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Interactive Sign Language Learning Platform: SignIt

Group 03 Thesis Report by

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Declaration

We hereby certify that this project proposal and all the artefacts associated with it are our own work and it has not been submitted before nor is currently being submitted for any degree program.

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ABSTRACT

SignIt is a web-based learning platform designed specifically for individuals with hearing impairment and any other passionate learners to learn Sinhala Sign Language. We have used a 3D hand tracking system and video resource to help the learners visualise while depicting the correct and standard hand gestures and movements for the signs of our chosen set of vocabulary in this platform. It also includes a feedback system using a pop-up message to communicate with learners. A custom dataset was created and taken whereas the AI model was integrated using an Agile Methodology while taking object-oriented analysis and design as the design methodology. In order to improve user experience and gather suggestions and feedback from the general public, a questionnaire was designed using google sheets and was distributed.

The ultimate goal of Sign It is to improve and promote communication between hearing-impaired and hearing communities while enabling individuals from any background to learn and communicate basic words in Sinhala Sign Language. The platform includes a 1D CNN sequential model and an LSTM model with an accuracy of 91% and 74%, respectively, to achieve this goal. The CNN model was chosen as the final model for implementation after careful consideration. SignIT has the potential to improve Sinhala Sign Language education, improve communication with the hearing-impaired community, and accelerate sign language interpreter training.

Key words: Web application,CNN, LSTM, AI model, Mediapipe, SSL Learning, Machine Learning, Dynamic gestures

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List of Abbreviations

Acronym	**Description**
SSL	Sinhala Sign Language
BSL	British Sign Language
ASL	American Sign Language
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
DNN	Deep Neural Network
RCNN	Region Based Convolutional Networks
SVM	Support Vector Machine
GMM	Gaussian Mixture Model
OOAD	Object Oriented Analysis and Design
SSADM	Structured System Analysis and Design Method
API	Application Programming Interface
KPI	Key Performance Indicator
CI / CD	Continuous Integration / Continuous Deployment
UI	User Interface

CHAPTER 01 : INTRODUCTION

1.1. Chapter Overview

The “SignIt” Sign language learning platform is an online web application that can be used to learn sign language which may be useful in day-to-day life of hearing-impaired society. The goal of the website is to increase awareness and acceptance of Sinhala sign language, particularly within the deaf and hard-of-hearing community around the nation. Currently, there are no implemented systems to learn Sinhala Sign Language(SSL) in such an interactive and innovative way using new machine learning techniques which include the latest AI technologies and real-time video gesture recognitions models to verify the user’s input to the system, that way users are given the best way to learn a sign for a word at their own pace.

1.2. Problem Domain

Hearing-impaired individuals communicate using a different language known as Sign Language. Different sign languages are used in different countries or regions. The most widely used are American Sign Language (ASL) and British Sign Language (BSL). ASL letters are signed in one hand while both hands are used in BSL. ASL is widely used in the United States and Canada, whereas BSL is widely used in Australia, New Zealand, India, and Sri Lanka. Sri Lankan hearing-impaired People use SSL, derived from BSL.

As of 2022, a population of 430 million globally is a part of the hearing-impaired community, according to the World Health Organisation (WHO) Hearing loss affects over 20% of the world's population or more than 1.5 billion people. Furthermore, more than 389,000 individuals in Sri Lanka are affected by the same problem. More than 74% of the people of Sri Lanka speak Sinhala as their first language. Despite the fact that schools for the deaf exist, there are no platforms to study SSL in Sri Lanka. There are students in remote regions of the country who do not have access to or afford these particular schools and equipment. There are also those who progressively lose their hearing, which implies they understand how their spoken word works.

This area of research in Sri Lanka is not really a popular area, and not much awareness has been raised on the situation for the education of sign language. This disability needs much more attention than what is received as of now and we aim to raise awareness about the severity of this situation in Sri Lanka. This research is going to be risky as it is innovative as there are not a lot of dynamic datasets available for words in SSL. We believe that it is possible to aid this community and have a positive impact on the deaf and mute society to take a step forward to better learning using the newest technologies and utilising better accessibility features.

For these reasons, our primary objective is to provide an effective technique for assisting the deaf community and other interested parties to learn sign language through the use of an online sign language learning platform.

1.3. Problem Definition

The deaf and hard-of-hearing community in Sri Lanka often encounter difficulties in communicating with the broader society due to a pervasive misconception that sign languages are inferior to oral languages. Our project aims to bridge this communication gap by promoting the use of Sinhala Sign Language, the most prevalent sign language in Sri Lanka, and elevating awareness of the language and the challenges faced by the deaf and hard-of-hearing community. By doing so, we hope to foster a more inclusive society where the deaf and hard-of-hearing community can communicate effectively with the rest of society and be recognized for the unique linguistic capabilities they possess.

By reducing the communication barrier between the deaf and hard-of-hearing community and the rest of society, we hope to create a more inclusive and equal society, where everyone has equal access to information and communication.

Artificial Intelligence and machine learning technologies are the centrepieces for this type of problem. However, utilising AI tools in this situation could be a matter of great debate. Additionally, there are limited amounts of datasets available for SSL to train the AI, which is a common problem in most underdeveloped and developing countries like Sri Lanka.

This major problem at the present time sparked our interest towards them and led us to try to find a solution to their difficulties and minimise them as much as possible. Proposing an innovative system that is best and the platform should be accessible, and affordable and should be the best solution so that it can be effective for a developing country like ours. We plan to provide an online free learning platform for the education of SSL. This makes it accessible even for the most rural provinces of the country and also making this version of the project freely available adds to the accessibility of our website.

1.3.1. Problem Statement

Sri Lanka, as of now, doesn't have an online learning platform for SSL education and a reliable method to acquire study material for learning SSL, which we intend to rectify by developing a web application that meets these requirements using machine learning implementations.

1.4. Research Motivation

Real-world problem-solving objectives, a need for intellectual fulfilment on a personal level, and motives for professional advancement are the driving forces behind this research. We feel that we should leverage the satisfaction we derive from curiosity and the desire to solve problems to offer and implement a system that is beneficial, novel, and useful to the world that might be used for a highly humanitarian cause. Here in Sri Lanka, we want to lower the information gap between the hearing community and the deaf community. With SSL as our selected research topic, our research paper has given us the chance to share our own answers to significant and humanitarian real-world problems. We did this by using an interactive learning platform. Future advances focused on assisting the head community, to shed light on subjects that are much or little discussed, may be interested in conducting an original study on a topic, without uncovering any previous work or inventions, and sharing its results with a community based on data science. Our activities generally strive to improve and support society in this endeavour. We have committed ourselves to this research as a result of these motivations.

1.5. Existing Works

Table 1.5 : Existing Works

Citation	Limitation	Technology/ Algorithm	Advantage
(Dissanayake, Maheshi & Herath, H.C.M. & W.A.L.V. Kumari, & Senevirathne, W.A.P.B., 2013) [Not a learning platform]	Machine learning techniques aren't used.	Image processing technologies.	Highly accurate recognition system because of accurate algorithms and calculations used to identify the number of fingers and positioning of the hand.
(S. Dilakshan and Y. H. P. P. Priyadarshana, 2020) [Not a learning platform]	Not using video input. Only supports 12 basic signs.	CNN Architecture	Accurate classification system because the CNN system is used. Good performance levels and outputs are given fairly quickly
(S.D. Hettiarachchi and R.G.N. Meegama, 2020) [Not a learning platform]	Limited number of texts. Only works for the right hand gestures.	Image processing along with CNN	The application is able to generate the relevant letter by getting an input of a hand gesture within 1.75 seconds of average time.
(R.M. Rishan, S. Jayalal and T.K. Wijayasiriwardhane, 2022) [Not a learning platform]	Leap Motion is unable to see through the fingers which causes inaccurate validation.	Image processing. Convolutional neural network. Leap Motion technology.	It describes the importance of visual language interpretation based on SSL and highlights the raw interpretation of gestures.
(L.L.D.K.Perera and S.G.V.S.Jayalal. 2021) [Not a learning platform]	Haven't touched upon dynamic sign language gesture recognition and combining facial expressions of sign language in the gesture recognition process.	Scale Invariant Feature Transform (SIFT) CNN Image processing	A combination of SIFT features with CNN, improved the robustness to scale variations in sign language recognition, was implemented at a low cost and improved the model accuracy compared to a single-channel CNN implementation

(Kumarawadu, P. and Izzath, M. 2022) [Not a learning platform]	Has used a limited Combination of the general position of hands and speed at which the hand signs are performed is not paid attention to.	CNN ANN DNN Leap Motion	Capable of handling both static and dynamic Signs. Uses LMC to capture hand gestures, processes captured information, identifies corresponding words and phrases refer to the communication in SSL and displays them as a message in Sinhala Language enabling the non-SSL speaker to understand and interact with a hearing-impaired person
Kumar, D.M., Bavanraj, K., Thavananthan, S., Bastiansz, G.M.A.S., Harshanath, S.M.B. and Alosious, J., 2020) [Not a learning platform]	The same words and phrases can have different meanings according to the context of a sentence and many words by using natural language processing.	Image classification along with CNN and Linguistic Data Consortium to identify the word segments. Natural language processing and speech digital processing.	The proposed system has the ability to detect high-resolution images as well as low-resolution images of hand signs. It's a highly accurate system which can also detect hand signs through live images.
Dissanayake, I.S.M., Wickramanayake, P.J., Mudunkotuwa, M.A.S. and Fernando, P.W.N., 2020) [Not a learning platform]	The recurrent neural network (RNN) which is used for analysing video segments in the system will slow down the computational speed of this neural network and training activities can be difficult.	Image processing along with CNN and leap motion technology.	The unique feature of the proposed system is that it can interpret both static and dynamic signs using two separate machine learning models. The proposed system also accepts video feed as the input.

1.6. Research Gaps

Table 1.6 : Research Gaps

Citation	Theoretical gap	Performance gap	Empirical gap

(Dissanayake, Maheshi & Herath, H.C.M. & W.A.L.V.Kumari, & Senevirathne, W.A.P.B., 2013)	Theoretically, this paper provides an advanced breakdown of the calculations used to identify ratios and fingers. However, no neural networks were used in the final implementation.	According to the paper, high levels of correlation were present in the signed gesture and other gesture databases. Additionally, this system also takes 10 seconds on average to recognize a single gesture, which highly affects performance levels.	Observationally, the system provided 100% successful matches for only 11 out of 15 gestures. The testing and verification processes show that this system overall has a 93.3% success rate.
(S. Dilakshan and Y.H.P.P.Priyadarshana, 2020)	A convolutional neural network is used in this research. They have utilised colour segmentation, gesture recognition techniques, convolution, pooling and feature extraction to gain the final output needed.	This system only utilises data for 12 basic gestures. Furthermore, this model has a good performance level because it doesn't use any motion-based recognition in its implementation, only identifying static gestures, also it mentions that no API service for video streaming was provided.	Empirically, the Confusion matrix produced for this CNN model shows that the 3rd and 8th image classes have produced a miscalculation. This system provides an error rate of 10.1% which affects the accuracy of the overall system, only for 12 gestures.
(L.L.D.K.Perera and S.G.V.S.Jayalal. 2021)	RGB is used to reinforce appearance. Preprocessing is finished by resizing representations and colour space change. HSV colour rooms are stronger than illuminations distinguished from RGB. Has also used SIFT descriptor and k-means clustering .	An average confirmation veracity of 86.5% was reached when the linked CNN-SIFT model was proven accompanying representations of 20 gestures of SSL. The most of the gestures accompanied accuracy, recall and F1 scores above 0.8 but any indication classes demonstrated reduced F1 principles. Out of the 20 sign classes, 13 displayed in addition 50% correct Sinhala quotation predictions when the distance between help and camcorder were exchanged to 40cm and 60cm individually. An average veracity of only 68% was worked out when the SIFT physiognomy was not linked accompanying the CNN classifier	Dynamic sign language gesture recognition and combining facial expressions of sign language in the gesture recognition process are not touched upon.

(Kumarawadu, P. and Izzath, M. 2022)	The DNN model was executed in Python using Keras and TensorFlow open beginning athenaeums. The proposed DNN included individual input coating accompanying 23 input knots, two hidden tiers accompanying every 128 nodes and a profit coating with 30 knots and provides a leading mishap of the calculations	The system does not pay attention to the speed at which the hand signs are performed.	Has only used a limited Combination of the general position of hands is not paid attention to.
(S.D. Hettiarachchi and R.G.N. Meegama, 2020)	A convolutional neural network is used and a 2D convolutional layer is used for better validation. The softmax function is also used for the activation of output layers.	It was only able to identify 26 hand gestures using a convolutional neural network with 91.23% validation accuracy and 89.44% training accuracy.	In this project, they limited the letters to 26 and when considering the Softmax activation function it is non-differentiable at zero and ReLU is unbounded.
(R.M. Rishan, S. Jayalal and T.K. Wijayasiriwardhane, 2022)	The image classification model utilised a CNN and an optimised ANN, while the Leap Motion method included an ANN.	The combined signs dataset consisted only of dynamic signs. Using a geometric template may affect the output timeline. validation	The research did not consider the output time and also the leap motion technology will not be able to see through the fingers which causes inaccurate values.
Kumar, D.M., Bavanraj, K., Thavananthan, S., Bastiansz, G.M.A.S., Harshanath, S.M.B. and Alosious, J., 2020)	A convolutional neural network is used as the system uses it for skin-colour based modelling and to feed the images into the relevant model. Leap motion technology is used to classify dynamic sign identification.	Instead of showing the accuracy value of the system it shows values such as precision value and recall value for both static and dynamic hand gestures. It achieves high precision and recall values for both static and dynamic signs (over 0.90).	Large number of images and high dimensionality of the data can be a problem for having two classifiers (static and dynamic) at the same time in the respective system.

Dissanayake, I.S.M., Wickramanayake, P.J., Mudunkotuwa, M.A.S. and Fernando, P.W.N., 2020)	A region-based convolutional neural network is used in the system. In the image classifier, the images will be sent through an application programming interface for other classifications.	The system shows an accuracy of more than 80% for almost all the scenarios and the responding speed was in milliseconds. In this project, the hands or the position of hands are not considered.	In the project, the region-based convolutional neural network had poor performance while the live feed of the images. In case they need to change or modify the existing code to add some extra features by using an application programming interface they have to go through so many files to make changes.

1.7. Contribution to the body of knowledge

1.7.1. Technological Contribution

Artificial Intelligence technologies, such as video recognition and Convolutional Neural Networks (CNNs), are utilised in our system. Video recognition is used to identify and enhance the captured video and use it in further processes. CNN algorithm is used in the process of classifying the signs.

1.7.2. Domain Contribution

- Our contribution provides a novel form of learning SSL in an online learning platform to the Sri Lankan community.
- This will be a much better method to learn SSL because users will not have to travel to and pay for physical sign language lessons. Users can save time and effort with ease by obtaining knowledge in this manner.
- All that is necessary is a functional webcam and a stable internet connection for the user to fully benefit from this online learning experience. This is especially useful for users in rural regions of the country where some cannot afford to pay for special education.

- They might also repeat activities in which they were unsure for additional practice, therefore, boosting the student's confidence in the lesson and what they have learnt so far.
- This website strives to be age-friendly and completely accessible to all sorts of SSL learners. The users can choose to learn in both English and Sinhala Languages as some users are more comfortable with one language than the other. The user will be provided with an option to choose their preferred language to use on the website.

1.8. Research Challenge

The research we are conducting for this humane project is expected to have a positive impact on the Sri Lankan community by increasing awareness of the hearing-impaired population and, eventually, easing the communication barrier. Our research was thorough and concise, with a focus on the currently proposed SSL solutions. We intend to improve these systems and make sign language learning more accessible to people of all ages and levels of experience. It is critical that we conduct extensive research and data collection efforts in order to provide a solid and well-supported foundation for our project. This necessitates a regular examination and assessment of existing literature reviews and data sources. Furthermore, it is critical that we remain informed.

1.8.1. Research Questions

RQ1: How would using a CNN architecture elevate the performance of the system?

RQ2: How do spoken languages influence sign languages and How do sign languages influence spoken languages?

RQ3: How can sign language be used for deaf people with moderate intellectual disabilities?

RQ4: Which CNN architecture is best for the proposed system and how can we increase the efficiency of that model?

1.9. Research Aim

The objective of our research is to design and develop an Interactive Sign Language Platform that facilitates the learning and acquisition of SSL in a user-friendly manner. The platform will enable users to learn basic SSL gestures, test their comprehension through a guessing game, and expand their SSL vocabulary. The camera feature will allow users to practise the gestures they have learned and receive feedback on their accuracy. The platform will track dynamic signs using image processing, video recognition, and pattern recognition technologies, including a CNN model for sign language classification and OpenCV architecture for capturing user input. Our aim is to enhance communication between hearing-impaired individuals and the broader society and bridge the language barrier through the development of this innovative and comprehensive platform.

1.10. Research Objective

Table 1.11 : Research Objectives

Research Objectives	Explanation	Learning Outcomes
Problem Identification	To identify the real-world issues in Sri Lanka and narrow down the scope to one topic	LO1
Literature Review	RO1: Figure out existing Sinhala Sign Language Systems RO2: To build and finalise a vocabulary of signs and words to work within our system RO3: To determine how the final output in the website will look like to have an idea about the design layout	LO1
Data Gathering and Analysis	To visit deaf community institutions to gather data from repositories and validate the needed data	LO2, LO3
Research Design	Gather information regarding the layout of the final design of the learning platform in comparison to the other available platforms in use.	LO3, LO4
Implementation	Developing the model and training with the necessary data, making edits to the system. Developing the front-end and back-end to lace it together as one functioning system.	LO2, LO3, LO4
Testing and	Using test data apart from the training data to see whether the	LO4

Evaluation	needed results are achieved, and using metrics to evaluate and rank the results.	

1.11. Project Scope

1.11.1. In - Scope

Table 1.12.1 : In - Scope

No	Description
1	Identify signs that the user does using image processing and AI.
2	Obtain relevant descriptions, pictures and a video of how to do the sign.
3	Creating a web application tool which will be user friendly when learning sign language.
4	Contains the basic categories of vocabulary for the beginner users.
5	Updatable with new vocabulary and signs; the system will detect it and inform the user of it.
6	Make sure, for images or videos with incorrect specifications outlined under the user manual, it gives an error by specifying the reason.

1.11.2. Out - Scope

Table 1.12.2 : Out - Scope

No	Description
1	Identifying only small phrases.
2	The user will receive a responsive web application.
3	Not introducing the alphabet to the user.
4	Used a limited set of vocabulary which will give some basic knowledge about SSL

1.11.3. Prototype Diagram

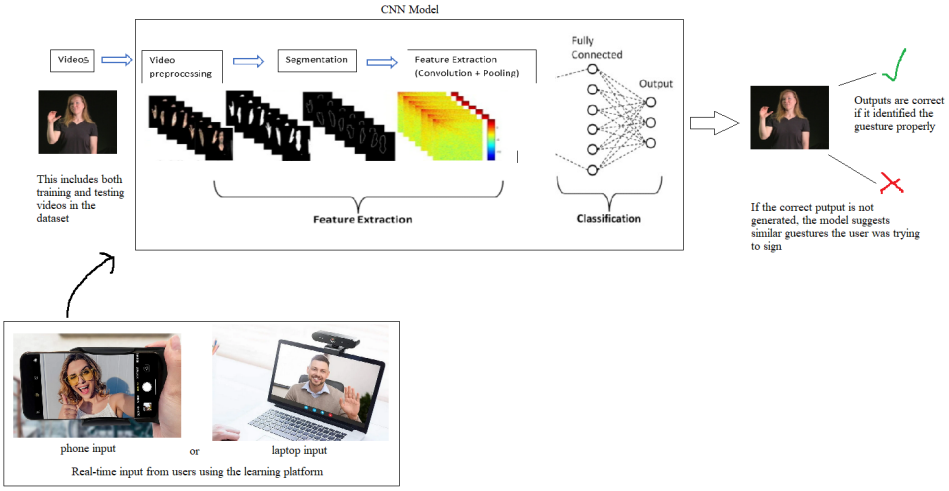


Figure 1.12.3 : Prototype Diagram

1.12. Resource Requirements

1.12.1. Hardware requirements

● Intel Core i5 10th generation processor or high - To be able to perform training the model and other high-priority tasks.

● 8GB RAM or high - To image processing the images and pre-process the images stored.

1.12.2. Software requirements

● Python – Main language to build the proposed system.

● Figma – To prototype the model architecture.

● Google Drive – To store data sets and other documents which were used in the process.

● MS Word – To write documents and drafts.

● Node js - we used node js to design the website.

● TensorFlow - Image pre-processing and training of the model are done using this.

● Keras - For image pre-processing and training the model of the system.

● Windows operating system – We used this to handle computational functionalities.

● Draw.io/star UML – To design wireframes for the system.

1.12.3. Data Requirements

- The number of datasets available for this project is limited so we have to create our own dataset and that has to be validated.

1.12.4. Skill Requirement

- Programming skills
- Design skills
- Mathematical application skills
- Time management skills
- Teamwork skills

1.13. Chapter Summary

Communication between hearing-impaired people and non-hearing-impaired people is narrowing because of the mode of communication. It is critical for non-hearing impaired people to learn sign languages in order to bridge the communication gap between these two parties. So an SSL learning platform would help them learn sign languages. The platform should be easy to use, convenient, and, most importantly, have an effective system to learn sign language.

CHAPTER 02: LITERATURE REVIEW

2.1. Introduction

According to the World Health Organisation (WHO) as of 2022, 430 million people around the world are suffering from deafness. Nearly 20% of the world's population, or more than 1.5 billion individuals, live with hearing loss (World Health Organization, 2022). Additionally, there are more than 389,000 people in Sri Lanka who unfortunately experience the same issue. In Sri Lanka, more than 74% of the population speaks Sinhala as their native language. Despite the fact that there are schools dedicated to teaching deaf people, there isn't an adequate online learning environment set up for learning Sinhala sign language. Our goal is to develop an effective method of aiding the deaf and mute community by bringing a fresh approach to learning sign language. Our project is broken down into 4 main components that we will focus on introducing machine learning to enhance this website. These are 1) Image processing and Skin colour modelling, 2) Gesture Recognition, 3) Convolution and Classification and 4) A helpful chatbot.

2.2. Relevant Work

2.2.1. Image Processing and Skin Modelling

There are various methods of skin colour modelling and image processing used in the existing published papers on SSL systems. In an article about Image Processing used for SSL (Dissanayake et al., 2013), they used Image processing technology to generate the image to be processed. They use a green background for the dynamic video input, break it down into frames and create a binary image of the hand by adjusting the RGB matrix of the skin colour. This allowed their model to have faster mapping but the accuracy of the binary image highly depended on the lighting conditions of the image captured (Perera & Jayalal, 2021). The article on using CNN architecture for SSL (Dilakshan & Priyadarshana, 2020), used a very similar approach where they converted the RGB image to grayscale and then to a binary image before being fed to the gesture database. With this vision-based approach come challenges such as illumination change, background clutter, etc (Kumarawadu & Izzath, 2022). To overcome some of the lighting issues, the Gaussian Mixture Model (GMM) is used.

In a system called EasyTalk (Kumar et al., 2020), the abstract sign image serves as the input for the image classifier. The API machine learning model is used and it is created using CNN. It processes the image and classifies it under different categories. This component was developed utilising a Faster (Region-Based Convolutional Neural Networks) RCNN setup on top of the TensorFlow model trainer. In another similar system (Dissanayake et al., 2020) First, the background is removed. In this first, the images are converted into grayscale images and thresholding is done to perform edge detection. Dilation and erosion methods were used to make the edges sharp. Next, the largest contour was taken as the person and the rest was taken as the image background. So the background is not focused and the accuracy is increased.

Sign Language gesture recognition follows stages of data acquisition, data preprocessing, segmentation, feature extraction, and classification of hand gestures (Perera & Jayalal, 2021). Gesture recognition can be achieved by using (Kumarawadu & Izzath, 2022) either vision-based approaches (camera images/videos) or sensor-based approaches.

Image preprocessing is done by resizing the images to 48x48 size, converting colour space from RGB to HSV and applying a skin colour mask to separate the hand region from the background. The HSV colour ranges used are HSV_min (0, 40, 30) and HSV_max (43, 255, 255)(Perera & Jayalal, 2021).

Research on SSL recognition and translation has been carried out focusing on (Kumarawadu & Izzath, 2022) appearance-based approaches, skeletal-based approaches and 3D module-based approaches. Research on image processing-based SSL recognition using skin colour filtering and centroid finding approach for the (Perera & Jayalal, 2021) development of a still gesture mapping prototype has been conducted considering 15 gestures of the SSL alphabet.

Hand-tracking devices with arrays of sensors have been used recently in sign language recognition research. After collecting hand gestures (Kumarawadu & Izzath, 2022). A depth sensor based real-time hand-pose estimation framework has been proposed to recognize the first ten digits in American sign language.

In the article (Hettiarachchi & Meegama, 2020), they have only considered 26 letters which have static hand gestures having green as the background colour. A

database of hand gestures is created and those digital images are processed. The images are taken under identical parameters such as background colour and the same side of the hand (Perera & Jayalal, 2021). When the user shows a sign from the hand to the web camera window in the computer, it proceeds 200 frames and the final frame will be captured to be used for further tasks. The selected images have a width and height as per a selected scaling factor. The image classification model utilised a CNN and an optimised ANN and Leap Motion method in gesture recognition (Rishan et al., 2022).

2.2.2. Gesture Recognition

The article concentrating on the image processing-based system (Dissanayake et al., 2020) employs a special technique to monitor the user's motions. In this instance, they allow the user to wear a wristband to distinguish the motion made in isolation from the complete hand. After it is complete, a contour map is created around the hand that has been filtered using a set of equations to position the hand and fingers (Kumarawadu & Izzath, 2022).

Next, the CNN-based article (Dilakshan & Priyadarshana, 2020) discusses using a straightforward gesture recognition pipeline. Starting with sensor, Feature extraction, classification and finally obtaining the gesture class label. It is said that the gesture recognition system may be divided into two categories: a three-dimensional (3D) hand model-based method and an appearance-based system. The 3D method is built using the ResNet architecture and depth-based sensor devices.

The gesture recognition in the system EasyTalk (Kumar et al., 2020), the Tensorflow model was used along with RCNN. For accelerated training and storage efficiency, the photos were captured at a resolution of 800 x 600 pixels. Laptop webcams with a lower resolution were used to capture the images. The detected images were divided into training and test datasets for a successful model. Next in the system UTalk (Dissanayake et al., 2020), the features were detected statically and dynamically. As micro-movements cannot be detected easily, and also it is not part of a particular gesture it has to be neglected. This problem was solved with more extended time duration in the required frames.

SL gesture recognition follows stages of data acquisition, data preprocessing, segmentation, feature extraction, and classification of hand gestures (Perera & Jayalal,

2021). Gesture recognition can be achieved by using either vision-based approaches (camera images/videos) or sensor-based approaches

Authors have used a hand model with a hierarchical skeleton for sign recognition and a model using artificial neural networks support vector machine has been utilised as a pose classifier (Kumarawadu & Izzath, 2022). Kinect sensors with high-performance 3D image capturing have been used for a gesture recognition system focusing on the fingertip position. A glove-based data acquisition technique has also been used as another approach wherein the position and orientation of hands were recognized using a special glove equipped with several sensors worn by a user (Kumarawadu & Izzath, 2022).

A database of hand gestures was created in the article and those digital images were recognized and classified by the Convolutional neural network (CNN). Then the authors identify the most appropriate design and then they implement a platform to develop the system to translate the gesture into Sinhalese (Hettiarachchi & Meegama, 2020).

Vision-based gesture detection and recognition systems are cheaper than sensor-based gesture recognition systems (Rishan et al., 2022). However, background effects, changes in light intensity, computational time against resolution and frame rate and background objects with similar skin colours or otherwise the hands will be a challenge for vision-based approaches.

2.2.3. Convolution

For the article that works on the Image Based processing system (Dissanayake et al., 2020), a convolutional approach is not taken on by the respective researchers. Instead, they segment the hand and crop the image using a series of equations to more accurately detect the user's gesture more.

Contrarily, the publication that discusses CNN architecture (Dilakshan & Priyadarshana, 2020) utilised convolutional neural networks (CNN), as the name implies, is used in the field of image classification. The CNN architecture consists of hidden layers that can learn features by repeatedly performing three actions. These were termed "Convolutional Blocks" by the authors (Perera & Jayalal, 2021). Each layer of

the convolution process uses matrices, and then a pooling mechanism is used to produce dense matrices.

In the system EasyTalk (Kumar et al., 2020), The Convolutional Neural network (CNN) is used in the process of building the machine learning API which gets the abstracted sign image as the input. When taking an image as an input those individual images are converted into Comma Separated Value files. The model is started to train using the TensorFlow model trainer and Faster RCNN Configuration utilising the CSV files. Since Python is used in building the EasyTalk (Kumar et al., 2020) system's backend implementation, the *Keras* library is used to build the CNN model. In the system UTalk (Dissanayake et al., 2020) the CNN is used to develop the static and dynamic sign classifier. The creators have used max pooling and some of the layers for the model-building process. The trained data set was transformed into a Numpy array, as such, it can translate a 3D array into a 1D array.

The methodology consists of the major stages of data acquisition, image preprocessing, feature extraction, classification and displaying Sinhala text. The classification model consists of two input channels, one from CNN and the other from the SIFT (Perera & Jayalal, 2021). The final fully connected layer will concatenate both feature vectors from SIFT and CNN layers to generate the final output of the gesture recognition model. This comprises three major components: builder, interpreter and classifier (Perera & Jayalal, 2021). The system architecture was all managed and executed with the help of the leap service of LMC, which was connected with the Interpreter and the Builder through the API service of LMC (Kumarawadu & Izzath, 2022). The gestures were recognized using the builder application and they were saved in a dataset. The interpreter was responsible for recognizing a sign from the dataset and displaying the text output of the sign. The Builder created the Sinhala hand signs, trained the data, and saved the gestures in the dataset (Kumarawadu & Izzath, 2022). A utility application was used to help the classifier extract features from hand gestures. A classifier was used to train the dataset value and to normalise hand gesture data received from the leap motion controller using its leap service (Kumarawadu & Izzath, 2022). The dataset was the storage and this was used to store the recognized values from the

leap motion controller (Kumarawadu & Izzath, 2022). This stored the raw data representing hand gesture values of the palm and fingertips in a numeric way.

The Leap Motion controller is a commercially available, inexpensive sensor for recognizing hand and finger motions, including bones and joints in a 3D interactive zone. The Leap Motion Controller can capture a user's hands and fingers by being surrounded by cameras with infrared light. Similar to the sign training model, a function is used to receive the performing sign recordings. Then, using another function, the data is recorded and the process begins (Rishan et al., 2022).

A 2D convolutional layer was used by them as it provides better validation accuracy than 3D convolutions (Hettiarachchi & Meegama, 2020). The main task of the convolution stage is to derive high-level features such as edges and quality from an input image. After inserting an image with 3 colours into the convolutional layer, it produces a 3 coloured image.

2.2.4. Classification

The "error in ratios" and the "error in fingers" were used to determine the "highest mark" in the image-processing system (Dissanayake et al., 2020). Each gesture in the sequence receives a determined score. The gesture that received the highest score is ultimately picked as the input gesture's best match.

The main aspect of the classification utilised is also part of the CNN architecture for the CNN-based article (Dilakshan & Priyadarshana, 2020). A callback list of matched motions is found using the final CNN architecture. A histogram will be generated and used for the segmentation process of the system. Each database includes categorised files for the Unicode characters that are used to correspond with a Tamil or Sinhala letter.

When considering the classification in the system (Kumar et al., 2020), the CNN classifier goes through a number of phases with an image. First, the image passes through a series of convolutional layers. Then the pooling process takes place. Then, several convolutional layers are added, and pooling is continued until the desired level of filtration is achieved.

In the system (Dissanayake et al., 2020), Static sign classification plays a major role in this system as at least one static sign supports getting a meaningful sentence.CNN

classification technique is used to create the dynamic sign classification model. CNN classifies dynamic signs using input and output layers as well as numerous hidden layers (Perera & Jayalal, 2021). And also image entropy is used to decide which pixels spread constantly through each frame and which regions are highlighted by the appearance of the frame. With the value of the image of entropy, it is decided whether it is a dynamic frame or a static frame (Kumarawadu & Izzath, 2022). Here VGG base 16 model is used for video classification.

The CNN consists of three convolution layers, and three max-pooling layers followed by a dense layer. The combined feature map from both channels is used in the fully connected layer of CNN as an enhanced set of features for scale variations (Kumarawadu & Izzath, 2022). The concatenated output at the final dense layer is given as the output of the model. The training dataset is fed to the gesture classification model as input in the CNN channel and the SIFT feature vectors are fed as the input for the SIFT channel to train the model (Perera & Jayalal, 2021).

In this study, the proposed DNN model was compared with a Naïve Bays model and a multi-class SVM model for the prediction of Sinhala Sign Language (Kumarawadu & Izzath, 2022). The DNN model was implemented in Python using Keras and TensorFlow open-source libraries. The proposed DNN consisted of one input layer with 23 input nodes, two hidden layers with every 128 nodes and an output layer with 30 nodes. The complete application consisted of three major system components: Interpreter, Builder and Classifier. Three classifiers were experimented with in the study (Kumarawadu & Izzath, 2022) DNN classifier, the Naïve Bayes Classifier and SVM based classifier which was trained and tested to classify a number of pre-identified Sinhala signs and words which have been pre-identified for feature extraction.

To classify the dataset in this project, an artificial neural network was added to the CNN (Hettiarachchi & Meegama, 2020). Basically, a fully attached layer looks at what high-level features most firmly correspond to a particular division to produce an effective output. A number of units were used, which is the number of nodes that should be present in a hidden layer to achieve non-linearity in the fully connected layer.

The Leap Motion and the Leap Trainer framework are also used in the sign recognition model (Kumarawadu & Izzath, 2022). In the article, the Leap Motion controller-based

sign language recognition, proposed a combined approach along with image and Leap Motion data classification for the identification of gestures (Rishan et al., 2022).

2.3. FAQ

The FAQ system is a novel system we tend to introduce to our website implementation. The FAQ system will help the user navigate around the system with ease and help them clear their doubts in a much easier way than waiting for a response from the support site.

2.4. GAP Analysis for Relevant Work

Table 2.4 : GAP Analysis for Relevant work

Research	Author(s)	Year	Dataset	Model Used	Metric
Image Processing Based Sinhala Sign Language Recording System	Dissanayake, Maheshi & Herath, H.C.M. & W.A.L.V.Kumari, & Senevirathne, W.A.P.B.	2013	User's own dataset of 15 different gestures	Image processing and Still gesturing techniques (No specific model used)	Accuracy: 93.3%
Convolutional Neural Networks: A Novel Approach for Sinhala Sign Recognition System	S. Dilakshan and Y. H. P. P. Priyadarshana	2020	Sign Language MNIST Kaggle	CNN	Accuracy: 89.9%
EasyTalk: A Translator for Sri Lankan Sign Language using Machine Learning and Artificial Intelligence	Kumar, D. & Kugarajah, Bavanraj & Thavananthan, S. & Bastiansz, G.M.A.S. & Harshanath, S.M.B. & Alosious, J	2020		CNN, RCNN	Accuracy: 97%

Utalk: Sri Lankan Sign Language Converter Mobile App using Image Processing and Machine Learning	Dissanayake, I.S.M., Wickramanayake, P.J., Mudunkotuwa, M.A.S. and Fernando, P.W.N.	2020	User's own dataset, 27 images and video segments	CNN	Accuracy: 90%
Translation of Sri Lankan Sign Language to Sinhala Text: A Leap Motion Technology-based Approach	Rishan, R.M., Jayalal, S. and Wijayasiriwardhane.	2022	Github Groundviews	CNN Leap Motion	Accuracy: 91.82%
Machine Learning Approach for Real Time Translation of Sinhala Sign Language into Text	Hettiarachchi, S. and Meegama, R.	2020	Sliit deskspace, arvix.org	CNN	Accuracy: 91.23%
Sri Lankan Sign Language to Sinhala Text using Convolutional Neural Network Combined with Scale Invariant Feature Transform (SIFT)	L.L.D.K.Perera and S.G.V.S.Jayalal.	2021	statistics by United Nations Economic and Social Commission for Asia and the Pacific in 2019	CNN	Accuracy:
Sinhala Sign Language Recognition using Leap Motion and Deep Learning.	Kumarawadu, P. and Izzath, M.	2022	IEEE, International Conference on Cyber-Enabled Distributed	CNN ANN DNN Leap Motion	Accuracy: 90%

2.5. Summary

Our project is an Interactive Sign Language Platform where users can learn some basic Sinhala sign language gestures. By using this technology, we promote interaction between hearing-impaired people and ordinary people. We will construct a system that recognizes hand motions using an image processing system. Additionally, a FAQ system

that assists in discovering website information will be developed. In this approach, real-world knowledge has been recorded using a CNN.

CHAPTER 03: METHODOLOGY

3.1. Chapter Overview

The methods utilised in research, project management, development, and evaluation are covered in this chapter. Here, you can find a number of different processes, appropriate theoretical and methodological management, prioritised designed principles and techniques for solving problems and anticipated project implementation plans.

3.2. Research Methodology

Table 3.2 : Research Methodology

Research Philosophy	The research philosophy for the system follows pragmatism and an understanding of linguistics. This methodology involves understanding the nature of sign language, choosing a theoretical framework, data collection, algorithm selection, evaluation metrics and user-centred design.
Research Approach	The study that will be used is deductive because it is founded on established methodologies, also the system needs to be trained using videos, and the performance needs to be evaluated using various metrics.
Research Strategy	The project will follow a grounded theory research strategy because patterns are derived from the data as a precondition for the study.
Research Choice	The usage of multi methods will be chosen because a wider selection of methods is used and they all fall within the same field of study.
Time zone	The research is cross-sectional, because the time horizon is already established, whereby the data must be collected at a certain point.

3.3. Development Methodology

3.3.1. What is the life cycle model and why?

Our project centres on incorporating the Agile methodology into the project life cycle development process. By utilising the Agile method, we aim to effectively prioritise the crucial elements of the project, resulting in the optimal utilisation of available time for project management. The frequent, short meetings enabled by the Agile approach allow for regular updates to be shared among team members and facilitate the reporting of weekly progress to the supervisor. This enhances the efficiency of the feedback process and enables the seamless integration of any necessary modifications.

3.3.2. Design methodology

Given our adoption of the Agile methodology, we have determined that the Object-Oriented Analysis and Design (OOAD) method is the most appropriate approach for our project's design methodology. The central goal of OOAD is to translate functional requirements into implementable solutions using multiple programming languages, making it an ideal fit for our project needs. While the Structured Systems Analysis and Design Methodology (SSADM) has its advantages, particularly in the application of the waterfall technique in its life cycle development, the rigidity of SSADM can hinder the ability to adapt to changes in requirements, a common occurrence in Agile projects. In contrast, the flexibility of OOAD makes it more suitable for complex projects with many objects and interactions, as opposed to SSADM's suitability for smaller, less complex projects. According to Kendall and Kendall (2005), "Object-oriented analysis and design (OOAD) is more suited to large, complex systems because it emphasises time management through modular design" (Garlan and Shaw, 1993)

3.3.3. Evaluation Methodology => Evaluation metrics and / or benchmarking

- We intend to evaluate this section using both metrics and benchmarking methods.
- Metrics could offer reliable numerical information on how this project was developed and benchmarking will evaluate the precision of results using important business KPIs to determine whether this software outperforms the market's rivals.

3.4. Project Management Methodology

3.4.1. Schedule using the Gantt chart after doing a WBS

SignIt
Read-only view, generated on 27 Oct 2022

	ACTIVITIES	ASSIGNEE	EH	START	DUE	%
	Topic Selection :		-	26/Sep	13/Oct	0%
1	Topic Selection		-	26/Sep	04/Oct	0%
2	Identifying the problem		-	05/Oct	06/Oct	0%
3	Read research paper		-	06/Oct	08/Oct	0%
4	Mentors feedback		-	09/Oct	13/Oct	0%
5	Discuss with domain expert		-	11/Oct	12/Oct	0%
	Literature Review:		-	08/Oct	16/Oct	0%
7	Reading and identifying exis...		-	08/Oct	11/Oct	0%
8	Collecting related research		-	10/Oct	12/Oct	0%
9	Literature Evaluation		-	13/Oct	13/Oct	0%
10	Reviewing gathered researc...		-	11/Oct	12/Oct	0%
11	Drafting LR		-	12/Oct	15/Oct	0%
12	Mentor reviewing LR		-	14/Oct	15/Oct	0%
13	Submitting LR		-	16/Oct	16/Oct	0%
	Project Proposal:		-	14/Oct	30/Oct	0%
15	Drafting Project Proposal		-	14/Oct	28/Oct	0%
16	Mentor review		-	27/Oct	29/Oct	0%
17	Finalizing project proposal		-	28/Oct	30/Oct	0%
18	Submitting Project Proposal		-	30/Oct	30/Oct	0%
	Software Requirement Specific...		-	27/Oct	27/Nov	0%
20	Analyzing Requirement		-	01/Nov	11/Nov	0%
21	Drafting SRS		-	11/Nov	20/Nov	0%
22	Mentor review		-	20/Nov	24/Nov	0%
23	Submitting SRS		-	27/Oct	27/Nov	0%
	Interim Progress Report :		-	20/Nov	17/Dec	0%
25	Drafting interim progress r...		-	20/Nov	11/Dec	0%
26	Mentors Feedback		-	12/Dec	16/Dec	0%
27	Submitting Interim Progress...		-	17/Dec	17/Dec	0%
	Prototype :		-	18/Dec	02/Jan	0%
29	Implementing prototype		-	18/Dec	28/Dec	0%
30	Demo prototype to the men...		-	29/Dec	30/Dec	0%
31	Refining prototype		-	02/Jan	02/Jan	0%
	Test Report:		-	03/Jan	22/Jan	0%
33	Identifying the best cases		-	03/Jan	06/Jan	0%
34	Identifying the requirements		-	06/Jan	10/Jan	0%
35	Creating test plan		-	10/Jan	20/Jan	0%
36	Test report submission		-	22/Jan	22/Jan	0%
	Final Project Report:		-	23/Jan	26/Feb	0%
38	Creating draft project reports		-	23/Jan	28/Jan	0%
39	Draft project submission		-	28/Jan	04/Feb	0%
40	Mentor review of project re...		-	05/Feb	09/Feb	0%
41	Refining project report		-	09/Feb	24/Feb	0%
42	Final report submission		-	26/Feb	26/Feb	0%

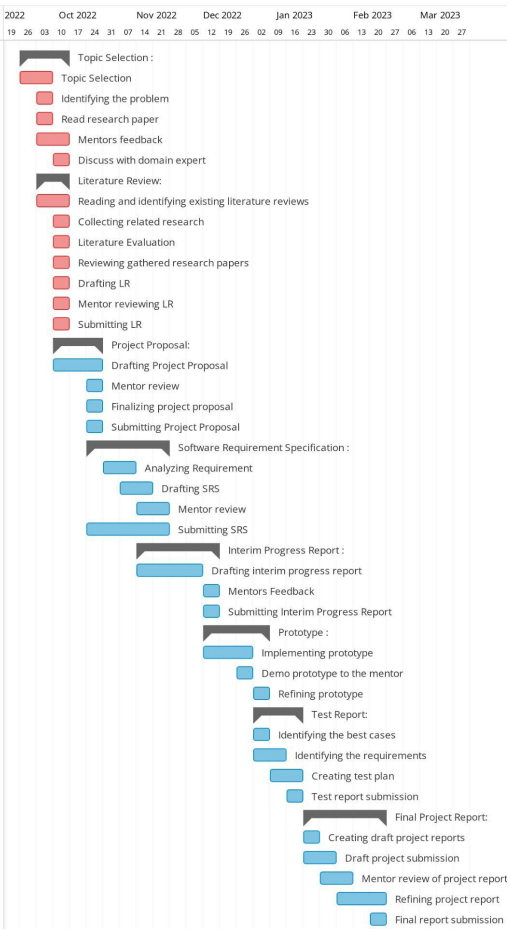


Figure 3.4.1 : Gantt Chart

3.4.2. Deliverables, milestones and dates of deliverables

Table 3.4.2 : Deliverables

Deliverables / Milestone	Due Date
Literature Review	October 16, 2022
Project Proposal	October 30, 2022
Software Requirement Specification	November 2022
Interim Progress Report	January 2023
Prototype	February 2023
Test Report	March 2023
Evaluation Report	March 2023
Final Project Report	April 09, 2023

3.5. Chapter Summary

Making conversations easier between non-hearing impaired and hearing impaired people in Sri Lanka is still at the research level and is currently being developed. Therefore, we have designed and started developing an SSL learning platform to make communication easier using modern technologies, concepts, and an integrated methodology. This is a very important milestone that we have reached, and the above-stated methodology proves the product's success in a pre-production view.

CHAPTER 04: SOFTWARE REQUIREMENT SPECIFICATION

4.1. Chapter Overview

This chapter provides a detailed analysis of the system requirements for SignIt. The stakeholders of the system are first identified and their responsibilities are outlined. The benefits and drawbacks of various techniques for requirement gathering are discussed and reviewed. The use case diagram and its definitions are included during the requirement analysis stage. Finally, a scope definition is used to specify the system's functional and non-functional requirements, which are then prioritised in relation to the function.

4.2. Rich Picture

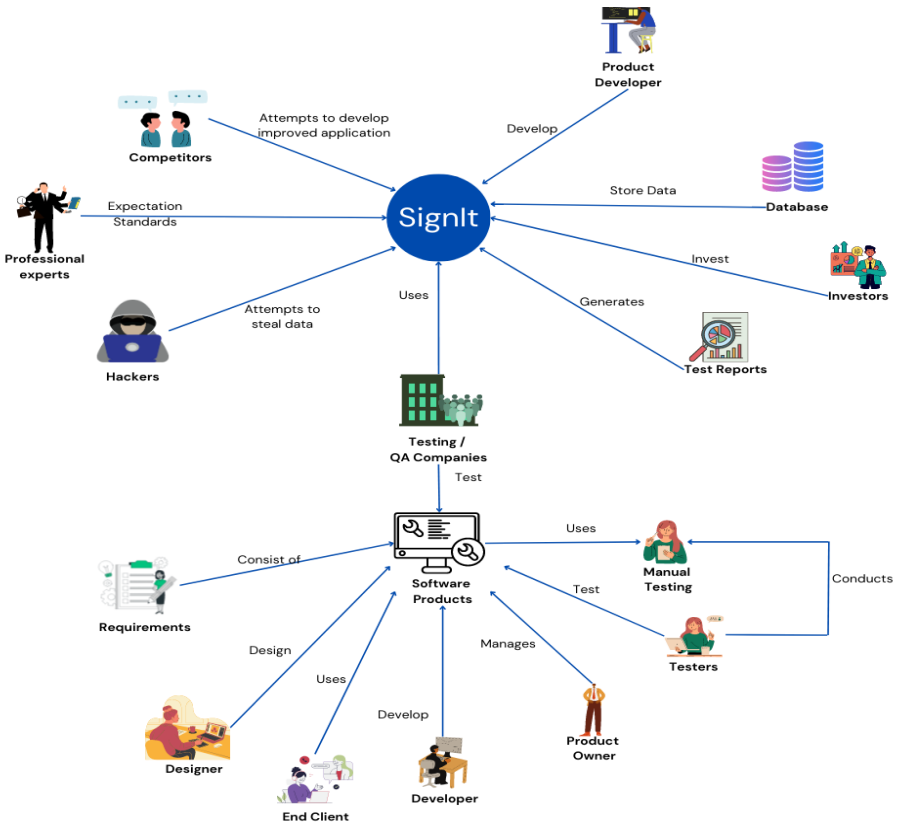


Figure 4.2 : Rich picture

4.3. Stakeholder Analysis

The system's established stakeholders are shown in the onion diagrams, along with a system overview and each stakeholder's role within it.

4.3.1. Onion Model

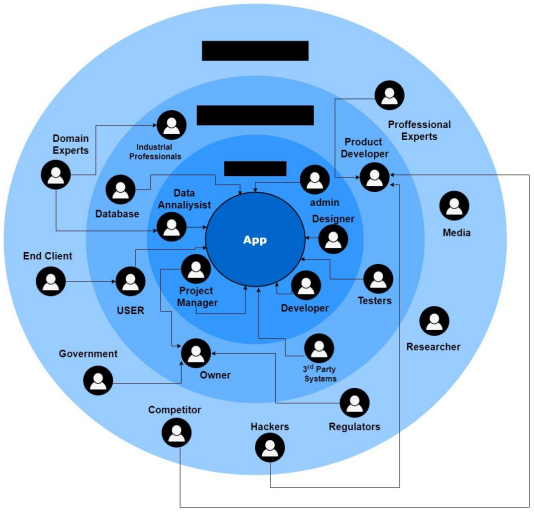


Figure 4.3.1 : Onion model

4.3.2. Stakeholder Viewpoints

Table 4.3.2 : Stakeholder Analysis

Stakeholder	Role	Benefits
System Admin	Functional Administration	Utilise the application and set up the essential environment.
Data scientists, ML Engineers, and Software Engineers	Functional Maintenance	Deploy the task and design and develop the model.
Users, 3rd party systems	Functional Beneficiary	Deploy the created application and integrate it with other systems, and programs.
Product owner	Functional Beneficiary	Owner of the proposed system or program.

Product Manager	Management Support	Managing and developing the process of application to ensure the effectiveness of the project.
Regulator	Quality regulator	Confirm that the application fits into its own individuality considering all the privacy policies.
Product developers	Functional Maintenance	They are in control of designing, maintaining and updating the system regularly.
NLP/NL experts	Expert	Gives an idea of the technology and methodologies to be used.
Domain experts	Expert	Give a domain perspective about the technology and methodologies used.
Technical writer	Functional Support	Support in the documentation process.
Researcher	Educational Support	Explore the current domain and provide ideas to improve the proposed process and techniques.
Competitor	Negative Stakeholder	Competes directly with the proposed system which could lead us to come up with the most innovative and fresh ideas.
Hacker	Negative Stakeholder	Unauthorised access can lead to problems which are sorted by difficulty and numbered by variety.

4.4. Selection of Requirement Elicitation Techniques / Methods

In order to elicit and analyse needs, three basic approaches were used to collect them. As far as we self brainstorm, these techniques helped us identify the elements essential for our learning platform and uncover new features that weren't included in other systems.

4.4.1. Literature Review and Gap Analysis of Existing Systems

We began the information-gathering process for this phase by examining the characteristics of existing systems and the implementations that are presently in place. This demonstrated the platform's suggestions for improvement and provided a way to contrast the new features of our system with those of other systems.

Advantages	Disadvantages
● Main features and functions that should be present in the learning platform were identified. ● GAP analysis in the literature review showed areas in which this learning platform could be improved from other models.	● As there were no systems discovered that were designed for the instruction of Sinhala sign language, not all current systems that were studied were learning platforms, just Sign languages to text translators. This indicates how the objectives of the two systems that were compared are different.

4.4.2. Questionnaire

We used a Google Sheets questionnaire to gather information from a larger audience and learn about their requirements for our learning platform. The questionnaire was open to anyone of legal age, and the results are discussed in more detail later on.

Advantages	Disadvantages
● This reaches a larger population of individuals. ● Google Forms provides tools to analyse results in bar charts and pie charts and other useful visualisation tools. ● Anyone who has knowledge of using a smart device could fill out the form, with no extra effort needed. ● Only takes a few minutes to complete the survey.	● Some questions would have been misunderstood ● Some would have answered in a manner that could negatively affect our requirements-gathering process. ● The older population may or may not have known how to respond to a Google Form, so that reduces the target population for gathering information.

4.4.3. Interviews

Interviews can be performed with individuals who have a connection to this area of study or who have dealt with the subject topic in question professionally. We conducted an interview with a person who had experience dealing with sign language

users and who thought our approach may be useful in the corporate sector. Therefore the sample population considered for this interview was a domain expert in the field of business and sign language.

Advantages	Disadvantages
• Questions were asked directly and with interviews, we receive a more direct and personal answer, than in surveys. • The person being interviewed has more knowledge than us and can therefore give more professional suggestions for the platform. • Interviews allow the interviewee to speak freely and provide an answer they wish to give rather than short-set and rigid answers.	• Interviews are time confusing and we have to respect the times when they are free to conduct the interviews, as opposed to our own schedules. • We may receive complicated answers which weren't the answers we were hoping to receive. • The questions might puzzle the interviewee and would have had to move on to another question instead. • Only a limited number of interviews can take place as they are time-consuming, as mentioned earlier.

The primary functions required for this learning platform were defined in the initial research done for present systems. The GAP analysis revealed additional properties that have not been included in the current systems, indicating innovative functionalities to be explored in the learning platform.

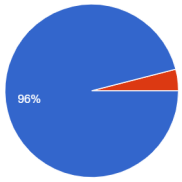
We found that both findings of the survey and interview are beneficial to us, therefore we used the survey results to evaluate the requirements of the general public and the interview questions to recognize the professional components of the system.

4.5. Discussion of Results

4.5.1. Questionnaire Discussion

The questionnaire's first four questions were designed to elicit basic information about the respondents. Such as the email address, name, age and the industry they work in. Later, the questions were tailored to our needs.

Question	Do you suffer from hearing loss?
Aim of the question	To count the number of people who suffer from hearing loss
Observation	



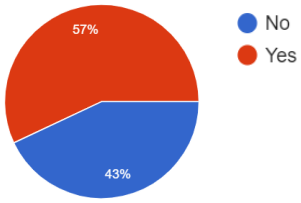
It has been discovered that 4% of the participants suffer from hearing loss. While the remaining 96% of the participants do not have any hearing loss.

Conclusion

According to the responses given by the participants that the number of people suffering from hearing loss appears to be low in Sri Lanka

Question	Have you ever faced difficulties when communicating with a hearing-impaired individual?
Aim of the question	Finding out if people have any difficulties communicating with hearing-impaired people.

Observation



We can see that 57% of respondents have had no difficulty communicating with hearing impaired people. While 43% responded that they were having troubles when communicating with people who are deaf.

Conclusion

We can conclude that more than half of the population has no difficulty communicating with deaf people. It could also be because they have not come into interaction with any impaired individuals. We could also assume that hearing-impaired people do not expose themselves to society a lot.

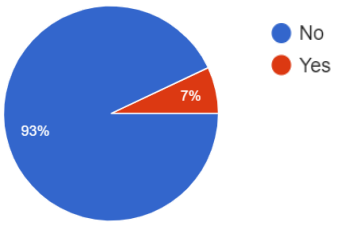
Question	If yes, share your experience
Aim of the question	To understand the problems they face when communicating with hearing-individuals

Observation

The majority of those who responded said they couldn't understand what they were saying. Some of them stated that there was some misunderstanding as a result of improper communication with hearing-impaired people. The majority of the participants expressed

regret over their inability to communicate effectively with them.
Conclusion
It is clear that communication between hearing-impaired and non-hearing-impaired people is ineffective. When deaf people use sign language to communicate and non hearing-impaired people use normal language, both parties are unable to understand what the other person is saying and some misunderstandings may occur. Because of this type of misunderstanding, both parties rarely communicate with one another.

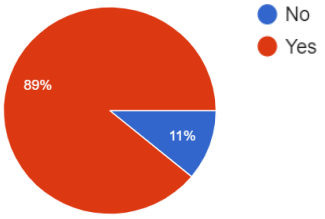
Question	Would you like to reduce the communication gap between people using spoken language and hearing-impaired individuals?
Aim of the question	To know whether both normal and deaf people like to communicate with each other
Observation	



93% of the participants were willing to reduce the gap between people using spoken language and hearing-impaired individuals while only 7% were interested in reducing that gap.

Conclusion
Even though a small number of people oppose the idea of reducing communication, the majority of people clearly prefer to reduce the communication gap between hearing-impaired and normal language speakers. It is clear that language is the primary barrier for both parties.

Question	Have you ever dealt with Sinhala Sign Language?
Aim of the question	Determining the number of people who have been exposed to Sinhala sign language
Observation	



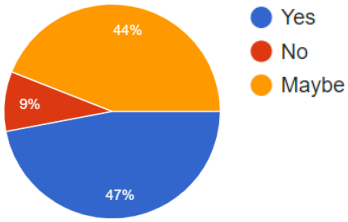
Only 11% of the respondents has not dealt with Sinhala sign language. But we can see 89% of them have dealt with SSL.

Conclusion

According to this survey, more than three-quarters of people have dealt with SSL. As a result, we can say that SSL is not a foreign language to Sri Lankans. In some way, Sri Lankans are aware of the use of SSL and exposed to the use of it.

Question	Would you like to learn SSL using a website?
Aim of the question	To know whether people are interested in learning SSL

Observation



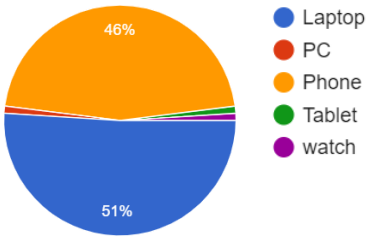
47% of respondents said they would like to learn SSL, while 47% said they were unsure. Only 9% of respondents said they disliked learning SSL.

Conclusion

It can be seen that the majority of people want to learn SSL, which will aid in closing the communication gap between hearing-impaired and non-hearing-impaired people. Only a small number of people are uncertain whether they like to learn SSL or not.

Question	Which device would you most like to use for the learning platform website?
Aim of the question	Understanding the user's needs so that we can design our website accordingly.

Observation



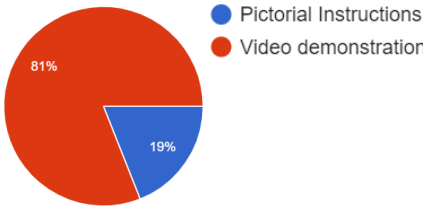
It is observed that 46% of the participants like to learn using phones and 51% like to learn using the laptop. Only 1% of them like to learn using PC, Tablet and watch.

Conclusion

We can see that the majority of users prefer to learn using their phones because they are very convenient to use. Using a laptop also appears to be more effective than using a PC, tablet, or watch.

Question	Would you rather learn how to sign words from pictorial instructions or from a short video clip of the signed word?
Aim of the question	This is also questioned in order to gain a better understanding of the user's requirements.

Observation



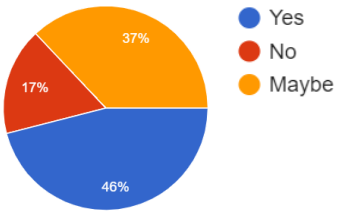
81% of the participants are willing to learn using a video demonstrator while only 19% need pictorial instructions to learn SSL.

Conclusion

Most of the users prefer video demonstrations rather than pictorial instructions. Since learning using video is more reliable, the majority of the users are likely to learn SSL using video.

Question	Would you be comfortable with using your device's camera to test out your knowledge? (No information would be stored from the camera for the user's privacy.)
Aim of the question	By asking this question we can reassure that users are comfortable with using their cameras.

Observation



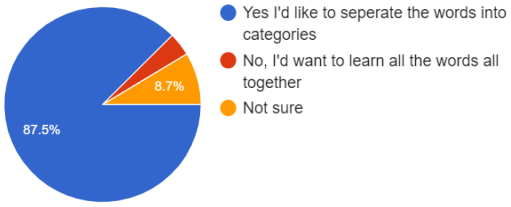
46% of the participants are willing to use the cameras during the learning process. And 37% of the participants are not sure about using the cameras while 17% responded saying they are not willing.

Conclusion

We can observe that most of the users are comfortable with using their cameras but only a small number of people oppose this idea.

Question	Would you prefer dividing your lessons into categories such as "Greetings", "Emotions"..etc?
Aim of the question	To determine whether users are comfortable learning in categories

Observation



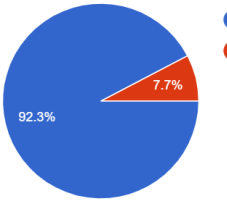
87.5% of the participants are willing to study using categories, while 8.7% are not sure about their choice. But 3.8% oppose this idea, and they are willing to learn all the words together.

Conclusion

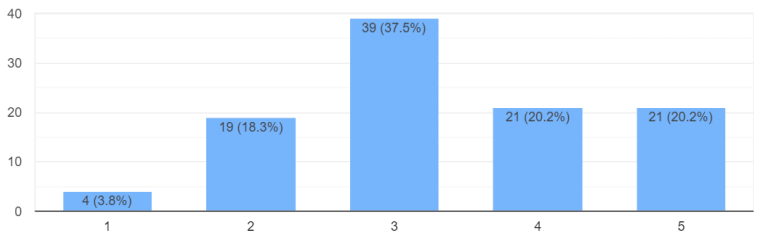
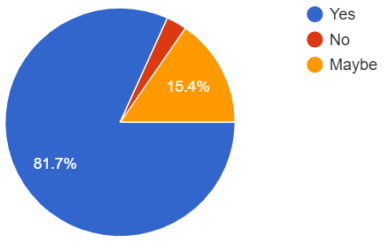
Many of the participants are interested in learning words through categorization. It is simple to learn by categorising the words.

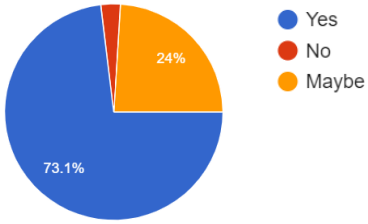
Question	Would you like to keep track of your learning progress on how far you've come?
Aim of the question	To determine whether users prefer to track their progress.

Observation



Only 7.7% do not want to track their progress. The remaining 92.3% of the participants prefer to track their progress.

Conclusion	
The majority of people like to keep track of their progress, which helps them learn better.	
Question	How useful will this website be in your day-to-day communication?
Aim of the question	To determine whether or not this website will be useful.
Observation	
	37.5% of the respondents has responded neutrally. Whereas only 3.8% have said it is not useful. While 21.2% of the participants have said it is useful in their day-to-day life.
Conclusion	
As per the survey, the majority of the participants agreed that it may or may not be useful. There is no certainty about the usefulness of this website in day-to-day life.	
Question	Do you believe that this system would be useful in the corporate sector when interacting with hearing-impaired employees?
Aim of the question	Determining whether this website will be useful in corporate sectors
Observation	
	81.7% of the participants say that the website is useful in the corporate sectors. While only 2.9% have opposed it. But 15.4% of the participants are not sure about this idea.
Conclusion	
It is very likely to be observed that most of the participants have agreed that the website will be useful in the corporate sector.	

Question	Would it be useful to customise this website according to the user/ organisation using this website? (Customizable words/phrases)
Aim of the question	To know whether the idea of customising the website according to user preference is acceptable.
Observation	
	Of the respondents, 73.1% of them agreed that customising the website according to user preference is useful. Only 2.9% of the participants oppose this opinion. While 24% say it may or may not be useful.
Conclusion	
It is clearly observable that the majority of people like to customise the website according to their preferences.	

4.5.2. Interview Discussion

Mr Tharusha Wikramasinghe, Manager of large-scale cooperation, was interviewed as a part of the requirement elicitation technique. We learned that they use sign language to interact with clients at their branches. During the interview, he mentioned that sign language is utilised in two branches, as well as the personnel who are deaf. We discovered that there will be 300 to 400 hearing-impaired employees by 2025.

As such, our interviewer inquired, how people react when they visit these outlets. He stated that the majority of the time, the first impression is not as optimistic as expected. Customers eventually understood the concept of their business and began to visit on a regular basis, appreciating their efforts. We also learned that Sinhala Sign Language is not widely used in Sri Lanka. He also stated that the sign languages used in their two branches are not the same, and that some gestures are made up. He also suggested that we could develop a system that could be used in all corporate sectors.

One of our interviewers asked him about using a sign language platform. He responded that it would be very useful and inclusive if we created a learning platform that would assist all corporate sectors in learning which is customizable.

4.6. Summary of Findings

Table 4.6.1 : Summary of Findings

Model	Description	Sample data	F1 Score	Complexity
3D Hand Pose with MediaPipe and TensorFlow (Google, 2021)	This updated version of the hand position detection model has enhanced 2D accuracy, novel 3D support, and the ability to forecast critical spots on both hands at once. One of the most frequent requests from the developer community was for support for multi-hand tracking, which was included in this release.	Our dataset was used	59	Machine time was high
Sign-language-gesture-recognition (Hthuwal, n.d.)	The goal of the research is to recognize sign language using deep neural networks that combine spatial and temporal features. The dataset contains 46 Argentine Sign Language gesture categories. The goal is to improve communication for those who primarily communicate through sign language.	Their own data set was used. (Argentinian Sign Language Gestures.)	95.2	Machine time was high
Sign Language Detection using ACTION RECOGNITION with Python | LSTM Deep Learning Model (Nochnack, 2021)	A key point detection model was used to construct key points for an action detection model in order to decode sign language. Tensorflow and Keras were used to create a deep neural network with LSTM layers. The model used MediaPipe Holistic Key Points to detect actions and predict sign language from video sequences in real time.	Their own data set was used	100	Machine time was high

Table 4.6.2 : Summary of Findings

Findings	Literature Review	Questionnaire and Interview
There are no online systems as of now to learn SSL	X	X

Accessibility to the camera to test user's knowledge is novel	X	X
Systems should support left and right-handed users and users with different skin tones	X	X
This area of sign language lacks data and research.	X	X
Environment disturbances and background interruptions may disrupt the final outcome of the system.	–	–
Most existing systems only focus on ASL or BSL	X	
This system should fully support hearing-impaired users	X	X

4.7. Context Diagram

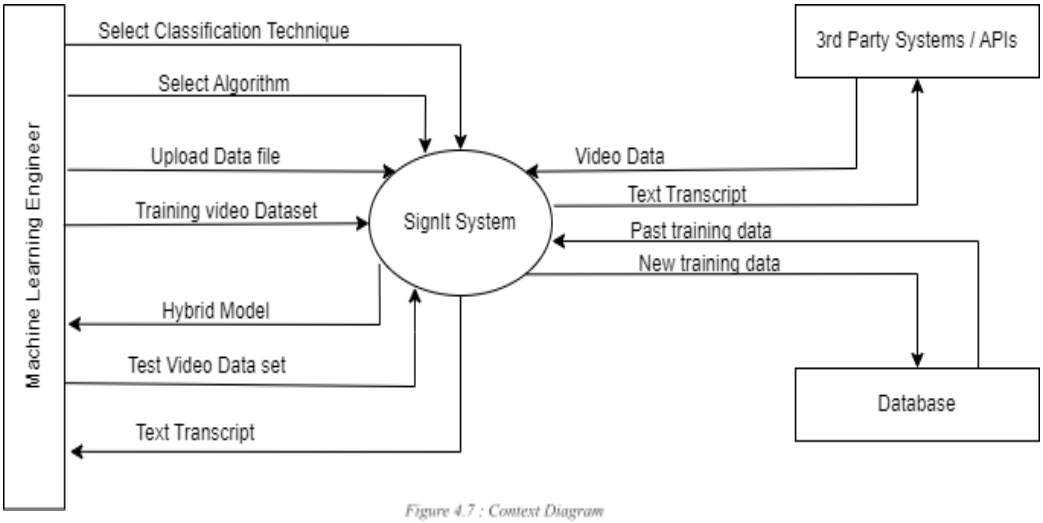
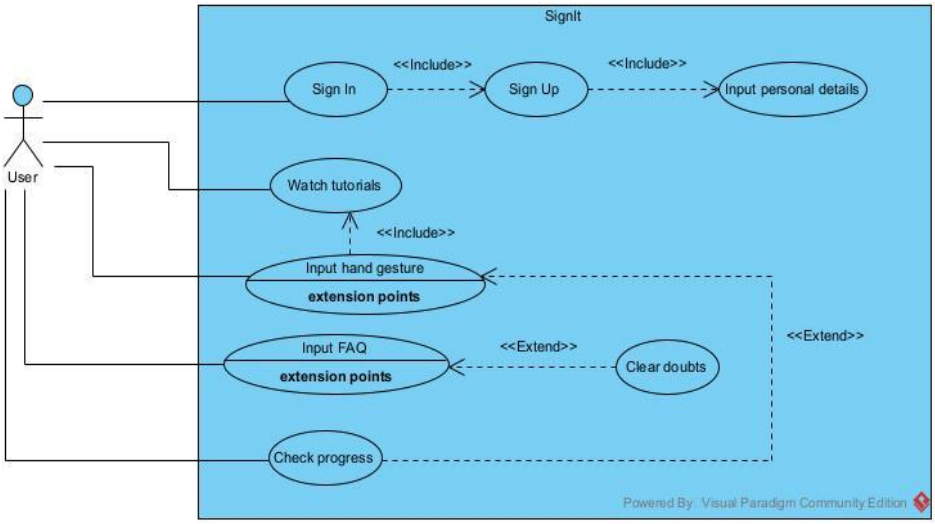


Figure 4.7 : Context Diagram

4.8. Use case Diagram



4.8.1. Use case Descriptions

4.8.1.1. Use Case - Sign up

SignIt		
Use Case	Sign up	
Section	Main	
Actor	User	
Purpose	Signing up to the website	
Overview	If the user is interested in learning SSL he/ she has to sign up to our website in order to proceed with the lessons	
Precondition	The user must not have an existing account with our website	
Typical cause of events	**Actor Action**	**System Response**
	Opens the website browser	Shows sign up/ sign in block
	Select sign up	Redirects to the sign up page
	Provide required credentials	Approve sign up
Include	• Include personal information such as, name, email address • User creates username and password • System creates a new account for the user	
Exclude	• User entering an existing username • User entering an already existing password • Password requirements are not satisfied	

4.8.1.2. Use case - Sign in

SignIt	
Use Case	Sign In
Section	Main

Actor	User	
Purpose	Signing in to the website	
Overview	The Sign In process allows users to access their account by providing their login credentials.	
Precondition	Users must have signed up to our website.	
Typical cause of events	**Actor Action**	**System Response**
	Opens the website browser	Pops up sign up / sign in block
	Select sign in	Redirects the site to sign in page
	Provide sign-in requirements	Approve sign in and directs the site to home page
Include	• System validates user credentials • System redirects the user to the home page upon successful sign in	
Exclude	• User enters incorrect credentials	

4.8.1.3. Input personal details

SignIt	
Use Case	Input personal detail
Section	Main
Actor	User
Purpose	While signing up user must provide required personal details
Overview	When the system directs the user to the sign-up page, the user must provide the required details to complete the signup process
Precondition	User must have clicked the relevant button to direct into the sign-up page User must not have an existing account User must have a valid email address

Typical cause of events	Actor Action	System Response
	Enters the sign-up page	Asks for required personal details
	Provide the required details	Check for detail validation
		Create an account after validating
Include	• User provides required and valid details • System confirms the details and creates a new account for the user	
Exclude	• User does not provide the required details and detailed being invalid • Failing to provide the details in relevant fields • System encounters a technical issue	

4.8.1.4. Watch tutorials

SignIt		
Use Case	Watch tutorials	
Section	Main	
Actor	User	
Purpose	Provide users with instructional videos that offer visual guidance and examples to help them better understand the features and functionality of our platform and to enhance the user experience.	
Overview	After successfully signing into the website, the user can watch the tutorials	
Precondition	User must have signed into the website	
Typical cause of events	**Actor Action**	**System Response**
	Sign Up to the page	Give access to the lessons
	Select tutorial option	Displays the list of

		available tutorial videos
	Select the relevant tutorial video	Displays the relevant video to the user
Include	• System displays the available tutorial videos • User clicks the relevant tutorial • System plays the video, the user can control the video by pausing, rewinding, fast forward etc.	
Exclude	• System does not have any relevant videos • Poor quality videos or error in playing the video	

4.8.1.5. Input hand gesture

SignIt		
Use Case	Input hand gesture	
Section	Main	
Actor	User	
Purpose	In order to proceed with the lesson, users must input the hand gesture they need to learn	
Overview	After users watch the relevant tutorials, they must proceed with the learning. In order to complete the learning process user must gesture the relevant sign through their web camera or mobile phone camera	
Precondition	User must have watched the relevant tutorials	
Typical cause of events	**Actor Action**	**System Response**
	Proceed with the learning process	Provides the learning materials
		Displays the input screen
	Gestures the word	Authenticate the input
Include	• System displays the input screen	

	• User enters the hand gesture they want to learn • System displays appropriate results
Exclude	• User enters an invalid gesture • System being unable to recognize the hand gesture

4.8.1.6. Input FAQ

SignIt		
Use Case	Input FAQ	
Section	Main	
Actor	User	
Purpose	Provide answers to the most commonly asked questions from the user	
Overview	If users have any questions or concerns about any aspect of this website, they can use the FAQ section as a resource to resolve their problems.	
Precondition	User must have access to interact with the FAQ section of our website	
Typical cause of events	**Actor Action**	**System Response**
	Presented with a question	Search for relevant questions and answers
		Provide answers
	Will clarify the questions with the provided answers	
Include	• User must be able to search for keywords related to their question • FAW must be in a clear and understandable format	
Exclude	• FAQ does not assist with technical issues	

4.8.1.7. Clarify the doubts

SignIt		
Use Case	Clarify the doubts	
Section	Main	
Actor	User	
Purpose	Clear the doubts that users encounter while using our website	
Overview	The user can receive support and clarification on any topic related to the learning material by accessing the FAQ section	
Precondition	User must have access to interact with the FAQ section of our website	
Typical cause of events	**Actor Action**	**System Response**
	Visit the FAQ section	
	Search for relevant answer	Provide with relevant questions and answers
	Clarify the doubts using the results provided by FAQ section	
Include	• Website must be able to provide with the relevant answers	
Exclude	• User's question violates the website's terms and conditions • Website failing to provide the expected answers	

4.8.1.8. Check Progress

SignIt	
Use Case	Check progress
Section	Main

Actor	User	
Purpose	To have track of the work completed by the user	
Overview	After correctly performing the hand gesture, the user will receive feedback indicating the result. The feedback will be saved to the progress bar, which the user can access at any time to view their progress.	
Precondition	User must have completed at least one task.	
Typical cause of events	**Actor Action**	**System Response**
	Makes the gesture	Validate the input and provide feedback
	Receives feedback	Record the feedback to the progress section
Include	• User must have completed at least one lesson • User has access to the progress bar	
Exclude	• User has not completed any lesson • User is not logged into their account • 'User does not have access to the progress tracking section	

4.9. Functional Requirements

4.9.1. Priority level indications

This is the reference used to map the priority to each functional requirement.

Table 4.9.1 : Priority Indication

Priority Level	Description
Critical	The system's main features and functionalities
Important	Not mandatory, but is thought to be needed
Non-important	Out of scope requirements

4.9.2. Functional Requirements

Table 4.9.2 : Functional Requirements

	Requirement	Priority
FR01	Accepting video input from device	Critical
	The device must be able to accept videos as input.	
FR02	Removing unnecessary background disruption	Critical
	Because background features can interfere with gesture recognition, unnecessary background disruptions are avoided.	
FR03	Enhancing video input	Critical
	Improving video input and applying it to building endeavours	
FR04	Breaking down video input into frames	Critical
	Using the trained model, break the videos into several set of frames	
FR05	Adding the image filters for broken down frames	Important
	After breaking the videos into set of frames, adding filters according to the trained model	
FR06	Extracting the gestures done by user	Critical
	Convert the videos to a series of frames.	
FR07	Accept the signed gesture	Critical
	Comparing the input gestures with the pre-existing datasets	
FR08	Determining the word or phrase signed	Critical
	Identifying the gestured word or phrase signed by the user	
FR09	Generating the results from the model	Critical
	After identifying the gestures generate results and give pop up messages	
FR10	Displaying the results and suggestions	Important
	Giving pop up messages including the results and suggestions	

FR11	Support user in all lighting background	Important
	The system must be able to recognize user inputs from various backgrounds.	
FR12	Support user with different skin tones	Important
	System should accommodate users with various skin tones	
FR13	Should support users signing from either hand	Important
	System must be able to recognize even if user inputs the gesture in different hands (left or right)	
FR14	GUI support for users	Important
	The GUI of the system must be user-friendly.	
FR15	FAQ system	Not-Important
	A FAQ section has been added to the website to help users clear up any questions they may have.	

4.10. Non - Functional Requirements

Accuracy: The system's accuracy is crucial, and it should check the video data given by the user through the camera panel and recognise the sign as correct or not. More transcription errors imply that the model or system is unusable.

Performance: The train and test sets' combined data quantity is enormous and will continue to grow over time. such that when using additional data, the model training time will be longer.

Usability: The command prompt is used for everything, from setting up the system to testing it with new video data.

Security: The system must read the video data for testing and training purposes. So that the system may be protected against unauthorised access and data misuse.

Table 4.10 : Non- Functional Requirements

	Requirements and Description	Specification	Priority
NFR01	Model must have high accuracy	Accuracy	Important
NFR02	All type of users must be able to use the system without much effort	Usability	Important
NFR03	System and data access should be restricted based on role.	Security	Important
NFR04	User friendly interface	Usability	Important
NFR05	The system should generate error messages.	Performance	Important
NFR06	The website must be responsive	Performance	Non-important

4.11. Chapter Summary

In this chapter, the stakeholder's views and demand was analysed for the SSL system using various methods of data collection. Main use cases and definitions defined the functional and non-functional requirements along with their priorities for implementing the System.

CHAPTER 05: SOCIAL, LEGAL, ETHICAL AND PROFESSIONAL ISSUES

5.1. Chapter Overview

The SLEP analysis aids in the assessment of all types of external influences on the product being built. This allows you to see the big picture of the entire/macro environment. All legal, social, ethical, and professional aspects of our project SignIt were thoroughly examined and addressed.

5.2. SLEP Issues and Mitigation

5.2.1. Social Issues

- To address privacy concerns, the platform could be built with data protection and security in mind. Only with their explicit consent could user data be collected and used for the sole purpose of providing the service. To protect user data from misuse or unauthorised access, strong data protection measures could be implemented.
- Since the platform is designed for SSL, careful consideration is given to the cultural norms, values, and practices of the corresponding community to ensure that the platform respects their cultural values.

5.2.2. Legal Issues

- The datasets employed for building the model were acquired with due permission, and we have received video consent letters from each of the individuals involved.
- The collected data is not shared with any external parties.
- The research papers that we have referred to and related works have been properly cited, and credit has been given to the relevant authors.

5.2.3. Ethical Issues

- The Google forms used for review do not reveal the user's identity.
- The datasets for the AI models were chosen by limiting the search to one that the follows proper ethical framework.

- User data is anonymised when appropriate, throughout the preparation processes before use in model training, and the data collection procedure was ethically sound.

5.2.4. Professional Issues

- Thorough testing and quality assurance measures will be implemented to identify and address technical issues prior to the platform's public release, thereby ensuring its smooth functionality and optimal performance for the target audience.
- The product is continuously developed and deadlines are scheduled and fulfilled according to the plan.
- Regular weekly supervisor meetings are held, and group meetings are scheduled at least once a week. Additionally, communication is maintained between meetings through phone calls and text messages.
- We used email for official communication with the supervisor, while Whatsapp was utilised for efficient day-to-day communication.

5.3. Chapter Summary

This chapter describes the Social, Legal, Ethical, and Professional issues related to our project and how they are alleviated. Developers can gain a comprehensive view of the project's macro-environment and make informed decisions to minimise the potential negative impact on their project by analysing these four factors.

CHAPTER 6: SYSTEM ARCHITECTURE DESIGN

6.1. Chapter Overview

The system's design and diagrams are presented in this chapter. UI/UX design, Component diagrams, Class diagrams, Sequence diagrams, and Process flow charts are all included.

6.2. Design Goals

Below table is based on the Non -Functional requirements of the system.

Table 6.2 : Design Goals

Accuracy	We are targeting a higher accuracy when training our model
Performance	It is designed in a way that the website will have less response time.
Security	User data will not be accessible to any other third party and will only be used in the process.
Usability	A user-friendly website will be created and it will increase the customer satisfaction
Correctness	The website is created in a way that it is free of bugs and it will provide the expected goals.
Reconfigurability	The website can be easily adjusted and modified to fit the new technology and can add many signs to learn.

6.3. System Architecture Design

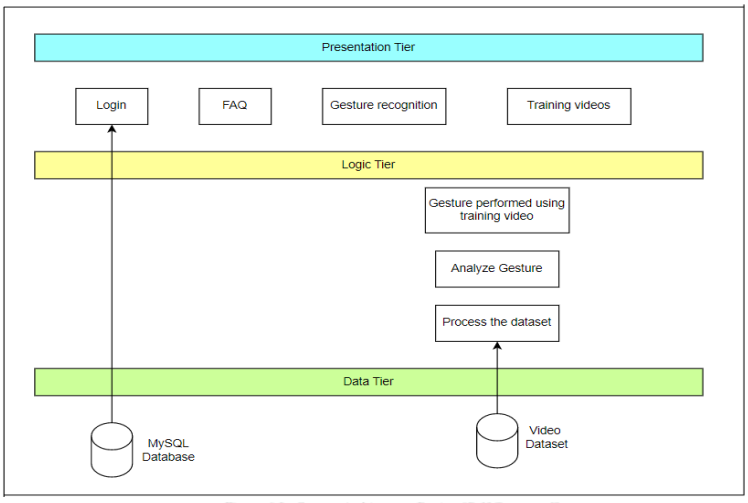


Figure 6.3 : System Architecture Design [Self Composed]

According to figure 6.3, shows that the architecture of the system displays three layers; Presentation tier, Logic tier and Data tier.

1. Presentation Tier
    a. Login - This gives users to get access to facilities provided by “Sign It”
    b. FAQ - This UI facilitates a frequently asked question page.
    c. Gesture recognition - This UI is to display a pop-up box to perform the gesture.
    d. Training videos – This UI provides and teaches the users with sample videos to correctly perform the gestures.
2. Logic Tier

    Logic tier is the data pre-processing and model training part of the system.
    a. Gesture performed using training video – It provides a better understanding of the gestures, so that the user can repeat it again and again till they do their best.
    b. Analyse gesture - The system will analyse the gesture provided by the user.
    c. Process the data – System will check for the necessary dataset here.
3. Data Tier
    a. MySQL Database - All the user details will be stored in a MySQL database to detect the users.
    b. Video Dataset - Data set used to train the gesture recognition system

6.4. System Design

System design is a methodology for achieving desired results by meeting user assumptions. Because each design is unique in its features, we can divide the entire system into two methodologies.

1. SSADM - Structured System Analysis and Design Methodology
2. OOAD - Object Oriented Analysis and Design Methodology

6.4.1. Choice of Design Paradigm

Our team determined that OOAD would be the most effective approach for our project due to its iterative nature and compatibility with agile methodology after careful

consideration. We believe that using OOAD will allow us to improve the system with each iteration, resulting in a more robust and efficient solution. In addition, we determined that SSADM, while a valid approach, was not the best fit for our project due to its waterfall technique and potential for increased development time. We are confident that by using OOAD, we will be able to deliver a high-quality product on time.

6.4.2. Component Diagram

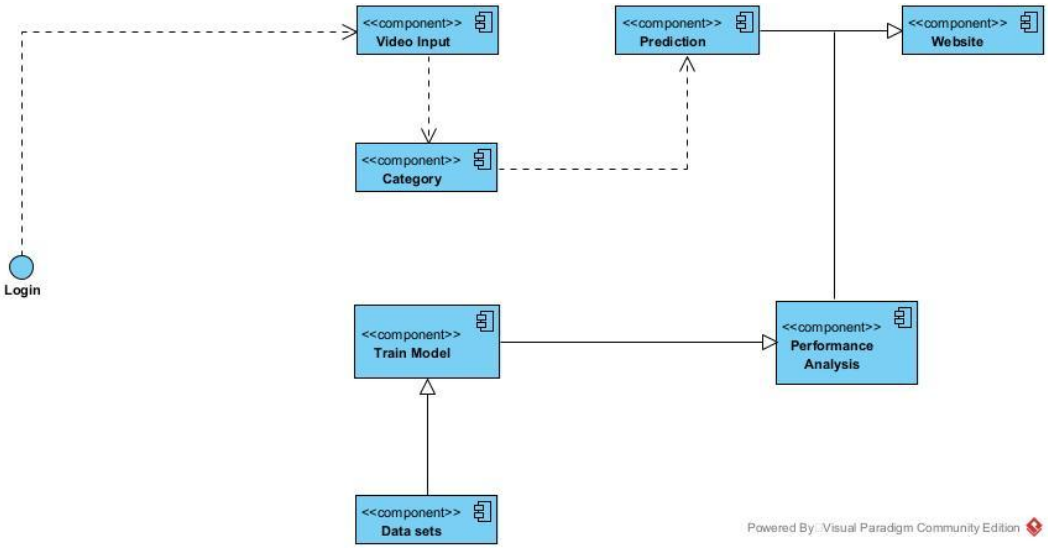


Figure 6.4.2 : Component Diagram [Self Composed]

6.4.3. Class Diagram

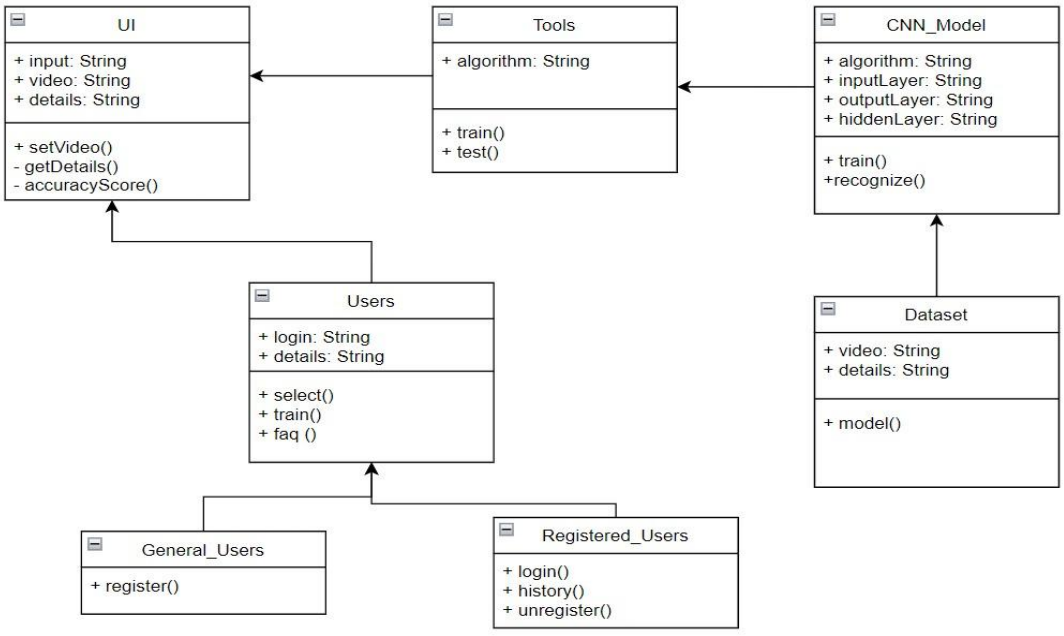


Figure 6.4.3 : Class Diagram [self composed]

6.4.4. Sequence Diagram

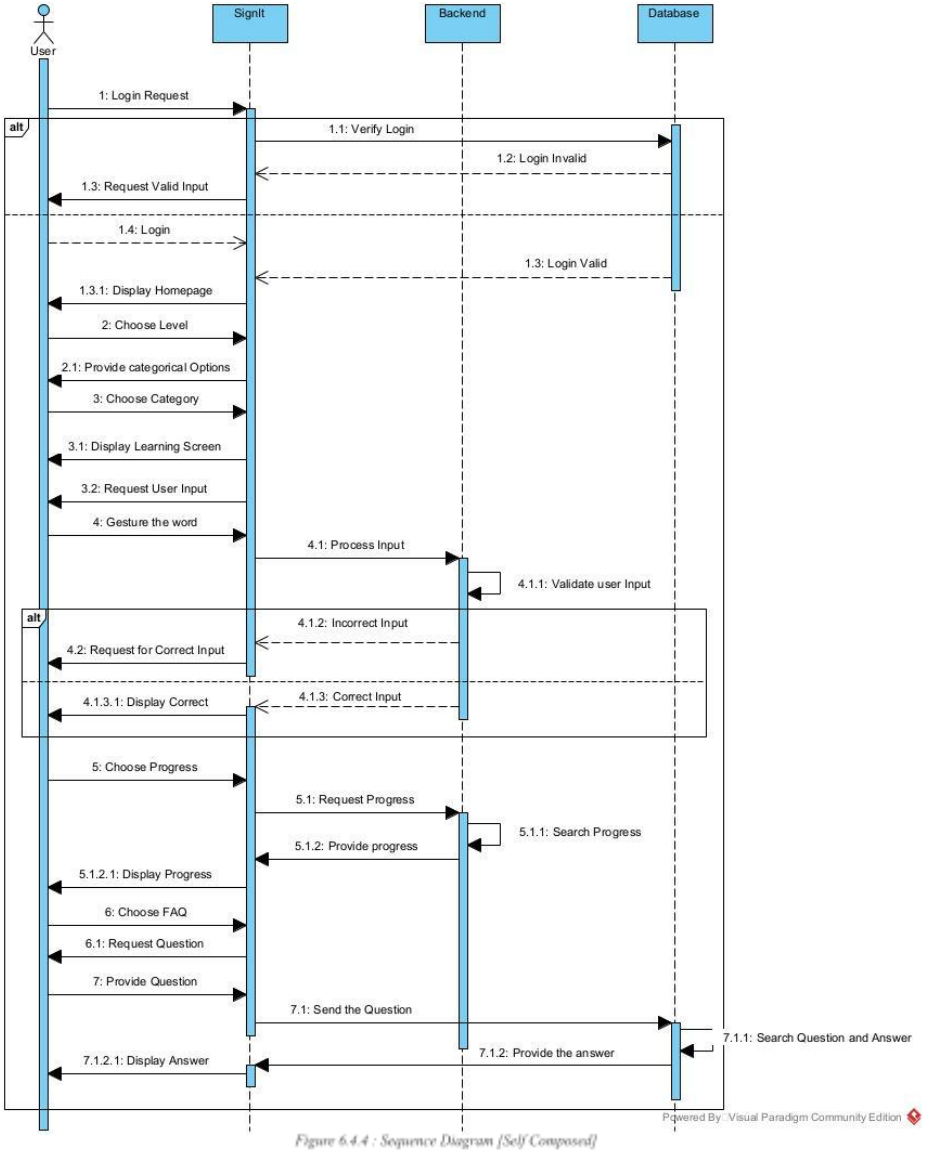


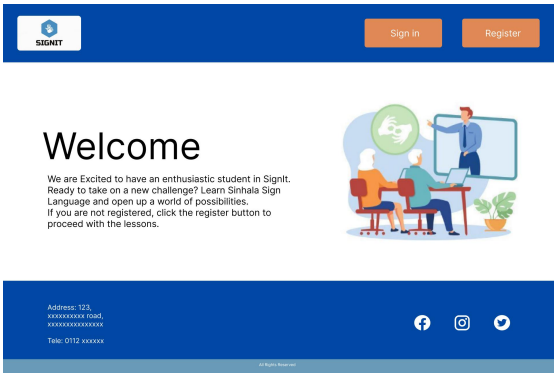
Figure 6.4.4 : Sequence Diagram [Self Composed]

6.4.5. UI Design

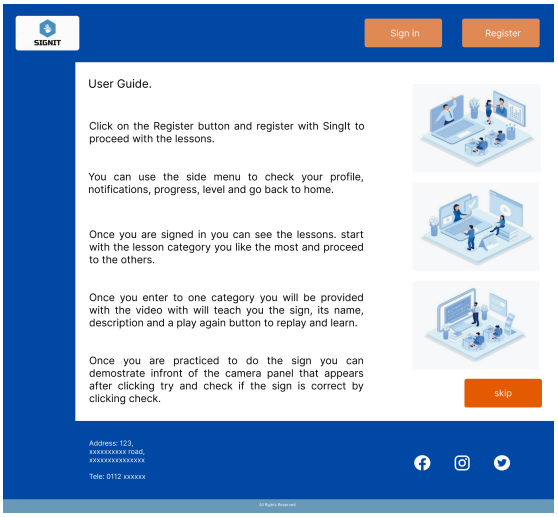
SignIt is a website that teaches SSL to users through intuitive and interactive gestures. The website is intended to be user-friendly and accessible on any device, including desktop, laptop, and mobile. SignIt contains a user-friendly interface.

Check our UI design:

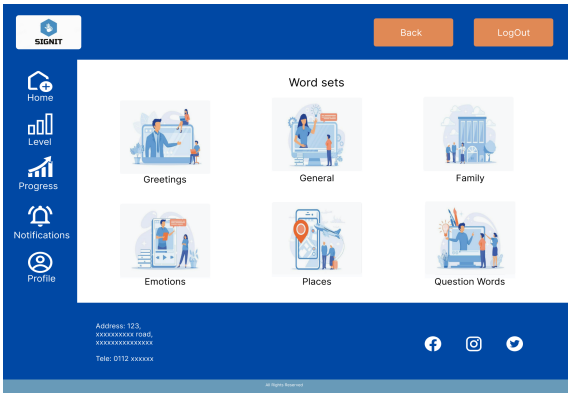
https://www.figma.com/file/wjt69cEOTzfAMfpXzf3iCB/Zeplin-(Community)?node-id=0%3A1&t=Oo46fSgmDgPo4UAZ-0



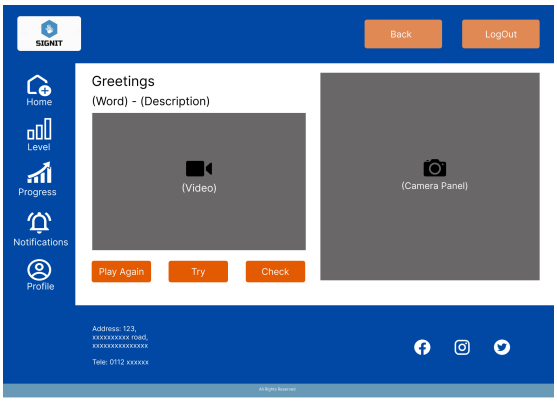
SignIt 1 : Welcome Page



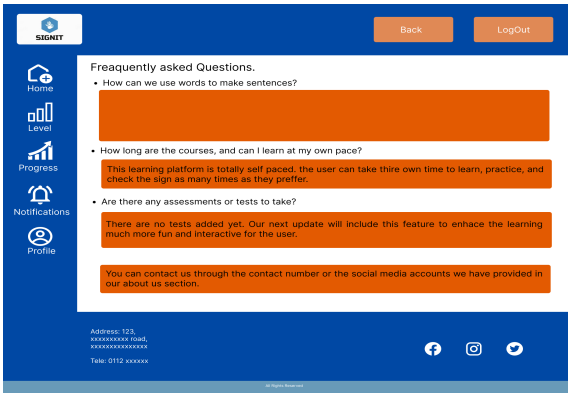
SignIt 2 : User Guide



SignIt 3 : Lesson Page



SignIt 4 : In-Lesson Page



SignIt 5 : FAQ

6.4.6. Process Flow Chart

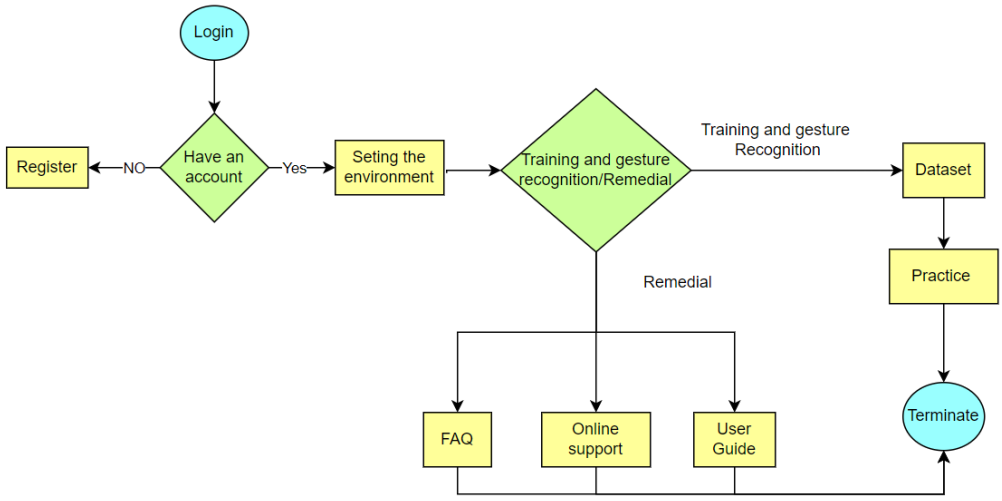


Figure 6.4.6 : Process Flow Chart [Self Composed]

6.5. Chapter Summary

The diagrams such as the component diagram, class diagram, sequence diagram and flow chart clearly explain the flow of our system SignIt. The provided UI design illustrates how our website will be presented.

CHAPTER 7 : IMPLEMENTATION

7.1. Chapter Overview

This chapter describes the main tools and language used to build our website SignIt. The technology stack, the data selection, languages and frameworks used to build our website will be analysed in this chapter.

7.2. Technology Selection

7.2.1. Technology Stack

Figure 7.2.1 : Technology Stack

We used a wide array of technologies when building SignIt. We used figma to design the UI; HTML, CSS, and JAVASCRIPT for the frontend and Flask for the backend. We used Google Docs for documentation and other technologies for the model.

7.2.2. Data Selection

We had to create our own dataset because there is no documented data for SSL. The below table shows an overview of the ways and types of data we used.

Table 7.2.2 : Data Selection

Domain	Dataset	Device description	Description
Image Processing - Video Processing	Custom Dataset	Laptop Device name: 11th Gen Intel(R) Core(TM) i5-1155G7 @ 2.50GHz 2.50 GHz	750 mp4 videos.

		Mobile Phone Device name: Redmi Note 10 pro Camera Quality: 1080p@30fps, 720p@120fps	750 mp4 videos

7.2.3. Selection of Development Framework

7.2.3.1. Frontend

For the Web Application, the frontend is built using HTML, CSS, and JAVASCRIPT.

HTML - provides the basic structure of sites, which is enhanced and modified by other technologies like CSS and JavaScript. HTML is at the core of every web page, regardless of the complexity of a site or the number of technologies involved.

CSS - CSS stands for Cascading Style Sheets. This programming language dictates how the HTML elements of a website should appear on the frontend of the page and this is used to control presentation, formatting, and layout.

JavaScript - JavaScript is supported by all modern web browsers and is used on almost every site on the web for more powerful and complex functionality. This is used to control the behaviour of different elements.

7.2.3.2. Backend

The “SignIt” platform which is a web application includes a Python backend because it's relatively easy to learn, has mature frameworks, important development tools and clean syntax. The model is hosted through Flask which is scalable, flexible and has the necessary micro framework which we can use in integration for a project like ours.

7.2.4. Programming Language

Python is the primary programming language used for building AI models due to its compatibility with a range of frameworks essential to data science, machine learning, and other AI-related packages. It offers developers access to powerful tools like Tensorflow and Keras, which enable the construction, training, and testing of machine

learning models. One of the key advantages of using Python for machine learning is that it significantly reduces the time required for development and implementation, making it the top choice for our project.

For the frontend HTML, CSS and JAVASCRIPT are used where HTML provides the foundation for websites, which is enhanced and modified by other technologies such as CSS and JavaScript. Regardless of the complexity of a site or the number of technologies involved, HTML is at the heart of every web page. CSS is an abbreviation for Cascading Style Sheets. This programming language specifies how HTML elements on a website should appear on the front end of the page and are used to control presentation, formatting, and layout. JavaScript is supported by all modern web browsers and is used for more powerful and complex functionality on almost every website on the internet. This is used to regulate the behaviour of various elements.

7.2.5. Libraries

Table 7.2.5 : Libraries

Libraries	Version	Usage
AI Models		
Keras	2.11.0	Creating a neural network with different layers Measure loss function Train the dataset and evaluate how it will work in new data
Numpy	1.21.5	Store and use the handmark data obtained from the Mediapipe Holistic model Stretch video to have the same number of frames
OpenCV	4.7.0	Capture video frames, convert the colour space of video frames Preprocess the frames before detecting hand landmarks Draw the detected hand landmarks on the frames for visualisation
Mediapipe	0.9.1.0	Detect landmarks in each of the frame of the video Helps the model to understand the hand movements in the videos
Matplotlib	3.5.2	Visualise the training process and performance of the neural network Plot the accuracy of the model Visualise the predictions made by the model

Sci-kit learn	1.0.2	Split data into training and testing sets Filter out unwanted data Optimise model hyperparameters
Tensorflow	2.11.0	Define and train a sequential model with LSTM and Dense layers Evaluate model performance on the training set
Flask	2.2.3	Provides a structure to follow when creating the website Provide libraries to ease the work
Website		
Google Fonts	-	Increase the personality performance of the website
Material Icons	6.2.95	Represent frequent operations and actions

7.2.6. IDE

To build the AI model we used the Jupiter Notebook run on top of Anaconda. To develop the UI we used Visual Studio. We chose VS because of the user friendly environment and it has several extensions.

7.2.7. Summary of Technology Selection

Table 7.2.7 : Summary of Technology Selection

Component	Tool/ Technology	Version
Programming Language	Python	3.7
UI Framework	Figma	93.4.0
IDE	Jupyter Notebook	6.4.12
	Google Colab	-
	Visual Studio code	1.63.1.0

7.3. Implementation of Core Functionality

7.3.1. Gesture Recognition from user input using camera

Gesture recognition from user input using a camera entails analysing and interpreting a person's hand or body movements to recognize specific gestures.

We will need to train a machine learning model that can recognize different gestures performed by the user to develop our Sinhala Sign Language Learning Platform. This

entails training the model to recognize each gesture accurately using a dataset of Sinhala sign language gestures. To train the model, we have used the Sequential Model and Long - Short-Term Memory (LSTM).

The pseudocode for our model is given below.

7.3.1.1. Importing necessary libraries

```
import os
import cv2
import numpy as np
import tensorflow as tf
import mediapipe as mp
from sklearn.model_selection import train_test_split
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from tensorflow.keras.callbacks import TensorBoard
```

7.3.1.2. Define a list of target words

```
words = ['angry', 'bank', ..., 'why'] # list of target words
```

7.3.1.3. Initialise the mediapipe holistic Drawing utilities

```
mp_holistic = mp.solutions.holistic # Holistic model
mp_drawing = mp.solutions.drawing_utils # Drawing utilities
```

7.3.1.4. Initialise an empty dictionary to store the preprocessed data

```
dic = {} # initialise an empty dictionary to store the preprocessed data
```

7.3.1.5. Preprocessing data for each target word

```
for each word in words:
    dire = os.path.join('src_2', word) # directory containing videos for the target word
    vids = os.listdir(dire) # list of video file names in the directory
    dic[word] = [] # initialise an empty list for the target word in the dictionary
    for each video in vids:
        dic[word].append([]) # initialise an empty list for the video
        vidcap = cv2.VideoCapture(os.path.join('src_2', word, vid)) # capture the video
        while the video has frames:
            read the next frame from the video
            convert the frame from BGR to RGB
            process the image with the Mediapipe Holistic model to detect hand landmarks
            if hand landmarks are detected:
                store the landmarks in the dataset array
```

```
            draw the hand landmarks on the image for visualisation
        end while
    end for
end for
```

7.3.1.6. Saving the preprocessed data to a binary pickle file

```
with open('preprocessed_all.pkl', 'wb') as handle:
    pickle.dump(dic, handle, protocol=pickle.HIGHEST_PROTOCOL)
```

7.3.1.7. Loading the pre processed data from the pickle file into dictionary

```
with open('preprocessed_all.pkl', 'rb') as handle:
    data = pickle.load(handle)
```

7.3.1.8. Stretching each video to have 63 frames using linear interpolation

```
stretch each video to have 63 frames using a linear interpolation method
```

7.3.1.9. Filter out words with fewer than 10 videos or more than 63 videos

```
filter out words with fewer than 10 videos or more than 63 videos
```

7.3.1.10. Splitting the preprocessed data into training and testing data sets

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

7.3.1.11. Converting the labels to one-hot encoded vectors

```
y_train = to_categorical(y_train, num_classes=len(words))
y_test = to_categorical(y_test, num_classes=len(words))
```

7.3.1.12. Defining a sequential model in Keras with LSTM and Dense Layers

```
model = Sequential()
model.add(LSTM(128, input_shape=X_train[0].shape, return_sequences=True))
model.add(LSTM(64))
model.add(Dense(64, activation='relu'))
model.add(Dense(len(words), activation='softmax'))

compile the model with Adam optimizer and categorical cross entropy loss function
train the model on the training set for 2000 epochs with TensorBoard callbacks
```

```
evaluate the model on the testing set and store the predictions in "res"
```

7.3.1.13. Defining a sequential model in Keras with Sequential and Dense Layers

```
Create a Sequential model:
  Add a Conv1D layer with 32 filters, kernel size of 3, ReLU activation function, and input shape of X_train
  Add a MaxPooling1D layer with pool size of 2
  Add a Flatten layer
  Add a Dense layer with number of units equal to the length of words and softmax activation function
Compile the model with adam optimizer and categorical cross-entropy loss function and add categorical accuracy as a metric
Train the model on X_train and y_train for 2000 epochs, using tb_callback as a callback and save the training history to history variable
```

The model architecture consists of a 1D convolutional layer with 32 filters and a kernel size of 3, followed by a max pooling layer with a pool size of 2, a flattened layer, and a dense layer with a softmax activation function to output the probabilities of each class. The model is then compiled with an Adam optimizer and a categorical cross-entropy loss function, with the categorical accuracy metric used to evaluate the model's performance during training. Finally, the model is trained on the training dataset for 2000 epochs, with TensorBoard used as a callback to monitor and visualise the training progress.

We have used padding and stretching features to increase the accuracy of the model. The number of frames in each video is not constant. So we had to find a solution that brings a constant number of frames. This issue was solved by padding and stretching the videos.

7.4. Chapter Summary

This chapter outlined the technology stack that was used to create SignIt. The main functionalities' pseudocode implementation was shown, providing a high-level understanding of how the system worked. The following chapter will go over the system's testing phase.

CHAPTER 8: TESTING

8.1. Chapter Overview

This chapter makes sure the product works as it should. After they are implemented, the features are each individually tested. These systems' performance has been assessed using a variety of testing approaches, including cross-validation and dataset partitioning. Due to the usage of the Agile methodology, testing begins as soon as a functional requirement is fulfilled. In the next section, let's go over the testing's objectives and goals before presenting the findings.

8.2. Objectives and Goal of Testing

The main objective of testing is to make sure that the system requirements are working appropriately in the implementation.

- To check the best practices and the quality of the code.
- To check and clear the bugs which were not found during the development process.
- To check if all the functional and non-functional requirements are satisfied by the system.

8.3. Testing Criteria

Measuring the code quality of the final code is one of the key components of testing. This can be done by doing integration tests, regression tests, performance tests, user acceptance tests, security testing, usability tests, etc.

- Performance – These measures how effectively the application uses its resources, with an emphasis on how this affects customer happiness, response times, and scalability.
- Efficiency - Code has been optimised for performance and has used resources efficiently, avoiding unnecessary computations and memory usage.
- Maintainability: This ensures that the programme can be easily modified and maintained over time, with a clear structure and logical organisation.

- Reliability – This determines whether there is a chance of errors or problems in the programs.

8.4. Module Evaluation

8.4.1. Experimental Setup

8.4.1.1. Data Preprocessing

Steps that are included in the data pre-processing are, detecting landmarks, stretching, padding the videos, and label encoding.

The detection of hand landmarks is done using the MediaPipe library. This helps us to detect the landmarks of a hand in each frame of a sign language video. Then the landmarks are stored in flattened arrays in a dictionary. Since the length of each video is not the same, we have applied a stretching algorithm to all videos ensuring that they all have 63 frames. The 'stretch' function is used to achieve this requirement.

We also have used the 'pad_sequences' from Keras to pad the videos with zero frames at the end to achieve the same requirement mentioned above. The labels of the SL videos are encoded using the label map dictionary, which maps each sign language word to a number.

8.4.1.2. Data Splitting

We have used the function 'train_test_split' and split the data into training and testing randomly, with the test data set of size 20% and 80% for the training data. The splitting is necessary to evaluate the model's performance on unseen data and avoid overfitting.

8.4.1.3. Confusion Matrix

Metric	Value
True Positive (TP)	Number of videos correctly classified as sign language video
True Negative (TN)	Number of videos correctly classified as non-sign language video
False Positive (FP)	Number of videos incorrectly classified as sign language video
False Negative (FN)	Number of videos incorrectly classified as non - sign language video

- **Accuracy**

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

- **Recall**

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

- **Precision**

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

- **F1 - score**

$$F1\ score = 2 * \frac{Precission * recall}{Precision + recall}$$

Source : (Nighania, 2019)

8.4.1.4. Evaluation Matrix

- Test Proportion: 20.05% of the dataset
- Test Accuracy: 91%
- Precision (Weighted): 93%
- Recall (Weighted): 91%
- F1-Score (Weighted): 91%

	precision	recall	f1-score	support
0	0.75	0.75	0.75	4
1	0.60	0.75	0.67	4
2	1.00	1.00	1.00	8
3	1.00	1.00	1.00	4
4	1.00	0.71	0.83	7
5	0.71	1.00	0.83	5
6	0.75	1.00	0.86	3
7	1.00	1.00	1.00	5
8	1.00	0.88	0.93	8
9	1.00	0.75	0.86	4
10	1.00	1.00	1.00	5
11	0.71	1.00	0.83	5
12	1.00	0.75	0.86	4
13	1.00	1.00	1.00	8
14	0.67	1.00	0.80	4
15	1.00	1.00	1.00	3
16	1.00	0.50	0.67	4
17	1.00	1.00	1.00	4
18	1.00	0.80	0.89	5
19	1.00	1.00	1.00	6
20	0.71	1.00	0.83	5
21	1.00	1.00	1.00	1
22	1.00	1.00	1.00	5
23	1.00	0.75	0.86	4
24	1.00	1.00	1.00	7
25	1.00	1.00	1.00	5
26	1.00	1.00	1.00	4
27	0.67	1.00	0.80	4
28	1.00	0.89	0.94	9
29	1.00	0.67	0.80	6
accuracy			0.91	150
macro avg	0.92	0.91	0.90	150
weighted avg	0.93	0.91	0.91	150

Figure 8.4.1.4 : Evaluation Matrix

8.5. Benchmarking

Benchmarking is the process of comparing a product, service, or process with the best practices or performance of other organisations, industries, or competitors. The goal

of benchmarking is to identify areas for improvement and opportunities to enhance performance, efficiency, and quality. This determines whether there is a chance of errors or problems in the programs.

Table 8.5 : Benchmarking

Type of benchmarking	Description
Competitive benchmarking	This evaluates the performance of the present product by contrasting it with those of the top companies
Technical Benchmarking	This is done by the employees to assess the product's capabilities by contrasting it with those of the top businesses.

Functional Testing

Table 8.6 : Functional Testing

Test Case	Description	Input	Expected Result	Actual Result	Status
1	Checking whether if user can enter details and sign up successfully	Username Email Password Confirming password	User creating the account successfully	User creates the account successfully	Passed
2	Checking if user can login successfully	Username Email Password	User entering the website successfully	User enters the website successfully	Passed
3	Checking if user can input the gesture through the camera panel	Gesturing through the camera panel	Detects the gesture and provide the results	Detected the gesture and provided result successfully	Passed

8.6. Module and Integration Testing

This chapter will cover the different types of modules and integration testing, including security testing, component testing, and accuracy and performance testing, as well as the different approaches and techniques used in each. The chapter will also discuss the importance of testing the integration between software components, including interface testing and compatibility testing, to ensure that the components work together seamlessly.

8.7. Non- Functional Testing

8.7.1. Accuracy and Performance Testing

The following tests were executed in computers with these specifications:

Sequential Model:

Processor	AMD Ryzen 7 5700U at 1.80 GHz
RAM	24GB
GPU	Radeon Graphics

Sequential model from Images

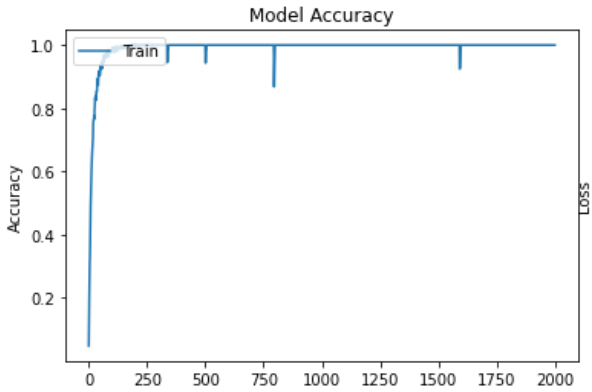


Figure 8.8.1 : Model Accuracy

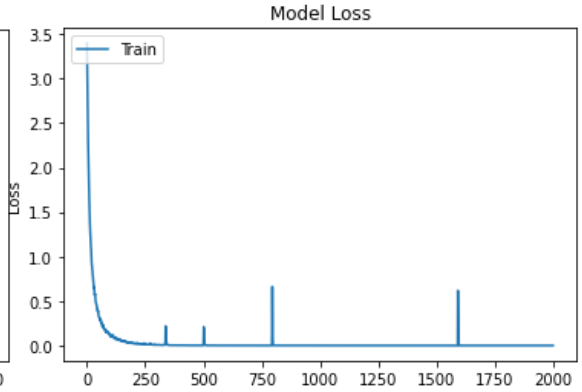


Figure 8.8.1 : Model Loss

8.7.2. Security Testing

When the user is using the website for the first time or has signed out, the welcome page will appear on the screen and will instruct the user to sign in. The user will be asked to enter the username, and password, to retype the password and the email

address if it is his or her first time using the website or else the username and the password will be required to enter. The usernames and emails will be added to the database.

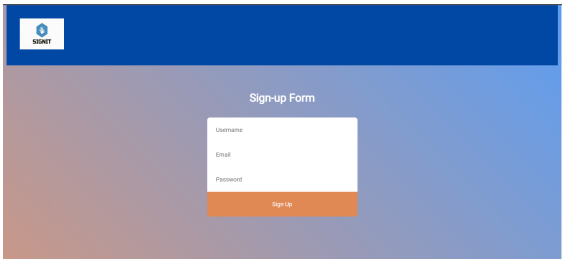


Figure 8.8.2 : Security Testing - 1

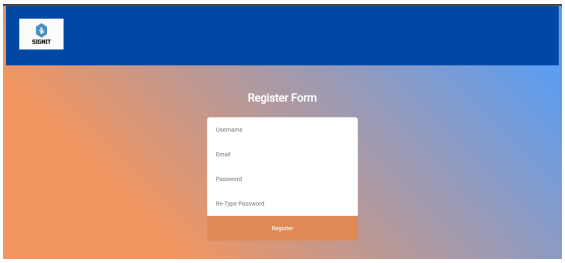


Figure 8.8.2 : Security Testing - 2

8.8. Limitations

- Our AI model requires a significant amount of processing power and GPU usage to run.
- A significant amount of time is required to train the model.
- We faced difficulties during the testing because we have to provide real-time data.
- It can be difficult to keep users engaged with the platform
- Impossible to test for all the gestures as it takes so much time

8.9. Chapter Summary

All the features of this web application are thoroughly tested as shown above. The objectives of the tests are identified and the importance of testing a system is depicted where as the functional and non-functional requirements. This chapter concludes by discussing the limitations of the testing process.

CHAPTER 9: EVALUATION CHAPTER

9.1. Chapter Overview

This chapter documents the evaluation of the system in various categories provided by domain experts and technical experts, as well as the authors' self-evaluation. A list of functional and non-functional requirements that have been implemented was also provided.

9.2. Evaluation Methodology and Approach

In this study, we developed a sign language recognition system using machine learning algorithms. The system consists of a video dataset and a gesture recognition model. To evaluate the system's performance, we collected a dataset of sign language gestures performed by 5 participants, each performing 30 different gestures. The dataset was split into training and testing sets. We used convolutional neural networks (CNNs) to train the system to recognize the gestures. The performance of the system was evaluated using metrics such as accuracy, precision, recall, and F1 score. To ensure the validity and reliability of the data, we used a data cleaning process to remove any errors or inconsistencies from the dataset.

9.3. Evaluation Criteria

The evaluators assessed the following criteria:

1. The project's overarching concept
2. Project Dimensions (scope)
3. Architecture and System Design
4. Prototype and solution
5. Application user interface and experience

9.4. Self-Evaluation

Table 9.4 : Self - Evaluation

Criteria	Author's Evaluation
Project Overall Concept	There has always been a communication gap between society and the deaf and hear-of-hearing community which proposed a barrier

	every time they had to communicate with each other. With our app, we plan on reducing the communication gap by providing easily accessible SSL learning material and an accurate recognition system for dynamic gestures.
Scope of the project	The scope of this project is to develop a machine learning model that can predict the correctness of user input, specifically whether it corresponds to a correct gesture or not.
System design, architecture, and implementation	Design and architecture are done in a way that encourages users to learn more and be more familiar with the sign. Because the system was built with a high-level architecture, it can be improved as needed.
Solution and Prototype	The proposed solution involves training a machine learning model on preprocessed hand gesture data to predict the correctness of user input. A prototype of the sign language learning platform will be developed, integrating the trained model to provide real-time feedback to users

9.5. Selection of Evaluators

We have selected the evaluators from two categories

1. Domain experts who are working with sign languages
2. Technical experts with expertise in UI/UX, and Machine learning applications.

Table 9.5 : Selected Evaluators

Group	Affiliation	Reason
Domain Experts	Mr. Tharusha Wickramasinghe Manager of Large Scale corporation	Extensive experience and expertise in managing a company that employs hearing-impaired individuals. He has a deep understanding of the challenges faced by individuals with hearing impairments and has valuable insights into how technology can be used to improve their lives.
Technical Experts	Mr. Kiruthiharan Basker (Software Engineer)	A Software Developer with expertise in full stack development

9.6. Evaluation Results

9.6.1. Overall Concept

Table 9.6.1 : Evaluation Results - Overall Concept

Question	
What do you think about the overall project?	
Person	Feedback
Mr. Tharusha Wickramasinghe	"This is good project with more potential to improve"
Mr. Kiruthiharan Basker	"Good project, need some more improvements"

9.6.2. Scope of the System

Table 9.6.2 : Evaluation Results - Scope of the system

Question	
What do you think about the scope of the project?	
Person	Feedback
Mr. Tharusha Wickramasinghe	" A unique project with great insight"
Mr. Kiruthiharan Basker	"A new approach on Sinhala Sign Language, covered some basic words"

9.6.3. Design, Architecture and Implementation

Table 9.6.3 : Evaluation Results - Design, architecture and implementation

Question	
What is your opinion on the design, architecture and implementation of the project?	
Person	Feedback
Mr. Tharusha Wickramasinghe	"With some more improvement of the interface this can be a way better project"
Mr. Kiruthiharan Basker	"User friendly, but design can be improved a bit more"

9.6.4. Solution and Prototype

Table 9.6.4 : Evaluation Results - Solution and prototype

Question	
What do you think about the solution and the prototype of the project?	
Person	Feedback
Mr. Tharusha Wickramasinghe	"The output can improve more"
Mr. Kiruthiharan Basker	"Output of the project is as expected"

9.7. Limitations

Table 9.7 : Limitations

Person	Feedback
Mr. Tharusha Wickramasinghe	"Can improve the project more with less limitations"
Mr. Kiruthiharan Basker	"Lesser limitations would have been better for this project"

9.8. Evaluation of Functional Requirements

Table 9.8 : Evaluation on Functional Requirements

FR ID	Description	Priority
FR01	The device should be able to accept videos as input.	Critical
FR02	Removing unnecessary background disruption because background features can interfere with gesture recognition, unnecessary background disruptions are avoided.	Critical
FR03	Improving video input and applying it to building endeavours	Critical
FR04	Breaking down video input into frames using the trained model.	Critical
FR05	After breaking the videos into a set of frames, adding filters according to the trained model	Important

FR06	Extracting the gestures and converting the videos to a series of frames.	Critical
FR07	Comparing the input gestures with the pre-existing datasets.	Critical
FR08	Identifying the gestured word or phrase signed by the user	Critical
FR09	After identifying the gestures generate results and give a pop-up message	Critical
FR10	The system must be able to recognize user inputs from various backgrounds.	Important
FR11	System must be able to recognize even if the user inputs the gesture in different hands (left or right)	Important
FR12	The GUI of the system must be user-friendly.	Important
FR13	A FAQ section has been added to the website to help users clear up any questions they may have.	Not-Important

9.9. Evaluation on Non- Functional Requirements

Table 9.8 : Evaluation on Non - Functional Requirements

Requirement ID	Requirement and Description	Evaluation	Priority
NFR 01	Website		
NFR 01.01	The website will be developed to be cross-platform and compatible with a variety of browsers.	Implemented	Critical
NFR 01.02	For the majority of common screen sizes, the website will be desktop responsive.	Implemented	Critical
NFR 01.03	To improve the website's performance, the AI features are included in it as APIs.	Implemented	Critical
NFR 02	UI/UX		
NFR 02.01	Make the website's interface user-friendly.	Implemented	Critical
NFR 02.02	Using approaches like webcam recognition and accessibility testing, design the user experience	Implemented	Critical

NFR 03	Performance		
NFR 03.01	While creating predictions and training AI models, aim for higher accuracy scores.	Implemented	Critical
NFR 03.02	Create a model that can draw conclusions more quickly.	Implemented	Critical
NFR 04	Security		
NFR 04.01	Unauthorised parties should not have access to user data.	Implemented	Critical
NFR 05	Scalability		
NFR 05.01	By implementing load balancers, the AI API endpoint must be able to support many queries at once.	Implemented	Critical

9.10. Chapter Summary

This chapter described how industry experts evaluated various criteria. To begin, mention the categories that were discussed with experts and briefly explain the evaluated criteria. The self-evaluation of the following author is also mentioned. The subsequent expert evaluation of various categories is also documented and Finally, functional and non-functional requirements are evaluated.

CHAPTER 10: CONCLUSION

10.1. Chapter Overview

In this section, a comprehensive summary of the SignIT project will be presented. The project's goals and objectives will be the primary focus of the discussion. Additionally, the challenges faced and skills acquired during the project's implementation will be highlighted. The current limitations of the development and potential future enhancements will also be explored. Lastly, ethical considerations will be taken into account before concluding with individual contributions.

10.2. Achievements of project aims and objectives

10.2.1. Project Aim

The website created is a Sign Language learning platform called 'SingIt,' which simplifies the learning and acquisition of Sinhala Sign Language. Users will be able to learn basic Sinhala Sign Language gestures, test their comprehension with a guessing game, and expand their Sinhala Sign Language vocabulary on the platform. The camera feature will enable users to practice their newly learned gestures and receive feedback on their accuracy. The platform will use image processing, video recognition, and pattern recognition technologies to track dynamic signs, including a CNN model for sign language classification and OpenCV architecture for capturing user input. The application is designed to be a one-stop platform that offers all of the features proposed as a bundle to users.

10.2.2. Completion of objectives of the project

Table 10.2.2 : Completion of objectives of the project

Description	Status
Literature Review	
Evaluation of the existing and previously published works and systems	Completed
Software Requirement Specification	
Overview of the product, requirements and stakeholder analysis	Completed
Design	

Designed the website	Completed
Development	
Developed the prototype of the website according to the design	Completed
Testing	
Testing the AI Model, Website and the backend	Completed

10.3. The utilisation of knowledge from the course

Table 10.3 : Utilization of knowledge from the course

Module	Description
Advanced Mathematics For Data Science (CM2607) & Simulation And Modelling Techniques (CM2605)	The mathematical principles taught in the module were instrumental in developing a deep understanding of the inner workings of AI models. Specifically, the module's emphasis on statistics enabled us to effectively analyse data and prepare it for use in machine learning algorithms and apply this knowledge in a hands-on manner.
Data Science Group Project (CM2603)	The module offered a comprehensive introduction to various critical aspects of the research process, including conducting a literature review, developing a Software Requirements Specification (SRS), crafting a compelling project proposal, and ultimately, producing this final thesis. Also, the module covered vital business thinking and product marketing concepts that are crucial for any successful project. These skills were applied specifically to the SignIt project.
Machine Learning (CM2604)	The module offered an extensive introduction to the world of machine learning algorithms, including their various types and applications. Furthermore, the module provided in-depth guidance on the process of developing a specific model and evaluating its effectiveness. This comprehensive approach to understanding machine learning allowed for a more nuanced and sophisticated understanding of the topic.

Object Oriented Development (CM2601)	This module provided a comprehensive and detailed overview of the most effective software and design practices utilised during the development process. These best practices were rooted in OOD concepts, which were extensively covered throughout the module. Also, we were introduced to the essential tool of Git version control, which proved to be an invaluable asset when it comes to managing codebases and collaborating on projects in a team environment

10.4. Use of existing skills

Existing skills laid the foundation when developing the project and were instrumental for implementation in a short period of time.

10.4.1. Machine learning

We used 'Coursera' to learn the fundamentals of machine learning. We also used other online resources and previously created models to improve our machine learning knowledge. The "Python for Machine Learning" course by GreatLearning was used by one of our Machine learning engineers to further expand their knowledge on the subject. This aided us in developing a good intuition when building the AI model using some necessary modules such as Mediapipe, Tensorflow, and Keras.

10.4.2. Web Development

Web Development is done using HTML, CSS and JavaScript which were learned during year 1, online platforms and other projects. The experience laid a good foundation for building responsive websites.

10.5. Use of new skills

During the course of the project, the team members were able to acquire new skills and further develop their existing skill set.

10.5.1. Practical Machine Learning

Through a comprehensive review of existing research and engagement with domain-specific literature, the team achieved a thorough understanding of the AI CNN models implemented in the project. This enabled the team to engage with the models at a deeper level, exploring the intricate workings of the technology beyond the abstract level. To build and refine the model, various pre-processing and fitting techniques were employed, adopting a data-centric approach. The Tensorflow library, which incorporates

Keras, was used to implement the model. The Media pipe hand pose method was used to extract the landmarks of the hand from each frame of the videos.

Furthermore, the team tackled the critical issue of data ethics, specifically in the handling of sensitive data such as videos of individuals captured with their consent. The project prompted the team to navigate this complex issue thoughtfully, considering the ethical implications of their work and promoting a responsible approach to data usage.

10.5.2. Integrating AI Models with Web Interface

Integrating AI models with a mobile and web interface is a complex process that must take performance and efficiency into account. We built Flask backends to serve the AI models in our Sinhala sign language learning platform, ensuring fast inference speeds and optimal model performance. This entailed optimising our algorithms and data structures to reduce resource usage and latency, resulting in a more seamless and responsive experience for users. We prioritised performance and efficiency throughout the development process, resulting in a platform that delivers accurate and reliable results while remaining fast and responsive.

10.5.3. Version Control

Using GitHub for version control on a large-scale project aided our development process. We were able to maintain an organised and structured workflow by working collaboratively and using version control tools, resulting in faster and more efficient development. We were able to track changes, manage conflicts, and maintain a high level of code quality and consistency throughout the project's development thanks to GitHub's advanced version control features. Overall, using GitHub for version control was critical to our success, allowing us to work more efficiently and effectively as a team.

10.6. Achievement of learning outcomes

10.6.1. Develop skills necessary to collaborate within a team on a software development project

- GitHub was used to collaborate on development. This aided in staying organised and effectively collaborating.

- Zoom was used for weekly and necessary task Management meetings. This improved our time management skills.
- Weekly meetings with the mentor were held using Google Meet, and official correspondence via WhatsApp kept everyone in sync and in clear communication with one another.

10.6.2. Present an analysis of the user-centred design process, cognitive aspects, research methods, modelling and prototyping used to produce applications related to Data Science with a reflection on legal, ethical, professional and social issues

- Prior to prototype development, a Literature Review and SRS document were drafted to lay the foundation for the project.
- A comprehensive review of existing work and research was conducted to ensure that our work did not overlap with previous projects or repeat any work already done.
- Business-centric principles were adopted in the development of the product design and features, with a focus on generating revenue.
- The initial product prototype was created using Figma, with a strong emphasis on UI/UX considerations.
- A cross-platform web application was developed to ensure accessibility across multiple platforms.
- The entire system was integrated with cutting-edge and robust AI models, developed with a focus on innovation and excellence.
- All datasets/data used in the project were obtained with permission from relevant individuals and parties and were anonymized to protect privacy. The ethical boundaries were upheld throughout the data collection and usage process.

10.7. Problems and challenges faced

Table 10.7 : Problems and challenges faced

Problems / Challenges	Solution/ Workarounds
Limited availability	Since SSL is not widely used, creating a dataset that

of SSL dataset	accurately represents the language's unique features can be difficult. To overcome this challenge, we created our own dataset to train our models. However, additional efforts may be required to collect and create larger and more diverse datasets to improve the platform's accuracy and effectiveness
Data Quality	The quality of the dataset used in developing an SSL learning platform is crucial. To ensure data quality, we employed several strategies, including data cleaning and augmentation, involving SSL experts to validate the dataset and provide feedback, and continuously monitoring and updating the dataset. These measures were taken to improve the accuracy and effectiveness of our models, as poor quality data can result in inaccurate sign recognition, leading to a suboptimal learning experience for users
Difficulty in designing an effective user interface	Designing an effective user interface can be challenging when developing an SSL learning platform. To address this issue, we took a user-centred approach and conducted user testing to gather feedback and make iterative improvements to the platform's interface. This allowed us to develop an intuitive and user-friendly interface that is tailored to the needs of our target audience
Hardware Requirements	Developing an SSL learning platform requires hardware capable of processing and storing large amounts of data. We utilised cloud computing services to host and manage the platform's infrastructure, enabling us to easily scale resources and optimise performance

10.8. Future Enhancements

To enhance the product's functionalities and marketability, there are several areas that can be improved. The AI models can be deployed in the cloud using a Human-in-loop infrastructure, which allows for continuous training, evaluation, and deployment, preventing the models from degrading and resulting in higher returns on investment.

Secondly, deploying the web application with AWS Elastic Beanstalk would enable easy scaling of the application, efficiently handling large spikes in users and minimising downtime.

Security is also a critical area that requires improvement, with encryption of data and adherence to data regulations necessary since clients are from different parts of the

globe. Additionally, incorporating two-factor authentication in the application would enhance security.

Expanding the subscription plan for the students with more modules and lessons could also be beneficial. For example, providing students with essential phrases in specific categories for daily use, including collecting new data and training the model, would help them learn sign language more effectively.

Furthermore, the project can be expanded to include ASL, BSL, and other common languages, giving users the option to choose the language they want to learn, regardless of their location.

Lastly, implementing new AI models and testing them regularly can lead to increased accuracy and a better user experience, given the continuous advancements in AI technology.

10.9. Achievement of the contribution to body knowledge

The project's development made several contributions to the body of knowledge. SignIt was one of the first learning modalities for Sinhala Sign Language. From pre-processing to feature engineering, the various AI model architectures used in the project can lead to additional research.

10.10. Individual contribution

Table 10.10 : Individual Contribution

Team Member	Contribution
Jathusharini Basker	Main Role: Data Engineer ● Led the team by assigning tasks, facilitating communication between the module leader, mentor, and group members, and organising meetings to ensure progress. ● Data Collection ● SignIT Information gathering questionnaire ● Data Preprocessing ○ Reading the videos ○ Processed the video data by segmenting the videos into individual frames. ○ Detected the hands in each frame and provided landmarks using Mediapipe

	○ Applied preprocessing techniques, such as squeezing, padding, and stretching, to ensure consistency across all videos ○ Transformed the data for use in the model training process ● Building the LSTM Model ● Getting predictions from the model using user input ○ Capturing the user video in the frontend using the webcam of the user and passing it to the backend ○ Preprocessing the captured video to make it suitable to pass it to the model to get prediction ○ Segmented the video into frames, and performed hand detection for landmark identification ○ Applied preprocessing techniques, such as video squeezing, padding and stretching and then used the model for prediction ● Fixing model bugs ● Optimising the model ● Domain and Technical Experts Consultation ● Documentation
Anuttara Rajasinghe	Main Role: Machine Learning Engineer ● Data Collection ● SignIT Information gathering questionnaire ● Data Collection Consultations ● Data Preprocessing ○ Reading the videos ○ Trying various preprocessing techniques for previous versions of models. ○ Processed the video data by segmenting the videos into individual frames. ○ Detected the hands in each frame and provided landmarks using Mediapipe ○ Transformed the data for use in the model training process ● Model research ● Building the Sequential Model ● Training and Testing ● Fixing model bugs ● Domain and Technical Experts Consultation ● Documentation ● Proofreading

A. B. Duweeja De Lima	Main Role: Web Developer ● Data Collection ● Documentation ● SignIT Information gathering questionnaire ● Translating all the chosen vocabulary. ● Designing the website UI ○ Have chosen appropriate colour pallets, typography, and layout. ● Making the UI functional ○ Has ensured that the site is easy to be navigated by any learner from a kid to an adult. ● Developing the website ○ Accessibility: The website's frontend is accessible to all users, regardless of ability. It is designed to be easily accessible to both kids and adults. ○ Performance: The website's frontend is optimised for performance, meaning it should load quickly and use resources efficiently. All of the buttons and panels (video, camera) work very well and quickly. ○ Interactivity: The website's frontend allows users to interact with it by performing actions such as clicking buttons, filling out forms, and scrolling through content. Seeing visual resources, testing with the web camera, and rewatching the provided resources improves user interaction. ● Fixing errors in frontend. ● Communicated with the backend developer and adjusted the design and frontend to his preferences and ease of work. ● Model research
Mathushan Manorangithan	Main Role: Web Developer ● Data Collection ● Documentation ● Database Connection ● SignIT Information gathering questionnaire ● Integration of Backend and Frontend. ○ Trained and saved the machine learning model in a format that can be loaded. ○ Set up a new Flask application and installed necessary packages and libraries. ○ Defined the API routes that the application will use to interact with the machine learning model. ○ Loaded the trained machine learning model into the Flask application. ○ Rendered all the templates. ○ Defined the prediction function.

	○ Returned all the predictions. ○ Tested the Flask application. ○ Deployed the application.

10.11. Chapter Summary

This chapter describes our project and the prototype we created for a Sinhala sign language learning platform. Through this project, our team gained valuable experience and exposure to the fields of Data Science and Software Development. The prototype we created has the potential to be further developed into a marketable business-ready product.

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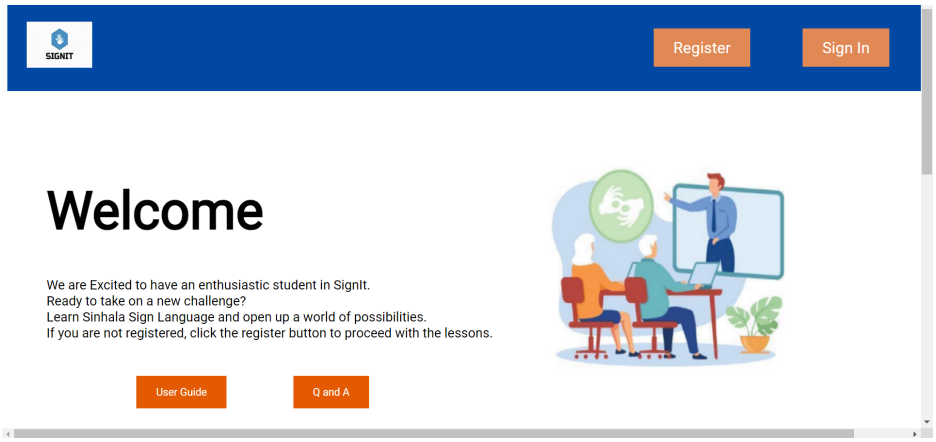
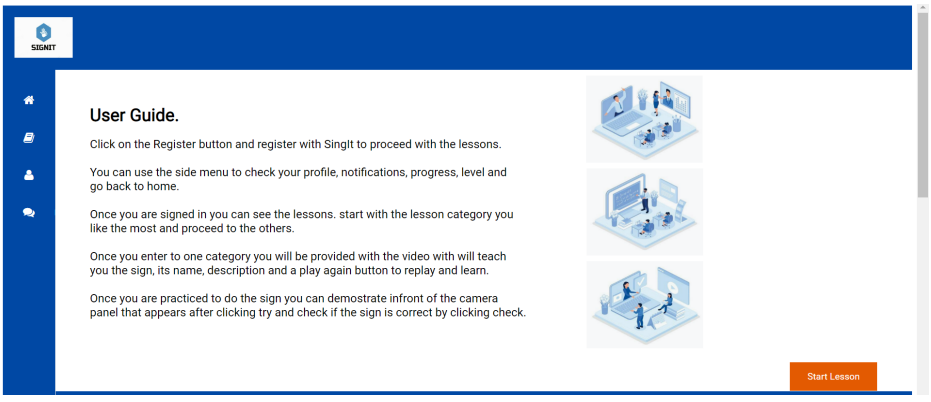
Appendix

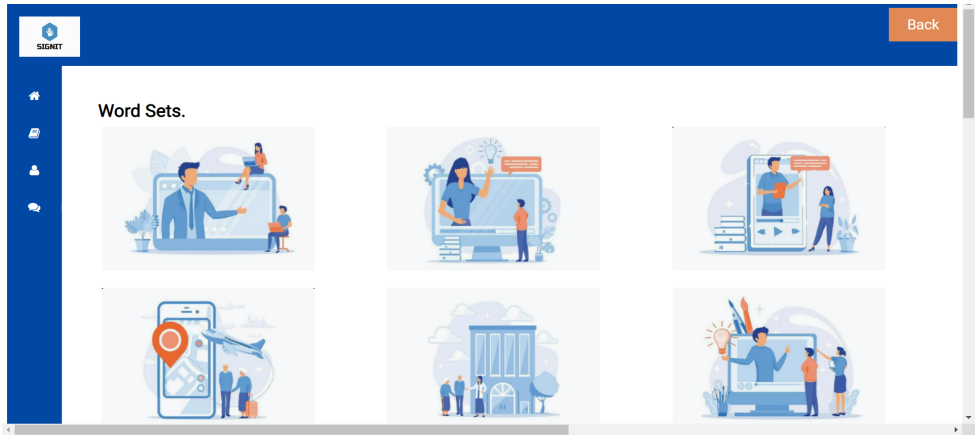
Questionnaire

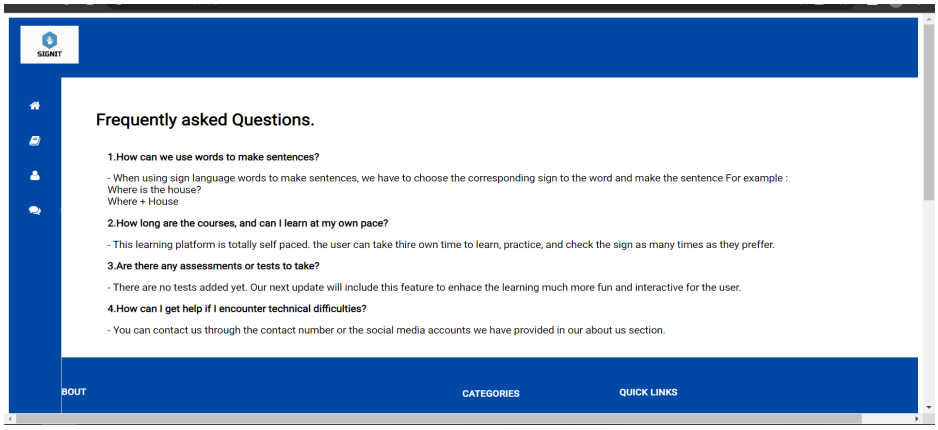
Form Link : https://forms.gle/ZG7iMYcNF8R3vXuV8

SignIt






SIGNIT
Back
Word Sets.


SIGNIT
Frequently asked Questions.
1.How can we use words to make sentences?
- When using sign language words to make sentences, we have to choose the corresponding sign to the word and make the sentence For example :
Where is the house?
Where + House
2.How long are the courses, and can I learn at my own pace?
- This learning platform is totally self paced. the user can take thire own time to learn, practice, and check the sign as many times as they preffer.
3.Are there any assessments or tests to take?
- There are no tests added yet. Our next update will include this feature to enhace the learning much more fun and interactive for the user.
4.How can I get help if I encounter technical difficulties?
- You can contact us through the contact number or the social media accounts we have provided in our about us section.
BOUT
CATEGORIES
QUICK LINKS