FAO ***Dr. Amina Souag, Dr. Hannan Azhar***

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BSc (Hons.) Computer Science

2023-2024

Individual Project 40

Title: *?????*

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This report is submitted in partial fulfilment of the requirement for the BSc in *Computer Science* at Canterbury Christ Church University

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Signed *Jamie Pinnington*

Date of Submission: *??????*

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3. Introduction

3.1. Background

- why is this topic (ASL) important? (e.g., accessibility, communication)
- what is the specific problem being addressed? (e.g., fingerspelling recognition) (bridges the gap in communication and enhances the learning/usage of ASL.) (makes ai more accessible to this audience?) ASL ,
- what is the impact of an AI recognizer for this problem? (e.g., enables real-time communication, improves accessibility, etc.) (can this effect broader technology?)

Sign language is the primary form of communication for the deaf and hard of hearing community. It allows communication when the spoken language is not possible, and or when the speaker or receiver is deaf or hard of hearing. Depending on the situation, and like any language, it requires both parties to be fluent in the language to communicate effectively. However, this is not always the case. American Sign Language(ASL) is a complete, complex language that employs signs made with the hands and other movements, including facial expressions and postures of the body, and is used natively in the United States of America and globally by many individuals.

Whilst no attempt has officially been made to survey the language, and most current estimates are based off of historical surveys that prove to be inaccurate Mitchell et al. (2006). It is estimated that there are over 1 million signers Ethnologue (2023), but others estimates are as high as 2 million Mitchell et al. (2006). ASL communicates through a variety of means including gestures, non-manual markers and lexical signs. The most understood are lexical vocabulary, each corresponding to a word or morpheme. Gestures and non-manual markers such as facial expression can complement and convey more interactive or meaningful lexical signs. Additional constructs include usage of space, role shifting and classifiers.

3.2. Purpose

- what is the purpose of the review?
- (e.g., to identify the state of the art in ASL fingerspelling recognition)

- (to identify the challenges and opportunities in ASL fingerspelling recognition)
- (to identify the most promising techniques for ASL fingerspelling recognition)
- * primary purpose is to build our own model, but we need to know what's out there first. *

3.3. Scope

- what is the scope of the review? (e.g., ASL fingerspelling recognition) (what is the scope of the problem? (e.g., real-time recognition of fingerspelling gestures) (what is the scope of the solution? (e.g., image-based recognition of fingerspelling gestures) (what is the scope of the evaluation? (e.g., accuracy, speed, etc.)
- what is the scope of the literature? (e.g., papers published in the last 5 years) (what is the scope of the sources? (e.g., peer-reviewed journal articles, conference papers, etc.)
- what we're not covering.
- only recognition and translation of ASL *fingerspelling* (not full ASL).
- specific the application/methodology (e.g., video-based recognition of fingerspelling gestures) (live/stream???)

3.4. Research Questions

- RQ-1: Comparative Analysis of Machine Learning Models: What are the strengths and weaknesses of different machine learning models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer models, in the context of ASL fingerspelling recognition?
- RQ-2: Performance Evaluation: How do various machine learning models perform in terms of accuracy, processing speed, and reliability for ASL fingerspelling recognition under different conditions (e.g., varying lighting, hand positions, backgrounds)?
- RQ-3: Dataset and Model Suitability: How does the choice of dataset, including its size, diversity, and quality, influence the effectiveness of different machine learning models in recognizing ASL fingerspelling?
- RQ-4: Real-World Applications: Considering practical applications like kiosk systems, which machine learning models offer the best balance between technical performance and user experience for ASL fingerspelling recognition?

- RQ-5: Technical Challenges: What technical challenges are commonly faced across different machine learning models in ASL fingerspelling recognition, and how adaptable are these models to address such challenges?
- RQ-6: Impact of Environment Variables: To what extent do environmental variables (like hand orientation, motion speed, and background noise) affect the performance of different machine learning models in ASL fingerspelling recognition?
- RQ-7: State of the Art and future directions: What are the most recent and influential works in the field of ASL fingerspelling recognition, and what are the emerging trends and future directions?

4. Methodology

4.1. Literature Identification

This literature search was completed using the databases IEEE Xplore, Google Scholar, ACM Digital Library, and ScienceDirect. Search terms such as ”ASL fingerspelling recognition”, ”Deep learning for ASL recognition”, ”ASL recognition with CNN”, ”Accuracy of ASL recognition models”, ”Latest trends in ASL recognition”, and ”ASL recognition in real-time” were used alone and in conjunction with boolean operators ”AND”, ”OR” to refine the search results. The search was limited to papers published in the last 5 years, and only peer-reviewed journal articles, conference papers, and high quality theses were considered. The search was also limited to papers written in English. The search was conducted in between November and December 2023, and the results were filtered to include only papers that were published between 2018 and 2023. In addition to this search which was completed in order to find relevant literature for the model architecture comparison, we also used the references of the papers that we selected to find additional relevant literature, that dates further back in order to substantiate our historical context and technical background.

4.2. Literature Evaluation

Of the literature that fit out search criteria, we selected the most relevant papers based on the following criteria: the relevance to the research questions, papers that specifically address ASL fingerspelling, machine learning models in sign language interpretation, papers that used widely recognized datasets relevant to ASL recognition, we chose to exclude editorials, opinion pieces, and non-peer reviewed articles. Papers also required a clear methodology, defined objectives and robust data analysis. Papers with high citation counts were also given preference.

Only papers that were published the aim of a newly developed application of a model for sign language/fingerspelling for the first time between 2018 and 2023 were considered.

- By understanding, the insight gained from this review will be used to inform the design and implementation of our own model.
- * evidence based approach is neccessary to be impactful *

5. Historical Context (RQ-7)

- Provide a brief overview of the evolution of ASL fingerspelling recognition.
- Highlight key milestones and breakthroughs in the field's history.
- Connect historical developments to current trends and future directions.

Early approaches to sign language recognition used robotic like data/power gloves which were wired, with sensors to capture hand movements and gestures Saeed et al. (2022). They aimed to record the finger position and flexion in order to classify shapes. These approaches were limited by the need for specialized hardware and the inability to capture facial expressions and other non-manual markers. Rule-based classifiers did the legwork by detecting specific input pattern of sensors to an output by programmatic rules. This approach was not practical or user-friendly.

The move to machine learning was occuring in parallel to the hardware based approaches, as vision-based approaches were developed to overcome the limitations of the hardware based approaches and was instrumental in the development of sign language recognition. This approach used computer vision techniques to detect and track the hand and fingers. They were able to capture more information than the hardware based approaches, but were limited by the need for a controlled environment and the inability to capture facial expressions and other non-manual markers, just as the hardware based approaches were. At this stage, there were no large datasets developed, and the datasets that were available were not standardized, and were not publicly available. The vocabulary was relatively small von Agris et al. (2008), which meant that the recognition was limited to a small number of signs. The recognition was also limited to a single signer, and was not robust to variations in lighting, hand orientation, and background noise.

A great deal of focus was on feature extraction and classification, various algorithms were being pursued to extract hand features like posture. Hidden Markov Models (HMMs) were used to solve this temporal sequential task, where each sign or gesture is defined by the transition from one state to another. HMMs use the transition state to understand meaning. This approach was limited by the need for a large amount of data to train the model von Agris et al. (2008).

Another leap with vision was the usage of support vector machines (SVMs) to together with HMMs to enhance classification. SVMs were more effective at classifying spatial features such as hand shape and geolocation of digits, and videos that have depth, where gestures or shapes could look similar in 2D or 3D Vogler and Metaxas (1999).

As we move around the late 00's, a significant feat was neural networks such as used in Munib et al. (2007), which used a 3-layer network with backpropagation and Hough transform. Although 92.3% accuracy was achieved, this was still comparable to models using SVMs and HMMs, as well as the hardware based approaches before. The dataset was still limiting, with" 300 samples of hand sign images; 15 images for each sign." Munib et al. (2007).

Perhaps the greatest leap was the rise of deep learning, as neural networks got deeper in terms of model layering. Image and video processing research as a whole was in full swing, convolutional neural networks (CNNs), recurrent neural networks (RNNS), and Long short-term memory (LSTMS), were a few which had significant impact. CNNs were adept at automatically extracting and learning

Yann Lecun is credited with setting the precedence of CNNs in 1998, with the LeNet-5 architecture Lecun et al. (1998). This was a significant leap in the field of computer vision, and was the first time that a model was able to learn features automatically, which is why due to greatly increased GPU processing power, CNNs came back into the fold at the 2012 ImageNet challenge Krizhevsky et al. (2012). CNNs are ideal and particularly adept at processing data that is grid-like, as in images that have dimensions. A series of layers are used to extract and identify features by breaking down the image into smaller parts, understanding that, and over and over, and combining them to understand the whole image. Functions and pooling layers are used to optimize the output for classification.

RNNs are a type of neural network that are adept at processing sequential data, such as text, audio, and video. They are able to remember previous inputs and use that information recurrently, because the network has a directed cycle network, meaning information can persist inside the network Sherstinsky (2020). This is particularly useful for ASL recognition, as the signs are sequential, and the order of the signs is important.

LSTMs are a type of RNN that are able to remember information for long periods of time, and are able to overcome the vanishing gradient problem that is common in RNNs Sherstinsky (2020).

While these models and approaches were valid for challenge of American Sign Language, commonly fingerspelling isn't factored in, and these model types struggle to perform well on fingerspelling. This is because fingerspelling is a sequential task, and the order of the signs is important.

Currently, the experimental methods are Connectionist Temporal Classification Graves et al. (2006); Shi et al. (2018), Attention Bahdanau et al. (2016), Transformers Vaswani et al. (2023), and using language models to improve accuracy.

Table 1: Summary and Analysis of ASL Fingerspelling Recognition Models (2018-2023)

Reference	Model Used	Framework	Dataset	Key Findings	Performance Metrics	Challenges Addressed
S Kumar et al. (2018)	RNN, LSTM, Attention, Encoder/Decoder	[Not Specified]	NCSLGR Corpus	Recognition and translation of ASL glosses	GRR: 86%, GER: 23%	Real-time recognition and translation
Weerasooriya and Ambegoda (2022)	RF, KNN, LR	[Not specified]	FASSL custom dataset	Developed a classifier for static signs using a small dataset	Accuracy: 87.9% (correct estimates)	Pose classification with limited data
Cihan Camgoz et al. (2020)	Transformers with CTC loss	PyTorch	PHOENIX14T	State-of-the-art results in recognition and translation	WER, BLEU-4 scores	Translation from sign language videos to spoken language sentences
Abiyev et al. (2020)	CNN, SSD, FCN	[Not specified]	Kaggle ASL Fingerspelling	High accuracy, vision-based translation	Accuracy: 92.21%	Real-time translation, robustness in ASL recognition
Bantupalli and Xie (2018)	CNN, LSTM, RNN	OpenCV	Self-created Dataset	Effective recognition with custom CNN model	Accuracy: 98.11%	Robust recognition in controlled environments
Kabade et al. (2023)	ResNet, Bi-LSTM, CTC, Attention	[Not specified]	ChicagoFSWild	Recognition using optical flow and attention, preprocessing for occlusions	Letter accuracy: 57%	Recognition in 'wild' conditions, occlusions

Reference	Model Used	Framework	Dataset	Key Findings	Performance Metrics	Challenges Addressed
Shi et al. (2018)	CNN, LSTM, CTC	Faster R-CNN	Custom YouTube Dataset	Improved accuracy with hand detection	Test Acc: 41.9% with CTC	Recognition in the wild, varying conditions
Shi et al. (2019)	CNN, RNN, CTC, Attention	TensorFlow	ChicagoFSWild, ChicagoFSWild+	Enhanced recognition in uncontrolled environments	Word Error Rate: 27.2	Recognition in diverse and challenging real-world scenarios
Shi et al. (2021)	2D/3D-CNN, Bi-LSTM	OpenPose	ChicagoFSWild, ChicagoFSWild+	Superior detection in uncontrolled environments	AP@IoU: 0.495, MSA: 0.386	Handling fine-grained handshapes and signer's pose
Nguyen and Do (2019)	1) LBP, HOG descriptors, multi-class SVM, 2) End-to-end CNN 3) CNN weights as feature extractor for Linear-kernel SVM	[Not specified]	Massey Dataset	Three diverse methods for fingerspelling recognition	Recognition rate: 97.49%, 98.23%, 98.30%	Adaptability in feature extraction and classification approaches
Chong and Lee (2018)	SVM and DNN	TensorFlow, Scikit-learn	Self-created Dataset	Comparison of SVM and DNN for ASL recognition; effective use of LOO approach for bias avoidance	Recognition rate: 72.79%, 88.79%	Multi-class classification with 36 classes (26 letters and 10 digits)
Bantupalli and Xie (2018)	CNN (Inception) for spatial features, LSTM for temporal features	TensorFlow, Keras	American Sign Language Dataset	Efficient extraction of temporal and spatial features; use of Inception and LSTM models	Accuracy up to 93% (Softmax Layer), 58% (Pool Layer)	Managing longer sequences with LSTM; preventing overfitting with dropout

Reference	Model Used	Framework	Dataset	Key Findings	Performance Metrics	Challenges Addressed
Shi et al. (2022)	FSS-Net (End-to-End Model for Fingerspelling Detection and Text Matching)	[Not Specified]	ChicagoFSWild, ChicagoFSWild+	Introduced explicit temporal localization for fingerspelling search and retrieval. Demonstrated effective fingerspelling detection in varying conditions.	mAP: 0.684 (YouTube), 0.584 (DeafVIDEO), 0.629 (Misc)	Fingerspelling detection in diverse visual conditions; handling open vocabulary and arbitrary-length queries; confusion between similar handshapes; detection failures.
Gajurel et al. (2021)	Fine-Grained Visual Attention with Transformer Model (CTC, CNN, LSTM)	[Not specified]	ChicagoFSWild	Significantly improved state-of-the-art performance in fingerspelling recognition using Transformer-based contextual attention mechanism	Letter Accuracy: 46.96 % (dev), 48.36% (test)	Addressed challenges in capturing fine-grained details in unsegmented continuous video data. Focused on improving generalization and regularization of the model.

6. Methods and Techniques (RQ-1, RQ-2, RQ-3)

- Offer an overview of the various methods used in ASL fingerspelling recognition.
- Discuss Image/Video-based methods, Framework-based approaches (e.g., MediaPipe), and Hybrid methods in detail.
- Include a discussion of common evaluation metrics and their relevance to different models and conditions.

6.1. Image/Video-based Methods

6.2. Transformers

squeezeformers

6.3. Attention

multi-head attention, self-attention, and cross-attention

6.4. CTC

6.5. Beam Search

6.6. Encoder/Decoder

7. Comparative Analysis of Machine Learning Models (RQ-1)

- Compare different machine learning models, specifically CNNs, RNNs, and Transformers, in the context of ASL fingerspelling recognition.
- Discuss the strengths and weaknesses of each model in detail.

8. Performance Evaluation and Model Suitability (RQ-2, RQ-3)

- Assess the performance of these models in terms of accuracy, processing speed, and reliability.
- Discuss how dataset characteristics influence model performance.

9. Challenges in ASL Fingerspelling Recognition (RQ-5, RQ-6)

- Identify and discuss the technical, data, and real-world challenges in ASL fingerspelling recognition.
- Include a discussion on how environmental variables, such as hand orientation and background noise, affect model performance.

10. Overcoming Obstacles (RQ-5)

- Propose techniques to enhance accuracy and address the challenges identified in the previous section.
- Discuss data augmentation strategies and the use of transfer learning and pre-trained models.

11. State of the Art and Real-World Applications (RQ-4, RQ-7)

- Present the most recent and influential works in ASL fingerspelling recognition.
- Compare the performance of different methods discussed in the literature.
- Highlight real-world applications, with a focus on practical aspects like kiosk systems.

12. Future Directions and Open Challenges (RQ-7)

- Discuss emerging trends in the field of ASL fingerspelling recognition.
- Identify areas that require further research and exploration.
- Explore the potential impact of future advancements, particularly in deep learning.

13. Ethical and Societal Considerations

- Address ethical considerations, including data privacy concerns.
- Discuss issues related to bias and fairness in ASL recognition models.
- Examine the implications of ASL fingerspelling recognition technology for the deaf and hard of hearing community.

14. Conclusion

- Summarize the main findings related to each research question discussed throughout the report.
- Reiterate the importance of the topic and its potential impact on the field of ASL fingerspelling recognition.

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15. MAIN CHAPTERS:

15.1. Chapter 1:

Appendices

Appendix A. Glossary

Appendix B. Marking Scheme

Appendix C. Changes to the Project Initiation Document

Appendix D. Current Environment Investigation Report

Appendix E. Requirements Specification

Appendix F. Design Report

Appendix G. Implementation

Appendix H. Testing

Appendix I. User Guide

Appendix J. Project Management

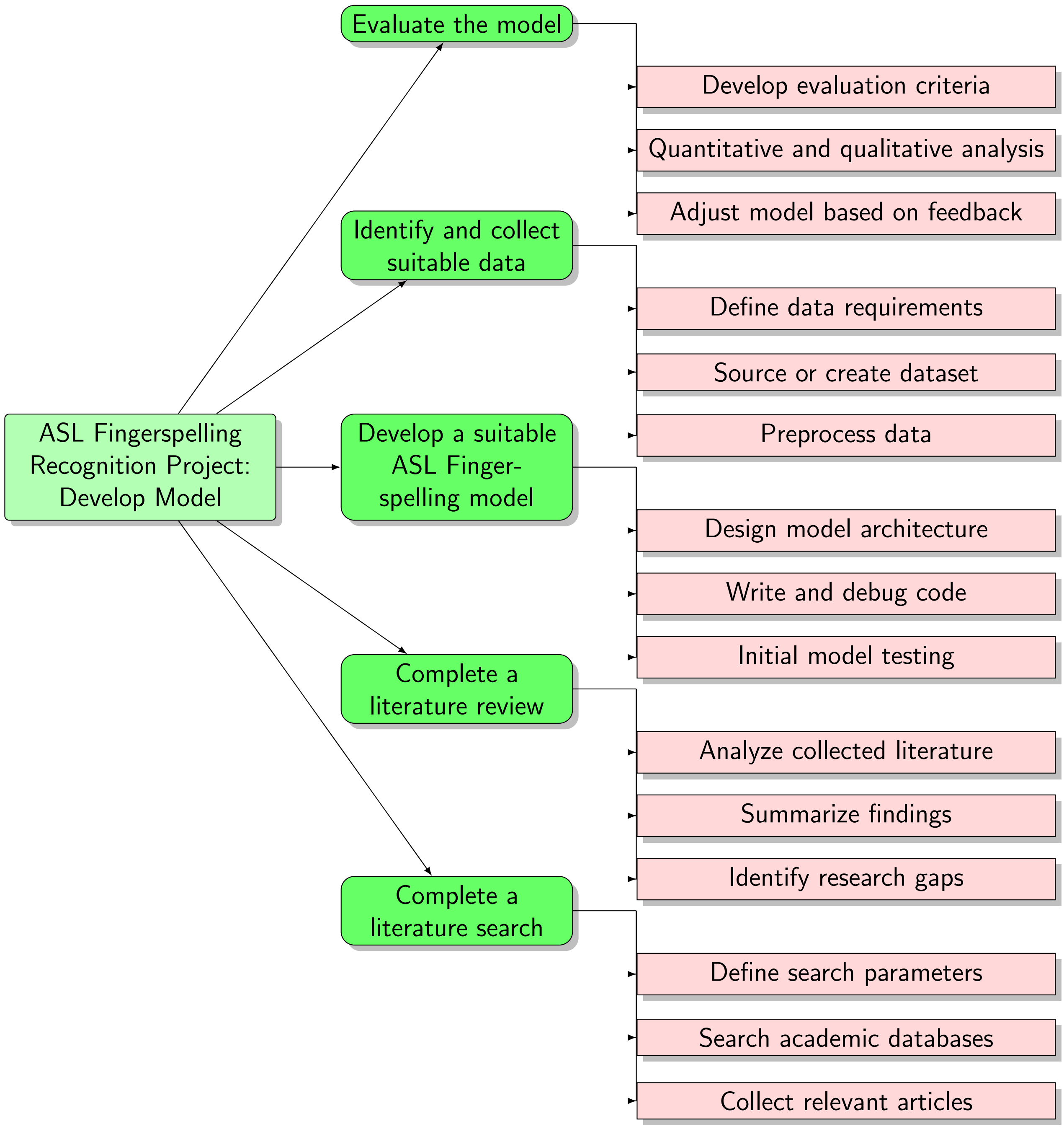

Figure J.1: Work Breakdown Structure: Develop Model

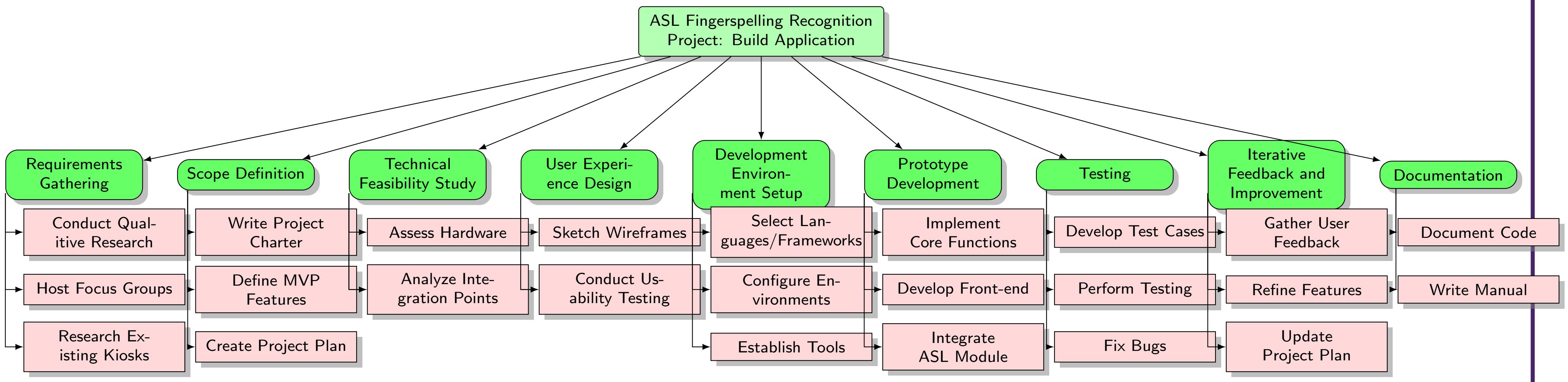

Figure J.2: Work Breakdown Structure: Build Application

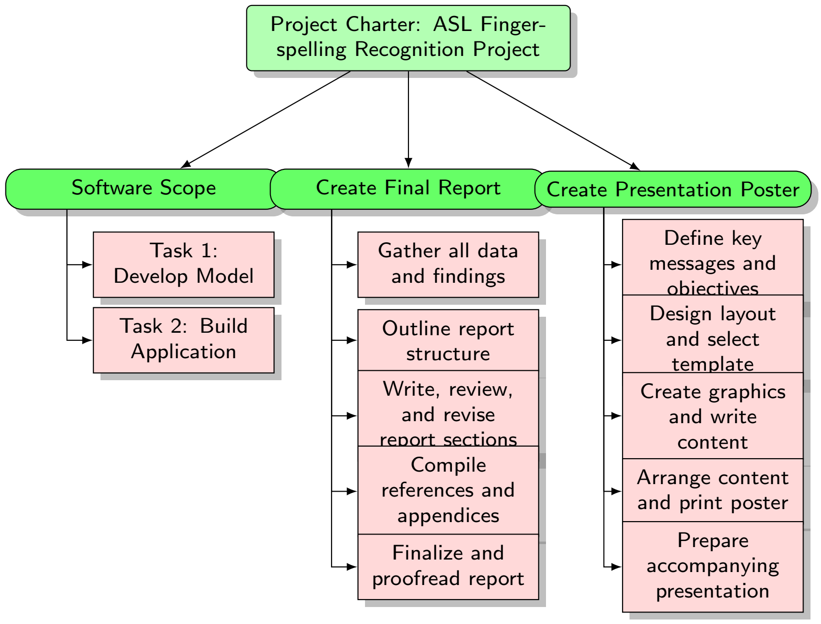

Figure J.3: Work Breakdown Structure

Gantt chart placeholder
(Refer to the accompanying zipped file for the full chart)

Figure J.4: Gantt Chart

In this report's accompanying zipped file, a detailed Gantt chart is included as a separate document. Due to its extensive size and complexity, it is provided as an individual file to facilitate detailed review and ensure clarity. Please refer to the zipped file named gantt-project.png for the complete Gantt chart, which offers an in-depth view of the project timeline and milestones.

Risk	Impact	Probability	Status	Mitigation Strategy
Inaccurate ASL Recognition	High	Medium	Open	Enhance data collection and improve algorithm accuracy.
Data Privacy Concerns	High	High	Open	Implement GDPR compliant data handling processes.
Loss of Data	High	Low	Open	Implement GoogleDrive and GitHub repository.
Loss of Project Supervisor	High	Low	Open	Maintain regular communication with supervisor.
Project Delays	Medium	High	Open	Develop a schedule with buffers and regularly update it.
User Adoption Challenges	Medium	High	Open	Engage with users early and incorporate feedback.
Technology Integration Issues	Medium	Medium	Open	Conduct compatibility testing.

Figure J.5: Risk register

Appendix K. Meetings With Supervisor

Date	Time	Location	Purpose	Description and Actions
15 November 2023	13:00 – 14:00	CCCU - Lg33	Discuss project and literature research	Reviewed current status, discussed challenges, and agreed on next steps including further research on ASL recognition and user-centric approach to requirements. Contact charities
29 November 2023	13:00 - 14:00	CCCU - Lg33	?	?

Appendix L. Agile Development: Timebox 1

Appendix M. Agile Development: Timebox 2

Appendix N. Agile Development: Timebox 3