Prediction of Remaining Useful Life of an Aircraft Engine Using LSTM Network

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Abstract: *The main issue in aircraft industry is to know the life time of an Aircraft Engine (AF) to make sure that the life of passenger travelling in the Aircraft and the expensive goods are being transported from one country to another land safe at the destination ports.*

To predict and be ahead of all these scenario we imply Artificial Intelligence (AI) and Deep Learning using long short term memory (LSTM) neural networks to predict when an aircraft engine might require to be serviced or replaced.

For these predictions we require a dataset of previous aircraft historical data having 21 sensor values of each aircraft. Aircrafts have three different settings = set1,set2,set3 so that we can manipulate the data and find out the relation / trend in the data so that our system gets capable of predicting remaining useful life(RUL) of an aircraft engine.

Keywords- *Artificial Intelligence; Long short term memory; Neural networks; Sensor value; Remaining useful life*

INTRODUCTION

During the past decades Aircraft engine were been developed with minimum number sensors as there was no requirement of various other sensor value which significance the engine condition of an Aircraft. Now having all the new 21 sensor embedded inside an engine of an aircraft makes us to do predictive maintenance so that we save a lot of time and energy to avoid the necessity of doing uncessasary maintenance service.

These sensors fitted the Aircraft Engine provide huge amount of previous data that Actually shows the real condition of the engine .These huge amount of data may be stored in Hard Disk of aircraft engine or on the servers located in closed making it easier to locate and work with it whenever it is required.

Hence by reducing the manual time to go work with the engines, so the maintenance service can be placed locally and can manipulate with the data stored in the closed and do predictive maintenance as and when required.

The deep learning approach of implementing Recurrent neural networks(RNN) and using long short term memory(LSTM) technique makes us predict the data set with time stamps which means the present data looks sixty time stamps in the past to predict the current remaining useful life(RUL) of the Aircraft engine and hence making it to be 96% accurate.

The need of implementing long short term memory (LSTM) neural network is with the necessity of arriving at higher accuracy since it looks back and forth and train itself with the whole data. This is evident to be the best neural networks techniques to predict future value which are in time series.

The first attempt to estimate is the Remaining useful life(RUL) based on number of cycle the Aircraft Engine has travelled. Long short term memory is clearly designed to avoid long short term dependencies issues. LSTM networks is suitable for learning from real time data and process it to a time series prediction.

The data has been taken from Prognostics Data Repository of NASA which has 3 different kinds of aircraft Id1, Id2, Id3… and its sensor values and the number of cycle to death. Based on the above data set of NASA data repository we propose a system while utilize LSTM to build a model which can get estimated RUL and the probability that the Aircraft Engine might fail after n number of cycle.

On the basis of having high accuracy this technique can be greatly imply and utilize providing better service to the Aircraft industry.

Existing System

In the past year prediction done using Machine learning approach which self learns the data implying different algorithm of Supervised learning. In Supervised learning Data set includes the input variable (sensor values) which is then divided into train and test set using which RUL was predicted. The Machine learning algorithm is trained using training set and the accuracy of the algorithm is tested by comparing it with the test set

To overcome the Drawback of low accuracy and less dependability of Machine learning algorithm we use Deep Learning Approach to solve this situation.

Proposed System

In this proposed techniques we implemented LSTM neural networks to improve the performance of our application .This LSTM techniques implies time stamps(steps) to look on to the past data and prepare our data set such that each row holds 60 values references to the original data sets. The LSTM neural network diagram for proposed system is shown in the figure

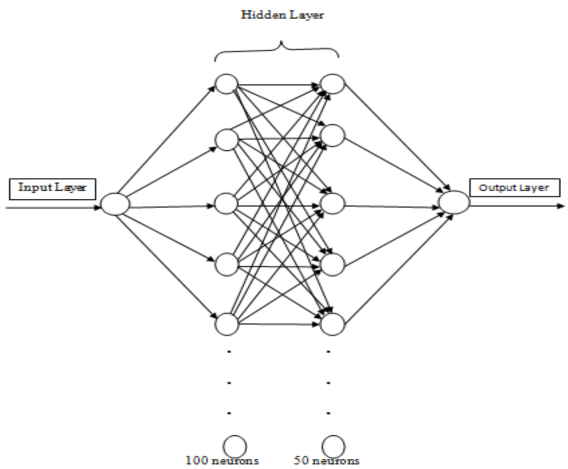


Figure: 1 LSTM neural network diagram for proposed system

i. Input data

A data set as been downloaded from Repository of NASA which as 21 individual sensor value and three setting values setting1, setting2, setting3 which shows below

Setting 1-This is the pilot1 prefers setting which shows the sensors which were activated during the life time of sensor.

Setting 2-This is the pilot2 prefers setting which shows the sensors which were activated during the life time of sensor.

Setting 3-All the sensor values is '0'which means the setting 3 value is '0' means the condition is considered when all the sensor value is 0.

ii. Data Pre-processing

One of the important challenges of giving input data set to neural networks is data Pre-processing where you manipulate with the data and remove different unused values, redundant values, null values which can be drawback in forming of accurate predict value of the model.

Steps included in Data Pre-processing are listed below

1. We delete the null values

2. We scale down the data using SKlearn library so that neural networks understand the data.

The scaling is done using Min-Max scaler library which scales down data between 0 and 1and hence making this data set completely comparable with the neural networks.

iii. Converting a data to 60 time stamps

LSTM model understand data in user defined time step, the size of the time step in choosing based on the preferences of the problem. Here we use 60 time stamps as shown in the fig

iv. Training and Testing

Data set is divided into 75% of the whole data and testing data which is 25% using Numpy, random c libraries. The libraries which we have used as SKlearn pre-processing, train test split format, np.random.seed(7) is a pointer in the data set.

v. Output

Accuracy is calculated based on Mean Absolute Error (MAE) and R-squared(R^2) error. MAE is a measured as the average sum of absolute difference between predicted and actual observation and R-squared is a statistical measure of how close the data are to the fitted regression line.

The Proposed RUL prediction Flowchart for the Machine Learning model is shown in the Figure

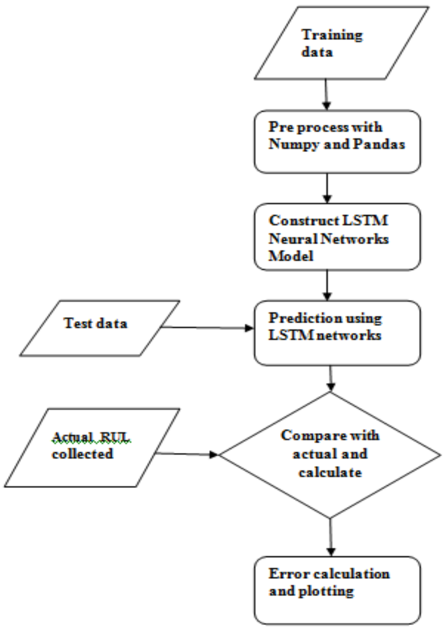
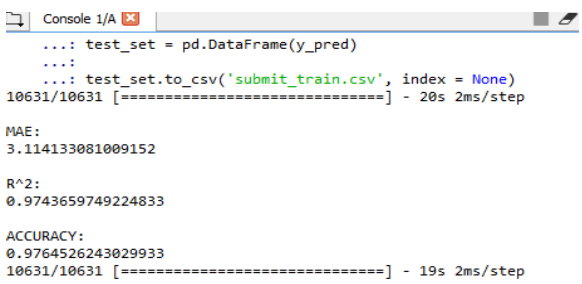


Figure: 2 The Proposed RUL prediction Flowchart for the Machine Learning model

Result Analysis

By implying LSTM techniques we were able to get 97% accuracy making one application to be best reliable in predicting RUL of Aircraft Engine and hence by making passenger life safer and predictive maintenance much easier. The Figure shows the MAE loss, R^2 loss and accuracy of the proposed method



```
Console 1/A
    ...: test_set = pd.DataFrame(y_pred)
    ...:
    ...: test_set.to_csv('submit_train.csv', index = None)
10631/10631 [==============================] - 20s 2ms/step

MAE:
3.114133081009152

R^2:
0.9743659749224833

ACCURACY:
0.9764526243029933
10631/10631 [==============================] - 19s 2ms/step
```

Figure: 3 MAE loss, R^2 error loss and Accuracy of the proposed method

RUL Prediction

Our proposed LSTM neural networks technique gives less MAE and R^2 error value that shows that the RUL predicted by the LSTM neural networks model for this set of data set is very close to the actual value. The actual and predicted points coincide shows the maximum accuracy. The graph plot shows the training data to visually represent the accuracy of the model .

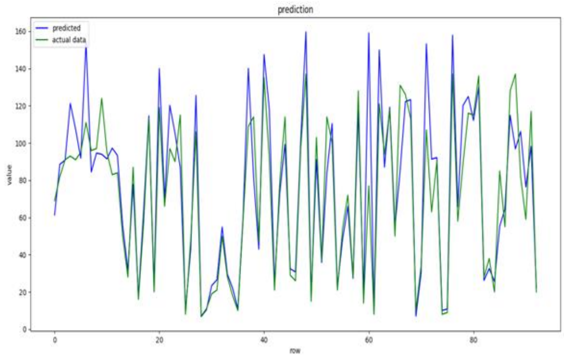


Figure: 4 the graph plot show the training data to visually represent the accuracy of the model.

Conclusion and Future Work

Our proposed LSTM neural networks based approach out performs get a lower MAE and R^2 value, indicating that the RUL predicted by the LSTM neural networks model for this set of data sets is very close to the actual value. The experimental results clearly show that the proposed method can accurately predict the RUL of aircraft engines. Moreover, we can conclude that the prediction method based on LSTM neural networks is better than the traditional statistical probability regression method under the large amount of data.

It is also concluded that RUL estimation of a unit with short history tends to produce great uncertainty which leads to inaccurate prediction. Hence, updating the RUL prediction is the key for effective planning. To further explore the new neural network architecture, to solve the PHM field of data prediction.

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