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| **Université d’Ottawa**  **Faculté de génie** |  | **University of Ottawa**  **Faculty of Engineering** |

**ELG5901 Electrical Engineering Project**

**Final Report**

Cover Page

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**Table of Contents:**

[1. Introduction 2](#_Toc2121097619)

[1.1. Problem Definition 2](#_Toc1828938020)

[1.2. Background 2](#_Toc1025841437)

[1.3. Project Context 2](#_Toc1519414331)

[2. Design Overview 3](#_Toc1527093272)

[2.1. Requirements 4](#_Toc2124545030)

[2.1.1 User Requirements 4](#_Toc169742028)

[2.1.1.1 Functional Requirements 4](#_Toc769893207)

[2.1.2.1 Non-Functional Requirements 4](#_Toc842801429)

[2.1.1 System Requirements 4](#_Toc1698159751)

[2.2. Detailed Design 4](#_Toc958674802)

[2.3. Implementation 7](#_Toc287056129)

[2.4. Testing 7](#_Toc1495364847)

[2.4.1. Data Plan 7](#_Toc1437955398)

[2.4.1.1 Data Collecting 7](#_Toc1420160775)

[2.4.1.2 Data processing 7](#_Toc53970045)

[2.4.1.2.1 Extracting Transcript 7](#_Toc1288214680)

[2.4.1.2.2 Data Segmentation 8](#_Toc926260849)

[2.4.1.2.3 Making Metadata 13](#_Toc1704763857)

[2.4.2 Validation & Verification 14](#_Toc491328431)

[4. Deployment Plan 18](#_Toc142083687)

[4.1. Frontend web development 18](#_Toc1425840596)

[4.2. Backend web development 18](#_Toc1074779456)

[5. Conclusions and Future Works 18](#_Toc157370075)

[6. References 18](#_Toc52077018)

**Table of Figures:**

[**Figure 1: The Project Context of End-to-End Translation** 7](#_Toc124691472)

[**Figure 2: The Flow Chart of End-to-End Translation** 8](#_Toc124691473)

[**Figure 3: Project Prototype** 9](#_Toc124691474)

[**Figure 4: Project System Decomposition** 10](#_Toc124691475)

[**Figure 5: Project Interactions** 10](#_Toc124691476)

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[**Figure 8: Before applying filer-subtitlies.py** 14](#_Toc124691479)

[**Figure 9: After applying filer-subtitlies.py** 14](#_Toc124691480)

[**Figure 10: Before applying wav-Merge.py** 15](#_Toc124691481)

[**Figure 11: After applying wav-Merge.py** 15](#_Toc124691482)

[**Figure 12: The final shape of the dataset** 15](#_Toc124691483)

[**Figure 13: WER Formula** 16](#_Toc124691484)

[**Figure 14 : The model with batch size of 16** 17](#_Toc124691485)

[**Figure 15 : The model with batch size of 8** 17](#_Toc124691486)

[**Figure 16: A Website of End-to-End Speech Translation in the Egyptian Dialect** 18](#_Toc124691487)

[**Figure 17: Uploading an Egyptian audio file and translating it into English text.** 18](#_Toc124691488)

[**Figure 18: Recording an Egyptian voice from the browser and translating it into English text.** 19](#_Toc124691489)

[**Figure 19: Adding an audio on the browser after recording** 19](#_Toc124691490)

**Table of Tables:**

[**Table 1: The Results of our model with Fine Tuning** 15](#_Toc124691846)

**Acronyms**

AI: Artificial intelligence

ASR: Automatic Speech Recognition

MSA: Modern Standard Arabic

MT: Machine Translation

GRU: Gated Recurrent Units

CNN: convolutional Neural Networks

RNN: Recurrent Neural Networks

TCEN: Tandem Connectionist Encoding Network

LSTM: Long Short-Term Memory

WER: Word Error Rate

VSE: Video-Subtitle-Extractor

# 1. Introduction

## **1.1. Problem Definition**

According to there is a high Demand on Egyptian dialect language translation, facing a problem as people even who are Arabic native speakers but not a specialist in Arabic cannot speak Arabic (MSA) for a long time without switching to their own dialect and there is no speech translation model based on the end-to-end architecture for the Egyptian dialect language, so we will deploy a model that can be supported as a service to understand Egyptian dialect. Our project is based on identifying the human voice audio extracted from films and YouTube videos and converting them into text to make communication easier.

## **1.2. Background**

End-to-end learning is the process of training a potentially complicated learning system represented by a single model particularly, a Deep Neural Network that represents the whole target system, excluding the intermediary layers that are typically present in standard pipeline designs. We discovered that academics have been working on deep learning techniques such as CNN models that can handle sequential data, the encoder-decoder model, and RNN models that do not need enormous parallel data sets to translate these languages. RNN-based approaches have been used to study speech recognition. RNNs come in two major varieties: GRU and LSTM. techniques centred on manual feature extraction, neural networks, RNNs and CNNs, and more recently transformers, which have demonstrated remarkable results on ASR. The studies that were pertinent to our subject lacked data, as we discovered.

There are many similarities between the areas of automated speech recognition (ASR) and machine translation (MT), including their conceptual foundations, continuous research interests, remarkable developments over the past two decades, and the extensive adoption that has followed. Both ASR and MT require improvement and, as a result, may not always yield reliable results. To create speech translation applications, MT and voice recognition algorithms that have each been trained using different datasets are typically integrated. Once the recognizer has sent all its errors to the MT system, it then adds its own errors. When errors combine, the results are typically catastrophic. Systems for text-to-text translation and speech recognition have advanced in recent years, thanks to the development of both hardware and software technologies. However, voice translation is most frequently carried out using a combination of speech recognition and machine translation technology. This project aims to develop an end-to-end speech translation system.

In [1] This project demonstrates that, when all systems are implemented using the Transformer architecture, the end-to-end speech translation system outperforms the concatenation of speech recognition and machine translation systems.

In [2] A popular topic in recent years, end-to-end speech translation tries to use an end-to-end paradigm to convert a segment of audio into a particular language. Traditional methods make use of techniques for multi-task learning, and pre-training is inadequate for this task due to the enormous time difference between pre-training and fine-tuning. They suggest a Tandem Connectionist Encoding Network (TCEN), which closes the gap by pre-training the attention module, reusing all subnets in fine-tuning, and maintaining the functions of subnets.

They propose two simple but effective methods to ensure that the semantic representation and sequence length of the voice encoder outputs, and the MT encoder inputs are consistent. Regardless of the model's underlying principles, experimental data show that our model significantly improves En-De and En-Fr translation.

In [3], they suggested using CNN and BiGRU along with an attention mechanism to perform MT between English and Arabic texts. By leveraging our corpora to identify the most important words in the input sentences, our approach will help Arabic MT perform better. The model used for this study, however, was only able to accept text input from users; there was no way to translate voice messages into the Egyptian dialect.

In [4], there a framework to translate the Jordanian dialect into Modern Standard Arabic (MSA) using Deep Learning the RNN encoder-decoder model, which provided superior results on the level of our manually created dataset. The framework in this research was limited for Jordanian dialect into Modern Standard Arabic Not Egyptian Dialect language and the user cannot enter an audio as an input to system just a text.

## **1.3. Project Context**

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| ***End-to-End Translation System***  *Audio in Egyptian Dialect*  *Translated text in English* |
| **Figure 1: The Project Context of End-to-End Translation** |

we used the open-source, free tool Video-subtitle-extractor (VSE) to extract subtitles from videos that don’t contain their transcripts. We used "the subtitle-Edit" tool for applying the data segmentation and cutting the Egyptian audios into a smaller length and exporting its sentences in the file (\*.txt). we used libraries to deal with audio signals and process them like "Librosa" to reduce the noise also, we used "Figma" design tool and "Adobe XD" to design our prototype. Finetuned Speech Translation model called "Whisper" also needed "the Hugging Face trainer" to define the training arguments during tuning the whisper model, and We used the "Flask tool" in the deployment phase and pushed our model onto a “hugging face web” to make the connection between the flask and our model easy to respond to translation. Lastly, because of the lack of resources we needed to work on "Saturn Cloud" to get the benefits of stronger processing power.

# 2. Design Overview

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| **Figure 2: The Flow Chart of End-to-End Translation** |

## **2.1. Requirements**

There is a big problem in the translation of Egyptian dialect speech as it considered as a low source language so, we followed some steps that included user and system requirements to provide a clear image of the problem to reach the optimal solution.

### **2.1.1 User Requirements**

#### **2.1.1.1 Functional Requirements**

In this section, we provided a series of operations to get our solution, which include:

* Collecting Data in order to have a dataset
* Applying preprocessing on the data using feature extraction techniques such as MFCC
* Training our model on a big-scale data
* Pushing our championed model on hugging face web.
* Creating the web interface
* Connecting the web Interface with the championed model to get out the English translation.

#### **2.1.2.1 Non-Functional Requirements**

We followed collection of steps to reach the optimal solution;

* Putting data as Egyptian videos in a suitable form.
* Using the open-source, free tool VSE to extract subtitles from Egyptian videos which haven’t contain their English transcripts.
* Using subtitle edit program which helped us to cut the audios in a professional way and extract their subtitles.
* Making the metadata file, each record in the metadata consists of the audio name and its translation.
* Maintain the data (segment it with a bigger length)
* How to process data for speech translation
* Reading papers to choose the suitable end to end speech recognition pretrained model.
* Training data with the suitable pretrained model.

### **2.1.1 System Requirements**

* Processing power needed (GPU).
* Framework versions
* Transformers 4.26.0.dev0
* Pytorch 1.11.0
* Datasets 2.1.0
* Tokenizers 0.12.1
* Ffmpeg version 4

## **2.2. Detailed Design**

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| **Figure 3: Project Prototype** |

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| **Figure 4: Project System Decomposition** |

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| **Figure 5: Project Interactions** |

## **2.3. Implementation**

In order to meet our requirements after many experiments and to get the benefits of transfer learning (save resources and improve efficiency) we chose to fine-tune Whisper model developed by OpenAI, which is trained on a large dataset of audio recordings to generate realistic speech and audio. Because among all the models that trained on Arabic it has the least error rate (18.1). The Whisper architecture is end-to-end approach, and an encoder-decoder model based on Transformers, often known as a sequence-to-sequence model. It converts a series of audio spectrogram features into a series of text tokens. The feature extractor first converts the raw audio inputs to a log-Mel spectrogram. The spectrogram is then encoded by the Transformer encoder to generate a series of encoder hidden states. Finally, the decoder anticipates text tokens based on both the preceding tokens and the encoder's concealed states.[5]

We'll fine-tune the small checkpoint version with 244M parameters (= 1GB). In terms of data, we'll train and test our system using our own dataset of Egyptian dialect which is low-source language.

We used transformers to load and train our version of Whisper model.

* We loaded Feature Extractor, Tokenizer and Data Whisper model has specific feature extractor and tokenizer, called WhisperFeatureExtractor and WhisperTokenizer respectively. Using The data collator for a sequence-to-sequence speech model that treats the input\_features and labels independently
* The input\_features are padded to 30s and converted to a log-Mel spectrogram of fixed dimension by action of the feature extractor and convert the input\_features to batched PyTorch tensors.
* For un-padded labels, we first pad the sequences to the maximum length in the batch using the tokenizer's pad method, then cut the BOS token from the start of the label sequence as we append it later during training.
* Define the training configurations using Hugging Face Trainer in constructing the training schedule

max\_steps

save\_steps

learning\_rate=1e-5 "The initial learning rate for AdamW optimizer"

train\_batch\_size

eval\_batch\_size

metric\_for\_evaluation

We trained our model with different values for arguments and different sizes of data

## **2.4. Testing**

### **2.4.1. Data Plan**

#### **2.4.1.1 Data Collecting**

We collected our data from multiple sources on websites as there weren’t sources for Egyptian dialect datasets, so, we extracted the English transcripts from 400 hours of Egyptian videos.

#### **2.4.1.2 Data processing**

##### **2.4.1.2.1 Extracting Transcript**

We extracted the videos, some with their transcripts and others without transcripts, so, we used the open-source, free object detection tool named Video-subtitle-extractor (VSE) as shown in figure 6 which detects the transcript from the film to extract subtitles from videos which don’t contain their transcripts.

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| **Figure 6:** **Video-subtitle-extractor (VSE)** |

##### **2.4.1.2.2 Data Segmentation**

After collecting the data, we used “subtitle Edit” tool as shown in figure 7 for applying the data segmentation process to filter the data and cutting the Egyptian videos into small audio maximum 15 seconds in length and exporting their sentences to files (\*.txt).

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| **Figure 7:** **Subtitle Edit 3.6.7** |

For data segmentation, we created a python script "srt-resync.py" for synchronization issues, as there was a synchronization between the audio and its translation, where the voice comes before the translation, or the translation comes before the voice.

Some transcripts contained words that didn’t in Egyptian videos as shown in figure 8, so we also created a python script "filter-subtitles.py" for:

1. Remove font tags and text contained within, e.g. <font color="#DF01D7">Hey\</font> is removed.
2. Remove subtitle entries containing asterisks: \*.
3. Remove subtitle lines containing ♪ or #
4. Remove sound effects: text contained with and including parenthesis (BANG) and brackets [boom].
5. Replace names with dashes, e.g. GARY: Hey or Gary: Hey to - Hey.
6. Remove author tags e.g. XoXo Subtitles by PwnedDude967 XoXo.
7. Fix erroneous comma spacing, e.g.

Hey, what's up? Nothing,my man

to

Hey, what's up? Nothing, my man.

1. Remove lone symbols such as, ?, -, #, \_.

So, we can filter subtitles as shown in figure 9.

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| **Figure 8: Before applying filer-subtitlies.py** |

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| **Figure 9: After applying filer-subtitlies.py** |

There was audio in the data for less than 5 seconds, so we made a Python script (wav-Merge.py) to merge that audio together to make the model get better results. As shown in figure 10 and 11.

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| **Figure 10: Before applying wav-Merge.py** |

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| **Figure 11: After applying wav-Merge.py** |

##### **2.4.1.2.3 Making Metadata**

For making the metadata, we used python script (MateData-make.py) for renaming wav files and making a Metadata file (\*.txt) that contains the wav file name and its transcript.

And this is the final shape of our dataset after data segmentation as shown in Figure 12.

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| **Figure 12: The final shape of the dataset** |

### **2.4.2 Validation & Verification**

For Evaluating our model, we used the WER metric it is a measure of how accurate an Automatic Speech Recognition system performs

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| **Figure 13: WER Formula** |

* Where:
  + S is the number of substitutions,
  + D is the number of deletions,
  + I is the number of insertions,
  + C is the number of correct words,
  + N is the number of words in the reference (N= S+D+C)

Factors that can affect the WER without necessarily reflecting the capabilities of the ASR technology itself, so it is okay to have a word error rate above 100

* Recording quality
* Microphone quality
* Speaker pronunciation
* Background noise
* Unusual names, locations, and other proper nouns
* Technical or industry-specific terms

First, we got our baseline -in order to compare it with our results-by testing the whisper pretrained model on our data –6 hours- and we got a WER with a value 121.657, And the model did not recognize most he audios language correctly

Second, we defined a function “compute\_metrics" that:

* takes our model predictions and returns the WER metric.
* replaces -100 with the pad\_token\_id in the label\_ids
* decodes the predicted and label ids to strings.
* computes the WER between the predictions and reference labels on test data "6h"

**3. Overall Results and Analysis**

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| |  |  |  |  | | --- | --- | --- | --- | | No. Of Trained Hours | Batch size | Max steps | Results (WER) | | 5 | 8 | 4000 | 125 | | 20 | 8 | 4000 | 112 | | 30 | 8 | 3000 | 116.6 | | 30 | 16 | 4000 | 104.1 | |
| **Table 1: The Results of our model with Fine Tuning** |

We trained our model with the max hours that our resources could handle which is 30H for training and 6 H for testing with different batch size once 8/batch, and another with 16/batch and we got that:

* The model with batch size of 16 gave us 104.12 WER and the validation loss decreased which means the model converges –figure 14

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| **Figure 14 : The model with batch size of 16** |

* The model with batch size of 8 gave us 116.6 WER and, the validation loss increased which means the model had an overfitting problem- figure 11

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| **Figure 15 : The model with batch size of 8** |

# 4. Deployment Plan

After selecting the Champion model, we built a website with a usable interface for the end user as shown figure 9. So, the user has two options to translate Egyptian speech into English text. This website includes two components: The Frontend and the Backend.

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| **Figure 16: A Website of End-to-End Speech Translation in the Egyptian Dialect** | |

## **4.1. Frontend web development**

We used HTML, CSS, JavaScript, jQuery, and Bootstrap to build the design of the website, so that users could view and interact with it. Through it, the user can upload an Egyptian audio file that has an extension, such as wav, mp3, flac, and others and translate an Egyptian audio into English text as shown in figure 10.

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| **Figure 17: Uploading an Egyptian audio file and translating it into English text.** | |

In addition, the user can record Egyptian voices from the browser by following the steps shown in Figure 11:

1. The user presses the button "Record from browser" and talks with his or her voice. The title of that button changes to "Click to stop recording".
2. To stop his or her recording, the user can press the button "Click to stop recording,"
3. After recoding, audio appears on the browser, so the user can download and remove it from the browser and submitting his or her Egyptian voice to our model to translate into English text.

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| **Step 1** |  |
| **Step 2** |  |
| **Step 3** |  |
| **Figure 18: Recording an Egyptian voice from the browser and translating it into English text.** | |

## **4.2. Backend web development**

We used the Flask library to interconnect our model with the website to show the results of Egyptian speech translation. After training, we pushed our model onto a hugging face web to make the connection between the flash library and our model easy to respond to translation.

We wrote a Python script called "Main.py" that takes Egyptian audio or recordings, sends them to our model on the hugging face web, and returns the translation as English text in 38.683963775634766-mile seconds. We created a script to make the user hear the Egyptian sound before the translation when the Egyptian audio file is uploaded. And we created a script that adds audio with options such as download and remove buttons on the browser as shown in figure 12.

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| **Figure 19: Adding an audio on the browser after recording** |

# 5. Conclusions and Future Works

We got to gain more depth into the practical aspects End-to-End Architectures, Transfer learning, Automatic Speech Translation (AST), and Hugging Face Transformers Hugging Face, to fine-tune the Whisper model, which is trained on a large dataset of audio recordings to generate realistic speech and audio for first time on the Egyptian dialect with our own dataset and got results with 104,1 WER.

Our future work will be evaluating our model using the Bilingual Evaluation Understudy and training our model on the entire 400 H of data

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