which can measure the accuracy of prediction.
- The model also calculates the probability of an engine failure in the next 30 days.

EXISTING SYSTEM:

Predictions have been made in the past year using a machine learning method that self-learns the results, suggesting a different algorithm of supervised learning. The input variable (sensor values) is split into test sets and train sets in supervised learning, and RUL is predicted using these sets. The training set is used to train the machine learning algorithm, and the consistency of the algorithm is determined by comparing it to the test set.

To address the drawbacks of machine learning algorithms' low precision and dependability, we use a Deep Learning Approach to solve the problem.

PROPOSED SYSTEM:

To increase the efficiency of our model, we used LSTM neural networks in this proposed technique. This LSTM technique uses time stamps (steps) to look back at previous data and plan our data set so that each row contains 60 values that point to the initial data sets. The flowchart for the proposed maintenance model is shown below in ***figure 1***.

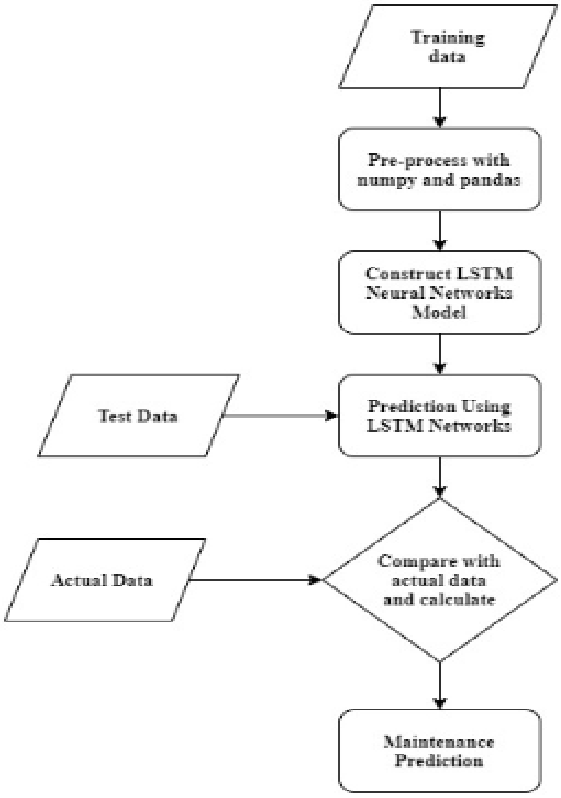

Figure 1: Proposed Maintenance prediction flowchart for the LSTM model

1. Input Data

A data collection was downloaded from NASA's repository, which included three setting values (settings 1, 2, and 3) and 21 individual sensor values.

Setting 1-This is the pilot1's preferred setting, which displays the sensors that have been triggered during the sensor's lifetime.

Setting 2-This is the pilot2 preferred setting, which displays the sensors that have been triggered during the sensor's lifetime.

Setting 3- All sensor values are set to ‘0'. This means that when the setting 3 value is ‘0,' the state is called when all of the sensor values are zero.

The dataset contains 3 datasets, consisting of training, test and ground truth datasets. The training results are made up of several multivariate time series with "cycle" as the time unit and 21 sensor readings per cycle. Each time series can be believed to have been produced by a particular form of engine. The data schema for the research data is the same as for the training data. The other exception is that the data does not specify where the malfunction happens. The sample data is shown in ***figure 2***.

Sample training data

~20k rows,
100 unique engine id

id	cycle	setting1	setting2	setting3	s1	s2	s3	...	s19	s20	s21
1	1	-0.0007	-0.0004	100	518.67	641.82	1589.7		100	39.06	23.419
1	2	0.0019	-0.0003	100	518.67	642.15	1591.82		100	39	23.4236
1	3	-0.0043	0.0003	100	518.67	642.35	1587.99		100	38.95	23.3442
...	...										
1	191	0	-0.0004	100	518.67	643.34	1602.36		100	38.45	23.1295
1	192	0.0009	0	100	518.67	643.54	1601.41		100	38.48	22.9649
2	1	-0.0018	0.0006	100	518.67	641.89	1583.84		100	38.94	23.4585
2	2	0.0043	-0.0003	100	518.67	641.82	1587.05		100	39.06	23.4085
2	3	0.0018	0.0003	100	518.67	641.55	1588.32		100	39.11	23.425
...	...										
2	286	-0.001	-0.0003	100	518.67	643.44	1603.63		100	38.33	23.0169
2	287	-0.0005	0.0006	100	518.67	643.85	1608.5		100	38.43	23.0848

Sample testing data

~13k rows,
100 unique engine id

id	cycle	setting1	setting2	setting3	s1	s2	s3	...	s19	s20	s21
1	1	0.0023	0.0003	100	518.67	643.02	1585.29		100	38.86	23.3735
1	2	-0.0027	-0.0003	100	518.67	641.71	1588.45		100	39.02	23.3916
1	3	0.0003	0.0001	100	518.67	642.46	1586.94		100	39.08	23.4166
...	...										
1	30	-0.0025	0.0004	100	518.67	642.79	1585.72		100	39.09	23.4069
1	31	-0.0006	0.0004	100	518.67	642.58	1581.22		100	38.81	23.3552
2	1	-0.0009	0.0004	100	518.67	642.66	1589.3		100	39	23.3923
2	2	-0.0011	0.0002	100	518.67	642.51	1588.43		100	38.84	23.2902
2	3	0.0002	0.0003	100	518.67	642.58	1595.6		100	39.02	23.4064
...	...										
2	48	0.0011	-0.0001	100	518.67	642.64	1587.71		100	38.99	23.2918
2	49	0.0018	-0.0001	100	518.67	642.55	1586.59		100	38.81	23.2618
3	1	-0.0001	0.0001	100	518.67	642.03	1589.92		100	38.99	23.296
3	2	0.0039	-0.0003	100	518.67	642.23	1597.31		100	38.84	23.3191
3	3	0.0006	0.0003	100	518.67	642.98	1586.77		100	38.69	23.3774
...	...										
3	125	0.0014	0.0002	100	518.67	643.24	1588.64		100	38.56	23.227
3	126	-0.0016	0.0004	100	518.67	642.88	1589.75		100	38.93	23.274

Sample ground truth data

100 rows

RUL
112
98
69
82
91

Figure 2: Sample dataset

2. Data Pre-processing

One of the critical tasks of data pre-processing in providing input data collection to neural networks is tomanipulate the data and delete various unused values, redundant values, and null values that may be a downside in forming an effective predict value of the model.

The Steps included in Data Pre-processing are listed below:
1. The Null values are removed.
2. We use the scikit-learn library to scale down the data so that neural networks can understand it.The scaling is achieved using the Min-Max scaler library, which reduces data to a scale of 0 to 1 and thereby makes this data collection entirely comparable to neural networks.

RESULT & DISCUSSION:

```
y_pred=np.argmax(model.predict(X_test), axis=-1)
print('Accuracy of model on test data: ',accuracy_score(y_test,y_pred))
print('Confusion Matrix: \n',confusion_matrix(y_test,y_pred))
```

```
Accuracy of model on test data:  0.9744536780547861
Confusion Matrix:
 [[12664     0]
 [  332     0]]
```

Figure 3: Accuracy of our model

We were able to achieve 97 percent precision using LSTM techniques, making one application the most accurate in forecasting aircraft engine maintenance and thereby making passenger life simpler and predictive maintenance much easier.

```
machine_id=16
print('Probability that machine will fail within 30 days: ',prob_failure(machine_id))
```

```
Probability that machine will fail within 30 days:  0.042760372
```

Figure 4:Probability of failure of engine in next 30 days

By looking at the above picture, we can see that the model predicts an expected failure rate of 4% in the next 30 days. Airline companies can use this result, and fix the issues in the engine to avoid any future issues.

CONCLUSION:

The Industrial Internet's distinguishing advantage is predictive maintenance. Digital tools can monitor and retain historical performance for individual assets as well as the entire fleet, linking them to continuous real-time performance. Any deviation from the "normal actions" resulting from these baselines or the expected activity would raise an alarm and prompt response. Advanced analytics can then decide if the variance indicates a possible future malfunction, as well as the root cause and expected timeline for the malfunction to occur. Cost-benefit analysis of how much longer and at what load an object will perform before it has to be replaced will become the standard.This will allow airlines and MROs to resolve problems until they become a problem, reorganize workflow around scheduled maintenance, and prevent unplanned downtime.

This will get us closer to a future without unscheduled downtime, maintenance-related delays and cancellations, or aircraft stuck on the ground due to technical failures. It would greatly increase power usage and reduce the time we already waste doing preventive maintenance and servicing due to a lack of knowledge on the assets' real condition.

The key is to realize the aviation industry's digital future. Industrial Internet technologies allow a transition to streamlined efficiency and predictive maintenance, resulting in significant cost reductions and benefit for anyone involved. When data is transmitted back from properties to be aggregated and processed, benchmarking between fleets and operators will become feasible. Airlines that perform better than predicted can be compensated, and operational anomalies can be detected and corrected.

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