Machine Learning based Predictive Maintenance Framework for an Industrial Internet of Things

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Dedication

Dedicated to My family

For their Love, Kindness, and Encouragement

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Contents

List of Abbreviation

Abbreviations	Full form
IoT	Internet of Things
IIoT	Industrial Internet of Things
SIIoT	Social Industrial Internet
M2M	Machine to Machine
PdM	Predictive Maintenance
RF	Random Forest
PPO-LSYM	Proximal Policy Optimization Long Short-Term Memory
ANN	Artificial Neural Network
NN	Neural Network
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
DNN	Deep Neural Network
AWE	Automatic Washing Equipment
ML	Machine Learning
IPdM	Instant predictive maintenance
AI	Artificial Intelligence
LoRa	Long Range
RFID	Radio Frequency Identification

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Abstract

The Industrial Internet of Things (IIOT) is everywhere. These days the devices are equipped with sensors, and they generate huge amounts of data. Predictive maintenance (PdM) of automobiles not only helps in saving maintenance costs, and time but also automobile health. The huge amount of data helped us in predicting the PdM schedules. In this paper, we predicted the PdM schedules for automobiles. The data set of various automobiles is collected, in Pakistan, using Avometer in phase 1. The data set consists of features including minimum voltage, crank current, crank bolts, crank resistance, volts off, volts start, amperes, start resistance, and labels. We have used resistance in deciding the labels. When an automobile faced a high resistance value it is considered as it is closer to getting maintenance, so the automobiles with fire resistance value may sign the label as 1 and with low resistance value we assign them the label of 0. Label one means the automobile needs maintenance, whereas level 0 means the car does not require any maintenance immediately. In phase 2, We undergo a deep learning algorithm LSTM for predicting PdM schedules for various automobiles. The proposed solution showed 99.9% accuracy in predictions in 30% of the test set. The proposed solution it's compared with the benchmark solutions including ANN and RNN. Ian produced better results than RNN but not good enough than LSTM. ANN could achieve an accuracy of 85.5%. But RNN due to its vanishing gradient problem, couldn't perform well. It achieved only 54% accuracy which means that it is not good enough to predict labels. The application of the proposed solution will be very helpful for the fleet management systems that have thousands of cars, and they cannot keep a check on every car that requires maintenance or not. so, using a machine learning-based solution it becomes very easy for them to maintain their automobiles, regularly. Moreover, the proposed solution suggests an accurate predictive maintenance schedule so that maintenance costs can be reduced, time can be saved, and vehicle health can be maintained.

Chapter 1
Introduction

1.1 Industrial Internet of Things

Internet of Things (IoT) is a computing concept off connects various devices to each other over the Internet. The concept of IoT is to connect billions and trillions of smart devices that can sense their environment, it can transmit signals, process data, and can provide feedback. According to an estimation, there were 28 billion connected devices were working in 2021. Connecting these devices over the Internet has numerous benefits i.e., improving sustainability, and better connection between human and digital devices. IoT is solving many issues of society for example intelligent transport, automated healthcare pollution monitoring, and smart cities. [1]

The Industrial Internet of Things (IIoT) is a computing concept that is connecting devices to devices or machines to machines (M2M) And makes them capable of communicating with each other over automation applications. In this way, we can make our industrial system automated, efficient, and become capable of sustainable production. [2]

To increase the flexibility and scalability of industrial devices, it is advisable to use wireless connections between them. Previously, only ad hoc solutions were connected as wireless solutions however, later they become very difficult when moving parts of devices and hard to reach the connecting device. So, connecting devices in the industrial sector are big concern scalability and coverage in a large area will become costly and difficult to manage. With advancements in technology, cellular technologies for example 3G, 4G, and 5G promises to connect massive devices over long distances. However, they require a licensed band and infrastructure support. Connecting a large number of devices over the Internet at a lower cost, with limited hardware capabilities and energy resources, have other limitations also. Latency, cost, reliability, security, privacy, and energy efficiency need attention when we connect devices over the Internet. [3]

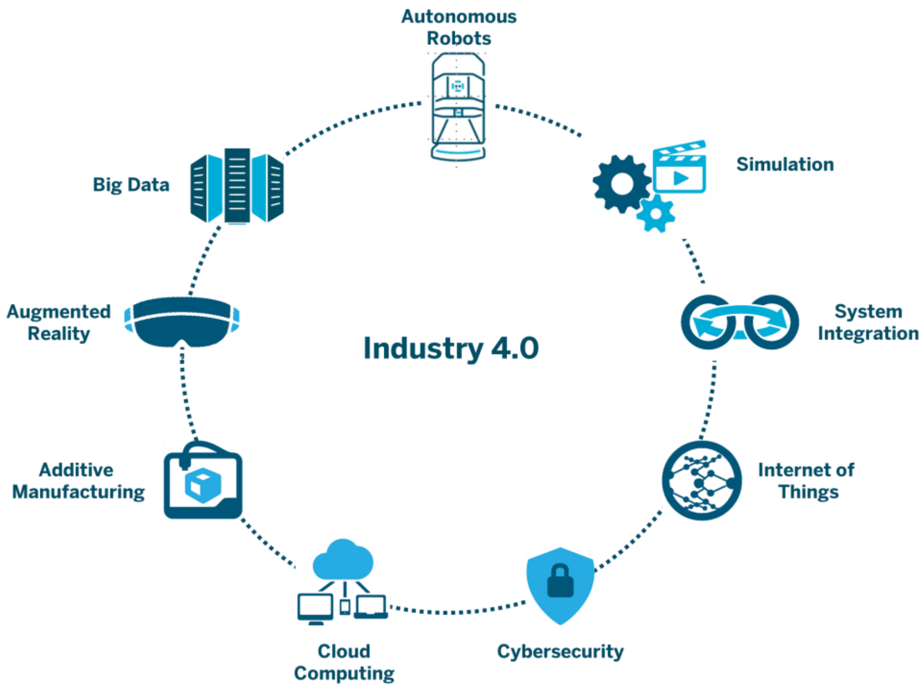


Figure 1: Introduction to internet of Robotic Things

1.2 Predictive Maintenance Framework

Predictive maintenance (PdM) is gaining attention in many multidisciplinary research groups. The prominence is because of its promise of creation, integration, data acquisition, storage, impressive, security, intelligence, and distribution. There happened 15 to 60% of total cost savings because of predictive maintenance on manufacturing operations [4]. So there is a need to study new technologies and apply them in the industry as they are bringing a revolution in the scenarios.

With the application of intelligent devices in the industrial sector, a huge amount of data is collected. The devices are incorporated with sensors, they collect data, and now the data is available to study and make sense. In the industry 4.0 environment, there are multiple scenarios where data is collected, so there are new opportunities to at least study the remaining life of the asset providing us data. With the help of predictive maintenance, action-based schedules can be generated for the equipment, according to its performance and conditions. This becomes exciting and the development of the future of the industrial sector can be seen through it. So disconnecting data from every part of the machine will become very important. this data will help save cost, and downtime and improves the quality and productivity of the machines. Besides other challenges, the main challenge faced by the industrial sector is knowing the Remaining Useful Life (RUL) often asset. This challenge is common in all disciplines, including automation, mechanics, and engineering [5].

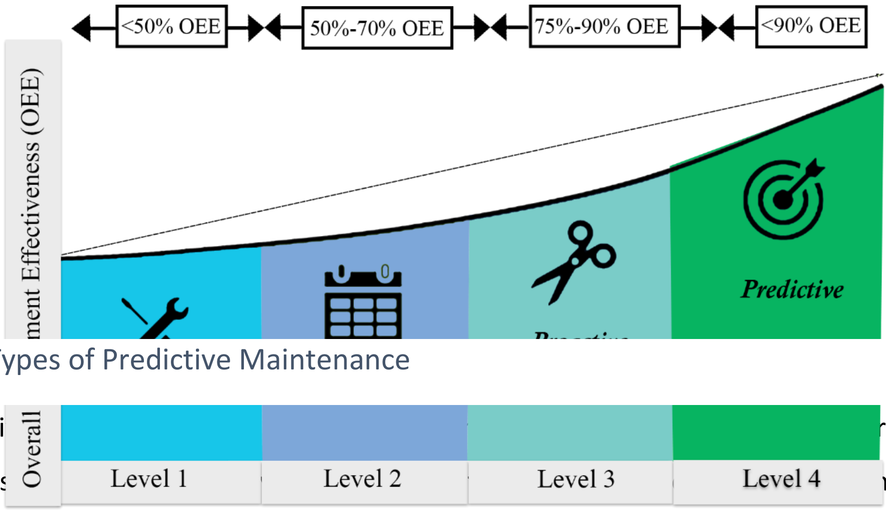


Figure 2: Types of Predictive Maintenance

correcti re are signs that it is hedules for maintaining a machine at specific times. In perspective maintenance, advice or discussions are made on how to avoid a machine to do a useless repetitive task. It is about decisions, optimizations, and improving the maintenance process. And in predictive maintenance schedules are made to utilize the time-based knowledge to report a failure before the breakdown of the machine happens [6].

According to Prognostics and Systems Health Management (PHM), there are four types of maintenance techniques, corrective, failure finding, fixed interval preventive, and condition-based maintenance. all these involve the use of sensors, algorithms, and math for finding the RUL. We have found another classification for the prediction that is physical model-based, knowledge-based, and data-driven. The physical model-based predictive maintenance involves mathematical modeling, conditions, the precision of conditions, statistical models, and measurement of failure. Similarly, knowledge-based productive maintenance involves hybrid strategies such as fuzzy logic or expert systems to reduce the complexity of a physical model. Data-driven predictive maintenance is the current modernized solution that involves statistics, artificial intelligence, pattern recognition, and machine learning algorithms [7].

1.3 Machine Learning based Predictive Maintenance

Predictive maintenance with machine learning is very tricky. Machine learning techniques perform differently on different data types, data sizes, and equipment collecting it. Predictive maintenance is also tricky in this case as there are many types of predictive maintenance techniques. selection of inappropriate predictive maintenance techniques, data size data sets, or equipment May leads to infeasible maintenance schedules that not only waste time but also resources. So, selection of accurate predictive maintenance techniques is important as the selection is a machine learning algorithm [8].

The huge amount of data collected by IoT devices, when applied to machine learning algorithms on it becomes valuable, knowledgeable information that can be used to increase the system dynamics, manufacturing process, decision support, monitoring, and condition-based maintenance. Data collection is not a difficult task these days. Information technology, communication networks, and computerized control It become possible to collect operational data. later with the application of different machine learning algorithms process the information and utilize it in different fault deduction and diagnosis processes [9].

Machine learning provides some advantages for example cost reduction, repair stop reduction, spare part life increases, inventory reduction, machine fault reduction, operator safety enhancement, repair verification, increase production, and an increase in overall profit. using machine learning is very beneficial in predictive maintenance scenarios. fault detection is one of the most important predictive maintenance components. it is very much needed in industries add every stage [10].

Machine learning is considered to be the most powerful tool that can be applied to several applications to develop intelligent productive maintenance algorithms. Machine learning grow very fast in that research area over the past decade. machine learning is basically the algorithms that became capable enough that on the historical or past data they learn the patterns and when new data is given to them, they analyze the previous pattern and give predictions on them in form of output. these are the general machine learning algorithms solving multiple problems, no machine algorithm is specifically designed for a particular domain to predict the specific task. Machine learning has wonderful advantages like the ability to handle multivariate data, extract hidden relationships within the data, deal with high dimensional data deal with complex dynamic and chaotic environments. Today machine learning is applied to several areas of the manufacturing industry, including maintenance, optimization, control, and troubleshooting [11].

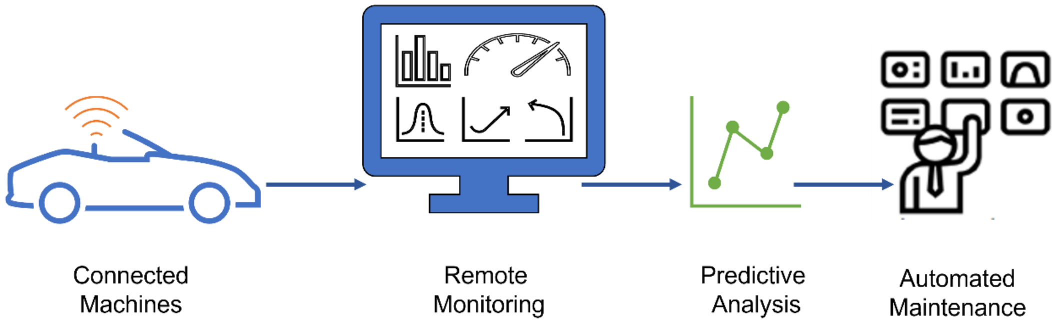


Figure 3: PdM Process

Fig 2 is dismonstrating that the sensors are installed on these connected machines, connecting them to the IoT platform. Real time data streaming happening with the help of sensor. Remote monitoring is basically the data monitoring that makes sure machines are in healthy condition. Machine learning model use historical data to predict failures, because proactive alerts of future maintenance are needed. And then automatic maintenance ticket generation for production scheduling, maintenance task schedule and technician assignment. operators only has to approve tickets for automated maintenance.

1.4 Problem Statement

There is a big potential for the Internet of Things (IOT) in private and industrial environments. Innovations, technologies, and developments in the automobile industry is happening every day, which in result producing a big amount of data. This data contains information that can be utilized in a productive way i.e., helping the end-users to save time, cost, and health of automobiles. [12] Industrial Internet of Things (IIoT) usually collect data by using smart devices, communication networks and by using big data analytics technique. The health of the automobile is associated with its maintenance of it. Any failure may lead to serious damages to automobiles. To avoid sudden failures, it is advisable to schedule automobile maintenance periodically.

Periodic maintenance can increase the maintenance cost. Most fleet management automobile companies face the issue of high maintenance costs or sudden failure. [13]

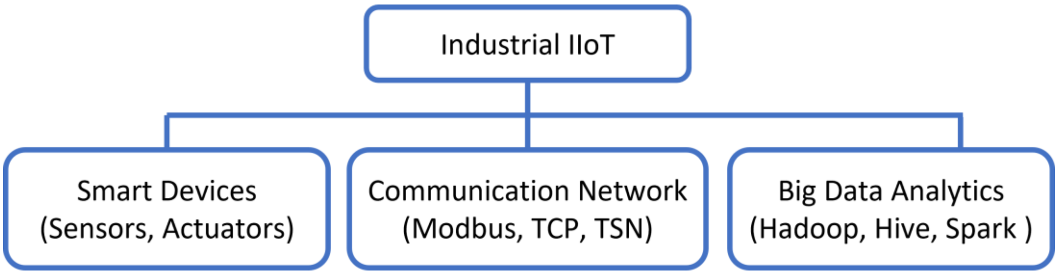


Figure 4: Key Elements of IIOT

There are two types of maintenance strategies Run to Failure (RTF) and Productive Maintenance (PdM). RTF is reactive maintenance in which the automobile undergoes maintenance when the breakdown occurs. This affects automobile health and increases maintenance costs as well. While in PdM, automobile undergoes scheduled maintenance. This maintenance is very tricky, it can either enhance the maintenance cost or reduce it. Moreover, when the automobile required maintenance, it is no longer useable until it got repaired or maintained. And when we prolong the maintenance schedule, accidents can happen, the repair costs can increase. So, predicting the Time Between Failures (TBF) accurately is very important. It not only helps in avoiding accidents but also saves time and reduced cost [14].

The interaction between the physical and digital world helped us in understanding the systems. The huge data that they produced is used in analyzing them and have predictions on them [15]. The predictions helped us in avoiding a situation or getting the maximum benefits out of them. In the case of automobile PdM schedule, predictions while utilizing the previous datasets helped us a lot in saving time, PdM cost, and health of automobiles.

In the modern era of technology, Deep Learning made our life much easier. The DL-based scientific studies of statistical models can solve tasks without explicit instructions but on inferences and patterns. PdM of automobiles is very highlighted these days. PdM-maintained automobiles have 20-30% more productivity than RTF-maintained automobiles [16]. In this way, they can help in enhancing the tangible company assets. So better predictions can not only help us in increasing automobile health, saves time and cost but also increase the company's assets. As a large number of devices are contributing to the IIoT environment, therefore, it is difficult to check the correctness of every device on daily basis [17]. Thus, the system requires an intelligent predictive maintenance framework that can alert the administration or replace the device before the actual fault or failure. In this paper, we will incorporate DL-based LSTM for PdM schedules of automobiles. This will help the automobile fleet management to have accurate predictions, for preventative maintenance.

1.5 Organization of thesis

The objective of this thesis is to device machine learning based predictive maintenance schedule for automobiles. in chapter one we have discussed Internet of Things, predictive maintenance, involvement of machine learning in these, and problem statement. in chapter 2 people discuss the literature in this regard. in chapter 3 we will discuss proposed methodology, that is a machine learning and deep learning-based solution. In chapter 4, we will discuss the results. And chapter 5 will be the concluding chapter of our research. We will mention the future advancement with this too.

Chapter 2

Related Work

Machine learning and deep learning continue to fascinate us with many possibilities of forecasting predictions and classifications. Here we are discussing some previous research that discussed the use of machine learning and deep learning efficiently predicting maintenance.

2.1 Machine Learning based Predictive Maintenance

Here we are presenting that review of those research papers that incorporated machine learning in their predictive maintenance proposed solutions. in our review we have explored multiple machine learning algorithms, in different scenarios. let's discuss machine learning proposing productive maintenance schedules in industrial sector, in real time, in medical sector, and some other miscellaneous sectors respectively

2.1.1 Predictive Maintenance in Industrial Sector

[18] discussed the Social Internet of Things (SIOT) in the industrial sector. In industries, there aremany types of machinery, all of them are made of axels, hangers, brackets, and many other elements. The concept of this paper was to predict the maintenance or the Remaining Useful Life (RUL) of the machine elements, predicting the downtime of the machine or to prevent it from complete disaster. The proposed solution was a three-layer architecture. The first layer was a base layer that contains sensors and actuators. The second layer was used in networking i.e., WLANs, GPS. The third layer was the application layer and was divided into two more layers interface sub-layer and SIoIT component sub-layer. The SIoIT component sub-layer includes the RUL predictor engine, relationship management, social agents, profile management, access control, performance management, ontologies, semantic engines, and data repositories. The interface sub-layer osf the application layer consists of industrial applications, human interface, machine interface, and service APIs. These layers are connected and share information to indicate a failure, predict maintenance and repair. The simulations are made in the Node-RED simulator. The time series dataset was taken from Prognostics and Health Management (PHM08). A template model was compared to a deep learning model i.e., Recurrent Neural Network (RNN). RNN predicts bearings remaining life with more accuracy (96%) than the comparison model. However, the proposed model should be implemented as a solution in the industrial sector.

This paper [19] presented machine learning approach for predicting concept drifts as predictive maintenance for many machines in industrial sector. Production machines produces the data. The stored data is in form of logs and online data is available in form of data streams. The data is fed to preprocessing pipeline for data consolidation, filtration, and buffering is performed and transform it in form of time series. For concept drift detection and prevention different regression-based machine learning algorithms were performed namely linear regression, random forest, and symbolic regression. This helps in saving time and material of industrial sector from machine breakdowns, thus increases predictability in industrial process. However, lack of good quality data, industries still lacked in practical implementations of predictive maintenance.

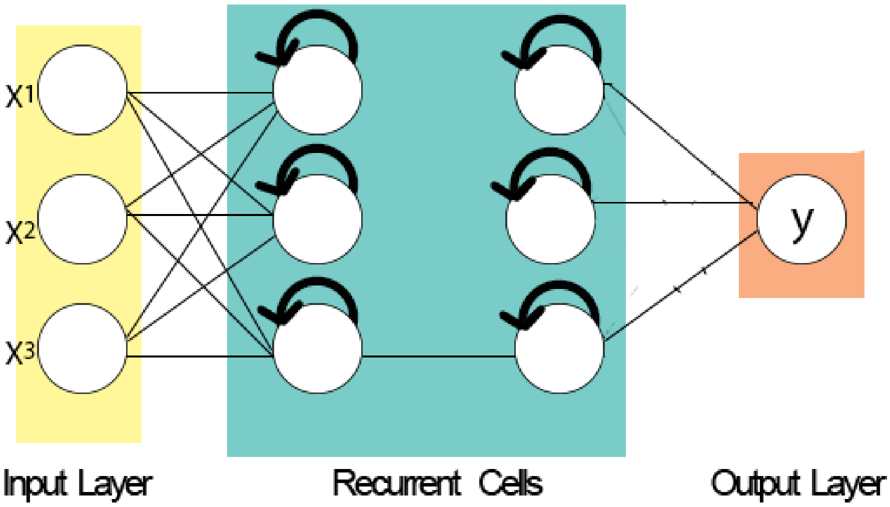


Figure 5: Basic Architecture of Recurrent Neural Network

In [20], proposed a ML based solution to predict predictive maintenance for production lines in manufacturing industry. Collecting data from sensors and detecting anomaly in real time helps in taking preventive measures without causing production to stop. The dataset is taken from baby diapers in a real-world production plant. RF (boosting and bagging ensemble models) outperformed the comparison models with 96.73% accuracy in detection results. However, the proposed solution should be tested with some other manufacturing line dataset.

Unplanned breakdown or critical machines in industries interrupts the production so there is a need to device data driven based predictive maintenance schedule. Many industries manually design schedule for machines for their maintenance. There exists human error as well. This causes a negative impact on overall production and down time of machines. This paper [21] designed deep reinforcement learning based predictive maintenance framework that automatically take decisions for machine

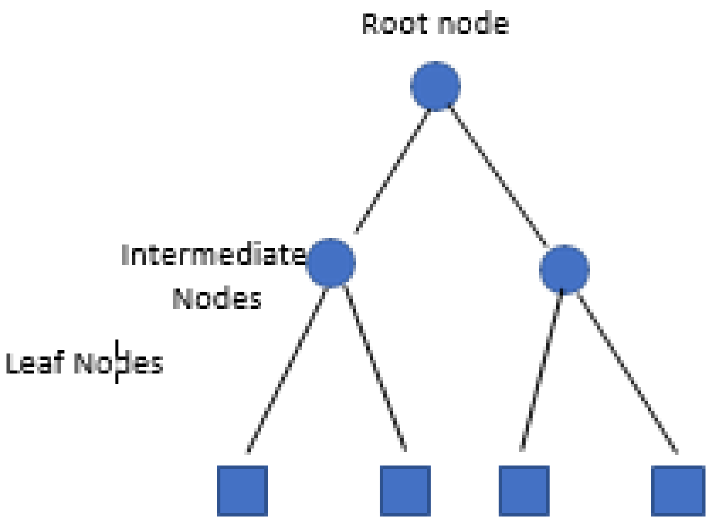


Figure 6: Basic Architecture of Random Forest

maintenance schedule based on stochastic environment. This framework involved sensors information resources of physical machines and humans for designing the optimal policies. The Proximal Policy Optimization Long Short-Term Memory (PPO-LSTM) solution is proposed, compared with human participants and other DRL models. The proposed solution outperformed the comparison human participants based predictive schedule and DRL models with 65% and 53% better results. Moreover, the proposed framework is performing better than the rest in terms of convergence, efficiency, flexibility, and simulation performance.

2.1.2 Real time Predictive Maintenance

Not only our industrial sector needs predictive maintenance, but our nuclear infrastructure also needs predictive maintenance our government, citizens, society, and many businesses rely on nuclear infrastructure systems. In paper [22] they used machine learning based algorithms to predict maintenance for nuclear infrastructure they have used support vector machines and logistic regression algorithms for this purpose. They explored and compared rare events in nuclear infrastructure dataset. They optimized parameters for both prediction algorithms. They bought novelty by correlating nuclear infrastructure data where the density of probability was very low.

Ref	Resource		Predictive Equipment Maintenance	Evaluation Matrices		Method	Fog/Cloud/Local /Edge
	Physical	Simulator		MSE	Accuracy		
[18]	✓	--	Machines in Industry	--	96%	3-layer Architecture	Local
[9]	--	--	Production Lines in Industry		96.73%	RF	Local
[10]	✓	--	Nuclear infrastructure		95%	SVM & LR	Cloud
[11]	--	✓	Machines in Industry	--	65%	PPO-LSTM	Edge
[12]	✓	--	Machines in Medical Center		84.116%	AI based architecture	Local
[14]	✓	--	Manufacturing Equipment		95.1%	GA	Fog
[15]	✓	--	Broken parcels in delivery	--	74.2%	GBC	Cloud
[16]	--	--	Installations in Buildings	In Range 0-0.11	--	LSTM	Local

Table 1 Comparison Analysis of different ML based PdM solutions

This framework classified number of cycles and predicted failure of nuclear plant infrastructure and engine. the proposed framework achieved 95% of accuracy in results with no performance overhead.

The aerospace industry started moving towards proactive and predictive maintenance so they can enhance efficiency, platform operational availability, RUL, and decrease lifecycle cost. The new paradigm of Digital Twin came into being when Multiphysics modeling was combined with data-driven analytics. The digital twin keeps the online data updated of different physical assets and predict the happenings of counterpart. This paper [23] proposed a framework for advanced aerospace that is formed by combining digital twins with IoTs. The dataset is collected from aircraft onboard sensors and offline non-destructive inspection and made them online by fog computing. Multiphysics, probabilistic and multiscale simulation was conducted using many soft and hard sensors. Multiple data fusion operations are used namely: sensor fusion, physics model fusion, data model fusion, sensor, physics-based model fusion, sensor and data model fusion, physics and data model fusion, sensor, physics, and data model fusion. The data utilized for high-level decision-making is possible by sensor-to-sensor, sensor-to-model, and model-to-model fusion. The designed model simulated successful results in predicting RUL. However, besides RUL many other factors needed to be predicted.

With the advancement in data science [24], ML based predictive maintenance started growing as it enhances the operational reliability, safety, and decreases the maintenance cost. In Aerospace, new aircrafts came with latest technologies and sensors. A large amount of data can be collected and should be used for benefits. Diagnostics and Prognostics techniques are more popular than predictive maintenance these days. ML base diagnostics and prognostics-based solution needs huge amount of data. Run-to-Fail Sensor data in running condition is in huge amount, but failure data is very restricted. To better capture this problem an Airbus DS has developed. In the roadmap of Technology development of ISHM and Predictive Maintenance, it's a simulation framework. The dataset was used from ISHM simulator, after preprocessing and feature engineering, SVM used for anomaly detection, KNN and SVM used for fault isolation, K means clustering measures hath level, RVM as degradation model and Arima for calculating RUL. However, the validity of this model should be checked with other aircrafts.

2.1.3 Predictive maintenance in Medical Sector

[25] presented an AI based framework for preventing machine failures in medical centers. The proposed solution is known as DeepHealth, that predicts sequence of time

series to have instant predictive maintenance (IPdM) of machines and health perceptions. DeepHealth were composed of two sub modules DH1 for health perceptions and DH2 for time series predictions. By utilizing self-attention mechanism, high-frequency vibration signals are captured to be used in DeepHealth. To collect the Automatic Washing Equipment (AWE) dataset, customized experiments were conducted on dual bearing rotating machine. On AWE and Case Western Reserve University (CWRU) the proposed solution achieves accuracy of 84.116% and 99.145% outperforming the comparison models. IPDM empowered AL model proposed is a generalized model and need customization to have efficient operation of industrial systems.

[26] proposed Green AI computing for IIOT application, by the utilization of edge computing that reduces energy usage in processing of high computational AI task. The research proposed a novel algorithm to gain the maximum usage by scheduling different AI tasks. It also proposed an edge computing based heterogeneous architecture that offload a task from servers to reduce the load. A small testbed is built with AI based IIOT applications to evaluate application energy efficiency with intelligent edge computing. The simulation results showed that the proposed architecture showed good accuracy with static scheduling and first in first out strategy in case of emergencies. The algorithm showed that 20-30% less energy consumed by static scheduling when doing online scheduling and first in and first out scheduling.

[27] discussed the use of smart devices including RFID tags LoRA tags QR code has been increased. All these are used in identification and tracking machines in industrial sectors. The data generated by these utilized in industrial automation. One of the most common problems faced is the failure of manufacturing equipment. The predictions help in repairing and replacing that machine or a part of it so that the whole production line will not affect. The paper presented a Genetic Algorithm based solution for predicting preventive maintenance in fog computing. The proposed GA model is compared with MinMin, FCFS, MaxMin, and RoundRobin, and simulations are performed in FogWorkflowsim. The results are evaluated on the real-time dataset and compared on the basis of execution time, cost, and energy usage. The proposed solution performed better than the comparison solutions by achieving 0.48% better execution time, 5.43% reduced cost, and 28.10% decrease in energy usage. As a whole model achieved 95.1% and 94.5% accuracy on two datasets. However, the introduction of reliability and security in the communication of IIoT devices should be considered.

2.1.4 Predictive maintenance in Other Sectors

[28] proposed a solution for the delivery of parcels effectively. A framework is proposed for monitoring and tracking the shipped parcels, named as RedTag. IoT-enabled devices tracks package at each step. The proposed solution designed for smart data transmissions, managing, and storing them, and analyzing them. ML based solution is designed that predicts weather the object inside parcel is breakable or not. The model is tested on event related real world dataset containing about parcels transport. Gradient Boosting Classifier classifies the parcels as broken or safe with 74.2% accuracy. This paper was first attempt in smart good transport logistics, however more work should be done to increase the accuracy in predictions.

[29] proposed machine learning based framework for installations in buildings. The framework included data collection, data processing, model development, fault notification and model improvement, respectively. LSTM based model was proposed to predict the failures in installations. The dataset was collected by using IoT devices from heating ventilation and air (HVAC) and a building automation system (BAS) for three months. The RMSE ranges between 0 to 0.0125. The limitations in the research are, the dataset should be of 1year so that proper training and testing can be performed, and there was no comparison model in the paper, the proposed solution should be tested with the latest techniques.

Chapter 3

Methodology

From the literature we reviewed, we concluded that machine learning and deep learning technologies are working better than the existing statistical techniques. So, the general methodology for label prediction is as follows:

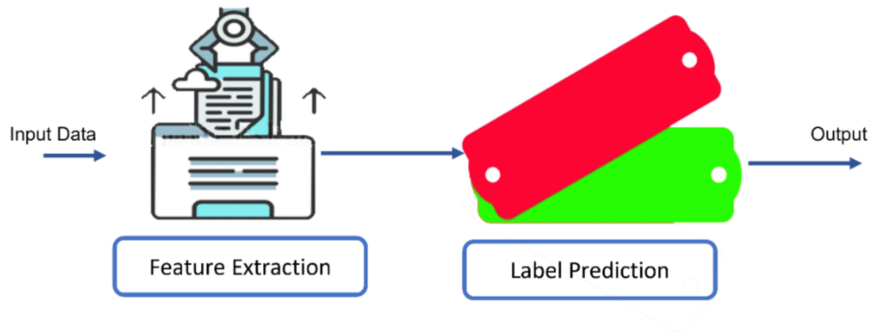


Figure 7: Generic Label Prediction Strategy [30]

3.1 Proposed Methodology

As we are working with predictive maintenance predictions for automobiles, we divided the model into two phases the first one is data collection and feature extraction, and the second one is predictions. Let's discuss each phase in detail as follow:

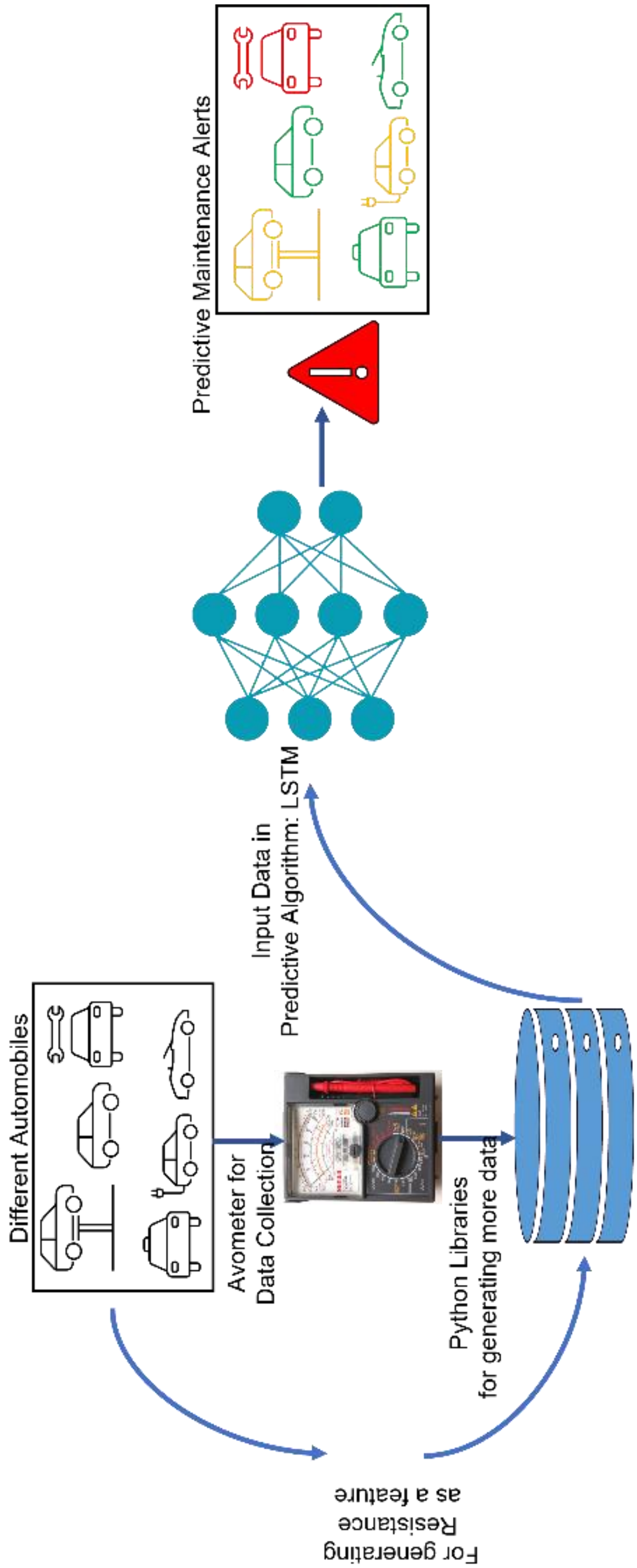


Figure 8: LSTM Based proposed Label Prediction Strategy for PdM schedules

3.2 Phase 1: Data Preparation

We have collected the data set from automobiles using an Avometer (AVO), in

Pakistan.

3.2.1 Avometer

AVO-meter stands for Ampere, Volt, Ohm- meter. It is an instrument which can measure the Current (both DC or AC in ampere), Potential Difference, (between two points in a circuit in Volts) and Resistance in a circuit in Ohms. It is an essential piece of equipment when locating fault in a circuit, electric or electronic.

Figure 9: Avometer

It is a vital instrument for estimating volts, ohms, and amperes rapidly and without any problem. As well as finding flaws in electric or electronic circuits. Multimeter essentially comprises of delicate moving curl galvanometer which can be changed over into Multirange ammeter by associating an ongoing estimating circuit. Multirange voltmeter by associating a voltage estimating circuit. Multirange ohmmeter by associating an obstruction estimating circuit. A switch called work switch is utilized. The capacity switch is the capacity selector switch that interfaces the galvanometer with the pertinent estimating circuit i.e., current, voltage, or obstruction. This is multirange voltmeter. This part comprises various protections every one of which is associated with the moving curl of the galvanometer in series. It connects with the assistance of a ring switch. The worth of every opposition relies on the reach voltmeter. The series protections are called multipliers. It can gauge AC voltage yet, for this reason, AC is first changed over into DC.
It is multirange ammeter. This part comprises the number of low protections associated with a galvanometer in the equal circuit. These protections rely on the scope of the

ammeter. This circuit likewise has a reach choice switch SR used to choose a specific reach. It is multirange ohmmeter. This part comprises a battery of emf Vo and a variable obstruction Rs associated with a galvanometer of opposition Rg in series. At the point when the capacity switch is changed to situate X3, the circuit is associated with the X and Y terminals of the Avometer.

Prior to estimating the obscure obstruction, it is first focused which implies that we cut off terminals X and Y of the Avometer and change Rs to deliver full-scale diversion. A computerized multimeter incorporates an electronic counter and LCD present as opposed to a moving needle and ruler. Computerized multimeters, which are somewhat significantly more costly than simple multimeters, have come to be a widely utilized multimeter type because of their basic perusing as well as high exactness aspect. The significant elements are more exactness and accuracy, simple to work, simple to peruse, eliminating the understanding blunder .

3.2.2 OHM's Law

Ohm's law states that the current through a conductor is proportional to the voltage across the conductor. This is true for many materials provided the temperature remain constant. The constant of proportionality, **R,** *R* is the resistance, and the unit is the ohm, with symbol **\Omega**. The relationship can be written as:

$$V=IR \qquad \text{Eq (1)}$$

where **V,** *V* is the voltage across the conductor and **I,** *I* is the current flowing through it. If a component is ohmic (it obeys Ohm's Law), then its resistance must be independent of current and voltage.

We computed the resistance starting, resistance stable by using ohm's law

$$R = \frac{V}{I} \qquad \text{Eq (2)}$$

Where R is resistance, V is voltage, and I is current. We have collected a dataset for 100 automobiles and generated the dataset for1,00,000 automobiles by using panda's library. Where there is higher resistance, there is lower current flow. This helped in assigning labels to the dataset. We assigned 1 to those automobiles that have low resistance values and 0 to those automobiles that have high resistance values [33].

3.3 Phase2: Predictions and Evaluations

In phase 2, we perform predictions on our data set. for this we have used LSTM based machine learning model. let's discuss the composition of in detail. at the end of this section, we will discuss the comparison benchmarks solutions and their composition. these includes ANN, and RNN.

3.3.1 LSTM (Long Short-Term Memory)

LSTM is a refined variety of RNN, resolving the issue of evaporating inclination. It was presented by Hochreiter and Schmidhuber in 1997. It deals with the backpropagation rule as it should compute slopes for the interaction enhancement. It changes weight as indicated by the blunder rate it works out at every c cortanaell level. LSTM is sufficiently skilled to learn long-haul conditions for quite a while utilizing its memory unit.

The critical part of the LSTM is the cell state. It runs straight down the whole-time ventures with just minor however significant communications. LSTM can add or eliminate data from the cell state utilizing a few entryways. Each door is made of a sigmoid brain network layer. These sigmoid layers produce yield numbers somewhere in the range of 0 and 1, which addresses how much data every part ought to be let through. 0 makes next to no difference through the layers though 1 addresses letting all that through 3 layers out of the four are utilized to control the cell state tanh.Consider the following diagram to understand the LSTMs architecture. LSTM consists of three functions of gate controllers.

•Forget gate f_t decides which part of long-term state C_t should be omitted.

• Input gate i_t controls which part of C_t should be added to long-term state *ct*

• Output gate O_t determines which part of C_t should be read and

Outputs to h_t and O_t.

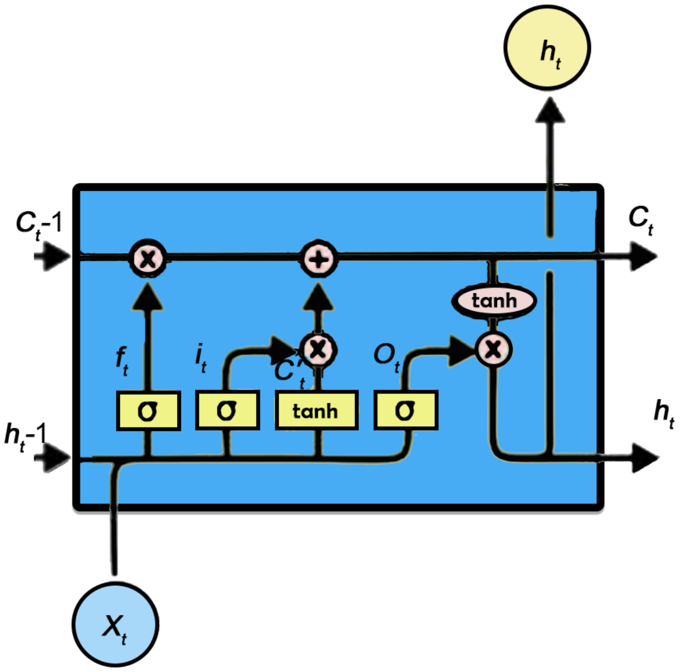


Figure 10:Basic Architecture of LSTM

In the above figure, x_t is the input into the LSTM cell, ht-1 is the output of the previous cell and ct-1 is the cell state that is received by the current cell. It helps in the prediction of the current cell. First gate is the forget gate, the equation is below:

$$f_t = \sigma\left(W_f.\ [h_{t-1}, x_t] + b_f\right) \quad (3)$$

The sigmoid of the multiplication of the input added with the bias value happened here. This layer helps in returning 0 and 1, whether we need this information in prediction or not.

The next gate is input gate, consider the below mentioned equation.

$$i_t = \sigma(W_i.\ [h_{t-1}, x_t] + b_i) \quad (4)$$

$$\tilde{C}_t = tanh(W_C.\ [h_{t-1}, x_t] + b_C) \quad (5)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (6)$$

The first part of the input layer equation is like the equation of forget gate, except by the weight and bias. It undergoes a sigmoid function. In the next two equations, it controls which part to add as cell state using tanh function.

The component of LSTM can be separated into 3 phases. The first is choosing what data is to be separated from the cell state. This is finished by the sigmoid layer otherwise called the ft neglect door. It notices ht-1 and xt from the last advance performed, to deliver a result range somewhere in the range of 0 and 1. The following phase of this cycle is to what data will be put away in the cell state. The sigmoid layer is named as the result entryway It decides the qualities that require refreshing. A while later, another vector of the proposed values is made by the layer. These qualities are named Ct and are added to the cell state. Then old cell state Ct-1 should be refreshed into the new cell state Ct. The last stage is to figure out what values are framework will give as the result. The result relies upon the cell state yet a filtered version of it. First, the sigmoid layer picks which parts of the cell state will be presented as a result. Then the cell state is put through the tanh capacity to change over the characteristics between - 1 and 1, the resultant of which is them increased with sigmoid layers result to come by the outcome [34].The mathematical equations for this stage are:

$$o_t = \sigma(W_o .\ [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t * \tanh(C_t) \tag{8}$$

3.3.2 Artificial Neural Network

ANN is moving nowadays; it is exceptionally involved in gauging. It works like a mind. It takes input and learns it, so that, later it can anticipate inconspicuous result on concealed information. A phony cerebrum network has something like three layers that are interconnected. The primary layer includes data neurons. Those neurons send data to the further layers, which subsequently will send the last outcome data to the last outcome layer. All of the interior layers are concealed and are molded by units that adaptively change the information got starting with one layer and then onto the next through a movement of changes. Each layer acts both as a data and result layer that allows the ANN to see more confounded objects. All in all, these internal layers are known as the cerebrum layer.

The units in the cerebrum layer endeavor to learn about the information gathered by checking it as shown by the ANN's internal system. These standards grant units to create a changed result, which is then given thus to the accompanying layer. An additional plan of learning rules uses backpropagation, a cycle through which the ANN can change its outcome results by thinking about botches. Through backpropagation, each time the outcome is named as an error during the coordinated readiness stage, the information is sent backward. Each weight is revived somewhat to the sum they were responsible for the error. In this manner, the goof is used to recalibrate the weight of the ANN's unit relationship by thinking about the differentiation between the best outcome and the authentic ones. Eventually, the ANN will "understand" how to restrict the chance for goofs and unwanted results.

Setting up a phony cerebrum network incorporates perusing allowed models for which there are a couple of related computations. An ANN partakes in a couple of advantages yet one of the most seen of these is the way that it can truly acquire from seeing enlightening records. Thusly, ANN is used as an erratic limit assessment device. These sorts of gadgets help with surveying the savviest and ideal techniques for appearing at game plans while describing handling limits or appointments. ANN takes data tests rather than entire instructive assortments to appear at plans, which saves both time and money. ANNs are seen as truly fundamental mathematical models to overhaul existing data examination progress [35].

They can be utilized for some functional applications, for example, prescient examination in business insight, spam email discovery, regular language handling in chatbots, and some more.

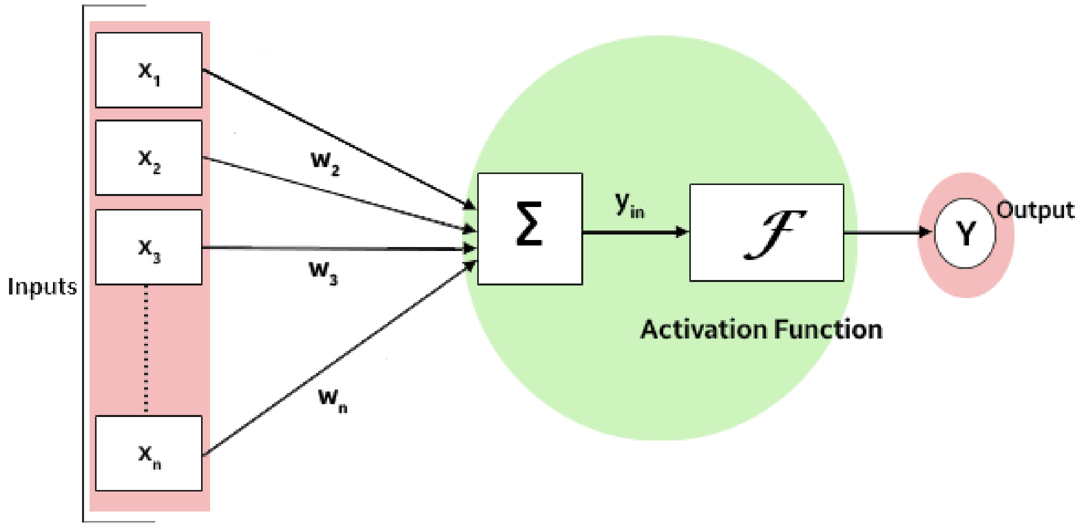


Figure 11: Introduction to Neural Networks

3.3.3 Recurrent Neural Network (RNN)

Recurrent neural networks are the cutting-edge calculation for consecutive or time series information. They are extremely strong, and hearty planned with interior memory. They were made during the 1980s. They have high computational power with huge information. The genuine potential was brought to light and the development of LSTM carried RNN to closer view during the 1990s.

RNN accompanied their inward memory. They think about the earlier contributions, as they impact the ongoing info and result. They dislike customary DNNs, taking into

account that the data sources and results are autonomous of one another. All things considered, the result of RNNs relies upon the past succession of data sources.
To exhibit the working of RNN, let us think about the accompanying figure. it is the contributions to grouping structure, ht is the result, where A is the RNN black box. From the figure, clearly, a measure of data is being passed to another cell. The cell used the data it got in estimating the arrangement. This is the manner by which it works.

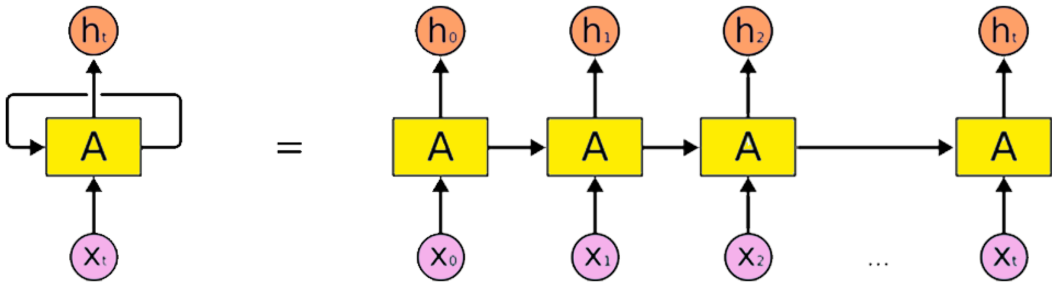


Figure 12: Recurrent Neural Network (RNN)

Not like all DNNs, RNN considers the information coming from the previous cell that increases the prediction accuracy but at the same time there was a problem with this structure. The problem is known as vanishing gradient or long short-term memory problem.
Now consider, if x2 is the input and it utilizes the information received from its previous cell. But in case, like word prediction, what happens if the x2 input requires information a few blocks behind it (not exactly behind it). In this case, the cell forgets that information that is a few cells behind that. This is called the vanishing gradient problem. It means the RNN structure could not remember the weight and biases value it utilized in the previous cells and that weight or bias vanishes. The similar condition is known as long term dependency problem, where the cell could not remember the long term stored information/weight/biases [36].

3.4 Evaluation

3.4.1 Accuracy

Accuracy is a metric that generally describes how the model performs across all classes. It is useful when all classes are of equal importance. It is calculated as the ratio between the number of correct predictions to the total number of predictions.

$$accuracy = \frac{True_{positive} + True_{negative}}{True_{positive} + True_{negative} + False_{positive} + False_{negative}} \qquad \text{Eq (8)}$$

Here is how to calculate the accuracy using Scikit-learn, based on the confusion matrix previously calculated. The variable acc holds the result of dividing the sum of *True Positives* and *True Negatives* over the sum of all values in the matrix [37].

3.4.2 Mean Absolute Error (MAE)

MAE measures the distance between the actual data and the predicted data. It provides us with the absolute average between the actual and forecasted data points [38]. The formula is as follows:

$$MAE = \sum_{i=1}^{N} \frac{(\widehat{y_i} - y_i)^2}{n} \qquad (9)$$

Where $\widehat{y_i}$ is predicted value, y_i is actual value and n is the number of observations. The more it is close to zero, the more accurate results are.

3.4.3 Mean Absolute Percentage Error (MAPE)

To calculate accuracy of any forecast system, we calculate the MAPE value. Accuracy is measured in percentage. It is calculated by below mentioned formula:

$$MAPE = \frac{100\%}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \qquad (10)$$

Where, N is the number of observations**,** yi is actual value and $\widehat{y_i}$ is forecasted value. The more it is close to zero, the more accurate results are [38. We have observed the limitations of MAPE when calculating it for Price forecasting. Fortunately, we have load values greater than 0, so we calculated the MAPE accurately. But we have 0 and negative values in price forecasting and thus we get a huge value of MAPE even when there happened a small deviation but in a negative or nearly zero value. For this purpose, we are calculating Mean Absolute Error (MAE) for Price forecasting especially and for load values as well.

3.4.4 Root Mean Square Error (RMSE)

The standard deviation of the prediction errors is known as RMSE. The prediction errors are generally consideration of prediction value that how far it is from the regression line [38]. It is calculated by below mentioned formula:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\widehat{y_i} - y_i)^2}{n}} \tag{11}$$

Where, i is the number of observations, yi is actual value and $\widehat{y_i}$ is forecasted value

Chapter 4

Results and Discussions

The proposed solution worked in two phases the first phase is data collection. In this phase, we used Avometer to collect a dataset of automobiles. We collected data on various features, the main feature is resistance that we calculated using ohms law. We assign labels to the data based on resistance. Higher the resistance, lower the current. So, the automobile facing high resistance needs maintenance.

4.1 Exploring Dataset

The data set consist of features including minimum voltage, crank current, crank volts, crank resistance, volts off, volts start, amperes, start resistance, and labels.

4.1.1 Minimum Volts

Minimum voltage means average voltage. In modern vehicle car batteries are of 12V DC. But the minimum voltage to start a car can be lower or higher than this limit. The attached craft representing the minimum boards required by an automobile to start.

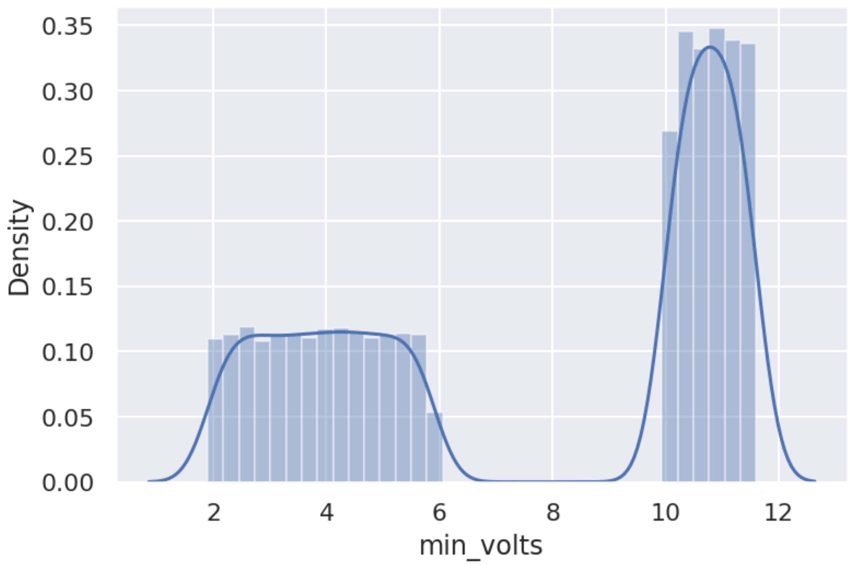
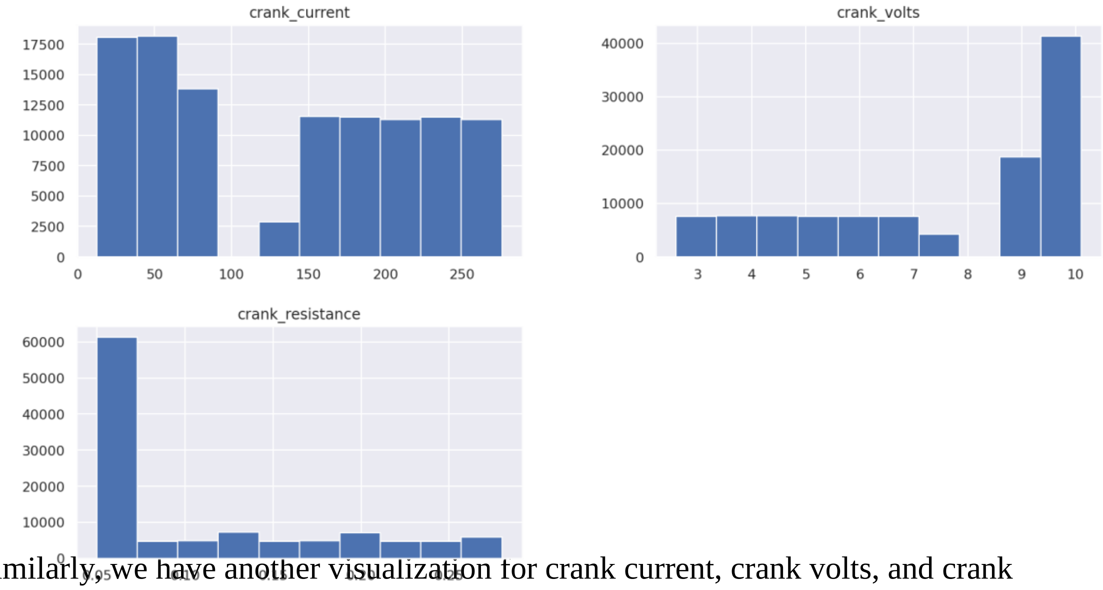


Figure 13: Visualization of Features: Minimum Volts

Knowing minimum volts of any automobile is very important these days. the graph representing the minimum votes required by the automobiles of the data set is somewhere between 2 and 12 volts, respectively.

4.1.2 Crank current, Crank volts, and Crank resistance

Crank current is the starting current that a battery can discharge end sustain for 30 seconds in normal climate conditions 0 degree Celsius, at least. To start any be vehicle, 400-500 cold crank current (CCA) are required. This includes SUVs and pickup trucks. However small car battery requires 150 CCA to start, and large trucks required 400-500 CCA. the graph attached showed that for automobiles the crank current value is up to 250. Crank volts is the current that starter motor draws from the battery to start, and it is usually 9 to 10 volts. as it is shown in the attached graph the crank bolt is between 3 to 10 and amperes. Similarly, crank resistance is from 0.05 up to 0.25, as seen in the graph.



Similarly, we have another visualization for crank current, crank volts, and crank resistance. The graphs showed crank rant variations between -100 to 400, flights between density 0.0 and 0.006. Similarly crank voltage lies between 0.0 to 125. And

Figure 14: Visualization of Features: Crank Current, Crank Volts and Crank Resistance

cra

of current, voltage and resistance required by different automobiles to start the engine.

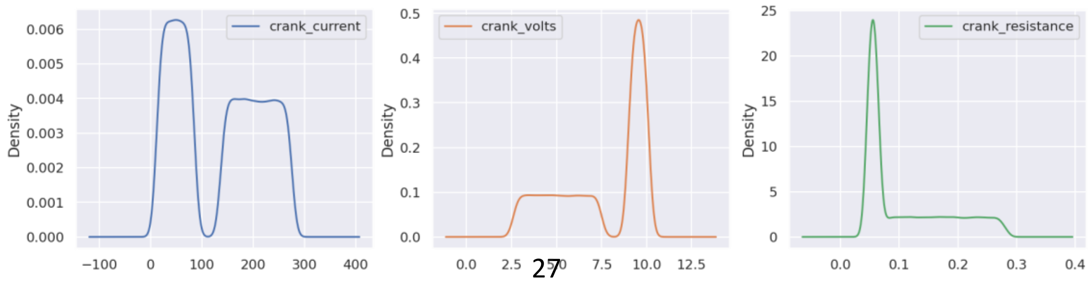


Figure 15: Another Visualization of Features: Crank Volts, Crank Current and Crank resistance

4.1.3 Volts off, Volts start

Volts off is that is required by the engine to stop, similarly what it starts is the voltage it is required by an agent to start. it is measured in ampere.

4.1.4 Amperes

The current is measured in amperes. the attached graph showed that the grant required by any automobile to start or perform activities is between 0 to 12 amperes.

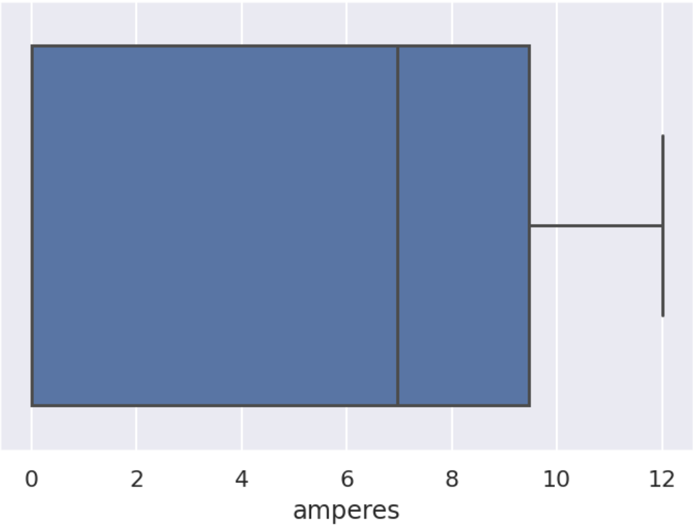


Figure 16: Visualization of Features: Amperes

4.1.5 Start resistance and Labels

The start resistance is that existence that is placed by the engine well it is about to start, the test crowd showed that it is maximum at the start and will eventually decreases with time. Another graph that showed the label, these are zero and one. The liberals showed the state of car either it requires maintenance or not.

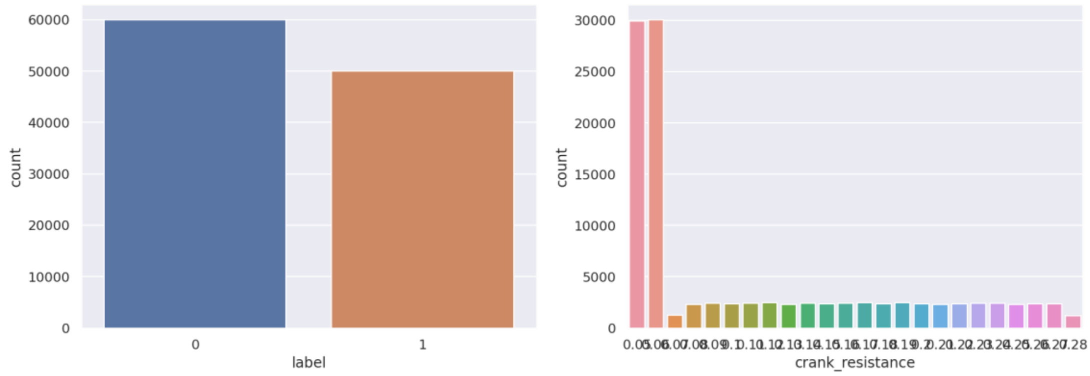


Figure 17: Visualization of Features: Start Resistance and Labels

4.2 LSTM based Model training

We used Keras-based LSTM layers for predicting the preventative maintenance schedule labels accordingly. We split the dataset using test_train_split. We used 70% data for training purposes and 30% data for testing purposes. We have used the LSTM model for automobile predictive maintenance predictions. The hyperparameters used for training the LSTM model are as follows: Stochastic Gradient Descent (SGD) is the best optimizer for regression problems. It is very efficient and easy to implement, however, it is sensitive to feature scaling. Sparse Categorical Cross entropy was used to calculate the loss between the labels and predictions.

Table 2:List of Hyperparameters for model tuning

LSTM units	128
Dense units	10
Optimizer used	Stochastic Gradient Descent
Loss function	Sparse Categorical Cross entropy
Activation Function	RelU, Sigmoid
Epochs	10

LSTM is an advanced version of Recurrent neural networks (RNN). LSTM solved the vanishing gradient problem of RNN. The proposed solution is compared to the benchmark RNN model, and it achieved almost 95% of the results. RNNs are the state-of-the-art algorithm for sequential or time-series data. They are very powerful and robust designed with internal memory. They were created in the 1980s. They have high computational power with massive data. The true potential was brought into the light and the invention of LSTM brought RNN to the foreground in the 1990s [22].

The training accuracy of NN, RNN and LSTM is 1 however there is a difference in accuracies of test set. The attached graph showing the training history of the LSTM model. blue line is representing the accuracy while orange line represents the validation of the model. both the lines are constant which means that training accuracy and its validation remains constant throughout the training. this means the model has been trained very well.

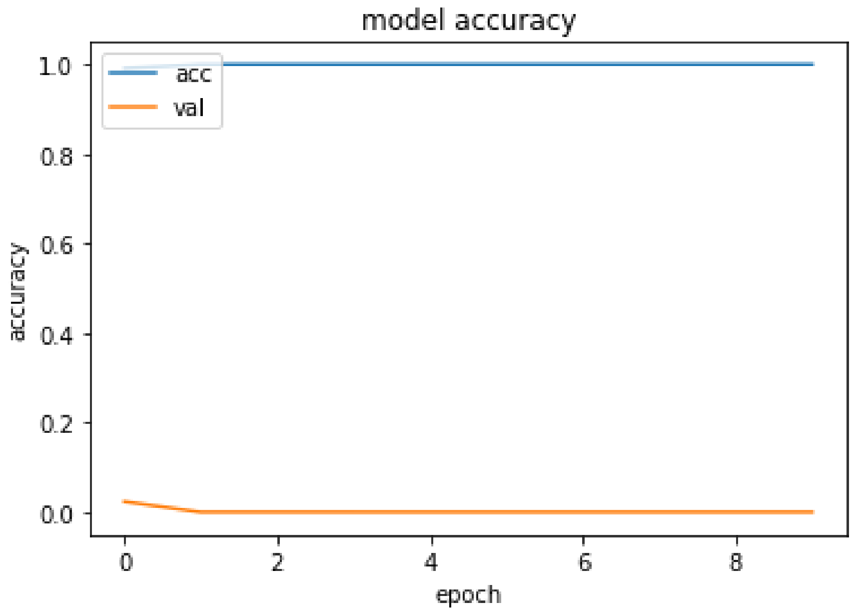


Figure 18: Model Training Graph

The model's accuracy remains consistent overall the 10 epochs, as seen in the attached graph. After considering the training of model, let's discuss the prediction accuracy of it. So, after training the model, we did predictions on the test set, that is 30% of that original set. the 30% of the original set comprises of 30,000 observations, so we can't we compile all the 30,000 observations in one graph. So here we are incorporating 100 observations in each graph, randomly. So, in the attached graph it is obvious that LSTM model produced almost 99% of the accurate results.

4.3 Predictions and Results

As already mentioned, the test set is 30% of the actual set. So, for testing purpose we have almost 30,000 rows predicted. Comparing all those 30,000 rows altogether is a difficult task, as you cannot go into details of the results. So, for our convenience, and to observe the results keenly we divided the results in sets of 100 observations. we randomly selected three sets of observations, one to 100, 1000 to 1100, and 2000 to

2100. So let's discuss the result of each observation in detail

4.3.1 1st Set of Observations (1-100)

We have selected set up observation from one to 100 to compare the actual and predicted labels for PdM schedules. We have represented the action values with local and the predicted values with orange color and it is clearly seen that orange line exactly overlaps the blue line. This means that the reserves are predicted with 100% accuracy

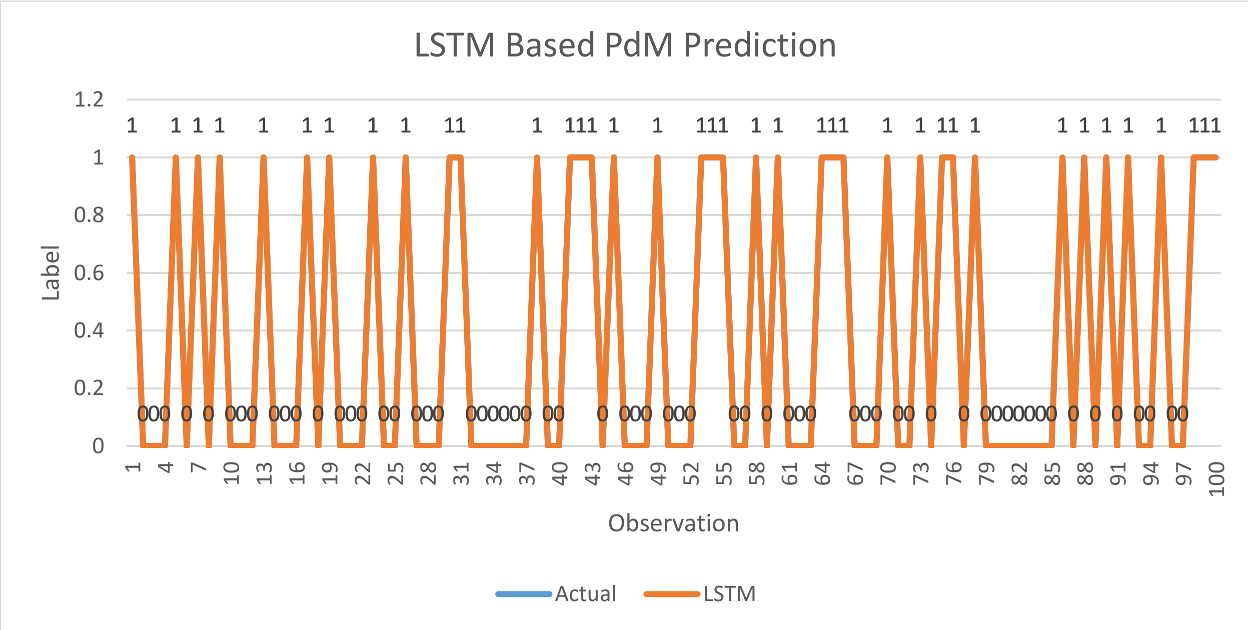


Figure 19: Results 1st Set of Observations

The above graph showed that the label predicted 99.9% times accurately when compared with the original labels. Here label 0 means, the automobile it is in good condition and does not require any maintenance. however, one label means the automobile require maintenance. On Y axis we have labels, while on X axis we have observations or number of cars whose labels are needed to be predicted. The above graph is of first 100 observations.

4.3.2 2nd Set of Observations (1000-1100)

The attached graph is of observation 1000-1100 and it is clearly seen that that the LSTM based model produced the accurate results when compared with the actual test dataset.

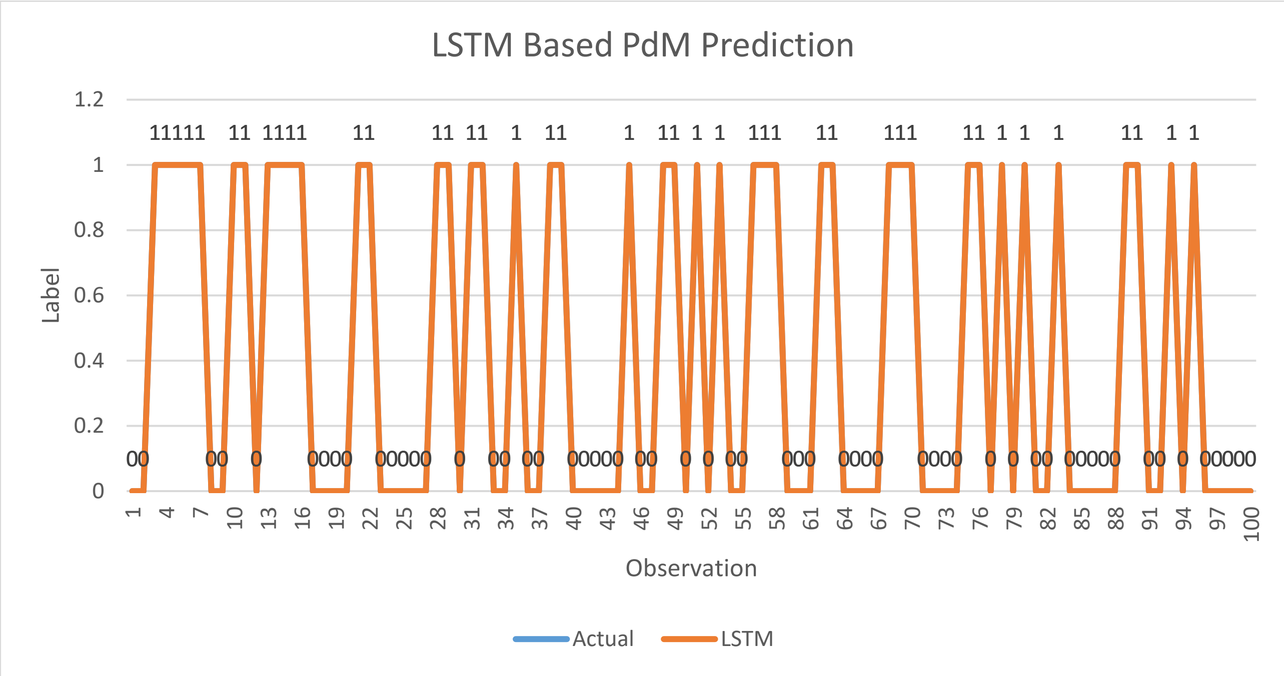


Figure 20: Results 2nd Set of Observations

The above graph showed that the label predicted 99.9% times accurately when compared with the original labels. Here label 0 means, the automobile it is in good condition and does not require any maintenance. however, one label means the automobile require maintenance. On Y axis we have labels, while on X axis we have observations or number of cars whose labels are needed to be predicted. The above graph is of 1000 to 1100 observations.

4.3.3 3rd Set of Observations (1000-1100)

The attached graph is of observation 2000-2100 and it is clearly seen that that the LSTM based model produced the accurate results when compared with the actual test dataset.

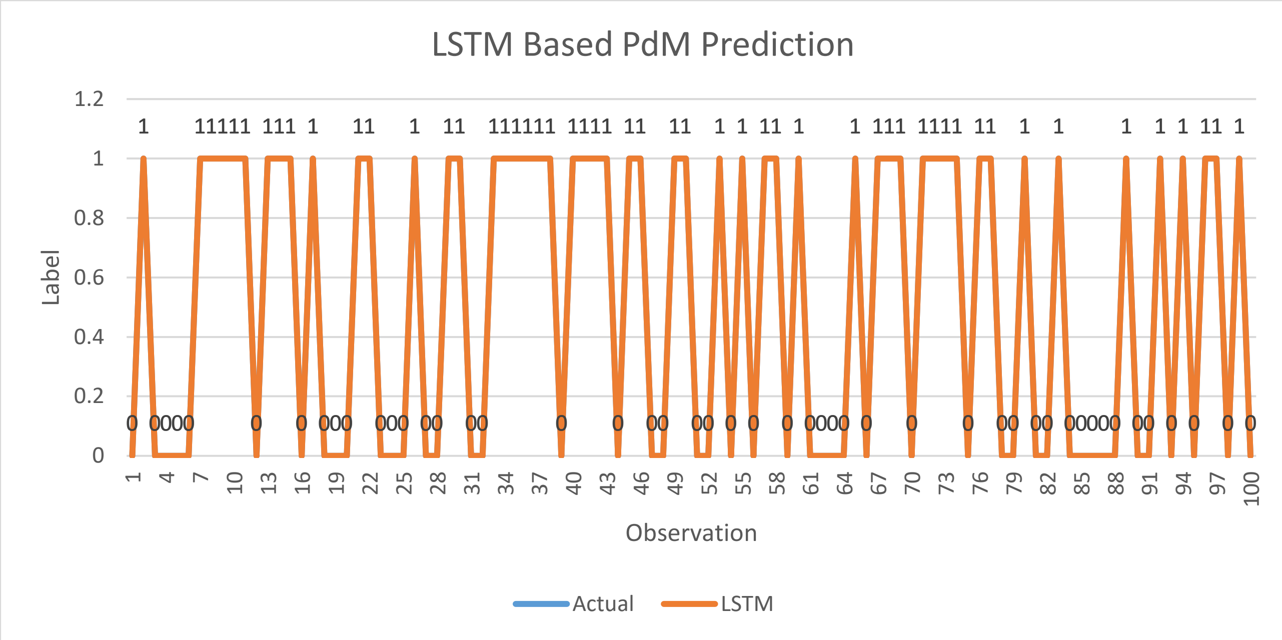


Figure 21: Results 3rd Set of Observations

The above graph showed that the label predicted 99.9% times accurately when compared with the original labels. Here label 0 means, the automobile it is in good condition and does not require any maintenance. however, one label means the automobile require maintenance. On Y axis we have labels, while on X axis we have observations or number of cars whose labels are needed to be predicted.

4.4 Comparison Graphs

We have discussed the results individually. In this section, we will compare the results with other benchmark solutions. we have considered artificial neural network, recurrent neural network as the benchmarks. If our model is having better accuracy than the benchmark solution then it is considered to be a best fit model for our problem, and if it fails, we need to find another solution for this problem. So, let's discuss the comparison with first set of observations

4.4.1 Comparison of Benchmark solutions with proposed LSTM best solution, 1st set of observations

In the attached graph we have compared Actual label values with proposed LSTM based solution and benchmark solutions including RNN and ANN, respectively. actual values are represented with blue line, ANN with gray line, RNN with yellow line and proposed solution LSTM with green line.

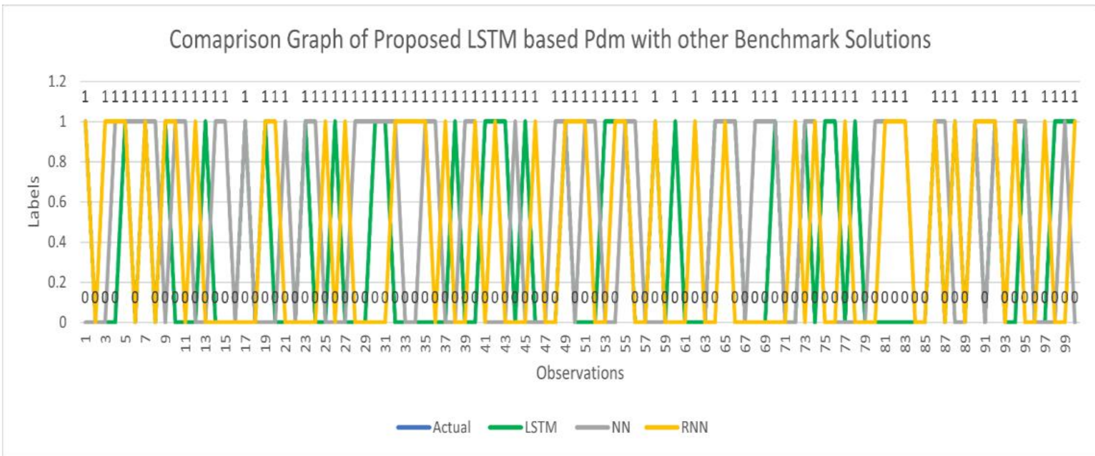


Figure 22 Comparison Graph of Proposed Solution with other Benchmark Solutions: 1st Observation Set

Here in the graph, we cannot see the blue line, because it is completely overlapped with green line which means the actual values predicted with LSTM are exactly the same or equal. However, the gray line of ANN sometimes matches with the green or blue line which means it shows some accuracy. But the yellow line it's showing dark completely different results then all other comparison models which means that RNN is showing the least accuracy in results. The behavior of RNN is because of vanishing gradient problem. So, concluding the above graph, LSTM is performing better than all the comparison models.

4.4.2 Comparison of Benchmark solutions with proposed LSTM best solution, 2nd set of observations

In the attached graph we have compared Actual label values with proposed LSTM based solution and benchmark solutions including RNN and ANN, respectively. actual values are represented with blue line, ANN with gray line, RNN with yellow line and proposed solution LSTM with green line.

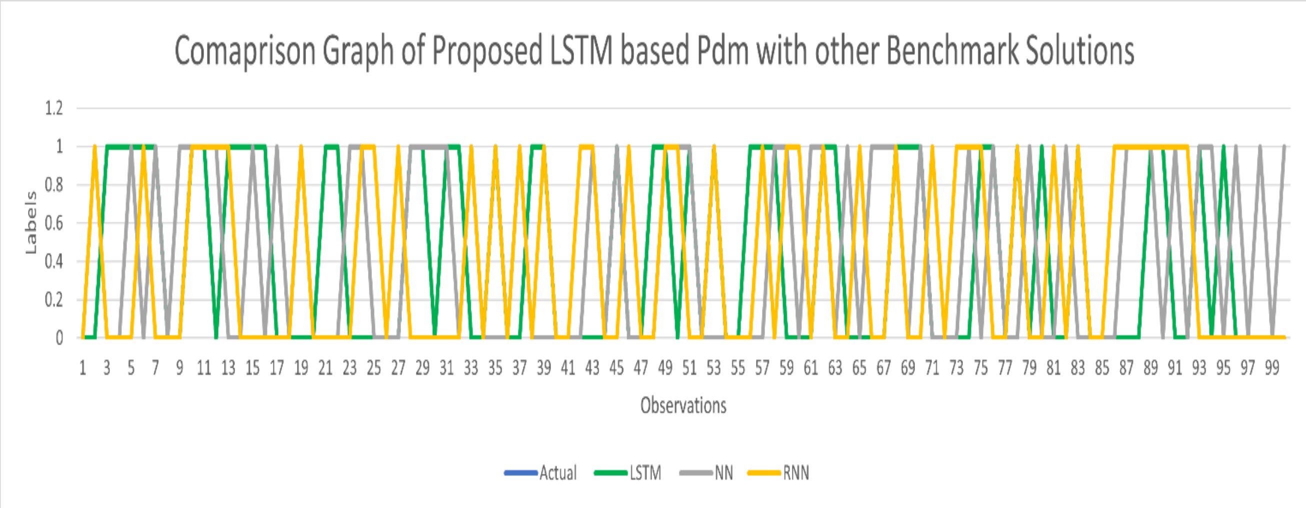


Figure 23: Comparison Graph of Proposed Solution with other Benchmark Solutions: 2nd Observation Set

Here in the graph, we cannot see the blue line, because it is completely overlapped with green line which means the actual values predicted with LSTM are exactly the same or equal. However, the gray line of ANN sometimes matches with the green or blue line which means it shows some accuracy. But the yellow line it's showing dark completely different results then all other comparison models which means that RNN is showing the least accuracy in results. The behavior of RNN is because of vanishing gradient problem. So, concluding the above graph, LSTM is performing better than all the comparison models.

4.4.3 Comparison of Benchmark solutions with proposed LSTM best solution, 3rd set of observations

In the attached graph we have compared Actual label values with proposed LSTM based solution and benchmark solutions including RNN and ANN, respectively. actual values are represented with blue line, ANN with gray line, RNN with yellow line and proposed solution LSTM with green line.

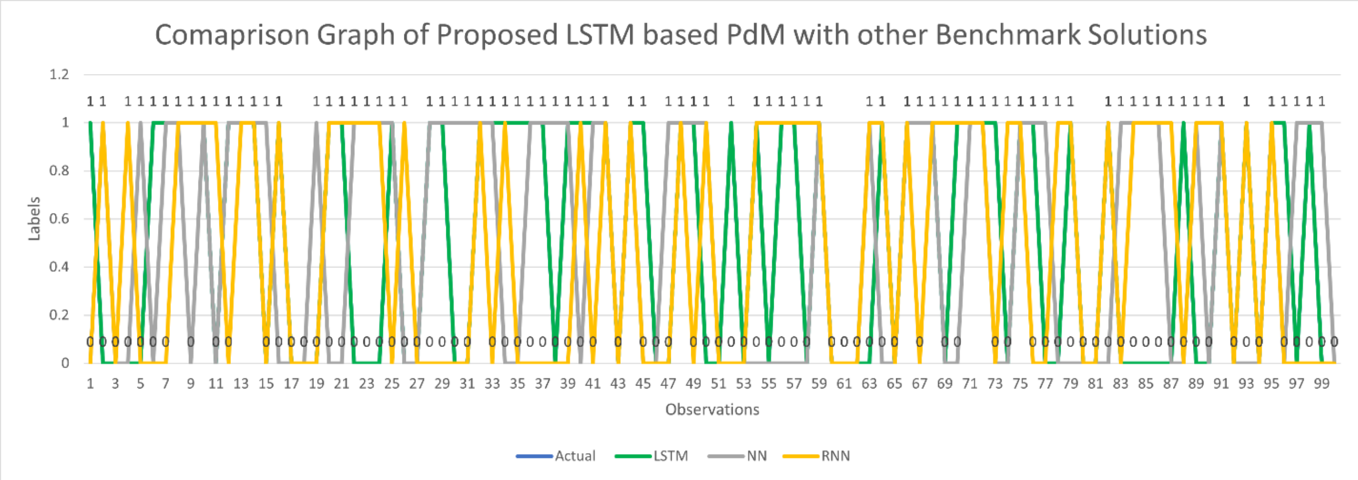


Figure 24: Comparison Graph of Proposed Solution with other Benchmark Solutions: 3rd Observation Set

Here in the graph, we cannot see the blue line, because it is completely overlapped with green line which means the actual values predicted with LSTM are exactly the same or equal. However, the gray line of ANN sometimes matches with the green or blue line which means it shows some accuracy. But the yellow line it's showing dark completely different results then all other comparison models which means that RNN is showing the least accuracy in results. The behavior of RNN is because of vanishing gradient problem. So, concluding the above graph, LSTM is performing better than all the comparison models.

4.5 Evaluation of Results

In this section we will evaluate the proposed solution in comparison with other benchmarks solutions. The performance matrices that we use to evaluate the model are accuracy, MAE, MAPE and RMSE.

Table 3: Performance Evaluation of Training Set

Predictors	**Testing Accuracy**	**Testing MAE**	**Testing** MAPE	**Testing** RMSE
LSTM	**100%**	**0**	**0**	**0**
RNN	**54.4%**	**0.45**	**46%**	**0.675**
ANN	**85.5%**	**0.145**	**14%**	**0.381**

Above mentioned table represents the accuracy of LSTM model as 100%, RNN as 54.4% and ANN as 85.5%. While MAE is 0 in case of LSTM, In RNN it is calculated as 0.45 and ANN it is 0.145. Similarly, for LSTM MAPE is 0%, for RNN it is 46% and for ANN it is 14%. So, the highest MAPE calculated is for RNN which means it is not capable enough of generating accurate labels for PdM schedules. However, LSTM is predicting PdM Schedules with 100% accuracy. RMSE for LSTM is again 0, and for RNN it is 0.675 and 0.381, respectively.

So, it is obvious from the evaluation matrices that the proposed solution is performing better than all other comparison benchmark solutions. The proposed solution suggests an accurate predictive maintenance schedule so that maintenance costs can be reduced, time can be saved, and vehicle health can be maintained.

So, in this chapter we have discussed in detail about the data set, explained each feature of it, hey they have discussed the complete model building, each hyperparameter we used, splitting datasets, predicting or proposed model and at the end we discussed the evaluation matrices in detail. in the next chapter we will discuss the conclusion and future work.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

The Industrial Internet of Things (IIOT) is everywhere. These days the devices are equipped with sensors, and they generate huge amounts of data. Predictive maintenance (PdM) of automobiles not only helps in saving maintenance costs, and time but also automobile health. The huge amount of data helped us in predicting the PdM schedules. In this paper, we predicted the PdM schedules for automobiles. The data set of various automobiles is collected, in Pakistan, using Avometer in phase 1. The data set consists of features including minimum voltage, crank current, crank bolts, crank resistance, volts off, volts start, amperes, start resistance, and labels. we have used resistance in deciding the labels. When an automobile faced a high resistance value it is considered as it is closer to getting maintenance, so the automobiles with fire resistance value may sign the label as 1 and with low resistance value we assign them the label of 0. Label one means the automobile needs maintenance, whereas level 0 means the car does not require any maintenance immediately. In phase 2, We undergo a deep learning algorithm LSTM for predicting PdM schedules for various automobiles. The proposed solution showed 99.9% accuracy in predictions in 30% of the test set. The proposed solution it's compared with the benchmark solutions including ANN and RNN. Ian produced better results than RNN but not good enough than LSTM. ANN could achieve an accuracy of 85.5%. But RNN due to its vanishing gradient problem, couldn't perform well. It achieved only 54% accuracy which means that it is not good enough to predict labels. The application of the proposed solution will be very helpful for the fleet management systems that have thousands of cars, and they cannot keep a check on every car that requires maintenance or not. so, using a machine learning-based solution it becomes very easy for them to maintain their automobiles, regularly. Moreover, the proposed solution suggests an accurate predictive maintenance schedule so that maintenance costs can be reduced, time can be saved, and vehicle health can be maintained.

5.2 Future Work

The data set contains all the features of automobiles, and levels are predicted against resistance only. In order to enhance her research in the future, we need to consider other features for contributing to the main feature in label prediction. We have used all the features discussed in model training; however, feature selection would help us in getting some more meaningful insights from the data set. Moreover, only resistance is not the feature to decide whether a car needs maintenance or not. There are other features that can contribute to the automobile's bad health. We need to explore them too, other than features related to automobiles we need to consider and involve the environmental and geological factors. These will help to enhance the proposed solution's accuracy. Hereby accuracy, we mean that factors contributing to car health other than resistance.

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