Predictive maintenance on an elevator system using machine learning

Law Jing Shen
School of Engineering
Asia Pacific University of Technology and Innovation (APU)
Kuala Lumpur, Malaysia
TP038474@mail.apu. edu.my

Jacqueline Lukose
School of Engineering
Asia Pacific University of Technology and Innovation (APU)
Kuala Lumpur, Malaysia
jacqueline.lukose@staffemail.apu.edu.my

Lau Chee Young
School of Engineering
Asia Pacific University of Technology and Innovation (APU)
Kuala Lumpur, Malaysia
laucheeyong@staffemail.apu.edu.my

***Abstract*— The aim of the project is to design and construct a predictive maintenance system on an elevator system using machine learning. Three objectives are set for the project for the system to be archived. The first objective is to develop the machine learning technique to monitor the health of the elevator system. The elevator system chosen for the predictive maintenance system was permanent magnet synchronous motor traction elevator. The PMSM data set was proceeded for the data analysis. Smoothening of the data were completed as there were too many peak data in the data set. Using the smoothen data set, threshold was created for the classification of the output (health condition) by comparing with the "time" parameter data. Once the output has been classified and tabulated into the data set, the completed information data set will be transferred into the model for training purpose. The second objective was to design a prototype framework of an elevator for data collection. Arduino Uno was chosen as the microcontroller for the elevator prototype. DC motor was selected to representing the elevator motor that drives the elevator car. Two sensors: LM35 and Encoder Sensor Module were selected for the data capturing objective. LM35 is capturing the temperature data ad Encoder Sensor Module will capturing the rotation per minute data form the DC motor. The data collected will be compiled into a file before transferring it to the MATLAB processing. The last objective is to evaluate the performance of efficiency of the system. Total of 5 testing were conducted for the implemented system. The first three was about the setting of training model, the result was Fine KNN algorithm has the most accuracy of 93.8%. The fourth testing was conducted on checking the prediction ability of the trained model. The analysis shows the trained model maintained its accuracy even when extending the range of time for prediction. The fifth testing is about unbiased prediction of the trained model. The final result of the unbiased prediction accuracy was 95.5%.**

Keywords*— *predictive maintenance, kNN, Arduino

I. INTRODUCTION

In this modern technology era, transportation is the key for people moving from one place to another. The transportation is not only about the road vehicle or flight vehicle, but the one important vehicle that is built in almost every tall building, elevator is too can be seen everywhere. Elevator is a type of transportation that transport load between floors in the building. Thus, it saves time and energy of one instead of them to travelling through stairs. However, elevator is still a machine and gone failure in time. Therefore, it would cause a lot of inconvenient and even tragic accident when the elevator failed during transportation. Hence, it is crucial to have maintenance on elevator done to prevent the possibility of it failed and result in accident.

Maintenance becomes an essential part to the modern technology world as it is highly relevant to modern production systems and product lifecycle management. Without maintenance, the machine would end up being failure and could result in casualty. According to New Straits Times, the Department of Occupational Safety and Health (DOSH) has recorded at least 111 accidents happened related to the failure of elevators since 2010 [1]. Thus, this shows that there is still a lot of building does not reach the standard of well-maintained elevator in Malaysia. The cause of this might be due to the high cost of the maintenance, many buildings that is under financial issues cannot afford the maintenance prize. Thus, to reduce the human casualty and the cost of the maintenance, appropriate maintenance must be done before the failure occurred. [2]

There are many types of the maintenance strategy systems, but the main three strategies are: Corrective Maintenance, Preventive Maintenance and Predictive Maintenance. Each maintenance strategy has their own procedure, but the outcome always the same, to prolong the life of the machine. Corrective maintenance is the most common and basic maintenance, it also known as the run-to-failure maintenance.

This type of maintenance strategy only would provide the maintenance once the machine has broken down. It does not just would not give noticing or warning when the machine is going to fail, or it is failing. Thus, corrective maintenance will be very dangerous if it is applying on the elevator maintenance system. It is not only time consuming when maintenance, but it also cost challenging as buying component during emergency period would cost much such as in shipping [3].

Preventive Maintenance is the type of maintenance strategy that is depends on the knowledge on the machine, engineers experience and previous similar machine data. Using those data to calculate and to set a certain period for the machine checking, whether it might be daily, weekly, monthly or annually. Engineer would come around for checking to see whether the machine is in good condition or needs to be fix or replaced component. The advantage of this strategy is that the user knows when the machine would need to be serviced from the schedule; thus, no interference affected as all the preparation work can be done before the maintenance. The disadvantage of preventive maintenance is the part that is replaced during the maintenance usually is not completely or nearly broken, it might still have their usage time. This strategy might cost a lot due to the acceptable part being replaced and unnecessary maintenance checking done while machine is in good condition.

Predictive maintenance is the latest type of strategy, it is very well known and famous as it is the only strategy that can achieve maximum lifetime of the machine while minimize the risk of the machine failure to its minimum. Furthermore, it reduces the number of times require to service the machine, result in annual cost of the maintenance become lower too. This type maintenance strategy carries on the philosophy of "execute at the right time", which it means the maintenance and action only taken place when it is only necessary. Researchers proposed a system of big data based predictive maintenance architecture for biomedical devices for health domain [4]. Predictive maintenance also requires big data to work, as it collected a lot of real-time data to run diagnosis. Then, it predicts the Remaining Useful Life (RUL) of the machine. Lastly, it established the final maintenance decision required for the machine.

Artificial Neural Network (ANN) is one of the used methods from Artificial Intelligence (AI). It is initially created to mimic the human brain. Thus, this method is inspired by biological structure. This method structure work as three steps: inputs, processing elements and outputs. They are three layers in this system, known as input layer, hidden layer and output layer. Hidden layer is where the processing elements working at, it processes the input data and get the best output data from it. Since the processing data might take a lot of steps; therefore, the hidden layer might consist more than one layer. Using this AI method, the big data from the elevator can be processed and diagnosis without the needed of human and manpower. Thus, it made the whole maintenance strategy become an automated system. The available ANN methods have been reviewed [5]. The Curve Fitting method has been employed for IOT implementation for predictive maintenance [6]. In addition the Random Forest method has also been adopted for the same end [7].

Elevators are mostly located in tall building, whether its residential building or office building. Both this building will be crowded with a lot of people; therefore, it will be very inconvenient if the elevator broken down unexpectedly. An unexpectedly broken-down elevator might lead to casualty accident, which every company is trying to avoid. The cost that need to cover up the casualty and maintenance will quite high. In the other hand, a broke down elevator requires a lot of time to be repair, it will result in inconvenient for the residents and workers. Commonly, the elevators are using the preventive maintenance strategy. With this strategy, schedule time for service and maintenance result in unnecessary work done if elevator is in good condition, and some parts will be replaced when it is still able to support and run in the machine for quite some time. Therefore, it leads to unnecessary cost spend on services and replaced part even when the elevator is under good condition. With the predictive maintenance system installed, the system will alert the user when the elevator is almost broken down; thus, no unscheduled or unpredicted maintenance will be done. Real-time data will be collected from the elevator using sensors to capture the current status of the elevator. The limitation of this strategy is big data will be used in this system; hence, the usage of Artificial Intelligent will be necessary. With this strategy installed, the annual cost for the maintenance will be reduce as the number of times of the maintenance is reduced too. It maximizes the lifetime of the elevator while minimizing the risk of the elevator failure.

II. PROPOSED METHODOLOGY

A. Proposed Block diagram

By referring to the block diagram in the Figure 1, raw sensor data will be captured from the motor by sensors, then it will get processed by Arduino. Data processing is necessary for the system to be able to read and understand the data during data standardization and decision making. Arduino will able to convert the raw sensor data to a digital readable data to the system. However, Arduino does not capable of doing the data analysis and machine learning Therefore, MATLAB is selected for the data analysis, data standardization and machine learning of the processed data. It is not advised to transfer the data in real time straight into the system; instead, data will be compiled into a file, such as excel form, for perhaps 30 minutes before it get transferred to the decision making system. It is to avoid and reduce the error that could be occurred in the sensor, such as data peaked from the sensor error for a short second. If the data is transferred in real time, the possible of data peaked from error then sending it to decision making will result in system giving wrong information of machine need to be fixed urgently when it is false. Thus, by borrowing the system created by the Parallax.Inc, PLX-DAQ will helps to compiling all the sensor data into excel form.

As mentioned, MATLAB will be used for the training model part, which also mean to deciding of the machine health condition. First, it will unpack the data that has been saving from the Arduino, then it will be proceed to the analysis of data. Data analysis is crucial for the first time running as it could help user to determine which part of the machine data that are only required for the predictive maintenance system. Not every part of the machine will affect the machine to gone failure, it will only add burden and slow down the system if too much unnecessary data is being processes. Therefore, data analysis will help for the extraction of only necessary data.

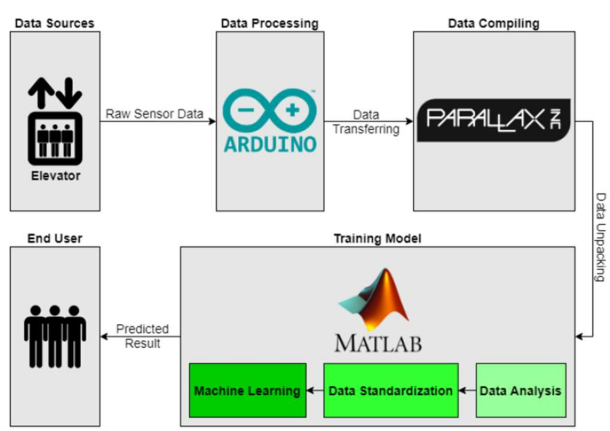

Fig. 1. Block diagram

The prepared data will be proceeded for the data standardization, it is to finalize of the data into four section: long, medium, short, urgent. Scope, also known as threshold, has been set for each of the section for the data to be characterized into one of the sections. With all the data has been processed and prepared, the finalization of the system will be completed by the machine learning section. Historical data that has been characterized into those four sections will be first used to train the model, for it to learn approximately which kind of data falls into one of the four sections, especially the “urgent”. Then, new data will be proceeded for the model to differentiate and characterize it to decide the health condition of the machine. The final predicted result of the health condition will be shown to the end user.

B. Constructional Details

The finalized system can be divided into two parts, which are hardware and software. Hardware is used for capturing real-time sensor data from the elevator prototype built for the predictive maintenance system, whereas the software part is focusing mainly on the predictive maintenance system and the machine learning itself. Therefore, only the hardware prototype is required to have wiring circuit built.

The wiring diagram drawn in the Figure 2 is the completed circuit built for the elevator prototype. Microprocessor selected for the circuit was Arduino Uno, it is the main body of the circuit to transfer all the sensor data into the digital system. However, there are two objectives needs to be completed by the prototype: to represent and function as a mock elevator, and to capture sensor data. Thus, the wiring diagram can be classified into two section. There are three types of sensors built in the prototype, ESM, SN04-N and LM35. The two main sensors are ESM, for capturing rotation per minute data, and LM35, for capturing temperature data. These two are under the capturing sensor data section. The rest of the components are all under the representing elevator section.

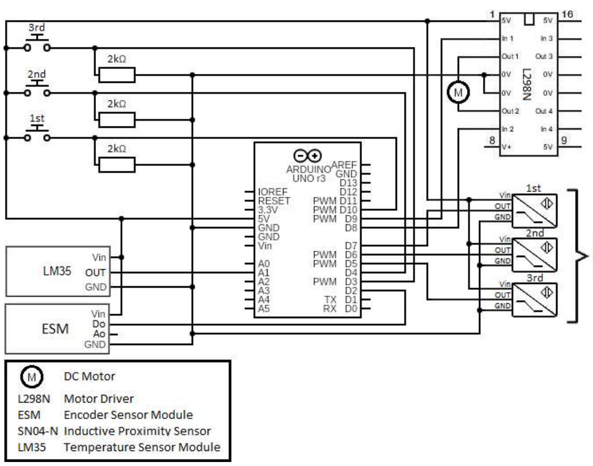

Fig. 2. Wiring diagram

C. Working Principle

Flowchart in Figure 3 shows the procedure of how the KNN method trained model was created using MATLAB. As mentioned before, 40000 training data will be randomly picked from the original data set for training model purpose. However, before the data was sampled, data smoothening was required to reduce the noises.

There are total of four outputs in the system, each output has its own scope for the data to be classified by it. For example, if “time” is more than 30000, then its output will be classified as “urgent”.

Once all the outputs from the 40000 training data have been classified and tabulated, the new training data with the output tabulated will be transfer to the training model.

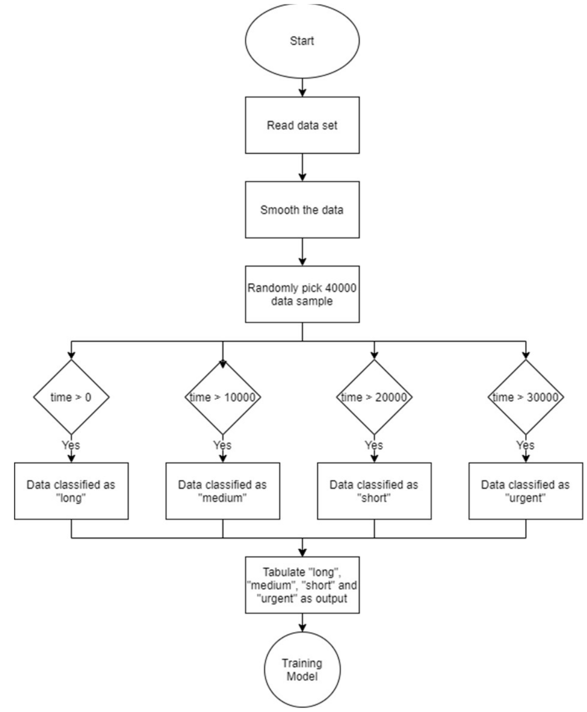

Fig. 3. Data analysis flowchart

The training model process was completed by using MATLAB classification learner toolbox. Before the training process started, the input and output (target) must be declare first. The inputs are the desire parameters want to be included in the prediction process, while the only outputs are the four classified outputs mentioned in previous flowchart. However, validation set must be extracted from the 30% of training data for the comparing with predicted result purpose. From all the classification methods available, KNN method has the highest accuracy prediction result.

Thus, KNN method model was selected and trained for the unbiased result prediction. Unbiased prediction is putting new inputs that the trained model does not seen during the training process; thus, if the unbiased prediction works successfully, it also means that the trained model is successfully trained to be working under unfamiliar condition as well. This is depicted in Figure 4.

KNN method is very versatile, it can be applied on many different conditions: classification or regression. KNN method is learning by using the concept of similarity, sometimes also known as distance. It believes that similar data will always be close to each other; thus, also means that similar data will have short distance between each point. It is incredibly useful and accurate when the input data is clear and less output available. Therefore, KNN is always been suggested when it comes to classification learning method, due to its simple understanding and implementation as well.

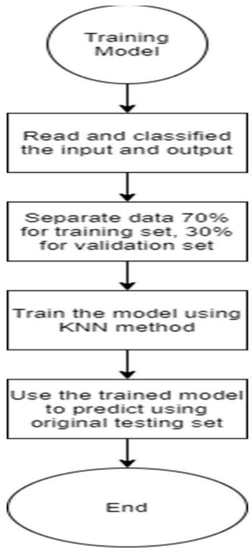

Fig. 4. Training flowchart

III. HARDWARE AND SOFTWARE RESULTS

A. Hardware Results

As seem from Figure 5, there are total of four views can be observed from the hardware figure, and each view has its own unique goals. The top view is the data capturing and elevator motor output section, the front view is the elevator car calling and detecting section, the right view is the microcontroller and motor driver section, and the back view is the wiring section. The important views are the top and front views as these views have inputs and outputs in it. The Arduino Uno will be powered by 5V that is directly connected to the power supply (laptop) itself. Once the Arduino is activated, the whole prototype will begin its objectives.

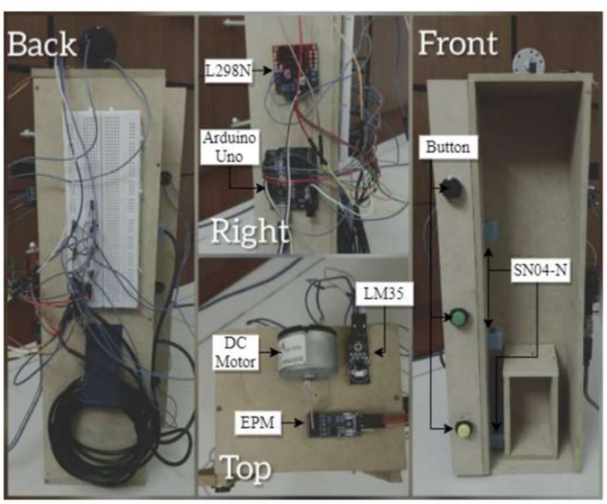

Fig. 5. Elevator control system

B. Software Results

Under the software results, it is mainly focus on the plotted graph and the predicted accuracy result by the training model. Figure 6 shows the plotted graph after the classification of four output into each data has been completed.

By observing to the figure above, there are four different colours regions in the plotted graphs. The four colours are the representation the four outputs classified to the data: purple for "long", blue for "medium", green for "short" and yellow for "urgent".

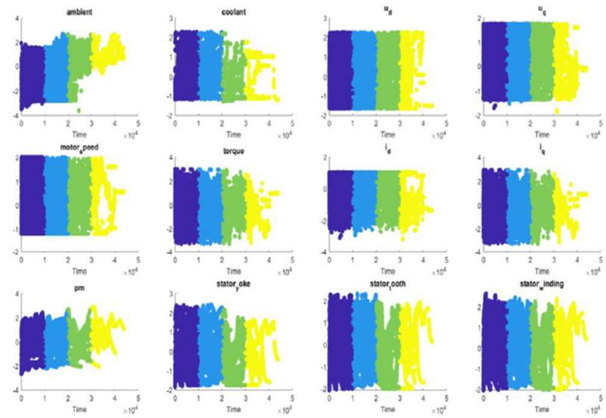

Fig. 6. Classified output by threshold

Figure 7 shows the confusion matrix from the result of the KNN method training model. The average accuracy result of the four outputs was 93.8%. However, by observing the confusion matrix, the "urgent" section has the accuracy more than 95%. Since the "urgent" output is the main output for the system; therefore, even though the overall accuracy was 93.8%, this training model will still be accepted.

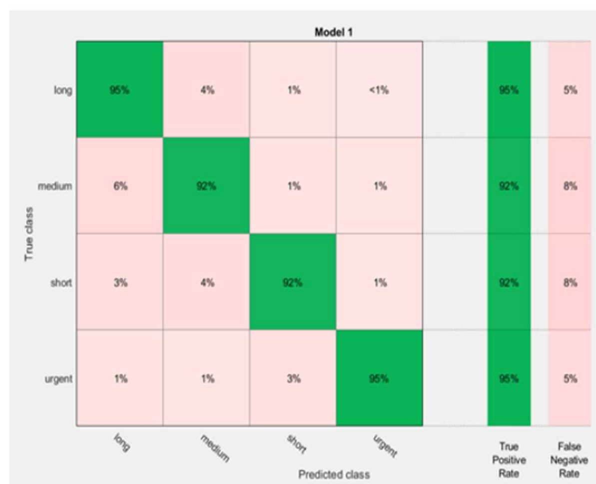

Fig. 7. Biased confusion matrix

Figure 8 shows the unbiased prediction result after the KNN method model was completed. The unbiased result was based on the input from the original data set. Confusion matrix above shows the accuracy of the predicted result from the original data set. By observing the confusion matrix, it shows that the overall accuracy is 95.5%; however, the "urgent" condition was higher than the overall accuracy, which is 96%. This confusion matrix shows the reliability of the trained KNN predictive maintenance model could be apply on the real elevator as well.

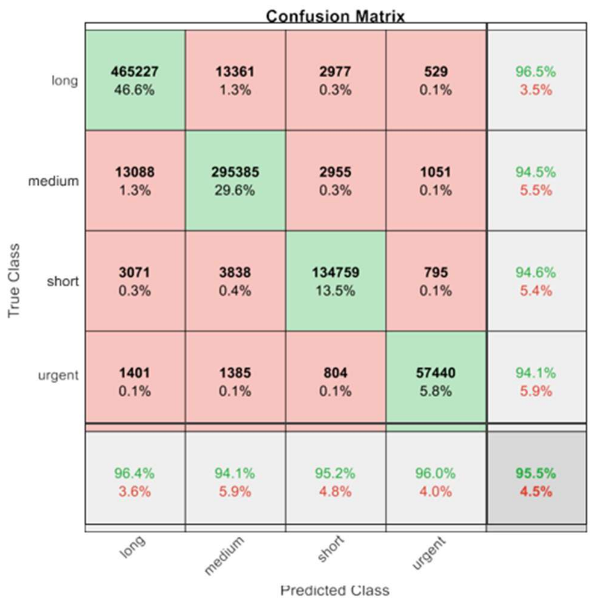

Fig. 8. Unbiased confusion matrix

IV. EXPERIMENTAL RESULTS

Every implemented system must overgoing some testing before getting publish into the public. It is to ensure the best result was produced by the system with the little error possible given. Therefore, some variable testing was conducted for the implemented predictive maintenance system to ensure the best accuracy and efficiency result was taken from all the possible methods.

A. Classification Learner Algorithm Performance

In the first testing of training method selection, there were two objectives considered during the testing: Accuracy and Time Taken. Accuracy is the efficiency of the prediction result completed by the trained model, and time taken is the time used by the trained model during the training process. Total of three algorithms were selected for the training process: Fine Tree, Linear Discriminant and Fine KNN. Each of the trained model will display some useful information results for more detail analysis. The data collected from the output information were accuracy and time taken in second. The differences in these two data will affect great different while in the selection of the algorithm methods. To observe the data more clearly, the two data were plotted into bar chart form for better visual aid analysis.

Figure 9 shows the plotted bar chart for the data collected from each of the trained model with different algorithms. Due to the time taken data was too little to be noticed if it is put beside accuracy data; thus, the time taken data was enlarged by 10 times for analysis purpose. By observing the bar chart above, it shows that the Fine KNN prediction has the most accuracy compare with the other two algorithms. However, if by comparing using the time taken data, Linear Discriminant has the fastest training time required. By observing the time taken between Linear Discriminant and Fine Tree, the time differences between them were little.

To concludes selection, Fine KNN is the best model available for the predictive maintenance system model. Even though Fine KNN took the longest to train the data, but Fine KNN provides an outstanding accuracy from all the three algorithms. Furthermore, 2.5 seconds for training process is considered as fast in training process as well.

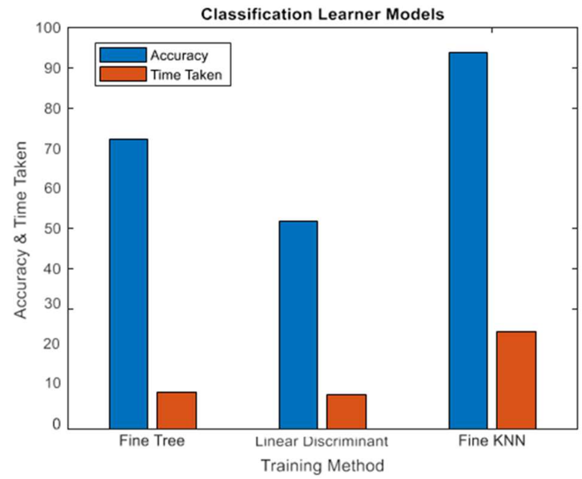

Fig. 9. Classification learner algorithms performance

B. KNN Algorithms Performance

The second testing conducted for the training model was the selection for the type of KNN algorithms. Even though the algorithm method selected for the training process was KNN algorithm, but there are still a lot of different type of KNN algorithms available that should be tested for its prediction efficiency as well. Similar as the first testing, the objectives of this testing are to get the highest prediction accuracy and fastest training process from the various KNN algorithms. There are total of 6 KNN algorithms model available in the selection: Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN and Weighted KNN.

Figure 10 shows the plotted bar chart for the data collected from each different KNN algorithm models available in the toolbox selection. The first observation can be made from the bar chart is the huge different of Cubic KNN time taken compare with all the other KNN algorithm models. Cubic KNN took the longest time taken for the training process, with the time taken of total 75.862 seconds. Therefore, Cubic KNN is immediately get kicked from the KNN algorithm model selection. Continue to observe the time taken from all the other KNN algorithms, it shows that each of them only got little differences between them; thus, the analysis will be proceeded to the prediction accuracy.

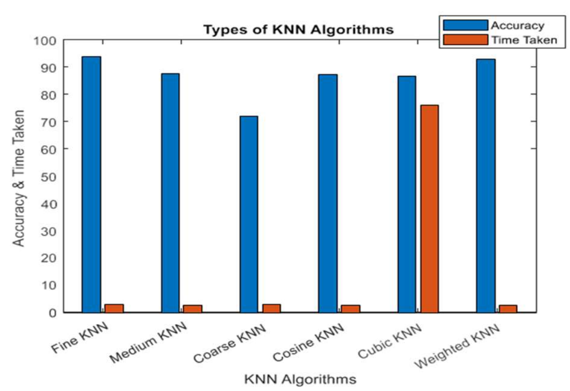

Fig. 10. kNN Algorithms Performance

Observe the prediction accuracy from the plotted bar chart, it shows the Fine KNN and Weight KNN both has the accuracy exceeded 90%, and the difference between them is only 1%. But, by observing the time taken and accuracy of them both together, Fine KNN has the highest accuracy and the least time taken for the training process; thus, Fine KNN will be taken as the training model for the predictive maintenance system.

C. Size Validation

After the training model selection was completed, the testing on the data set will be proceeded. The first testing on the data set will be adjusting the validation size of the training data. By adjusting the validation size, the training set will be affected as well. The bigger the validation size, the smaller the training set available for training. Therefore, it also means that if validation size is too large, they will me lac of information for the model to be trained. But it is not completely benefit if the validation size is too small as well, as it will be unnecessary to put too much information into the training set if the model already can obtain a good accuracy in certain size. Therefore, the objective of this testing is to find the suitable validation size for the training model. The details of the outputs, accuracy and time taken of the training process were recorded and plotted in a bar chart form for analysing purpose.

Figure 11 shows the bar chart plotted by using the data collected from the prediction results from the various validation sizes. Four different sizes of 20%, 25%, 30% and 35% were the x axis in the plotted chart. By analysing the details collected, the validation size of 20% has the most promising result. The accuracy of other validation sizes was all similar each other. However, the time taken by the validation size of 25% was the longest; thus, it will be eliminated in the selection. Even though the size of 20% has the most accurate and shortest time taken, but due to the validation size is considered as quite small; therefore, the size of 20% was also eliminated in the selection as well.

By comparing the size of 30% and 35%, 30% has the better results than the size of 35%. Furthermore, the accuracy difference between 20% and 30% were only 1%. By downsizing 10% of the validation size to get only 1% of increasing in accuracy could be risky and not worth. Therefore, validation size of 30% was selected for the predictive maintenance model and for further testing purpose.

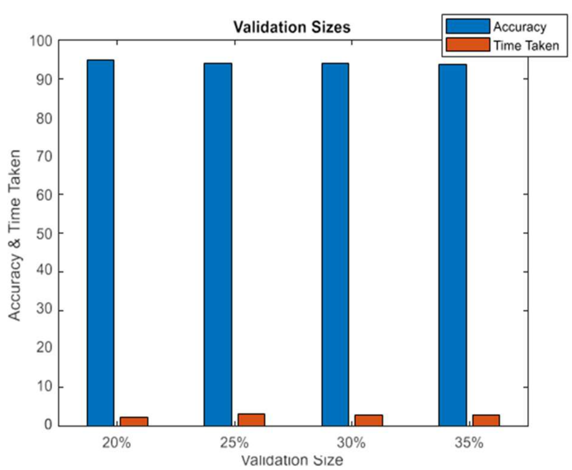

Fig. 11. Validation Size Performance

D. Prediction Ability

With the testing conducted during the training of the model were completed, the further testing is all about analyzing the ability of the trained predictive maintenance model. In this testing, the analysis of checking how long the trained model can predict further for without losing too much accuracy data. This testing is important as it can analyze the ability of the predictive model and to check how much further the predictive model can predict the possible output from the input data. If the trained model can predict much further future possible output, the user can plan for the maintenance on the elevator much earlier if failures were to be detected in the future.

By increasing the number of cycles turned by the elevator motor, it also means that the range of time of the trained model must predict is increasing as well. Therefore, increasing the number of cycles is similar as increasing the range of time of the prediction must achieve. Once the prediction for each increasing of cycles turned has been completed, the collected data will be plotted into bar chart form for further analysis.

Figure 12 shows the bar chart plotted for the prediction ability. By observing the bar chart, it shows that the accuracy in all the testing by different number of cycles were very constant and similar. This proved that the trained predictive maintenance model can predictive much further possible output without resulting in much losses. The trained model maintained its accuracy throughout the whole prediction ability testing. This conducted testing proved that the trained model able to predict possible outputs that is almost 40% further from its own input training data.

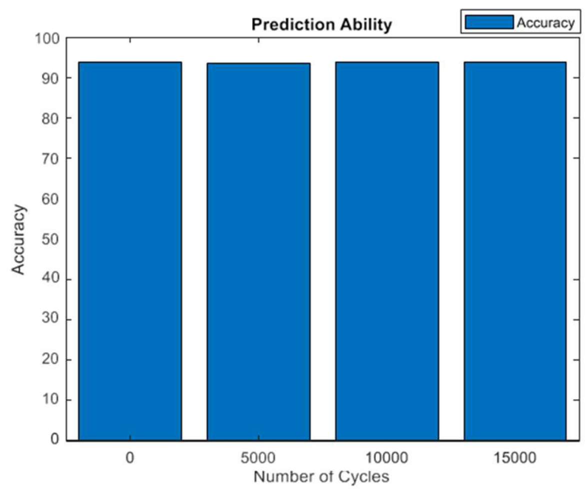

Fig. 12. Prediction Ability Performance

E. Biased and Unbiased Testing

With all the testing conducted, the last testing that will be analyzed for the implemented system is to test if the trained model is capable for unbiased prediction. Biased prediction is when the trained model was inserted with the input that is same as the input applied during the training of model. Unbiased prediction is when the trained model is applied by the input that is not seen before during the training of the model. A trained model can be mark as successful when it is capable of unbiased prediction and maintaining the accuracy similar as the result during the training process. In this testing, the comparison of the biased and unbiased accuracy will be conducted to analyze if the unbiased prediction was successful. Using the accuracy data collected from the biased and unbiased prediction, a bar chart was plotted as shown as figure below. However, there are two types of accuracy data were taken for analyzing purpose: Overall Accuracy and "urgent" Accuracy.

Figure 13 shows the prediction results from both biased and unbiased prediction. Looking at the bar chart, it can be noticed that both the "urgent" accuracy was higher than the overall accuracy. This shows that most of the corrected prediction were occurred in the "urgent" section. It is important to have higher accuracy at "urgent" condition, as it is hinged on the edge of failure. Furthermore, the results shows that the unbiased prediction has more accuracy than the biased prediction, this not only proved the trained Fine KNN model was successfully functioning, but it also proved that the trained model was learning during the unbiased prediction testing as well.

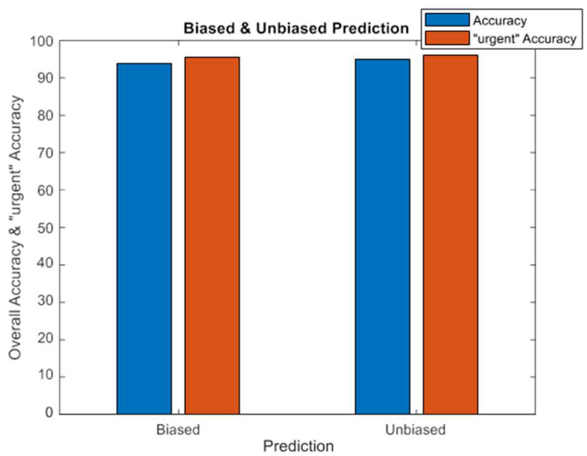

Fig. 13. Unbiased confusion matrix performance

F. Comparison with previous research

For the predictive maintenance system, the most important result that needs to be compared is the accuracy of the prediction ability. The higher the accuracy will justify the better the predictive system is. The machine learning algorithm selected for this implemented predictive maintenance model was k-nearest neighbors' algorithm (KNN). Using the KNN trained model as the predictive maintenance system, two predictions were conducted for the ability analysis: biased prediction and unbiased prediction. Both prediction results were similar, biased prediction accuracy was 93.8% and unbiased prediction accuracy was 95.5%. Since the unbiased prediction was the main objective to be achieved in this implemented system; therefore, the accuracy of 95.5% will be taken for the comparison with the previously researched papers.

Table 1 shows the accuracy of all the predicted results from the four system: Elevator System Failure Detection, ATM Machine Fail Spare Part Prediction, Mechanical Damage and Crack Detection, Electrical Devices Fault Detection, and Pneumatic System Fault Detection. The Elevator System Failure.

TABLE 1: COMPARISON WITH RESEARCHES

System	Machine Learning Algorithms	Accuracy
Elevator System Failure Detection	KNN	95.5%
ATM Machine Fail Spare Part Prediction (Rachburee, Jantarat & Punlumjea, 2016)	SVN	88.24%
	ANN	87.07%
Mechanical Damage and Crack Detection (Krenek et al., 2016)	RBF	96%
	MLP	80%
	GA	93%
	MLP	95%
	MLP	95%
	FF	89%
	FF	87%
Electrical Devices Fault Detection (Krenek et al., 2016)	MLP	83%
Pneumatic System Fault Detection (Krenek et al., 2016)	ART	93%

V. CONCLUSIONS

The implementation of the predictive maintenance on an elevator system using machine learning was completed. Three objectives set as the goal for the system to be achieved were also successfully achieved by the implemented system as well. In this chapter, the explanation and justification of how the three objectives were achieved by the implemented system were completed. The first objective main focusing on the software implementation, it aims to implementing a system that can predict the health condition of the elevator system. The implemented system was using the Fine KNN algorithm model to make unbiased prediction and obtained the result accuracy of 95.5%. The second objective was focus on hardware building and sensor data capturing. The elevator prototype was completed and result of it was shown in the Hardware Result section. Two sensors, temperature sensor and encoder sensor were installed beside the elevator motor for data capturing purpose. All the data collected will be compiled in a excel file. The third objective was the evaluation of the performance and efficiency of the implemented system. Five testing were conducted on the predictive maintenance system to prove the reliability of the result. First three testing were conducted for selecting the best setting for the training method: Fine KNN algorithm and 30% of validation size. Forth testing were conducted on analysing the prediction ability of the trained model, and the last testing was conducted on comparing the biased and unbiased prediction result. The testing results shows that the unbiased prediction achieved the accuracy of 95.5%, To improve the system, by adding the Remaining Useful Life prediction ability into the predictive maintenance system will help in displaying clear future failure occurred time. Furthermore, the implemented system can only be applied on one elevator system; hence, it is suggested to enhance the predictive maintenance system become capable of predicting health condition of different elevator system.

REFERENCES

[1] C. P. Au-Yong, N.F. Azmi, and N.A. Mahassan, "Maintenance of lift systems affecting resident satisfaction in low-cost high-rise residential buildings. Journal of Facilities Management", 16(1). p.17 – 25, 2018

[2] C. Chen, Y. Liu, X. Sun, C.D. Cairano-Gilfedder and S. Titmus, "Automobile Maintenance Prediction Using Deep Learning with GIS Data. In 52nd CIRP Conference on Manufacturing Systems", Ljubljana and 12th – 14th June 2019. pp.447 – 452, 2019

[3] J. Krenek, K. Kuca, O. Krejcar, P. Blazek and D. Jun, "Application of Artificial Neural Networks in Condition Based Predictive Maintenance", Germany: Springer Verlag, 2016

[4] S. Coban, M.O. Gokalp, E. Gokalp, P.E. Ern and A. Kocyigit, "Predictive Maintenance in Healthcare Services with Big Data Technologies. In 2018 IEEE 11th International Conference on Service-Oriented Computing and Applications", Paris and 1st – 25th Oct 2018. pp.93 – 98, 2018

[5] A. Simon, M.S. Deo, S. Venkatesan and D.R.R. Babu, "An Overview of Machine Learning and its Applications. International Journal of Electrical Sciences & Engineering. 1(1). p.22 – 24, 2015

[6] X.M. Koh, "Development of Predictive Maintenance Data Analytic for Internet of Things (IoT) Implementation", 2017 [Online]. 2018. Available from: https://www.academia.edu/37320463/Development of Predictive Maintenance Data Analytic for Internet of Things IOT Implementation [Accessed 24th September 2019]

[7] P. Straub, M. Schmitz, R. Wostmann and J. Deuse, "Enabling of Predictive Maintenance in the Brownfield through Low-Cost Sensors, an IIoT- Architecture and Machine Learning. In 2018 IEEE International Conference on Big Data. Seattle and 10th – 13th Dec 2018. pp.1474 – 1483, 2018