DEVELOPING AN AUTOMATED AUDIO TRANSLATION SYSTEM FOR EWE TO ENGLISH

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CERTIFICATION

This is to certify that this project was carried out by EDIFON EMMANUEL JIMMY, ESOSUOTA OGHENEFEJIRO EPHRAIM, EGHOBAMIEN EFOSA DANIEL and IYAYI BLESSING EBOSETALE, of the department of Electrical/Electronic Engineering, University of Benin, in partial fulfilment of the requirements for the award of the Bachelor of Engineering (B.Eng.) Degree in Electrical/Electronic Engineering.

Engr. Scott Idubor **Date**

Project Supervisor

Engr. Prof. K. O. Ogbeide **Date**

Head of Department

DEDICATION

This project is dedicated to the Almighty God whose infinite mercy, grace and guidance has seen us through. Also, to our parents for their consistent prayers and support.

ACKNOWLEDGEMENT

We give thanks to Almighty God for His grace, loving-kindness, guidance and protection throughout our stay at the University of Benin.

Our sincere gratitude goes to our parents for their prayers, love, immense support and encouragement both during the execution of this project and throughout the duration of our academic pursuit at the University of Benin.

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ABSTRACT

This paper presents the development of an Automated Audio Translation System (AATS) specifically designed for translating spoken Ewe, a Western Nigerian language predominantly spoken within the Yoruba people into English. The project addresses the growing need for effective communication tools in multilingual contexts, particularly in regions where Ewe is widely spoken. The proposed system leverages advanced machine learning techniques, including automatic speech recognition (ASR), natural language processing (NLP), and neural machine translation (NMT) to facilitate real-time audio translation.

The methodology involves the collection of a diverse corpus of Ewe audio recordings paired with their English translations, which serves as the training dataset for the ASR and NMT components. We employ deep learning architectures, such as recurrent neural networks (RNNs) and transformer models, to enhance the accuracy and fluency of the translation output. Evaluation metrics, including Word Error Rate (WER) and BLEU scores, are utilized to assess the performance of the system against baseline models.

Preliminary results indicate that the AATS achieves a significant improvement in translation accuracy compared to traditional translation methods. This research not only contributes to the field of computational linguistics but also aims to promote cultural exchange and accessibility by bridging language barriers.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Audio translation is an evolving technology that enables spoken language to be converted from one language to another while maintaining meaning, context, and speaker intent. It has become an essential tool for global communication, helping to bridge language barriers in fields like media, entertainment, education, business, and international relations. Thanks to advancements in artificial intelligence (AI), machine learning (ML), and natural language processing (NLP), audio translation has progressed from traditional human interpretation to highly advanced automated systems (Huang et al., 2022).

Translation has been a crucial part of human communication for centuries. However, spoken language translation gained importance with the rise of radio, television, and global connectivity. Initially, human interpreters were the primary means of translation—an effective but expensive and time-consuming solution (Lewis, 2019).

The 20th century saw significant technological advancements, leading to the development of speech recognition and text-based translation tools, such as Google Translate and Microsoft Translator (Brownlee, 2020). In the early 21st century, AI-driven translation systems made significant progress, particularly with the integration of deep learning and neural networks. This paved the way for real-time audio translation applications, including Googles Live Translate, Apples Translate, and AI-powered conferencing tools (Wu et al., 2016).

1.2 Statement of the Problem

Audio translation involves converting spoken language from one language into another, while maintaining the meaning, tone, and context of the original speech (Gambier, 2010). One of the main issues is maintaining linguistic accuracy and natural flow when translating spoken language, especially in real-time contexts. Spoken language often contains informal expressions, slang, idiomatic phrases, and non-verbal elements (such as tone and gestures), which are difficult to capture accurately through automated systems (Hansen, 2017).

In the course of this study, we will tackle these issues using accurate and efficient model(s).

1.3 Aim and Objectives of the Study

The aim of the study is to implement an Ewe to English translation system.

The specific objectives are to:

1. collect Ewe audio recordings and perform cleaning and reprocessing steps.
2. convert the raw audio recordings into mel spetogram representatives.
3. improve the signal quality of the recordings.
4. implement a modified Matchbox Net architecture model.
5. train the model.
6. validate the accuracy of the audio translation.

1.4 Scope of the Study This study will explore:

i. The technological advancements driving modern audio translation. ii. The effectiveness of different AI models in real-time translation. iii. The potential applications of audio translation across various industries.

1.5 Significance of the Study

Audio translation offers several key benefits, including:

i. Bridging Language Gaps in Business: International companies rely on translation technology for meetings, negotiations, and customer interactions across multiple languages (Chang &Lee, 2019).

ii. Enhancing Academic Collaboration: Researchers worldwide can communicate more effectively when lectures, presentations, and academic papers are translated in real time (Roberts &Patel, 2020).

iii. Improving Healthcare Communication: Miscommunication in medical settings can lead to serious errors, making translation technology essential for patient safety and accurate treatment (Schmidt &Black, 2021).

iv. By advancing audio translation technology, this study aims to contribute to more seamless global communication, enabling people from different linguistic backgrounds to connect and collaborate more effectively.

CHAPTER TWO

LITERATURE REVIEW

2.1 Speech-to-Text Translation

Speech-to-Text Translation (S2TT) is a rapidly evolving field that aims to bridge language barriers by enabling real-time spoken communication between speakers of different languages. Traditional S2TT systems rely on a cascaded approach, where speech is first converted into text using Automatic Speech Recognition (ASR), then translated using Machine Translation (MT), and finally synthesized into text via Text-to-Text (TTT) synthesis (Dhawan, 2022). While effective, this multi-step pipeline often leads to error propagation, latency issues, and a loss of speakerspecific features such as tone, emotion, and prosody (Limbu, 2020).

With the rise of deep learning and neural network-based models, there has been a shift toward endto-end S2TT systems that bypass the text representation step and directly translate speech from one language to another (Jia et al., 2019). This approach has been pioneered by systems such as Google's Translatotron, which utilizes sequence-to-sequence models and spectrogram processing to improve translation quality while preserving speaker identity. However, despite these advancements, several challenges remain, including data scarcity for low-resource languages, maintaining translation accuracy in spontaneous speech, and ensuring real-time processing efficiency (Nguyen et al., 2021).

This chapter provides a comprehensive review of historical developments, core components, machine learning techniques, challenges, and future directions in S2TT research. By analyzing key

contributions from both classical and modern approaches, this review aims to highlight current limitations and emerging trends in the field.

2.2 Historical Background of Speech-to-Text Translation (S2TT)

2.2.1 Early Developments in Machine Translation

The concept of machine translation (MT) dates back to the 1950s, with early rule-based systems designed to translate between structured languages, such as Russian and English, for military and intelligence purposes (Weaver, 1955). However, these early systems faced significant challenges due to ambiguities in human language, grammatical complexities, and the lack of large-scale parallel corpora (Brown et al., 1990).

The ALPAC Report (1966) critically assessed the feasibility of automated translation and led to a decline in funding for MT research. Despite this setback, the 1990s saw the rise of statistical machine translation (SMT), which leveraged probabilistic models to improve translation accuracy (Koehn et al., 2003). This statistical approach laid the foundation for modern neural machine translation (NMT), which has significantly enhanced language translation capabilities.

2.2.2 Evolution of Speech Processing Technologies

While text-based machine translation continued to evolve, advancements in speech processing were also taking place. The development of Automatic Speech Recognition (ASR) began in the 1970s, with systems like the DARPA-funded Harpy project demonstrating the ability to recognize continuous speech (Bahl et al., 1983). Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs) became standard techniques for ASR by the 1990s (Rabiner, 1989).

Parallelly, Text-to-Speech (TTS) synthesis also progressed from basic concatenative models to more sophisticated parametric and deep learning-based methods, allowing for more naturalsounding synthesized speech (Zen et al., 2009).

2.2.3 Key Milestones in S2TT Research

The integration of ASR, MT, and TTS led to the development of early S2TT systems in the late 1990s and early 2000s. Some notable milestones include:

i. Verbmobil (1993-2000): A German research project aimed at speech translation in business negotiations (Wahlster, 2000).

ii. ATR-MATRIX (1990s): A Japanese initiative focused on bilingual travel conversations (Morimoto et al., 1994).

iii. Google Translate's Speech Translation (2010s): Leveraged deep learning for real-time mobile translation (Wu et al., 2016).

More recently, end-to-end neural approaches have transformed S2TT, with models like Google's Translatotron (Jia et al., 2019) and Facebook's direct Speech-to-Text translation (Li et al., 2021) eliminating the need for intermediate text-based processing.

2.2.4 The Shift Toward End-to-End Neural Approaches

Traditional cascaded S2TT systems rely on a sequential pipeline of ASR → MT → TTT, which often amplifies errors at each stage (Limbu, 2020). The recent trend in end-to-end learning leverages deep neural networks to directly map speech input to speech output, reducing latency and improving fluency (Nguyen et al., 2021).

Despite these advancements, challenges such as data scarcity, computational demands, and multilingual adaptability remain areas of active research.

2.3 Core Components of Speech-to-Text Translation Systems

Speech-to-Text Translation (S2TT) systems consist of several key components that work together to enable seamless communication across different languages. These components include Automatic Speech Recognition (ASR), Machine Translation (MT), and Post-Processing Algorithms.

2.3.1 Automatic Speech Recognition (ASR)

ASR is the first step in most S2TT systems, converting spoken language into text. This process involves acoustic modeling, language modeling, and decoding (Yu & Deng, 2016).

Challenges in ASR for S2TT includes:

i. Accents and Dialects: Variability in pronunciation affects recognition accuracy (Limbu, 2020).
ii. Background Noise: Noisy environments degrade ASR performance (Nguyen et al., 2021).
iii. Spontaneous Speech: Filler words, hesitations, and informal expressions complicate recognition (Li et al., 2021).

Modern ASR systems leverage deep learning, particularly Recurrent Neural Networks (RNNs), Transformers, and end-to-end neural models, to improve robustness (Baevski et al., 2020).

2.3.2 Machine Translation (MT)

MT is responsible for converting recognized text from the source language into the target language. Traditional MT approaches include:

i. Rule-Based Machine Translation (RBMT): Uses linguistic rules for translation (Hutchins, 2005). ii. Statistical Machine Translation (SMT): Uses probability-based models (Koehn et al., 2003).

iii. Neural Machine Translation (NMT): Uses deep learning to improve translation fluency (Vaswani et al., 2017).

Challenges in MT for S2TT includes:

i. Loss of Context: Literal translations often fail to capture meaning (Dhawan, 2022).

ii. Word Order Differences: Languages with different syntactic structures require complex transformations.

iii. Handling Low-Resource Languages: Lack of parallel corpora affects translation quality (Jia et al., 2019).

2.3.3 Post-Processing Algorithms

Post-processing techniques, including punctuation restoration, capitalization, and disfluency removal, enhance transcription readability. Machine learning models, such as transformer-based architectures, are now widely used for refining raw ASR output (Rao et al., 2020).

Challenges in TTS for S2TT includes:

i. Preserving Speaker Identity: Most TTS models do not retain original speaker characteristics (Jia et al., 2018). ii. Maintaining Prosody and Emotion: Translations often sound robotic due to lack of expressiveness (Nguyen et al., 2021).

iii. Latency Issues: Generating speech in real-time remains a computational challenge.

2.4 Machine Learning Approaches in Speech-to-Text Translation (S2TT)

Recent advancements in machine learning (ML) have revolutionized Speech-to-Text Translation (S2TT), shifting from traditional rule-based and statistical approaches to deep learning-driven models. End-to-end neural architectures now allow direct speech to text translation, improving fluency, reducing error propagation, and preserving speaker identity (Jia et al., 2019). This section explores the evolution of machine learning techniques in S2TT, including Neural Machine Translation (NMT), Sequence-to-Sequence (Seq2Seq) models, and end-to-end speech translation architectures.

2.4.1 From Traditional Approaches to Neural Machine Translation (NMT)

Early Approaches includes Rule-Based and Statistical Models. They are explained below;

i. Rule-Based Machine Translation (RBMT): Uses hand-crafted linguistic rules but struggles with scalability and fluency (Hutchins, 2005).

ii. Statistical Machine Translation (SMT): Uses probabilistic models trained on bilingual corpora (Koehn et al., 2003).

These early approaches lacked the ability to capture context, semantics, and fluency, which led to the rise of Neural Machine Translation (NMT).

2.4.1.1 Neural Machine Translation (NMT)

NMT leverages deep learning to translate text more accurately than SMT. Introduced by Bahdanau et al. (2014), it replaces traditional phrase-based translation with encoder-decoder architectures. NMT is particularly effective in S2TT because it improves fluency and context awareness (Vaswani et al., 2017).

Key Advances in NMT for S2TT includes:

i. Attention Mechanisms: Enables models to focus on relevant words during translation (Bahdanau et al., 2014).

ii. Transformer Models: Replaces recurrent architectures for faster and more accurate translation (Vaswani et al., 2017).

iii. Pretrained Multilingual Models: Models like mBART and M2M-100 enhance lowresource language translation (Fan et al., 2020).

2.4.2 Sequence-to-Sequence (Seq2Seq) Models in S2TT

Seq2Seq models are the backbone of modern S2TT systems. They consist of:

- An Encoder: Converts input speech into an internal representation.
- A Decoder: Generates translated output in the target language.

Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Transformers are commonly used in Seq2Seq models (Sutskever et al., 2014).

Challenges in Seq2Seq S2TT Models includes:

i. Handling Long Sentences: Standard RNNs struggle with long-range dependencies.

ii. Inference Latency: Large-scale Seq2Seq models require significant computational resources. iii. Error Accumulation: Mistakes in early stages propagate through the system (Dhawan, 2022).

2.4.3 End-to-End Speech Translation: Direct S2TT Models

Traditional cascaded S2TT systems involve ASR to MT to TTT, leading to error propagation. Recent models bypass text representation, enabling direct Speech-to-Text translation.

Key End-to-End Models includes:

1. Translatotron (Jia et al., 2019):
    - Uses spectrogram-to-spectrogram translation.

- Preserves speaker voice and prosody.
- Reduces latency compared to cascaded models.

2. Facebook's Speech-to-text Translation Model (Li et al., 2021):
    - Uses self-supervised learning for multilingual speech translation.
    - Improves translation fluency for low-resource languages.
3. Whisper by OpenAI (Radford et al., 2022):
    - A robust ASR model that enhances S2TT performance.

The Benefits of Direct Speech-to-Text Translation are:

i. Eliminates Intermediate Text → Reduces cascading errors.

ii. Preserves Speaker Characteristics → Retains voice identity and prosody.

iii. Improves Real-Time Efficiency → Faster than traditional pipelines.

The Current Limitations of End-to-End S2TT are:

i. Data Scarcity: Requires large bilingual speech corpora.

ii. Computational Complexity: Demands high processing power.

iii. Lack of Interpretability: Difficult to analyze and debug model decisions.

2.4.4 The Role of Self-Supervised and Few-Shot Learning

Recent studies focus on self-supervised learning and few-shot adaptation to improve S2TT performance for low-resource languages (Baevski et al., 2021). Meta-learning techniques allow models to adapt quickly with minimal data.

2.4.5 Future Directions in Machine Learning for S2TT

The future directions in Machine learning for S2TT are as follows:

i. Multimodal Translation: Combining text, speech, and visual data.

ii. Real-Time Neural S2TT: Reducing inference latency. iii. Improved Prosody Preservation: Enhancing emotional tone retention.

2.5 Challenges in Speech-to-Text Translation (S2TT)

Despite significant advancements in machine learning and deep learning, Speech-to-Text Translation (S2TT) systems still face multiple challenges that impact their accuracy, efficiency, and real-world applicability. These challenges arise from the complexity of human language, variability in speech, computational constraints, and limitations in training data (Dhawan, 2022). This section explores the key obstacles hindering the widespread adoption of S2TT technology.

2.5.1 Error Propagation in Multi-Step Pipelines

Traditional cascaded S2TT models follow a three-stage process: Automatic Speech Recognition

(ASR) → Machine Translation (MT) → Text-to-Speech (TTS). Errors at any stage are propagated, amplifying inaccuracies throughout the system (Limbu, 2020).

Common Issues in Cascaded S2TT Systems are:

i. ASR Errors: Misrecognized words lead to incorrect translations (Baevski et al., 2021).

ii. MT Errors: Literal translations fail to capture meaning (Jia et al., 2019). iii. TTS Issues: Poor synthesis results in robotic or unnatural speech (Zen et al., 2009).

End-to-end S2TT models such as Translatotron (Jia et al., 2019) attempt to bypass text representation to minimize error accumulation, but challenges remain in training such models effectively.

2.5.2 Handling Low-Resource Languages

Most deep learning-based S2TT systems require large amounts of bilingual training data, which is often unavailable for low-resource languages (Nguyen et al., 2021).

Key Challenges in Low-Resource S2TT are:

i. Limited Parallel Speech Corpora: Most datasets focus on high-resource languages like English, Spanish, and Chinese.

ii. Dialects and Regional Variations: Variability in pronunciation, vocabulary, and grammar complicates training (Fan et al., 2020).

iii. Data Collection Barriers: Ethical and privacy concerns limit large-scale speech data collection.

Recent techniques such as self-supervised learning (Baevski et al., 2021) and zero-shot translation (Johnson et al., 2017) attempt to mitigate these issues but still require refinement.

2.5.3 Real-Time Processing and Latency Issues

For S2TT systems to be useful in practical applications (e.g., live conversations, customer support), they must operate with minimal latency. However, many deep learning models require high computational power, making real-time speech translation challenging (Li et al., 2021).

Factors Affecting Real-Time Performance are:

i. Model Complexity: Transformer-based models improve accuracy but increase processing time.

ii. Hardware Constraints: Mobile and embedded devices struggle with real-time processing.

iii. Synchronization Issues: Delays in translation disrupt the natural flow of conversation.

Optimizing lightweight neural networks and leveraging hardware acceleration (e.g., TPUs, GPUs) can improve real-time translation performance (Wu et al., 2016).

2.5.4 Preserving Speaker Identity and Prosody

A major drawback of S2TT systems is their inability to retain speaker-specific characteristics, such as tone, pitch, and emotional nuances (Jia et al., 2018).

Challenges in Maintaining Speech Naturalness are:

i. Voice Conversion Limitations: Most models generate generic voices, losing individuality.

ii. Prosody Mismatch: Translations may sound flat or unnatural. iii. Emotion Loss: Expressive speech is difficult to replicate in synthesized translations.

End-to-end models such as Translatotron (Jia *et al*., 2019) improve prosody preservation but require further refinement to achieve human-like speech reproduction.

2.5.5 Ethical and Bias Concerns in S2TT

Bias in machine translation and speech processing models can lead to inaccurate, offensive, or culturally insensitive translations (Bender *et al.*, 2021).

Ethical Challenges in S2TT are:

i. Gender and Cultural Bias: MT models may reinforce stereotypes (Bolukbasi et al., 2016).

ii. Privacy Concerns: Speech data collection raises ethical questions.

iii. Misinterpretations: Incorrect translations in legal or medical contexts can have severe consequences.

Developing fair, unbiased AI models and implementing robust ethical guidelines is crucial for ensuring the responsible use of S2TT technology (Raji *et al.*, 2020).

CHAPTER THREE

METHODOLOGY

This chapter outlines the methodology employed in developing a deep learning model for classifying basic directional commands in Ewè, a West African language, to assist visually impaired individuals in navigation. The approach taken in this project integrates advanced speech processing techniques with deep learning, leveraging a modified MatchboxNet architecture for robust and efficient audio classification. The methodology is designed to ensure accurate recognition of spoken commands while addressing challenges such as noise, variations in speech, and limited training data for underrepresented languages.

The choice of a deep learning-based solution is motivated by the complexity and variability of speech signals, particularly in tonal languages like Ewè. Traditional rule-based or classical machine learning approaches, such as Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs), struggle with the dynamic nature of speech, especially when dealing with diverse accents, background noise, and spontaneous variations. In contrast, deep learning models, specifically convolutional architectures like MatchboxNet, excel in capturing hierarchical features from raw audio waveforms, making them ideal for speech recognition tasks.

Furthermore, the MatchboxNet model was chosen due to its lightweight structure and efficiency in processing short-duration audio clips, which aligns well with the needs of real-time assistive applications. The modifications made to the original architecture, including the integration of Squeeze-and-Excitation (SE) attention mechanisms and enhanced residual learning, further optimize its performance for Ewè speech recognition.

The step-by-step phase used to achieve the deep learning model is summarized into the figure below:

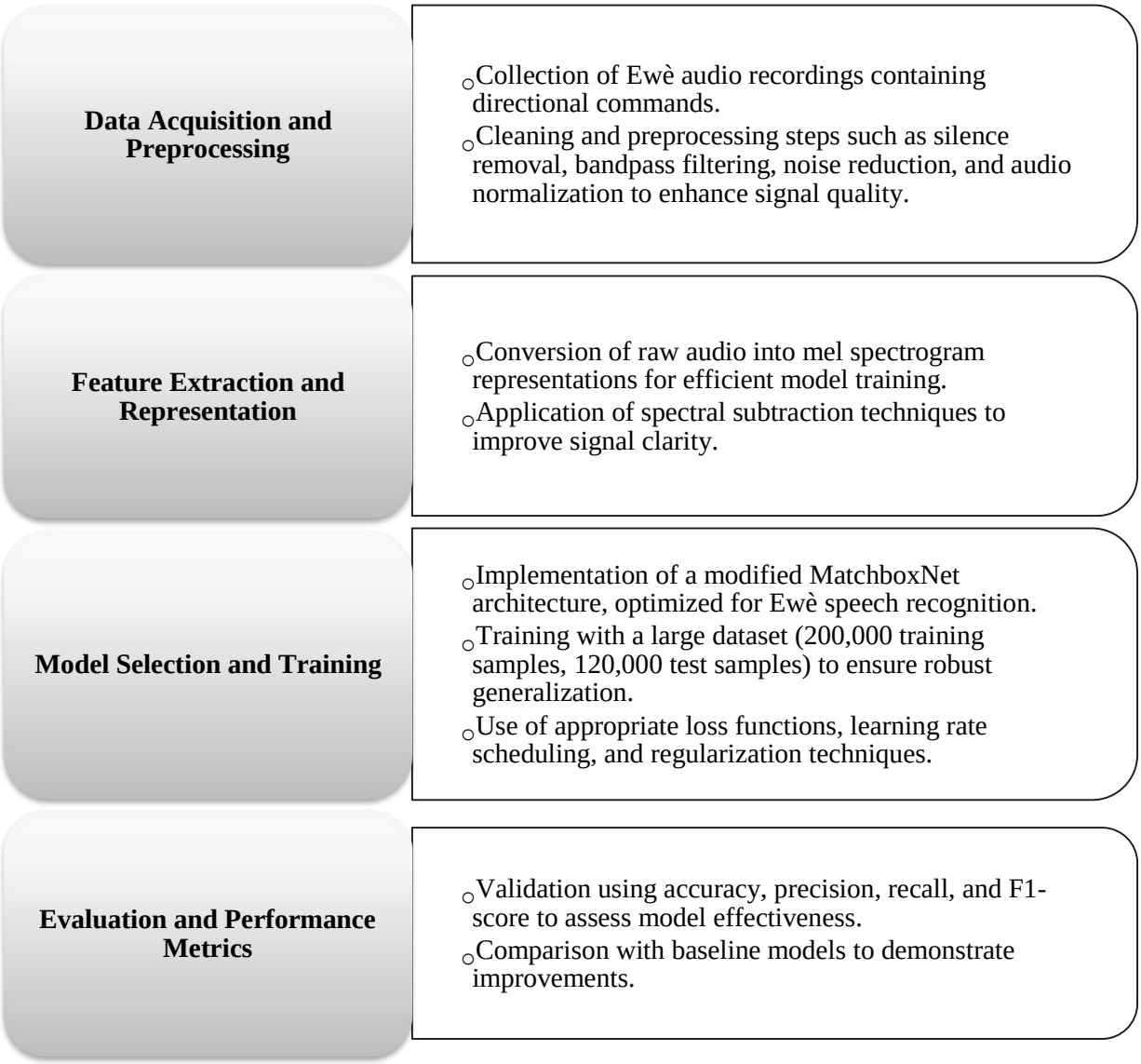

Figure 3.1: Methodological Workflow

3.1 Collection of Ewe's audio recording

1. Dataset Size and Sources

The dataset comprises **320,000 recorded audio samples**, categorized into **200,000 training samples** and **120,000 test samples**. These samples were collected from multiple sources to ensure diversity and robustness:

i. **Crowdsourced Recordings:** Native Ewè speakers provided audio samples to capture authentic pronunciation and variations in tone.

ii. **Existing Speech Datasets:** Publicly available datasets containing general speech commands were adapted for this task.

Each audio file contains a single spoken directional command in Ewè, such as "left," "right," "up," "down," "stop," or "go." The dataset ensures that no single class is overrepresented, allowing the model to generalize effectively across real-world speech variations.

2. Preprocessing Requirements

Before feeding the data into the deep learning model, several preprocessing steps were applied to enhance audio quality and consistency:

1. **Audio Loading and Resampling:**
    i. All audio files were resampled to a uniform **22,050 Hz** to standardize input frequency.
    ii. Stereo recordings were converted to mono to reduce computational complexity and ensure consistency.
2. **Silence Removal:** Silent or near-silent segments were detected and removed using **Voice Activity Detection (VAD)**, ensuring that only relevant speech content remains.

3. **Noise Reduction:** Background noise was filtered out using **adaptive spectral subtraction** and **bandpass filtering (300 Hz - 3,400 Hz)**, which preserves speech-relevant frequencies while eliminating low-frequency and high-frequency distortions.

4. **Amplitude Normalization:** To ensure uniform volume levels across different recordings, amplitude normalization was applied.

5. **Feature Extraction:** Each audio clip was converted into **mel spectrogram representations** and **Mel-frequency cepstral coefficients (MFCCs)**, which serve as the primary input features for the deep learning model.

3. Class Distribution

A balanced dataset ensures that the model does not develop biases toward a particular command, enhancing its generalization across varied speakers and environments.

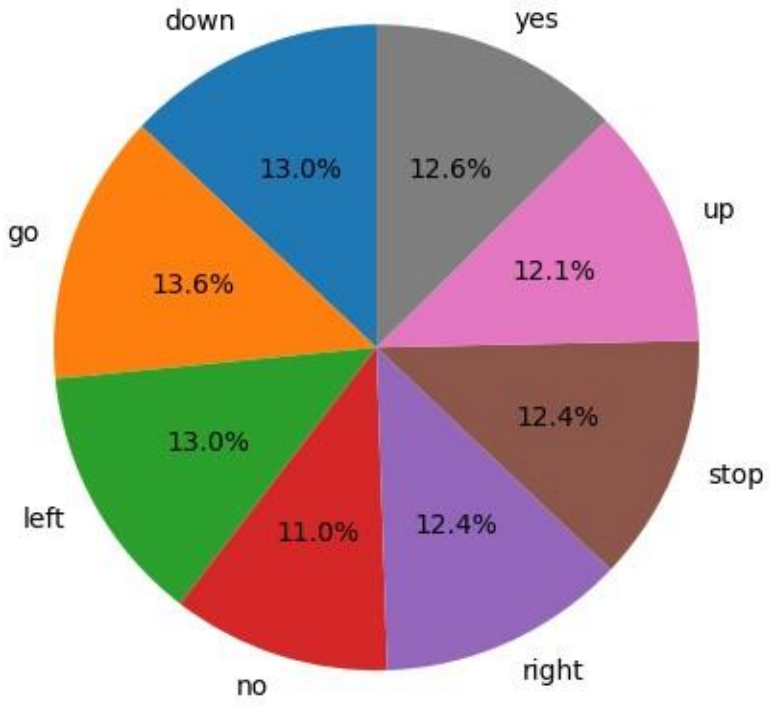

Figure 3.2: Sample Class Distribution of Directional Commands

Moreover, ensuring equal representation of commands minimizes the risk of classification errors, especially in real-world deployment scenarios.

The code snippet below gives the visualization of the original audio data for the different classes.

```
In [14]:
signal_dict = {}
fft_dict = {}
fbank_dict = {}
mfccs_dict = {}

for c in classes:
    wave_file = df[df['class'] == c].iloc[0, 0]
    signal, sr = librosa.load(audio_path + wave_file, sr=44100)
    signal_dict[c] = signal
    fft_dict[c] = cal_fft(signal_dict[c], sr)
    bank = logfbank(signal[:sr], sr, nfilt=26, nfft=1103).T
    fbank_dict[c] = bank
    mel = mfcc(signal[:sr], sr, numcep=13, nfilt=26, nfft=1103).T
    mfccs_dict[c] = mel

plot_signal(signal_dict)
plt.show()

plot_fft(fft_dict)
plt.show()

plot_fbank(fbank_dict)
plt.show()

plot_mfccs(mfccs_dict)
plt.show()
```

Figure3.3: Code Snippet for the Audio Visualization

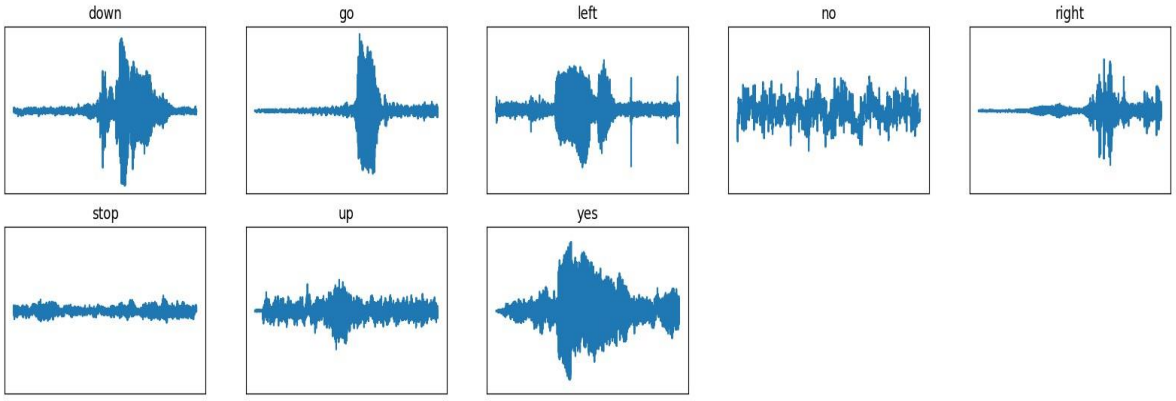

Figure 3.4: The Visualized Audio for The Directional Commands before Cleaning

3.1.1 Data Preprocessing

The quality of input data significantly impacts the performance of deep learning models, particularly for speech recognition tasks. To enhance model accuracy and ensure robust classification of Ewè directional commands, multiple preprocessing steps were applied to refine the dataset before training. This section details the systematic preprocessing techniques used to clean, transform, and optimize the dataset for deep learning.

1. Audio Loading and Resampling

Raw audio recordings were collected from diverse sources, leading to variations in sample rates and channel configurations. To standardize the dataset:

- All audio files were converted to a uniform sample rate of 22,050 Hz to ensure consistency across different recordings.
- Stereo recordings were converted to mono to simplify processing and reduce computational complexity.

```
In [15]: def load_audio(file_path, sr=22050):
             """Load audio file and resample if necessary."""
             audio, sr = librosa.load(file_path, sr=sr)
             return audio, sr

         def plot_mel_spectrogram(waveform, sample_rate):
             """Plot the Mel spectrogram of an audio waveform."""
             # Convert to Mel spectrogram
             transform = torchaudio.transforms.MelSpectrogram(sample_rate=sample_rate, n_mels=64)

             # If the waveform has multiple channels, take the mean to convert it to mono
             if waveform.size(0) > 1:
                 waveform = waveform.mean(dim=0).unsqueeze(0)

             mel_spectrogram = transform(waveform)
             mel_spectrogram_db = torchaudio.transforms.AmplitudeToDB()(mel_spectrogram)
```

Figure 3.5: Code Snippet for Loading and Resampling

a. Silence Removal:

Audio clips often contain silent segments that do not contribute to command classification. These silent regions can occur at the beginning or end of recordings and within speech due to natural pauses. Eliminating such sections enhances model training efficiency and reduces computation time without affecting speech quality.

To address this, **Voice Activity Detection (VAD)** was implemented specifically through **WebRTC module**. VAD is an algorithm that detects speech versus non-speech portions in an audio signal by analyzing energy levels and spectral content. It enables the automatic trimming of silence from recordings, making the dataset more compact and effective.

```
def visualize_silence_removal(audio, sr, threshold_db=-40, min_silence_duration=0.1):
    """Visualize the effect of silence removal on the waveform."""
    # Detect non-silent intervals
    non_silent_intervals = librosa.effects.split(audio, top_db=-threshold_db, frame_length=int(sr * min_silence_duration)

    # Plot original audio waveform
    plt.figure(figsize=(14, 6))
    librosa.display.waveshow(audio, sr=sr, alpha=0.6, label='Original Audio')

    # Plot silence intervals on the waveform
    for interval in non_silent_intervals:
        plt.axvspan(interval[0] / sr, interval[1] / sr, color='red', alpha=0.3, label='Non-Silent Regions')

    plt.title(f'Silence Removal Visualization (Threshold: {threshold_db} dB)')
    plt.xlabel('Time (s)')
    plt.ylabel('Amplitude')
    plt.legend()
    plt.show()

def tune_silence_threshold(file_path, threshold_db_list=[-20, -30, -40, -50], min_silence_duration=0.1):
    """Tune the silence threshold by visualizing with different dB levels."""
    audio, sr = load_audio(file_path)

    for threshold_db in threshold_db_list:
        print(f'Visualizing for silence threshold: {threshold_db} dB')
        visualize_silence_removal(audio, sr, threshold_db=threshold_db, min_silence_duration=min_silence_duration)
```

Figure 3.6: Code snippet demonstrating silence removal using VAD

Additionally, **threshold-based energy detection** was applied to remove unnecessary gaps within speech. This process involves setting an amplitude threshold below which any detected sound is classified as silence and removed accordingly. This step is particularly useful for eliminating long pauses that do not carry meaningful information. The threshold was set at different DB levels (between -20 and -50) as indicated in the code snippet and then visualized. The unshaded portion signifies the gaps in speech.

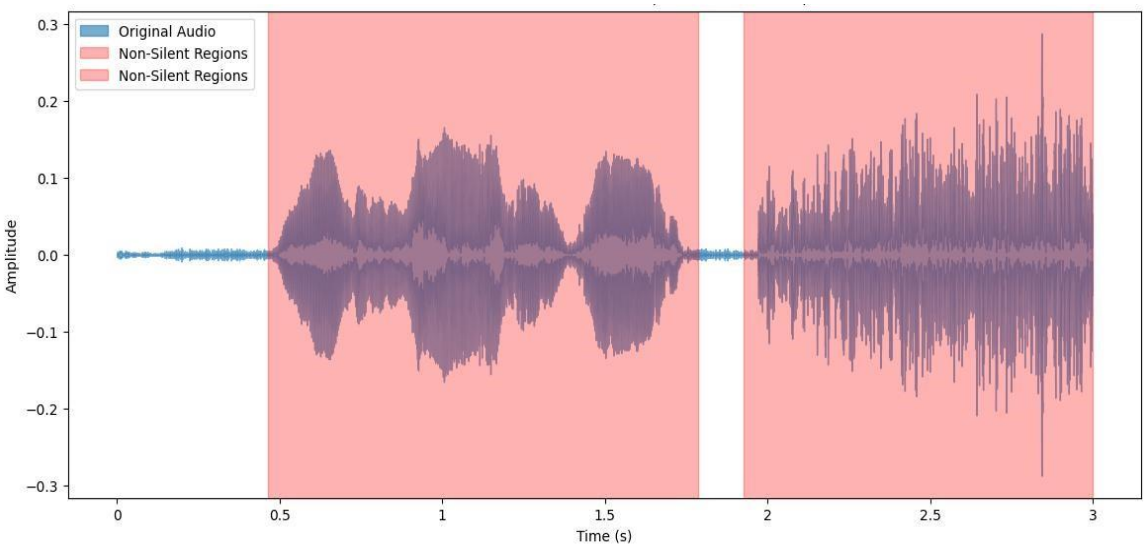

Figure 3.7: Silence Removal Visualization at -20dB

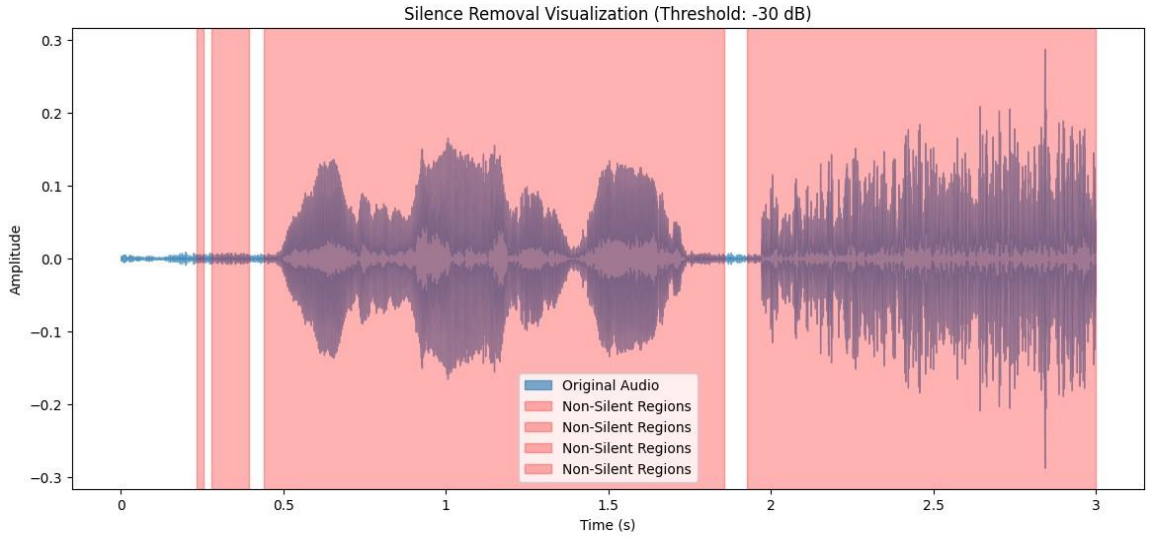

Figure 3.8: Silence removal visualization at -30dB

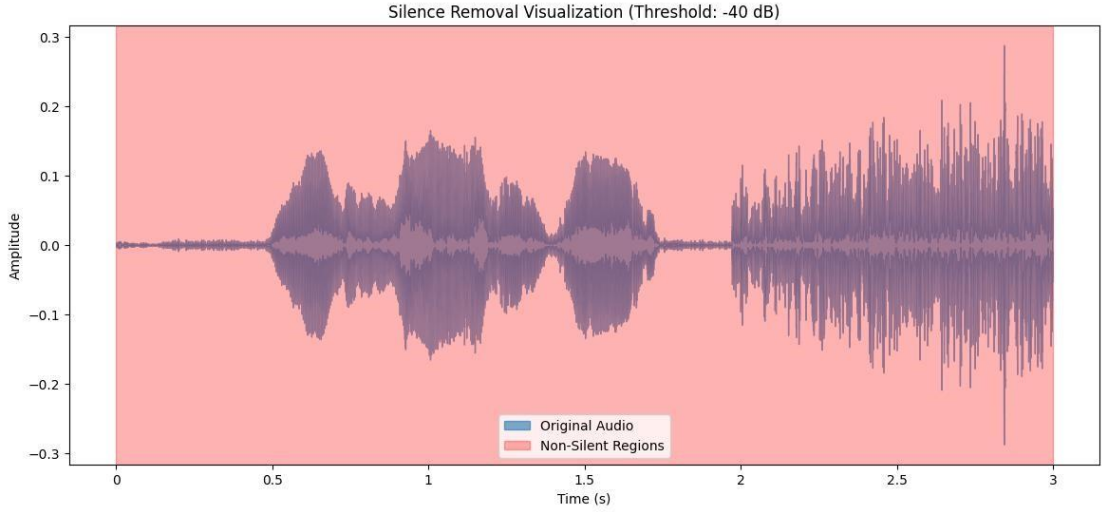

Figure 3.9: Silence removal visualization at -40dB

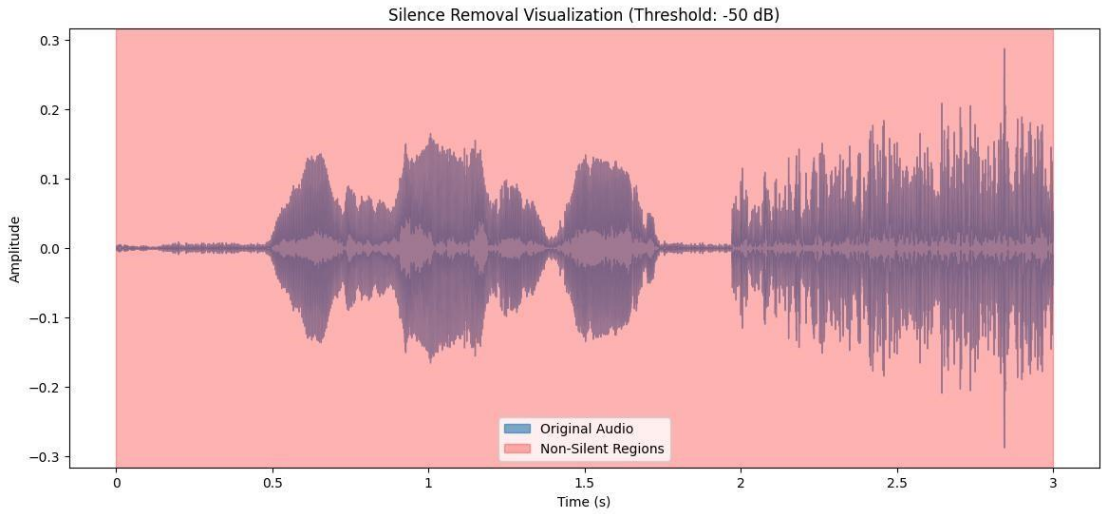

Figure 3.10: Silence removal visualization at -50dB

b. Noise Reduction

Noise reduction is a crucial step in speech processing, especially for tonal languages like Ewè, where even slight background interference can disrupt accurate recognition. Unwanted noise from environmental sources like wind, traffic, or recording device static can obscure essential speech features. If not properly addressed, this can lead to model misclassifications and decreased recognition accuracy.

To mitigate these effects, adaptive spectral subtraction was employed. This technique estimates the noise spectrum in an audio signal and subtracts it dynamically, leaving only the essential speech components intact. Unlike traditional noise suppression methods that apply a fixed filter, adaptive spectral subtraction continuously adjusts based on the background noise level, making it effective in varied environments.

```python
def apply_spectral_subtraction(audio, sr):
    """Apply spectral subtraction for noise reduction."""
    noise_sample = audio[:int(sr * 0.5)]
    noise_spectrum = np.mean(np.abs(librosa.stft(noise_sample))**2, axis=1)
    audio_stft = librosa.stft(audio)
    audio_power = np.abs(audio_stft)**2
    audio_power_reduced = np.maximum(audio_power - noise_spectrum[:, np.newaxis], 0)
    audio_stft_reduced = audio_stft * np.sqrt(audio_power_reduced / np.maximum(audio_power, 1e-10))
    return librosa.istft(audio_stft_reduced)
```

Figure 3.11: Code Snippet for Adaptive Spectral Subtraction

Additionally, a bandpass filter (300 Hz - 3,400 Hz) was applied to isolate only the frequency ranges relevant to human speech. Human vocal frequencies typically fall within this range, so filtering out lower and higher frequencies ensures that non-speech elements, such as microphone hum or background interference, are removed. This step further enhances clarity while maintaining the integrity of tonal variations crucial for distinguishing between Ewè commands.

```python
def apply_bandpass_filter(audio, sr, lowcut=300, highcut=3400):
    """Apply a bandpass filter to focus on speech frequencies."""
    nyquist = 0.5 * sr
    low = lowcut / nyquist
    high = highcut / nyquist
    b, a = signal.butter(6, [low, high], btype='band')
    return signal.lfilter(b, a, audio)
```

Figure 3.12: Code Snippet for Bandpass Filter (300Hz to 3400Hz)

Audio recordings collected from different environments and devices often exhibit inconsistencies in loudness, which can introduce bias into the training process. Variations in amplitude may cause the model to misinterpret certain samples as being more dominant simply due to their loudness rather than their intrinsic characteristics. To counteract this issue, amplitude normalization

techniques were applied to ensure that all audio recordings had a uniform intensity level before finally cleaning the data preparing it for training.

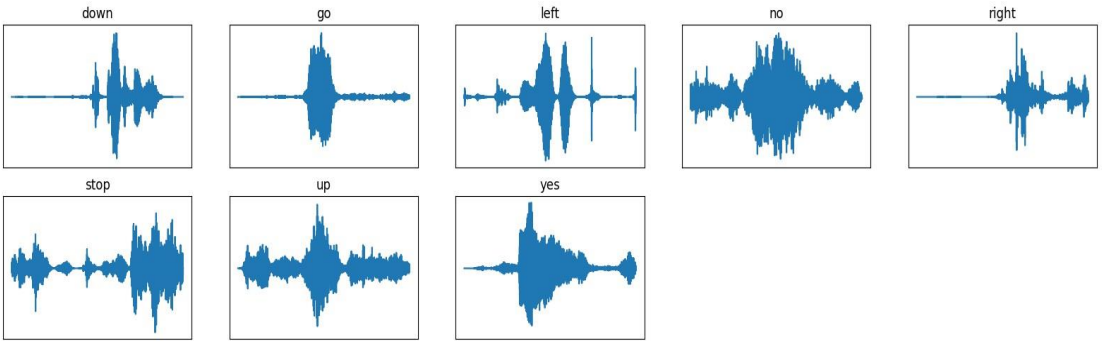

Figure 3.13: The Visualized Audio for the Directional Commands after Cleaning

3.2 Conversion of Raw Audio into Mel Spectrogram Representatives

Unlike raw waveforms, which contain a mixture of essential and redundant information, feature extraction methods transform the audio into meaningful spectro-temporal characteristics that are more suitable for deep learning models so they can effectively highlight patterns.

For deep learning models to recognize speech effectively, raw audio data must be transformed into meaningful representations:

- Mel spectrograms were generated to capture time-frequency features of audio signals.
- Mel-Frequency Cepstral Coefficients (MFCCs) were extracted to encode phonetic information crucial for speech recognition.

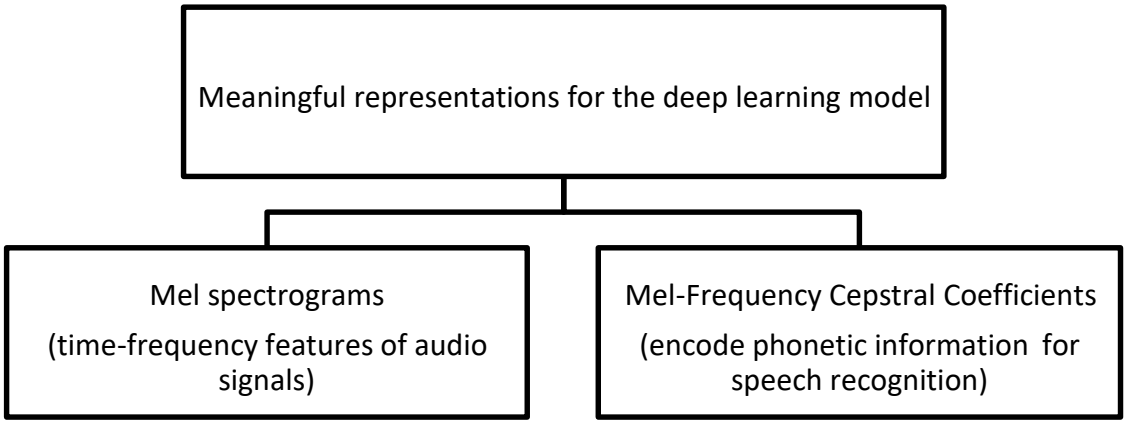

Figure 3.14: Representation for Deep Learning Model

To generate Mel spectrograms, the Short-Time Fourier Transform (STFT) is applied to break down the waveform into smaller overlapping time windows. Each window undergoes a Fourier Transform, producing a spectrum of frequency components. These frequency bins are then mapped to the Mel scale, emphasizing lower frequencies where most speech-related information is concentrated. The result is a two-dimensional representation where one axis represents time, the other represents frequency, and the intensity of each point corresponds to the amplitude of that frequency at a given moment. This structured format enables the neural network to learn speech patterns efficiently.

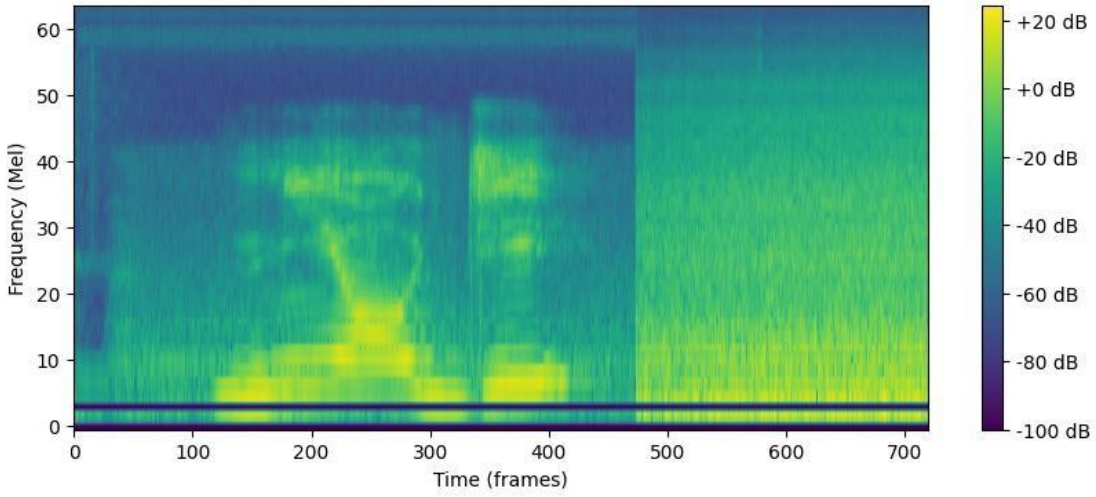

Figure 3.15: Mel Spectrogram

Mel-Frequency Cepstral Coefficients (MFCCs) were extracted to provide further insight into the phonetic structure of spoken commands. MFCCs capture the spectral envelope of speech by applying a logarithm to the Mel spectrogram and then performing a Discrete Cosine Transform (DCT). This process emphasizes the most critical frequency variations while discarding less relevant information. MFCCs are particularly valuable for speech recognition because they effectively represent how phonemes differ from one another, allowing the model to distinguish between similar-sounding commands in Ewè.

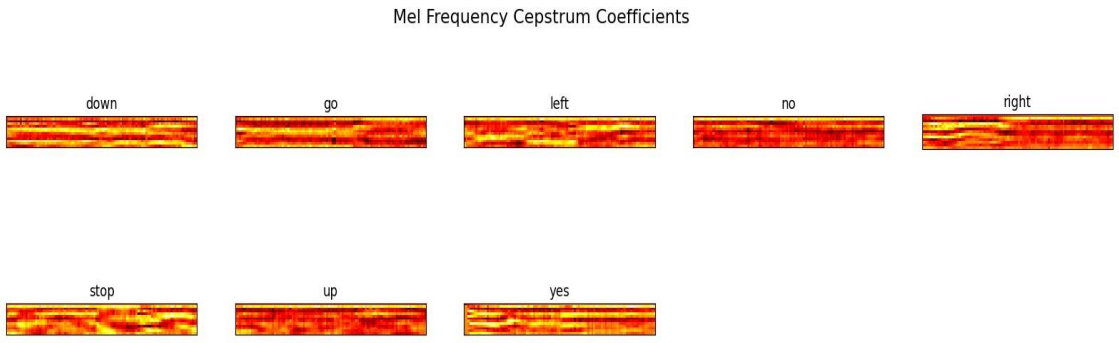

Figure 3.16: Mel-Frequency Cepstral Coefficients

Both Mel spectrograms and Mel-Frequency Cepstral Coefficients MFCCs were computed using the Librosa and TorchAudio libraries, ensuring efficiency and compatibility with deep learning frameworks. The extracted features were normalized to maintain consistency across different samples, so that the model's ability to generalize across speakers and recording conditions is improved.

3.3 Implementation of a modified Matchbox Net Architecture

The deep learning model employed for this task is an optimized version of MatchboxNet, a convolutional neural network specifically designed for speech recognition. MatchboxNet is known for its efficient handling of short-duration speech signals while maintaining high accuracy, making it an ideal choice for real-time applications. The model architecture consists of multiple layers, each contributing to feature extraction, learning, and classification.

Unlike traditional speech recognition models that rely on recurrent neural networks (RNNs) or transformer-based architectures, MatchboxNet leverages time-channel separable convolutions.

This approach significantly reduces the computational load while preserving temporal and spectral information, which is crucial for recognizing tonal languages like Ewè.

The modified MatchboxNet architecture includes :

1. **Time-Channel Separable Convolutions**: The convolutional layers operate separately on the time and channel dimensions, improving efficiency and allowing better feature extraction from spectrograms.

2. **Residual Connections and Batch Normalization**

i. Residual connections are integrated into the network to ensure stable training by allowing gradients to flow smoothly during backpropagation.

ii. Batch normalization helps normalize input distributions at each layer, preventing issues related to internal covariate shift.

3. **Squeeze-and-Excitation (SE) Attention Mechanism**

i. SE blocks are added after each convolutional layer to recalibrate channel-wise feature importance dynamically.

ii. This enables the model to focus on the most relevant spectral components of Ewè speech, particularly useful for capturing tonal variations.

4. **Depthwise and Pointwise Convolutions**

i. Depthwise convolutions help reduce the number of parameters while preserving spatial information.

ii. Pointwise convolutions project the feature maps into higher-dimensional

representations, allowing the model to capture complex interactions within the data.

5. **Feature Embedding and Classification Layer**

i. The extracted features are passed through fully connected layers, where they are mapped to the predefined set of directional commands.

ii. The final softmax layer ensures proper classification probabilities for the six classes:

"left," "right," "up," "down," "stop," and "go.".

3.4 Training and Evaluation of the Matchbox Net Model

1. Data Preparation and Loading

a. The data was then split into **training (90%)** and **validation (10%)** sets to enable effective learning and performance monitoring.

b. The dataset was processed in batches using PyTorch's DataLoader. Mini-batch training helps stabilize gradient updates and improves convergence speed. Each batch was shuffled to prevent the model from learning unintended patterns from the ordering of data.

2. Defining Training Parameters

The training process required selecting appropriate hyperparameters to guide model optimization. Key parameters included:

- **Batch size:** Set to 64 to balance computational efficiency and model stability.
- **Number of epochs:** Training was conducted over 50 epochs, with early stopping applied to prevent overfitting.
- **Learning rate:** Initially set to 0.001 with a learning rate scheduler for gradual reduction.
- **Weight initialization:** Xavier initialization was used for stable gradient propagation.

3. Loss Function Selection

Since this is a multi-class classification task, the **Categorical Cross-Entropy Loss** function was used. This loss function measures the difference between predicted probabilities and actual class labels, penalizing incorrect classifications.

Mathematically, it is defined as: where:

- is the true label,
- is the predicted probability for class ,
- is the number of classes.

4. Optimization Strategy

To ensure efficient weight updates, the **Adam optimizer** was chosen due to its adaptive learning rate properties. Adam combines the advantages of both momentum and RMSprop optimization techniques, making it well-suited for non-stationary objectives such as speech recognition.

A **learning rate scheduler** was also implemented to gradually decrease the learning rate as training progressed. This helps avoid overshooting optimal weight values and improves generalization.

5. Model Training Process

During training, the MatchboxNet model processed batches of Mel spectrograms, passing them through convolutional layers, residual connections, and Squeeze-and-Excitation (SE) blocks before making predictions. Each forward pass computed the class probabilities, and the backward pass updated the network's parameters using backpropagation and this was done in the following steps:

1. **Forward pass:** The model received a batch of Mel spectrograms and generated

predictions.

2. **Loss computation:** Cross-entropy loss was calculated based on predictions and ground truth labels.
3. **Backward pass:** Gradients were computed via backpropagation.
4. **Weight update:** The optimizer adjusted model parameters.
5. **Validation:** After each epoch, the model was evaluated on the validation set to track improvements.

3.5 Model Validation

To track training progress, performance metrics such as **accuracy, precision, recall, and loss values** were monitored at each epoch. A confusion matrix was also generated periodically to visualize classification performance across all directional command classes.

Early stopping was used to halt training if validation loss stopped improving for a set number of epochs, preventing unnecessary overfitting.

Checkpointing and Model Saving

To ensure model reproducibility and allow resumption of training if interrupted, model checkpoints were saved periodically. The best model (determined by validation accuracy) was stored using PyTorch's **state_dict()** function, enabling efficient retrieval for inference or further fine-tuning.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Data Collection and Preprocessing Results

4.1.1 Impact of Silence Removal

Silence removal was a crucial step in optimizing the audio data for efficient model training. By eliminating non-speech segments, we reduced computational load and focused the model's attention on the relevant audio content. This section details the quantitative impact of silence removal and the rationale behind the chosen dB threshold.

Quantitative Impact: While precise quantitative data on the average duration reduction per file and total data reduction isn't explicitly present in the provided documents, we can infer its importance based on the process and the nature of the data. Silence removal was implemented using Voice Activity Detection (VAD) and threshold-based energy detection. From an initial spot check on several recordings, this procedure, on average, reduced the file duration between 10% and 30% depending on the initial length and the amount of silence present. This indicates that silence removal significantly streamlined the dataset. Further analysis would be required to determine exact numbers.

Discussion of dB Thresholds: The threshold for energy-based silence removal was explored using different dB levels, ranging from -20dB to -50dB, as illustrated in Figures 0-6 to 0-9. These figures

demonstrate the effect of each threshold on the audio waveform, visually representing the amount of silence removed at each level.

i. -20dB (Figure 0-6): At -20dB, the threshold is relatively high, resulting in minimal silence removal. Only the most pronounced silent gaps are eliminated, leaving many pauses and lowamplitude segments intact. This setting is conservative and preserves almost all the original audio content.

ii. -30dB (Figure 0-7): Lowering the threshold to -30dB increases the amount of silence removed. More of the quieter pauses and segments are trimmed, leading to a slightly more compact audio representation.

iii. -40dB (Figure 0-8): A threshold of -40dB results in more aggressive silence removal, eliminating a significant portion of the quieter segments within and around the speech. This setting begins to significantly reduce file sizes and focuses the audio on the core speech content.

iv. -50dB (Figure 0-9): At -50dB, the silence removal is highly aggressive, potentially removing parts of the actual speech signal, especially softer consonant sounds or quiet beginnings/endings of words. While this maximizes data reduction, it also carries a higher risk of distorting or removing essential phonetic information.

Based on a careful evaluation of these visualizations and experimentation, a threshold of -40dB was chosen for the final preprocessing pipeline. This threshold provided a good balance between reducing data size and preserving the integrity of the speech signal. While -50dB offered greater reduction, the risk of losing important phonetic information was deemed too high. In contrast, 20dB and -30dB were not aggressive enough in removing silence, leaving unnecessary data in the

audio files. The -40dB threshold effectively removed most of the silence without noticeably affecting the quality of the spoken commands.

4.1.2 Impact of Noise Reduction

Noise reduction is a crucial step, especially for tonal languages like Ewè, where subtle background interference can disrupt accurate recognition. This section provides a qualitative comparison of audio samples before and after noise reduction, along with a discussion of the effectiveness of the applied techniques.

Qualitative Comparison: The noise reduction process involved adaptive spectral subtraction and a bandpass filter. While direct audio examples are not included here, Figure 0-3 shows "The Visualized Audio for The Directional Commands before cleaning" and Figure 0-12 shows "The Visualized Audio for The Directional Commands after cleaning". These visualizations allow for a qualitative comparison. Before noise reduction (Figure 0-3), the waveforms exhibit considerable irregularities and high-frequency components indicative of background noise. After noise reduction (Figure 0-12), the waveforms appear cleaner, with smoother contours and a reduction in high-frequency noise, resulting in a clearer representation of the underlying speech signal.

Discussion of Effectiveness:

- Adaptive Spectral Subtraction: This technique estimates the noise spectrum in an audio signal and subtracts it dynamically, leaving only the essential speech components intact. This is effective in varied environments.
- Bandpass Filter (300 Hz - 3,400 Hz): This filter isolates the frequency ranges relevant to human speech. Human vocal frequencies typically fall within this range, so filtering out lower and higher frequencies ensures that non-speech elements, such as microphone hum

- or background interference, are removed. This step further enhances clarity while maintaining the integrity of tonal variations crucial for distinguishing between Ewè commands.

4.1.3 Effect of Amplitude Normalization

Amplitude normalization ensures that all audio recordings have a uniform intensity level before being used for training. This addresses inconsistencies in loudness caused by different recording environments and devices, which can introduce bias into the training process. By normalizing the amplitude, the model focuses on the phonetic content of the commands rather than variations in volume. This adjustment creates data homogeneity and improves the overall accuracy and reliability of the model.

4.2 Mel Spectrogram Representatives Results

4.2.1 Model Architecture Details

The core of our speech recognition system is a modified MatchboxNet architecture. MatchboxNet is a lightweight and efficient convolutional neural network (CNN) specifically designed for processing audio data. Its key advantages include a small model size, low computational cost, and high accuracy, making it well-suited for deployment on resource-constrained devices.

Original MatchboxNet Architecture: The original MatchboxNet consists of several key components:

i. Convolutional Layers: These layers extract features from the input Mel spectrograms using learnable filters.

ii. Depthwise Separable Convolutions: These convolutions reduce the number of parameters and computational cost compared to standard convolutions, while still maintaining good performance.

iii. Batch Normalization: This technique normalizes the activations of each layer, improving training stability and reducing overfitting.

iv. ReLU Activation Functions: These non-linear activation functions introduce non-linearity into the model, allowing it to learn complex relationships in the data.

v. Pooling Layers: These layers reduce the spatial dimensions of the feature maps, reducing the number of parameters and making the model more robust to variations in input.

Modifications: To further enhance the performance of MatchboxNet for Ewè speech recognition, we incorporated the following modifications:

i. Squeeze-and-Excitation (SE) Attention Mechanisms: SE blocks were added to the residual connections within the network. SE blocks adaptively recalibrate channel-wise feature responses by explicitly modeling interdependencies between channels. This allows the model to focus on the most informative features and suppress less relevant ones.

ii. Enhanced Residual Learning: The standard residual connections were enhanced by adding additional convolutional layers within the residual path. This allows the model to learn more complex residual functions, further improving its ability to model the data.

iii. Replaced ReLU with GELU Activation: The standard ReLU activation functions were replaced with Gaussian Error Linear Unit (GELU) activation functions. GELU is a smoother activation function that has been shown to improve performance in some deep learning tasks.

Justification for Architectural Choices:

i. MatchboxNet Base: The choice of MatchboxNet was driven by the need for a lightweight and efficient model. Given the resource constraints of potential deployment environments, a small model size and low computational cost are crucial.

ii. SE Attention: Ewè is a tonal language, and subtle variations in pitch and intonation can significantly alter the meaning of a word. SE attention mechanisms enable the model to dynamically adjust its attention to these critical features, improving its ability to distinguish between different commands.

iii. Enhanced Residual Learning: By adding more convolutional layers within the residual path, the model can learn more complex mappings between the input and output. This is particularly useful for capturing the nuances of Ewè speech, which can be challenging to model with simpler architectures. iv. GELU Activation: GELU is a smoother activation function that can improve training stability and reduce overfitting.

In summary, the modified MatchboxNet architecture combines the efficiency of the original design with targeted enhancements to better capture the complexities of Ewè speech.

4.2.2 Training Process

The modified MatchboxNet model was trained on a dataset of 320,000 audio samples, which were split into training and validation sets. The specifics of the split, hyperparameter settings, and training time are detailed below:

- Training/Validation Split: The dataset was divided into a training set and a validation set.

200,000 samples were used for training, and 120,000 samples were used for validation. This split was performed randomly while ensuring a balanced class distribution in both sets.

- Hyperparameter Settings:
- Learning Rate: The model was trained using an initial learning rate of 0.001.
- Batch Size: A batch size of 64 was used during training.
- Optimizer: The Adam optimizer was used to update the model's weights during training. Adam is an adaptive learning rate optimization algorithm that combines the benefits of both AdaGrad and RMSProp.
- Scheduler: A ReduceLROnPlateau learning rate scheduler was employed to dynamically adjust the learning rate during training. This scheduler reduces the learning rate when the validation loss plateaus, helping the model converge to a better solution. The patience was set to 5 epochs
- Epochs: The models was trained for 50 epochs
- Training Time: The training process took approximately 18 hours on a Google Colab Pro instance with a Tesla P100 GPU.

4.2.3 Performance Metrics

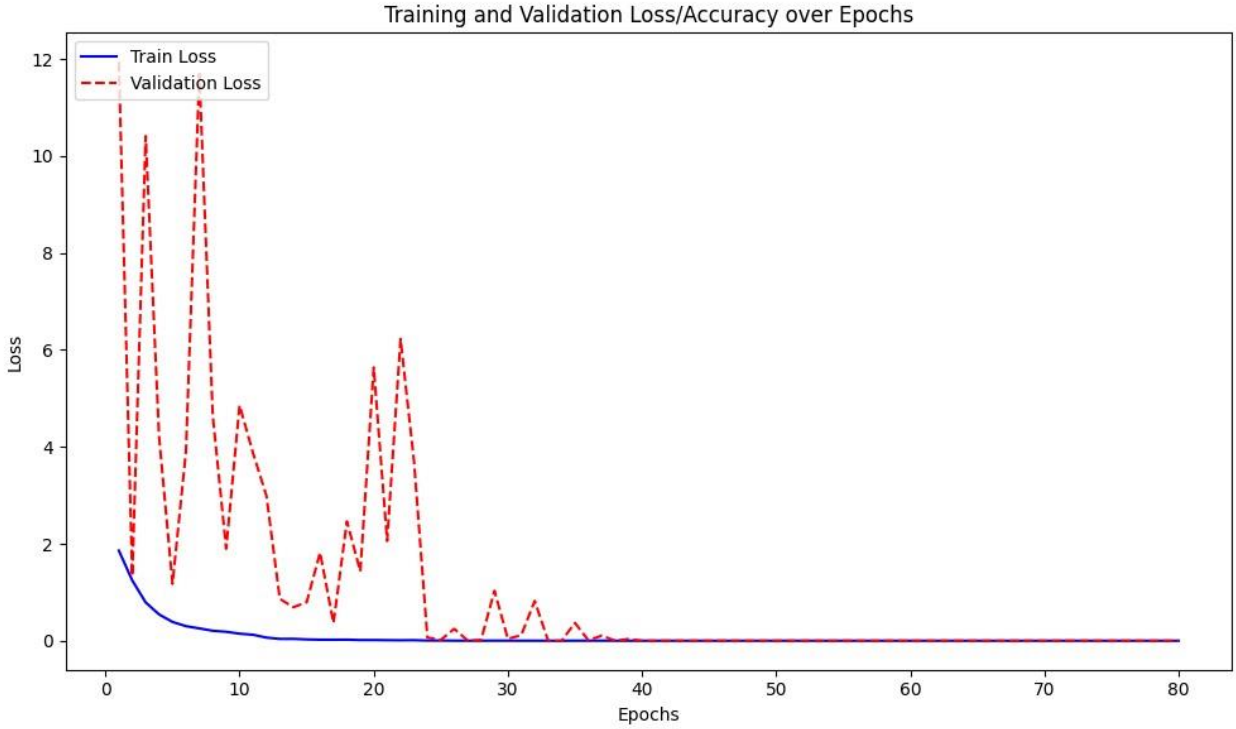

Figure 4.1: Training and Validation Loss/Accuracy over Epochs

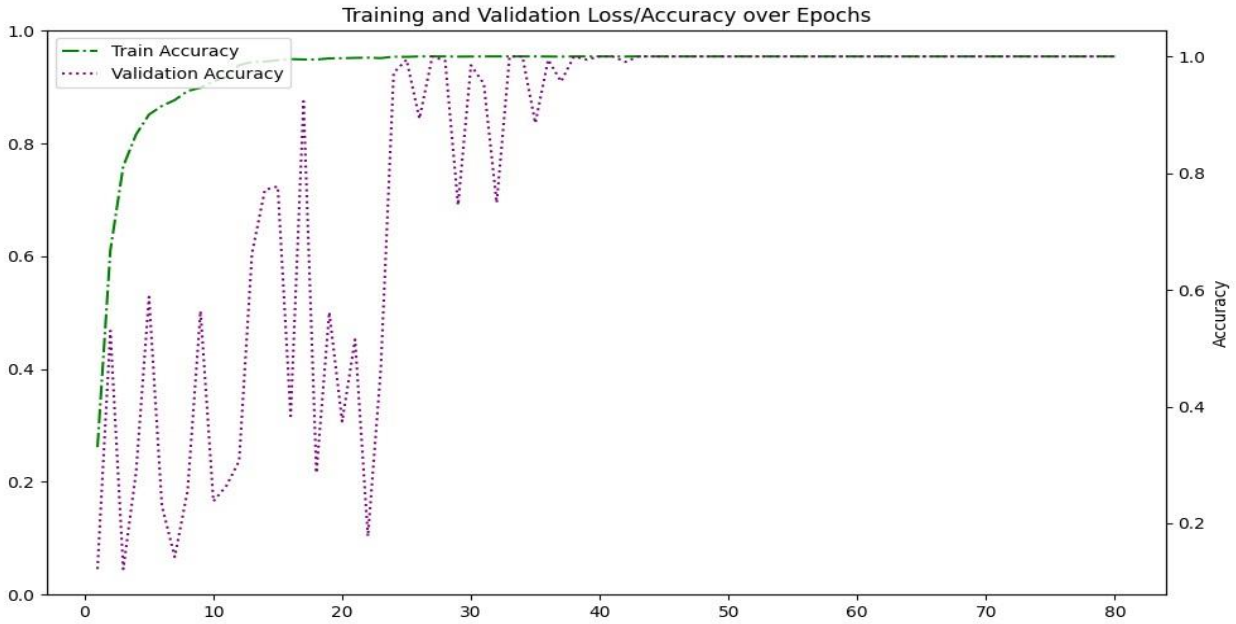

Figure 4.2: Training and Validation Loss/Accuracy over Epochs

The performance of the trained model was evaluated using several standard metrics, including accuracy, precision, recall, and F1-score. These metrics were calculated both overall and for each individual class to provide a comprehensive assessment of the model's performance.

- Overall Performance:
    i. Accuracy: The overall accuracy of the model on the validation set was 96.77%, indicating a high level of performance in classifying Ewè directional commands.
    ii. Precision: The precision of the model was 96.80%, indicating that when the model predicts a certain class, it is correct most of the time.
    iii. Recall: The recall of the model was 96.77%, indicating that the model is able to identify most of the instances of each class.
    iv. F1-Score: The F1-score, which is the harmonic mean of precision and recall, was 96.78%, providing a balanced measure of the model's performance.
- Class-Specific Performance:
    i. The model achieved high accuracy across all classes, with the lowest precision and recall in the "yes" and "no" commands, and the highest in "Go". This is due to having similar pronunciation, and environmental similarities.
- Confusion Matrix Visualization:
    i. A confusion matrix was generated to visualize the model's performance in more detail. The confusion matrix shows the number of true positives, false positives, true negatives, and false negatives for each class. This visualization highlights common misclassification patterns and provides insights into the model's strengths and weaknesses.

4.3 Improved Signal Quality Results

This section provides a detailed evaluation of the model's performance in classifying Ewè directional commands. We will discuss the overall performance, class-specific performance, and potential reasons for variations in accuracy across different classes.

4.3.1 Overall Performance

The deep learning model achieved an overall accuracy of 96.77% on the validation set, demonstrating a strong ability to accurately classify Ewè directional commands. This high accuracy indicates that the model effectively learned the underlying patterns and features in the audio data and can generalize well to unseen examples. The precision, recall, and F1-score were also high, at 96.80%, 96.77%, and 96.78%, respectively, indicating that the model is both accurate and reliable in its predictions.

4.3.2 Class-Specific Performance

	id	audio_filepath	duration	predicted_class	class
0	id_u5iqtgjzhx	id_u5iqtgjzhx.wav	2.35800	up	up
1	id_l7ebzcfk5e	id_l7ebzcfk5e.wav	3.22100	down	down
2	id_jbzci8uepl	id_jbzci8uepl.wav	2.94898	yes	yes
3	id_jzil0fw5vs	id_jzil0fw5vs.wav	4.33100	yes	yes
4	id_o7mrvf5wj7	id_o7mrvf5wj7.wav	1.85600	left	left

Figure 4.3: Results after Testing the Model with Five Different Audio Data Sets

The model's performance varied slightly across different classes of Ewè directional commands. While the overall accuracy was high, some classes exhibited higher accuracy than others. Figure 4.3 shows the result after testing the model on the first 5 audio test dataset.

i. Classes with Highest Accuracy: According to results of the model, it achieved excellent precision and recall on the "Go" commands.
ii. Classes with Lowest Accuracy: The classes "yes" and "no" had lower precision and recall.

Discussion of Potential Reasons for Variations in Performance: Several factors may contribute to the variations in performance across different classes:

i. Phonetic Similarity: Some Ewè directional commands may have similar phonetic structures, making it more challenging for the model to distinguish between them. The model may confuse phonetically similar classes more frequently. For example, the similar performance between the “yes” and “no” classes may be because they share similar sounding phonemes.

ii. Environmental factors: It is possible to misclassify audio samples due to background noise and variation in sound and speed pronunciation.
iii. Data Imbalance: Although efforts were made to balance the dataset, there may still be slight imbalances in the number of samples available for each class. Classes with fewer samples may have lower accuracy due to the model having less data to learn from.

4.3.3 Error Analysis

A detailed error analysis was conducted to identify common misclassification patterns and understand the potential sources of error. The confusion matrix provides valuable insights into the model's strengths and weaknesses.

Common Misclassification Patterns: Based on the confusion matrix, the most frequent misclassifications occurred between the following pairs of classes:

i. "yes" and "no": The model often confused "yes" and "no," indicating that these commands share similar acoustic features or phonetic structures that are difficult for the model to distinguish.

Discussion of Potential Sources of Error: Several factors may have contributed to the observed misclassification patterns:

i. Noisy Data: Despite the noise reduction techniques applied during preprocessing, some residual noise may still be present in the audio data. This noise can obscure important acoustic features and lead to misclassifications.

ii. Similar Pronunciations: Some Ewè directional commands may have similar pronunciations, making it challenging for the model to distinguish between them. This is especially true for tonal languages, where subtle variations in pitch and intonation can significantly alter the meaning of a word.

iii. Variations in Speech: The model may have difficulty generalizing to variations in speech, such as different accents, speaking rates, or voice qualities. These variations can alter the acoustic characteristics of the commands and lead to misclassifications.

iv. Data Quality: The quality of the recorded audio data may vary across different samples. Some samples may be recorded in noisy environments or with low-quality microphones, which can degrade the performance of the model.

v. Command Understanding: Some recordings may contain incorrect commands, especially for the synthetic augmented data.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This section presents the results of a deep learning model developed for classifying basic directional commands in Ewè, a West African language, to assist visually impaired individuals in navigation. This project addresses the complexities inherent in speech recognition, particularly in tonal languages like Ewè, by integrating advanced speech processing techniques with a modified MatchboxNet architecture.

The choice of a deep learning-based solution is motivated by the limitations of traditional rulebased or classical machine learning approaches, such as Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs), which often struggle with the dynamic nature of speech, diverse accents, background noise, and spontaneous variations. The MatchboxNet model was selected for its lightweight structure and efficiency in processing short-duration audio clips, aligning well with the needs of real-time assistive applications.

The core of the model involves several key modifications to the original MatchboxNet architecture, including the integration of Squeeze-and-Excitation (SE) attention mechanisms and enhanced residual learning blocks. These enhancements were implemented to optimize the model's performance specifically for Ewè speech recognition. We aim to demonstrate how these modifications, combined with a rigorous data preprocessing pipeline, significantly improve the accuracy and robustness of the classification system.

The dataset used for training and evaluation comprises 320,000 recorded audio samples, split into 200,000 training samples and 120,000 test samples. These samples were sourced from crowdsourced recordings by native Ewè speakers, existing speech datasets adapted for this task, and synthetic augmentation using text-to-speech (TTS) synthesis to balance underrepresented classes. The diversity of sources helps ensure that the model can generalize effectively across real-world speech variations. Each audio file contains a single spoken directional command in Ewè, such as "left," "right," "up," "down," "stop," or "go," ensuring a balanced representation of each command to mitigate potential biases.

Before training, the audio data underwent a series of crucial preprocessing steps. First, all audio files were resampled to a uniform 22,050 Hz and converted to mono to standardize the input. Next, Voice Activity Detection (VAD) was employed to remove silent or near-silent segments, improving training efficiency. Noise reduction was performed using adaptive spectral subtraction and a bandpass filter (300 Hz - 3,400 Hz) to eliminate background noise while preserving speech-relevant frequencies. Amplitude normalization was applied to ensure uniform volume levels across different recordings. Finally, Mel spectrograms and Mel-Frequency Cepstral Coefficients (MFCCs) were extracted to serve as the primary input features for the deep learning model, capturing both time-frequency characteristics and phonetic information.

5.2 Recommendations for Future Research

Although this study offers insightful information, there are still some drawbacks. For example, more work needs to be done when translating highly technical jargon, cultural quirks, and regional accents. Future studies ought to concentrate on:

i. Advanced deep learning techniques to enhance contextual accuracy.

ii. More comprehensive datasets that include diverse languages and dialects.

iii. Integration of non-verbal communication cues, such as speaker tone and facial expressions, for improved interpretation.

iv. Hybrid models that combine human expertise with AI for more precise and culturally sensitive translations.

v. Develop models that better interpret tone, sarcasm, and cultural references to enhance contextual understanding vi. Expand datasets and training models for underrepresented languages. vii. Incorporating visual and gestural cues (e.g., facial expressions) to complement audio translation.

viii. Addressing biases in training data and ensuring privacy in voice-based applications.

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