Predictive Aircraft Engine Maintenance

MSc Research Project

MSc in Data Analytics

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Project Submission Sheet – 2019/2020

Student Name:	Vikas Chhikara		
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Lecturer:	Dr Catherine Mulwa		
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I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own

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Date: 17th August 2020

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Predictive Aircraft Engine Maintenance

Definitions and acronyms

CNN -In deep learning, a convolution neural network is a class of deep neural networks, most normally connected to breaking down visual symbolism. CNNs utilize a variety of multilayer perceptron's intended to require negligible preprocessing

R-CNN -It shows the region of interest and it focuses on a certain point

Training – A stage during compile-time where the CNN model identifies the dataset and classifies them according to their identification labels (if any).

Keras - Keras is a deep learning framework or language which is built on Thanos and TensorFlow

RUL - Remaining useful life of engines

Abstract

For maintenance decisions and selecting a suitable operation for a machine, it's necessary to analyze the remaining useful life of the machine accurately. Machine learning techniques for RUL are usually focused as they are faster and easy to use. The existing models for RUL prediction are a single path or based on a top down approach. For increasing the accuracy and to achieve promising results this report proposes a methodology that combines the Convolutional neural networks (CNN) and Long short-term memory in order to predict the useful life of the machine. A different approach than existing models for this report CNN and LSTM model is actually combined rather than just using CNN for extracting features. But as for input single timestamp is used that can further lead to the same batch padding which could affect the model's prediction. The proposed methodology is used to overcome these issues by sliding the time one step size. For this report turbofan engine degradation data by NASA is used for training, testing, and validation of the RUL Model. By comparing the model using different Models like simple LSTM and transfer learning using the same dataset. With comparison, it will be easy to examine the performance of the proposed approach.

1. Introduction

Machines in aircraft are the main parts of an aircraft. Machine Failure is one of the major causes of aircraft accidents and causalities. (Wang, K et.al 2017) . Therefore, Mechanical tools health management paid much attention to the prediction of the remaining useful life of the engine (R. Zhao et 2008).al Early prediction can help in the maintenance of the machine and proposing a suitable strategy for the issue. However, the prediction of failure is not easy to ensure reliability and safety as they have a complex structure. Engine failure mostly raises due to the aging of parts, variable loading, and environment. That is why it is necessary to predict underlying degradation so that we know how soon an engine is going to fail. As to perform suitable maintenance.

Basically, for the prediction of RUL, there are three methods proposed data-driven prognostic, hybrid (data-driven + Model base) prognostic, and physics model base prognostic. Data-Driven prognostic is based on past monitoring data and uses Machine Learning algorithms to predict the status of system and data on degradation. It is best for a complex system as it can work with less understanding of the system. Model base prognostic is based on the model understanding that includes mechanical knowledge, failure regulation, and uses monitoring data to predict RUL that can be further categorized into Macro and Micro based on Modeling physics. Damage propagation Model (Micro level Models) deals with supposition and simplifications that can cause many limitations of the method. On the other Macro, Models presents a simplified model, that defines relations among system data such as input, output, and state variables. For data-driven strategies, there are two types of models. (I) RUL Learning from data (II) Cumulative damage modeling and damage threshold inferring.

In this report, a hybrid approach is proposed based on LSTM and CNN to get the promising results and increased accuracy for RUL prediction. The remainder of this paper is organized as follows Related work, Methodology, Performance Evaluation, and Final conclusion are drawn.

1.1 Motivation and Project Background

RUL prediction gained much popularity due to its contribution to system health management to improve the performance degradation warning systems and failure detection with high accuracy. The problem is itself a challenge due to uncertainties involved in the prediction process. All around the world governments and industry supported pushing the trust in RUL prediction development. As technology and its applications are improved and the understanding of RUL prediction is improved from the last many years. Data-driven and physics-based models both show advantages in the different application contexts. However, the main reason for data-driven approaches failure after so many improvements is due to fault signature in growing fault data and there is no precise data capture fault evolution to failure. As actual fault progression data is difficult to get because its time consuming and expensive. The Lack of related data that researchers can use for their different approaches and their comparison is the main reason to progress in prognostics. To resolve this problem many datasets are introduced such as 'PHM08', 'CMAPSS', and prognostics data repository (Saxena & Goebel, 2008).

From the last five years' turbofan degradation dataset received almost thousands of unique downloads with almost eighty publications using different approaches but there is still no proper comparison is available due to inconsistency and confusion about dataset usage. That is why this paper is focused on using advanced approaches to implement prognostic using the CMAPSS dataset. By using these approaches some unique characteristics of these approaches show promising results and virtuous differences are pointed. In this paper, several issues are also discussed so that researchers in the future keep these facts into account while comparing different approaches.

1.2 Research Questions

RQ: Investigate how Can remaining useful life of aircraft engines are identified and detected using Machine Learning Techniques (LSTM, LSTM+CNN and Transfer Learning).

1.3 Research Objectives

Obj1: A precise Analysis of the Literature on Machine learning data-driven Model for remaining useful life prediction of aircraft engines.

Obj2(a): investigating the use of the proposed approach for remaining useful life prediction of aircraft engines by training and testing the model on sensor dataset proposed in the report.

Obj2(b): Implementation of proposed methodologies (LSTM, Hybrid model LSTM+CNN and transfer learning), their evaluation, and results.

Obj2(c) Implementation of CNN and Random forest

Obj3: Compare the performance of the proposed Model that is developed and with the models discussed in Literature.

2 Literature Review on RUL Prediction (2011-2020)

Previously data-driven identification techniques mostly utilize a stochastic model to identify degradation in the system. It is hard to figure a suitable solution because of the state-dependent Model. In past, many years as deep learning is raises and data-driven approaches are more focused and many publications have worked on these issues.

2.1 Literature Review on Remaining useful cycle Prediction using Data-Driven Approaches

In (Ekaterina Yakovleva et.al 2008) used two approaches for the solution of this problem 1) Physical model driven and 2) Data driven approaches to predict run time failure of aircraft engines. In both approaches they used non-linear and linear prediction models. Also provided a general statement and framework to solve this kind of problem using C-MAPSS dataset. Results can be more improved by using linear regression and ARIMA application. According to system prognostics and health management (PHM) is based on prior knowledge about components to predict RUL (Zheng et al. 2008)used data-driven approach for the prediction of remaining useful life of Aircraft engine's. They argued the importance of predicting the the remaining useful life of an aircraft's engine in a timely and correct manner for appropriate maintenance safety decisions. The authors of this research used historical data to train the model using data driven predictive method. The proposed approach was validated on the turbofan data sets widely employed by other literature. Experimental results demonstrated the accuracy and efficiency of the proposed approach. The prediction method was based on the sliding window (TW) and extreme learning machine. In further work Zheng et al. considered other turbofan data set for demonstrating the generality and effectiveness of the proposed methodology. (Xiang Li et.al 2015) had research on data driven methods for turbofan engines they used data for RUL prediction and health state estimation and use raw data and CMAPSS dataset. For better Extraction Time Window approach were used. (Xiao-Sheng et.al 2006) review statistical data driven approaches which was based on available past observed data and statistical models. Approaches are divided into two broad types of models, 1) models that based on directly observed state information of the asset and 2) those do not. Zheng et al. Deep learning models allows us a generic mechanism for learning the right representations of input data in a manner that these representations can be efficiently transformed into output without domain knowledge and human intervention. This is achievable because deep neural networks (DNN) are composed of hierarchical layers of neurons based on simple mathematical functions operating on tensors(Chollet et.al 2012).

2.2 Literature Review on Remaining useful cycle Prediction using CNN Based Approach

As other approaches CNN based approaches are also good and show efficient results in RUL prediction. In (Jialin Li et.al 2006) proposed a DAG network Structure combined with LSTM and CNN to estimate RUL. Experiments was on dataset provided by NASA and also on C-MAPSS. In past few years C-MAPSS was used mostly so author compared results of both dataset and prove that that NASA dataset give better results with proposed model. (Ren et.al.(2018) proposed a new method based on deep convolution neural network (DCNN) to predict RUL of bearings. Also new feature extraction method suggested to obtain the spectrum-principal-energy-vector. (Li et al. 2008) proposed a new deep CNN model to predict turbofan engine RUL using Long short-term memory (LSTM). (Ansi-Zhang et.al 2109)used deep recurrent neural network and proposed a transfer learning algorithm for RUL estimation and prognostics. That model is based on bi-directional BLSTM (Long Short-Term Memory). Proposed model trained on different dataset and tuned for target dataset in this way they got excellent results. By comparing results of transfer learning and non-transfer learning models they prove transfer learning is more efficient in this kind of work. (Altay et al. 2008) used genetic algorithm using artificial neural network to predict the Aircraft engine failure. The aviation field survived the worldwide monetary emergency by mergers and a survey of cost cent factors. They argued that maintaining a fleet is more fragile than any time in recent memory since low cost is the focal point of interest, however giving security is the greatest cost. These realities lead to dynamic support of the aircraft so as to dispose of unnecessary support costs while guaranteeing security. Proposed work of Altay et al. shed light on predicting in advance when the disappointment will occur via airplane type and age. By utilizing data from sixty aircraft, they used artificial neural systems and hereditary calculations, which are known to be the favored anticipating devices, to predict 532 disappointments. The proposed model provided decent estimate of relationship rate among the target and genuine disappointment calendars of airplane. In authors et.al present a convolutional neural network base method for estimation of RUL using deep learning. They trained model on C-MAPSS dataset and they achieve high accuracy using that model. According to author they also see very small error between estimated RUL and Actual RUL.

2.3 Literature Review on Remaining useful cycle Prediction using other Machine Learning Approach

With the development in sensor technology almost every project is based on sensors. To track and handle the degradation patterns of jet engines (Zhang et.al 2019) proposed a method in which can predict future health of engine of aircraft with help of Bayesian inference. This approach is dependent on informative sensor selection and degradation modeling. Proposed approach selects sensors based on metrics and health index to mark engine degradation by merging the selected informative sensors. (Zhong zhe Chen et.al 2007) investigate two methods for RUL estimation of aircraft engines. SVM model suggested to check these two schemes Modified-similarity base method and deteriorated data of samples, which scheme is better for RUL estimation. (Racha Khelif et.al 2018) presented unsupervised kernel regression for RUL. Author proposed IBL (instances-based learning) for RUL findings and it illustrate prognostics of machine problems and faults. This model use to degradation trajectories without having prior information about the health of aircraft engine. (Yan et.al 2015) presented a device electrocardiogram (DECG) concept for estimation of RUL of industrial equipment Using deep denoising auto encoder (DDA) and regression operation.(Ellefsen et al. 2006) Used semi-supervised learning and present a semi supervised model for RUL prediction to gain high RUL prediction accuracy, also using reduced amounts of labeled training data. (Ordóñez et al. 2017) Used auto-regressive integrated moving average (ARIMA) model and support vector machine algorithms to estimate turbofan engine RUL. Many engine RUL prediction models have been developed by establishing a degradation model (chen 2018) Although conventional Machine learning has been used by research community for RUL prediction using data driven models, scarce amount of work is available on developing data driven models for predictive maintenance estimation of aircraft engines using deep learning. Deep Learning is a branch of Machine Learning which applies simple mathematical functions as neurons for learning tasks Goodfellow et.al From all methods for engine RUL estimation, DNN-based methods are majorly used. Yan et al. discussed different applications of Random Forest learning algorithm for Aircraft Engine Fault Diagnosis. They argued that precisely diagnosing aircraft engines issues is a difficult classification problem because of inherent attributes related with aircraft engines. Accordingly, aircraft engine issue analysis had been a diagnosis exploration point drawing in huge research premiums in ML community. Authors applied random forest classifier to aircraft engine fault diagnosis. Yan et al. (tahel2017) also investigated strategies for improving random forest performance specifically for aircraft engine fault diagnosis problem shortcoming analysis issue.

2.4 Comparison of Reviewed Techniques

Recent approaches proposed for remaining useful life prediction of aircraft engine maintenance on CMAPSS Data is shown in table below:

Table 1:Comparison of methods

Authors and reference	Approaches	RMSE
Sateesh Babu G et.al [15]	CNN + FNN	29.16
Zhang C et.al [20]	MODBNE	28.66
Zheng S et.al [18]	LSTM + FNN	28.17
Li X, Ding Q et.al [19]	CNN + FNN	23.31
J. Gu et.al [21]	Semi supervised setup	22.66

3 Scientific Methodology Approach Used

3.1 introduction

The report proposed an approach combining LSTM and CNN for RUL Although prediction of Aircraft engines. Proposed methodology is already discussed in Literature review in introduction but the method we proposed is different. Existing literature combined the CNN and LSTM in general manner. Using CNN for feature extraction and using those feature for LSTM network training but CNN cannot be changed according to LSTM output. To avoid this limitation, the approach we are using both algorithms LSTM and CNN are used Parallel manner. Using Parallel approach can increase the accuracy of the Model. The collected Data is Processed and used as input to the model. Further explanation of the processes is given below.

Data Preparation: health to failure data is input for the model so firstly we should do all the processing required. Signal has Ls cycles with n features sliding time window data is tl cycles with size one. Extracted array size for each time window is tl * n with Ls – tl number of arrays that is why the input size is tl*n and output is corresponding. The processed data is used in model and performance is discussed forward in the paper. Further Data is input to the model, convolutional parameters are set as filters is 5 the number of kernels is 3 and strides are (3,3). The data is finally processed through the convolutional layer and output of conv layers is used in LSTM layer correcting the error in training repeat the process until max training epochs. Finally, the trained model can be used to identify RUL.

3.2 Process Flow

For this research report we will follow the Core of knowledge discovery Process KDD as shown in figure 1.

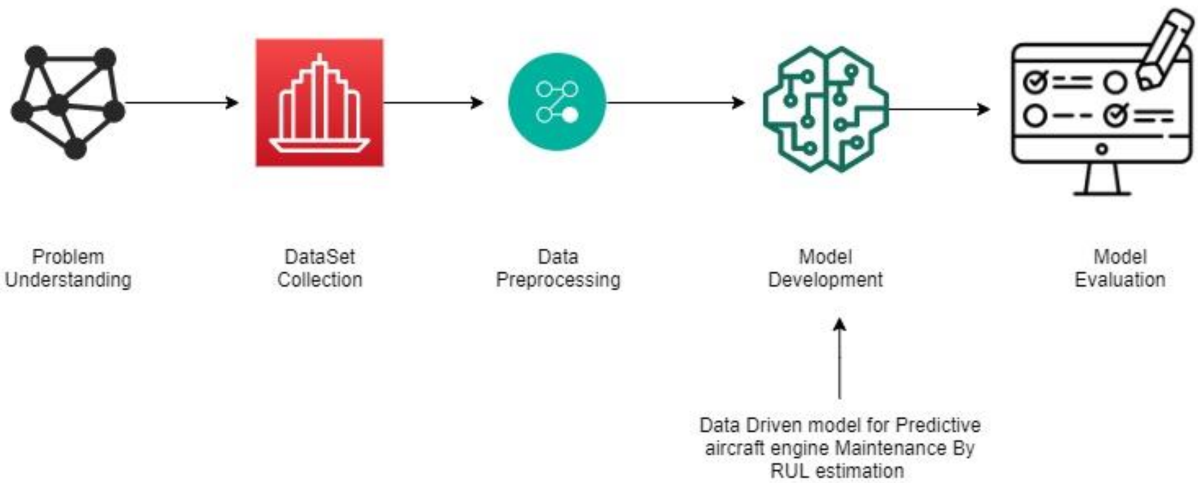

Figure 1: Flow diagram for proposed research

3.3 LSTM (Long short term memory) Network

Long shot term Memory Network Known as LSTM **(XI peng 2017)** It is one of the best kind of RNN with capability of avoiding gradient dispersion. It is designed to avoid long term dependencies. LSTM Cells are where data is transfers and updated, cell states of the LSTM is changed as compared to RNN. Network is based on short term states, long term states and its three gates: input gate, output gat and forget gate. Where ft is forget gat use to forget the information that is no longer required.

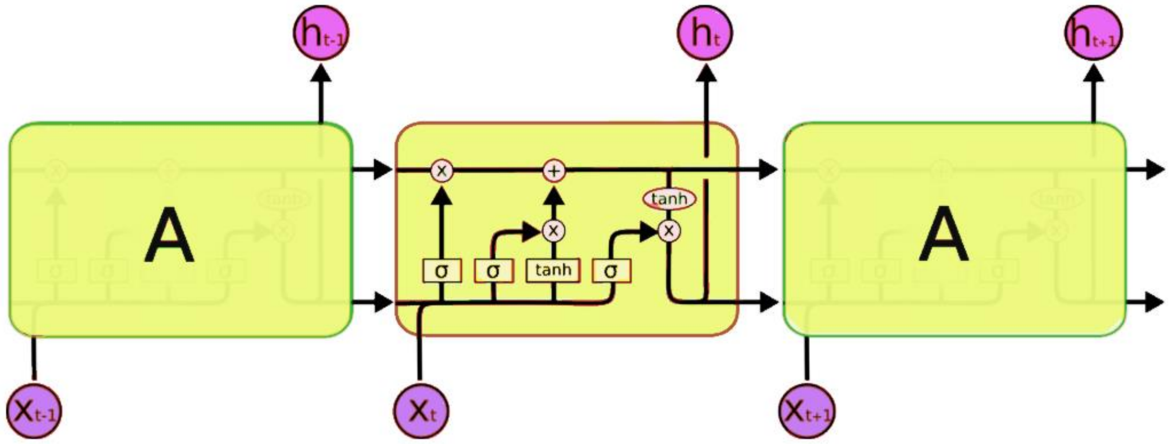

Figure 2: LSTM architecture

$$ft = \sigma(Wf \cdot [ht-1, xt] + bf)$$

here σ is activation function x is input to the gate and b is bias vector.

The input gate contains two path one for the new input and second for vector I generated by forget gate, which is use to modify the cell state.

$$it = \sigma(Wi \cdot [ht-1, xt] + bi)$$

$$C\tilde{}\ t = \tanh(Wc \cdot [ht-1, xt] + bc)$$

Where W are the weight matrices and b are the bias vectors for input gate with activation function of tanh. And updated state of gate is:

$$Ct = ft \otimes Ct-1 + it \otimes C$$

output gates have two parts as input gate.

$$ot = \sigma(Wo \cdot [ht-1, xt] + bo)$$

$$ht = ot \otimes \tanh(Ct)$$

3.4 Convolutional Neural network

Convolutional neural network also known as CNN . it is one of the emerging Machine learning technique after many years' effort. It gains popularity in speech analysis and image recognition as le-Net is known for good accuracy in image recognition. it contains many hidden layer and each hidden layer contains several neurons and all neurons are connected to each other. Certain weights are given to model which are optimized by time and our model. All the hidden layers are connected with each other which form as full connected layer and is responsible for output. In our model first we provide our dataset to our model then use our conventional layer which contains set of neurons and weights which provides image features. The conv layer consists of filter size which decides how much features we want to extract. We reduced our data until it give us maximum sharp feature then we apple dense layer which is responsible for prediction.

3.4.1 Pooling Layer

Pooling layer is used in between hidden layer of Conventional neural network. It reduces the size of images without losing useful information and reduces computation in network. It also helps in reducing over fitting. It depends on which layer you want to use it. It usually consists of filter size which tell how much you want to reduce features e.g. 2*2, 3*3. When matrix of image is gathered it takes maximum value of filters. Maxpool is not always same it is dependent on our model and our dataset. Excessive maxpooling will result in loss of useful features.

3.5 Conclusion

The methodology proposed is changed as requirements for the project modified methodology is used for the report. Data is downloaded from kaggle CMAPSS Data. the implementation Evaluation and results are discussed below.

4 Implementation, Evaluation and Results

For validating the proposed methodology C-MAPSS dataset by NASA is used to predict the RUL. In this section we will discuss the dataset description all the preprocessing that is applied on the dataset.

4.1 Dataset Description & Preprocessing

Dataset used in this report is CMAPSS simulated turbofan engine dataset developed by NASA using Simulink on MATLAB. The main objective for this dataset is to predict the remaining useful life of engines. It contains multiverse time series data. Each dataset is further divided into test, training, and validation data with many editable input parameters is provided for user-specific values. There are 14 main factors that causes the degradation and for engine health condition is represented by sensors output.

The dataset(CMAPSS) can be further divided into four subsets based on fault mode and other conditions. Each data set has separate training set, test se and RUL set. All the engine data is merged in training data that leads to fault of an engine. And test data contains the reading before the engine falls to fault. There are many readings for many different engines in different states due to different states the running cycles of the engines are different. For example, in FD001 dataset there are 100 different engines test data with running cycle from 31 to 303. There 17731 training samples with respect to time window with 100 test sample size as shown in figure 3.

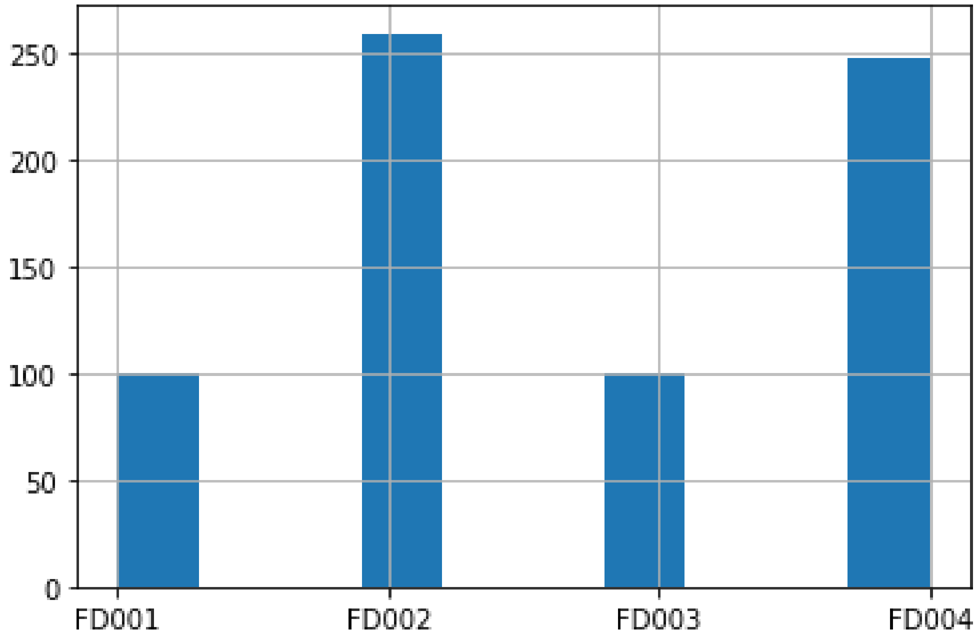

Figure 3: All the training samples with respect to time window

Dataset size is shown in fig above

Table 2:Dataset conditions

Sub datasets	FD001	FD002	FD003	FD004
Engines in training set	100	260	100	249
Engines in test set	100	259	100	248
Max/Min cycle for training	362/128	378/128	525/145	543/128
Max/Min cycles for test	303/31	367/21	475/38	486/19
Operating Condition	1	6	1	6
Fault Modes	1	1	2	2
TW Length	30	2	36	18
Training samples	17731	48558	21120	56815
Test samples	100	259	100	248

The figure 4 shows the all sensor data traces of dataset on with random 10 units. Just before it's about to failure. Where x-axis presents the time before failure cycles and y-axis represents the sensor values.

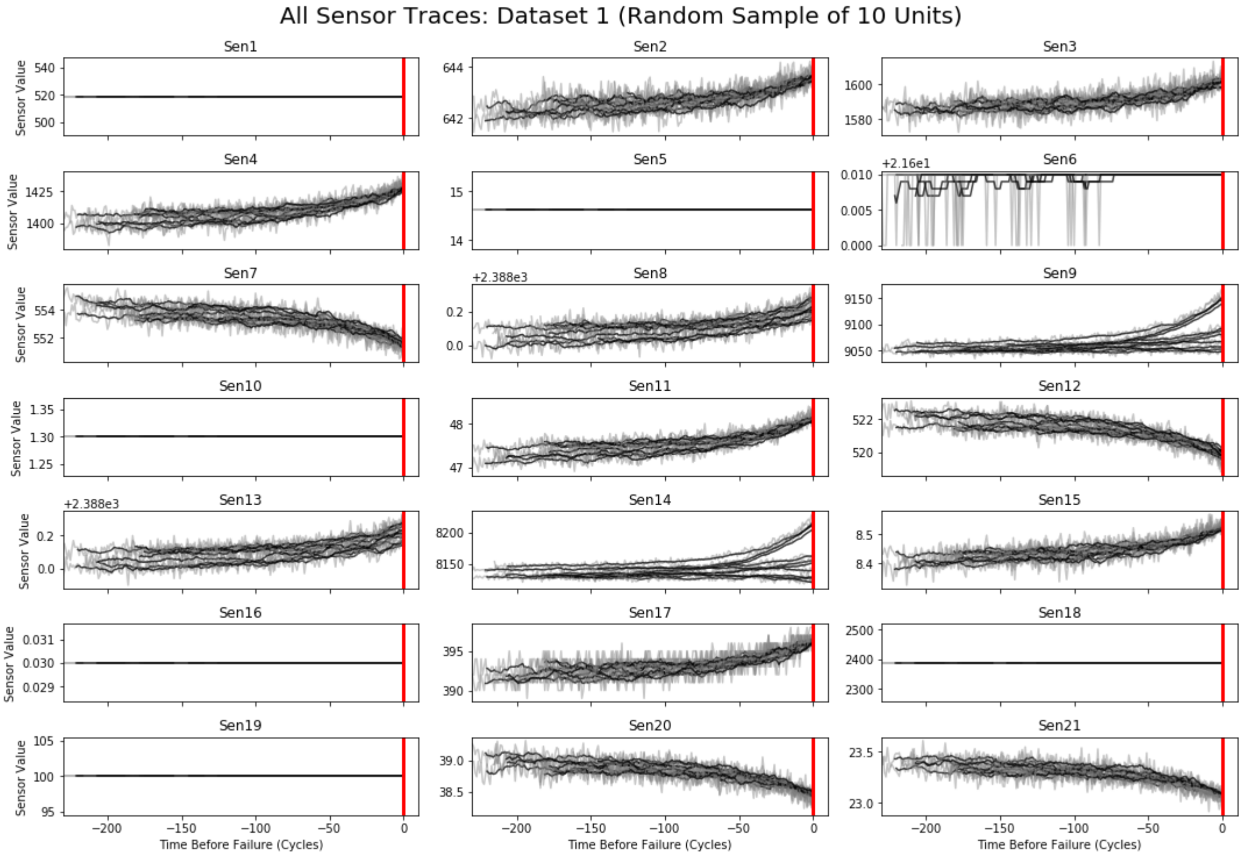

Figure 4: All sensor trace

For this report, we have used the subset of CMAPSS Data Which is FD004 with 249 engine training set, 248 engine test set, and with total 56815 training samples and 248 test samples with time window length of 18 and 486/19 cycles for test with 543/128 training cycles.

In figure 5 plot represents the correlation between sensors values.

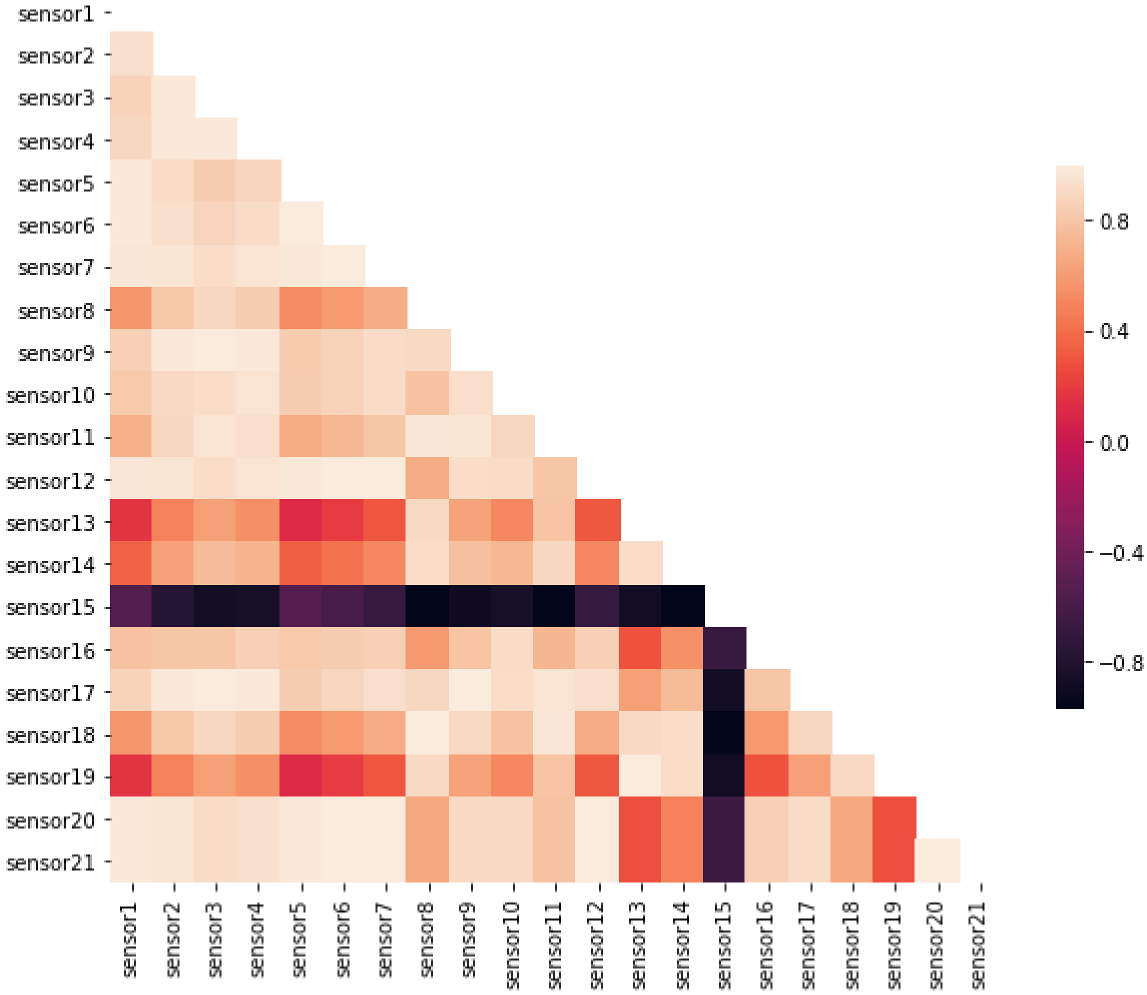

Figure 5:Correlation Plot of sensor values in FD004

Data Scaling

Scaling is applied on data set using “Stander Scaler” and “MinMaxScaler” from SKLearn preprocessing on training and test data after scaling the data distributions of the data are still same as shown in figure 6.

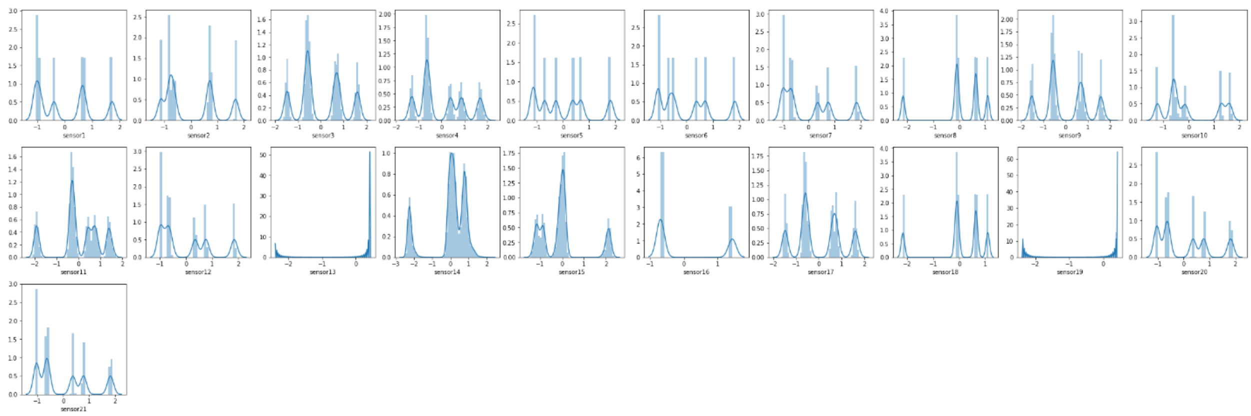

Figure 6 : Distribution of data after scaling

- Data Augmentation and Padding

After scaling the data piece wise Augmentation and random padding is applied on data according to columns order.

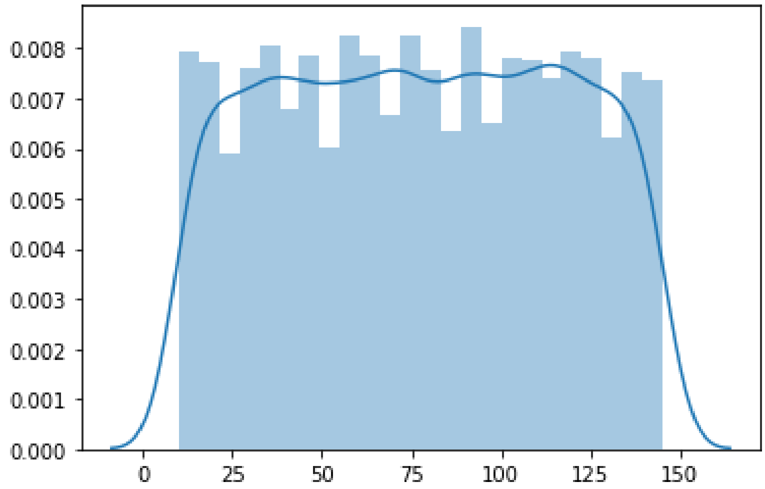

Figure 7: Data padding variation

Finally, the data is divided into training data, test data and validation data ready for model training

4.2 Implementation, Evaluation and Results of LSTM

In this Experiment Long short term memory Architecture is used to Predict the remaining useful life of the turbofan engine. 2 LSTM Layers were used. 3 Dense Layers are used. Activation was 'relu'. Loss was 'MSE' and the Optimizer was 'ADAM'. Model's Summary is given below.

Implementation:

LSTM Model is implemented using "Keras" Framework by python the procedure require from keras for model implementation are "keras.layers", "keras.models" and Keras "regularizers". Other than these SKLearn Library by python is used for Data Preprocessing. Than data set is splatted in to three folds. At the end Model is evaluated on the bases of Mean Square Error.

Evaluation and Results:

Mean Square Errors for each fold on training data.

Table 3:Mean Square error of LSTM

Folds	Mean Square Error
Fold 1	1091.4838755355156
Fold 2	634.5424610845727
Fold 3	789.9235032983678

Table 4:Mean Square Error on Test Data after Evaluation.

Folds	Mean Square Error
Fold 1	2168.0150343371974
Fold 2	1140.2524847215223
Fold 3	1480.1892798639112

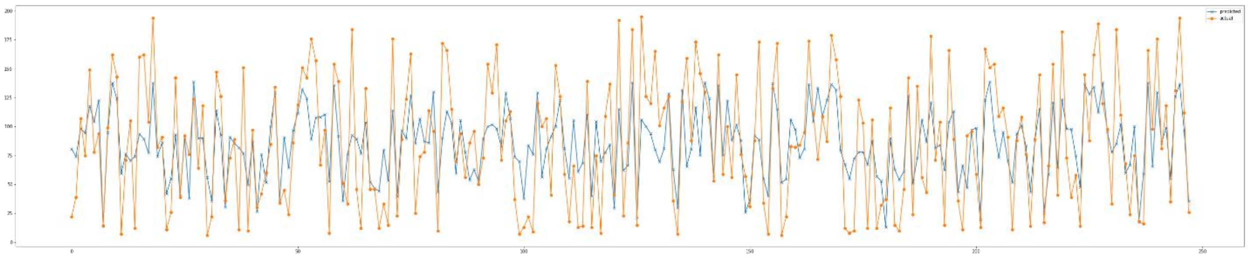

Figure 8 : Model's Prediction Plot with actual and predicted value

The graph corresponds to the Models performance the x-axis represents the number of engines and y–axis presents the RUL Predicted where blue solid line represents the predicted RUL for test data and Yellow solid line presents the actual RUL Values for the engines.

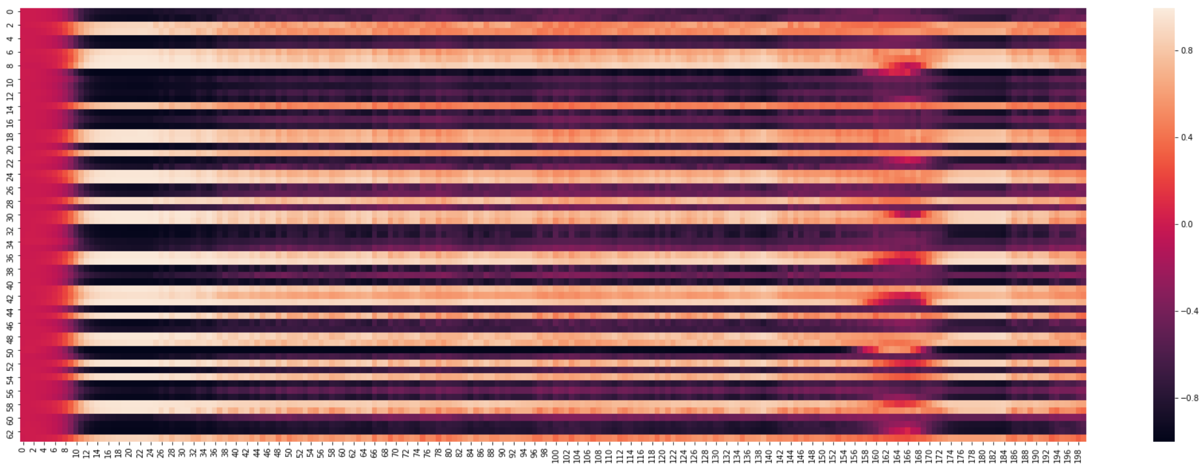

Figure 9 : Heat map of output

4.2 Implementation, Evaluation and Results of LSTM+CNN (hybrid Network)

In this experiment Convolutional neural network and Long Short Term Memory architecture is combined to predict the remaining useful life of an engine. 3 convolutional 1 D Layers are used forward by 3 Maxpool 1 D Layers. 2 LSTM Layers are used forwarded by dropouts. 3 dense layers are used as well. Activation is 'relu' and optimizers is 'Adam'. Maxpool size is 2 and strides are 3 with padding = 'same'.

Implementation:

The model is implemented using "Keras" Framework by python. The functionalities required from keras for model implementation are "keras.models" which is sequential and functionalities from "keras.layers" such as "Convolution1D", "MaxPooling1D", "Flatten" ," LSTM", " Dense", "Activation" and "Dropout".

Other than these SKLearn Library by python is used for Data Preprocessing. Than data set is splatted in to three folds. At the end Model is evaluated on the bases of Mean Square Error.

Evaluation and Results:

Table 5:Mean Square Errors for each fold on training data.

Folds	Mean Square Error
Fold 1	1155.0911572789407
Fold 2	1155.764778411328
Fold 3	1153.2789476611947

Table 6:Mean Square Error on Test Data after Evaluation.

Folds	Mean Square Error
Fold 1	2307.540314705141
Fold 2	2273.5552466607865
Fold 3	2357.3983272429437

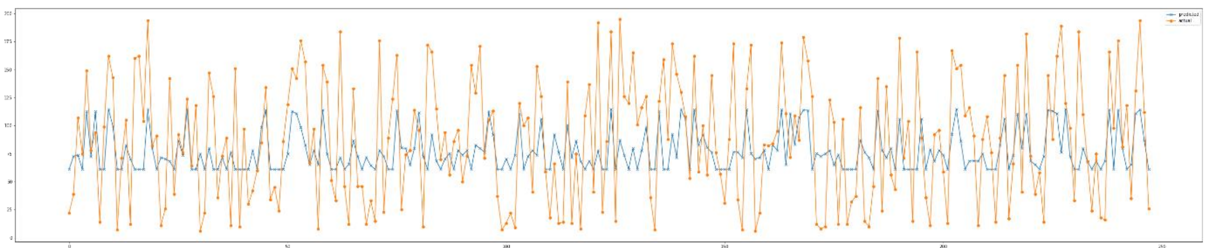

Figure 10: model prediction plot of hybrid learning

The graph corresponds to the Models performance the x-axis represents the number of engines and y–axis presents the RUL Predicted where blue solid line represents the predicted RUL for test data and Yellow solid line presents the actual RUL Values for the engines.

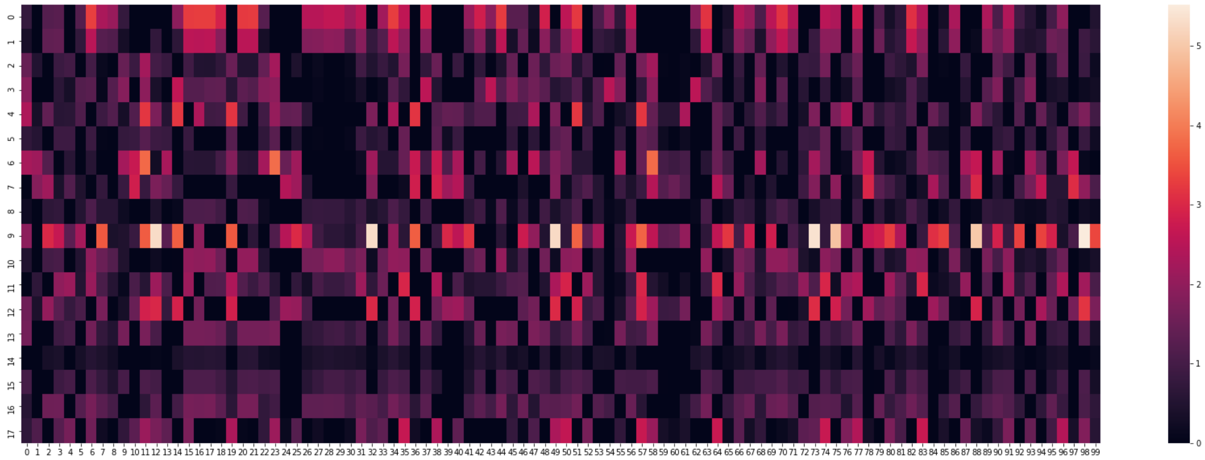

Figure 11: Heat map of hybrid method

4.3 Implementation, Evaluation and Results of transfer Learning

In this experiment A Trained Model is used to use as start point for another training data and testing it on test data. we uses the LSTM Base transfer learning model to apply on CMAPSS Data set

Implementation:

The model is implemented using "Keras" Framework by python. The functionalities required from keras for model implementation are "keras.models" to load the pre trained model on new dataset.

Evaluation and Results:

Mean Square Errors for each fold on training data.

```
mean_absolute_error: 2800.9747
```

Model's Prediction Plot

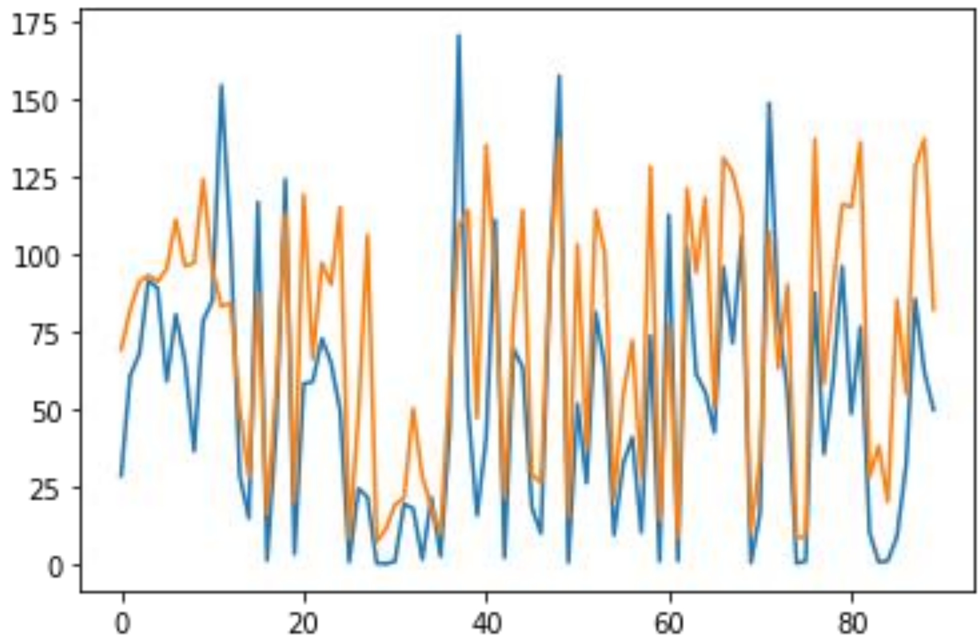

Figure 12: actual vs predicted of transfer learning

The graph corresponds to the Models performance the x-axis represents the number of engines and y–axis presents the RUL Predicted where blue solid line represents the predicted RUL for test data and Yellow solid line presents the actual RUL Values for the engines.

4.4 Implementation, Evaluation and Results of CNN

To predict the RUL of engine, the data is first prepared in order to apply CNN. In data preparation label column is added based on remaining useful cycle time if the time is greater than fifty label has given value of zero , if time is between 10 to 50 then label has given value 1 and if it is less then 10 then label is two , so when label value is two then the situation is more critical and our prediction is necessary in this situation. Then we generate array of sequence for both train and test data based on unique id number from the dataset like suppose first engine is failing after 302 cycle then the sequence is generated in new array by iterating loop on 0 to 50 , then 1 to 51 and so on. After generating sequence and labels of train and test data, one part of data is converted into images using recurrence plot so 50*50 images are generated.

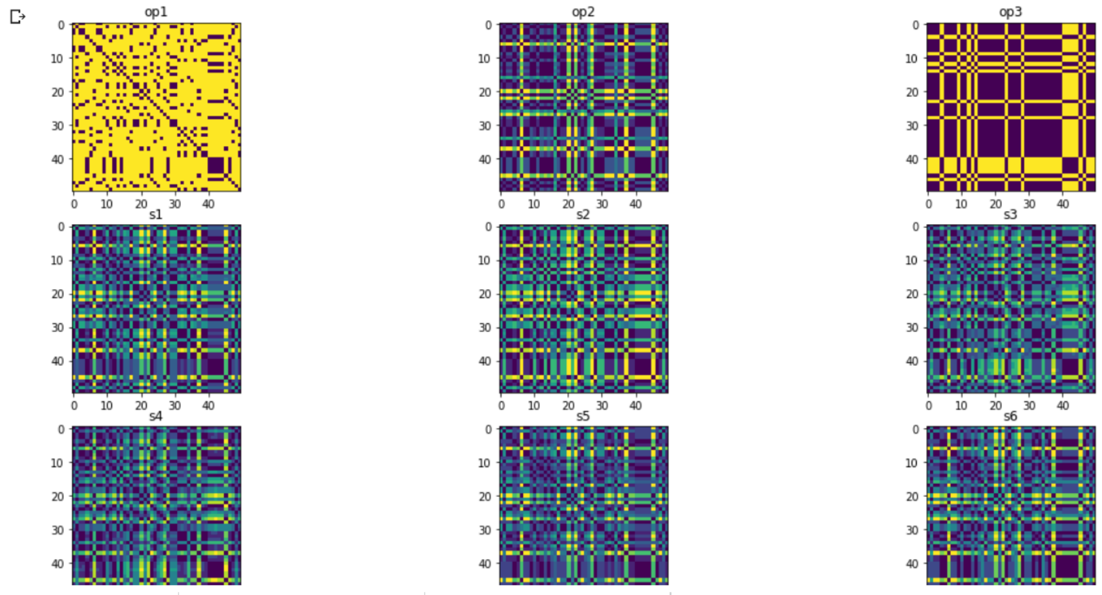

Figure 13: Time series data is converted to images

Implementation: two dimensional CNN has been applied to dataset with epochs 25, in this CNN it have mainly three parts convolutional layer , pooling layer and fully connected layer ,
1.After reshaping inputs the model is build using sequential add function
2. pooling layer is added along with it using MaxPooling function.
3.Then flatten layer is added which prepare a vector for fully connected layer and it is achieved using Flatten function.
4. Add more fully connected layer using sequential Dense function which allow fully connected layer with dropout layer.
5.then model is compiled and fitted in dataset to evaluate the result.

Evaluation and result: Training accuracy achieved is 67percentage and testing accuracy is 83 percentage , the accuracy and loss plot is also shown for training and validation separately , in the plot accuracy with each epoch is plotted to get full view of result.

4.5 Implementation, Evaluation and Results of Random Forest

Implementation: For prediction of RUL of aircraft engine , the ensemble learning is applied in which different type of algorithms are joined to form more powerful prediction model, in this case random forest is used which is combination of decision tree, first random records is taken from the dataset , 2. Then build the decision tree based on records , then number of tree are chosen and repeat the steps above 3. then for each tree in forest predict the remaining useful cycle of engine that is output which is the average of all values predicted by all trees in forest.4.Random forest regressor class of sklearn is used to solve this problem

Evaluation and result: To evaluate the random forest, the metrics used are mean absolute error , mean squared error and root mean squared error ,

Mean squared error is 1782,root mean absolute error is 30 and r squared is 0.6 which is not that far from value 1. So model is moderate fit for NASA dataset.

4.6. Developed Models Comparison

The Comparison among the proposed models (LSTM, Hybrid and transfer learning model) is given below in table. As the coincidence degree between predicted and actual RUL can be seen roughly.

Table 7:Developed technique comparison

Model	Fold 1MSE	Fold 2 MSE	Fold 3 MSE
LSTM	1091.4838755355156	634.5424610845727	789.9235032983678
LSTM+CNN	2307.540314705141	2273.5552466607865	2357.3983272429437
Transfer Learning	2800.9747	2800.9747	2800.9747
Random forest	1783.89	1745.78	1723/96

4.7. Developed Models Comparison with exiting models

The Comparison among the proposed models (LSTM, Hybrid and transfer learning model) and the existing models discussed in literature is given below in table.

Table 8:Comparison with exiting models

Model	Fold 1MSE	Fold 2 MSE	Fold 3 MSE
LSTM	1091.4838755355156	634.5424610845727	789.9235032983678
LSTM+CNN	2307.540314705141	2273.5552466607865	2357.3983272429437
Transfer Learning	28.9747	28.9747	28.9747
C. Okoh (2014) MLP	6.25	6.25	6.25
L. Redding (2015) SVR	7.35	7.35	7.35
J. Mehnen (2013) Deep LSTM	2.80	2.80	2.80

4.8. Conclusion

Based on Above discussion and results from proposed models the report completely answered the research question. The developed model and report will help a lot to other researchers and surely increase the knowledge about the field of remaining useful life prediction.

5. Conclusion and future work

Fault detection is complex and time consuming task because turbofan engines has excessive demands on safety and reliability. For this report a combined approach is proposed with comparison with other latest algorithms. The turbofan engine simulation data by NASA is used to validate the model Performance. Finally, Models result is compared using CMAPSS Dataset subset FD004 and scores are impressive than other methods. The research main purpose is to explain and propose a procedure for improvement maintenance planning and efficient use of aircraft engines. The proposed method is better than other RUL prediction methods. As the performance degradation the model has deeper memory during model training for degradation. Which results in better prediction and accuracy.

Future Work

Research work confirm that VAE Models has a notable impact on RUL prediction other than that Training and evaluating the model only on single subset of Dataset is one of the major limitation. As VAE is recently used for anomaly detection. Thus in future VAE Model can be used to create supervised Fault Prediction system for each engine and subset in dataset.

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