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Implementing Deep Learning Model to Predict the Maintenance of an Elevator System

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***Abstract*- In this world, where everything is becoming automated, humans have also got used to this fast-paced life. One of the machines that we widely use in our day-to-day lives are elevators. Elevator systems have become an important part of the buildings. Hence, in order to perform well, even elevators require proper maintenance. Therefore, it becomes very much essential to strengthen the maintenance procedure of elevators. Here, the role of predictive maintenance comes into play. It helps to find out the proper time period, in which the maintenance should be done without wasting the maintenance cost along with Remaining Useful Life of elevator. The technique used here is deep learning. It gives us finer outcomes because of the new deep attributes, that are extracted from the dataset in contrast with already existing attributes. This work consists of implementing a deep learning algorithm for fault detection and prediction of an elevator system. LSTM has been implemented on the dataset, which consisted of sensor data which was recorded on the basis of maintenance actions being taken. The experimental results present mean absolute error of about 7.05%.**

Keywords*- *LSTM, Deep Learning, Elevator System, Predictive Maintenance

I. INTRODUCTION

In recent times, commercial buildings and offices make use of elevators extensively. Even though elevators bring comfort in the lives of people, therefore, the safety issues of elevator systems have been brought up by the parties because of the recurrent fall occurrence in elevator systems. Hence, elevators require constant maintenance to check that the elevator systems can run stably, efficiently, and safely. When it comes to the actual maintenance of elevator equipment, there may occur several issues that make it hard to ensure the proper functioning of an elevator system, that includes inappropriate approach towards maintenance, improper re-equipment of elevator equipment, high-cost maintenance.

It is true that all appliances break down at some point of time in their lifetime, unless it's being taken care of. It is also true that we don't know when the failure can happen, but we need to be mindful while doing our planning. If we schedule maintenance at an early, we will be wasting the resources as well as the remaining useful life of the appliance, which becomes costly. But, it will be really impactful if we could predict the appliance failure in advance. For this we have predictive maintenance. It will allow us to predict the time of appliance failure. Along with that, it will also allow us to pinpoint the issues in our appliance. With the help of this approach, we can minimize the downtime and maximize the appliance lifetime. By this we will be able to prevent unplanned reactive maintenance. Main objective of predictive maintenance is to predict the remaining useful life, or RUL[11,15,19].

When it comes to maintenance of the machine, we humans become careless. From a final customer point of view, it is quite simple: nobody cares about elevators until they are not working. This carelessness, in the long run, can result in loss of human life as well as financial losses. To overcome both, the machine requires timely maintenance.

Looking at the global elevator problem, it can be executed with the right product vision with the help of predictive maintenance. "It automates the mechanism of identifying the potential equipment failure and can recommend actions to solve the problem."

The conventional predictive maintenance models are built on feature engineering. It is a manual assembling of right attributes. This shapes these models very complex to reuse, as feature engineering is certain to the problem that is occurring. The data that is available differs from place to place. The most intriguing thing about implementing deep learning in the domain of predictive maintenance is that the right attributes can be extricated from the data by the networks. And this in turn, eliminates the feature engineering. As a result, we tend to get a self-reliant model that can extract new features and compute them to achieve further reliable results [1-3,18].

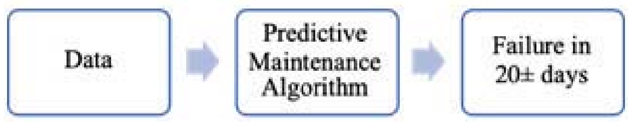

Fig. 1. Predictive Maintenance Model

Our goal is to create a prediction model for predicting the health of the elevator robust elevator predictive maintenance model, which is suitable for any elevator system in the world.

The objective of the work was to explore the elevator system's optimal maintenance policy to reduce the average maintenance cost. The rest of the paper has been structured as follows: Section 2 provides the Problem Description, Section 3 represents Literature Review, Section 4 showcases Methodology, Section 5 represents the Results and

Discussion, and Section 6 showcases the conclusion along with the future scope.

II. LITERATURE REVIEW

Various search engines were used for online library search, including Springer Link Online Library, Elsevier ScienceDirect, and IEEE. Several authors have used deep learning models in order to attain the results. Paper [3] showed the most optimal way from the outlook of preventive maintenance. This was done to bring down the rate of failure of elevator systems. A mathematical description was presented regarding the maintenance of elevator system equipment. Some improvement factors were also initiated during the planning of maintenance strategy. In [21], paper presented a model for imbalanced fault diagnostics and prognostics. Algorithm named Easy-SMT was proposed in this research, along with an oversampling method, named as SMOTE. Good performance was seen on multiclass imbalance learning. [22] proposed a new algorithm in order to extricate data from the time-series data. Additionally, there was automatic calculation of the deep features. Here, both the start and stop occurrence was extricated from the sensor data. On the basis of maintenance, this data was further classified as healthy and faulty. Furthermore, healthy data was then used as testing data. Of and about 100% accuracy was attained. Paper [5], represented the in-depth analysis of how intelligent predictive maintenance is better than preventive maintenance, keeping in mind the concept of Industry 4.0. In [9], this paper showcases the case study on predictive maintenance as a solution for non-critical machinery. Monitoring along with diagnosis has been done using neural networks, whereas, tools of the appliance were being observed and being implemented using bayesian networks. It also displayed the work done in MINICON project, likely to evolve as economically integrated SPUs.

III. METHODOLOGY

A. *Predictive Maintenance Workflow*

When it comes to acquiring data, it was extricated from the elevators with the help of sensors. That elevator data was then selected as part of the pre-processing phase. Deep autoencoder model was then developed in order to further perform feature extraction. Basically, an autoencoder is built upon a feed-forward neural network.

In our model, we fed the elevator data by observing the movement of the elevator in up and down directions, individually. In the deep autoencoder model new deep features were also extricated from the same data. After that implemented random forest classifier to detect faults built on newly extricated deep attributes from the already existing data. Further, it was converted into time-series data with the help of LSTM.

Fig. 2. Predictive Maintenance Workflow

B. *Long Short-Term Memory (LSTM)*

Long short-term memory or LSTM is an enhanced version of the RNN [1-7]. The main difference is that LSTM consists of LSTM cell and an extra connection from every cell called cell state. The main motive behind the design of LSTM was to reduce the vanishing gradient. Apart from hidden state vector, state vector is maintained by each LSTM cell and because of incremental change in time, the cell can pick via gating tool to read, write or reset it. Each LSTM cell consists of 3 gates: Input, Forget and Output Gate.

Predictive maintenance is all about time series type of data and Recurrent Neural Networks are good with time-series type of data. As the name implies time-series data is a continuous sequence of data points represented in a consecutive order. For example, if there is a time series data then for every X number of elements there will be consecutive singular Y element. Issues with simple RNN have been listed below:

- No-long term memory
- Network can't use data from the distant past
- Can't learn pattern with long dependencies

Here, LSTM comes into play. LSTMs are a special type of recurrence neural network. There are memory cells that will enable to learn longer term patterns [18].

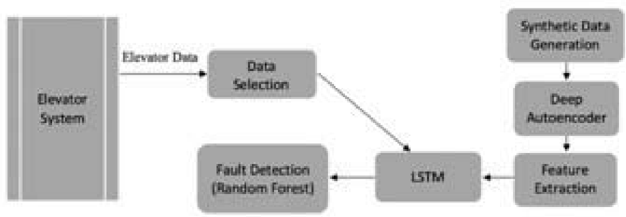

Fig. 3. Predictive maintenance model layout

C. *Synthetic Data Generation*

Synthetic data is data created via means other than direct measurement of whatever the task or system that you're focusing on is for our purposes synthetic data is usually data that we generate in order to match and increase the size of our training data or to introduce changes in the data. It offers us a cheaper and usually more time efficient method of expanding our data set. It can also help us rebalance data sets if the distribution of the data that we have doesn't match the distribution of that data in real life or can help us focus on rarer cases.

When an elevator is being operated, various attributes can be seen. Out of all the attributes, "distance" measure was selected. It shows the total distance covered by the elevator in a day. The data could have been represented differently. But, we chose to represent the data in the form of time-series analysis as we have applied LSTM, which works best with time-series forecasting [18].

For unexpected elevator usage, random data generation was done. We added the random elements to our dataset in the feature "distance" in the range of [0, 400] to expand the dataset, for better efficacy.

IV. RESULTS AND DISCUSSION

According to the classification condition, the range of samples are classified into 3 distinct states: Good(0), Fair(1), Poor(2). An accuracy of about 91.50% was achieved using random forest classifier[24].

The following graph, Fig. 4 showcases the train data as well the validation data. The minimum epochs in order to apply early stopping function should be 2. Here, negligible loss was being seen after 2 epochs.

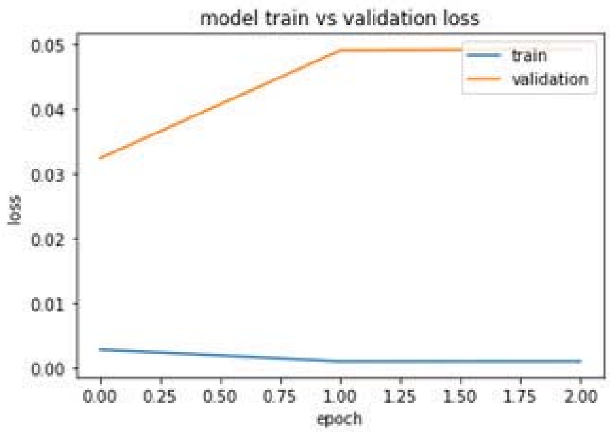

Fig. 4. Training vs. Validation Data

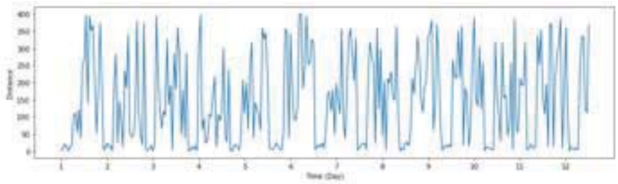

Fig. 5. Distance Travelled vs Time

During the pre-processing of data, during the application of the LSTM model, an early stopping function has been used. This was done, as negligible changes were being seen in the loss. The final loss was about 0.011%. Time series generator function was also used in order to convert the data in the form of time-series.

```
scores = model.evaluate(train_generator, verbose=0)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))

mean_absolute_error: 7.05%
```

Fig. 6. Mean Absolute Error

Fig. 7. Elevator Health Status Dashboard

A web interface has been created that showcases the graph and focuses on which part of the elevator is going to become defected soon. The dashboard takes input from the user in the form of starting date and ending date. Hence, it then shows the health condition of the elevator during that period. It also tells an overall state of the elevator, by showcasing “Good” in green, “Fair” in yellow and “Poor” in red. Below the graph, the weekly usage activity of the elevator is also shown.

Below the graph, the weekly usage activity of the elevator is also shown. The graph not only showcases the current state of the elevator, but it also shows the part that has been affected. In conclusion, it shows which part needs attention!

The dashboard is very user-friendly. It can be seen that the condition of an elevator showcases the graph in the form of not only dates, but also includes the timestamp. Along with it, the graph is interactive in nature. It showcases the flow of graphs on hovering.

Fig. 8. Elevator’s Condition: Healthy (green color)

Fig. 9. Elevator’s Condition: Average (yellow color)

Fig. 10. Elevator’s Condition: Poor (red color)

For the real-time notifications, a database has been created to perform CRUD operations. For each operation separate APIs have been created in order to avoid exploitation of databases, every database operation has been done on the backend side to ensure maximum security. For the frontend, HTML/CSS and Javascript has been used. And for the database MongoDB has been used. It is mostly used for NoSQL databases. The database takes information of the subscriber in the form of first name, last name and phone number. Once the user is registered, the model sends the notifications/alerts to the user, as well as the maintenance staff in regular intervals (weekly).

Also, for sending the alerts, Twilio was used. With the help of Twilio, regular message notifications were being sent to a registered user. A separate API is created in order to manage all operations and authentication for Twilio.

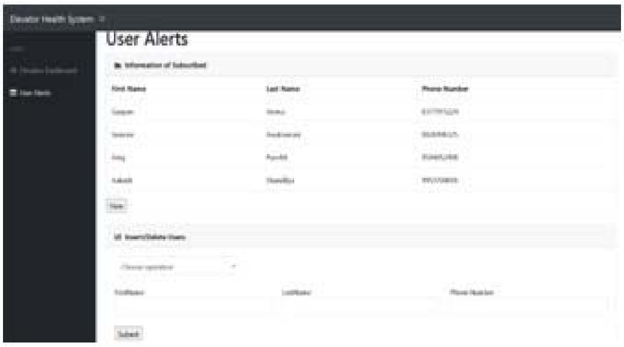

Fig. 11. CRUD Operations

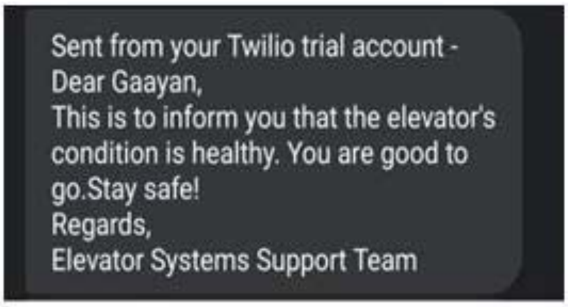

Fig. 12. Message Notifications via Twilio

V. CONCLUSION AND FUTURE WORK

Our paper comprises of detection of anomalies using LSTM and random forest, which will then predict the future usage of elevator. The main goal behind this work was increase the robustness of the elevator system. After pre-processing of the data, our LSTM model predicts the overall loss of an about 0.011%, after the application of early-stopping function.

During the work, some issues were faced that could be part of the future work. It would also include the measurement of level of uncertainty due to unforeseen circumstances, which would in turn increase the reliability.

As part of the future work, alerts will be sent to the residents of the society as well as maintenance staff about the state of an elevator system regarding its present safety level, as well as Remaining Useful Life(RUL). Our future work will also include the inclusion of holidays as part of our data. As during the holidays, elevators will be used less in the offices all around the globe[20].

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