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Live Video Sign Language Numbers and Alphabet Recognition

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A report submitted in partial fulfilment of the requirements for the degree of Bachelor of Science

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Abstract

This dissertation addresses communication barriers faced by individuals with hearing and speech disabilities by developing a live video sign language recognition system for British Sign Language (BSL) numbers and the alphabet. According to the research, a sizeable section of the world's population suffers from hearing loss, which causes communication difficulties in a variety of areas, including healthcare and education. Through the use of machine learning algorithms, the project aims to improve hand gesture recognition in live video, addressing communication barriers for those who are deaf or mute.

With the Waterfall Hybrid Methodology, the recognition system is developed in stages using a hybrid approach that combines Agile and Waterfall methodologies. In order to archive this, datasets have been generated and trained, machine learning algorithms have been implemented for gesture recognition, and various metrics have been used to evaluate an accurate system.

Acknowledgements

This dissertation would not have been possible without the guidance and the help of several individuals who in one way or another contributed and extended their valuable assistance in the preparation and completion of this study.

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To my family, thank you for providing me with the encouragement and space to pursue my academic interests. Your unwavering belief in my abilities has given me the strength and confidence to complete this journey.

Lastly, I could not have completed this dissertation without the support of my friends, who provided both academic and emotional support throughout this process. Their belief in my capabilities has been a significant source of motivation for me.

I am truly grateful to everyone who has been part of my journey in completing this dissertation.

I certify that the work presented in the dissertation is my own unless referenced.

Signature Eren Taştepe

Date 03/04/2024

Total Words: 6481

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1 Introduction

1.1 Problem Definition

In our daily lives, people use languages to communicate with each other to fulfil their vital activities, such as getting food, sharing their life stories with their loved ones, discussing a topic with their colleagues, et cetera Language can be described as a method of human communication that uses speaking and writing used by the people of a particular country. However, not everyone can use all of their senses in this world. Some people can't talk (mute), some can't hear (deaf), or some can't see (blind). Almost twenty percent of the world's population is facing hearing loss or deafness. Those who are deaf and mute use sign language to communicate with other people by using their hands and body movements to represent words *(World Health Organisation, 2023; World Health Organisation, 2011; National Institute of Deafness and Other Communication Disorders, 2016; Stacey L. Buck, LTD, 2023)*.

People with these disabilities have or may have problems meeting their health needs. In an article from the University of Michigan, it is stated that "deaf individuals struggle with accessing mental health services because of language and cultural discordance" *(Pertz et al., 2018)*. The World Health Organisation estimates that in approximately thirty years, one in every ten people will be facing a hearing loss problem *(World Health Organisation, 2023)*.

For these problems, using machine learning algorithms to track hand gestures in live video capture and try to improve the accuracy, or even try different machine learning algorithms to test which algorithm could or should be used in this process. "Machine learning is a branch of artificial intelligence (AI) and computer science that focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy" *(IBM, 2023)*.

Research Question 1: How can machine learning algorithms improve British Sign Language numbers and alphabet recognition in live video to address communication barriers for individuals with hearing and speech disabilities?

1.2 Aims and Objectives

The aim of my project is to discover and implement a machine learning algorithm for live video recognition of sign languages, with the goal of addressing communication barriers faced by individuals with disabilities, such as deaf and mute individuals. In pursuit of this aim, I will be implementing machine learning algorithms to track live video and accurately capture the gestures of a hand for sign language, which includes both the alphabet and numerical representations. The objectives I have chosen for this purpose are:

- **Objective 1:** Review as much research or sources as possible about machine learning algorithms to track hand gestures for sign language recognition in live video to solve my project's problem.
  - Gather and review existing research and sources on machine learning algorithms specifically focused on tracking hand gestures for sign language recognition in live video. This step is crucial for the project due to the waterfall hybrid methodology being used for the project approach. A well completed research is essential for the waterfall hybrid methodology.
- **Objective 2:** Generate suitable data for the signs requires one hand of the British Sign Language (BSL) numbers and alphabet.
  - Generating suitable data requires both taking images of the signs and generating a .csv data for the project. This data will be used for the training model later on.
- **Objective 3:** Generate suitable data for the signs requires two hands of the British Sign Language (BSL) numbers and alphabet.
  - Generating suitable data requires both taking images of the signs and generating a .csv data for the project. This data will be used for the training model later on.
- **Objective 4:** Implement a machine learning algorithm for recognising British Sign Language (BSL) numbers in live video.
  - Implement a dedicated machine learning algorithm designed to recognise British Sign Language (BSL) numbers in live video. This involves developing a training model and a model that can accurately recognise hand gestures for the British Sign Language (BSL) numbers in live video.
- **Objective 5:** Implement a machine learning algorithm for recognising British Sign Language (BSL) alphabet in live video.
  - Implement a machine learning algorithm for recognising British Sign Language (BSL) alphabets in live video. This involves developing a training model and a model that can accurately recognise hand gestures for the British Sign Language (BSL) alphabet in live video.
- **Objective 6:** Getting better accuracy at recognising British Sign Language (BSL) numbers in live video.
  - Work towards improving the accuracy of the machine learning model for recognising British Sign Language (BSL) numbers in live video. This involves refining the algorithm and optimising parameters to achieve better performance.
- **Objective 7:** Getting better accuracy at recognising British Sign Language (BSL) alphabet in live video.
  - Similarly, enhancing the accuracy of the machine learning model for recognising the British Sign Language (BSL) alphabets in live video. Implement iterative

improvements, explore feature engineering, et cetera to achieve higher accuracy levels.

By addressing these objectives, I hope to make a beneficial system that can quickly recognise sign language from a live video. By using machine learning, I want to improve technology and make it easier for people with disabilities to communicate.

1.3 Project Approach

Gather Relevant Research Materials: In order to find a solution to the issue, collect relevant research materials by using Google Scholar, search engines, the Brunel library, or the Brunel electronic library. The materials may consist of articles, machine learning models and algorithms, databases, information on the problem, or even solutions that are already in existence.

Revise Research Materials: Review the most effective materials for the solutions.

Request Ethical Approval: Using the Brunel Research Ethics Online (BREO) system, submit an ethical application for institutional approval.

Prepare Data for Training Model: Data that can be used in practice should be prepared for the training model.

Implement the Machine Learning Model: An accurate machine learning model should be implemented based on the materials. The Python programming language will be utilised in order to carry out this implementation, which will be carried out using Virtual Studio Code.

Test the Machine Learning Model: In order to ensure that the code is functioning without any problems, testing the machine learning model for errors and bugs is essential. It will be possible to determine whether or not the goal has been accomplished by testing the machine learning model and comparing the sign language gestures with the model's predictions.

Analyse Results: Conduct an analysis of the results to determine whether or not the project was successful based on the extent to which the project goal was accomplished.

1.4 Project Flowchart Diagram

This flowchart describes the steps involved in developing a British Sign Language (BSL) numbers and alphabet recognition model, which include background research, research material revision, design, data generation, implementation, testing, and evaluation. Finding workable British Sign Language (BSL) numbers and alphabet image data is the next step. Data generation is necessary if the data is not practicable; if not, the process moves on to generating hand positioning data. The model is then trained, and hyperparameter tuning is carried out if the model is not accurate. A model for recognising sign language is established once the accuracy of the training model is determined. Next, the recognition model's accuracy is assessed; if it is not accurate, issues are found and resolved. In order to wrap up the development process, the model is finally evaluated.

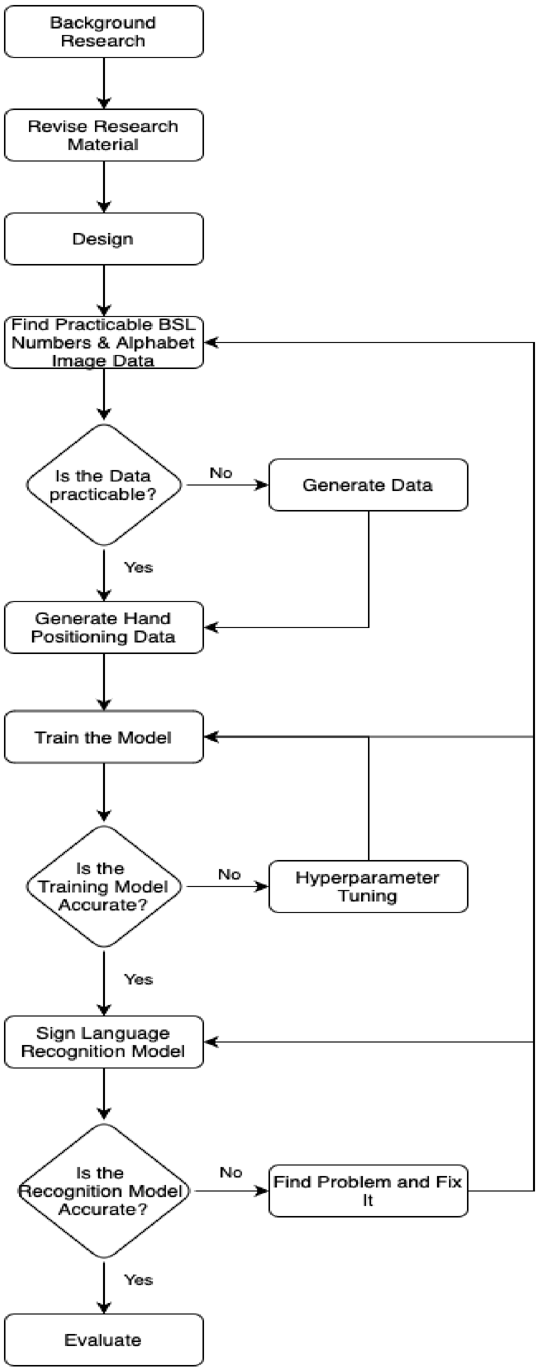

Figure 1 – Project Flowchart Diagram

1.5 Ethics

An application was made to the Brunel Research Ethics Online (BREO) system to obtain ethical approval for this project. The application issues relate to the followings:

- This project does not involve human participants.
- This project is designed to facilitate the communication of a person using sign language.
- There are no risks because this project does not involve human participants.

Approval from the Brunel Research Ethics Online (BREO) system has been granted and can be found in Appendix B.

1.6 Dissertation Outline

There are eight main chapters in this report. Below, each one is specified with a brief explanation of what the chapters contain.

Chapter 2 – Background:

Reviewing the collected practicable literature and existing projects to identify key points, strategies, and methods to fulfil the problem. Explains how a neural network can be used for recognising sign language numbers and alphabets. This chapter addresses Objective 1.

Chapter 3 – Methodology:

Describes how the project will achieve its aim and objectives. It explains how requirements, data, et cetera will be gathered and used and that the chosen approach is right for the project.

Chapter 4 – Design:

Defines the visual appearance of the project's design.

Chapter 5 – Data Preparation:

Presents how the data will be prepared for the project. The collected data will be tested for suitability for the project. If there is not any suitable data, the necessary data will be generated. This chapter addresses Objectives 2 and 3.

Chapter 6 – Sign Language Recognition:

Explains the steps for how to solve the problem by implementing a machine learning model using the collected or generated data. This chapter addresses Objectives 4 and 5.

Chapter 7 – Testing and Evaluation:

Testing the functionality and efficiency of the model in order to achieve the aim. To obtain more accurate solutions, evaluate the model only if the results of the tests are as desired. This chapter addresses Objectives 6 and 7.

Chapter 8 – Conclusions:

Concludes the project by summarising the results of the project. Discusses if the aim and objectives are achieved or failed and explains the limitations, future work, et cetera.

2 Background

2.1 Sign Language for Communication & Problems

Sign language refers to a visual language that emphasises the use of body language rather than the use of spoken words. Hands, eyes, gestures, and facial emotions are all examples of visible hints that are used in language to facilitate communication. There are many different variations of sign language, just like there are many different spoken languages. There are currently over three hundred different sign languages that are used all over the world. As stated in the problem definition section, the estimated prevalence of hearing loss or deafness worldwide is around twenty percent of the world's population. Despite the fact that the deaf and hard of hearing are the main users of sign language, many hearing people also use it *(National Geographic Education, 2023; Pertz et al., 2018).*

There is too much population in this area to disregard it. Therefore, it is impossible to overlook these people's issues. The health care system is one of the main issues this heterogeneous group faces, and they frequently have negative experiences there, typically as a result of a lack of communication. In the United Kingdom, a survey found that seventy seven percent of people who use British Sign Language (BSL) had trouble communicating with hospital personnel *(Alexander et al., 2012)*. This poor communication can cause incorrect medical treatment. Due to the lack of communication between the medical staff and the patient, an interpreter must be present at the hospital. As a result of the high demand for interpreters and the fact that they require reservations in advance, they are frequently unavailable for urgent care or medical consultations. According to the findings of another study, just seventeen percent of deaf signers receive an interpreter when they go to the doctor. Just seven percent of these interpreters are working in the emergency departments of those hospitals *(Alexander et al., 2012)*. Deaf patients lip-read or use a sequence of handwritten notes to communicate if an interpreter is not available. These communication channels are not dependable or efficient. However, the great majority of general practitioners think they can interact with their patients who use British Sign Language (BSL) and are hard of hearing in an efficient manner. More concerning is the fact that thirty percent of British Sign Language (BSL) users jeopardise their health by refusing to see their general practitioners due to communication barriers *(Alexander et al., 2012; Reeves et al., 2003; Royal National Institute for the Deaf, 1999; McKee et al., 2011; McKee et al., 2015; Barnett et al., 2011; Harmer, 1999)*.

According to a study conducted in Oman, there is a big communication gap between teachers and deaf students, which is mostly the result of social knowledge. Around fifty percent of the sample group thinks that deaf students cannot accomplish their academic objectives because of social barriers *(Zainulabdeen et al., 2023)*. Workshops, educational resources, and campaigns supporting the deaf are examples of solutions. Educational barriers are another reason that keeps deaf students from reaching their goals. According to almost fifty-two percent of participants, these barriers result from a lack of communication between teachers and deaf students *(Zainulabdeen et al., 2023)*. According to the study, a lack of social awareness regarding the disabled community is the reason why assistive technology is not being used. Although most people are only briefly familiar with this problem, deaf people depend heavily on the portability of technology, such as laptops and mobile devices. Sign language recognition systems are desperately needed, as evidenced by the almost fifty-eight percent of Omani interviewees who strongly agreed that sign language technology should improve *(Zainulabdeen et al., 2023)*. Achieving fluency in sign language takes around three months, but it facilitates communication for the deaf and mute. Just nineteen percent of the participants are against the idea of learning sign language, compared to more than fifty-three percent who are interested in learning. The adaptation of sign language programmers in educational institutions would promote more accessibility and comprehension, thereby elevating the demand for assistive technology such as sign language recognition systems. It is important to consider the talents and contributions of students with disabilities when developing sign language technology, as demonstrated by the interest that authorities working on education for the deaf community have shown in learning about new assistive technology *(Suharjito et al., 2017; Zainulabdeen et al., 2023)*.

When sound is not available, lip reading is a technique for understanding speech by visually interpreting lip movements. But because they can't see the speaker's lips or struggle with other tasks like writing or asking something of a friend, students with hearing impairments find it difficult to do this, which causes some information to be missed. In order to solve this, assistive technology is required to instantly translate audio into text that can be accessed and saved on student smartphones. Students with hearing impairments can learn more effectively and conveniently with the use of this technology *(Santoso et al. 2020)*.

2.2 Artificial Intelligence & Image Recognition & Gesture Recognition

Artificial intelligence, also referred to as AI, is a technology that allows computers and machines to mimic human intelligence and problem-solving abilities. It can carry out tasks like digital assistants, GPS guidance, autonomous cars, and generative AI tools like Chat GPT that would otherwise require human input. Artificial intelligence (AI) includes machine learning and deep learning, which create AI algorithms inspired by the way the human brain makes decisions *(IBM, 2023)*.

Image recognition is the process of using machine vision and artificial intelligence (AI) to identify objects, locations, people, writing, and actions in digital images. Computers are not as good at recognising objects as humans or animals. Image processing uses both machine learning and deep learning models; deep learning approaches are applied to more difficult issues. The particular use case determines the method that is selected *(TechTarget, 2023)*.

Gesture recognition is a branch of computer science that employs mathematical algorithms to identify and interpret human gestures, allowing us to read and understand human body language. Gestures can be made from any part of the body or state, but they are mostly made with the face or hands. Face expressions and hand gestures are the sources of emotion recognition. These non-verbal communication techniques are applied in a variety of fields, including home automation, human-computer interaction, deaf-mute communication, and healthcare *(Wikipedia, 2024; Oudah et al. 2020)*.

2.3 Artificial Intelligence & Sign Language Recognition

Artificial Intelligence technologies can address the communication gap between hearing and deaf people, significantly improving the social involvement and communication of those who are deaf or experience difficulties with their hearing. In order to assist individuals who have hearing difficulties in fully engaging in society, a major field of research called sign language recognition, or SLR, attempts to identify sign language from video streams *(Papastratis et al., 2021)*.

For live video hand gesture recognition, I will be using an API called MediaPipe. This API provides landmarks and results for the hands that are detected. It can be used to recognise gestures made by users and to activate features within applications. MediaPipe outputs hand landmarks in image and world coordinates, handedness, and hand gesture categories of multiple hands using image data and a continuous stream. Twenty-one hand knuckle coordinates are detected as key points within detected hand regions by the hand landmark model. The model was trained using multiple hand models and thirty thousand real-world images. It consists of two detection models: one for palms and the other for hand landmarks. While the hand landmarks detection model locates landmarks on the hand, the palm detection model locates the region of the hands from the entire input. Gesture recognition reduces the time needed for palm detection in video or live stream modes by focusing the region of hands in the following frame using bounding boxes defined by detected hand landmarks *(MediaPipe, 2023, Google Research, 2019)*. The figure below displays twenty-one landmarks:

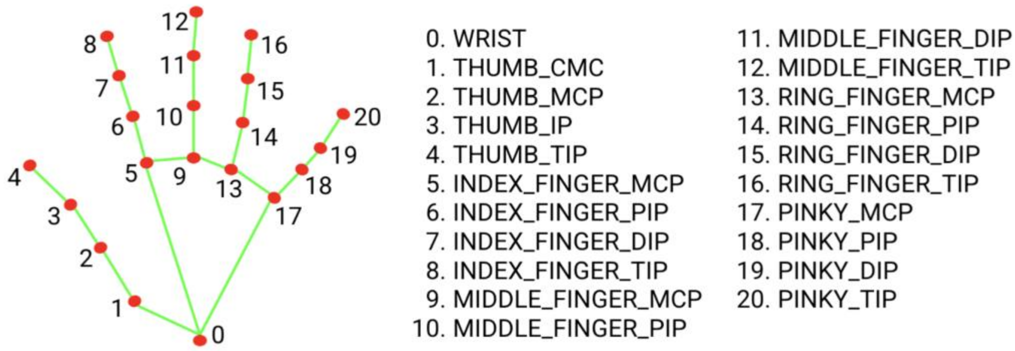

Figure 2 – 21 Landmarks of MediaPipe API *(MediaPipe, 2023)*

2.4 Existing Solutions

Advances in sign language recognition technology have made a big step towards helping the deaf and hard-of-hearing communities overcome communication barriers. One noteworthy example is the incorporation of advanced machine learning and computer vision algorithms, which have completely changed the precision and effectiveness of gesture recognition systems. These technological advancements help create inclusive and accessible social and educational settings for people with hearing loss, in addition to facilitating real-time sign language translation. Interpreting sign language has become more natural and fluid with the use of deep learning models and high-precision sensors, which can now recognise facial expressions and hand gestures. To further improve sign language recognition systems, hybrid approaches that fuse the flexibility of neural networks with the stability of classical algorithms are a promising new direction. These developments highlight how technology can break down long-standing barriers to communication and promote an inclusive society where the linguistic diversity of sign languages is fully accepted and understood *(Joksimoski et al., 2022)*.

3 Methodology

3.1 Approach

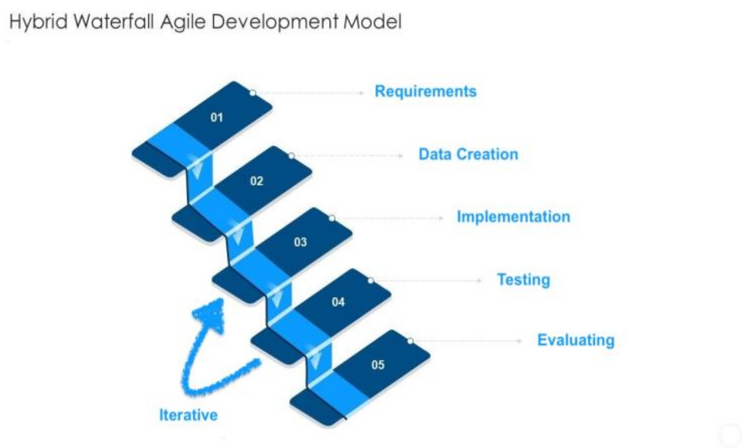

Figure 3 – Waterfall Hybrid Methodology Stages

The approach I will be using for my project is the Waterfall Hybrid Methodology. The Waterfall Hybrid Methodology combines both Waterfall and Agile Methodologies. There are five stages in the Waterfall Hybrid Methodology for my project: Requirements, Data Creation, Implementation, Testing, and Evaluation. I will be making my implementation and testing stages iteratively to increase the accuracy and get better results for the sign language recognition in live video. Researching the requirements is a need for the Waterfall Hybrid Methodology. This well completed research will be a key instruction for the implementation.

3.2 Requirements Gathering

Requirement 1 – Data Creation for Signs Requires One Hand:

It is necessary to take images of the signs requires one hand and organise them in each value folder. Afterwards, generate a .csv file containing twenty-one landmark locations using the images taken.

Requirement 2 – Data Creation for Signs Requires Two Hands:

It is necessary to take images of the signs requires two hands and organise them in each value folder. Afterwards, generate a .csv file containing twenty-one landmark locations using the images taken.

Requirement 3 – Training Model:

It is essential to build a training model using the generated .csv files. Overfitting must be avoided to increase the accuracy.

Requirement 4 – Sign Language Recognition:

Using the training model, a live sign language recognition model must be developed. In live video, the model must accurately recognise signs and output the recognised gloss.

Requirement 5 – Accuracy:

The sign language recognition model must be detecting the signs accurately.

Requirement 6 – Displaying Output:

The model needs to output the recognised gloss in live video.

Requirement 7 – Displaying Framerate:

The framerate in live video needs to be displayed by the model.

3.3 Use-Case Diagram

In Figure 3, the system's capabilities are described from the user's perspective in the use case diagram. The model aims to recognise British Sign Language (BSL) numbers and alphabets in live video, leading to the system displaying the recognised glosses to the user.

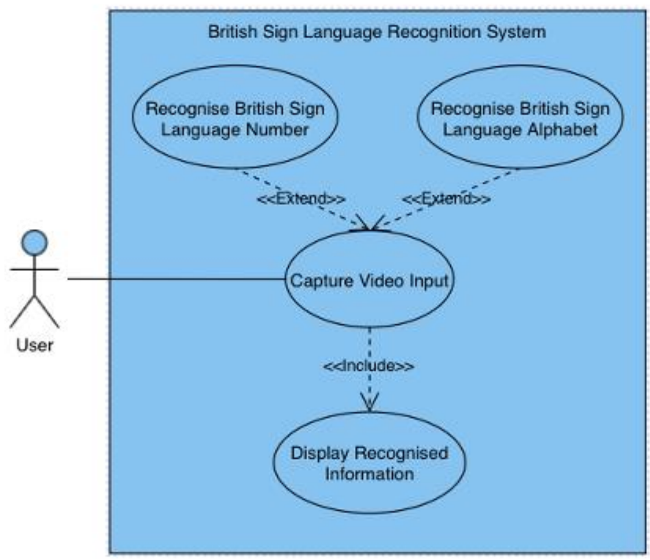

Figure 4 – Use Case Diagram of BSL Recognition System

3.4 Sequence Diagram

In Figure 4, the sequence diagram shows a user interacting with a British Sign Language (BSL) recognition model that uses a machine learning model in live video. When the user starts the live video input, the model interprets their gestures as British Sign Language (BSL) numbers or letters and displays the output until the user ends the process.

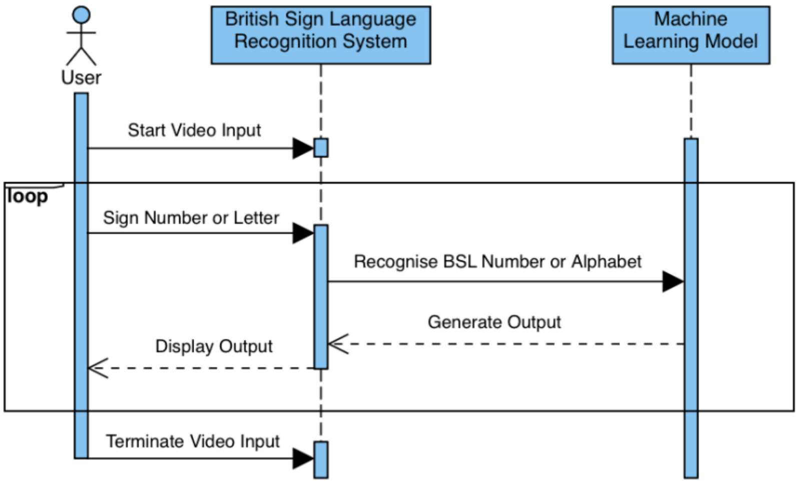

Figure 5 – Sequence Diagram of BSL Recognition System

3.5 System Flowchart Diagram

The system's operational procedure for recognising British Sign Language (BSL) numbers and alphabet signs is illustrated in the flowchart. A user first signs an alphabet or number in British Sign Language (BSL). Next, the number of hands used in the sign is detected by the model. The model predicts the British Sign Language (BSL) number or alphabet if only one hand is detected by using a model specifically created for one-handed signs. A separate model designed for two-handed signs is used for prediction if two hands are detected. The recognised sign is displayed by the model following the prediction. The system then looks to see if the user has provided any more input. The process repeats itself if new input is received; it stops if no new input is received.

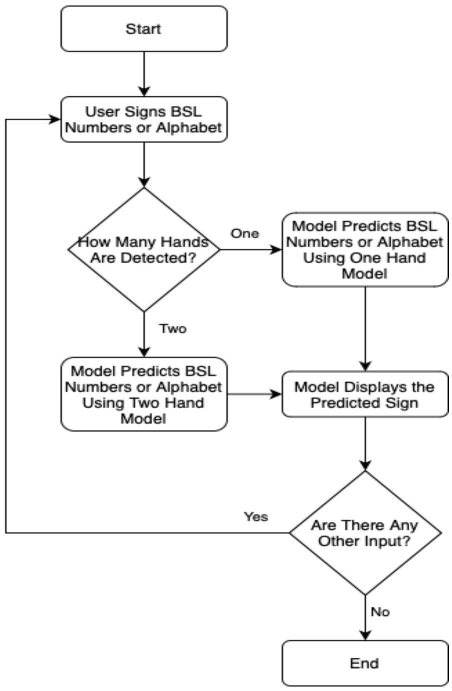

Figure 6 – System Flowchart Diagram

4 Design

Figure 7 – Design of the Project 1

Figure 8 – Design of the Project 2

Figures 5 and 6 illustrate the design of the project that is being built. It is displayed in the upper left corner of the frame, along with the output and the frames per second (FPS). Figure 6 illustrates how the model displays the predictions of the British Sign Language (BSL) numbers and alphabet on the output section whenever the model recognises a sign for the British Sign Language (BSL) numbers or alphabet.

5 Data Preparation

During my research on databases, I found a British Sign Language (BSL) numbers hand positioning dataset for MediaPipe on Kaggle. This dataset contained the twenty-one landmark positions for British Sign Language (BSL) numbers zero to ten. Within the dataset, there was a Python notebook. This notebook contains a model to train hand positioning and recognition model for British Sign Language (BSL) numbers in live video. After conducting a greater amount of digging on this source, I was able to locate the original project on GitHub. The original project recognises American Sign Language (ASL) numbers one to five and the sign for “I love you” and contains four files: one for taking images for generating data; one for generating a .csv file that contains twenty-one landmark positions using those images taken; one for training a model using the .csv file; and one for sign language recognition. The projects can be found in Appendix C. I will be evaluating the original project as creating my own data for British Sign Language (BSL) numbers zero to ten, plus the alphabet. Also, I will be using several accuracy models for image processing and different image processing model in my project.

5.1 Image Data Creation

The first step in data preparation is to take images of the British Sign Language numbers and alphabet signs. I have created two folders as signs require one hand, two hands. In these folders, each gloss has its own folder containing a total of a thousand images of that sign. The classification of the signs and conditions of the images taken can be visualised below:

5.1.1 Condition of the Images

A total of one thousand images of four different conditions were taken during the data preparation process, as shown in Figures 7, 8, 9, 10, 11, and 12. In Figure 5, a green screen is being used, wearing a black t-shirt, and signing the British Sign Language (BSL) numbers and alphabets in the lower portion of the body while moving horizontally in the frame. In these conditions, there are two hundred images for each sign in the dataset. In Figure 6, a more complex environment than a green screen is being used, wearing a more colourful t-shirt, and signing the British Sign Language (BSL) numbers and alphabets in the lower portion of the body while moving horizontally in the frame. In these conditions, there are two hundred images for each sign in the dataset. In Figure 7, a more complex environment than a green screen is being used, wearing a more colourful t-shirt, and signing the British Sign Language (BSL) numbers and alphabets in the same level at my face while moving horizontally in the frame. In these conditions, there are four hundred images for each sign in the dataset. In Figures 8, 9, and 10, a more complex environment than a green screen is being used, wearing a more colourful t-shirt, and signing the British Sign Language (BSL) numbers and alphabets, moving my hands horizontally without moving my body around my neck. In these conditions, there are two hundred images for each sign in the dataset.

Figure 9 – Condition of the Images 1

Figure 10 – Condition of the Images 2

Figure 11 – Condition of the Images 3

Figure 12 – Condition of the Images 4.1

Figure 13 – Condition of the Images 4.2

Figure 14 – Condition of the Images 4.3

5.1.2 Classification of the Signs

There are two classifications of British Sign Language (BSL) numbers and alphabets for my project: signs require one hand, and signs require two hands. In Sign Requires One Hand, there are eleven classes. These are the numbers zero to nine and the letter ‘C-c’. In Sign Requires Two Hands, there are twenty-three classes. These are the alphabet, excluding the letters ‘H – h’, ‘J – j’, ‘Y – y’, and the number ten.

5.2 Hand Positioning Data Creation

The second step in data preparation is generating a .csv file that contains twenty-one landmark positions for MediaPipe. There will be three files for each class. These files will be generated from the images taken before. For signs that require one hand, there will be 63 columns for x-y-z coordination’s of twenty-one landmarks and the output column, for a total of 64 columns. For signs that require two hands, there will be 126 columns for x-y-z coordination’s of twenty-one landmarks for both hands and the output column, for a total of 127 columns.

6 Sign Language Recognition

6.1 Training Model

The first step in sign language recognition is training the model for live video recognition. Before training the model, the datasets are separated into features and labels using the Pandas library. For training the dataset, a supervised learning model called the Support Vector Machine (SVM) model for multiclass classification is used *(Wikipedia, 2024)*. In order to classify data, a Support Vector Machine (SVM) model looks for an ideal line or hyperplane in an N-dimensional space that maximises the distance between each class *(IBM, 2023).* The mathematical formula for the Support Vector Machine (SVM) model for multiclass classification can be visualised below *(Scikit-Learn, 2024)*:

Primal Problem:

$$\min_{\{w,b,\zeta\}} \frac{1}{2} w^T w + C \sum_{\{i=1\}}^{\{n\}} \zeta_i$$

$$subject\ to\ y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i, \zeta_i \geq 0, i = 1, \ldots, n$$

Dual Problem:

$$\min_{\{\alpha\}} \frac{1}{2} \alpha^T Q\ \alpha - e^T$$

$$subject\ to\ y^T \alpha = 0, 0 \leq \alpha_i \leq C, i = 1, \ldots, n$$

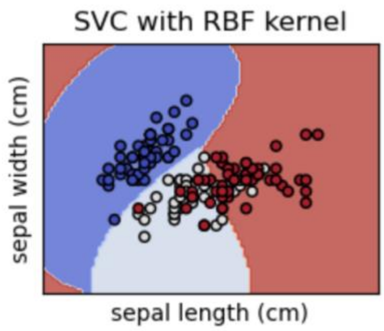

Figure 15 – Support Vector Machine (SVM) Model for Multiclass Classification with RBF Kernel *(Scikit-Learn, 2024)*

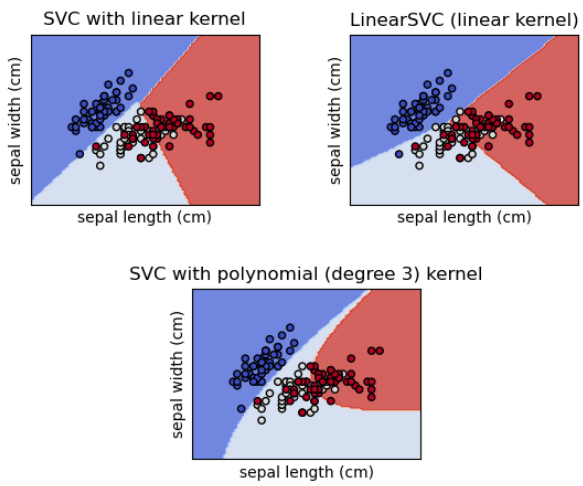

Figure 16 – Support Vector Machine (SVM) Model for Multiclass Classification with Different Kernels *(Scikit-Learn, 2024)*

Figure 13 illustrates a machine learning model called Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel for classification tasks. The model, which refers to measurement of various iris flower parts, employs sepal width and length as features to differentiate between different classes. Based on the values of sepal width and length, the model predicts a different class for each of the blue and red areas that serve as decision boundaries. Circles are used to represent data points, and the colour of the circle indicated the data point's actual class. The decision boundary, which is a line or curve that divides various decision areas, can take complex shapes in support of more complex class distinctions in Support Vector Machine (SVM) model that use Radial Basis Function (RBF) kernels. Other examples of kernels can be visualised for the iris flower parts study in Figure 14.

Supervised learning is a subset of machine learning that trains algorithms to recognise patterns and predict outcomes via labelled datasets *(Google Cloud, 2024)*. A multiclass classification task includes more than two classes in the classification process. There can only be one class assigned to each sample *(Scikit-Learn, 2024)*. A methodological error occurs when a model repeats the labels of samples it has just seen, leading to a perfect score but an inability to predict anything useful on data it has not yet seen. This is the result of learning the parameters of a prediction function and testing it on the same data. Overfitting is the term for this sort of situation. When conducting a supervised machine learning experiment, it is typical to keep a portion of the available data as a test set, x_test and y_test, in order to prevent overfitting *(Scikit-Learn, 2024)*. For this particular reason, the datasets are split into train and test using an eighty-twenty split.

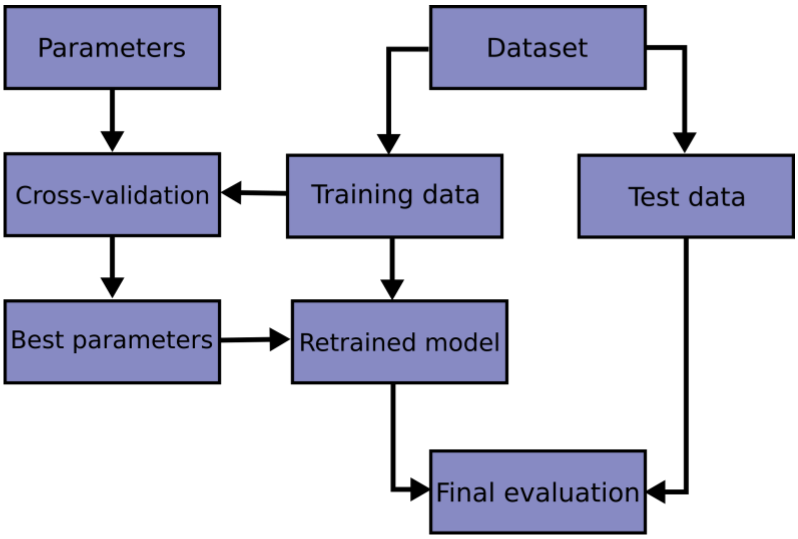

Figure 17 – Cross-Validation *(Scikit-Learn, 2024)*

The Support Vector Machine (SVM) model requires a kernel function. Kernel functions can be linear, $\langle x, x' \rangle$; polynomial, $(\gamma \langle x, x' \rangle + r)^d$, $d = degree$ and $r = coef0$; radial basis function (RBF), $\exp(-\gamma\, |\boldsymbol{x} - \boldsymbol{x}'|^2)$, $\gamma = gamma$ and $\gamma > 0$; or sigmoid, $\tanh(\gamma \langle x, x' \rangle + r)$, $r = coef0$. Support Vector Machine (SVM) uses the "one-vs-one" method *(Scikit-Learn, 2024)*. For the Support Vector Machine (SVM) model of the project, hyperparameter tuning was made for each model. Hyperparameters are parameters that are not obtained directly from estimators. The parameters have been provided as arguments to the estimator class constructor in Scikit-Learn. C, kernel, and gamma (γ) for the Support Vector Classifier (SVC) are typical examples.

Looking for the best cross-validation score in the hyperparameter space will be possible and recommended *(Scikit-Learn, 2024)*. The results of these hyperparameter tunings can be visualised below:

Hyperparameter Tuning for Signs Requires One Hand:

- **Kernel:** Radial Basis Function (RBF)
- **C:** 100
- **Gamma:** 1

Hyperparameter Tuning for Signs Requires Two Hands:

- **Kernel:** Radial Basis Function (RBF)
- **C:** 100
- **Gamma:** 1

As stated in the Figure 13 section, Support Vector Machine (SVM) models that use Radial Basis Function (RBF) kernels can take complex shapes in support of more complex class distinctions. Due to the complexity of the dataset, Radial Basis Function (RBF) kernel is the perfect fit for this use-case. Two parameters need to be taken into account when training a Support Vector Machine (SVM) using the Radial Basis Function (RBF) kernel: C and gamma (γ). All SVM kernels include the parameter C, which trades off decision surface simplicity against training example misclassification. Gamma (γ) indicates the degree of impact that a single training example has. Finally, each training model is being saved as a .pkl file for sign language recognition.

6.2 Sign Language Recognition

The second step of the Sign Language Recognition is live video recognition for British Sign Language (BSL) numbers and alphabet, and image processing and hand landmark detection models are required. For image processing, a library for computer vision and machine learning called “OpenCV” is being used. By offering a common infrastructure for computer vision applications, OpenCV aims to accelerate the integration of machine perception into commercial products *(OpenCV, 2024)*. For hand landmark detection, MediaPipe is being used. OpenCV stores colour in the BGR format, even though RGB is its default colour space *(GeeksforGeeks, 2023)*. However, RGB colour space is supported for MediaPipe. For this reason, an RGB converter parameter is used for the image processing model. The model determines whether one or two hands are present in the frame based on the landmarks it has detected. It then chooses the suitable trained model for gesture prediction. Then, the predicted gesture (output) and the frame rate (FPS) are displayed on the frame.

7 Testing and Evaluation

7.1 Testing

Testing the results is done by signing the British Sign Language (BSL) numbers and alphabet in live video to the model. If the model predicts the results correctly, the model is working successfully; otherwise, the previous steps must be checked and corrected to implement an accurate model for British Sign Language (BSL) numbers and alphabet recognition.

7.2 Evaluation

As described in the Data Preparation chapter, I will be evaluating the original project as creating my own data for British Sign Language (BSL) numbers zero to ten, plus the alphabet. Also, I will be using several accuracy models for image processing and different image processing model in my project. For the training model, evaluation metrics like F1 score, recall score, precision score, accuracy score, Intersection over Union (IoU) score, and Confusion Matrix are being implemented.

F1 Score: The F1 score can be considered the harmonic mean of precision and recall, with a maximum score of 1 and a minimum score of 0. Recall and precision both contribute equally to the F1 score in terms of their respective significance. The mathematical formula for the F1 Score evaluation metric can be visualised below *(Scikit-Learn, 2024)*:

$$\boldsymbol{F1} = \frac{\boldsymbol{2 * TP}}{\boldsymbol{2 * TP + FP + FN}}$$

The variables TP, FN, and FP represent the number of true positives, false negatives, and false positives respectively. When there are not any true positives, false negatives, or false positives; F1 score is automatically computed as 0.0.

Recall Score: Recall can be expressed as $TP/TP + FN$, where TP represents the number of true positives and FN represents the number of false negatives. The classifier's ability to locate every positive sample is known as recall. One is the ideal value, and zero is the worst *(Scikit-Learn, 2024)*.

Precision Score: The ratio of $TP/TP + FP$, where TP represents the number of true positives and FP represents the number of false positives, is the precision. It makes sense that the classifier's precision is its capacity to reject labelling a negative sample as positive. One is the ideal value, and zero is the worst *(Scikit-Learn, 2024)*.

Intersection over Union (IoU) Score: A set of predicted labels for a sample is compared to the corresponding set of labels in y_true using the Jaccard similarity coefficient, which is calculated by dividing the size of the intersection by the size of the union of two label sets *(Scikit-Learn, 2024)*.

Confusion Matrix: To evaluate the accuracy of a classification, a confusion matrix is being computed. A confusion matrix C is, by definition, one in which $C_{i,j}$ is the number of observations that are predicted to belong to group j and known to be in group *(Scikit-Learn, 2024)*.

Prior to the hyperparameter tuning, the confusion matrixes for both one-handed and two-handed data contained values that were overlapping with one another. Using the benefit of hyperparameter tuning on the training model resulted in an increase in accuracy by reducing the amount of overfitting and resulting in fewer values overlapped. The evaluation metrics and the confusion matrix can be visualised below:

Evaluation Metrics for Signs Requires One Hand:

- **F1 Score:** 0.998149005090236
- **Recall Score:** 0.998149005090236
- **Precision Score:** 0.998149005090236
- **Accuracy Score:** 0.998149005090236
- **Intersection over Union (IoU) Score:** 0.9963048498845266

Evaluation Metrics for Signs Requires Two Hands:

- **F1 Score:** 0.9989855440020289
- **Recall Score:** 0.9989855440020289
- **Precision Score:** 0.9989855440020289
- **Accuracy Score:** 0.9989855440020289
- **Intersection over Union (IoU) Score:** 0.9979731441601216

Confusion Matrix for Signs Requires One Hand:

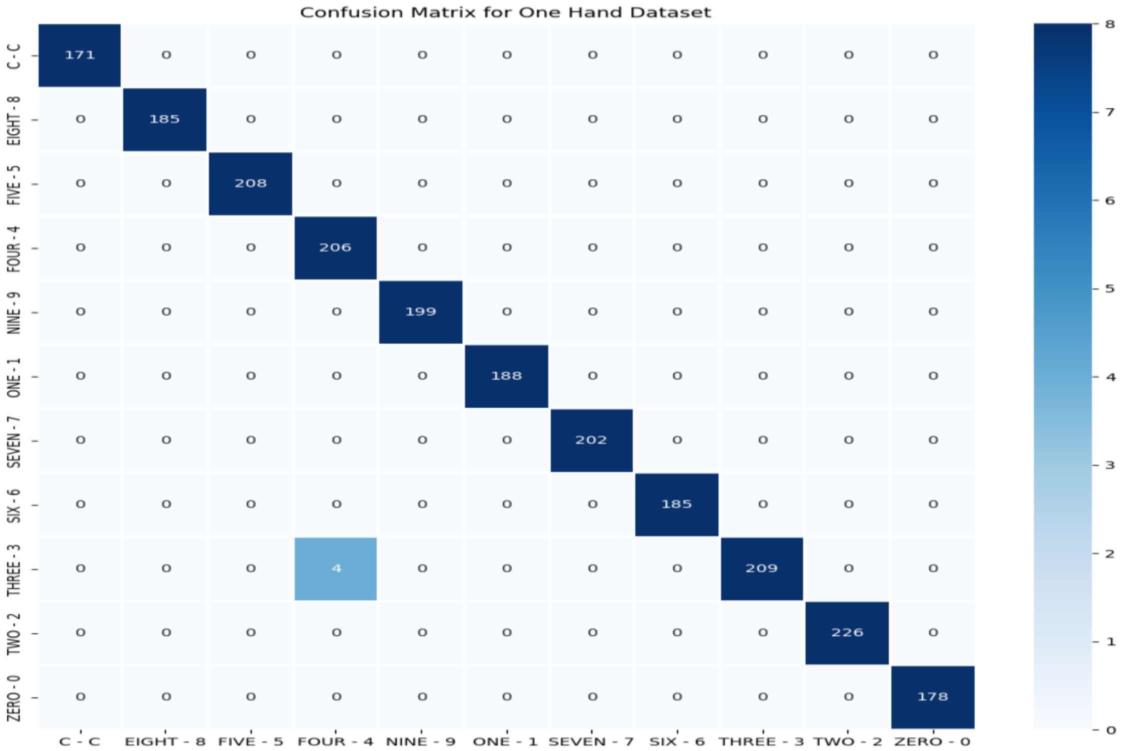

Figure 18 – Confusion Matrix for One Hand Dataset

Confusion Matrix for Signs Requires Two Hands:

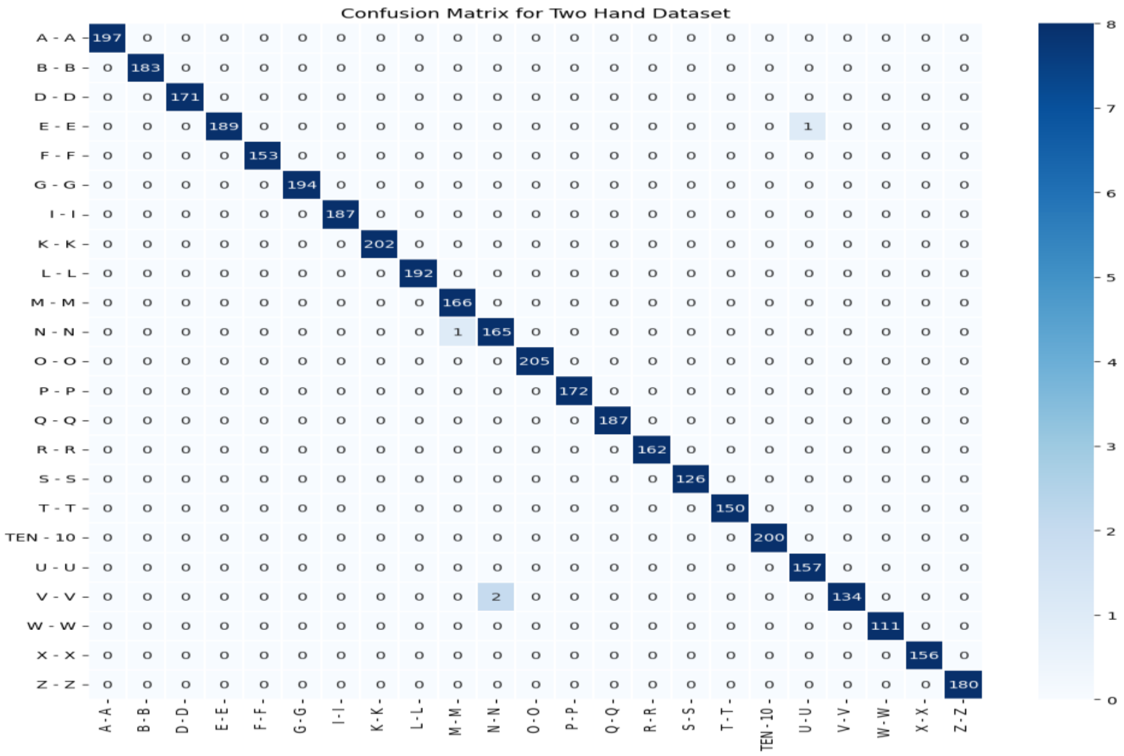

Figure 19 – Confusion Matrix for Two Hand Dataset

8 Conclusions

8.1 About the Project

The project aims to implement a machine learning algorithm for live video recognition of British Sign Language (BSL) numbers and alphabet, for individuals with disabilities such as deaf and mute individuals, with a goal of addressing communication barriers faced by these individuals by accurately tracking hand gestures of British Sign Language (BSL) numbers and alphabet.

Waterfall Hybrid Methodology is the approach used for this project, and the stages are requirements, data creation, implementation, testing, and evaluation. The implementation and testing stages will be iterative to improve accuracy and results in sign language recognition in live video.

8.2 Limitations

The limitation of data creation has the biggest effect on accuracy. Taking the images with the camera of a single phone limited the camera angles for the images of the signs. This caused collusion of the body parts and made it hard to train the model. This can be solved by using multiple cameras for multiple angles at the same time or by using hand tracking gloves for more consistent hand positioning data. The other effect on the accuracy is condition of the images and the size of the data. Increasing these factors and decreasing overfitting will be key solution for improving accuracy.

8.3 Future Work

In the future, my project can be evaluated as a more beneficial one. Features like below can be added to the project:

Evaluation of My Project:

In light of my project's limitations and in an effort to improve accuracy, may use hand tracking gloves to collect more reliable hand positioning data or multiple cameras to record data from several angles simultaneously.

British Sign Language (BSL) Word Recognition:

Adding British Sign Language (BSL) word recognition can be added to my project easily. Adding data of the word glosses to the dataset will finalise this feature.

Different Sign Language (SL) Recognition:

Different sign language numbers, alphabet, or word data can be generated. Furthermore, a dropdown box can be integrated for sign language (SL) selection within the model’s frame.

Sign Language (SL) Translator:

All of the features can be combined, and a more functional sign language (SL) translator can be implemented. This translator can be translating signs to text, signs to speech, audios to sign for a healthier and faster communication between oral speaking individuals with deaf or mute individuals.

With the addition of these functions this project will hopefully address communication barriers faced by individuals with disabilities. Also, different approaches can be used to generate the data on MediaPipe hand positioning. Multiple high-resolution cameras, hand location recogniser gloves, or 3D scanners can be used for capturing the hand movements. For accuracy improvements, the data size can be increased with changing the conditions of the images, and overfitting can be avoided.

8.4 Final Thoughts

My personal experience with this project has shown that this model is not capable of addressing the communication barriers that are experienced by individuals who are deaf or mute; however, it has the potential to serve as the initial step towards a fully functional Sign Language (SL) translator model in order to accomplish this objective. The addition of additional functions, an interface, or an application, as well as the evaluation of the data and the project, can both contribute to the development of a beneficial and useful model in the field of sign language recognition and help these individuals overcome the obstacles that prevent them from communicating effectively.

9 References

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Appendix A Personal Reflection

A.1 Reflection on Project

Changing the method that is used to generate the hand landmark data could be done in a different way, as was described in the conclusion chapter, in order to reduce the overall limitations that are associated with the project. This would be done in order to make the project more comprehensive. Additionally, the participation of participants in the process of data generation will significantly increase the variations in the conditions of the images that are used in the generation of the dataset. This is because the participants will actively participate in the process. The model will achieve a higher level of accuracy as a result of this, and it will also prevent the presence of overfitting scenarios. In addition to the process of having participants test the model and provide feedback, there is another factor that can be modified.

In order to complete the project, a number of different generative artificial intelligence tools will be utilised. With the assistance of ChatGPT, it is possible to quickly fix any errors that could occur during the process of putting the project into action. Using Grammarly, which is also used as a plagiarism checker, the dissertation is examined to determine whether or not it contains any grammatical errors or instances of plagiarism.

A.2 Personal Reflection

This project was an opportunity to learn British Sign Language (BSL) and understand the difficulties faced by deaf and mute individuals. As a result, the project raised an awareness about this heterogenous group for me.

While simultaneously working on the implementation of the project and writing the dissertation, it is recommended that both activities be carried out simultaneously. As part of the process of conducting research, it would be advantageous to have notes from the articles in order to save time and improve efficiency for the purpose of writing the dissertation. There are two aspects of the project that are extremely important: time management and a commitment to meeting deadlines. When I find myself working on projects in the future, I will make it a point to pay more attention to the specifics like these.

Appendix B Ethics Documentation

B.1 Ethics Confirmation

College of Engineering, Design and Physical Sciences Research Ethics Committee
Brunel University London
Kingston Lane
Uxbridge
UB8 3PH
United Kingdom

www.brunel.ac.uk

3 January 2024

LETTER OF CONFIRMATION

Applicant: Mr Eren Tastepe

Project Title: Live Video Sign Language Numbers and Alphabet Recognition

Reference: 45433-NER-Dec/2023- 48451-1

Dear Mr Eren Tastepe

The Research Ethics Committee has considered the above application recently submitted by you.

This letter is to confirm that, according to the information provided in your BREO application, your project does not require full ethical review. You may proceed with your research as set out in your submitted BREO application, using secondary data sources only. You may not use any data sources for which you have not sought approval.

Please note that:

- **You are not permitted to conduct research involving human participants, their tissue and/or their data. If you wish to conduct such research (including surveys, questionnaires, interviews etc.), you must contact the Research Ethics Committee to seek approval prior to engaging with any participants or working with data for which you do not have approval.**
- The Research Ethics Committee reserves the right to sample and review documentation relevant to the study.
- If during the course of the study, you would like to carry out research activities that concern a human participant, their tissue and/or their data, you must submit a new BREO application and await approval before proceeding. Research activity includes the recruitment of participants, undertaking consent procedures and collection of data. Breach of this requirement constitutes research misconduct and is a disciplinary offence.

Good luck with your research!

Kind regards,

Simon Taylor

Professor Simon Taylor

Chair of the College of Engineering, Design and Physical Sciences Research Ethics Committee

Brunel University London

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Appendix C Projects & Data's

C.1 My Project & Data

- GitHub (2024) datMaul/BSL_Numbers_and_Alphabet_Recognition, datMaul. Available at: https://github.com/datMaul/BSL_Numbers_and_Alphabet_Recognition (Accessed: 19 March 2024)
- Kaggle (2024) BSL Numbers & Alphabet Hand Position for MediaPipe. Available at: https://www.kaggle.com/datasets/erentatepe/bsl-numbers-and-alphabet-hand-position-for-mediapipe (Accessed: 19 March 2024)

C.2 Project on GitHub (Original Project)

- GitHub (2022) Dongdv95/hand-gesture-recognition, dongdv95. Available at: https://github.com/dongdv95/hand-gesture-recognition (Accessed: 4 December 2023)

C.3 Project on Kaggle

- Kaggle (2023) British Sign Numbers Dataset (BSL numbers), datazone25 (Asanka). Available at: https://www.kaggle.com/datasets/datazone25/bsl-british-sign-language-numbers-dataset (Accessed: 13 October 2023).
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