Real Time Malaysian Sign Language (MSL) Translator – Tuturjom

by

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Dissertation submitted in partial fulfilment of

the requirements for the

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Perak Darul Ridzuan

CERTIFICATION OF APPROVAL

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Approved by,

____

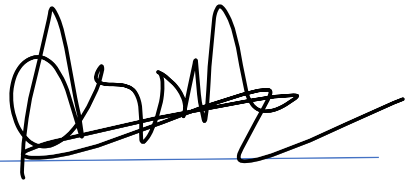
(Dr Said Jadid A Kadir)

UNIVERSITI TEKNOLOGI PETRONAS

TRONOH, PERAK May 2021

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.



Name: Arsh Obeidy

ABSTRACT

Malaysian Sign Language (MSL) is an essential language that is used as the primary means of communication between deaf people in Malaysia. Malaysians are currently very unfamiliar with MSL, and the present platforms for learning the language are inadequate, not to mention the lack of utility of the available mobile and web learning tools. Therefore, this project aims to provide a model for real time translation of MSL. In the below report I would be explaining various phases of creating this model and we will look through various finding and important algorithms. I also hope to provide a clear understanding of Hand gesture and pose recognition, Long Short-Term Memory (LSTM) networks and their uses in our understanding of sign languages.

ACKNOWLEDGMENT

I want to take this chance to thank Universiti Teknologi Petronas for providing me various opportunities throughout my studies and by also providing me many experiences which have helped me develop my knowledge and skills.

This particular project is possible through joint efforts of my Final year Project supervisor, Dr aid Jadid A Kadir. I want to thank him for his continuous guidance and helpful solutions. He guided me through various hurdles and provided upstanding opinions for various problems.

Lastly, I want to thank my family and friends who have always encouraged me to do better and have believed in me.

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ABBREVIATIONS AND NOMENCLATURES

ASL - American Sign Language

LSTM - Long Short-Term Memory

CRISP-DM - Cross-Industry Standard Process for Data Mining

MSL - Malaysian Sign Language

CHAPTER 1

INTRODUCTION

1.1 PROJECT BACKGROUND

A sign language is a method of communication that involves the use of the hands and other body parts. Manual expressions are used in conjunction with non-manual components to express sign languages. These languages are natural languages, with their own grammar and lexicon. As such many countries have their own sign languages which have developed with its country's environment and people's experience.

Malaysian Sign Language (MSL) is an essential language that is used as the main mode of communication between deaf people in Malaysia. With the foundation of the Malaysian Federation of the Deaf in 1998, Malaysian Sign Language was born, and its use has grown among deaf organizations. (Hafit et. all 2019)

Malaysian sign language is mostly based on American sign language (ASL). In fact , Manually Coded Malay which is based heavily on ASL has 80% similarity to ASL. Mr. Tan Yap initially introduced American Sign Language (ASL) to Malaysia in the early 1960s, when he took a year off from work to study ASL and assist Malaysia's deaf.

In Malaysia, deaf children make up a small percentage of the student population. Only around 20% of Deaf children are listed with the Social Welfare Department, indicating that only about 20% of Deaf children attend school. Also, Despite the fact that Malaysian Sign Language is commonly used among the deaf-mute community, hearing people frequently have little or no exposure to it due to a lack of a ubiquitous environment for its use.

Above shows that the accessibility of MSL is very scarce to the general public, Malaysians are unfamiliar with the MSL, and the present system for learning the sign language is ineffective. As a result, there is a communication gap between the deafmute group and the hearing community.

This project's main aim is to bridge this gap and provide a platform from which it is easy to communicate in sign language and also learn it. Since, today's technology has come a long way this project will make use of Machine learning Algorithms and computer vision technology to create the application.

1.2 PROBLEM STATEMENT

1.2.1 Lack of Application for learning Malaysian Sign Language

As discussed above many Malaysians are unfamiliar with the MSL. The current system placed for learning the sign languages are not effective.

1.2.2 No Application for translation of MSL in real time

Real time translation of MSL is important to make it more accessible and easier for people to learn. But unfortunately, currently there is no such application in the market.

1.3 OBJECTIVE

The project demands to fulfil the objectives mentioned below: -

1. **To Analyse** various datasets of MSL for research, and analyse various algorithms required to translate hand and pose gestures.

2. **To Develop a** real Time MSL translation model, to aid people in learning and understanding the language

3. **To Validate and test** the working of MSL translation application, for effective working.

1.4 SCOPE OF STUDY

The study's scope refers to the limits within which the project will be carried out. Defining the scope of project can help in its proper execution and also keeps budget and scope creep in check. This will also make sure that the project is completed on time. The scope for this project is described below-:

1.4.1 Market Segmentation

Market segmentation is the process of dividing a large market of potential clients into identifiable groups or parts based on various characteristics. The segmentation of the market field could be determined by the variables listed below.

Demographic

This type of segmentation can help recognize user requirements. This application would target people of all ages and gender who have interest in Malaysian Sign Language and want to learn the language to communicate with different communities.

Location

Currently the application would be available to Malaysian citizen as they would be using MSL the most.

CHAPTER 2

LITERATURE REVIEW

2.1 OVERVIEW

This literature review examines the previous research that explore on gesture recognition using LSTM, previous research on Malaysian Sign Language (MSL) and existing apps for learning MSL.

2.2 MALAYSIAN SIGN LANGUAGE

2.2.1 History

Malaysian Sign Language is related to American Sign Language which was introduced by Mr. Tan Yap in 1960s when he took a year off from work to study ASL and assist Malaysia's deaf. The sole school for the Deaf in Malaysia at the time was in Penang, and the method of instruction was oralism. The pupils created their own native sign language, which is today known as Penang Sign Language (PSL). ASL was first used in a trial class at the school in 1976, and it was later approved for wider usage in 1979. PSL's use has declined since the advent of ASL, and it is now primarily used by the elderly.

2.2.2 Current Usage and Schools

According to recent survey the current number of native speakers for MSL is 58,700 which is approximately 0.2% of the population. Only around 20% of Deaf children are enrolled with the Social Welfare These figures exclude youngsters who have lost their hearing due to sickness or an injury. In Malaysia, there are 23 primary schools for deaf students, with a few deaf children enrolled in regular classes. (Maarif et. All 2012)

Some of these students continue their education in secondary school. In Peninsular Malaysia, there are currently approximately 500 Deaf pupils in secondary school, 225 attending Penang Special Education High School and with 300 attending Shah Alam Vocational School. There are around fifty Deaf students in high school in Sabah, and Sarawak.

Malaysian Sign Language is also taught to students through individual courses, the main sources for these are YMCA KL Sign Language Courses, Malaysian Federation of the Deaf and The Sarawak Society for the Deaf.

2.2.3 Online Presence and Mobile Applications

MSL learning videos and applications are scarce with only a few of them making into the market and lesser apps continuously maintained. The two apps which are currently in the market are-:

Eddy: Digital Learning of Sign Language -The app Eddy is a digital sign learning application , which adopts a gamified approach of teaching MSL. The programme, which was developed by three 24-year-olds – BAXS multimedia developer Mohd Zuhairi Zulkiflee, software engineer Niezwan Abdul Wahid, and business development Mohammad Atiff Riduan – seeks to make learning MSL more engaging by adding gamification features and an animated vocabulary. The app features include 15 instructive game scenarios in Malaysian Sign Language with quizzes, 3D animated dictionary covering MSL signs and also a spelling tool.

Figure 2.1 : Eddy the digital sign Learning App

Besides Eddi, currently there is no other app in the market which is popular or visible to the users. Considering ASL one of the most popular app in the market is Sign

Language ASL-Pocket Sign, the app has regular updates and many useful functions such as Interactive video lessons, quizzes and American Sign Language ASL dictionary.

2.3 GESTURE RECOGNITION AND SIGN LANGUAGE

2.3.1 Gesture Recognition

Gesture recognition is a computer technique that use mathematical algorithms to identify and understand human gestures. Gesture recognition isn't just for human hand motions; it can also be used to identify everything from head nods to various walking gaits. (Chen et.all 2014)

Many individuals have gotten accustomed to recognising touch screen gestures. While certain computers and operating systems provide customised gesture detection, most people are familiar with pinch-to-zoom on a touch screen to get a closer look at anything. This particular motion is applicable to virtually all user interfaces, including smartphones and personal computers.

Vision-based gesture recognition technology employs a camera and motion sensor to monitor and translate human motions in real time. Newer cameras and programmes can also capture depth data, which can aid with gesture recognition. Users may engage with the application instantly to get the desired outcomes thanks to real-time picture processing.

2.3.2 Hand Gesture Recognition

The user intent is determined via gesture recognition, which recognises the gesture or movement of the body or body components. Many academics have worked for decades to develop hand gesture recognition technologies. Many applications, such as sign language recognition, augmented reality (virtual reality), and sign language interpreters for the deaf, rely heavily on hand gesture recognition.

There are two primary techniques to sign language recognition: image-based and sensor-based. However, a lot of research is being done on image-based techniques due to the benefit of not having to wear complicated gear like hand gloves, helmets, and so on, as with sensor-based approaches.

Image-based sign recognition is divided into two phases: detection and identification of signs. Sign detection is the process of extracting a feature from an item based on specific characteristics. Recognizing a certain shape that distinguishes an object from the other forms is known as sign recognition.

The three steps of an image-based gesture recognition system are as follows: Colour to binary conversion and noise filtering are done for the recorded picture in image pre-processing. The term "tracking" refers to the process of tracing a hand gesture from a recorded picture.

Moreover, for detection of hands and pose in the image two main methods are used, both of which are equally popular. First, method is the hand detection through skin colour. The skin colour can be used to discriminate the hand region from the other moving objects in the background. The colour of the skin is measured with the HSV model. The HSV (hue, saturation, and value) value of the skin colour is 315, 94, and 37, respectively. The image of the detected hand is then resized to make the gesture recognition invariant to image scale.

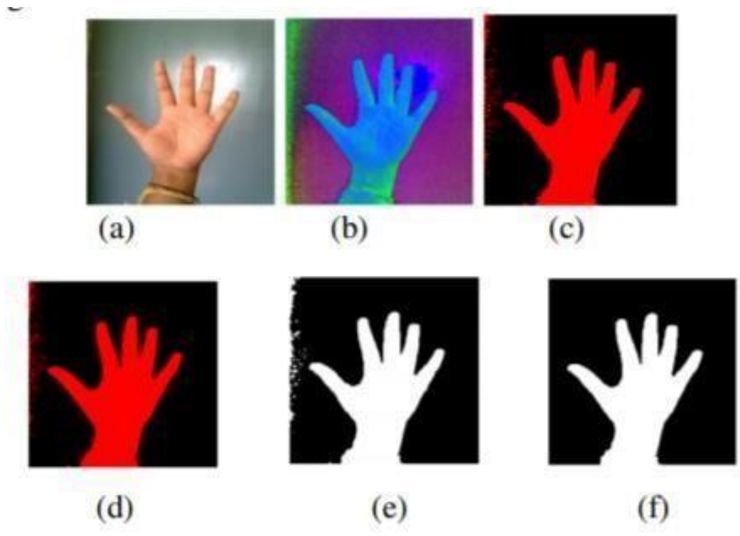


Figure 2.2: Skin colour detection (Singha et.al 2013)

The second method is Human action recognition which is a subset of video content assessment that seeks to recognise actions from a set of observations on the behaviours of humans and their surroundings.

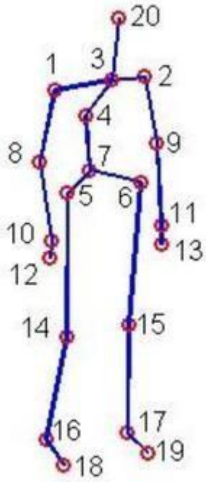


Figure 2.3: Action recognition *Papers with Code*. (2018).

Finally, several Algorithms that have been created based on computer vision approaches to recognise hands using various types of cameras are used to do recognition. Skin colour, appearance, motion, skeleton, depth, and other features are all attempted to be segmented and detected by the algorithms. One of these learning methods is Long Short-Term Memory networks.

2.4 Long Short-Term Memory (LSTM) networks

Long Short-Term Memory (LSTM) networks are recursive neural networks that can learn order dependency in sequence classification challenges. This is a necessary behaviour in complicated problem areas such as translation software, voice recognition, and also gesture recognition. LSTMs' success stems from its ability to be one of the first tools to conquer technical challenges and deliver on the promise of recurrent neural networks. (Felix 2000)

CHAPTER 3

METHODOLOGY

3.1 OVERVIEW

This chapter will discuss about the tools and the methodology used for making this project. The rationale behind the particular process would be explained with various concepts and algorithms used to build the machine learning model for MSL recognition.

The project would be using CRISP-DM as its main framework. The CRISP-DM (Cross Industry Standard Process for Data Mining) is a six-phase model developed that accurately represents the machine learning life cycle. It is one of the most common practice in the industry for building machine learning models. The six phases of the model are explained in detail below.

3.2 RESEARCH METHODOLOGY

3.2.1 Preliminary Research

Before starting the project some of the research was performed to get a better grasp of the existing market and the tools available. To Methods were used to get the necessary information and to continue the project further, these two methods are explained in detail below-:

3.2.2 Literature Review

There is a lot of material and relevant previous works on the internet, which is why a literature study is essential. Existing papers, writings, and other verifiable sources include material that would give insights into my study since they contain thorough analysis, assessment, investigations, and synthesis performed by past scholars.

These papers and literature are widely accessible on the internet through services like

Google Scholar, IEEE, and Science Direct, which hold published articles. To synthesise an analysis for my project literature review, other sources such as electronic books and journals may also be employed as literature review materials.

The knowledge and insights acquired from these literature studies provide a comprehensive grasp of current existing models as well as other relevant initiatives. I was able to properly understand what is necessary to do this project, as well as a solid guidance on how to conduct this project, with a clear comprehension.

3.2.3 Survey

The survey included 122 participants across Malaysia and asked them about their interest and view for Learning Malaysian Sign Language (MSL) through a digital app.

This section provides an overview and summary of key analytical points of the survey. For developing this application, I wanted to conduct this survey to gather and visualize general people view on Malaysian Sign Language and how they would perceive it while learning through an app. This survey also pointed out some of the functions that the people would want to see inside the app if they were to use it.

The analysis of the survey data identifies key points about public attitudes toward the MSL. For example, as seen below out of all the participants 73% of the participants had an interest to learn the MSL.

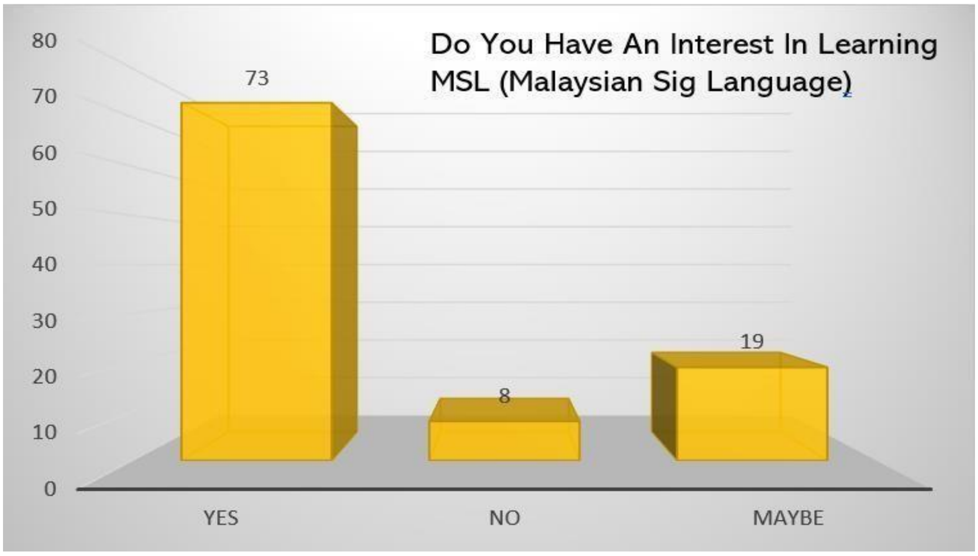


Figure 3.1: Pre Development survey result

While below graphs show that around 77% of them would like to use an application to learn MSL. All in all the survey showed that people are willing to explore and learn MSL if right sources are available to learn the language.

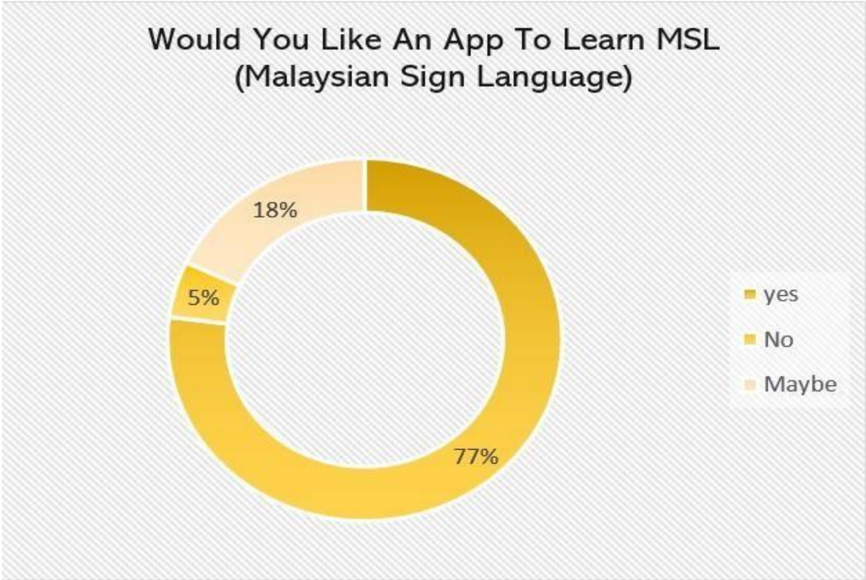


Figure 3.2: Pre Development survey result

3.3 PROJECT FRAMEWORK

As mentioned above the main framework that this project would be using is CRISPDM which stands for and has six main phases, it can be noted that main of these

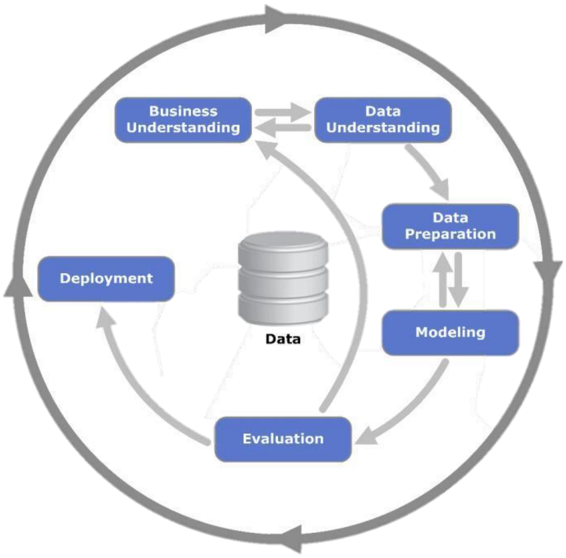


Figure 3.3: Cross Industry Standard Process for Data Mining

3.3.1 Business Understanding

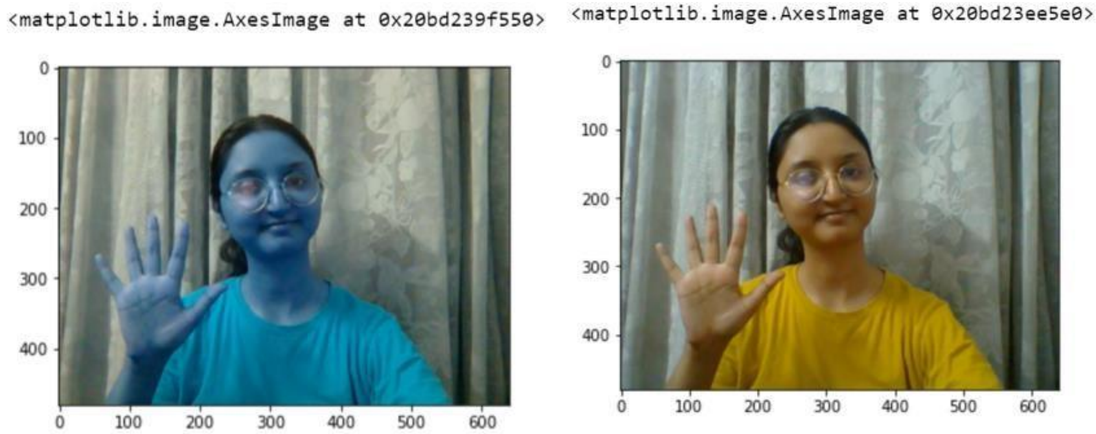
The first step in the CRISP-DM process is to figure out what we want to achieve in terms of business. The objective of this stage of the process is to identify key elements that may have an impact on the project's result. This stage also helps in finding the primary objectives of the project. This entails explaining the key goal from a business standpoint. It should be noted that after the above research it was decided that the main objective of this project would developing an application which translates MSL in real time through camera. This was achieved after market research and also after finding the requirements of the interested users.

3.3.2 Data Understanding and Preparation

The data specified in the project resources must be acquired in the second stage of the CRISP-DM procedure. If data loading is required for data interpretation, this is included in the initial collection. The understanding of the data is very important in creating an efficient machine leering model. Here I would be describing data resources gathered from different location and also the format of the data.

Since, the project entails the interpretation of MSL through camera. So, to train a machine learning model that could recognise the MSL, I need a dataset of images or videos of people signing in MSL or Malaysian Sign Language, coupled with what English or Malay word that each photo represent. This kind of data exists for ASL, but as it turns out, there is no proper dataset for MSL. So, for this particular problem I came up with two solutions, either continue to research more on existing MSL databases or combine an ASL database with a database created by myself (The videos for this were collected through a webcam using opencv). This can work because MSL is highly based on ASL. Consequently, the end database was a mixture of different basic MSL signs with each sign having its own folder which had 30 videos for that particular sign and each video has 30 frames. These videos include alphabets signs, number signs and basic words needed for daily conversations.

Next data preparation will take place which entails bringing the data quality up to the standards required by the analytic methodologies. We would be using media pipe holistic to determine various landmarks and key point on our face and hands which will ultimately help us to build the machine learning model. In first step images are collected using open cv which essentially uses BGR as the colour channel, but to determine key points through media pipe holistic we would need an image in RGB channel. So, we will be converting the image from BGR to RGB and then run it through media pipe model to extract the key points.



BGR image **RGB image**

Figure 3.4: BGR image (left) converted to RGB image (right)

As mentioned above media pipe holistic can be used to determine various key points from face, pose and hands. An example is shown below for a frame where key points are detected and displayed. The landmarks styling was also formatted for thickness and colours of the lines.

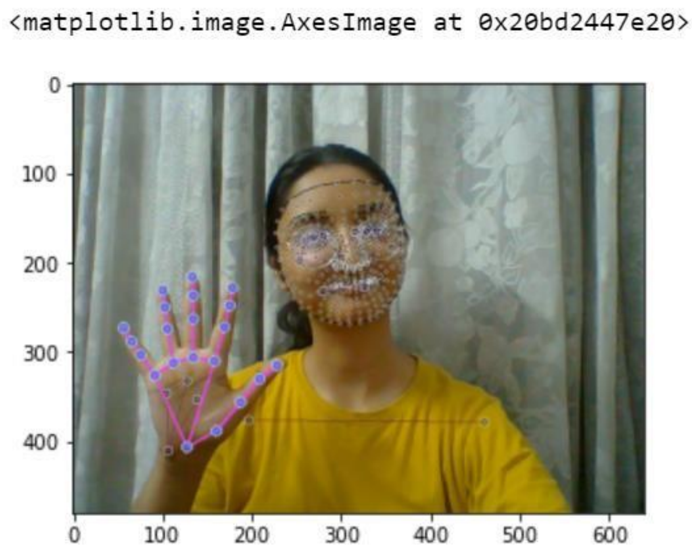


Figure 3.5: Detecting key points using media pipe holistic

Now that all our frames have their landmarks and key points, we would be extracting them, joining them (face+ pose + hands landmark) and then saving them as NumPy arrays. This will help us in the labelling of the signs and for the model to easily classify a gesture.

```
len(results.pose_landmarks.landmark)
```

```
33
```

As we can see the number of pose landmarks for a frame would be 33, we would be extracting all of these and saving them in a single flatten array. This will be done for all four types of landmarks which are left hand and marks, right hand landmarks, pose landmarks and face landmarks.

Lastly, we would be making a loop and labelling all our images according to their given signs, it should be noted that each sign has its own folder, which has thirty videos of 30 frame each. So, each video would be labelled according to the sign and in total every sign will have 900 frames.

3.3.3 Modelling

For modelling we would be using an LSTM model, lstm is basically an advanced version of RNN (Recursive neural network) model, it solves a main problem of RMM which is vanishing gradient problem. In RNN as we progress through the network, our gradient decreases and it becomes more difficult to train the weights, meaning in later stages the model does not learn much and cannot progress further. LSTM solves this problem by only remembering the important information learned from previous run or sequence. Another reason for choosing this particular model is its large number of parameters so there is less need for fine adjustments.

Next, we will be first splitting our training and testing data, we will be dividing the data into a split of 50%

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.05)
```

```
y_train.shape
```

```
(85, 3)
```

```
X_train.shape
```

```
(85, 30, 1662)
```

```
X_test.shape
```

```
(5, 30, 1662)
```

```
y_test.shape
```

```
(5, 3)
```

Before, training our LSTM model we will be login into tensor board dashboard, to record the loss and the best seed value as the model trains over an epoh value of 800. An epoch is a phrase used in machine learning that denotes the number of runs the machine learning model has made across the full training dataset. Typically, datasets are organised into batches. These are also referred to as iterations.

```
model.fit(X_train, y_train, epochs=800, callbacks=[tb_callback])
```

```
Epoch 1/800
3/3 [==============================] - 6s 609ms/step - loss: 1.1120 - categorical_accuracy: 0.2837
Epoch 2/800
3/3 [==============================] - 0s 162ms/step - loss: 4.1366 - categorical_accuracy: 0.3423
Epoch 3/800
3/3 [==============================] - 0s 169ms/step - loss: 1.2259 - categorical_accuracy: 0.3835
Epoch 4/800
3/3 [==============================] - 1s 174ms/step - loss: 3.9865 - categorical_accuracy: 0.3816
Epoch 5/800
3/3 [==============================] - 1s 179ms/step - loss: 1.5424 - categorical_accuracy: 0.3288
Epoch 6/800
3/3 [==============================] - 0s 134ms/step - loss: 2.5389 - categorical_accuracy: 0.3190
Epoch 7/800
```

Further we will be applying our LSTM model and recognize MSL in real time.

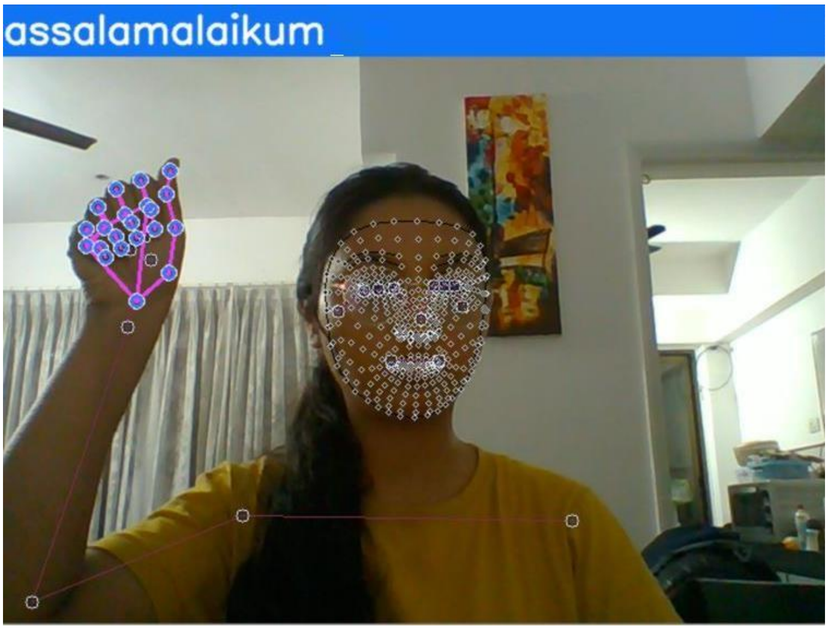


Figure 3.6: Using Model to recognize MSL in real time

The model recognizes most of the signs accurately, for sentence prediction a loop was created so that model can join consecutives words to make different sentences. Though it should be noted that a proper wait time is to be allocated towards each sign so that model can accurately predict the sentence.

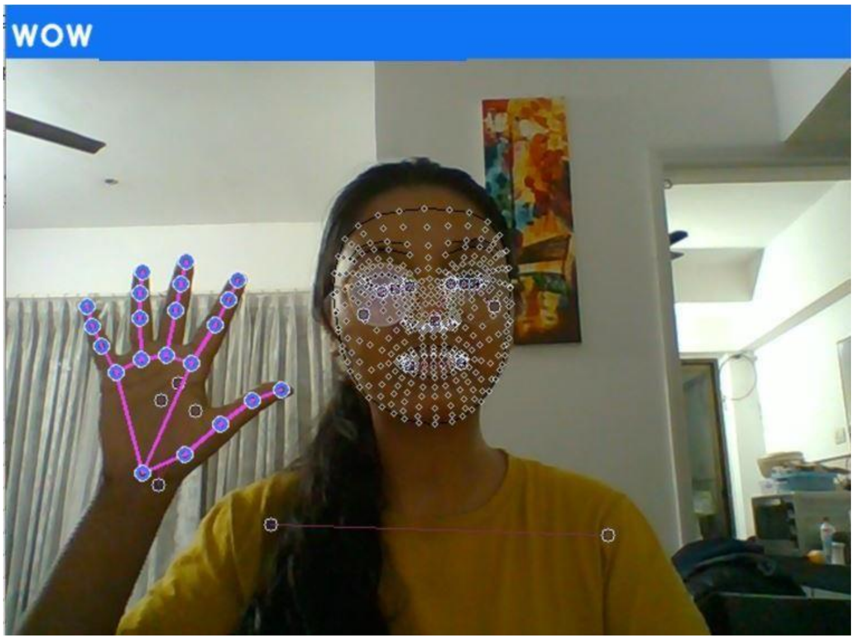


Figure 3.7: Figure showing different words that can be determined

Figure 3.8: hiding key point lines to show the visible expressions used for MSL sign

3.3.4 Evaluation

This phase requires to assess the software, or the model built against its original business goals. The evaluation phase also involves assessing any other data mining results that have been generated. Data mining results involve models that are necessarily related to the original business objectives and all other findings that are not necessarily related to the original business objectives, but might also unveil additional challenges, information, or hints for future directions.

I will evaluate the model using various metrics. Accuracy is generally the first measure that comes to mind. It's a straightforward measure that calculates the proportion of correct to incorrect predictions. Another metric that can be used is recall. Recall gives the fraction you correctly identified as positive out of all positives. Both can be calculated using Confusion matrix for example.

First let’s look at the confusion matrix obtained. A Confusion matrix used to assess the effectiveness of a classification algorithm, where N is the number of target classes. The matrix compares the actual target values to the deep learning model's predictions.

The top left of the matrix shows the values of true positive for any given classification and the value on bottom right show true negative, remining values are false positive and false negatives. A higher number of true negatives and true positive implies that the model is accurately predicting the class values.it can also be a good estimation of whether the model is overfitted or not.

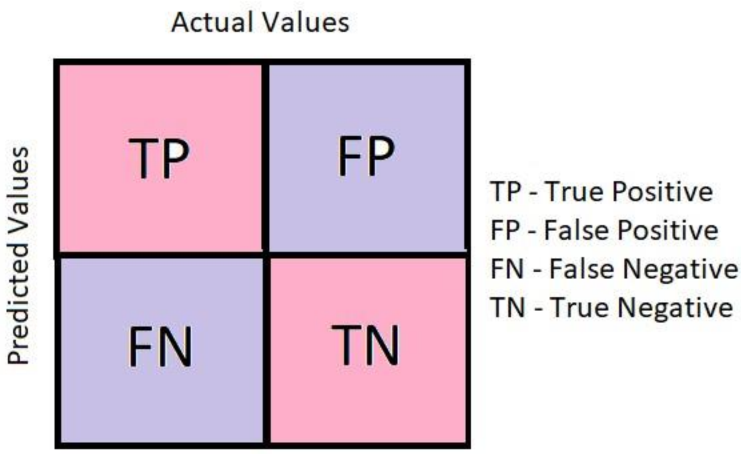


Figure 3.9: Working of confusion matrix

```
multilabel_confusion_matrix(ytrue, yhat)

[[[57  0]
  [ 0 28]]

 [[57  0]
  [ 0 28]]

 [[56  0]
  [ 0 29]]]
```

Figure 3.10: Confusion matrix obtained for evaluation

For our results all values of the confusion matrix lie in the true negative and true positive part, meaning the model is predicting the values quite accurately. But in this case a very small group of signs is used, as the dataset becomes more bigger and more signs are included, it can't be said that the model will remain this accurate.

```
print("accuracy score is:" , accuracy_score(ytrue, yhat))
print("precision score is:" ,precision_score(ytrue, yhat,average='weighted'))
print("recall score is:" ,recall_score(ytrue, yhat, average='weighted'))
```

```
accuracy score is: 1.0
precision score is: 1.0
recall score is: 1.0
```

We also see here the accuracy score, precision score and the recall score of the model all of them are very high for the same reason above.

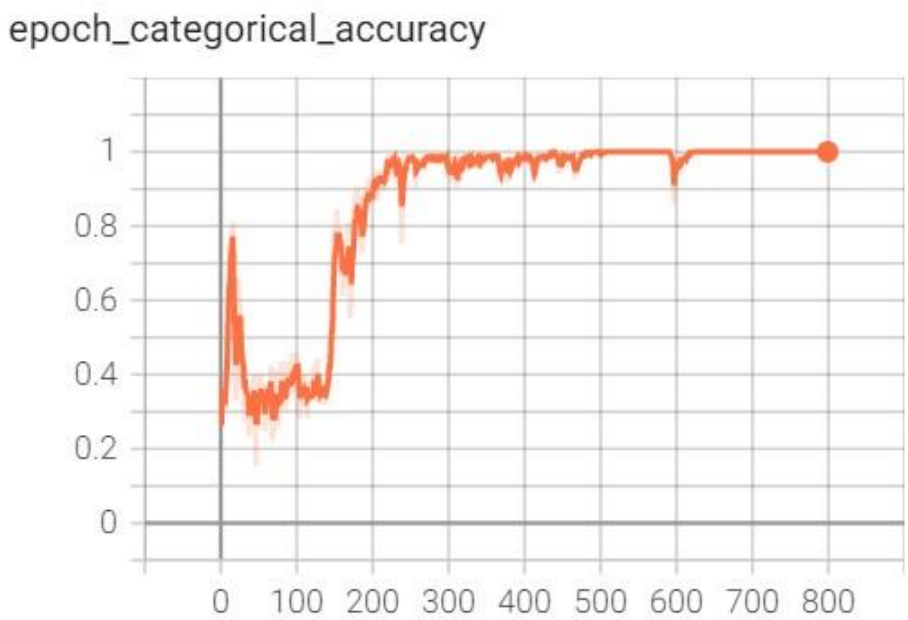


Figure 3.11: categorical accuracy changing with epoch

The above picture was obtained through tensor board when the model was training Here, we see the categorical accuracy of the model as the epoch value changes over time. It can be seen the accuracy of the model gradually increase and comes to a peak value at around 500 from there the values are constant, except when they take a dip at the value of 600 and again increase to reach the maximum value. Here we can see the model is not overfitted so an epoch value of 800 is considerably good.

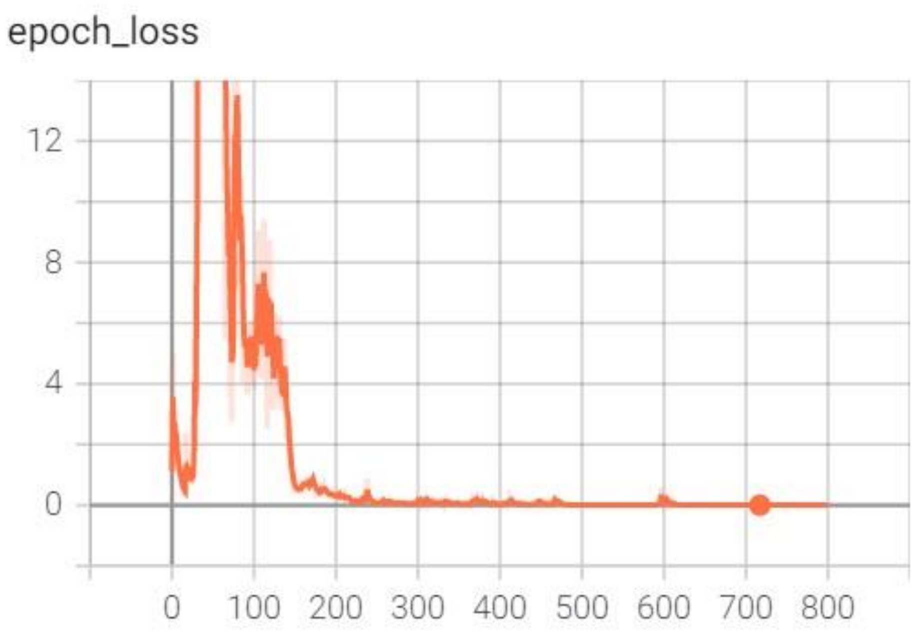


Figure 3.12: epoch loss changing over each iteration

Here we observe the loss experienced as the model is trained, we observe that the loss is quite high in the beginning but as the model trains and reaches the value of 800 the loss becomes almost negligent.

After the model is evaluated and a satisfactory result is obtained the last phase of the framework would be implemented which is the deployment phase.

3.3.5 Deployment Phase

After iterative process of data preparation and modelling which leads to evaluation the application would be deployed for the use of the target market. If the data mining results become part of the day-to-day company and its surroundings, monitoring and maintenance become critical. Preparing a maintenance strategy in advance helps to avoid excessively lengthy periods of inaccurate data mining results utilisation. The best way to deploy the completed project would be Model deployment as a service, if the time and the resources presents then deployment is certainly possible.

3.4 TOOLS USED

3.4.1 Python Language

The vast number of machine learning-specific modules and frameworks available in Python make development easier and faster. Python's simple syntax and readability make it simple to swiftly test complex algorithms, and it's also suitable for nonprogrammers.

3.4.2 Media pipe

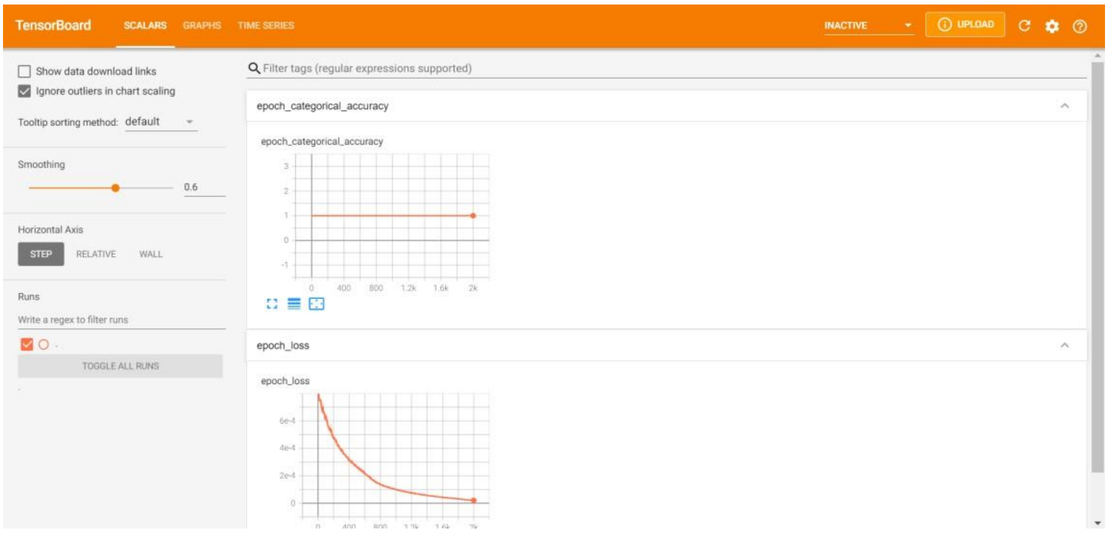
Media Pipe is a cross-platform framework for creating multifunctional machine learning pipelines. In this project media pipe holistic is used which integrates different models for pose, hand and face for gesture detection.

3.4.3 Open CV

OpenCV (Open-Source Computer Vision Library) is a free software library for computer vision and machine learning. OpenCV was created to offer a standard infrastructure for computer vision applications and to let commercial goods incorporate machine perception more quickly.

3.4.4 TensorFlow

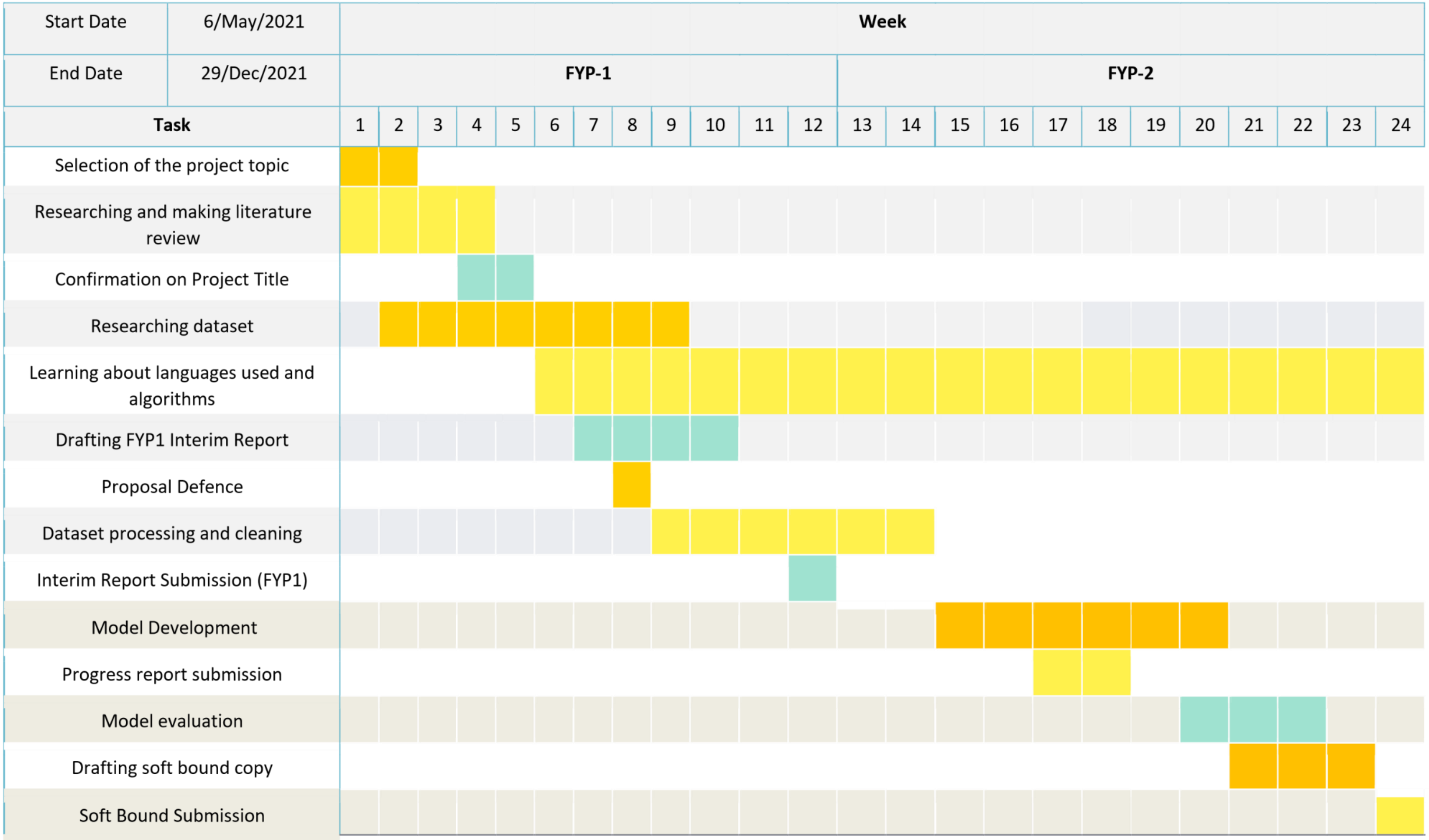
TensorFlow is a complete machine learning platform. It features a robust, adaptable wide range of libraries, and community resources. Additinally to using TensorFlow libraries we will be using tensor board which will help us to determine loss and accuracy of the model and it is trained in real time. It will also help us in keeping progress of previously trained models.



3.4.5 sklearn

Scikit-learn (Sklearn) is Python's most useful and powerful machine learning package. We will be using sklearn to evaluate the model through its accuracy, precision an recall functions.

3.5 GANTT CHART



CHAPTER 4

RESULTS AND DISCUSSIONS

In this project we have looked through how the hand and gesture detection can be achieved through machine learning. We were able to use media pipe holistic to extract and display various key points and landmarks that can be used in action recognition. Then LSTM was used training the model which in turn gave us quite high accuracy considering the dataset provided. It was also noted that the model had high precision and recall value which means there were less false positive and false negatives values.

4.1 Limitation of the project

Lack of proper database - The application would be the most efficient if a database containing proper pictures of MSL words and expression exist. These images should be very clear, this becomes a limitation as currently MSL is not extensively researched upon which makes it difficult to include such a database.

It should also be noted that the model currently contains the basic words, letters and numbers for Malaysian sign language translation. As this database increases and more word are added it can be said that the model parameters would have to be hyper tuned accordingly.

User testing - The testing for this project was very limited, most users who tested the models were adults, since the model is used for sign language determination and also to educate people about sign language. It is better to include children for user testing, this is to determine whether the model is able to detect the key points as accurately in the case of children as it is with adults.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

The current situation necessitates the use of a machine-based sign language interpreter. People are indeed interested learning the Sign language but there are not many sources available. The problem can be solved by creating the real time translation model. As a result, the suggested gesture recognition approach may pave the way for the creation of effective automated sign language translation systems. For those who are unable to speak or have hearing loss, such systems offer the potential to facilitate efficient communication and human–machine interaction. The most common areas where this may be employed are public venues such as ticketing desks, hospitals, and so on. This may even be used to educate regular people sign language.

5.2 FUTURE WORK

The development of current prototype offers an application which can translate MSL in real time. In future there are hopes to include the feature of directly translation translated MSL text to speech. This will not only allow the application to work faster, but it will be more convenient for the user.

I also hope to continue improving the dataset for a more precise translation and classification. Because having clean data will ultimately increase overall productivity and allow for the highest quality information in your decision-making. Lastly, I hope to integrate the software into a smaller hardware such as a wristwatch so that it is easier to use anywhere, this will make the communication through application seamless.

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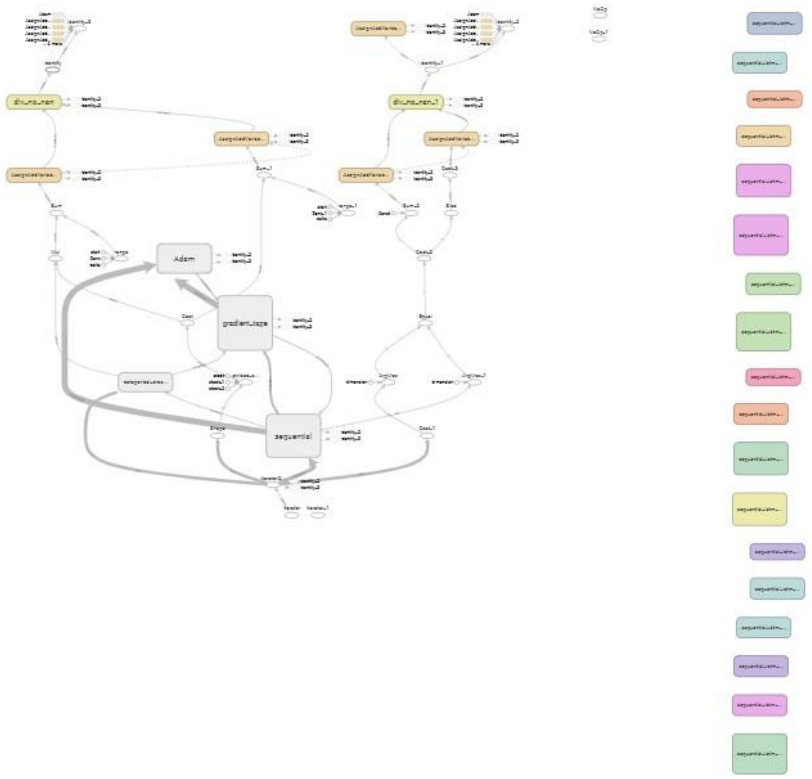
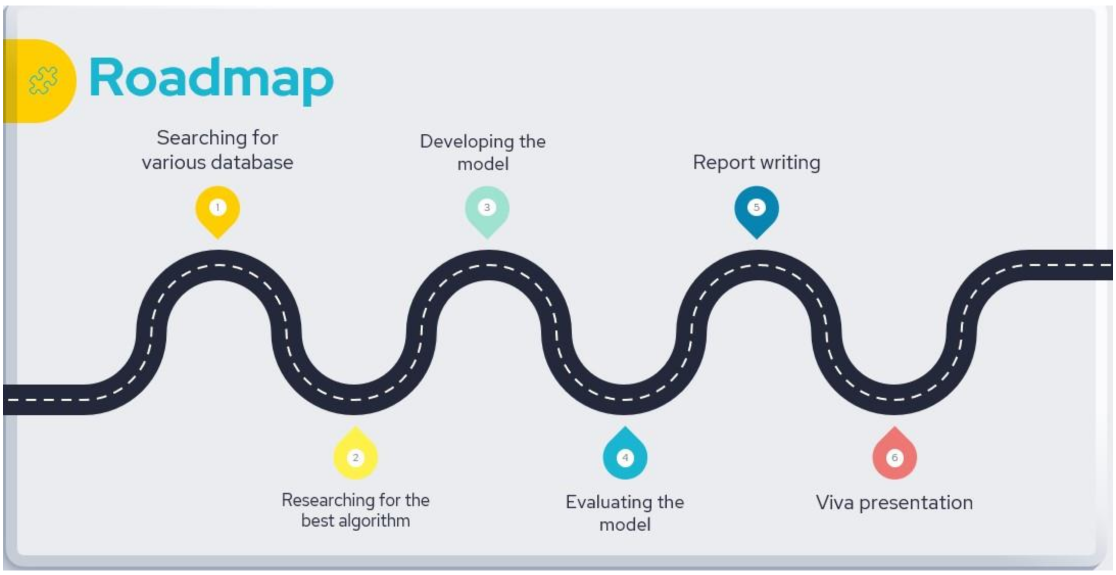
Appendix



Adam
gradient_tape
sequential



Roadmap
Searching for various database
Developing the model
Report writing
Researching for the best algorithm
Evaluating the model
Viva presentation