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Predictive Maintenance of Machines on Large Scale Industrial Units Using Machine Learning

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ABSTRACT- Anticipating machine breakdowns is one of Industry 4.0's primary goals. It's critical to be able to prevent failures since downtime costs money and results in a loss of productivity. That's why it's critical for machine maintenance to figure out how many cycles or RULs are left till the breakdown occurs. The And where ever possible, RUL estimations should have been based on previous direct observation under the same circumstance. The construction of tracking the present status of technology is at the heart of RUL estimation technology. While there has been a lot of study done on this subject, there is no one-size-fits-all solution. This method, which makes use of nn (RNN) to solve problems, predictive maintenance of the proposed solution, is motivated by the lack of a universal technique.

KEYWORDS- Machine failures, Preventive maintenance, RUL, RNN.

I. INTRODUCTION

Several elements in the civil aviation industry put pressure on airlines' costs. For example, so-called "low-cost" airlines allow for low-cost public transportation, resulting in a large reduction in the running expenditures [10] are examples of other airlines on the market. Attempts to reduce fuel consumption or air navigation finance ideas, like as leasing, have resulted in a situation where only minor gains are expected in the future. The goal of lowering maintenance costs, on the other hand, has recently been underlined [3]. Maintenance expenses are expected to account for up to 20% of airline operating costs, dependent upon the planes and its age, or US$40 trillion dollars every year [2]. The quality, time, and cost of aerospace in civil aviation are all optimising problems [Grü02]. Maintenance, repair, and overhaul (MRO) activities assure the flight operations and availability of aircraft (quality).

The needed ground periods (time) should be as short as feasible in order to maximise the aircraft's operational efficiency while remaining as cost-effective as possible (costs). Additional quality-related performance metrics are introduced in [Lin05]: Security, assurance, and ease. "Air transport safety and safety are significant aims," especially in terms of air navigability [3]. Reliability is one of the aspects of timeliness that is influenced by maintenance efforts [2]. In contrast to the preceding requirements, comfort is not required. It allows for more competitiveness, for example, through upgraded cabin gadgets [1]. The "hues" are the colours that are in their purest form on the outermost perimeter in the circle. This process can continue to fill in wheel colours. The next level colours are those between the secondary and primary colours, the tertiary colours. Figure 1 illustrates the categorisation of degrees of preventative action ("act before failure") as well as their impact on maintenance expenses. As part of all activities, the quantity of predictive procedures is shown on the x-axis.. The "hues" are the hues on the circle's outside edge that are in their simplest form. This method can be repeated to fill in the remaining colours on the wheel. The tertiary colours, which are intermediate between the tertiary colours, are the next stage.. Figure 1 depicts the identification of stages of prevention measure ("act within a week of failure") and respective influence on costs in relation to care approaches. The intensity of periodic servicing is represented on the x-axis as part of all events.

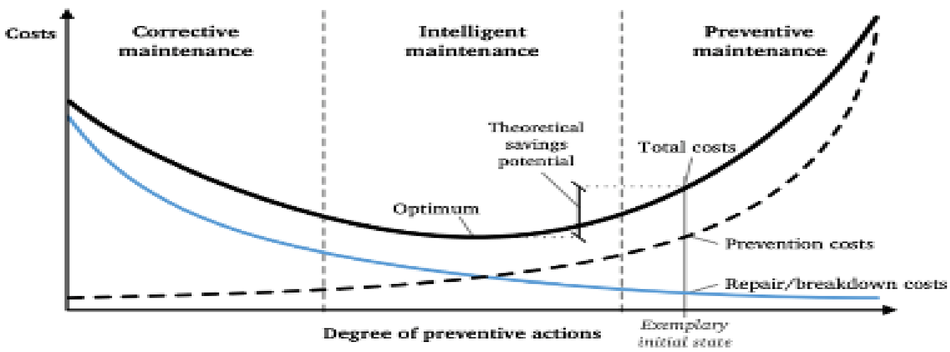

Figure 1: Impact of maintenance strategies on costs. [17] (image source: researchgate.net)

I4.0 and its tools are critical to making corporate system personality [5] and autonomous [6]. therefore enabling automatic data collection from industrial machinery/components. Machine learning techniques may be used to automate fault detection and diagnosis based on the gathered data. However, selecting appropriate approaches, types of data, data amount, and gear for ML in industrial systems, in machine learning, is quite complex (ML). The wrong predictive maintenance (PdM) strategy, data collection, and data size can lead to time waste and wasteful capacity planning.[18]

As a consequence, the goal of this study is to conduct a thorough content analysis in order to discover study findings and machine learning apps, supporting investigators in finding suitable Algorithms and techniques, throughput, and file name in order to produce a valid ML proposition. Because it was developed to achieve near-zero possible dangers, errors, wastes, and crises in the whole system of manufacture, industrialized equipment predictive (PdM) may recognize declining performance.

These vast volumes of data acquired for machine learning provide incredibly valuable information that may be used to increase the average output of commercial and erratic events, as well as disease and illness management to makes easy]. Thanks with recent changes in technology . ..., computerized monitoring, and communications systems, data from a variety of electrolytic capacitors for automate fault detection and treatment (FDD) may still be received from a broad variety of activities and process parameters.[16]

The goal is to draw attention to the material's complexity as well as common educational strategies. To enhance classifier, multiple approaches might be used. In addition, several techniques may be used for both unsupervised learning learning.[14]

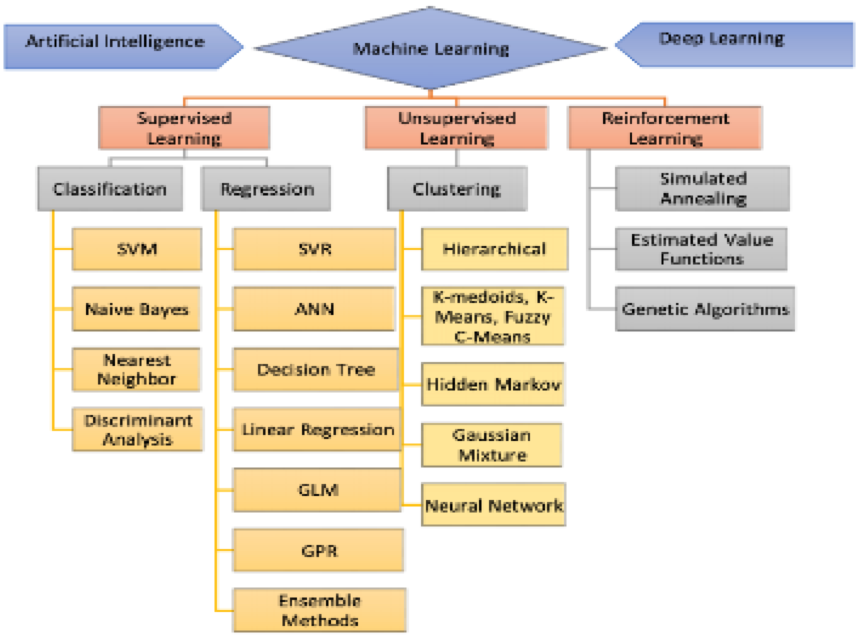

Figure 2: Algorithmic Inference Technologies Categorization (Image: roadtoreliabillity.com)

In unmanned machine learning, no external teacher or certified expert provides input. On the basis of the The system calculates the clusters based on the data supplied. The major purpose of classification techniques was to use clumping to uncover previously unknown classes of things. Unsupervised machine learning (unsupervised ML) is a term that refers to nearly any machine learning method that seeks to learn order in the exclusion of a declared input (such as regular ML) or data. (such as reinforced learning (RL)).[13]

As illustrated in Figure 2, there are a variety of machine-learning methods available. Each of these strategies has its own set of advantages and limitations when it comes to application (either PdM or manufacturing). The selection of the best and most appropriate ML approach for the PdM issue is a major challenge. It is also critical to practise on a variety of additional datasets when using applied machine learning. As a result, each challenge necessitates a different level of nuance, as well as different data preparation and modelling approaches. Heterogeneous, consecutive, temporal, incremental, uniform, text, and theory of domain are the seven kinds of data sets.

II. OBJECTIVES

Based on the foregoing insights, an evaluation approach is needed to estimate the cost-saving potential of today's aviation maintenance, as well as to counteract the varied repercussions of a predictive maintenance strategy on the starting state of the real world. As a result, a component-level cost-benefit analysis of civil aviation aircraft maintenance is conducted. The initial state maintenance characteristics are specified and analysed in order to construct a generic process model and identify cost-cutting opportunities. After examining and comparing prediction-based maintenance approaches, the exact consequences on costs and other measurements may be identified. The bilateral effects must be evaluated evenly because of the impact on both the airlines and the MRO business.

A thorough examination of particular prediction errors allows for the management of risks and assists in the completion of a general assessment that may be used to make future choices regarding potential adjustments to real-world maintenance plans. Based on the availability of deterministic real-world data, a full study of particular causes and effects will be done. Because analytical approaches are ineffective for such complex optimization problems, simulation is used to analyse the situation.

New virtual concepts may be broadly assessed using this method without affecting real-world operations. This thesis is intended for decision-makers in the realm of preventative maintenance as well as engineers who create prediction algorithms utilising the basic design criteria.

III. LITERATURE REVIEW

Fawaz et al. [11] or detector model data and [14] for median filter Dnns. Some methods employ classical or eye data, and even use DL features to tackle the issues and provide the most prevalent DL FE strategies, thus according Zhao et al. [12]

They claim that in DL models, which are both enabled by their SotA revision, everything functions well. Many of these research use methodologies such as model design and problem optimization, as well as leveraging architectures that are now used in the SotA system, to improve model performance as data grows. They also change the way learnings work to increase model extensions and reduce overlaps. They also change the number of neurons and connections, as well as using transfer learning and stack models.

Khan et alassessment [15] s shows that the DL structures manufactured are app or infrastructure, and so there is no obvious way to choose, create, or manufacture them. incorporate such structures; they don't appear to favor the decision that one architecture over another will indeed work for the contest, such as CNN vs. LSTM for RUL. An issue in the design of DL models is not appreciated, [9] s the academics Khan et al. point out. They also argue that VAE was very well to modeling complex structures, claiming that it provides great prediction despite sacrificing precision. knowing of their health. Regardless of whether it employs sliding windows, CNN, or LSTM technology, the most successful algorithms for analysing information while maintaining the relationship by examining the items individually, of its dataset are: The bulk of SotA algorithms are AD-focused, but RUL can be modified using regression or RNN, with the majority using LSTM.[23]

Features learned for the AD models in issue, as well as more standard and hand-crafted features, are widely used in regressions. The performance of GAN and other obtained by utilizing is not as good as it should be. CNN, on the other hand, works admirably with far. Data and considerable computational are reduced. This demonstrates that Implementations may be as reliable as normal or shallow features collected from data without any assistance.

IV. METHODOLOGY

Zhang et al. [22] look at the quality of ANN, Deep ANN, and AE models in a variety of databases, but they don't make any correlations. using models that are relevant to a variety of data sets. Nonetheless, their results are quite accurate, with the majority of them ranging from 95% to 100%, indicating that DL models may provide positive performance. They believe that deeper architectures and uplifting vectors result in increased fidelity models, however more data is required. Transfer learning may be used for limited amounts of training data, and PdM is an imbalance caused by a lack of or inaccurate data.

As processing power and data expansion in pdm expand, research in. This field focuses on data-driven methodologies, particularly deep learning frameworks. The Implementations, but in the other hand, have no understanding of or appreciation for the decisions that have been made.

An issue in the design of DL models is not understood [21] s the authors Khan et al. point out. They also argue that VAE is well-suited to modelling complex processes, claiming that it provides great prediction without sacrificing precision. knowledge of their health. Regardless of whether it employs sliding windows, CNN, or LSTM technology, the most successful algorithms for evaluating information while maintaining the relationship of its time series by analysing the variables together are: The bulk of SotA algorithms are AD-focused, but RUL can be modified using regression or RNN, with the majority using LSTM.

Features learned for the AD models in question, as well as more standard and hand-crafted features, are widely used in multiple regression. The performance of GAN and other generative models is not as good as it should be. CNN, on the other hand, works admirably with There is a significant reduction in data and processing effort. This demonstrates that Data sets using typical or deep selected features unassisted from material may achieve similar correctness.

A. Deep learning for Predictive Maintainence

This section provides the most important publications and applications' citation DL approaches for PdM analysis. For peer-reviewed studies, quizzes, and fields reviews, precise SOTA DL equations are supplied. Although most papers incorporate many strategies and implement multiple PdM stages in the same design, this one does not. categorises the works by their major DL methodology in the first five subdivisions. This part also applies to DL for pre-processing and other feature design, as mentioned in the preceding section.

This categorization allows for a step-by-step DL approaches are analyzed and compared. The sixth comment section exhibits works that skillfully combine the former in order to showcase the possibilities of combination in an infinite number of ways. tactics to construct more extensive structures that conduct one or more PdM phases. Finally, the final section compiles the most important information and examines the relevant tests and surveys found in similar publications.[23]

SotA works may be classified based on the underlying machine learning job or approaches that relate directly to the case and its data requirements. Binary classification is used when the training data contains labelled failure and non-failure observations. Multi-class classifying is similar to binary classification, but there are more than one mode of failure to be classified, hence at least three classes are required: one for non-failure and one for each type of failure. One-class classification (OCC) is used when the training dataset only contains non-failure data, which often consists of acquiring machine data in early functioning phases or when technicians check the asset is working appropriately.[25]

Finally, when views of training data sets are not marked, no one knows which pictures belong to schools of failure and non-failure, unmonitored processes are used. Unsecured operations might also be included in this category. A variety of other research on machine and deep learning, including as active learning, improved learning, and transferring, are also available.[24]

B. Data set

Initially, the goal was to use a large number of real data sets for predictive maintenance to evaluate the RNN's experience in a range of scenarios where time to failure could be estimated. Unfortunately, obtaining datasets that match these requirements is Quite difficult. Finally, I opted to concentrate on the Turbofan Engine Degradation data set [26]. This dataset originates from NASA's Ames Research Center in California, despite the fact that it is a simulation. The CMAPSS, or commerce flexible aero launch vehicle simulating package, is a suite of tools for modeling large-scale, actual industry turbofan datasets, and this prototype is based after it.

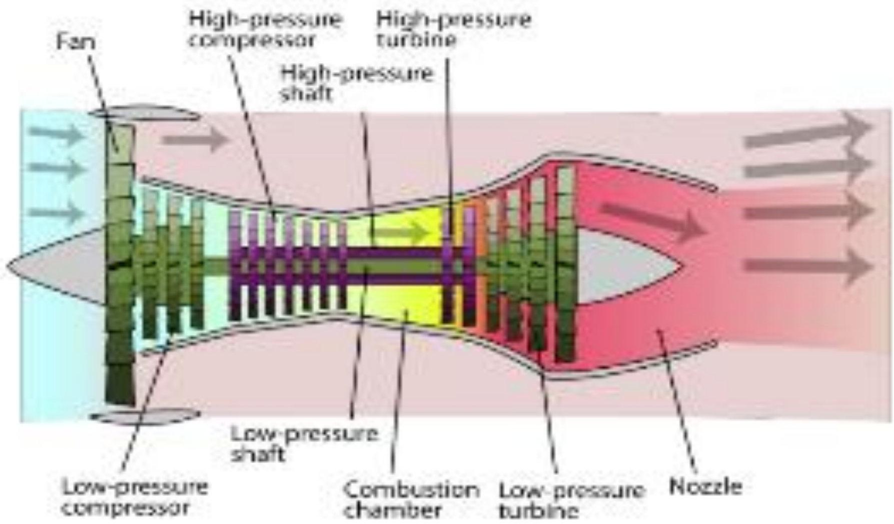

Figure 3: Turbofam Operation diagram from Aainsqatsi, 2008 (image: smglobal.com)

Saxena et al. [19] resented a study on large data, which is mostly made up of many time - series data. Each time a tv show is formed from a different engine, the data could be compared to a fleet of similar cylinders. So every engine has a unique initial wear patter production differences that the user is unaware of. This wear and variation is regarded as typical, rather than a flaw. Engine performance is heavily influenced by three operational characteristics. These variables are also accounted for in the data. Scanner sound has polluted the data.

Statistics for teaching, benchmarking, and dataset may be found in the Collection Portal. The data incorporates a variety of time series with the "cycle" as the period element and 21 sensor measurements one per cycle. Each row was most likely created by a different model of the very same type. The test and practice data are identical.

The only exception is that even if the failure happens, the data is not shown. Finally, the grounded truth data indicates how many operating cycles remain in the vehicle test data.

FD001 contains one system parameters and one modulus of rupture; FD002 has six labor environments and one failed mode; FD003 contains one process conditions and two distinct types; and FD004 contains one process conditions and two fault strategies. The two types of failure are degradation of the fan and deterioration of the high-pressure compressor, respectively. Altitude, flight speed, and TRA are combined to create the six operating conditions. Any season succeeds at the start and then loses at certain point all through the run. Figure 7 shows that motor 1 was being closely monitored until it collapsed in cycle 192. The purpose is to predict number of times operative cycles are remaining until all cycle fails, for examples, number of times cycles are left for cycle 172.

C. Validation Process

In the initial training set of the Turbofan Engine Degradation Simulation Data Set, the issue grows in scale until system breakdown. Before the system fails, the time series in the test set comes to an end. Since the time series are "interrupted" and not monitored until the end, we will recover 20% of the original train data set as a validation data set. Since there are 100 engines in the training set and another 100 in the test set, there will be 20 batches totaling roughly 200 cycles. The split will be done with a random number generator for consistency's sake (42). Batch refers to the order in which cycles are detected per engine.

A number of metrics will be consistent throughout all experiments, in addition to the loss function utilised. It's important to notice that the WTTE-RNN models predict two Weibull Distribution parameters. This statistical model may be used to predict the number of remaining cycles until failure, also known as Remaining Useful Life, in a variety of ways (. As a result, certain models will be evaluated many times in order to compare alternative strategies for calculating RUL.

D. Software

Deep learning is receiving a lot of attention these days, and there are a lot of new technologies being developed. It's challenging to keep up with the fantastic work that's being done while investigating all of the frameworks that are popular among developers. We'll rely on Google's TensorFlowTM project and the Keras API instead.

Pos.	Name	Description	Language	Stars
1	tensorflow	Computation using data flow graphs for scalable machine learning	C++	106193
2	keras	Deep Learning for humans	Python	30954
3	opencv	Open Source Computer Vision Library	C++	26246
4	caffe	Caffe: a fast open framework for deep learning.	C++	24886
5	TensorFlow-Examples	TensorFlow Tutorial and Examples for Beginners with Latest APIs	Jupyter Notebook	23594
6	machine-learning-for-software-engineers	A complete daily plan for studying to become a machine learning engineer.	None	19241
7	deeplearningbook-chinese	Deep Learning Book Chinese Translation	TeX	18754
8	Deep-Learning-Papers-Reading-Roadmap	Deep Learning papers reading roadmap for anyone who are eager to learn this amazing tech!	Python	18143
9	pytorch	Tensors and Dynamic neural networks in Python with strong GPU acceleration	C++	17857
10	awesome-deep-learning-papers	The most cited deep learning papers	TeX	15939
11	Detectron	FAIR's research platform for object detection research, implementing popular algorithms like Mask R-CNN and RetinaNet.	Python	15242
12	CNTK	Microsoft Cognitive Toolkit (CNTK), an open source deep-learning toolkit	C++	14815

Figure 4: Top deep learning projects from Badry, 2018 (image: slideshare.com)

As given in figure 4, my list of Github deep academic courses was updated in July 2018. The far more widespread is TensorFlowTM. it is designed for high speed digital computing in addition to an open source software library. Flexible design makes computing easy to deploy on a number of platforms (CPUs, GPUs, TPUs). Keras, on the other hand, is a well developed Python neural network API that works with TensorFlow, CNTK, and Theano. Most significantly, it aims to facilitate quick experimentation.

To do so, we'll combine these frameworks with Jupyter Notebook, an active workspace that lets you create and send files that include Live Codes, Equations, Visualization, and Narrative Texts. Collaboratory, another Google programme that provides free GPU support for operating systems, is an extension of this concept.

V. SYSTEM ANALYSIS

I constructed an LSTM network based on the [1] and [2] scenarios to predict the residual useable life of aircraft engines (or time to failure)[3]. The network uses simulated sensor readings to forecast maintenance in order to prevent future aircraft breakdown. "Can we predict when a running engine will fail, considering the history of these aircraft engine operations and failure events?" is the question. To restate and offer an explanation, two distinct types of ml algorithms can be used:

- Model was used to determine: So how many runs does a vehicle have before it fails?
- Will this engine fail in the w1 cycle?
- Binary grading: Will this engine fail in the w1 cycle?

One of the most important decisions to make during the construction of a model is how to appropriately represent the data. To do so, the specific question to which the model is supposed to reply must be defined in great detail. In this case, we limited the options by stating that we'd want to estimate how long each combustion cycle will be useable in the future (RUL). So, if we were to start running one of the turbines from the beginning, we'd want to know when it would fail. Please bear in mind that by modifying the query we wish to give to the engine, we may alter the course of this large dataset.

For example, we may train a binary algorithm to predict if the engine would fail in the next n cycles. It's perhaps more intriguing to know the chances of failure. Or perhaps we'd like to know if the engine would survive after a specific period of time. Next, we'll show how the parameters of a Weibull distribution may be predicted to answer a variety of queries.

Even with these limitations on the model's purpose, there are a variety of methods to prepare the data and a variety of ways to use the Recurrent Neural Network. When due to statistical for that problem, we may use two fundamental techniques if we think of the data set as a 3D tensor:

1. Rolling Window: It operates by specifying a look-back period, or a number of previous cycles to investigate. As a result, determining the right look-back period for the model is a critical decision. For the beginning cycles where there isn't enough prior knowledge, we may The advantage is that while the RNN layer's state is kept one per batch, and

2. We are not restricting our use of all previous batch information to a predetermined number of "time steps" past in this instance. The benefit is that the state of the RNN layer is preserved for each batch, and the amounts can easily be shuffled during each training period. To implement this using Keras, we'll need the necessary padding for each sequence so that they're of the same length, which means: (The total number of batches, the maximum batch length, and the number of attributes)

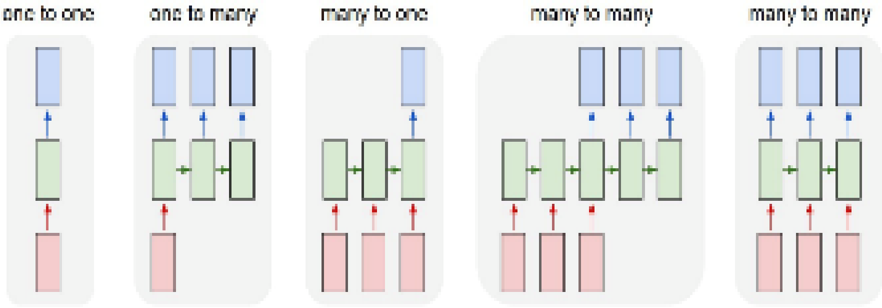

Figure 5: Setups for RNN form Karpatahy 2015 (image: dynaway.com)

Because the Rolling Window instance considers each sequence of the look-back time automatically, the intrinsic implementation is a many-to-one application. In Keras, there's a workaround that tries to keep the RNN unit state in the same batch across sequences. It's a well-known API called static, and it's not small to use.

There are several ways to use Batch Mode, but they are less clear and more prone to blunders Instead, we'll focus on the Batch Mode method, which looks to be more suited to the CMAPSS data set. Keras uses masks, sampler weights, and certain other approaches to accomplish this phase, which will be detailed later.

A. Baseline

We create a model that predicts how long recurrent neural networks will be functional. The purpose is to find a model that produces adequate results using the validation approach specified. The model will then be changed to compare the results using the WTTE-RNN architecture. Baseline Topology Network (TOP 5.2) Based on a popular Github repository, the model is divided into two stacked LSTM layers with a total of 100 and 50 Units (Griffo 2019). At the top, a masking layer hides each motor's padding, which is subsequently sent layer by layer and utilised for the loss..

As a result, the padding platform holders are not encouraged . In the LSTM, it was dropped, and in the team losing, it was disregarded. A time-divided barrier, and that is a keras object that applies a same couple of layers to every generation of the LSTM unit, is also present.

B. Regularization

As can be seen in figure 6, there are a substantial number of parameters (80k) compared to sample numbers (13k from 100 engines), making "learning" the issue simple. To avoid overfitting2, two major regularisation approaches are employed. Early termination and abandonment.

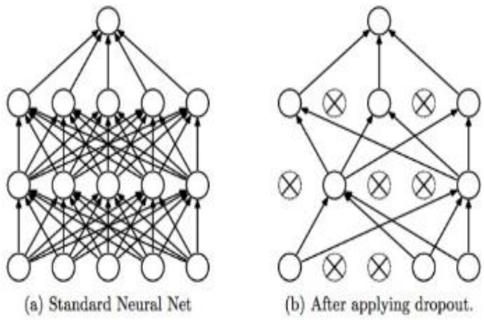

Figure 6: Dropout representation from Srivastava el al,2014 (image: researchgate.com)

Dropout is a simple yet powerful notion based on ignoring neurons with a specific frequency at random [27] Many alternative neural networks may be evaluated in Dropout, and it is well known that Ensemble learning can typically produce superior outcomes (i.e., multiple independent models).

An average is avoided since each of these models has a different overfit. This is due to the fact that the RNN is connected to the layer; if the RNN units are terminated, the noise will grow for lengthy durations, drowning the signal, regardless of the link between the units.

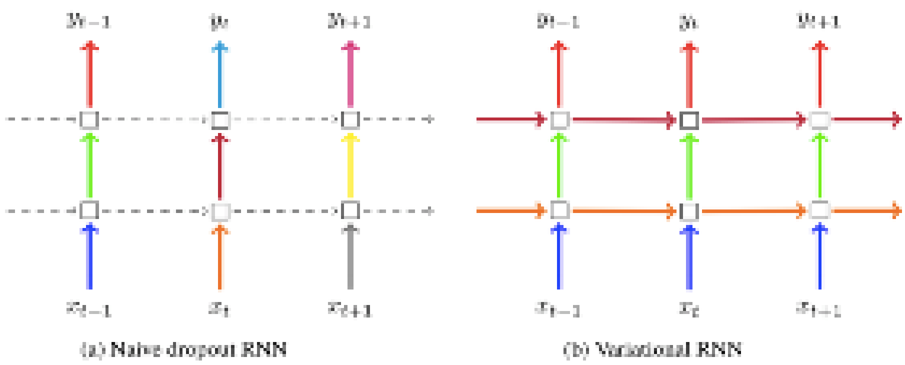

Figure 7: Recurrent droupout from Gal and Ghahramani, 2016 (image: researchgate.com)

As a result, the theory is somewhat sophisticated, and it is built on interpreting drop-off as a variational. a Deep q network's backend calculation The theoretical research is based on Gal and Ghahramani's premise. In practise, it also entails Figure 7 hows the insight; coloured linkages represent outputs with colours that correspond to various dropout masks.

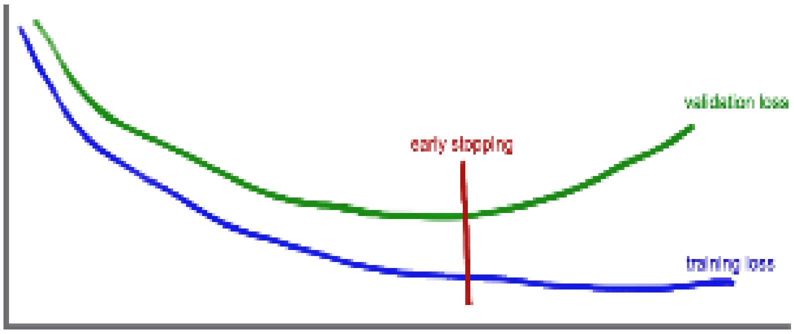

Figure 8: When overfitting, there is a loss of training and validation (image: researchgate.com)

When it comes to Early Stopping, we simply monitor the validator loss and halt training if it begins to climb. This is often performed by setting a patience period p,after which the execution is terminated if the validation loss does not surpass the most recent best score in p epochs.

VI. RESULTS AND OBSERVATIONS

We trained the Collaboratory -Model for 318 glaciations (14 seconds each epoch) over test dataset using an Effective Erm perseverance for 30 epochs. Because the Keras guide suggests it, we use the RMS Prop estimator at 0.001. The data has been scaled (min, max) and organised into batches (batch size = 16) to keep the RNN units in good shape.

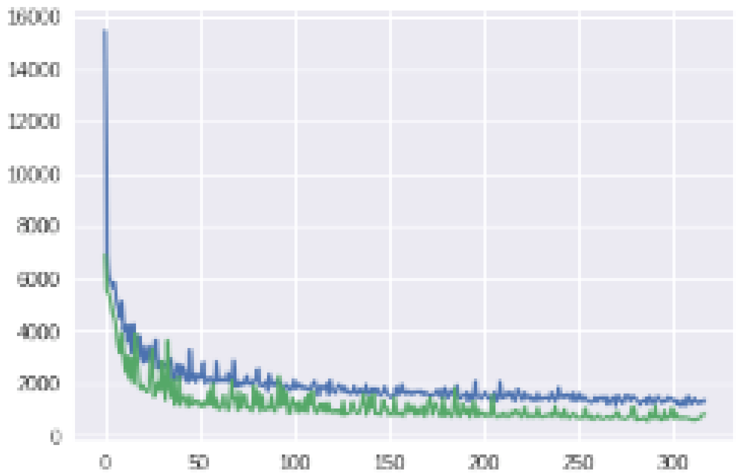

Figure 9: Training loss and validation loss (image: researchgate.com)

A. Results of Regression Model

Table 1: Mean absolute error

Mean Absolute Error	Coefficient of Determination (R^2)
12	0.7965

The following pictures from figure 10 to figure 12 show the trend of loss Function, Mean Absolute Error, R^2 and actual data compared to predicted data:

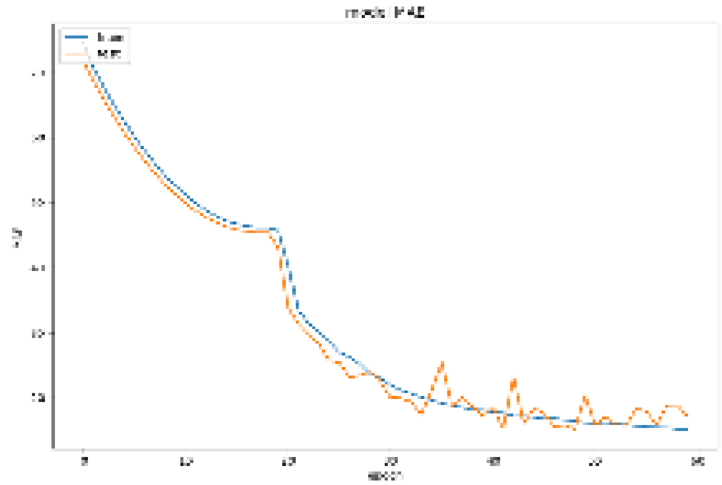

Figure 10: Train and test model in MAE

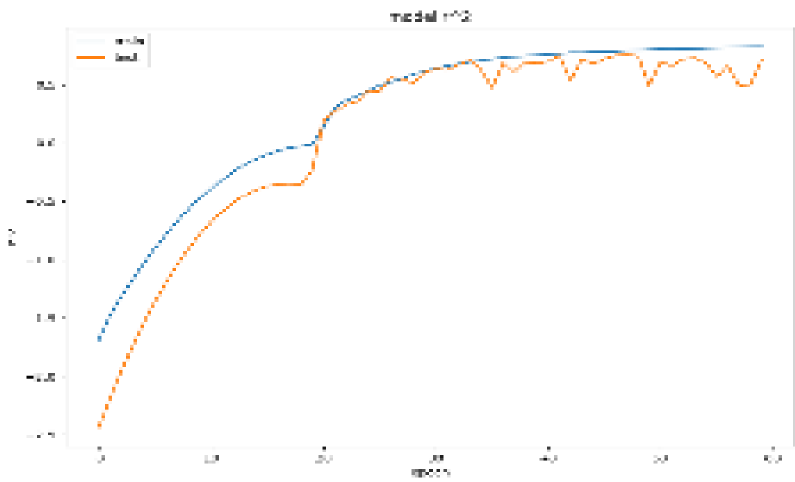

Figure 11: Train and test model r^2

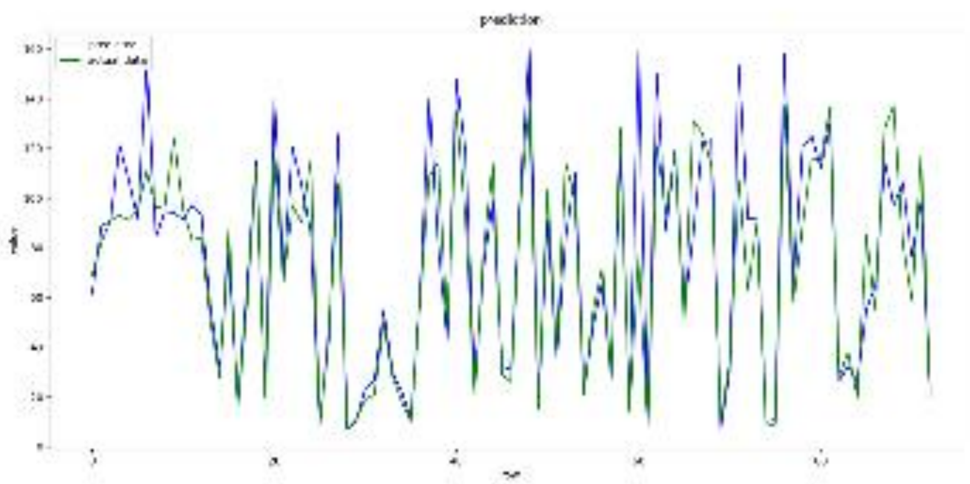

Figure 12: Comparison between actual and predicted data

B. *Results of Binary Classification*

Table 2: Accuracy and precision

Accuracy	Precision	Recall	F-Score
0.97	0.92	1.0	0.96

The following pictures from figure 13 to figure 14 show trend of loss Function, Accuracy and actual data compared to predicted data

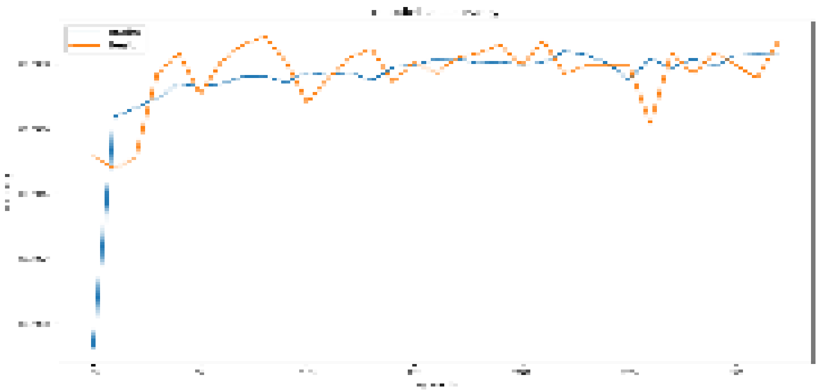

Figure 13: Train and test model in MAE

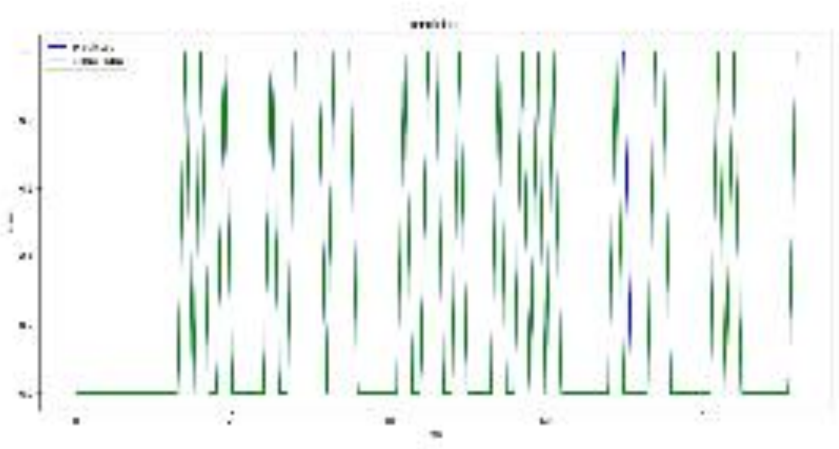

Figure 14: Comparison between Predicted and Actual data

VII. CONCLUSION AND FUTURE SCOPE

After successfully executing the fundamental model, the RNN framework theory is more comfortable, and a large number of viable improvements are worth a try. These are some of the ideas we came up with, which range from changing every component of the proposal to creating complex experiments:

- Training on CMAPSS Data Sets: Since the log-like loss supports filtered data, training a model on the CMAPSS Data Sets might be interesting. The test set's sequences are all "interrupted," making the model's job more challenging. We tried a few things, but they didn't work out.
- Lack of information. The capacity to estimate uncertainty is one of the benefits of projecting a data set. We may practice with introducing 'holes' mostly in data to see how the Quantile pdf works, except from the mask, which again is disregarded for every simulation layer. As an outcome from these openings, we predict the range to grow.
- Noise measurement: Sensors degrade with time, resulting in erroneous or missing values. However, two things usually happen throughout this process: the signal's amplitude increases and the pitch decreases. It's fascinating to see how the variance of the Weibull distribution affects the performance of new and old sensors.
- Various spreads: Why a woman? Perhaps there are alternative options that are better suited to certain conditions. The parameter would be interesting to try.

This strategy might be used to solve a variety of research difficulties. It may be used to determine if a hybrid is low yielding or high yielding depending on its performance in comparison to other hybrids in the same place.

REFERENCES

[1] (2016), 36. https://doi.org/10.1186/s13014-016-0602-1
[2] (2018), 1–15. https://www.ndt.net/article/aero2018/papers/We.5.B.3.pdf
[3] doi.org/10.1109/IEA.2018.8387124
[4] [H. O.A. Ahmed, M. L.D. Wong, and A. K. Nandi. 2018. Intelligent condition monitoring method for bearing faults from highly compressed
[5] 2017.06.027
[6] 4th International Conference on Electrical and Electronics Engineering, ICEEE 2017. IEEE, 281–285. https://doi.org/10.1109/ICEEE2.2017.79358
[7] analysis. International Journal of Engineering, Science and Technology 2, 6 (2011). https://doi.org/10.4314/ijest.v2i6.63730
[8] based clustering. Applied Sciences (Switzerland) 8, 9 (2018), 1468. https://doi.org/10.3390/app8091468
[9] Charles M. Able, Alan H. Baydush, Callistus Nguyen, Jacob Gersh, Alois Ndlovu, Igor Rebo, Jeremy Booth, Mario Perez, Benjamin Sintay, and
[10] Damla Arifoglu and Abdelhamid Bouchachia. 2017. Activity Recognition and Abnormal Behaviour Detection with Recurrent Neural Networks.
[11] Fazel Ansari, Robert Glawar, and Wilfried Sihn. 2020. Prescriptive Maintenance of CPPS by Integrating Multimodal Data with Dynamic Bayesian
[12] Framework for Aircraft Predictive Maintenance. 10th International Symposium on NDT in Aerospace, October 24-26, 2018, Dresden, Germany Ml
[13] Heidelberg, Berlin, Heidelberg, 1–8. https://doi.org/10.1007/978-3-662-59084-3_1
[14] Khalid F Al-Raheem and Waleed Abdul-Karem. 2011. Rolling bearing fault diagnostics using artificial neural networks based on Laplace wavelet
[15] Manufacturing Diagnosis. In IFIP Advances in Information and Communication Technology, Hermann Lödding, Ralph Riedel, Klaus-Dieter Thoben Gregor von Cieminski, and Dimitris Kiritsis (Eds.), Vol. 513. Springer International Publishing, Cham, 407–415. https://doi.org/10.1007/978-3-319-66923-6_48
[16] measurements using sparse over-complete features. Mechanical Systems and Signal Processing 99 (2018), 459–477. https://doi.org/10.1016/j.ymssp.
[17] Michael T. Munley. 2016. A model for preemptive maintenance of medical linear accelerators-predictive maintenance. Radiation Oncology 11, 1
[18] Nagdev Amruthnath and Tarun Gupta. 2018. A research study on unsupervised machine learning algorithms for early fault detection in
[19] Networks. In Machine Learning for Cyber Physical Systems, Jürgen Beyerer, Alexander Maier, and Oliver Niggemann (Eds.). Springer Berlin
[20] of Mechanical and Civil Engineering 7, 4 (2013), 52–60. https://doi.org/10.9790/1684-0745260
[21] Olgun Aydin and Seren Guldamlasioglu. 2017. Using LSTM networks to predict engine condition on large scale data processing framework. In 2017
[22] Partha Adhikari, Harsha Gururaja Rao, and Dipl.-Ing Matthias Buderath. 2018. Machine Learning based Data Driven Diagnostics & Prognostics
[23] predictive maintenance. In 2018 5th International Conference on Industrial Engineering and Applications, ICIEA 2018. IEEE, 355–361. https:
[24] Procedia Computer Science 110 (2017), 86–93. https://doi.org/10.1016/j.procs.2017.06.121
[25] Toyosi Toriola Ademujimi, Michael P. Brundage, and Vittaldas V. Prabhu. 2017. A Review of Current Machine Learning Techniques Used in
[26] Tsatsral Amarbayasgalan, Bilguun Jargalsaikhan, and Keun Ho Ryu. 2018. Unsupervised novelty detection using deep autoencoders with density
[27] Vimal and Saxena. 2013. Assessment of Gearbox Fault DetectionUsing Vibration Signal Analysis and Acoustic Emission Technique. IOSR Journal