RECURRENT NEURAL NETWORK BASED VIBRATION DATA CLASSIFICATION

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This report is submitted in partial fulfilment of the requirements for the degree of Bachelor of Electronic Engineering with Honours

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DECLARATION

I declare that this report entitled "Recurrent Neural Network Based Vibration Data Classification" is the result of my own work except for quotes as cited in the references.

Signature :

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Date : 26 JUNE 2020

APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Bachelor of Electronic Engineering with Honours.

Signature : ....

Supervisor Name : Dr. Amat Amir Basari

Date : 2 July 2020

DEDICATION

To my beloved parents Mohd Zamberi bin Hussain and Shafina binti Mohd Salleh, my grandparents and my siblings Nurul Syafiqah and Muhammad Aiman Zikry, thank you for all of your doa and support, without each and every one of you I would not able to finally reach this stage of my life. I love you guys so much <3

ABSTRACT

Vibration is the main part in the machinery, the type of vibration is the important for the best output result and to avoid major breakdown for the production. Vibration data classification has been research mainly focusing of improving the efficiency and the operation of the production. The dataset are mixed with numbers of vibration data with different type of vibration produced from the cutting machine, which bring difficulty to analysis the dataset for accuracy result. Other than that, the sampling time of analysing the vibration data also affect the accuracy result. The sampling time that will be analysed is between 10 microseconds to 50 milliseconds. Recurrent neural network (RNN) is a type of artificial neural network which can be embedded with multiple of time sequence data. The capacity of RNN had been prove outstanding for entering time relevance about the time sequence data. This paper proposed a method for recurrent neural network based vibration data classification. The RNN algorithm will be build using the MATLAB software. From the total datasets it will be divided into three parts for training, validation and testing. The final result of this analysis will be determine by the confusion matrix which shows the accuracy result of the data classification. The final accuracy result of 10 microseconds is 75.7% and for 50 milliseconds is 65.4%.

ABSTRAK

Getaran adalah bahagian utama dalam mesin, jenis getaran adalah yang penting untuk hasil keluaran terbaik dan untuk mengelakkan kerosakan besar dalam pengeluaran. Klasifikasi data getaran adalah penyelidikan yang memfokuskan peningkatan kecekapan dan operasi pengeluaran. Set data yang telah bercampur dengan berbagai jenis getaran lain yang dihasilkan dari mesin pemotong, menyebabkan kesukaran untuk menganalisis set data untuk hasil ketepatan. Selain daripada itu, masa pengambilan sampel menganalisis getaran juga mempengaruhi hasil ketepatan. Masa persampelan yang akan dianalisis adalah antara 10 mikrodetik hingga 50 milisaat. Rangkaian neural berulang (RNN) adalah sejenis rangkaian saraf tiruan yang dapat disisipkan dengan banyak data urutan masa. Kapasiti RNN telah terbukti luar biasa. Makalah ini mencadangkan kaedah untuk klasifikasi data getaran berdasarkan rangkaian saraf berulang. Algoritma RNN akan dibina menggunakan perisian MATLAB. Dari jumlah set data itu akan dibahagikan kepada tiga bahagian untuk latihan, pengesahan dan pengujian. Hasil akhir analisis ini akan ditentukan oleh matriks kekeliruan yang menunjukkan hasil ketepatan klasifikasi data. Hasil ketepatan akhir 10 mikrodetik ialah 75.7% dan untuk 50 milisaat adalah 65.4%.

ACKNOWLEDGEMENTS

‘In The Name Of Allah, the Most Gracious and the Most Merciful’

Alhamdullilah for the health, patient and endless courage that has been given to me and my family from The Most Gracious that finally I successfully managed to finish my final year report. First and foremost, I would like to pay my special regards to my parents, Encik Mohd Zamberi bin Hussain and Puan Shafina binti Mohd Salleh. The calmness, faith and their prayers to me has given me the strength and believe that completing this final year project is achievable.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

RNN	:	Recurrent Neural Network
ANN	:	Artificial Neural Network
AI	:	Artificial Intelligence
GRU	:	Gated Recurrent Unit
CNN	:	Convolutional Neural Network
LSTM	:	Long Short Term Memory
PC	:	Personal Computer
SNR	:	Signal-to-Noise-Ratio
DCM	:	Dynamic Cortex Memories
SBD	:	Sequence Boundary Dropout
RAP	:	Random Activation Preservation
SVM	:	Support Vector Machine
DRNN	:	Deep Recurrent Neural Network
TCM	:	Tool Condition Monitoring
FFBP	:	Feed Forward Back Propagation
RNFC	:	Recurrent Neuron Fuzzy Classifier
ANFIS	:	Adaptive Network Fuzzy Inference System

CHAPTER 1

INTRODUCTION

This part introduced about the last perspective on the project following by the background and problem statement. The objectives and scope of project additionally examined during this section. All the primary concerns for each area of the project are remarked during this section.

1.1 Project Overview

Recognising on condition of the data vibration of a machine is important to reduce the error risk. While visual classifications by human naked eyes are lack of accurate data in real time. Visual classification is important for the decision on how the machine operates at the maximum or minimum requirement to produce the best output and to avoid major breakdown and losses from an accurate vibration signal data produce that very important.

The conditions may be dealing with the aid of the signals of vibration sensors that implanted on the cutting machine. From the highest wide variety of accuracy of fault analysis which by means of removing fault statistics from the original dataset. Effective features extracting methods, as the accurate fault analysis can assist to filter out repeated records. Besides, in the first dataset signal bring the problem in removing all the essential point from the mixed observed statistics produce.

The construction of RNN model is fit for finding significant highlights that will aides and qualities among the numerous time grouping information. Likewise of the extraordinary possible focal points of RNN model, the utilization of RNN on shortcoming examination for information vibration has hard to be found in the writing.

In this paper, a technique based totally on RNN model is proposed for fault classification of vibration data. Multiple vibration dataset under different health conditions are obtained for the training. The model is educated to copy the more than one vibration data of the cutting system from the previously signal produced. Few experiments were carried out to affirm that the proposed learning method can obtained maximum accuracy for data classification.

1.2 Problem Statement

Sampling time will determine the characteristic of the vibration data that we measure. With high sampling time, number of data per period of time will be very high and precisely the vibration can be plotted and observed. However, in the case of low sampling time, the number of data that will be stored will be much less and it will affect the characteristic of the vibration. Self-powered sensor like piezoelectric sensor has very low sampling time. If classification of vibration data with low sampling time is to be done, powerful classification technique is needed. In this project, applicability of recurrent neural network will be analysed for this task.

1.3 Objectives

1) To model Recurrent Neural Network (RNN) for vibration data classification at a low sampling time.
2) To investigate and analyse the performance of the accuracy.
3) To classify bad and good vibration data correctly.

1.4 Scope of Project

The project scope for this paper is focusing on the applicability of recurrent neural network (RNN) in diagnosing vibration data that captured by piezoelectric sensor. The data captures are from copper plate cutting machine. The data is from copper plate cutting machine. The sampling time of vibration is between 10 microseconds to 50 milliseconds since the piezoelectric device will produce energy at low sampling time. The number of vibration data is two set of data. There is good sampling vibration data and bad sampling vibration data for this project.

Layer recurrent neural systems are like feed forward systems, then again, actually each layer has a repetitive association with a tap delay related with it. This permits the system to have a limitless unique reaction to time arrangement input information. This system is like the time delay (timedelaynet) and distributed delay (distdelaynet) neural systems, which have limited information reactions.

This task use MATLAB neural system tool kit. For the most part to train a neural system give some training and testing information and the net item deals with separating the information. Be that as it may, what the need to do is separate the information and set the training and testing information precisely in the net article. From memory can determine which extents are utilized for training, validation and testing.

From the input vibration data which represented in numbers that are going through the network it will then give an output accuracy which the data has been successfully classified accordingly into two classifications of vibration data which are good vibration data and bad vibration data. The accuracy result will be determined and showed by the confusion matrix.

1.5 Project Significant

Improvise solution to be design a network with a system that will classify data automatically. This Vibration Data Classification to be use at cutting machines that produce vibration from the blade. The industry will have these advantages, as this data classification able to classify and detecting a good or bad vibration data produce by the machine. It helps to monitor the vibration data to the highest accuracy. Lastly, the data classification will produce an accurate data percentage.

1.6 Expected Outcome

The expected outcome of this project is to develop an algorithm of Recurrent Neural Network (RNN) in classifying the vibration data at a low sampling time. The performance of the accuracy in classifying the vibration data will be evaluated. Lastly, the system can identify and classify correctly between a good vibration data and a bad vibration data.

1.7 Summary

The principle focus of this task is to explore the appropriateness of Recurrent Neural Network (RNN) in vibration information arrangement that having diverse inspecting pace of time. A key test in Artificial Intelligence (AI) is to investigate and fuse the mind boggling nature of true information structures into the preparation models. Conventional methodologies concentrate on removing helpful highlights that fill in as contributions for AI models. The element structuring process is costly as it requires space specialists and the high quality highlights are not versatile through learning. An increasingly conceivable methodology is to configuration models that can straightforwardly deal with the structure data of information.

1.8 Thesis Outline

This proposal includes five chapters. Chapter 1 gives the prologue to the project. The descriptions portrayed in Chapter 1 are project overview, objectives, problem statement as well as scope of work. Chapter 2 presents the foundation learn about the utilization of Recurrent Neural Network (RNN) and the finding of vibration. Related works of utilizing other neural system additionally introduced in this part. In Chapter 3, the general progression of the project methodology such as project flowchart and project block diagram in designing, testing and training the RNN algorithm is portrayed in detail in this chapter. Chapter 4 is the discussion of the outcomes acquired from the vibration information utilized in the project. Lastly, Chapter 5 conveys the end for this project. Recommendations for forthcoming works have been evaluated and commented in the end of this chapter.

CHAPTER 2

BACKGROUND STUDY

This chapter tends to the past examination applicable to the Recurrent Neural Network in characterizing vibration information and depicts the legitimization for the past analysis paper and articles in detail. Those journals and analysis papers has given a few thoughts and methods to direct the undertaking of this project. The best arrangement was picked and applied as the procedure to this task dependent on the techniques utilized in those past related analysis.

2.1 Introduction

The motivation behind a writing study is to break down fundamentally a section of a distributed group of information through outline, order, and correlation of earlier examination considers, surveys of writing, and hypothetical articles. The study on all previous project been made on the title for the project which is Recurrent Neural Network based vibration data classification.

2.2 Machine Learning

The world is loaded up with a ton of information, for example, pictures, music, words, and recordings. Artificial Intelligence (AI) is a man-made reasoning innovation that furnishes frameworks with the capacity to gain and grow naturally as a matter of fact without express programming [12]. AI centres on PC programs that can get to information and use it to learn all alone [10]. The learning procedure begins with discoveries or information, for example, models, direct understanding, or guidance, so as to search for information structures and use sound judgment dependent on the models gave. The essential objective is to naturally permit PCs to learn without human association or direction and to change activities likewise.

Artificial Intelligence systems are frequently sorted as supervised or unsupervised. Regulated AI algorithms can utilize named guides to anticipate future occasions and apply what has been realized in the past to new information [11]. Starting with the investigation of a known training dataset, the learning algorithms produces a construed capacity to anticipate the yield esteems. After adequate training, the program can give desires to any new information. The learning calculation can likewise make correlations between the yields to the exact yield and discover blunders to alter the model correspondingly.

Unsupervised AI algorithms are utilized when the information utilized for preparing is not marked or labelled. Unsupervised learning investigates how frameworks can foresee a capacity from unlabelled data to characterize a shrouded structure [13]. The framework does not choose the proper yield, however inspects the information and can make ends from datasets to clarify concealed structures from unlabelled data. Support AI algorithms is a type of realizing which manages its condition through activities and finds mistakes or rewards and accelerating pace [14]. The most significant attributes of support learning are experimentation search and deferred reward. This strategy permits machines and programming operators to assess the ideal conduct naturally inside a particular setting to advance their effectiveness. For the specialist to realize which activity is ideal, straightforward prize input is required and this is known as the fortification sign.

Artificial Intelligence makes it conceivable to break down a lot of information [15]. While for the most part conveying quicker, increasingly precise outcomes to distinguish gainful chances or perilous dangers, it might likewise require broad time and assets for legitimate preparing. It very well may be made much increasingly successful in preparing huge volumes of information by coordinating machine learning with Artificial Intelligence (AI) and subjective innovation [16].

2.3 Deep Learning

Deep learning is a gathering of numerical units that can be prepared and an intricate capacity can be determined for single modalities [17]. Such recreated capacities can be supervised, unsupervised and reinforcement learning. It is a piece of the more extensive AI framework. Deep learning in AI is a significant theme to study and read through subtleties on different training forms so as to have additionally comprehension of the recurrent neural system between actions and effects [18]. Deep learning is a decent method to accomplish great acknowledgment results.

Yann LeCun et.al (2015) guaranteed that deep learning is a method of AI, which is found out straightforwardly from the information. Deep learning permits multi-layered computational models to learn information portrayals with numerous reflection levels. These strategies have altogether improved the most recent voice acknowledgment, acknowledgment of visual items, object location, and numerous different capacities, for example, sedate revelation and genomics. Deep learning investigates mind boggling structure in huge measures of datasets by utilizing the backpropagation calculation to show how a machine will change its interior boundaries utilizing the portrayal in the past layer to decide the portrayal in each layer. Deep convolutional systems have made advancements in picture, video, voice and sound handling, while at the same time repeating systems have revealed insight into consecutive data, for example, text and voice [1].

2.4 Neural Network

Neural system structure the base of deep learning and a subfield of AI where the calculations are influenced by the structure of a human mind. Neural systems take in information, train themselves to perceive the examples in the information and afterward foresee the yields for another arrangement of comparative information. Figure below shows the fundamental development of neural system which contains an input layer, hidden layer and output layer to create the outcome [19].

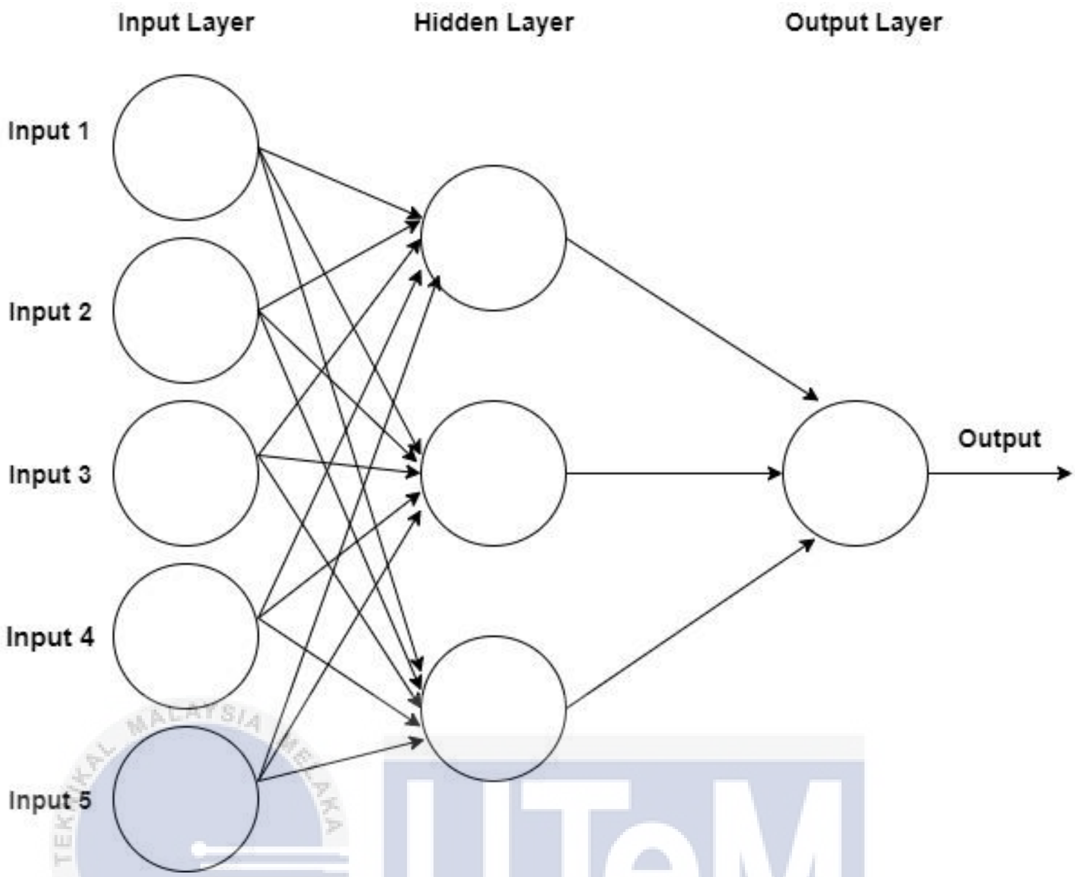


Figure 2.1 Connection of Neural Network

Neural systems are comprised of layers of neurons. These neurons are the centre preparing units of the systems keeping numbers from the previous time step [20]. Every roundabout hub speaks to a counterfeit neuron and a bolt speaks to an association from the yield of one fake neuron to the contribution of another. The input layer gets the information and the output layer predicts the last yield. In the middle of exist the hidden layers which perform the vast majority of the calculations required by the system. The essential procedure of a neural system is every information is taken care of as contribution to every neuron of the main layer. Neurons of one layer are associated with neurons of the following layer through channels. Every one of these channels is allocated a numerical worth known as weight. The information sources are increased to the comparing weights and their whole is sent as a contribution to the neurons in the hidden layer. Every one of these neurons is related with a numerical worth called the bias which is the additional to the info entirety. This value is then gone through an edge work called the activation function. The aftereffects of the activation function decide whether the specific neuron will get enacted or not.

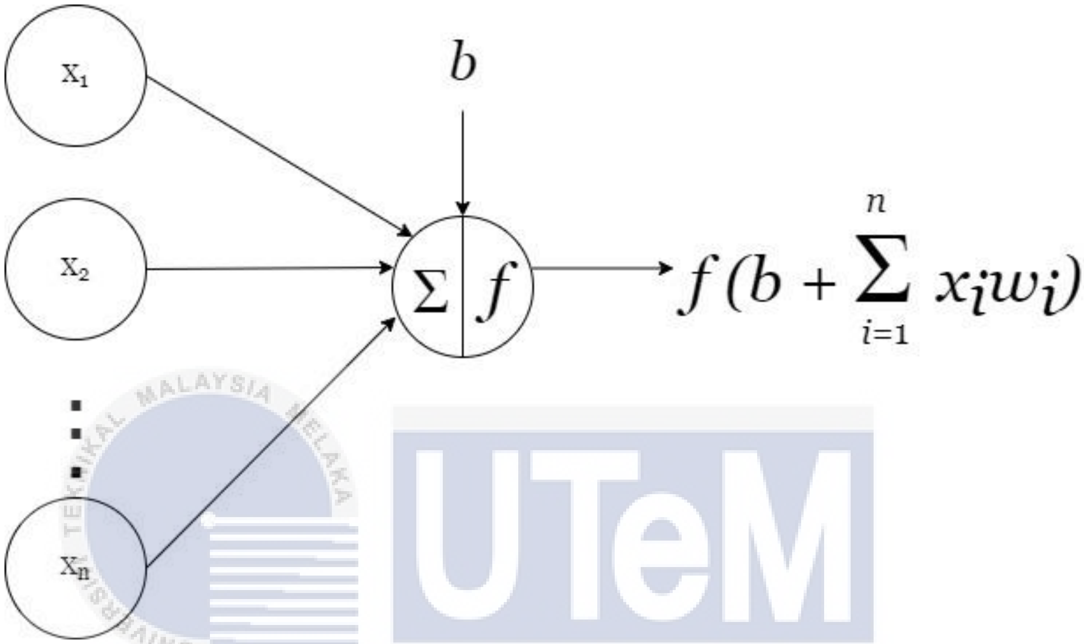


Figure 2.2 Activation function

An initiated neuron transmits information to the neurons of the following layer over the channels. Thus, the information is engendered through the system. This is called forward propagation. In the output layer, the neuron with the most elevated worth moves and decides the output by varying the control points [21]. The qualities are fundamentally a likelihood and that is the output anticipated by the neural system. Now and again if the neural system has made an off-base expectation it should be trained. In the preparation procedure, alongside the input, the system likewise as the output took care of to it. The anticipated output is contrasted against the real output with understand the error in expectation. The size of the error will demonstrates how wrong it is. The data is then moved in backward through the system. This procedure is known as the back propagation. In light of the data the weights are balanced. This pattern of forward propagation and back propagation is continuously performed with various sources of input. This procedure proceeds until the weights are doled out such the system can foresee the information effectively in the majority of the cases.

The prime applications of neural networks are mostly to recognize pattern in the real world data which are text, images or audio.

2.5 Recurrent Neural Network (RNN)

According to the basic concept of neural network, all data input and output are not depending on each other. Nevertheless, a Recurrent Neural Network (RNN) used a sequential information which the previous data will be included in the future prediction. RNNs are called recurrent because for every element of a sequence they perform the same process, with the output based on the previous calculations [22]. Otherwise speaking, RNNs have a "memory" that stores data about what has been measured since then.

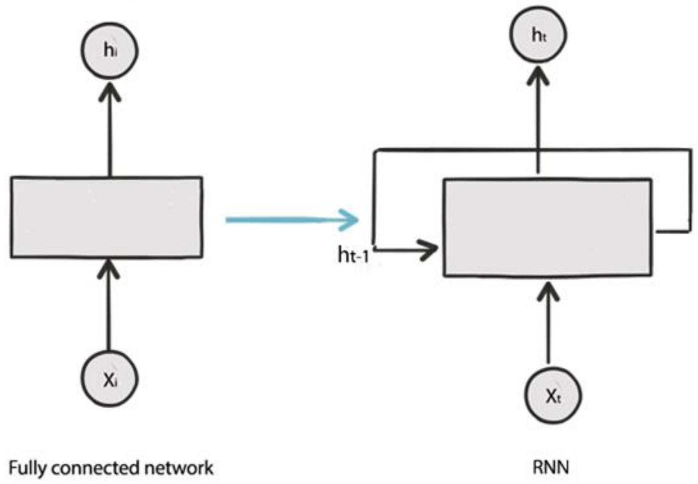


Figure 2.3 Recurrent Neural Network (Self-loop network)

Figure above shows that RNNs have a loop connection between the input, Xt and the output, ht. Fundamentally, it feed the output of the previous time frame back to the network's next time frame and feedback connection [23]. If the networks being unroll, the following structure below will be obtained.

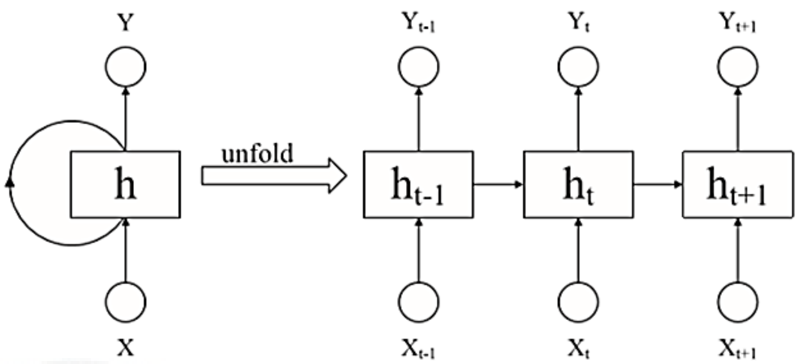


Figure 2.4 Basic architecture of RNNs

In fact, in discretionarily long arrangements, RNNs may utilize information, however practically speaking they are constrained to simply thinking back a couple of steps to solve gradient problem [24]. Figure above is a case of traditional RNN design, with RNNs unfolding for the total succession into a full system. For instance, if the sequence we care about is a 5-word sentence, the system would unfold into a 5-layer neural system, one layer for each word. The numerical conditions for the estimation in a RNN are as per the following,

At time step, t:

$$H\_t = \sigma(X\_t * U + W * H\_(t-1)\ )$$ – Equation (2-1)

$$Y\_t = SoftMax(V * H\_t\ )$$ – Equation (2-2)

$$U = Weight\ vector\ for\ hidden\ layer$$

$$V = Weight\ vector\ for\ output\ layer$$

$$W = Same\ weight\ vector\ for\ different\ timesteps$$

$$X = Word\ vector\ for\ input\ word$$

$$Y = Word\ vector\ for\ output\ word$$

The major differences between neural network and RNN are neuron communication patterns in output generation. Each input neuron in a layer is associated with each output neuron in the following layer in the neural system as appeared in Figure 2.1. For RNN, the output is generated by recurrent operation in which hidden layers of neurons may learn to convert a lifelong sensory input stream into a sequence of useful outputs. Recurrent neural networks (RNN) are programmed to recognize sequences for a voice signal or a message as an example. There are loops inside the recurrent network that indicate the existence of short memory in the network. RNNs are suitable for the study of text and speech. In a short sequence dependent on chronicled information, this model will attempt to foresee the following worth. In addition, RNN models can produce long sequences based on past data. It can be modified to produce text as well. Prediction quality will depend on training data, network architecture, hyper parameters, and the time distance predicted, and so on. However, it will depend on whether the training data will contain examples of the behaviour we are trying to predict.

2.6 Application of Recurrent Neural Network (RNN)

In this part, a review of some papers that all have the same purpose in which using the RNNs method will be discussed. The concept of reviewing these selected articles is based on the accuracy of RNNs can classify a different data. The problem statement, methods being used, results, strength and weaknesses in every previous research obtained will be highlight.

Han Liu et.al (2018) talked about that as the moving course being the key piece of revolving machine, its good condition is very significant for wellbeing creation. Fault diagnosis of rolling bearing has been research centre for improving the monetary proficiency and ensuring the activity security. In any case, the gathered signs are blended in with encompassing commotion during the activity of turning machine, which carries extraordinary test to the specific analysis results. Utilizing signals gathered from different sensors can maintain a strategic distance from the loss of nearby data and concentrate increasingly accommodating qualities. Recurrent Neural Networks (RNN) is a kind of counterfeit neural system which can manage various time arrangement information. The limit of RNN has been demonstrated exceptional for getting time pertinence time grouping information. This paper proposed a novel technique for bearing fault diagnosis with RNN as an autoencoder. In this methodology, numerous vibration estimation of the moving orientation of the following time frame are anticipated from the past period by methods for Gated Recurrent Unit (GRU)- based denoising autoencoder. These GRU-based non-direct prescient denoising autoencoders (GRU-NP-DAEs) are prepared with solid speculation capacity for each extraordinary shortcoming design. At that point for the given info information, the recreation errors between the following time frame information and the yield information created by various GRU-NP-DAEs are utilized to identify peculiar conditions and group issue type. Exemplary turning hardware datasets have been utilized to affirm the adequacy of the proposed finding technique and its prevalence over some best in class strategies. Analysis results demonstrate that the proposed technique accomplishes suitable presentation with solid power and high order exactness. [2]

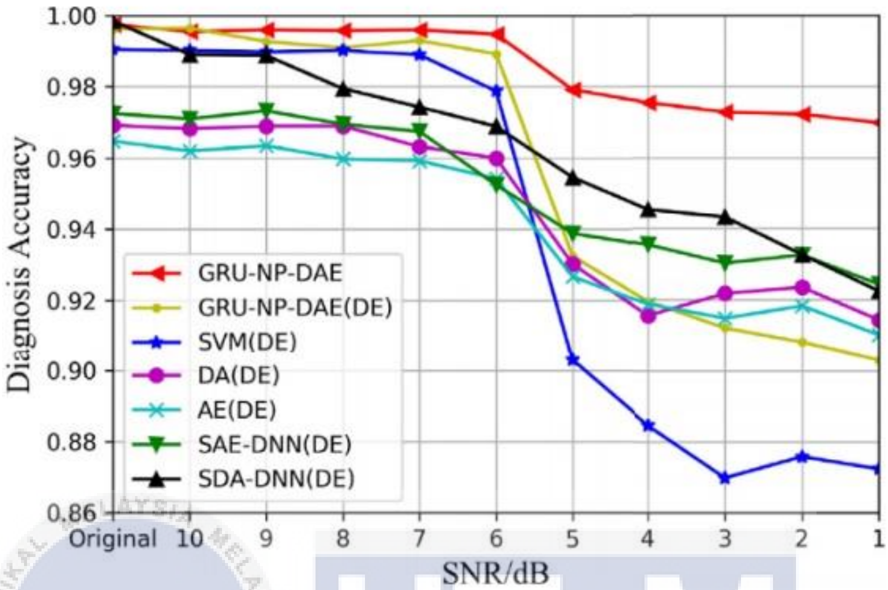


Figure 2.5 Diagnosis accuracy of employed methods with different SNRs [2]

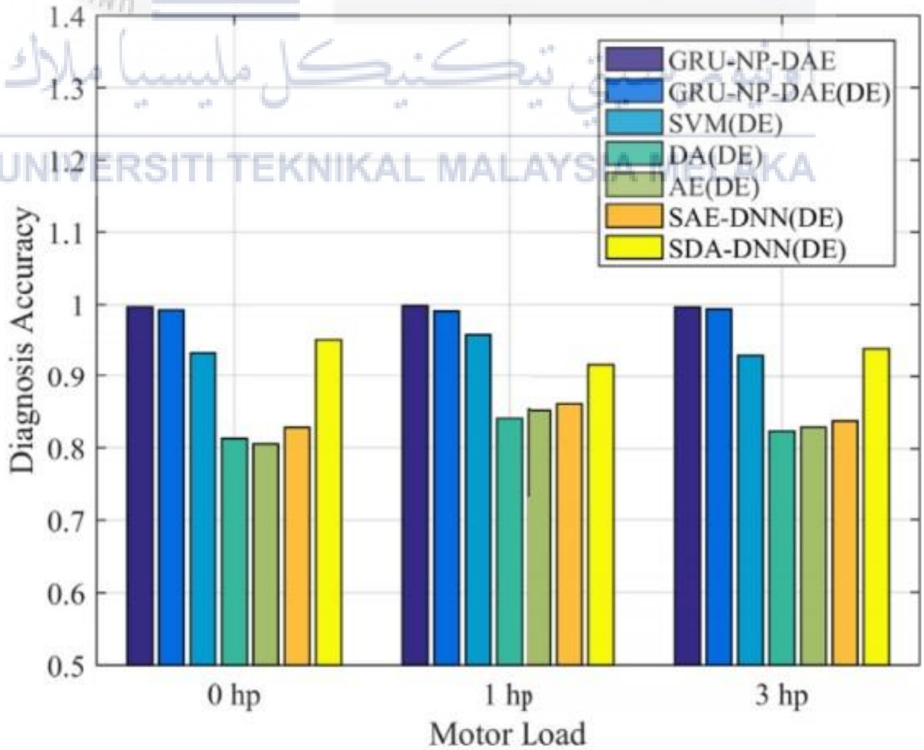


Figure 2.6 Diagnosis Accuracy of employed method with different motor load [2]

Sebastian Otte et.al (2016) introduced a paper explores Recurrent Neural Networks (RNNs), especially Dynamic Cortex Memories (DCMs), an expansion of Long Short Term Memories (LSTMs) for classification of 14 diverse ground types dependent on vibration information. Additionally a straightforward regularization method called Sequence Boundary Dropout (SBD) is presented, which adequately develops the preparation set and improves speculation. The neural systems act in the time space with no unequivocal component calculation, while past best in class strategies extricate includes for the most part in the recurrence area. The introduced approach does not require a period window, is causal, and works in the nick of time, with the end goal that a classification should be possible online at each new time step. Besides, we show that the neural systems outflank past techniques significantly as far as classification exactness. At last, we show that the systems retrained with Random Activation Preservation (RAP) can order ahead of schedule in inside a small amount of a second yet vigorously simultaneously in a persistent acknowledgment situation with differing classes. [3]

Class	Acceleration only (6 features)							Acceleration + gyroscope (12 features)					
	SVM [6]	LSTM			DCM			LSTM			DCM		
		16	32	64	16	32	64	16	32	64	16	32	64
Indoor	56.36	74.54	83.51	87.90	74.05	83.48	88.73	77.62	86.95	91.36	76.92	84.49	90.90
Asphalt	63.12	65.49	72.96	74.10	67.75	72.94	75.02	70.22	75.84	80.28	73.00	77.60	79.49
Fine gravel	72.64	53.07	62.31	67.86	56.67	66.16	68.12	58.26	69.06	74.44	63.41	68.98	74.67
Coarse gravel	90.99	90.76	89.63	90.89	90.06	90.85	90.53	89.67	91.45	92.38	92.02	91.99	93.23
Tiles	60.48	62.12	73.67	80.31	64.67	75.90	79.46	67.25	74.16	82.79	68.92	76.79	80.99
Quadratic paving	82.19	67.64	71.36	75.43	68.79	71.54	76.00	69.46	73.71	77.82	69.50	75.86	77.14
Circular paving	76.39	54.85	64.36	67.62	56.49	62.69	67.35	66.51	71.59	76.27	67.38	71.48	77.74
Clay	91.32	80.20	84.25	84.31	83.35	84.62	85.51	83.57	84.84	87.88	84.68	86.11	87.96
Dirt	84.23	64.52	67.84	67.66	64.34	66.95	67.75	66.98	71.11	73.57	69.18	71.45	71.71
Small bushes	22.40	47.52	51.70	48.54	49.07	50.55	52.75	54.93	59.48	60.18	51.52	58.29	62.07
Grass	92.55	87.56	84.74	85.58	85.36	84.03	84.33	84.86	84.91	85.84	86.59	85.09	85.83
Medium-high grass	84.15	71.33	77.93	77.85	78.66	78.65	79.47	78.22	79.17	79.12	76.80	77.62	77.90
Mowed grass	83.68	95.01	94.92	95.30	95.69	94.67	94.54	94.80	95.42	95.21	94.96	94.92	95.71
Mix grass/gravel	90.45	93.47	94.14	94.62	94.36	94.43	94.62	95.58	95.86	95.90	95.78	95.51	96.24
All	75.07	75.91	79.68	81.52	77.18	79.97	81.73	78.66	82.03	84.57	79.60	82.32	84.47

Figure 2.7 Mean Classification Results Accuracy in % of SVMs compared with Recurrent Neural Network (RNN) [3]

Ramadevi R. et.al (2012) planned to introduce the result of an examination directed on the cavitation information gathered from accelerometer which is introduced at the downstream of the cavitation test circle, to represent that the concealed neurons in an ANN modelling tool, in reality, do have tasks to carry out in level of grouping of cavitation signal. It reveals insight into the job of the concealed neurons in an Elman Recurrent sort ANN model which is utilized to group the cavitation signals. The outcomes affirmed that the covered up yield association loads become little as the quantity of concealed neurons turns out to be huge and furthermore that the exchange off in the learning dependability between input-covered up and covered up yield associations exists. The Elman recurrent system engenders information from later handling stage to prior stage. A duplicate of the past estimations of the shrouded units are kept up which permits the system to perform grouping expectation. In the current work, the ideal number of shrouded neurons is developed through a detailed experimentation method. It is presumed that the methodology has a noteworthy improvement in learning and furthermore in arrangement of cavitation signals. [4]

Train Data Percentage of Detection: 64.93% (Totally 15 signals, 5 signals on each category from all zones)		
ZONE	**CHANNEL**	**% OF DETECTION**
		Test Data
II	1	61.21
IV	1	56.72
	2	59.13
VI	1	68.97
	2	100
VII	1	56.44
	2	54.85
Over all %		**65.34%**

Figure 2.8 Performance analysis [4]

Yan Xu et.al (2016) directed an examination to improved connection characterization by deep recurrent neural systems with information enlargement. These days, neural systems assume a significant job in the assignment of connection order. By structuring distinctive neural designs, scientists have improved the exhibition to a huge degree in examination with conventional techniques. In any case, existing neural systems for connection arrangement are as a rule of shallow structures (e.g., one-layer convolutional neural systems or recurrent systems). They may neglect to investigate the potential portrayal space in various deliberation levels. In this paper, deep recurrent neural systems (DRNNs) for connection characterization to handle this test has been proposed. Further, an information growth strategy by utilizing the directionality of relations also has been proposed. The DRNNs on the SemEval-2010 Task 8 has been assessed and accomplish a F1-score of 86.1% beating past state-of-the-art recorded results. [5]

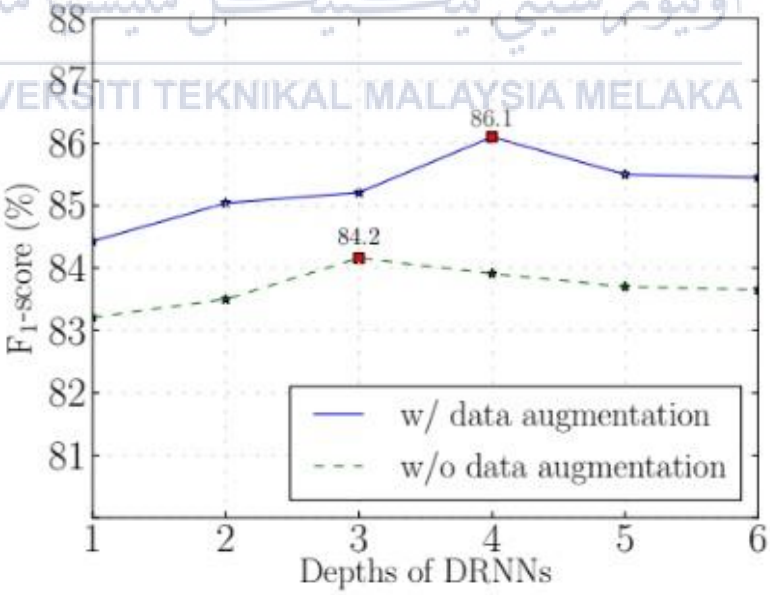


Figure 2.9 Analysis of the depth [5]

Author	Year	Proposed Method	Results
Han Liu, Jianzhong Zhou, Yang Zheng, Wei Jiang.	2018	Recurrent Neural Network (RNN) and Gated Recurrent Unit (GRU)-based denoising auto encoder for bearing fault diagnosis.	The strength of the prepared model is acceptable, considerably under the state of a low SNR and fluctuant motor loads. Subsequently, the proposed GRU-NP-DAE strategy is approved to be practical for the fault diagnosis on rolling bearings.
Sebastian Otte, Christian Weiss, Tobias Scherer, Andreas Zell.	2016	Recurrent Neural Networks (RNNs), particularly Dynamic Cortex Memories (DCMs) and an extension of Long Short Term Memories (LSTMs) for classification of 14 different ground types based on vibration data.	The RNNs accomplished a normal exactness of generally 85%, while the recently detailed cutting edge precision for the tended to informational collection comprising of 14 terrain classes was about 75%.
Ramadevi R, Sheela Rani B, Prakash V	2012	Elman Recurrent Neural Network in Classification of Cavitation Signals.	The general level of cavitation recognition for train information is 64.93% and for test information was seen as 65.34%.
Yan Xu, Ran Jia, Lili Mou, Ge Li, Yunchuan Chen, Yangyang Lu, Zhi Jin	2016	Deep recurrent neural networks (DRNNs) for relation classification with data augmentation.	The performance generally improves when the depth increases; with a depth of 4, our model reaches the highest F1-measure of 86.1%.

Table 2.1 Summarize of related work that uses Recurrent Neural Network (RNN)

2.7 Diagnosis of Vibration

In this section, summary of some articles is provided which all have the same goal as classifying the imported data and diagnose a vibration data. The concept of the review of these selected articles is based on their method used to classify and imported the dataset for each method. Most of these articles focused on classifying a vibration data.

Issam Abu-Mahfouz (2003) expressed that in robotized flexible assembling frameworks the location of hardware wear during the cutting procedure is one of the most significant contemplations. This examination presents a correlation between a few models of the multi-layer feed-forward neural system with a back propagation training algorithm for instrument condition observing (TCM) of twist drill wear. The algorithm uses vibration signature examination as the fundamental and just wellspring of data from the machining procedure. The goal of the proposed investigation is to create a TCM framework that will prompt a progressively proficient and efficient drilling apparatus utilization. Five diverse drill wear conditions were artificially acquainted with the neural system for expectation and classification. The trial strategy for procuring vibration information and separating highlights in both the time and recurrence areas to prepare and test the neural system models is itemized. It was discovered that the recurrence area highlights, for example, the found the middle value of consonant wavelet coefficients and the greatest entropy range tops, are more effective in preparing the neural system than the time space factual minutes. The outcomes show the viability and power of utilizing the vibration signals in a directed neural system for drill wear discovery and classification. [6]

ANN Structure	Speed (rpm)	Feed (mm/min)	Percentage of Correct Predictions Chisel	Crater	Flank	Edge	Corner
	300	400	85	82	76	81	77
	400	300	88	81	75	82	78
	600	200	87	79	72	85	73
FFBP-I	900	150	83	78	72	77	71
	350	400	84	80	78	75	78
	1000	130	80	75	71	75	68
	300	400	92	88	87	90	88
	400	300	94	92	89	90	89
	600	200	94	91	89	91	88
FFBP-II	900	150	89	90	82	90	87
	350	400	88	89	85	88	82
	1000	130	89	88	79	86	84
	300	400	92	91	91	93	90
	400	300	95	92	90	93	90
	600	200	96	92	90	94	91
FFBP-III	900	150	93	93	90	95	90
	350	400	88	90	88	92	90
	1000	130	92	90	89	93	85
	300	400	93	91	90	92	89
	400	300	96	94	91	95	91
	600	200	94	94	93	95	91
FFBP-ALL	900	150	94	92	92	93	90
	350	400	94	91	88	88	86
	1000	130	90	90	92	85	85
	300	400	91	89	91	88	90
	400	300	92	91	91	89	87
	600	200	90	90	90	92	88
FFBP-FULL	900	150	95	90	86	92	87
	350	400	91	90	89	84	86
	1000	130	88	85	85	82	84

Figure 2.10 Performance of FFBP with different network structures during testing phase of ANN [6]

Jafar Zarei et.al (2014) propose a paper with respect to a brilliant technique dependent on counterfeit neural systems (ANNs) to distinguish bearing defects of induction motors. In this strategy, the vibration signal goes through expelling non-bearing issue part (RNFC) channel, planned by neural systems, so as to evacuate its non-bearing issue segments, and afterward enters the second neural system that utilizations design acknowledgment procedures for issue arrangement. Four unique classes incorporate; solid, inward race deformity, external race imperfection, and twofold openings in external race are researched. Contrasted with the normal issue identification techniques that utilization recurrence area includes, the proposed strategy depends on breaking down time-space highlights which needs less computational exertion. In addition, machine and bearing boundaries and the vibration signal range circulation are not required in this technique. It is indicated that better outcomes are accomplished when the sifted part of the vibration signal is utilized for shortcoming order as opposed to normal strategies that utilization straightforwardly vibration signal. Test results on three-stage enlistment motor check the capacity of the proposed technique in deficiency determination regardless of low quality (noisy) of estimated vibration signal. [7]

Net number	Neurons number	Correct classification percent							
		Healthy (%)		Inner race defect (%)		Outer race defect (%)		Double holes in outer race (%)	
		With filter	Without filter	With filter	Without filter	With filter	Without filter	With filter	Without filter
1	[4 3 2]	100	4	96	0	80	34	100	44
2	[4 8 2]	100	24	100	20	100	78	100	0
3	[4 3 5 2]	100	72	100	8	96	48	100	24

Figure 2.11 Fault detection in presence of low quality sampled signals using RNFC filter [7]

Jeng-Fung Chen et.al (2016) expressed that forecasts of cutting vibrations are essential for improving the operational efficiency, item quality, and security in the machining procedure, since the vibration is the principle factor for bringing about machine flaws. "Cutting vibration" might be brought about by setting in right boundaries before machining is initiated and may influence the accuracy of the machined work piece. This raises the need to have a successful model that can be utilized to anticipate cutting vibrations. In this examination, an artificial neural system (ANN) model to estimate and characterize the cutting vibration of the intelligent machine instrument is introduced. The factor that may cause cutting vibrations is firstly identified and a dataset for the examination reason for existing is developed. At that point, the relevance of the model is delineated. In light of the outcomes in the similar investigation, the artificial neural system approach performed superior to the others. Since the vibration can be estimated and classified, the item quality can be overseen. This work may assist new specialists with avoiding working machine devices wrongly, and consequently can diminish producing costs. It is normal that this investigation can upgrade the exhibition of machine instruments in metalworking parts. [8]

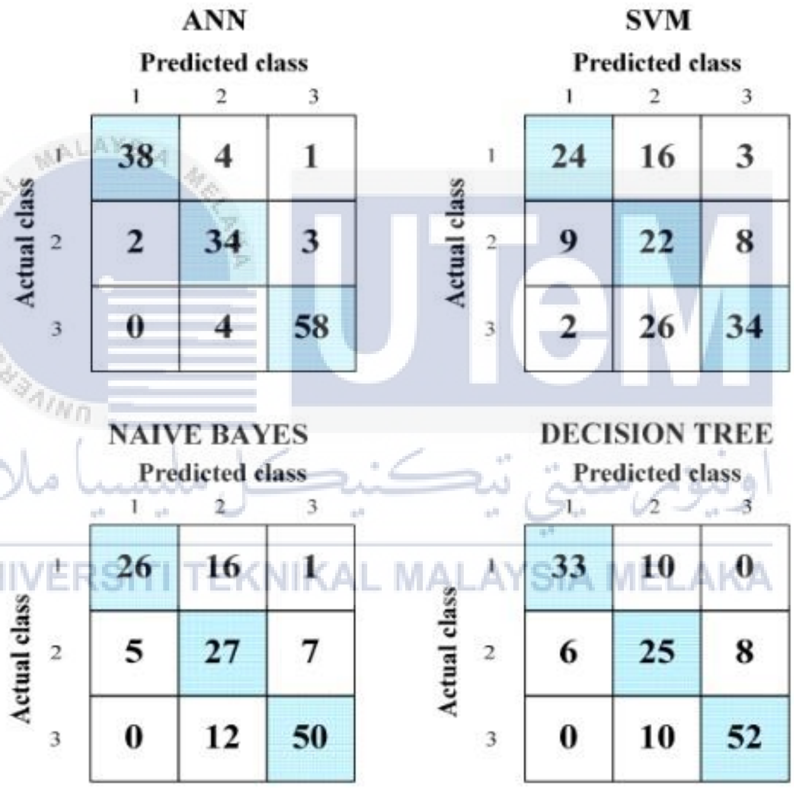


Figure 2.12 Confusion matrices obtained by different classification approaches [8]

Astapov, S. et.al (2012) found that ongoing checking of hardware and frameworks at the shop floor is basic for some assignments in the assembling setting. One of the potential application zones of apparatus and framework observing is machine usage checking, which gives the source information to arranging. Ideal set up arranging is a basic advance in amplifying the productivity of an assembling office. The paper considers a lot of sign handling and investigation methods that empower apparatus observing by utilizing sound and speeding up sensors which can be effectively introduced. Testing consequences of the proposed framework show great nature of machine state identification. [9]

	Sp. means	MFCC
Laser audio	92,68	97,56
Laser accel.	91,80	65,80
Router audio	91,76	95,72
Router accel.	98,39	99,85

Figure 2.13 Correlation classifier result (%) [9]

	Sp. means	MFCC
Laser audio	89,02	98,05
Laser accel.	73,40	87,65
Router audio	98,68	98,72
Router accel.	99,85	99,49

Figure 2.14 Fuzzy classifier result (%) [9]

Author	Year	Proposed Method	Results
Issam Abu-Mahfouz	2003	Used the vibration signals in a supervised neural network for drill wear detection and classification. Artificial Neural Network (ANN)	During the testing stage, a triumph pace of 100% was acquired for location of the presence of drill wear, and a rate more prominent than 80% for achievement in drill type classification was figured it out. For some ANN configurations the pace of exact classifications was more prominent than 90%.
Jafar Zarei, Mohammad Amin Tajeddini, Hamid Reza Karimi	2014	Vibration investigation for bearing fault detection and classification using an intelligent filter. Intelligent strategy dependent on counterfeit neural systems (ANNs) to recognize bearing imperfections of induction motors.	It is indicated that utilizing RNFC channel not just prompts higher exactness in issue arrangement contrasted with ANFIS yet additionally improves the unwavering quality on account of low quality estimated signal.
Jeng-Fung Chen, Shih-Kuei Lo, Quang Hung Do	2016	An artificial neural system (ANN) model to predict and group the cutting vibration of the intelligent machine device.	The outcomes show that the general precision of the ANN classifier was 90.27%. The ANN model is able to do viably arranging the vibration conditions.
Astapov, S., Preden, J. S., Aruväli, T., Gordon, B.	2012	Signal processing and investigation strategies that permit machinery checking by using sound and acceleration sensors which can be simply introduced.	Testing results have indicated that the proposed framework is equipped for recognizing the activity conditions of these machines with high proficiency.

Table 2.2 Summarize of related work in Diagnosis of Vibration

2.8 Summary

After the real factors and finding in this part, there is a ton of data that can assist me with improving my insight and understanding idea on each segment. From the writing survey of Recurrent Neural Network, finding of vibration, related ventures, characterizing preparing procedures, information assortment strategies and programming language it shows that how the past researchers continue with their thoughts. In view of their hypotheses, it demonstrated that it can used to be the foundation of my venture as the hypothetical nuts and bolts and application. This part truly gave the rule on achievement of my task.

CHAPTER 3

METHODOLOGY

This section is about the structure procedure for Recurrent Neural Network based vibration data classification. This part additionally spread and clarifies all the subtleties for each means of the project with block diagram. For the execution of Recurrent Neural Network (RNN), MATLAB has been utilized, which is an elite language for specialized figuring. It integrates computation, representation, and programming in a simple to-utilize condition where issues applied to absorb the vibration energy [25] and arrangements are communicated in natural scientific documentation created by MathWorks which helps analysts in the AI ventures. In addition, the RNN engineering and the arranging engaged with this project will be introduced in this part.

3.1 Project Flowchart

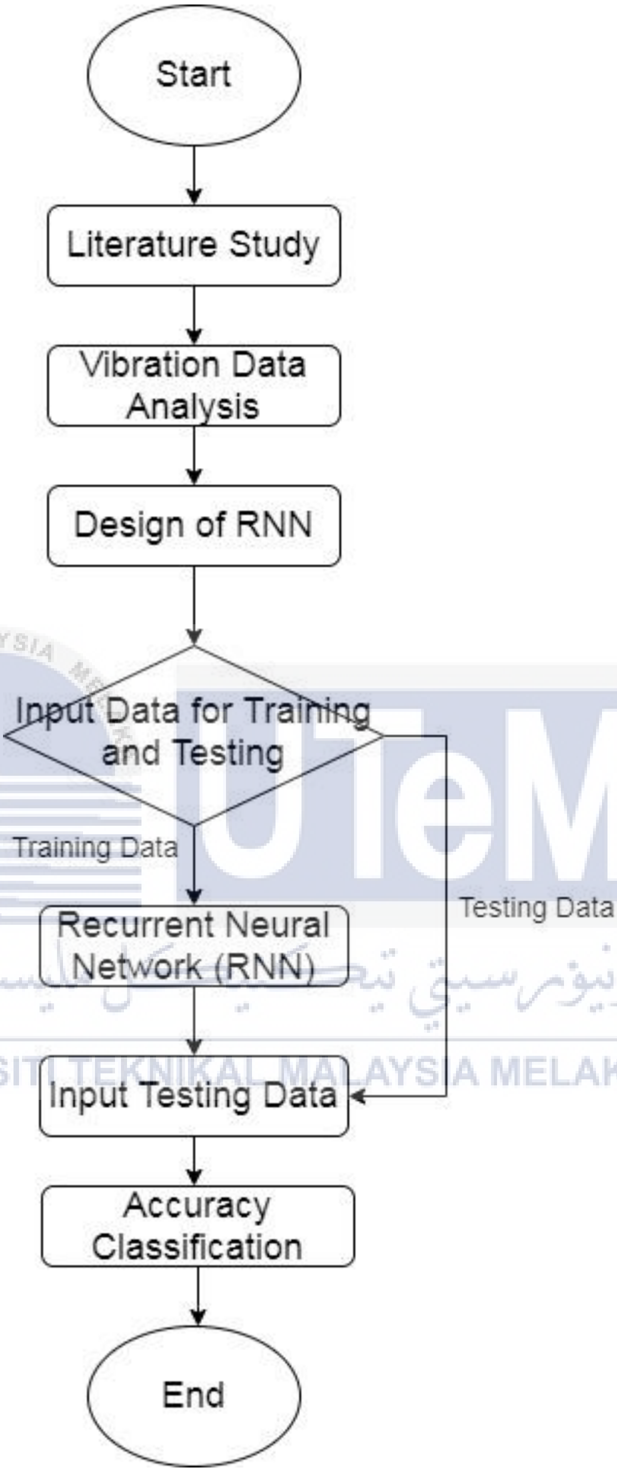


Figure 3.1 Project flowchart

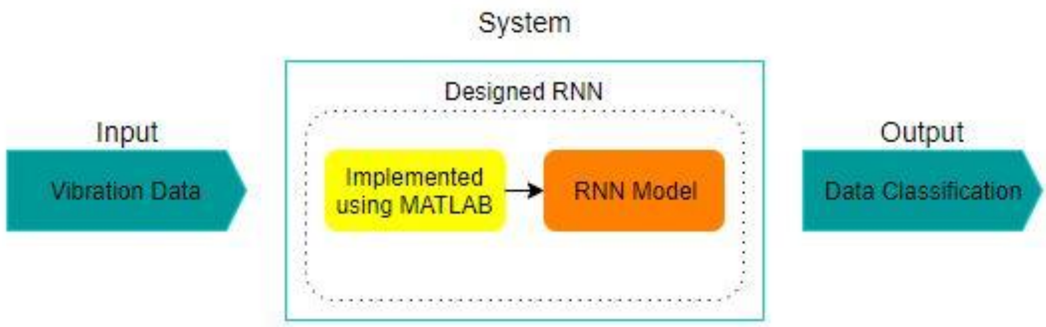


Figure 3.2 Project block diagram

The flowchart in Figure 3.1 above shows the work flow in designing a system to classify a vibration data using RNNs. It starts with collecting the data for analysis. The data used in this project analysis is the vibration data obtained from a copper cutting machine. The RNN algorithm has been designed in the MATLAB software. From the total datasets, it then divided into 3 stages which is the training, validation and testing process. For training and validation data, the data will be fed into the network that has been designed for it to learn and recognize the data in new condition which is good and the data after chipping which is bad. For testing process, a different data will be fed into the network which is a data that the network has never seen. As for the output, it will based on the accuracy of classification the data which the network has never seen based on what it has learn. Figure 3.2 is the basic block diagram of this system which contains the input which is the vibration data, system which is the designed RNNs and the output result is the accuracy of the data classification.

3.2 Vibration Data Analysis

Vibration investigation is a procedure of searching for inconsistencies and observing change from the set up vibration mark of a framework. The vibration of any article moving is portrayed by varieties of adequacy, power, and recurrence [26].

These can connect to physical wonders, making it conceivable to utilize vibration information to pick up bits of knowledge into the strength of hardware. This nature is in high speed cutting operation where strong nonlinearities with regenerative effects [27]. Vibration investigation can be utilized to:

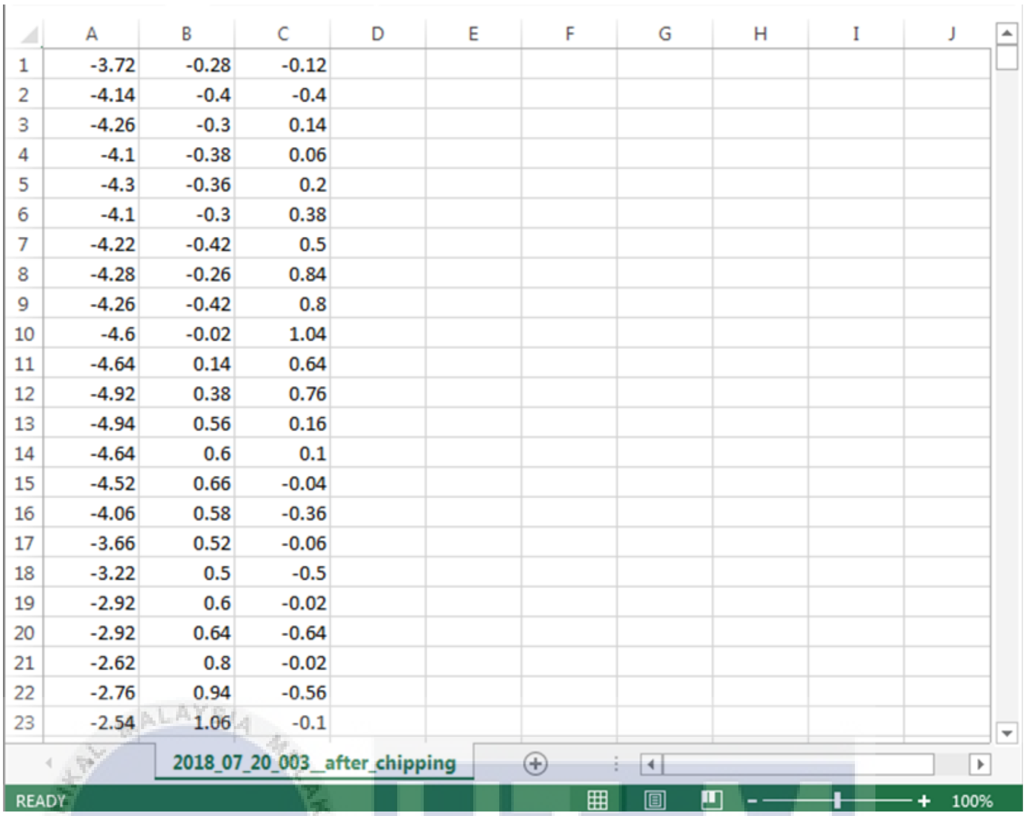
1) Detect and screen a vibration information made by the machines when cutting the copper.
2) Establish acknowledgment testing models to guarantee that vibration information are ordered and shortcoming examination.
3) Continuous vibration checking can be utilized to foresee issue investigation as a component of an information vibration.

	A	B	C
1	-9.16	-1.68	-6.86
2	-7.9	-3.78	-6.98
3	-5.18	-6.48	-6.54
4	-4.28	-10.04	-7.34
5	-3.08	-15.34	-8.38
6	-0.72	-18.38	-7.08
7	2.86	-18.12	-6.44
8	5.12	-16.44	-5.88
9	6.04	-14.2	-1.02
10	6.86	-11.14	1.62
11	9.02	-8.06	4.32
12	10.92	-5.74	6.74
13	11.32	-5.04	7.92
14	10.64	-6.62	8.72
15	11.32	-8.72	7.12
16	13.18	-9.54	7.8
17	13	-9.28	4.62
18	12.04	-9.22	6.94
19	11.32	-6.76	7.7
20	11.1	-3.36	8.86
21	10.98	1.96	8.98
22	8.4	5.4	10.62
23	6.58	6.38	10.86

2018_07_20_025_new

READY 100%

Figure 3.3 The new condition vibration data



	A	B	C
1	-3.72	-0.28	-0.12
2	-4.14	-0.4	-0.4
3	-4.26	-0.3	0.14
4	-4.1	-0.38	0.06
5	-4.3	-0.36	0.2
6	-4.1	-0.3	0.38
7	-4.22	-0.42	0.5
8	-4.28	-0.26	0.84
9	-4.26	-0.42	0.8
10	-4.6	-0.02	1.04
11	-4.64	0.14	0.64
12	-4.92	0.38	0.76
13	-4.94	0.56	0.16
14	-4.64	0.6	0.1
15	-4.52	0.66	-0.04
16	-4.06	0.58	-0.36
17	-3.66	0.52	-0.06
18	-3.22	0.5	-0.5
19	-2.92	0.6	-0.02
20	-2.92	0.64	-0.64
21	-2.62	0.8	-0.02
22	-2.76	0.94	-0.56
23	-2.54	1.06	-0.1

2018_07_20_003__after_chipping

READY 100%

Figure 3.4 The after chipping vibration data

The vibration data used in this project is obtained from a cutting machine. This data shows the performance of the cutter when it is in the new condition and condition after it has been used. This observation is to prevent a defect in cutting an item which causes losses and waste. Impact of this action also it will give an information of when the cutting blade is in good or bad condition and a preventive method can be done while conducting the process.

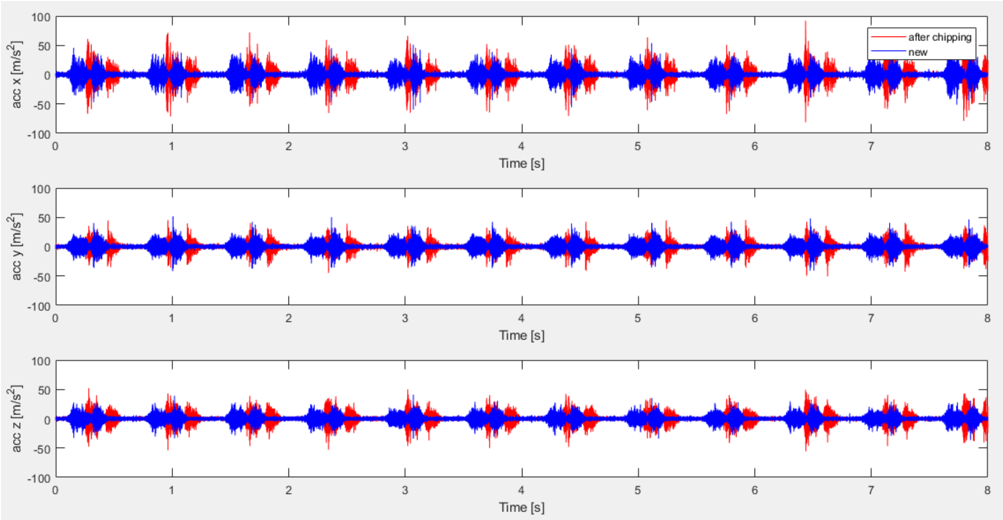


Figure 3.5 Vibration signal

Figure above shows the vibration signal made by the cutting machine when the cutter is being used. The blue signal shows the vibration signal when the cutter is still in perfect condition while the red signal shows the vibration signal when the cutter is used several times. As you can see, there is a difference between both of this signal. However, this vibration signal has been plotted at a high sampling rate which gives a more sample value and precisely the signal vibration can be observed. A method using Recurrent Neural Network will be used in the event of analysing a lower sample rate of vibration signal.

3.3 Design of Recurrent Neural Network

Layer recurrent neural networks are similar to feedforward networks, except that each layer has a recurrent connection with a tap delay associated with it. This allows the network to have an infinite dynamic response to time series input data. This network is similar to the time delay (timedelaynet) and distributed delay (distdelaynet) neural networks, which have finite input responses.

3.4 MATLAB and Neural Networks

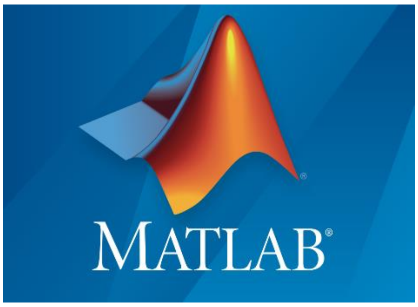


Figure 3.6 MATLAB Logo

MATLAB was originally designed by Cleve Moler and developed by the MathWorks. It is one of the tools that can be used for deep learning frameworks and comes with a lot of documentation and walkthroughs for guidance. MATLAB additionally gives supports to Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Deep Learning Toolbox which earlier known as Neural Network Toolbox gives a system to planning and executing deep neural systems with algorithms, pretrained models, and applications. The convolutional neural systems (ConvNets, CNNs) and long short-term memory (LSTM) systems can be utilized to perform arrangement and relapse on picture, time-arrangement, and text information [28]. This product likewise can manufacture propelled arrange structures, for example, generative ill-disposed systems (GANs) and Siamese systems utilizing custom preparing circles, shared weights, and programmed separation. Applications and plots assist you with imagining actuations, alter and investigate arrange models, and monitor training progress.

Moreover, MATLAB likewise can trade models with TensorFlow and PyTorch through the ONNX configuration and import models from TensorFlow-Keras and Caffe. The tool kit bolsters move learning with a library of pretrained models (counting NASNet, SqueezeNet [29], Inception-v3, and ResNet-101). The training procedure can be accelerate on a solitary or various GPU workstation with Parallel Computing Toolbox or scale up to groups and mists, including NVIDIA GPU Cloud and Amazon EC2 GPU examples with MATLAB Parallel Server. The system likewise can be convey onto stages, for example, Intel CPUs or their Arm-Mali GPUs, NVIDIA GPUs, and ARM processors utilizing coder items to auto produce code. This auto-created code gives a huge exhibition support in deduction applications.

Deep Network Designer makes it easy to make and adjust deep systems. The intuitive interface permits us to imagine the layers and associations and include learnable layer boundaries with gradient descent [30]. In the wake of making a system, it can rapidly check the engineering for mistakes. At long last, trade the system to the workspace for training, or create its relating MATLAB code others can without much of a stretch imitate and refine the work. As per the predominance in neural systems and deep learning, MATLAB has been chosen for this undertaking so as to classify the vibration information utilizing Recurrent Neural Networks (RNNs).

3.5 Accuracy Classification

From the input vibration data which represented in numbers that are going through the network it will then give an output which has been classified into two classifications of vibration data which are good vibration data and bad vibration data. Validation with independent in the vibration data will validate the accuracy [31].

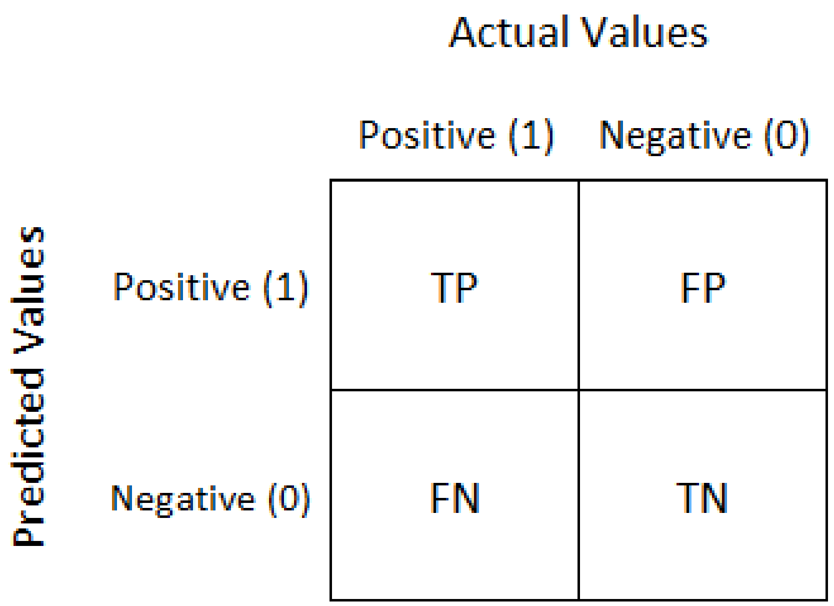


Figure 3.7 Confusion Matrix

For the output result of this analysis, the final result is determine by the confusion matrix as shown in the above figure. Confusion matrix is a performance estimation for machine learning classification issue where the output result can be at least two classes. There are four types of table combined together which is for the predicted values and the actual values.

Both values are separated into two conditions which is the positive and negative value. For actual values, there are true positive (TP) and false positive (FP) while for predicted values there are true negative (TN) and false negative (FN). TP is when the predicted value is positive and it is true. FP is when the predicted value is positive but it is false. TN is when the predicted value is negative and it is true. FN is when the predicted value is negative but it is false.

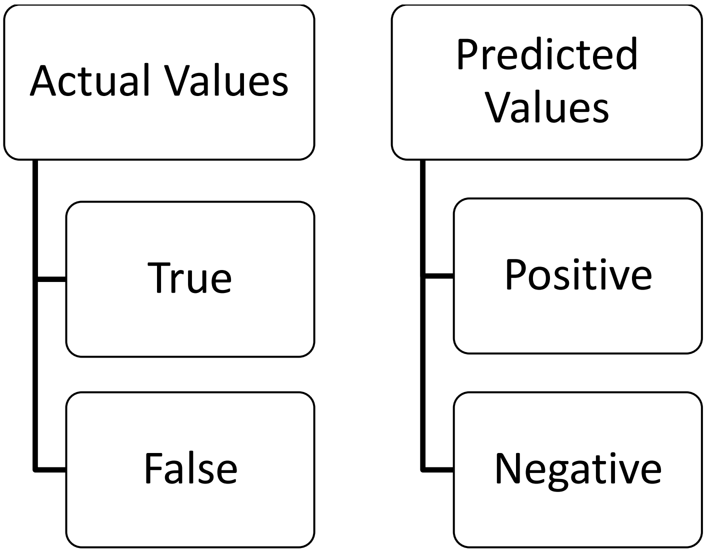


Figure 3.8 Confusion matrix values

From there the confusion matrix will determine the final accuracy of classifying the data. There are three different formula that should be taken into which is recall, precision and accuracy. The formula are as follows:

Recall,

$$recall = \frac{TP}{TP+FN} \times 100\% \text{ - Equation (3-1)}$$

Recall is from the positive classes, how much from it is predicted correctly.

Precision,

$$precision = \frac{TP}{TP+FP} \times 100\% \text{ - Equation (3-2)}$$

Precision is from all of the positive classes that are predicted correctly, how much from it are actually positive.

Accuracy,

$$accuracy = \frac{TP+TN}{Total} \times 100\% \text{ - Equation (3-3)}$$

Accuracy is the total of true positive and true negative sums up together and divided by the total testing data.

3.6 Summary

As an outline, this section mostly talked about the strategies that applied on this task regarding RNNs algorithms, programming language, programming library and dataset procurement. Each part in the approach assumes a major job for this project analysis. In accomplishing the fundamental destinations in this analysis, each assignment must be arranged astutely and as needs be. Along these lines, a systematic working process has been practiced for finishing this project analysis to ensure that all the work flow is going easily during the procedure.

CHAPTER 4

RESULTS AND DISCUSSION

This part presents the outcomes accomplished by using the MATLAB software and the RNN algorithm in determining the accuracy of data classification and training. There are two datasets being used in this research as an input to train the RNN algorithm in MATLAB which is the vibration data of a cutting machine before the chipping and after the chipping. The RNN algorithm will be able to classify the data at 10 microsecond and 50 millisecond sampling time. All the results of training loss and accuracy of the network will be presented in the form of numbers and graphs.

4.1 Project Description

Recurrent neural network (RNN) can be characterized numerically as differentiable capacity that maps of one sort of factor to another sort of factor like how in grouping issues. The transform vector to vectors and in relapse issue can change over vectors to scalars of Recurrent Neural Network (RNN) by simply toss successions in with the general mixture and end up with various engineering that can be utilized in different applications. The design is a vector to grouping model, take the vector and produce an arrangement of wanted length. Inclining research that utilizes this is picture subtitling the info can be a vector portrayal of a picture and the output is grouping of vibration information that depicts that from Excel document.

A second engineering that talked about is arrangement to vector models. The input is a grouping of words and the output is appended length vector. Ordinarily use case would be in feeling examination. The information could be the vibration information that gathered from accelerometer from cutting machine. The output will be two-dimensional vector demonstrating the audit was sure or negative. The third engineering took a gander at is succession to arrangement models where both the input and the output are groupings in the model of same sort. To anticipate the following vibration information in grouping with adequate preparing this vibration information from both new and broken informational collection. The vibration information can produce its new exactness. The arrangement model had equivalent measured information.

Another engineering that takes in an information grouping however yields an arrangement of various lengths from the information it exist and it is known as the encoder or decoder design. The encoder changes over the grouping to vector and the subsequent part is the decoder that changes over the vector to a succession and arrangements can be vast.

4.2 Project Implementation

The RNN algorithm is implemented using MATLAB software. This network is used to classify the vibration data between good vibration data and bad vibration data. There are two datasets as an input to the network which is the data of a cutting machine in new condition and after chipping for several times. The data has been collected from the vibration produced by a cutting machine.

The datasets is in Excel format which is being save in the same folder with the MATLAB program. The csvread work peruses a comma-separated value (CSV) organized document into exhibit of the information that will be utilized. The document must contain just mathematical values. This code is to import the data from excel into the MATLAB. The sampling time is then set at a required value which is 10 microseconds and 50 milliseconds. The total number of datasets contains in the Excel file are over I million and is being taken at 3 different axis which is X, Y and Z. The analysis has been conducted to a certain range of the datasets using the function nod_start, nod and nod_end=nod_start+nod-1. The data is then being plotted into a graph with their separated axis and at a certain range of datasets.

From the data range that has been set, the data then will be splice into a certain value that are required for training and validation. According to the range of datasets that has been sets previously; the data is then being plot into the MATLAB in form of column and row using the loop function. Both good and bad vibration data are being plotted separately.

After the information has been plotted as needs be, the information will be partitioned into two sections for training and validation. Datasets are isolated into three sections which is training, validation and testing. In the training process, the system gains from the datasets that has been taken care of into it while validation causes the system to keep from overfitting. After going through training and validation the data is then being tested in measuring the final predictive power of the model. Logically, this process is done by running the model on a new data set it has not seen before. That is equivalent to applying the model in real life.

The accuracy of the prediction we get from the test is the accuracy we would expect the model to have if we deploy in real life. The test dataset is the last step being done. There is no set rule in splitting the data that has been chose to undergo each process. Commonly, the dataset which being used to train the model should be considerably larger than the other two so that there are as much data as possible to the training of the model while having enough samples to validate and test on.

The network model should be train using the training dataset only. Every now and then, the model will be validating by running it for the validation dataset. Usually, the dataset is validated for every epoch every time the weights been adjusted and calculate the training loss while validating. If the training loss and the validation loss go hand in hand the training model process can be carried on. If validation loss is increasing that is when it has overfitting and needs to be stopped. Final step is to test the model with the test dataset and the accuracy obtained from the process is the accuracy of the network algorithm.

4.3 Analysis Result of RNN at 10 microseconds sampling time

Input	Number of Hidden Layer	Accuracy
50	10	75.7%
100	20	73.8%
150	30	74.3%
200	40	70.2%
250	50	74.4%
300	60	65.3%
350	70	67.6%
400	80	58.1%

Table 4.1 10 microseconds analysis result

Table above shows the value of the accuracy of data classification made by the network. In this analysis there are 8 different values of input and hidden layer being used to compare at which specification that the network can classify the data accurately. The highest accuracy of data classification is 75.7% with the number of input 50 and the hidden layer is 10. As for the lowest accuracy of data classification in this case is 58.1% and the number of input being fed into the network is 400 with 80 hidden layers being used.

4.4 Analysis Result of RNN at 1000 microseconds sampling time

Input	Number of hidden layer	Accuracy
50	10	74.3%
100	20	73.5%
150	30	57.1%
200	40	70.0%
250	50	61.5%
300	60	71.6%
350	70	71.8%
400	80	67.4%

Table 4.2 1000 microseconds analysis result

Table above shows the value of the accuracy of data classification made by the network. In this analysis there are 8 different values of input and hidden layer being used to compare at which specification that the network can classify the data accurately. The highest accuracy of data classification is 74.3% with the number of input 50 and the hidden layer is 10. As for the lowest accuracy of data classification in this case is 57.1% and the number of input being fed into the network is 150 with 30 hidden layers being used.

4.5 Analysis Result of RNN at 10 milliseconds sampling time

Input	Number of hidden layer	Accuracy
10	5	53.1%
20	10	52.1%
30	15	62.5%
40	20	58.3%
50	25	52.6%
60	30	56.3%
70	35	65.4%
80	40	58.3%

Table 4.3 10 milliseconds analysis result

Table above shows the value of the accuracy of data classification made by the network. In this analysis there are 8 different values of input and hidden layer being used to compare at which specification that the network can classify the data accurately. The highest accuracy of data classification is 65.4% with the number of input 70 and the hidden layer is 35. As for the lowest accuracy of data classification in this case is 52.1% and the number of input being fed into the network is 20 with 10 hidden layers being used.

4.6 Analysis Result of RNN at 50 milliseconds sampling time

Input	Number of Hidden Layer	Accuracy
10	5	52.1%
20	10	54.2%
30	15	53.1%
40	20	41.7%
50	25	47.4%
60	30	43.8%
70	35	65.4%
80	40	41.7%

Table 4.4 50 milliseconds analysis result

Table above shows the value of the accuracy of data classification made by the network. In this analysis there are 8 different values of input and hidden layer being used to compare at which specification that the network can classify the data accurately. The highest accuracy of data classification is 65.4% with the number of input 70 and the hidden layer is 35. As for the lowest accuracy of data classification in this case is 41.7% and the number of input being fed into the network is 40 with 20 hidden layers being used.

4.7 Project Results

The system model were coded and executed in the MATLAB programming edition R2020a. While leading the examination, a cross validation technique was utilized to stay away from over-fitting. A straightforward method to test how well a model sums up to new information is to hold out validation. The information should be part arbitrarily into a training set and a validation or test set. This works well when we have enough data that the validation set is likely to be a good statistical representation of the whole dataset. However, if it does not have enough dataset, the test results can depend heavily on how the data happened to be divided. To avoid the problem, the cross validation method can be performed.

In k-fold cross validation the information is arbitrarily split into K sets known as folds. One of those folds is held as the validation set and the remainder of the information is utilized for training process. The procedure at that point rehashes with an alternate envelope saved for validation and others until the sum total of what folds have been utilized once as the validation set. The common losing from all the folds is the general K overlay loss. This decreases the reliance of the loss on the specific way your information happened to be split. It requires progressively computational exertion to fit and assess numerous models. The greater the estimation of K the more calculation yet the more strong the loss predicts.

4.7.1 Result at 10 microseconds sampling time

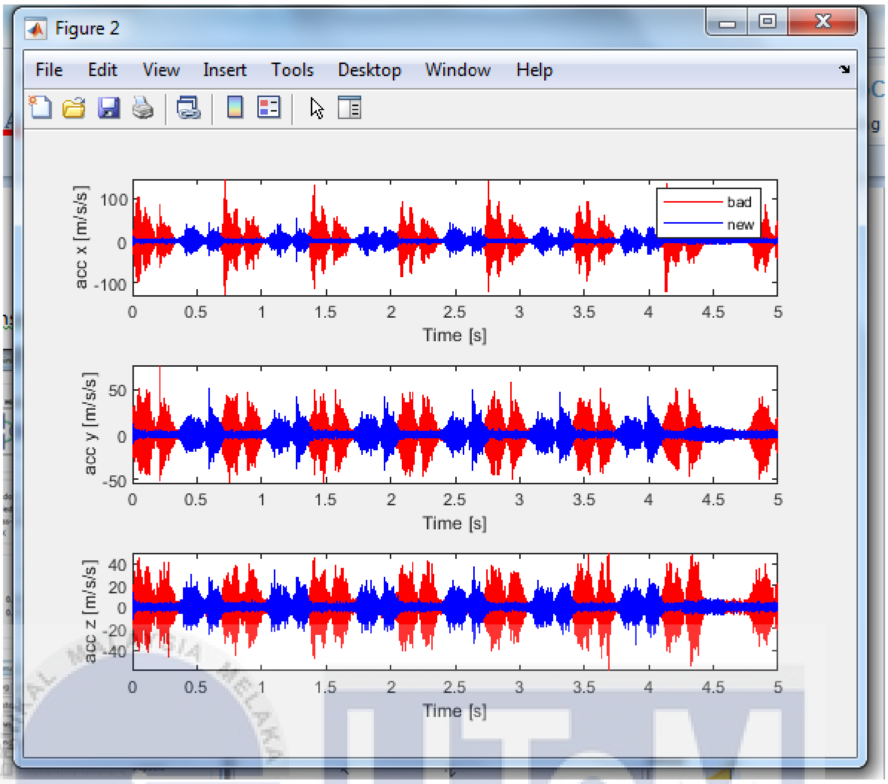


Figure 4.1 Data plot in a graph at 10 microseconds sampling time

Figure above shows the value of the vibration data that has been chose to used in training, validating and testing the data. The vibration data has been plot in a graph at 3 different axis x,y and z. The blue graph is the vibration data of a cutting machine which is in new condition while the red graph is the vibration data of the cutting machine that has been used multiple times. As we can see here, with 10 microseconds sampling time the graph has been plotted very rough as it has more plots in it and the time interval between the data is shorter.

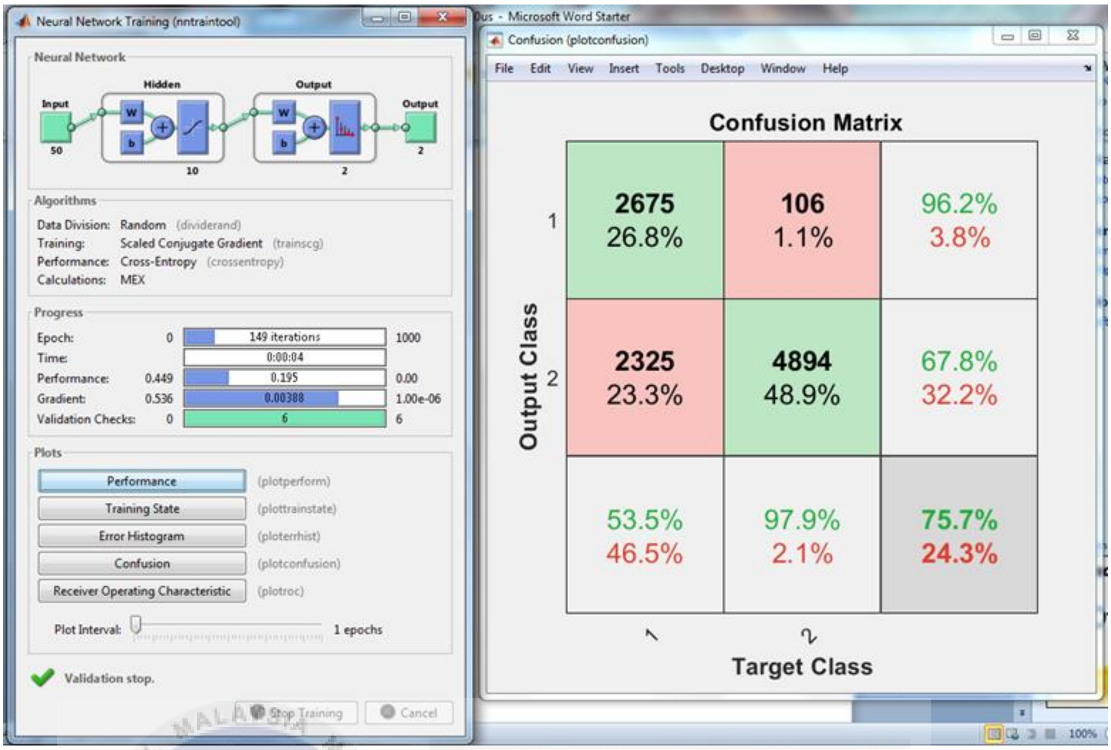


Figure 4.2 Result in confusion matrix

The final accuracy result is shown in the confusion matrix plot. The analysis result for the network model at 10 microseconds sampling time is 75.7%. It is the highest accuracy being obtained for that network. The number of input and hidden layer used for that network are 50 for the input and 10 for the number of the hidden layer.

4.7.2 Result at 1000 microseconds sampling time

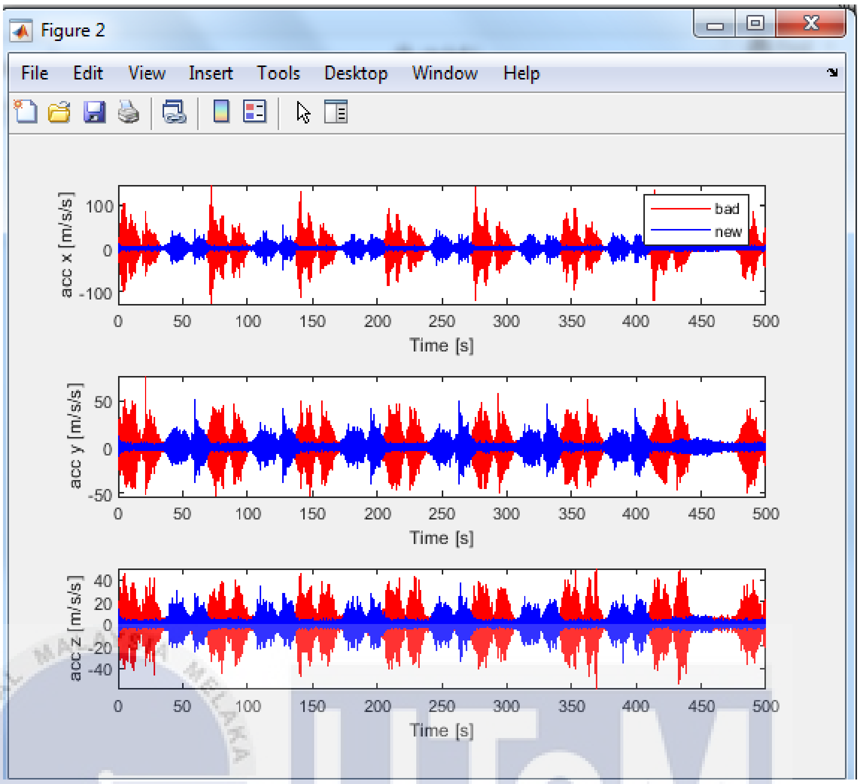


Figure 4.3 Data plot in a graph at 1000 microseconds sampling time

Figure above shows the value of the vibration data that has been chose to used in training, validating and testing the data. The vibration data has been plot in a graph at 3 different axis x,y and z. The blue graph is the vibration data of a cutting machine which is in new condition while the red graph is the vibration data of the cutting machine that has been used multiple times. As we can see here, with 1000 microseconds sampling time the graph has been plotted is still very rough as it has more plots in it and the time interval between the data is short.

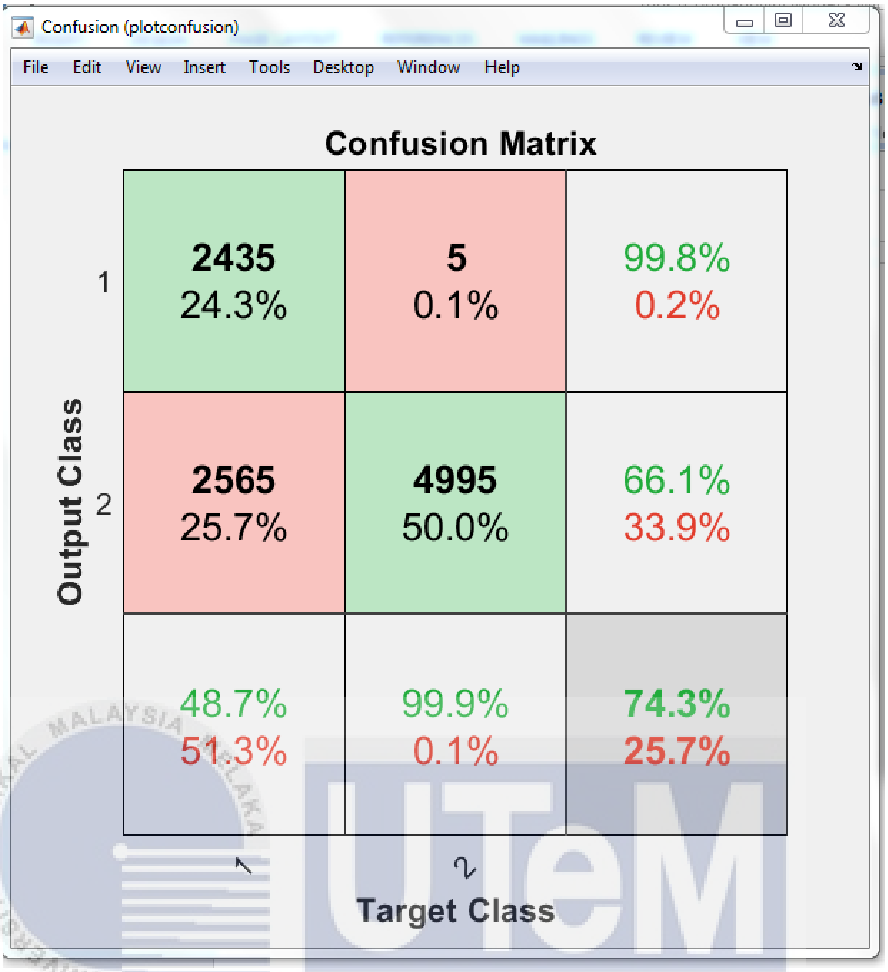


Figure 4.4 Result in confusion matrix

The final accuracy result is shown in the confusion matrix plot. The analysis result for the network model at 1000 microseconds sampling time is 74.3%. It is the highest accuracy being obtained for that network. The number of input and hidden layer used for that network are 50 for the input and 10 for the number of the hidden layer.

4.7.3 Result at 10 milliseconds sampling time

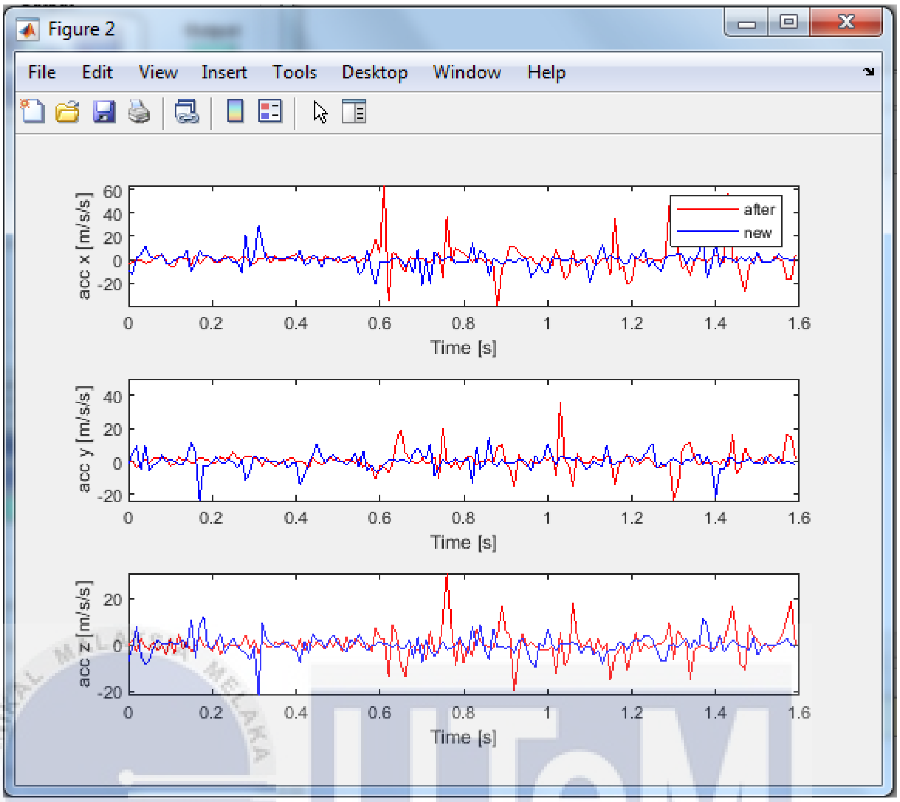


Figure 4.5 Data plot in a graph at 10 milliseconds sampling time

Figure above shows the value of the vibration data that has been chose to used in training, validating and testing the data. The vibration data has been plot in a graph at 3 different axis x,y and z. The blue graph is the vibration data of a cutting machine which is in new condition while the red graph is the vibration data of the cutting machine that has been used multiple times. As we can see in the figure, with 10 milliseconds sampling time the graph has been plotted differently from the 10 microseconds and 1000 microseconds because the time interval between two data is larger make it more precise and sharp.

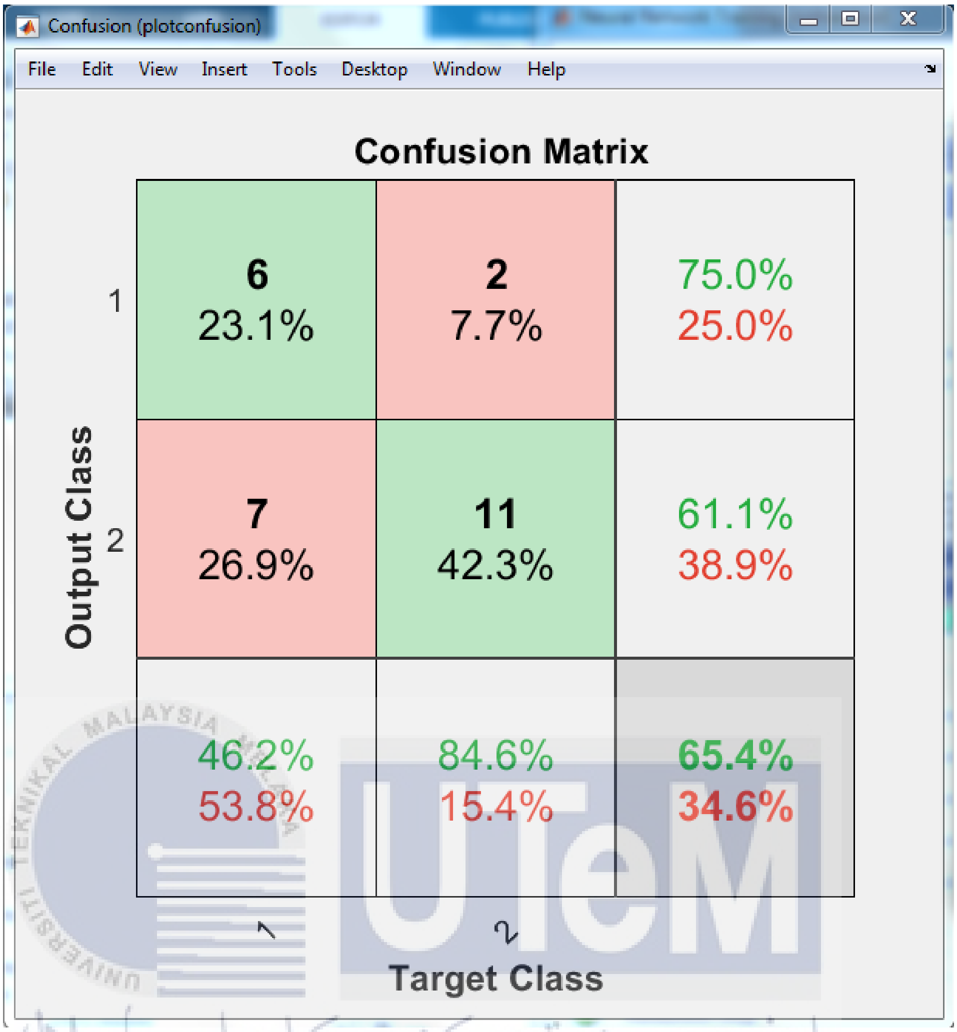


Figure 4.6 Result in confusion matrix

The final accuracy result is shown in the confusion matrix plot. The analysis result for the network model at 10 milliseconds sampling time is 65.4%. It is the highest accuracy being obtained for that network. The number of input and hidden layer used for that network are 70 for the input and 35 for the number of the hidden layer.

4.7.4 Result at 50 milliseconds sampling time

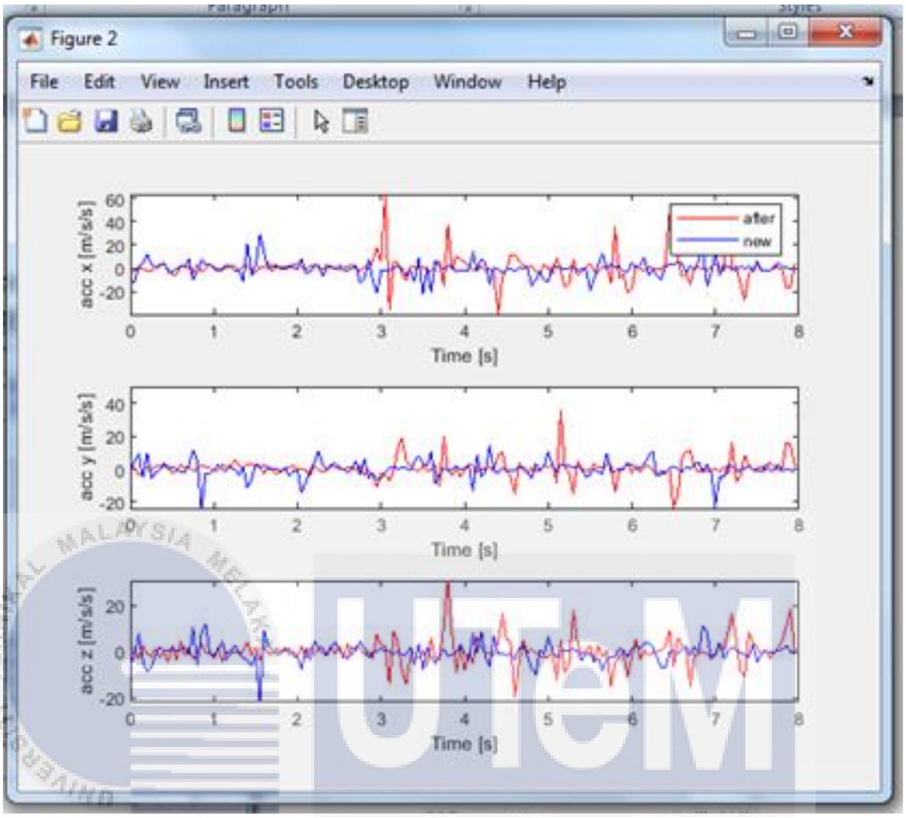


Figure 4.7 Data plot in a graph at 50 milliseconds sampling time

Figure above shows the value of the vibration data that has been chose to used in training, validating and testing the data. The vibration data has been plot in a graph at 3 different axis x,y and z. The blue graph is the vibration data of a cutting machine which is in new condition while the red graph is the vibration data of the cutting machine that has been used multiple times. As we can see in the figure, with 50 milliseconds sampling time the graph has been plotted differently from the 10 microseconds and 1000 microseconds because the time interval between two data is larger make it more precise and sharp.

Figure 4.8 Result in confusion Matrix

The final accuracy result is shown in the confusion matrix plot. The analysis result for the network model at 50 milliseconds sampling time is 65.4%. It is the highest accuracy being obtained for that network. The number of input and hidden layer used for that network are 70 for the input and 35 for the number of the hidden layer.

4.7.5 Project main result

Sampling time	Number of Input	Number of Hidden layer	Accuracy Classification
$10\mu s$	50	10	75.7%
$1000\mu s$	50	10	74.3%
$10ms$	70	35	65.4%
$50ms$	70	35	65.4%

Table 4.5 Highest accuracy obtained

Table above concludes the final results of the analysis between 4 different values of sampling time. It shows the highest accuracy of classification obtained at particular sampling time with varies value of input number and hidden layer. The purpose of analysing the data at a certain range of sampling time is to shows the changing gap in accuracy classification at different sampling time.

As observed, the best fit that the network can give highest accuracy classification are for 10 microseconds and 1000 microseconds is at input of 50 and 10 number of hidden layers while for 10 milliseconds and 50 milliseconds is at input of 70 and 35 number of hidden layers. This is because the accuracy result does not only depends on highest number of input and hidden layer. It takes count other value such as the number of weights and bias when the network is running the process.

There are two cases in machine learning which is underfitting and overfitting. Underfitting is the case where a factual model or AI calculation cannot catch the fundamental pattern of the information. Naturally, underfitting happens when the model or the calculation does not fit the information perfectly. In particular, underfitting happens if the model or calculation shows low variance yet high bias. Underfitting is regularly an aftereffect of an exorbitantly straightforward model.

While for overfitting, it happens when a factual model or AI calculation catches the noise of the information. Instinctively, overfitting happens when the model or the calculation fits the information excessively well. In particular, overfitting happens if the model or calculation shows low bias yet high variance. Overfitting is regularly a consequence of an unreasonably muddled model, and it very well may be prohibited by fitting different models and utilizing the validation or cross-validation method to look at their expected accuracy on test data. If the system has gone through both cases of underfitting and overfitting it can lead to a poor predictions on the data which the network has never seen.

The thought behind cross-validation is equivalent to with a solitary holdout validation set, to evaluate the model's expected performance on inconspicuous data. Cross-validation just does this all the more powerfully, by rehashing the test on various occasions, utilizing all the various pieces of the training set as validation sets. This gives a progressively precise sign of how well the model sums up to concealed data. At the end of the day, cross-validation does not forestall overfitting in itself, however it might help in distinguishing an instance of overfitting.

If the loss is low on both sets, then the goal might have been achieved. The test set can be used to get an unbiased estimate of the generalization performance. There are also many different performance metrics that can be used such as accuracy, precision, and recall. As for the output result, it is unlikely to have a lower loss on the validation set than the training set. If the training loss is significantly higher than the validation loss, then the training and validation sets needs to be checked to make sure that the training process by the network model is on the right dataset.

4.8 Environmental and Sustainability

For the environmental and sustainability of this project, if the Recurrent Neural Network (RNN) can be used to classify a low sampling time of vibration data, then self-powered system can be realized. This project is environmentally friendly as only computer and software are used in the process of building the system. It does not cause any harm or contributes a bad aftereffect to the surrounding. Deep learning in computer technology is an eco-friendly tools. Therefore, it does not radiates any harmful waves.

4.9 Summary

In this chapter we have discussed about the result of this project on how the network can classify the data accurately with two different sampling times which is 10 microseconds and 50 milliseconds. Before achieving the highest frequency obtained, the network have to undergo the analysis process. During the process, the network has been train, validate and test several times with different value of input and hidden layer. This is to make a comparison at which number of input and hidden layer that the network works best. This step has been applied at both 10 microseconds and 50 milliseconds sampling time. At 10 microseconds, the highest accuracy of data classification made by the network is 75.7% with the value of 50 input and 10 hidden layers while at 50 milliseconds, the highest accuracy of data classification made by the network is 65.4% with the value of 70 input and 35 hidden layers.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

In this chapter will cover about complete implementations of this project and the recommendation to student or individual that research and study deeper in future and continuing this project.

5.1 Conclusion

The Recurrent Neural Network (RNN) was successfully created and the architecture manages to classify the vibration data. In the research, there is variously type of research data with same concept of neural network architecture in different type of data to be observed. The features of this project with same applications features compared to other project, for the real time weather forecast. In other research, there are plenty of research papers about Recurrent Neural Network (RNN). Most of the research papers are about classification of number and images. The Recurrent Neural Network (RNN) for this research is to study on the efficiency of Recurrent Neural Network (RNN) to classify the vibration data. The vibrations data collected and recorded in Excel file then transferred to MATLAB to trained and test the architecture model of Recurrent Neural Network (RNN) to classify the data accordingly to the dataset with new and broken vibration data. The highest accuracy that achieved from this architecture is 75.7% for 10 microseconds sampling time and 65.4% for 50 milliseconds sampling time.

5.2 Recommendation

In this project, for student to study and research about Recurrent Neural Network (RNN). Recurrent Neural Network (RNN) are still interesting to learn because it still can train image captioning, generating poems after being trained on shakespeare poems, reading handwriting from left to right and generating music. When trained Recurrent Neural Network (RNN) with sentences they generate similar sentences they've shown amazing result with chatbot image captioning machine translation.

Recurrent Neural Network (RNN) then again catch data about the arrangements or the time arrangement information. They can catches the data about the successions or the time arrangement information. Recurrent Neural Network (RNN) can take variable size of info and give variable size yields and work truly well with time arrangement information. Understanding Recurrent Neural Network (RNN) sort of dubious. A great deal of portrayal lead to confusions and with an essential method of Recurrent Neural Network (RNN) and afterward envision it. Presently Recurrent Neural Network (RNN) chip away at the recursive method. The new province of Recurrent Neural Network (RNN) at time T is an element of its old state.

To improve the Recurrent Neural System (RNN), the response for improve the accuracy by add negligible more collaboration to Recurrent Neural Network (RNN) and this is the idea behind LSTM. LSTM will dissipating the point and give much better exactness that Recurrent Neural Network (RNN). The LSTM work and subsequently imagine by included three gateway and one cell state. The entryway and cell state are additional joint efforts for the LSTM to work. The ignore entryway which takes the old state and the data and copies it with the individual burdens. By then went it through a sigmoid commencement. The plan will have input gateway and yield entryway and every entryway has different courses of action of weight.

This feedback loops in the recurrent layer lets them keep up information in storage after some time. Regardless, it might be difficult to plan standard Recurrent Neural Network (RNN) to handle gives that require learning long stretch transient conditions. This is because the tendency of the setback work spoils exponentially with time. LSTM frameworks are a sort of Recurrent Neural Network (RNN) that uses unprecedented units despite standard units. LSTM units fuse a memory cell that can keep up information in memory for critical time frames. A great deal of entryways is used to control when information enters the memory, when its yield, and when is it escaped its attention. This designing lets them learn longer-term conditions. GRUs resemble LSTMs, anyway use an unravelled structure. They moreover use a great deal of ways to control the movement of information, anyway they don't use separate memory cells, and they use less doors.

5.3 Summary

The classification of vibration data by using Recurrent Neural Network (RNN) is to classify the vibration data from Excel file to MATLAB. The Excel file is split into two part, new and broken data. The data is captured from accelerometer that collecting vibration data from cutting machine. The total data is over 1 million data with multiple angle of axis that is X, Y and z axis. From the total data, the Recurrent Neural Network (RNN) model will plot the data to vary number of nod been set. The nod is set for train and test the dataset to evaluate the accuracy from Recurrent Neural Network (RNN) to classify the vibration data.

The architecture of Recurrent Neural Network (RNN) model classy for two type of data that is 50 millisecond to 10microsecond. The data are plotted with two type of time sampling to study on does Recurrent Neural Network (RNN) can classify the data with highest number of accuracy. The plotted data for 50 millisecond is smooth compared to 10 microsecond with rough view of data at low sampling time. From the research, Recurrent Neural Network (RNN) manages to validate the data and achieve the highest accuracy for 50 milliseconds is 65.4% meanwhile for 10 microseconds is 75.7%.

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