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Predictive Maintenance of Aircrafts on Large Scale Industrial Units Using Machine Learning Algorithms

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Abstract: Anticipating aircraft 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 aircraft maintenance to figure out how many cycles or RULs are left till the breakdown occurs. The RUL estimates should be based on earlier observations wherever feasible under the same conditions. The research of RUL estimation is primarily centered on the creation of systems that monitor the current condition of equipment. While this topic is extensively researched, there is no single universal approach. This concept, which employs recurrent neural networks (RNN) for the predictive maintenance of the planned system, is motivated by the lack of a generic technique
Keywords: Recurrent Neural Network, RUL, Aircrafts, Maintenance

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 operating expenditures of other airlines on the market [But04, Dog10]. Efforts to lower fuel usage or new concepts of aviation finance, 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 [Sch03].

Maintenance expenses are expected to account for up to 20% of airline operating costs, or US$40 billion per year, depending on the kind of aircraft and its age [Jen07, Hei02]. The quality, time, and cost of flight operations in civil aviation are all optimizing problems [Grü02]. Maintenance, repair, and overhaul (MRO) activities assure the flight safety and affordability of aircraft (quality).

The needed ground periods (time) should be as short as feasible in order to maximize 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[Int03]. Reliability is one of the aspects of timeliness that is influenced by maintenance efforts [Pom01]. In contrast to the preceding requirements, comfort is not required. It allows for more competitiveness, for example, through upgraded cabin gadgets [Sha11, Hol02, Pom01].

The "hues" are the colors on the circle's outermost perimeter that are in their purest form. This method can be repeated to fill in the remaining colors on the wheel.. The tertiary colors, which are intermediate between the secondary and primary colors, are the next stage.

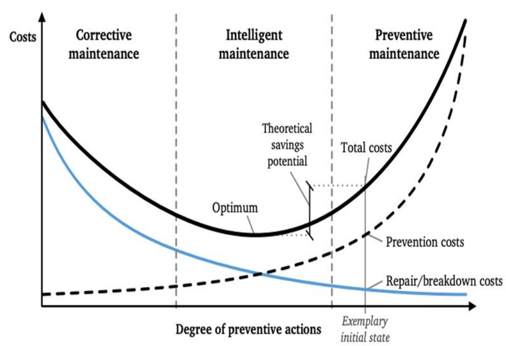

Figure 1: Impact of maintenance strategies on costs. [TWO+ 14, Lei 14] (image source : researchgate.net)

The classification of degrees of preventative action ("act before failure") and their impact on expenses in connection to maintenance solutions is shown in Figure 1.1. As part of all activities, the degree of preventative maintenance procedures is shown on the x-axis. If no preventative maintenance is performed (on the left), it is assumed that maintenance is still required, but that the system and component failures are remedial. . Because of the nature of these incidents, most maintenance is done on a need-to-know basis, resulting in increased effort (e.g. ad-hoc troubleshooting) and operational disruptions (e.g. flight delays), resulting in so-called breakdown costs. As a consequence, the qualitative curve for repair and breakdown costs (thin line) indicates a downward trend for higher degrees of preventative measures. Because the majority of problems are resolved before they become defects or failures, it is expected that almost no corrective actions will be necessary if all maintenance activities are preventive (right).

As a result, the proper preventative costs (dashed line) are exactly equal to the inverse of action, and so preventing any corrective activity is likely to be indefinitely uneconomic. The quality relationship between the two traditional procedures becomes ideal when both qual cost curves are incorporated (thick line). At this level, as described in [TWO+14], intelligent support, also known as value-driven preservation, is being done..

Either the concept refers to the fusion of two traditional concepts or sophisticated maintenance processes, such as predictive maintenance [Lei14]. Forecasting is the process of continuously monitoring and evaluating the current state of a system in order to determine whether maintenance activities are required (diagnostic) and when they should be performed (prognosis).

It tries to overcome the shortcomings of traditional maintenance ideas in two ways: first, it is thought to improve the planning of existing ad-hoc defects that have been rectified, hence reducing the effect of a breakdown.

It may, on the other hand, reduce the number of ineffective preventative efforts without adding any benefit or risking more failures [Cro99, And02]. However, there are ongoing debates over the specific impact of predictive maintenance principles on real-world maintenance.

The overall advantage against developing new risks is unknown since statistical errors frequently include the stochastic nature of prediction-based maintenance proposals. Furthermore, it is frequently unknown how much money is saved (see Figure 1.1). Furthermore, in order to create a solid business case, the required investment should not exceed the acquired savings [KBGB10].

The "hues" are the colors on the circle's farthest perimeter that are in their purest form. This method can be repeated to fill in the remaining colors on the wheel. The tertiary colors, which are intermediate between the secondary and primary colors, are the next stage..

I4.0 and its underlying technologies play a critical role in making industrial systems self-contained[2,3] and therefore enabling automatic data collection from industrial aircraftry/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 equipment 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 maintenance scheduling.

As a result, the goal of this research is to provide a comprehensive literature review in order to uncover current studies and Machine learning applications, thereby assisting researchers and practitioners in selecting appropriate Machine learning techniques, data volume, and data type in order to build a viable ML apps. Industrial device prescriptive analytics (PdM) can identify decreasing performance since it was designed to achieve near-zero hidden hazards, failures, pollutants, and tragedies in the whole atmosphere of manufacturing techniques [4].

II. OBJECTIVES

A comprehensive analysis of the specific forecast mistakes allows for the accounting of uncertainties and aids in the performance of a general evaluation that may be used to make future decisions about possible changes to real-world maintenance plans. A comprehensive examination of specific causes and consequences will be undertaken based on the availability of deterministic real-world data. As analytical methodologies are not appropriate to such complicated issues of optimisation, the assessment is carried out through simulation.

III. LITERATURE REVIEW

The survey by Chalapathy and Chawla [31] looks at the SotA DL approaches for anomaly detection. Rieger et al. [5] conduct a qualitative examination of the SotA quick DL models for PdM in IIoT (industrial internet of things) scenarios. They argue that real-time processing is crucial for IoT applications, and that a high latency system may result in unintended reactive maintenance due to a lack of time to plan maintenance. They also demonstrate how DL models may be improved. Weight-sharing on RNNs, they argue, allows for simultaneous learning, which can help in the construction of these sorts of nets that achieve SotA results in most PdM applications.

As a result, while dealing with CNNs, the use of max-pooling layers justifies removing and optimizing redundant processing. Two DL reviews that may be used to PdM fields are:

Fawaz et al. [10] for the sensor model data and [13] for the DL models for time series classification. According to Zhao et al. [206], some algorithms use normal or hand-made elements, while others use DL attributes to fix the issues and give the most common DL FE techniques

IV. METHODOLOGY

A. Maintenance, Repair and Overhaul in Civil Aviation

The civil aviation MRO industry is heavily influenced by safety regulations. Regulatory authorities, such as the International Civil Aviation Organization (ICAO) or the European Aviation Safety Agency, must specify safety norms that must be observed by the aviation sector (EASA). These guidelines are always being updated and amended. EASA defines the following fundamental guidelines (see Figure 3.1):

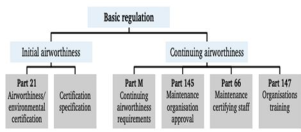

Figure 2 EASA basic rules in civil aviation Based on [Hin10, Eur 03](image: arcweb.com)

The first acceptance of the aircraft, for example, is one of the original airworthiness characteristics (Part 21). The continuous maintenance of aircraft navigability (Part M) by licensed maintenance groups is one of the ongoing requirements controlling airworthiness (Part 145). In addition, standards for employee certification (Part 66) and training have been established (Part 147). Maintenance activities must be carried out using approved tools and components in accordance with current rules and regulations..

A single aircraft manufacturer creates the Legal Maintenance Program, which can be amended by the airline or licensed MRO companies. Maintenance work is documented using logbooks. An airworthiness certificate of release [Eur03] documents will be issued when the task is completed. Civil aviation MRO businesses are allowed to organize and build their infrastructure, while dedicated authorities certify and monitor them.

B. Assignments and Goals of Aircraft Maintenance

[Jac92] claims that maintenance assures the continued ongoing improvement of a manufacturing facility's functioning, even if its nominal state is expected to deteriorate with time. A system's nominal state is defined by the fulfilment of all functional conditions [Deu12]. If operationally essential requirements are not met, the system or component operates outside of its specification and is labeled inoperative. The difference between the nominal and minimal condition is the wear-out reserve.

A system's or component's remaining service life is defined by its degree of wear. As a result, the essential maintenance goal is to slow or stop the wearing-out process and restore nominal conditions [Bie85, Lin05]..

The airplane is the above-mentioned production facility, and in the case of aircraft maintenance, the nominal condition is comparable to the aircraft's airworthiness [Eur03]. Following first airworthiness approvals, aircraft maintenance must continue to maintain aviation status by performing prescribed maintenance procedures..

'All of the processes that guarantee that the aircraft conform with all airworthiness requirements and can operate safely,' according to [Eur03]. From a macroscopic perspective (Figure 3.2, in box) [Lin05], the following processes can be depicted as aviation maintenance:

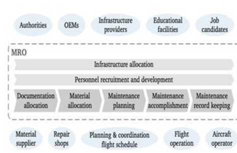

Figure 3. Aircraft maintenance global process. Based on [Lin05] (image: reliableplant.com

According to [Lin05], the maintenance planning, performance, and record-keeping operations are the basic jobs. Supporting functions include infrastructure allocation, personnel, records, and supplies. Significant stakeholders are also highlighted at key MRO interfaces. The next sections go through the documentation, material functions, and three important operations in further detail.

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C. Types of Maintenance

The goal of aircraft maintenance is to restore component condition to the manufacturer's specifications. Rodrigues [9] must enlist the help of skilled personnel to carry out these tasks, which entails a series of specific protocols that can be time-consuming. According to Serrano[10], the maintenance routine entails doing a series of tasks in order to keep the planes in constant airworthiness.. Aeroplane operators, according to Almeida[11], frequently employ five basic maintenance techniques that are divided into two categories: unplanned maintenance and service planning. Preventive, forecasting, and detecting procedures will be included in scheduled maintenance, however unplanned maintenance will necessitate immediate correction and a chance to address the problem of non-compliance. On sometimes, this is maintenance. Each kind has distinct characteristics and is utilized in accordance with the operational and complexity requirements of the equipment.

1) *Unscheduled Maintenance:* Unplanned Maintenance is defined as ad hoc defect correction, such as maintenance and repairs. When the fact is that there is a flaw or performance that is less than ideal, this type of maintenance is performed. According to Almeida[11], there is no time to prepare for the service. This maintenance usually comes at a high cost since an unexpected breakdown can result in a loss of productivity, a loss of quality, and large indirect maintenance costs.
2) *Planned Maintenance:* Planned maintenance seeks to prevent or correct everything that results from a performance or failure that isn't as expected. This upkeep may be divided into three categories: prevention, prevention, and control. A strategy based on defined time intervals is used in preventative maintenance to reduce the chance of failures or performance degradation. Preventive maintenance entails a set of procedures and actions targeted at keeping the aircraft functioning, which may be supplemented, if necessary, by a series of inspections followed by a number of corrective actions..

Manufacturers have adopted a routine of defect prevention, such as adopting component replacements based on working cycles or time, thanks to the use of precautionary parts wear tools observed in the experimental measurements and operational data. This implies that throughout the execution of the aircraft design, the components are changed according to prior timetables, as specified in design, safety, safety of life, or damage tolerance..

These components were frequently removed before they were genuinely affected, or failures occurred throughout the component's "useful life." Parts are replaced according to manufacturer-specified criteria in aeronautical follow-up, and all mechanic actions should be documented in the relevant documentation. According to Silva [8, preventive maintenance is always attempting to avoid failure, that is, to prevent.

According to the author, preventive maintenance is a set of programs that are typically repeated and allow a particular operational level to be validated and maintained. In protective systems, detective maintenance is undertaken to aid in the early discovery of flaws that are hidden or unknown to operators and maintenance employees.

This type of maintenance is made possible by computer technology and increasingly reliable data processing and transmission systems that operate directly on planes. Implementing preventive and detective maintenance methods is a potential option not just for decreasing unscheduled maintenance stoppages, but also for anticipating part requests for replacement during scheduled maintenance.

Based on the degree to which an aircraft's usage or failure is impacted and the strategy used, three traditional maintenance approaches can be employed (see Figure 3.3) [Zero]. [Zero]. [Men13] or [Vac06], for example, may have other classes of maintenance approaches.

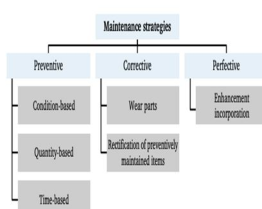

Figure 4 Overview of the conventional maintenance strategies. Based on [AM15, Zer00] (Image: researchgate.com)

Preventive maintenance is the proactive maintenance of a system's or component's nominal state before it fails (also see Figure 2.4). This is especially true when it comes to airplane safety-critical equipment. If a breakdown is expected, preventive maintenance is also undertaken. Preventative work relies heavily on maintenance. Condition-based maintenance causes crucial performance measures to exceed preset thresholds that are frequently assessed through inspections (CBM).

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The goal of corrective maintenance (or curative) is to fix a problem. Faults can be caused by components that are unavoidable, such as non-safety related failures, redundancy, or imprevised breakdowns of preventive measure parts that occur prior to the next planned operation (wear parts). Corrective maintenance, as shown in Figure 2.4, restores a component's nominal state and is only used when the wear-out reserve is low or non-existent. One advantage of this technology is the maximum functioning of a wear-out component reserve [AM15, Lin05, JAC92, Ach10]..

The best maintenance procedure, as seen in [Vac06, Deu10], is considered optional. When a certain technical advancement occurs, perfect maintenance seeks to not only restore nominal circumstances but also to attain an even higher level of safety or performance than before [Lin05]. ADs, SBs, and firmware upgrades are just a few examples.

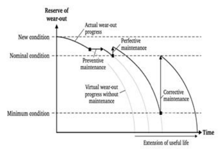

Figure 5 impact of maintenance concepts on reserve of wear out idealized Based on [Lin05] (Image : researchgate.com)

Figure 5 depicts the aforesaid wear-out reserve maintenance principles over time. Every servicing has been shown to help extend the usable life of a component by restoring or improving it. While preventive and perfect maintenance is generally offered for system conditions that are above or equal to standard, corrective maintenance is performed when the wear out state has deteriorated below nominal circumstances.

D. Predictive Maintenance Concepts

Despite having a lot of expertise and statistical data on the aforementioned maintenance approaches, MRO companies have only recently began to study new strategies, as the old methods have their own set of issues. Preventative maintenance is usually not carried out at the most opportune time. As indicated in Figure 2.4, this would be at the nominal condition's undercut. If no discoveries (above nominal condition) are discovered during a time-based evaluation, the work may have been done later, reducing maintenance efforts..

On the other hand, if the reserve for wear out is still big enough with preventative component replacement, the remaining useable life of a component may be lost. Ad hoc maintenance typically leads to profound operational faults since corrective maintenance is unplanned [Hei02]. These may arise from the airlines, such as an airline that is unable to adhere to the flight schedule, or from MRO, where immediate action is required that was not foreseen in terms of resources. Time constraints can occasionally lead to misconceptions, resulting in the implementation of subsequently ineffective measures (conserving failures) [Ach10].

As a result, further MRO activities may be unnecessary. Furthermore, a higher chance of consecutive failures reduces general safety[MS13].

Predictive maintenance concepts to prevent mistakes and failures are meant to be handled (see Section 2.3) by improving operational, resource, and resource planning to overcome such inconveniences while focusing on the core operations. This strategy is expected to save costs and enhance upkeep. Predictive maintenance is designed to function with only the bare minimum of needs [KM12].

Further, unneeded attempts would be undertaken if the minimum requirement was exceeded (similar to preventive maintenance). Any action taken under these conditions might result in an immediate failure (such as corrective repair) with operational consequences [Mik15]. Within known approaches, the classification of predictive maintenance in the literature varies. Predictive maintenance is a common method for preventing failure before it occurs (see Figure 6).

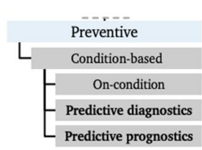

Figure 6 Classification of predictive maintenance strategies. Based on [Deu10] (sideteam.net)

A predictive maintenance strategy's impact may be varied when compared to standard techniques. Figure 3.6 demonstrates how its impact may be divided into aircraft (over time) and maintenance (under time) impacts:

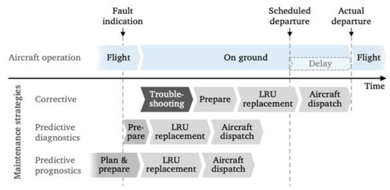

Figure 7 Visualisation of impacts of predictive maintenance (image: roadtoreliability.com

The two flight and terrain repeating stages in the upper section of Figure 2.6 represent aircraft operations. In the case of corrective maintenance, it is necessary to create a fault indication that must be taken into account. Because this is often not possible before landing, the subsequent maintenance processes (prepare, replace LRU with component faults, and dispatch of aircraft) are postponed. If the aircraft is put into service after the scheduled departure, there will be a delay.

Predictive techniques have an influence on maintenance, as seen in Figure 2.6. For starters, processes may be changed. Preparatory activity in the case of predictive techniques might be minimized or hastened, as shown in Figure 3.6. This is related to a rise in a priori understanding of a subject.

It's also possible that processes will become obsolete (troubleshooting in Figure 3.6). While maintenance repair necessitates insulation of the flaw in order to identify the appropriate steps, a predictive technique may allow the problematic component to be automatically identified ahead of time. Further troubleshooting automation [Fro09] aims to reduce misinterpretations and, as a result, errors in decision-making.

Figure 3.6 depicts the contrast between diagnostic and prognostic approaches, but it is simplified. Prognosis approaches are helpful for gathering data on the progression of deterioration.

While RUL prediction is still focused on identifying current fault states, it allows for planning ahead of time before critical fault states occur. It is possible to calculate the remaining useful life. Depending on how specific criteria are defined and data interpretation is done, diagnostics may also be used for prediction. Alternatively,.

In contrast to a corrective strategy, the formation of inaccurate statements may result in greater effort, such as the starting of extra maintenance events, depending on the sensitivity of a prediction model [Mik15]. The next section discusses component-specific maintenance in order to offer insight into the feasibility of predictive maintenance for components..

E. Component-specific maintenance

[Ver14] defines a system as "a separate arrangement of components that produce a working entity," defining a component as "the smallest constituent of the system." Many parts of airplanes are referred to be line replaceables (LRU). This indicates that these parts are made to be replaced quickly in a maintenance line during a typical flight operation at a maintenance station[Men13]. In most cases, LRUs may be found in the ATA-6 digits of chapter ATA-6.

From the aircraft level to the sector level, the air transport association establishes the numbering system (ATA). The subsystem and LRU levels are described below by unnamed OEMs. The PN, which identifies a specific component model and a single serial number, defines an LRU (SN). [MEN13, HIN10] TRADUCTION For further information on the ATA system, see [Air09]. In the following expressions, the terms LRU and component are interchangeable. The relevance of a certain LRU is determined by whether it requires immediate repair following a malfunction signal. As a result, the Minimum Equipment List (MEL) has been created (see Table 3.1). The Master-MEL is a component information required to keep an aircraft airworthy. It is given by the aircraft manufacturer. The MEL is just for LRUs that are linked to safety..

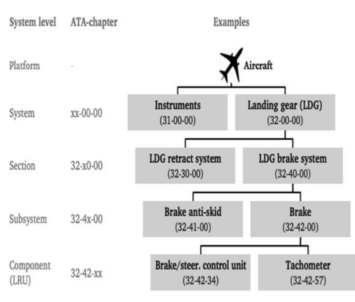

Figure 8 system levels and ATA numbering for the Airbus A320 family.

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V. SYSTEM ARCHITECTURE

A. Data set

Initially, the goal was to use a large number of real data sets for predictive maintenance to evaluate the RNN's performance in a variety of scenarios where time to failure could be estimated. Unfortunately, obtaining datasets that match these requirements is quite challenging. Finally, I decided to focus on the data set for Turbofan Engine Degradation (Saxena and Goebel, 2008). While this is a simulated dataset, it comes from NASA's Ames Research Center in California. This simulator is named after the CMAPSS, or commercial adaptable aero rocket motor simulation system, which is a suite of tools for modeling large-scale, authentic commercial turbojet data.

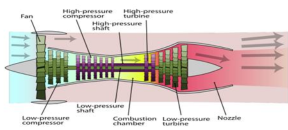

Figure 9 Turbofam Operation diagram from Aainsqatsi, 2008 (image: smglobal.com)

Saxena et al. (2008) published a paper on data generation that mainly consists of numerous multidimensional data. Each time a series is created from a separate engine, the data may be reviewed from a fleet of engines of the same type. Each engine has different starting wear and 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 factors are also included in the data. The data is contaminated by sensor noise.

The Dataset Directory contains datasets for training, testing, and algorithm is applied. Many multiple time series with the "cycle" as the time device and 21 sensor readings for each cycle are included in the data. Each row is likely to have been generated by another engine of the same type. The test data is the same as the practice data. The only difference is that the data is not shown when the failure occurs. The data is separated into four subsets: FD001 with one operating condition and one failure mode; FD002 with six working conditions and one failed mode; FD003 with one operating condition and two fault modes; and FD004 with one operating condition and two fault modes. The two failure modes are degradation of the fan and deterioration of the high-pressure compressor, respectively (Figure 3.16). Altitude, flight speed, and TRA are combined to create the six operating conditions. The engine usually starts up at the start of each series and then fails at some point throughout the run. When we look at figure 4.2, we can see that motor 1 was being watched until it failed in cycle 192. The goal is to estimate how many operational cycles are left until each component fails.

B. 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. Because 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. Because there are 100 engines in the training set and another 100 in the test set, there will be 20 batches totalling roughly 200 cycles. The split will be done with a random seed for consistency's sake (42). Batch refers to the sequence of observed cycles per engine..

C. 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++	105193
2	keras	Deep Learning for humans	Python	31664
3	opencv	Open Source Computer Vision Library	C++	26216
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++	17157
10	awesome-deep-learning-papers	The most cited deep learning papers	TeX	15409
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 10 Top deep learning projects from Badry, 2018 (image: slideshare.com)

Figure 4.3 shows a list of Github deep learning projects that were updated in July 2018. The most popular is TensorFlow TM, which is an open source software library built for high-speed digital computation. Computing can be easily deployed on a variety of platforms because to the flexible architecture (CPUs, GPUs, TPUs). Keras, on the other hand, is a robust Python neural network API that integrates with TensorFlow, CNTK, and Theano. Most importantly, it seeks to make fast experimentation easier.

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To do so, we'll combine these frameworks with Jupyter Notebook, an interactive workspace that lets you create and share documents that include Live Codes, Calculations, Diagrams, and Dramatic Texts. Colaboratory, another Google program that provides free GPU support for operating systems, is an extension of this concept.

VI. SIMULATION AND RESULTS

We trained the Collaboratory Model for 318 epochs (14 secs/epoch) using an Early Stopping patience for 30 epochs over validation loss. We utilize the RMSProp optimizer at 0.001 since the Keras handbook recommends that we do so. The data is scaled (min-max) and organized into batches (batch size = 16) to keep the RNN units in good shape.

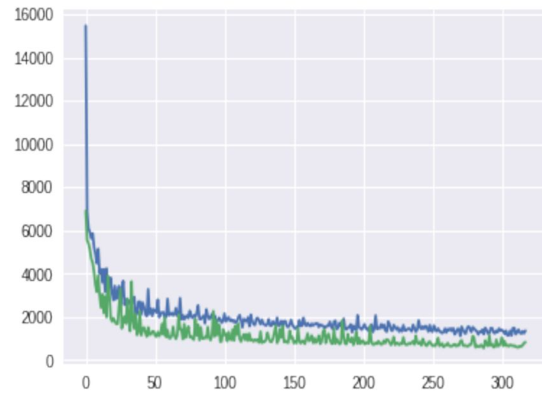

Figure 11 Training loss and validation loss (image: researchgate.com)

A. *Results of Regression Model*

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

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

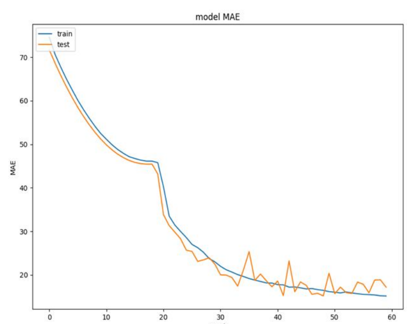

Figure 12 Train and test contrast in model MAE

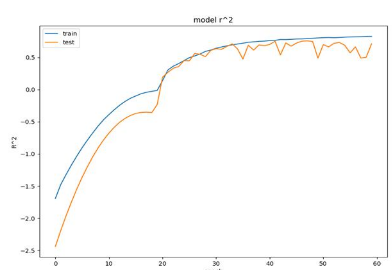

Figure 13 Train and test contrast in model r^2

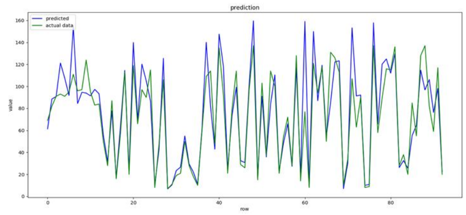

Figure 4.8 Comparison between actual and predicted data

B. Results of Binary Classification

Accuracy	Precision	Recall	F-Score
0.97	0.92	1.0	0.96

The following pictures show trend of loss Function, Accuracy and actual data compared to predicted data:

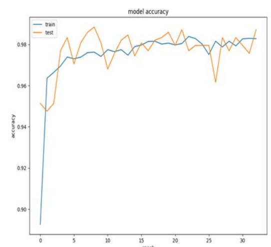

Figure 14 Model accuracy

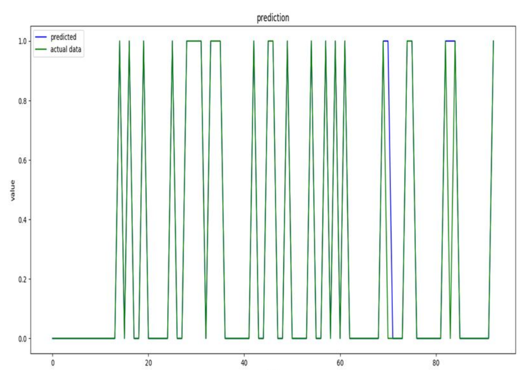

Figure 15 predicted data in comparison to the actual data

VII. CONCLUSION

1) 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:
2) Training on CMAPSS Data Sets: Because 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.
3) Lack of information: One of the advantages of predicting a statistical distribution is the ability to assess uncertainty. Aside from the mask, which is ignored by every model layer, we may experiment with inserting 'holes' in the data to observe how the Weibull Distribution pdf operates. We expect the variance to rise as a result of these gaps.

4) 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..
5) Weak students: This is a little out of scope, but Martinsson supplied me with a fascinating idea using several weak RNNs rather than a single stacked RNN. As a form of boosting strategy.
6) Various spreads: Why a woman? Perhaps there are alternative options that are better suited to certain conditions. The beta distribution would be interesting to try.
7) Regularization: While Martinsson's work on this subject is already excellent, I am certain that more can be done. Considering that explosive gradients are guaranteed over a suitable scale.

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

VIII. FUTURE SCOPE

In this study, the work done is based on LSTM model and is quite reliable in predicting the remaining useful life with good accuracy. The work takes in consideration the past data is in text form. In future the physical condition of the machine can be taken into the consideration as well. With that, the system will be more reliable. The utilization of images and extracting features from them to predict the condition of machine can also help in refining the results.

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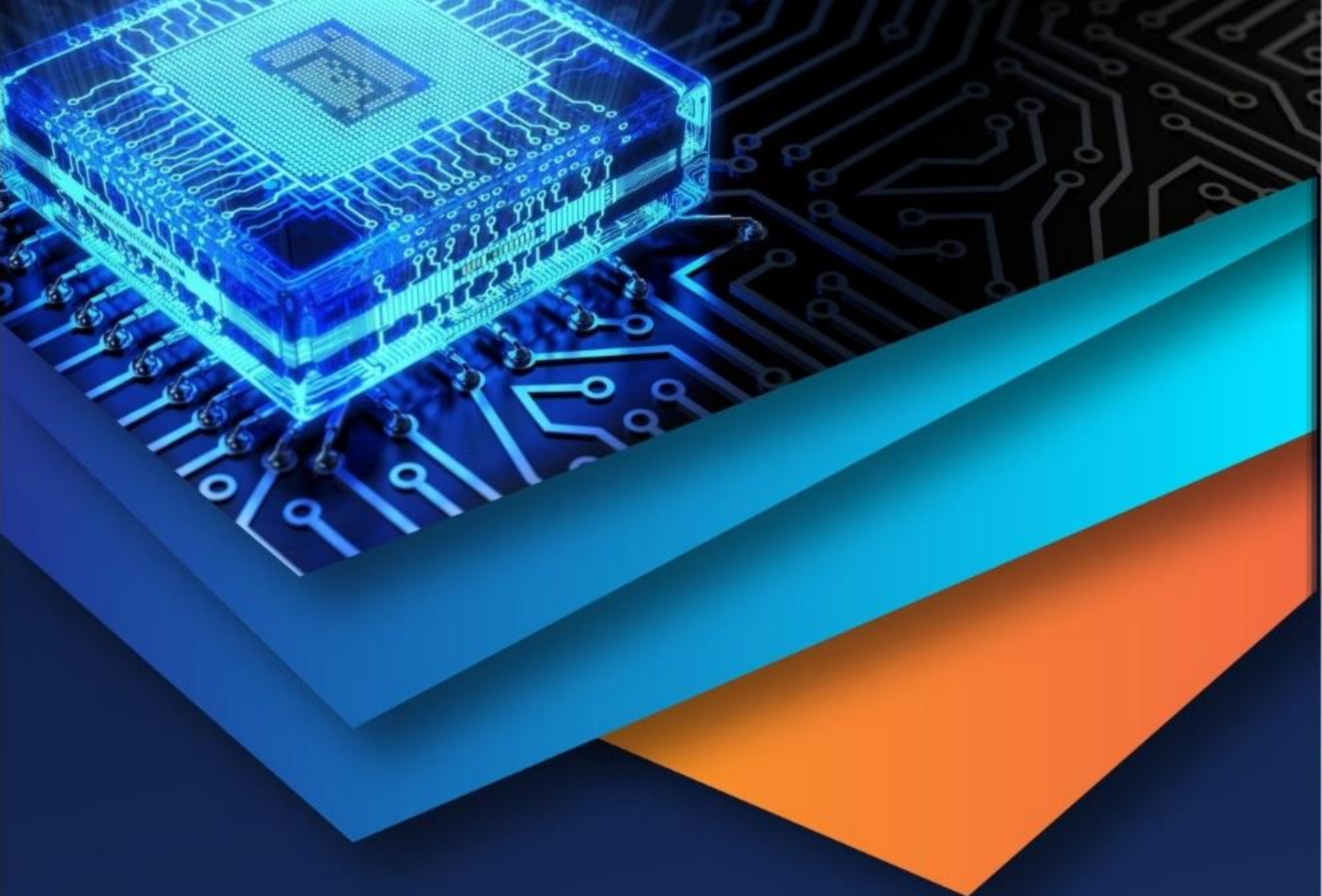

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