Fine-Tuning SOTA sEMG Silent Speech Models for Multiple Downstream Tasks

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School of Computing
Final Year Research Project

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Abstract

No more than 300 words summarizing this dissertation.

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Acknowledgements

Thanks.

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Introduction

A gentle reminder not to get this chapter perfect until the dissertation is nearing its completion...

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Chapter 2

Literature Review

2.1 Silent Speech Interfaces for Speech Restoration: A Review

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2.2.1 Text Classification

2.2.2 Data Augmentation

It might be possible to use GANs (Generative Adversarial Networks) or VAEs (Variational Auto Encoders) to create a model which can generate more data samples.

One possible data augmentation method for sEMG based silent speech is to reverse a SOTA transduction model. Existing transduction models for EMG to speech use either EMG features or raw EMG data and transduce it into speech features (typically mel spectrograms or MFCCs). However, it may be possible to predict the EMG data from the mel spectrograms.

2.2.3 Improving Existing Model

Use RL-Learning to find a model which can outperform the original model (problem is small dataset size which means that the benefits of using RL to create a model might not be as applicable to this problem).

Use CapsNet on top of the CNNs to improve the generalisability of the detected EEG features (there are papers which show that these are feasible).

2.3 Connectionist Temporal Classification (CTC)

For any speech recognition task, a model must know the alignment between the input (e.g. audio, EMG features, etc.) and the target transcription. On the surface, this makes training any speech recognition model difficult.

Without having the alignments between the input and the transcription, simpler approaches aren't available to us, such as mapping a single character to a fixed number of inputs. This is because people's rates of speech vary, regardless of the input modality (e.g. audio, EMG features, etc). Another option is to hand-label the alignments between the input and the text transcriptions. This would produce a performant model, however, hand-labeling the alignments is time consuming, especially for larger datasets.

Connectionist Temporal Classification (CTC) is a method to train a model without knowing the alignment between the input and the output and is especially well suited to labeled datasets such as speech recognition.

Chapter 3

Approaches

This chapter will describe the main dataset used for this research, why it was chosen, the main EMG signals of interest from the dataset, methods of feature selection and visualisation and the machine learning approaches used to transcribe the EMG data into a text transcription.

3.1 Data Preprocessing

3.1.1 Audio Speech Features

For the purposes of the fine tuning experiments, the ground truth audio files are preprocessed into mel spectrograms rather than MFCCs as in the original two papers (Gaddy and Klein, 2020, Gaddy and Klein, 2021). The reason for this is because mel spectrograms contain more raw data than MFCCs which makes them more appropriate for speech recognition and also the vocoder used for this paper uses mel spectrograms as the input, as do most SOTA vocoders.

3.2 Fine Tuning Speech Recognition on Model Predictions

The intuition behind fine tuning a speech recognition model on the predicted mel spectrograms predicted by the transduction model comes from the literature for speech recogntion. Typical speech recognition models suffer from a loss of accuracy when they are only trained on clean audio data and then evaluated on a noisy dataset (Amodei et al., 2015).

This issue is also reflected in the transduction task. The state-of-the-art transduction model within the Improved Voicing (Gaddy and Klein, 2021) paper will always produce audio outputs with artefacts because of the final vocoder layer.

This becomes problematic if you want to use the transduction model as a basis for a speech recognition system. This is because most pre-trained speech recognition systems are trained on clean audio datasets.

3.2.1 Closed Vocabulary Dataset

The closed vocabulary dataset is the first dataset used to determine how much better a speech recognition model can be improved by training on the predicted mel spectrograms from an already trained transduction model.

Table 3.1: DeepSpeech2 Silent Speech ASR Results

Dataset	**CER**	**WER**
Ground Truth (GT)	87.10	100.50
Voiced	51.27	87.33
Silent	38.80	78.10
Silent, Voiced	**35.26**	75.33
Silent, Voiced, GT	35.72	**70.83**

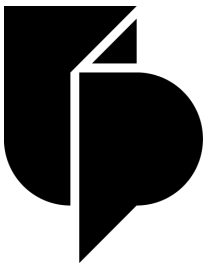
The above results do not use phonemeic prediction and only use greedy decoding in the decoder. DeepSpeech2 is also not the SOTA model for speech recognition which also reduces the performance. This means that the best

WER of 70.83 could be improved upon a lot more.

3.2.2 Open Vocabulary (Parallel-Only) Dataset

Appendix A

Project Initiation Document



UNIVERSITY OF PORTSMOUTH

School of Computing
Project Initiation Document

Tada Makepeace

sEMG Silent Speech Research

Research Project

1. Basic details

Student name:	Tada Makepeace
Draft project title:	sEMG Silent Speech Research
Course:	BSc Computer Science
Project supervisor:	Dr Dalin Zhou
Client organisation:	N/A
Client contact name:	N/A

2. Degree suitability

This project satisfies the criteria for my course as it involves using computer science to solve a novel problem. This project relies on using a custom electronic device, i.e. a surface electromyography (sEMG) device to record electrical signals from a person's facial muscles to be able to convert their speech articulations to either digitally voiced speech (reproducing their voice) or text, without the user having to produce sound or strongly move their facial muscles. This project provides a novel way for humans and computers to interact with one another, in other words, it proposes a novel brain-computer interface (BCI).

This project uses a computer based information processing architecture to process the signals acquired from the BCI device by preprocessing multiple channels of sEMG signals which are recorded from the device and converting the data into a format which is suitable for processing. This is performed by removing the noise from the signal and converting the new data into features which can be used in a machine learning transduction (sEMG to digitally voiced speech) or classification architecture (sEMG to text). Then the features extracted from the processed multi-channel sEMG signal can be used to either reproduce the user's voice as they are speaking, or to just classify the signal into text.

The entire project from end to end uses computer science methods to acquire surface electromyography (sEMG) signals from a user's facial muscles, preprocess the data into a suitable representation as features for a machine learning system and then either feed these features into a transduction model or classification model.

3. Outline of the project environment and problem to be solved

The problem I will investigate is how to classify electrical signals from a person's facial muscles captured using non-invasive surface electromyography (sEMG) into text without them speaking (i.e. silently articulated speech). I believe this project is worth working on because non-invasive silent speech devices are a brain-computer interface which offers unique benefits which other methods do not. A non-exhaustive list of examples is provided below:

Privacy of conversation: Typical speech recognition systems have users broadcast what they're saying to the environment (e.g. issuing commands to an Amazon Alexa device) and therefore privacy is not maintained. A silent speech device does not require the user to say anything aloud, rather they're only required to slightly move their facial muscles to mouth out what they would like to say.

Eavesdropping: Voice interfaces are always listening in on conversations, when not desired, only to be visibly activated later on by a specific trigger-word such as "Ok Google". A silent speech device could avoid this entirely by providing a physical mechanism for the user to start recording what they would like to say instead.

Attention requiring: Existing voice interaction devices have low usability as they require the user to pay full attention to what they're saying and how the device is responding. Also, proximity to the device is required as using any voice system from far away reduces it's effectiveness. Silent speech systems would avoid this issue as they would be directly recording what the user is intending to say directly from the electrodes which are attached to the surface of the skin of the user.

The advantages above will benefit all users of sEMG silent speech systems. However, these systems could also uniquely benefit users who have medical issues which make regular speech difficult such as people who suffer from Multiple Sclerosis with Dysphonia. There has already been promising research into using silent speech devices to help individuals with varying levels of speech impairments which can benefit from silent speech systems, and further research into healthy or unhealthy people will benefit all future users of silent speech systems.

4. Project aim and objectives

The overall aim of this project is to contribute to open-source research concerning sEMG based silent speech systems. This means creating an improved model for sEMG silent speech and acquiring an EMG dataset from participants, including myself, and then open-sourcing the acquired data from each participant who consents to having their data shared in public.

The first and most important objective which will lead to achieving this objective is a combination of using the literature review and open-source code with their datasets to achieve a machine learning model which outperforms the state-of-the-art according to at least a single metric. My initial literature review before starting this project has highlighted the following metrics as being of interest: inference time (milliseconds between the model receiving an input and producing an output) and WER (word-error-rate, a raw measure of the accuracy of the model).

So my initial objectives will be replicating the results of existing sEMG silent speech approaches which are open-source, then creating a model which can either produce a better WER, or to create a model with a similar WER and decrease the inference time of the model. The inference time of the model is important as it can become very uncomfortable for a user using a silent speech system if the system takes more than a few hundred milliseconds to respond. The metrics which I'm optimising along may change depending on how the pilot studies and initial research progress or the direction of research may change entirely.

The second objective is to acquire an OpenBCI device and use it to first acquire EMG data from myself as I will be able to acquire the most data from myself, and then additionally, to acquire EMG data from other participants. The purpose of acquiring data from other participants is to increase the robustness of the model against different people speaking, and this may lead to discoveries for generalising sEMG silent speech technology across different users.

My last objective will be to release my final model and EMG dataset (from consenting participants) as open-source. This means releasing the code and weights of my final model on GitHub, and the EMG dataset using a reliable storage provider who will provide access to the dataset long-term. The specifics regarding the open-sourcing of the model need to be determined as the project progresses, as if the participant refuses to consent to sharing their data, the weights within the trained model would still implicitly contain their data. Related to this objective, I aim to make the model and dataset releases as reproducible as possible by including the code, model, data (consenting participants data, parameters (along with hyperparameters) and environment setup (i.e. using containerisation, etc.) available.

5. Project deliverables

Information system artefacts: Open-source sEMG Silent Speech Machine Learning System
Datasets: Open-source sEMG Silent Speech Dataset (My own sEMG dataset and participants who consent to share their data publically), closed-source sEMG Silent Speech Dataset (Participants who do not consent to share their data publically)
Documentation: Project report

For this research project, the information system artefact will be the machine learning system itself trained with user data and used in conjunction with an OpenBCI device attached to the skin of a user. And the documents which will be produced are the project report which describes the research undertaken, relating to the information system artefact and acquiring data from participants.

6. Project constraints

The key constraint for this project is that it is dependent on using an sEMG device to record EMG data from participants. This requires participants to be physically attached to the device (non-invasively) to make the recordings which means that data can only be gathered from one participant at a time. Also, the data collection process from each participant is time consuming as it may require hours of data from each participant (not including setup, briefing and other mandatory stages). This will limit how many participants can be used within the research because it will take a lot of each individual's time. I will mitigate this by strongly focusing on collecting data from myself in the early stages. This will guarantee I have enough data to train my system and will reduce the amount of data required from other participants.

7. Project approach

The background research I will do for this project will involve how to acquire and set up a surface EMG device as I have no prior experience with EMG / EEG acquisition. However, once I have completed this step, my previous experience in digital signal processing (working with audio datasets with ASR), will help along with looking at the Digital Voicing of Silent Speech code repository to figure out the rest.

I will establish the research direction of this project by finding prior research during my literature review and identifying directions for future research, as well as trying to replicate previous findings for open-source projects which have code and data available. From these open-source projects and the literature, I attempt to implement new methods after reproducing old ones, either by reimplementing methods from one domain into sEMG silent speech, or by innovating entirely new methods. I will also be performing ablation studies (removing components of a system to determine their contribution) during my project to justify the contribution of individual components and the summary of this will be included in the writeup with full details included in the appendix.

After this, I will use my findings from the previous stage in combination with the data I will acquire from participants to create a new model which improves on the metrics found within my literature review. Which metrics I choose will be guided mainly by the initial model prototyping stage as well as the data acquisition stage. The data acquisition stage will be guided by the literature review and initial attempts at improving on different metrics (word-error rate, inference time in ms, etc).

The methodology I will be using in this project will be a combination of the iterative and incremental approaches as that is the current recommended methodology for MLOps (machine learning operations) projects. Although this project is more of an academic research project than an industry service focused one, I still need to create a working demo of my final model (ideally with the OpenBCI device).

This means that I will need a stable working model as I am going along and as I complete the data acquisition stage and parts of my training infrastructure are finalised (e.g. feature selection, training pipeline, data quality checking, etc.), I will be creating automated systems to allow me to just adjust my model or other parts of the system and then start new training runs. The key idea behind the management of this project's artefacts is CACE (changing anything changes everything). This means that tracking code, datasets and models (along with model parameters) is imperative along with combinations of those three is imperative.

8. Literature review plan

The main starting point for my research is the Digital Voicing of Silent Speech paper by David Gaddy and Dan Klein and their further paper An Improved Model for Voicing Silent Speech which improves upon their initial paper. This paper provides the greatest depth of explanation out of any paper along with an accompanying dataset and working code. I will also refer to meta-review papers which sample the entire landscape for sEMG Silent Speech, and silent speech research in general (including fMRI research as taking signals directly from the scalp may also be beneficial).

I will also refer to other seminal works in this field such as the MIT AlterEgo paper released by Arnav Kapur and colleagues as Kapur also released a 60 page thesis which goes into great detail about the biological, biosensing and machine learning aspects of the problem. The paper released by Kapur and colleagues also describes a Convolutional Neural Network (CNN) based model, which is typically used in complex Digital Signal Processing (DSP) problems such as automated speech recognition (ASR) as CNN based models are highly suitable for DSP due to the convolution theorem.

From these papers, I will research papers which are related in the fields of ASR (due to the high overlap between EMG to speech transduction), encoding data into latent space (due to several recent sEMG related papers finding success with this and particularly performant

general models which encode information into latent space and can be used to perform multiple tasks by querying this latent space representation of data).

After reviewing these papers and related fields and methods, I will collate the most relevant methods and any other relevant findings, and I will trial different methods on the open-source dataset released in the Digital Voicing of Silent Speech paper to find what is successful. From this, I will use this information to inform the construction of my own machine learning model which I will use firstly on the Digital Voicing of Silent Speech dataset, then on my own acquired data.

9. Facilities and resources

The main hardware I need for this project is an OpenBCI device which is a relatively cheap, open-source device which is used to record EEG signals and can also be used for recording EMG signals. Depending on which device is used for research, the cost of the device along with electrodes, will be around £500, give or take £150. However, I will need to get this device shipped from either China or the USA, which means I need to account for shipping time as well during this project. The estimated shipping times are around 1 month so this device will need to be ordered as soon as possible in case the shipping is delayed, or the device and it's related components have an issue.

The second most important hardware I need is a modern GPU as I will be training machine learning models using 10s of GBs worth of data. Fortunately I have an RTX 3060 Ti at home which is suitable for at least prototyping machine learning models and I have also built my own library for utilising preemptible (interruptible) cloud processing devices, which means I can use cloud computing for 20% of the price. However, my local GPU should suffice for this project.

10. Log of risks

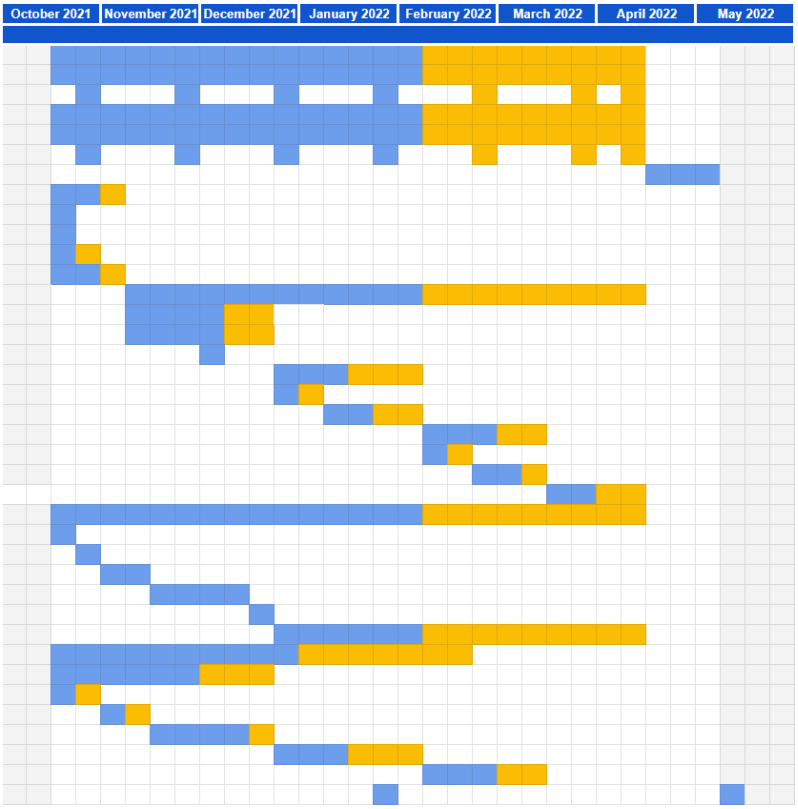
Description	Impact	Likelihood	Mitigation	First indicator
COVID-19 infection risk between research team and participants	*Severe*	*Likely*	*Ask participants if they have any symptoms of COVID-19: high temperature, cough, loss of taste*	*Either the research team starts displaying COVID-19 systems or a participant does after gathering data*
EMG dataset data loss	*Severe*	*Unlikely*	*I will set up automatic encrypted*	*I am unable to access a part of*

			at rest backups for all of the data I gather both locally and on external storage providers	*my gathered data or there is a change in size of the original dataset*
OpenBCI hardware is damaged during testing (electrodes, main device, etc.)	*Severe*	*Unlikely*	*I will personally store the OpenBCI device in my home and only take it out when acquiring data. I will also acquire more electrodes than necessary for backup.*	*Device is either unusable or shows other signs of reporting faulty data or working improperly.*
Ten20 Conductive Paste electrode paste allergy	*Severe*	*Depends on the participant*	*I will not accept any participants who carry a risk of an allergic reaction to the electrode paste. This includes anyone with a history of skin allergies or a history of sensitivity to cosmetics or lotions.*	*Any persistent redness, soreness, burning, itching, or swelling on the skin.*

My plan for reviewing risks will be identifying what risks have already occurred and what new risks may occur based on changes between different revisions of the risk assessment checklist (e.g. if I am unable to acquire a certain electrode paste and have to get a different brand, checking with the manufacturers guidance on skin irritation, etc.)

11. Project plan

Task Name	Duration
Google Calendar Tracking	***15 wks - 6 mths***
Weekly Writeup (Week Conclusions)	15 wks - 6 mths
Project Analysis (Project Statistics)	4 wks - 7 wks
Report Documentation	***15 wks - 6 mths***
Weekly Writeup	15 wks - 6 mths
Writeup Google Calendar Insights	4 wks - 7 wks
Report Finalisation	3 wks
Ethical Approval	***2 wks - 3 wks***
Submit to Supervisor	1 wk
Participant/Project Ethics Documents	1 wk
FEC Discussion (Open-Sourcing)	1 wk
EMG Data Acquisition Decision (Yes, No)	2 wks - 3 wks
sEMG Data Gathering	***12 wks - 19 wks***
Acquire OpenBCI Device	***4 wks - 6 wks***
Shipping Time	4 wks - 6 wks
Check Device Works	1 wk
Personal Data Gathering	***3 wks - 6 wks***
Pilot Data Gathering	1 wks - 2 wks
Main Data Gathering	2 wks - 4 wks
Participant Data Gathering	***3 wks - 5 wks***
Pilot Data Gathering	1 wks - 2 wks
Main Data Gathering	2 wks - 3 wks
Final Data Compilation and Analysis	***2 wks - 4 wks***
Literature Review	***15 wks - 6 mths***
Initial Literature Review Notes	1 wks
Initial Literature Review Draft	1 wk
Novel Approaches Literature Review Notes	2 wks
Test Novel Approaches from Literature	4 wks
Novel Approaches Literature Review Draft	1 wk
Ongoing Literature Review	6 wks - 15 wks
sEMG Model R&D (incl. training time)	***10 wks - 17 wks***
Digital Voicing & Other Datasets	***6 wks - 9 wks***
Data Analysis	1 wk - 2 wks
Reproduce Results	1 wk - 2 wks
Test Novel Approaches from Literature	4 wks - 5 wks
Personal Data (Analysis, Model Training)	***3 wks - 6 wks***
Participant Data (Analysis, Model Training)	***3 wks - 5 wks***
Project Demo Showcases (Progress, Final)	***2 wks***



12. Legal, ethical, professional, social issues (mandatory)

The main security implication of this project is the generation of EMG and possibly audio data unique to each participant. Secure storage and processing of this data is the main security concern and will be achieved by only processing the data on my local device or a trusted cloud computing provider. The data itself will only be named with a unique number instead of any personally identifiable information so if the data is lost, it is not easily identifiable. This will ensure that only I know whose data the unique numbers correspond with. This security obligation is also consistent with the data protection legal requirement.

However, as I intend to open-source as much of this project, including the code and dataset, I will be releasing the data from participants who consent to having their data released publically. This will be added as an additional option in the <> document provided to participants. Participants are fully within their rights to not consent to having their data shared and it will not be included in the open-source model or dataset release. At a minimum I will be releasing the dataset and model which I record of myself, which will likely comprise a large portion of the collected data.

Appendix B

Ethics Review

Certificate of Ethics Review

Project title: sEMG Silent Speech Research

Name:	Tada Makepeace	**User ID**:	904749	**Application date**:	14/10/2021 16:55:45	**ER Number**:	TETHIC-2021-101306

You must download your referral certificate, print a copy and keep it as a record of this review.

The FEC representative(s) for the **School of Computing** is/are **Philip Scott, Matthew Dennis**

It is your responsibility to follow the University Code of Practice on Ethical Standards and any Department/School or professional guidelines in the conduct of your study including relevant guidelines regarding health and safety of researchers including the following:

- University Policy
- Safety on Geological Fieldwork

It is also your responsibility to follow University guidance on Data Protection Policy:

- General guidance for all data protection issues
- University Data Protection Policy

Which school/department do you belong to?: **School of Computing**
What is your primary role at the University?: **Undergraduate Student**
What is the name of the member of staff who is responsible for supervising your project?: **Dr Dalin Zhou**
Is the study likely to involve human subjects (observation) or participants?: Yes
Will peoples` involvement be limited to just responding to questionnaires or surveys, or providing structured feedback during software prototyping?: No
Will the study involve National Health Service patients or staff?: No
Do human participants/subjects take part in studies without their knowledge/consent at the time, or will deception of any sort be involved? (e.g. covert observation of people, especially if in a non-public place): No
Will you collect or analyse personally identifiable information about anyone or monitor their communications or on-line activities without their explicit consent?: No
Does the study involve participants who are unable to give informed consent or in are in a dependent position (e.g. children, people with learning disabilities, unconscious patients, Portsmouth University students)?: No
Are drugs, placebos or other substances (e.g. food substances, vitamins) to be administered to the study participants?: No
Will blood or tissue samples be obtained from participants?: No
Is pain or more than mild discomfort likely to result from the study?: No
Could the study induce psychological stress or anxiety in participants or third parties?: No
Will the study involve prolonged or repetitive testing?: Yes
Will financial inducements (other than reasonable expenses and compensation for time) be offered to participants?: No
Are there risks of significant damage to physical and/or ecological environmental features?: No
Are there risks of significant damage to features of historical or cultural heritage (e.g. impacts of study techniques, taking of samples)?: No
Does the project involve animals in any way?: No
Could the research outputs potentially be harmful to third parties?: No
Could your research/artefact be adapted and be misused?: No
Does your project or project deliverable have any security implications?: No

I confirm that I have considered the implications for data collection and use, taking into consideration legal requirements (UK GDPR, Data Protection Act 2018 etc)
I confirm that I have considered the impact of this work and and taken any reasonable action to mitigate potential misuse of the project outputs

I confirm that I will act ethically and honestly throughout this project

Supervisor Review

As supervisor, I will ensure that this work will be conducted in an ethical manner in line with the University Ethics Policy.

Supervisor's signature: Dalin Zhou Date: 19/10/21

Faculty Ethics Committee Review

Faculty Ethics Committee Member's signature: Date:

Appendix C

DeepSpeech2 ASR Model

```
SpeechRecognitionModel(
  (cnn): Conv2d(1, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
  (rescnn_layers): Sequential(
    (0): ResidualCNN(
      (cnn1): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (cnn2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (dropout1): Dropout(p=0.1, inplace=False)
      (dropout2): Dropout(p=0.1, inplace=False)
      (layer_norm1): CNNLayerNorm(
        (layer_norm): LayerNorm((64,), eps=1e-05, elementwise_affine=True)
      )
      (layer_norm2): CNNLayerNorm(
        (layer_norm): LayerNorm((64,), eps=1e-05, elementwise_affine=True)
      )
    )
    (1): ResidualCNN(
      (cnn1): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (cnn2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (dropout1): Dropout(p=0.1, inplace=False)
      (dropout2): Dropout(p=0.1, inplace=False)
```

```
      (layer_norm1): CNNLayerNorm(
        (layer_norm): LayerNorm((64,), eps=1e-05, elementwise_affine=True)
      )
      (layer_norm2): CNNLayerNorm(
        (layer_norm): LayerNorm((64,), eps=1e-05, elementwise_affine=True)
      )
    )
    (2): ResidualCNN(
      (cnn1): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (cnn2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (dropout1): Dropout(p=0.1, inplace=False)
      (dropout2): Dropout(p=0.1, inplace=False)
      (layer_norm1): CNNLayerNorm(
        (layer_norm): LayerNorm((64,), eps=1e-05, elementwise_affine=True)
      )
      (layer_norm2): CNNLayerNorm(
        (layer_norm): LayerNorm((64,), eps=1e-05, elementwise_affine=True)
      )
    )
  )
  (fully_connected): Linear(in_features=2048, out_features=512, bias=True)
  (birnn_layers): Sequential(
    (0): BidirectionalGRU(
      (BiGRU): GRU(512, 512, batch_first=True, bidirectional=True)
      (layer_norm): LayerNorm((512,), eps=1e-05, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (1): BidirectionalGRU(
      (BiGRU): GRU(1024, 512, bidirectional=True)
      (layer_norm): LayerNorm((1024,), eps=1e-05, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (2): BidirectionalGRU(
```

```
      (BiGRU): GRU(1024, 512, bidirectional=True)
      (layer_norm): LayerNorm((1024,), eps=1e-05, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (3): BidirectionalGRU(
      (BiGRU): GRU(1024, 512, bidirectional=True)
      (layer_norm): LayerNorm((1024,), eps=1e-05, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (4): BidirectionalGRU(
      (BiGRU): GRU(1024, 512, bidirectional=True)
      (layer_norm): LayerNorm((1024,), eps=1e-05, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
  )
  (classifier): Sequential(
    (0): Linear(in_features=1024, out_features=512, bias=True)
    (1): GELU()
    (2): Dropout(p=0.1, inplace=False)
    (3): Linear(in_features=512, out_features=29, bias=True)
  )
)
```

Appendix D

Hyperparameters

Throughout the course of this research, many different machine learning models were trained to evaluate their performance on tasks. During these experiments, the hyperparameters of the individual models were tweaked to improve the performance of the models on the individual tasks. This section lists the final hyperparameters of the individual networks.

D.1 DeepSpeech2 Audio Hyperparameters

Table D.1: DeepSpeech2 Audio Model Hyperparameters

Hyperparameter	Description	Value
n_cnn_layers	Number of CNN block layers	3
n_rnn_layers	Number of RNN block layers	5
n_class	Number of model classes	Vocabulary size
n_feats	Number of CNN block features	128
stride	CNN stride value	2
dropout	Dropout value	0.1
learning_rate	Initial learning rate	5e-4
batch_size	Examples per single minibatch	20
epochs	Number of full dataset training iterations	500

D.2 Silent Speech Transduction Hyperparameters

D.2.1 Initial Fine Tuning Experiments

The hyperparameters for the transduction model were reduced from the original SOTA model due to hardware constraints. In the Additional Reproducability Information of the Improved Voicing (Gaddy and Klein, 2021) paper, they state that to train the full model takes roughly 12 hours on an Nvidia Quadro RTX 6000 which has 24GB VRAM. The GPU I was experimenting on only had 8GB VRAM which meant that I had to halve the number of transformer layers and reduce the hidden dimension size.

Table D.2: SOTA Silent Speech Transduction Model

Hyperparameter	Description	Value
n_transformer_layers	Number of Transformer Encoder layers	3
stride	ResNet Block stride value	1
learning_rate	Initial learning rate	1e-3
batch_size	Examples per single minibatch	32
epochs	Number of full dataset training iterations	80
model_size	Size of hidden dimension for transformer encoder	512

References

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