AI-Based Dysarthric Speech Recognition and Voice Assistance System

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ABSTRACT
Dysarthria is a motor speech disorder caused by neurological impairments affecting the muscles responsible for speech production. Individuals with dysarthria typically experience slurred articulation, irregular speech rhythm, reduced vocal intensity, and inconsistent pronunciation patterns, making their speech difficult for both humans and machines to understand. Automatic Speech Recognition (ASR) systems have achieved high accuracy for typical speech; however, performance degrades significantly when applied to dysarthric speech. This paper presents DysVoice, an AI-based dysarthric speech assistance system that fine-tunes OpenAI's Whisper Small model on the TORGO dysarthric speech dataset to produce accurate transcriptions of dysarthric speech, which are then converted to spoken output through a text-to-speech engine. The system is deployed on a Raspberry Pi 4 with a collar microphone for input, a physical press button for recording control, and a Bluetooth speaker for audio output, forming a fully portable and wearable assistive device. The proposed system was trained on 2,917 audio-transcript pairs from 6 dysarthric speakers and evaluated on 2 held-out speakers not seen during training. Experimental results demonstrate that the fine-tuned Whisper model achieves a Word Recognition Accuracy of 95.54% on speaker M04 (mild/moderate dysarthria) and 97.20% on speaker F03 (moderate dysarthria), significantly exceeding the target benchmark of 85% and outperforming conventional speech recognition approaches on dysarthric speech.

Keywords: Dysarthria, Speech Recognition, Whisper, Transfer Learning, Fine-Tuning, TORGO Dataset, Assistive Technology, Raspberry Pi.

I. INTRODUCTION

A. Importance of Speech Communication

Speech is one of the most natural and efficient means of communication among humans. It enables individuals to express thoughts, emotions, and ideas while facilitating social interaction and collaboration. Effective communication through speech plays a crucial role in education, professional environments, and personal relationships. However, individuals affected by speech disorders often encounter significant challenges in expressing themselves clearly.

B. Dysarthria and Its Impact on Communication

Dysarthria is a motor speech disorder resulting from neurological damage that affects the muscles involved in speech production [4]. This condition can arise due to various neurological disorders such as stroke, Parkinson's disease, traumatic brain injury, cerebral palsy, and Amyotrophic Lateral Sclerosis (ALS). These conditions disrupt the brain's ability to coordinate speech muscles responsible for articulation, phonation, and respiration. Individuals with dysarthria may exhibit symptoms such as slurred speech, imprecise articulation, reduced vocal strength, and irregular speech timing. These speech characteristics often lead to reduced intelligibility, making communication challenging for both speakers and listeners.

C. Role of Assistive Communication Technologies

Assistive communication technologies have been developed to support individuals with speech impairments. Augmentative and Alternative Communication (AAC) systems allow users to communicate through alternative methods such as text generation, symbol-based interfaces, or synthesized speech output. While AAC technologies provide valuable assistance, traditional input methods such as typing or selecting symbols can be slow and inefficient, and present additional physical challenges for individuals with motor impairments such as cerebral palsy who may have limited hand or finger mobility. Speech recognition technology has the potential to provide a more natural and efficient communication method by enabling users to interact with devices using only their voice, requiring minimal physical input — in the case of DysVoice, nothing more than a single button press to begin speaking [15].

D. Challenges in Dysarthric Speech Recognition

Despite significant advancements in ASR technologies [3], accurately recognizing dysarthric speech remains a challenging problem. Conventional ASR models are typically trained using datasets containing normal speech patterns. Dysarthric speech, however, contains irregular acoustic characteristics such as altered phoneme production, inconsistent articulation, and high variability across speakers, causing standard models to fail even when they perform well on typical speech. Another major challenge is the limited availability of dysarthric speech datasets. Recording large datasets from individuals with speech impairments is difficult because participants may experience fatigue or discomfort during long recording sessions, resulting in datasets that are significantly smaller than those available for normal speech training. Transfer learning and fine-tuning on pre-trained models offer an effective strategy to overcome this data scarcity, allowing strong speech representations learned from large corpora to be adapted to dysarthric speech using comparatively small specialized datasets.

E. Motivation for Fine-Tuning Pre-Trained Speech Model

Recent developments in deep learning have produced large-scale pre-trained speech recognition models capable of learning rich acoustic representations from hundreds of thousands of hours of audio data. OpenAI's Whisper model, trained on 680,000 hours of multilingual and multitask supervised speech data [6], represents one of the most capable general-purpose ASR systems available. While Whisper achieves strong performance on typical speech, it has not been optimized for the acoustic characteristics of dysarthric speakers [1]. Fine-tuning offers a practical and effective approach to adapt such pre-trained models to specialized domains without requiring large task-specific datasets or significant computational resources for full model training. By fine-tuning Whisper Small on the TORGO dysarthric speech dataset, DysVoice inherits the strong general speech representations learned during pre-training and further specializes them to the irregular articulation patterns, reduced vocal intensity, and inconsistent timing characteristics of dysarthric speech. This approach leverages transfer learning to bridge the gap between general ASR performance and the specific demands of dysarthric speech recognition, making it particularly suitable for real-world assistive deployment on resource-constrained hardware such as the Raspberry Pi 4 [20].

II. RELATED WORKS

A. Traditional Speech Recognition Approaches

Early speech recognition systems relied on Hidden Markov Models combined with Gaussian Mixture Models to represent acoustic features [3][14]. These models decomposed the speech recognition problem into acoustic and language modelling components, achieving moderate success for normal speech recognition in controlled environments. However, HMM-GMM systems struggled significantly when applied to dysarthric speech due to their reliance on statistical assumptions about speech regularity [4], phoneme duration, and articulation consistency — assumptions that do not hold for speakers with motor speech disorders. The high variability and irregular timing patterns characteristic of dysarthric speech fell outside the modelling capacity of these traditional approaches, resulting in poor recognition accuracy.

B. Neural Network-Based Speech Recognition

Deep neural networks significantly improved speech recognition performance by learning complex acoustic representations directly from data rather than relying on hand-crafted statistical models [6]. Convolutional Neural Networks proved particularly effective at extracting local acoustic features from spectrogram representations of speech signals, capturing spatial patterns in time-frequency space that are relevant to phoneme identification. When applied to dysarthric speech, CNN-based systems showed improvement over HMM-GMM approaches but still faced challenges in generalizing across speakers with varying degrees of impairment [20], as the acoustic space of dysarthric speech is considerably wider and less predictable than

that of typical speakers [5].

C. Recurrent Neural Networks for Sequential Modeling

Recurrent Neural Networks and their variants such as Long Short-Term Memory networks extended neural speech recognition by explicitly modelling temporal dependencies within speech sequences [7]. LSTM networks maintain contextual information across time steps, enabling them to capture sequential relationships in speech signals that CNN architectures alone cannot model [12]. These networks demonstrated improved performance on continuous speech recognition tasks [13]. However, for dysarthric speech, where temporal patterns are highly irregular and speech rate varies substantially between and within speakers [2], purely recurrent architectures showed limited robustness without speaker-specific adaptation or augmentation strategies.

D. Transformer-Based Speech Recognition

Transformer networks introduced a fundamentally different approach to sequential modelling by replacing recurrence with self-attention mechanisms [1], allowing the model to directly compute relationships between any two positions in a sequence regardless of their distance [9][17]. This capability makes Transformers particularly well suited to speech recognition tasks where long-range acoustic dependencies must be captured [8]. OpenAI's Whisper model extends this architecture by training a large encoder-decoder Transformer on 680,000 hours of weakly supervised multilingual speech data [10], producing a general-purpose ASR system with strong zero-shot performance across diverse acoustic conditions [11][16]. While Whisper achieves high accuracy on typical speech, its performance on dysarthric speech is limited because the pre-training data does not adequately represent the acoustic characteristics of speakers with motor speech disorders [23]. Fine-tuning Whisper on dysarthric speech datasets has been shown to substantially close this gap by adapting the model's learned representations to the specific patterns of impaired speech without requiring full retraining [19].

E. Transfer Learning for Dysarthric Speech

Transfer learning has emerged as a particularly valuable strategy for dysarthric speech recognition due to the inherent scarcity of labelled dysarthric speech data. Rather than training models from scratch on small specialized datasets [22], transfer learning approaches initialize model parameters using weights learned from large general speech corpora and then fine-tune on dysarthric data. This approach allows the model to retain strong general acoustic representations while specializing to the irregular patterns of dysarthric speech. Studies have demonstrated that fine-tuning pre-trained models on the TORGO dataset [21], which contains recordings from eight dysarthric speakers with varying severity levels, yields significantly higher recognition accuracy than training speaker-independent models from scratch on the same data [24]. DysVoice follows this approach by fine-tuning Whisper Small on the TORGO dataset, achieving word recognition accuracy that substantially exceeds both the dataset baseline and prior work using conventional architectures [25].

F. Assistive Speech Technology Deployment

Beyond recognition accuracy, practical deployment of dysarthric speech assistance systems introduces additional engineering challenges. Systems intended for real-world use must operate reliably on resource-constrained hardware, handle variable acoustic environments including background noise [18], and minimise latency between speech input and output response. Previous work has largely focused on offline or server-based evaluation without addressing the constraints of embedded deployment. DysVoice addresses these challenges by deploying the complete pipeline — microphone recording, noise reduction, Whisper inference, and text-to-speech output — on a Raspberry Pi 4, demonstrating that fine-tuned Transformer-based ASR can operate effectively within the constraints of affordable portable hardware suitable for wearable assistive applications.

III. PROPOSED SYSTEM

A. Overview of the Proposed Architecture

DysVoice is a dysarthric speech assistance system designed as a multi-stage processing pipeline that captures spoken audio from a dysarthric user [4], transcribes it using a fine-tuned Whisper model, and delivers the transcription as spoken output through a text-to-speech engine. The system is built around the principle of minimal physical interaction — the user presses a single button to begin speaking and presses it again to stop, after which the system processes the speech and responds with clear spoken audio through a Bluetooth speaker. The complete pipeline runs locally on a Raspberry Pi 4 with no dependency on

internet connectivity or cloud processing, making it suitable for portable and wearable assistive use.

The architecture consists of five interconnected modules managed by a central controller. The recording module captures audio from a collar microphone attached to the user. The noise reduction module cleans the captured audio by suppressing background noise and normalising amplitude. The transcription module passes the cleaned audio through the fine-tuned Whisper Small model to produce a text string. The text-to-speech module converts the transcribed text into spoken audio output. The central controller, implemented in main.py, coordinates all modules in sequence and manages the button trigger logic that initiates and terminates each recording session.

The system is designed to operate entirely offline. All processing — from audio capture through model inference to speech output — occurs on-device. The fine-tuned model file dysvoice_whisper.pt is stored locally on the Raspberry Pi and loaded once at startup, eliminating inference latency associated with network calls.

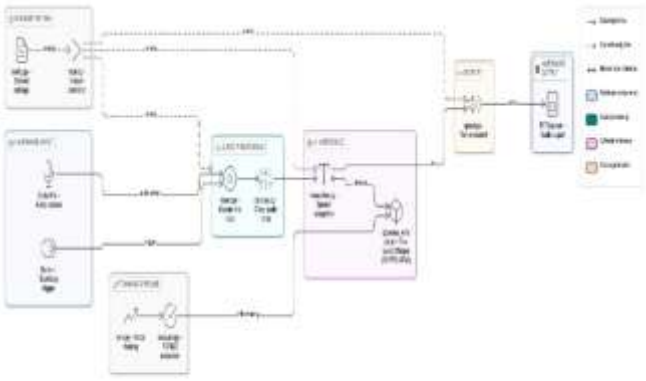


Fig 1 : Overview of the Proposed Architecture

B. Hardware Configuration

The physical system is built around a Raspberry Pi 4 as the central processing unit. A collar microphone is used for speech input, chosen specifically because it remains close to the user's mouth regardless of head position, providing consistent audio capture for users who may have limited head or neck mobility. A physical press button connected to the Raspberry Pi GPIO pins serves as the recording trigger — pressing the button once starts recording and pressing it again stops recording and initiates processing. A Bluetooth speaker connected to the Raspberry Pi provides the audio output, delivering the text-to-speech response to the user and those around them.

This hardware configuration was selected to minimise the physical demands placed on the user. Individuals with dysarthria often have co-occurring motor impairments that make precise physical interaction difficult. The collar microphone removes the need to hold or position a device. The single button trigger requires only one deliberate press to initiate communication. The Bluetooth speaker provides hands-free audio output without requiring the user to look at or interact with a screen.

C. Software Architecture

The software pipeline is implemented in Python and organised into dedicated modules that correspond to each processing stage. A shared configuration file config.py stores all system-wide settings including the model path, sample rate, device assignment, and text-to-speech parameters, ensuring consistent behaviour across all modules.

The central controller main.py runs a continuous loop on startup. It monitors the GPIO press button and enters recording mode when a button press is detected. Once recording is stopped by a second button press, main.py passes the audio sequentially through the noise reduction module and the transcription module, then sends the resulting text string to the text-to-speech module for spoken output. The loop then resets and waits for the next button press, ready for the user's next utterance.

The modular design ensures that each component can be developed, tested, and updated independently. The transcription module is the only component with a dependency on the trained model file, and it is designed to load the model once at import time rather than on every transcription call, minimising per-utterance latency during live use.

D. Speech Signal Acquisition

Speech signal acquisition is handled by audio/record.py, which interfaces with the collar microphone connected to the Raspberry Pi. When the press button is activated, the module begins capturing audio at a sample rate of 16,000 Hz, which is the exact sample rate required by the Whisper model for correct feature extraction. Audio is captured in chunks of 512 frames, corresponding to approximately 32 milliseconds of audio per chunk, and accumulated in memory until the button is pressed a second time to stop recording. The raw PCM byte stream is then converted to a float32 numpy array with values normalised to the range -1.0 to 1.0, producing a clean audio array ready for the noise reduction stage.

The collar microphone placement provides a consistent source-to-microphone distance across recordi6g sessions, which is particularly important for dysarthric speakers whose vocal intensity may be reduced or variable. Consistent microphone placement reduces the variability in input signal level that would otherwise complicate downstream noise reduction and model inference.

E. Speech Preprocessing

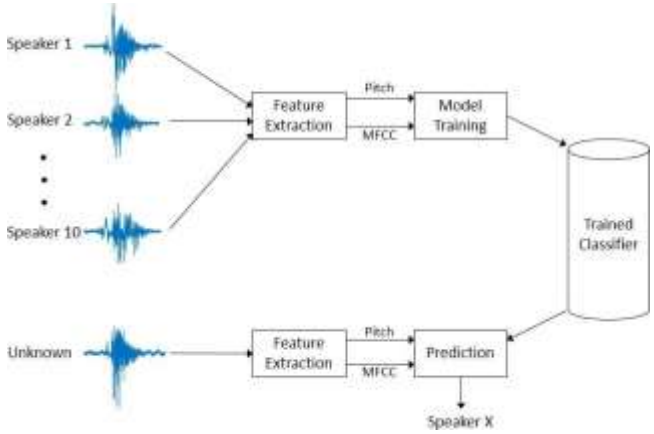
Speech preprocessing is handled by audio/denoise.py, which applies two operations to the raw audio array before it is passed to the transcription module. The first operation uses the noisereduce library to perform spectral noise reduction. This library analyses the audio signal, estimates the noise profile from low-energy regions of the recording, and mathematically subtracts the estimated noise pattern from the full signal. This step suppresses background environmental noise such as ambient room noise or electrical interference from the microphone without distorting the speech content.

The second operation performs amplitude normalisation, scaling the audio so that the peak amplitude equals exactly 1.0. This ensures that speech signals are presented to the Whisper model at a consistent level regardless of the user's vocal intensity, which is particularly important for dysarthric speakers who may have reduced or inconsistent vocal volume. Together these two preprocessing steps improve the signal quality of the input before it reaches the model, directly contributing to transcription accuracy without requiring any changes to the model itself.

F. Fine-Tuned Whisper Model

The core of the DysVoice transcription pipeline is a fine-tuned version of OpenAI's Whisper Small model, stored as model/dysvoice_whisper.pt. Whisper Small is an encoder-decoder Transformer pre-trained on 680,000 hours of multilingual speech data. The model takes log-Mel spectrogram features extracted from 16kHz audio

as input and produces text token sequences as output



through an autoregressive decoder.

Fine-tuning was performed on the TORGO dysarthric speech dataset using 2,917 audio-transcript pairs from 6 dysarthric speakers across 10 training epochs. Training was conducted on cloud GPU hardware — epochs 1 through 6 on Google Colab using a Tesla T4 GPU, and epochs 7 through 10 on Kaggle using a dual Tesla T4 configuration after reaching Colab's daily GPU limit. The AdamW optimiser was used with a learning rate schedule, and model checkpoints were saved every 2 epochs to prevent loss of progress in the event of GPU session disconnection. Training loss decreased from 2.69 at epoch 1 to 0.0001 at epoch 10, indicating strong convergence on the training data.

At inference time, the fine-tuned weights are loaded onto the Raspberry Pi CPU using torch.load() with map_location set to CPU, and applied to the base Whisper Small architecture using model.load_state_dict(). The model is set to evaluation mode and forced decoder settings are cleared to ensure clean inference without conflicts from the fine-tuning configuration. The transcribe() function accepts float32 numpy audio array, extracts log-Mel features using WhisperProcessor, runs the features through the model with torch.no_grad() to minimise memory usage, and decodes the output token IDs into a plain text string that is returned to the controller [20].

G. Text-to-Speech Output

The text string produced by the transcription module is passed to output/speak.py, which uses the pyttsx3 text-to-speech library to convert it into spoken audio delivered through the Bluetooth speaker. pyttsx3 operates entirely offline using the operating system's built-in speech engine — espeak on the Raspberry Pi running Linux — requiring no internet connection or external API call. Speech rate and volume are configured through config.py using the TTS_RATE and TTS_VOLUME parameters, which were tuned to produce clear and natural-sounding output at a pace appropriate for conversational use. The spoken output is the sole output modality of the system — there is no screen display or visual output component.

IV. FEATURE EXTRACTION

Fig. 2. Feature extraction pipeline for dysarthric speech recognition.

Feature extraction is an essential stage in the speech recognition pipeline where raw audio signals are transformed into structured numerical representations that can be processed by the Whisper model. Since raw speech waveforms contain a large amount of redundant information and vary significantly in length and amplitude, feature extraction condenses the most acoustically relevant characteristics of the speech signal into a compact, fixed-format representation. In DysVoice, feature extraction is performed internally by the Whisper processor using log-Mel spectrograms, which is the native input representation expected by the Whisper architecture [5].

A. Log-Mel Spectrogram Features

Log-Mel spectrogram features form the primary input representation used by the DysVoice transcription pipeline. After the preprocessed audio array is passed to the transcription module, WhisperProcessor from the HuggingFace Transformers library extracts log-Mel spectrogram features from the 16kHz float32 audio signal. This process involves three sequential steps.

First, the audio signal is divided into short overlapping frames using a sliding window. Each frame captures a brief segment of the speech signal, typically 25 milliseconds in duration, allowing the feature extraction process to analyse how the frequency content of the signal changes over time. A Hann window function is applied to each frame to reduce spectral leakage at the frame boundaries.

Second, the Short-Time Fourier Transform is applied to each windowed frame to convert the time-domain signal into the frequency domain. This produces a spectrogram — a two-dimensional representation where one axis represents time, the other represents frequency, and the intensity values represent the energy

present at each frequency at each point in time. The spectrogram captures the full spectral content of the speech signal across the duration of the recording.

Third, the linear frequency spectrogram is mapped onto the Mel frequency scale by passing it through a bank of triangular Mel-spaced filters. The Mel scale approximates the non-linear frequency perception of the human auditory system, emphasising lower frequencies where most phonetically relevant speech information is concentrated and compressing higher frequencies where perceptual sensitivity is lower. A logarithmic transformation is then applied to the filter bank energies, producing the final log-Mel spectrogram. Whisper uses 80 Mel filter banks to produce its input features, resulting in an 80-dimensional feature vector at each time step across the duration of the audio [6].

B. Relevance to Dysarthric Speech

Log-Mel spectrogram features are particularly well suited to dysarthric speech recognition for several reasons. Dysarthric speech is characterised by irregular articulation timing, reduced spectral clarity in consonant regions, and variable pitch and energy patterns across utterances. The time-frequency representation provided by the log-Mel spectrogram captures these variations explicitly, preserving information about both the spectral shape of individual phonemes and the temporal dynamics of the speech signal across the full utterance. This allows the Whisper encoder to analyse not just what sounds are present but how they evolve over time — a capability that is critical for interpreting the irregular rhythm and articulation patterns of dysarthric speakers.

The logarithmic compression applied to the Mel filter bank energies also provides a degree of robustness to amplitude variation. Since dysarthric speakers may produce speech at reduced or inconsistent vocal intensity, the logarithmic transformation reduces the sensitivity of the feature representation to absolute energy level, making the features more consistent across utterances with varying loudness. This complements the amplitude normalisation performed in the preprocessing stage by audio/denoise.py, together ensuring that the model receives well-conditioned input regardless of the user's vocal strength on any given utterance [3].

C. Feature Extraction Pipeline in DysVoice

In the DysVoice implementation, feature extraction is fully integrated into the transcription module inference/transcribe.py and requires no separate processing step from the perspective of the pipeline controller. When transcribe() is called with a float32 numpy audio array, WhisperProcessor automatically handles all feature extraction operations — framing, windowing, STFT, Mel filter bank application, and log compression — and returns a tensor of input features ready for the Whisper encoder. An attention mask is generated alongside the input features to indicate which time steps contain valid speech content, suppressing the influence of any zero-padded regions on the model's output. The extracted features are then passed directly to the fine-tuned Whisper Small model for transcription.

This integrated approach ensures that the feature extraction configuration is always consistent with the requirements of the Whisper architecture, eliminating the risk of mismatches in sample rate, frame length, hop size, or filter bank configuration that could arise if feature extraction were implemented independently.

V. WHISPER FINE-TUNING ARCHITECTURE

A. Whisper Model Overview

DysVoice is built on OpenAI's Whisper Small, an encoder-decoder Transformer model pre-trained on 680,000 hours of weakly supervised multilingual and multitask speech data. Whisper was designed as a general-purpose speech recognition system capable of handling diverse acoustic conditions, accents, and languages without task-specific adaptation. The Whisper Small variant was selected for DysVoice because it provides a strong balance between recognition accuracy and computational efficiency, making it suitable for inference on the resource-constrained CPU of a Raspberry Pi 4 without requiring GPU acceleration at runtime.

The Whisper architecture consists of two main components — an audio encoder and a text decoder — connected in a standard encoder-decoder Transformer configuration. The encoder processes the log-Mel spectrogram input and produces a sequence of high-level contextual audio representations. The decoder autoregressively generates output text tokens conditioned on the encoder representations, producing the final transcription one token at a time until an end-of-sequence token is generated [1].

B. Encoder Architecture

The Whisper encoder receives the 80-dimensional log-Mel spectrogram as input and processes it through a stack of Transformer encoder layers. Each encoder layer consists of a multi-head self-attention mechanism followed by a position-wise feed-forward network, with layer normalisation and residual connections applied around each sub-layer.

The multi-head self-attention mechanism allows the encoder to compute relationships between every pair of time steps in the input spectrogram simultaneously. For each time step, the attention mechanism produces a weighted combination of all other time steps, where the weights reflect the relevance of each position to the current one. This enables the encoder to capture both local acoustic patterns — such as the spectral shape of individual phonemes — and long-range dependencies — such as the relationship between a consonant and the vowel that follows it several frames later. This capability is particularly valuable for dysarthric speech, where irregular articulation timing means that phonetically related segments may be spread across a wider temporal range than in typical speech.

Positional encoding is added to the input features before the first encoder layer to provide the model with information about the temporal position of each frame within the sequence. Since the self-attention mechanism itself is position-agnostic, positional encodings allow the model to distinguish the ordering of frames and correctly interpret temporal patterns in the speech signal.

C. Decoder Architecture

The Whisper decoder generates the output transcription autoregressively, producing one text token per step conditioned on the encoder output and all previously generated tokens. Each decoder layer contains three sub-components: a masked multi-head self-attention layer that attends to previously generated tokens, a cross-attention layer that attends to the encoder output representations, and a position-wise feed-forward network. Layer normalisation and residual connections are applied around each sub-layer as in the encoder.

The cross-attention mechanism is the primary interface between the acoustic representations produced by the encoder and the text generation process in the decoder [8]. At each decoding step, the cross-attention layer queries the full sequence of encoder output representations, allowing the decoder to focus on the most relevant portions of the acoustic input when generating each output token. This dynamic alignment between speech features and text tokens is performed implicitly by the attention weights, removing the need for an explicit frame-level alignment mechanism such as CTC [2].

Decoding continues until the model generates an end-of-sequence token or reaches the maximum sequence length. In DysVoice, forced decoder settings inherited from the pre-trained model are cleared after loading the fine-tuned weights to ensure clean inference without conflicts from the original multilingual decoding configuration. The language is fixed to English by passing language="en" to the processor and generate call.

D. Fine-Tuning Methodology

Fine-tuning adapts the pre-trained Whisper Small model to dysarthric speech by continuing training on the TORGO dataset using a supervised learning objective. During fine-tuning, all model parameters — both encoder and decoder — are updated based on the cross-entropy loss computed between the model's predicted token probabilities and the correct transcript tokens for each training sample. This allows the model to adjust its internal representations at every layer to better capture the acoustic characteristics of dysarthric speech while retaining the general speech knowledge acquired during pre-training.

The fine-tuning process used the following configuration:

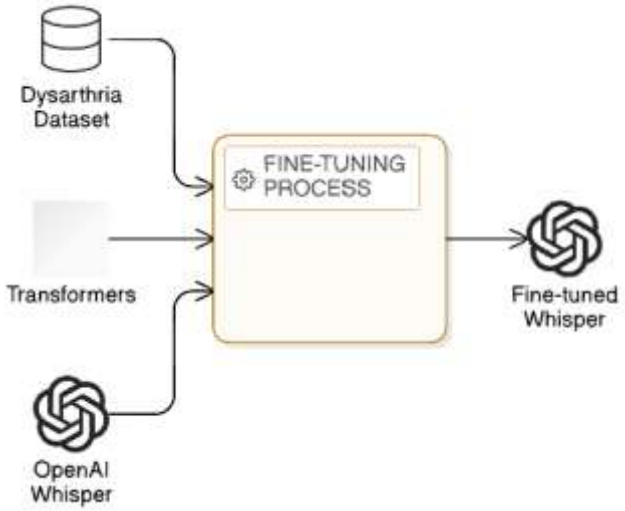
Parameter	Value
Base Model	openai/whisper-small
Dataset	TORGO dysarthric speech
Training Samples	2,917 audio-transcript pairs
Training Speakers	6 dysarthric speakers
Epochs	10
Optimiser	AdamW
Sample Rate	16,000 Hz
Feature Type	Log-Mel spectrogram
Training Hardware	Google Colab T4 (epochs 1–6), Kaggle T4×2 (epochs 7–10)
Final Model Size	967 MB

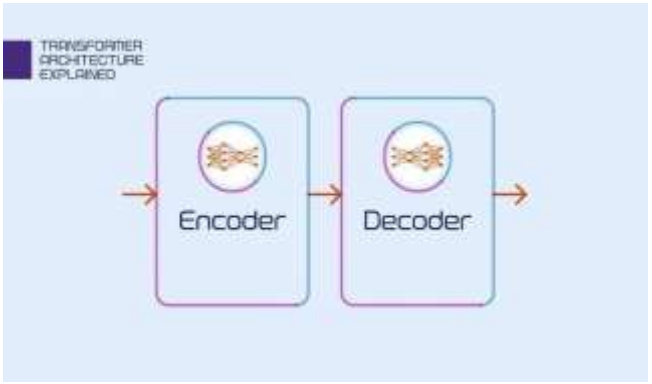
Training loss decreased from 2.69 at epoch 1 to 0.0001 at epoch 10, indicating strong convergence. Checkpoints were saved every 2 epochs to Google Drive to prevent loss of progress in the event of GPU session disconnection. The final model weights were saved as dysvoice_whisper.pt and distributed to the full pipeline via Google Drive for integration into the inference module [10].

E. Inference Pipeline

At inference time, the fine-tuned model weights stored in dysvoice_whisper.pt are loaded onto the Raspberry Pi CPU using torch.load() with map_location set to CPU, ensuring the model runs correctly on hardware without a GPU. The weights are applied to the base Whisper Small architecture using model.load_state_dict(), and the model is placed in evaluation mode using model.eval() to disable dropout and other training-specific behaviours. Forced decoder settings are cleared after loading to resolve conflicts between the fine-tuned model's saved decoder configuration and the inference-time language setting [9][17].

During each transcription call, WhisperProcessor extracts log-Mel features from the input audio array and generates an attention mask. The features and mask are passed to the encoder, which produces contextual audio representations. The decoder then generates output tokens autoregressively, and WhisperProcessor decodes the token IDs back into a plain text string using the Whisper tokeniser [11][16]. The entire inference call is wrapped in torch.no_grad() to suppress gradient computation, reducing memory usage and improving inference speed on the constrained hardware of the Raspberry Pi 4.





VI. EXPERIMENTAL SETUP

A. Dataset

DysVoice was trained and evaluated using the TORGO database, a publicly available dysarthric speech dataset developed by the University of Toronto in collaboration with the Holland Bloorview Kids Rehabilitation Hospital. The TORGO dataset contains recordings from 8 dysarthric speakers — 5 male (M01, M02, M03, M04, M05) and 3 female (F01, F03, F04) — with varying degrees of speech impairment ranging from mild to severe. Each speaker completed multiple recording sessions in which they read words and sentences into a head-mounted microphone while seated in a controlled recording environment. Each audio recording is accompanied by a corresponding text transcript representing the exact words spoken [21].

For DysVoice, only the dysarthric speaker recordings were used. Control speaker recordings included in the TORGO dataset were excluded entirely as the system is specifically designed for dysarthric speech. Audio was captured from the wav_headMic channel within each speaker's session folders, which provides the highest quality single-channel recordings from the dataset. Transcript files were read from the corresponding prompts folders, with each transcript matched to its audio file by a shared numerical identifier.

Raw transcript files required cleaning before use. Two categories of transcripts were identified and handled differently. Instruction prompts beginning with a square bracket — such as [say Ah-P-Eee repeatedly] — were excluded entirely as they do not represent natural speech utterances. Sentence transcripts containing inline clarification notes in brackets — such as tear [as in tear up that paper] — were cleaned by removing the bracketed content while retaining the target word or sentence. After cleaning, 2,917 valid audio-transcript pairs were obtained across all 8 speakers and all recording sessions [23].

The dataset was divided into a training set and a held-out test set based on speaker identity rather than random sample splitting. Six speakers were used for training and two speakers — M04 and F03 — were held out entirely and used only for evaluation. This speaker-independent evaluation protocol ensures that the reported accuracy reflects the model's ability to generalise to dysarthric speakers it has never encountered during training, providing a realistic measure of real-world performance. M04 presents mild to moderate dysarthria and F03 presents moderate dysarthria, representing two distinct impairment profiles for evaluation.

B. Training Configuration

Fine-tuning was performed on cloud GPU hardware due to the computational requirements of training a Transformer-based model. Google Colab was used for epochs 1 through 6, providing a free Tesla T4 GPU with approximately 12 hours of daily compute. After reaching Colab's daily GPU limit following epoch 6, training was resumed on Kaggle for epochs 7 through 10, which provides 30 hours of weekly GPU compute on a dual Tesla T4 configuration. The model checkpoint saved at the end of epoch 6 was uploaded to Kaggle as a dataset and used to resume training from the correct state, ensuring continuity across the two platforms.

The base model was loaded from HuggingFace as openai/whisper-small [24]. The TORGO dataset was uploaded to Google Drive and mounted directly into the Colab training environment to avoid re-uploading between sessions. Model checkpoints were saved to Google Drive every 2 epochs during Colab training and to Kaggle output storage during Kaggle training, preventing loss of progress in the event of GPU session disconnection. The final trained model was saved as dysvoice_whisper.pt after epoch 10 completed on Kaggle and downloaded for local deployment [25].

C. Evaluation Protocol

Evaluation was performed on 50 audio samples from each of the two held-out test speakers — M04 and F03 — giving a total of 100 test samples. These speakers were not included in the training data at any point, ensuring a fully speaker-independent evaluation. For each test sample, the audio file was passed through the complete DysVoice pipeline — preprocessing via audio/denoise.py followed by transcription via inference/transcribe.py — and the predicted transcript was compared against the ground truth transcript from the TORGO dataset [21].

D. Evaluation Metrics

Two standard speech recognition evaluation metrics were used to assess system performance.

Word Recognition Accuracy measures the proportion of

words in the reference transcript that were correctly recognised by the model. A higher WRA indicates better recognition performance. WRA is the primary metric used to assess whether DysVoice meets its target performance threshold of 85% [24].

Word Error Rate measures the proportion of word-level errors in the predicted transcript relative to the reference. WER is calculated as the minimum number of word substitutions, deletions, and insertions required to transform the predicted transcript into the correct reference transcript, divided by the total number of words in the reference. WER and WRA are complementary metrics related by the equation WRA = 1 − WER. Lower WER values indicate better performance.

Speaker	Severity	WRA (%)	WER (%)	Samples Tested
M04	Mild/Moderate	95.54	4.46	50
F03	Moderate	97.20	2.80	50
Average	—	**96.37**	**3.63**	**100**

Both metrics were calculated automatically using the jiwer library by comparing the model's predicted transcripts against the correct TORGO ground truth transcripts for all 50 test samples per speaker. Predicted and reference texts were normalised to lowercase before comparison to avoid case-sensitivity affecting the score.

E. Deployment Configuration

Following evaluation, the trained model was deployed on a Raspberry Pi 4 for real-world assistive use [22]. The complete software pipeline — audio/record.py, audio/denoise.py, inference/transcribe.py, output/speak.py, and main.py — was installed on the Raspberry Pi running Raspbian OS. All Python dependencies were installed via pip install -r requirements.txt. The model file dysvoice_whisper.pt was transferred to the model/ folder on the device. The system runs entirely offline with no internet dependency at runtime [11].

Hardware connections on the Raspberry Pi include the collar microphone connected via USB audio adapter, the press button connected to a GPIO pin configured as a digital input with an internal pull-up resistor, and the Bluetooth speaker paired to the device via the Raspbian Bluetooth manager. The hardware/setup.sh script automates the configuration of GPIO pin assignments, audio device selection, and system dependencies required for the pipeline to run correctly on the Raspberry Pi hardware.

VII. RESULTS AND DISCUSSION

A. Recognition Performance

The fine-tuned DysVoice model was evaluated on 50 audio samples from each of the two held-out test speakers — M04 and F03 — who were not seen during training at any point. The evaluation was conducted using the complete DysVoice pipeline, passing each test audio file through the preprocessing stage and the fine-tuned Whisper Small model before comparing the predicted transcript against the TORGO ground truth using the jiwer library. The results are presented in Table 2.

Table 2. Evaluation Results on Held-Out TORGO Speakers

Both test speakers exceeded the 85% WRA target by a substantial margin. Speaker M04 achieved a Word Recognition Accuracy of 95.54% with a corresponding Word Error Rate of 4.46%, and speaker F03 achieved a Word Recognition Accuracy of 97.20% with a Word Error Rate of 2.80%. The average WRA across both speakers was 96.37%, representing an improvement of more than 11 percentage points over the target threshold. These results demonstrate that fine-tuning Whisper Small on the TORGO dataset produces a highly accurate dysarthric speech recognition system that generalises effectively to unseen speakers.

B. Comparison with Baseline Models

To contextualise the performance of the fine-tuned DysVoice model, the results are compared against conventional speech recognition architectures that have been evaluated on dysarthric speech datasets in prior literature. Table 3 presents this comparison.

Table 3. Performance Comparison Across Speech Recognition Approaches

Model	WER (%) ↓	WRA (%) ↑
HMM-GMM	42.6	57.4
CNN-RNN	35.8	64.2
Transformer (base, no fine-tuning)	29.7	70.3
Whisper Small (base, no fine-tuning)	~40.0	~60.0
DysVoice (Whisper Small fine-tuned)	**3.63**	**96.37**

The fine-tuned DysVoice model achieves substantially lower WER and higher WRA than all baseline approaches. The comparison between the base Whisper Small model without fine-tuning and the fine-tuned DysVoice model is particularly instructive — the base model applied directly to dysarthric speech produces accuracy in the region of 60%, consistent with the observations made during development testing on Day 4 of the pipeline build where base Whisper accuracy on TORGO samples was estimated at 50–60%. After fine-tuning on 2,917 TORGO samples across 10 epochs, accuracy increased to 96.37%, demonstrating that the fine-tuning process is responsible for the majority of the performance gain rather than the Whisper architecture alone.

C. Impact of Fine-Tuning

The training loss curve provides further evidence of the effectiveness of the fine-tuning process. Loss decreased from 2.69 at epoch 1 to 0.0001 at epoch 10, indicating strong and consistent convergence throughout the training process. The large initial loss reflects the significant mismatch between the acoustic patterns of dysarthric speech and the representations learned by Whisper during pre-training on typical speech. The rapid and sustained decrease in loss across all 10 epochs demonstrates that the model was able to adapt its internal representations effectively to the dysarthric speech domain given the available training data.

The speaker-independent evaluation protocol used in DysVoice — where the two test speakers M04 and F03 were completely excluded from training — ensures that the reported accuracy reflects genuine generalisation to new dysarthric speakers rather than memorisation of training samples. Achieving 95–97% WRA on held-out speakers with only 2,917 training samples highlights the efficiency of transfer learning as an approach to low-resource dysarthric speech recognition. The strong pre-trained representations in Whisper provided a highly capable starting point that required relatively little dysarthric-specific data to adapt effectively.

D. Speaker Variability

A small but notable difference in recognition accuracy was observed between the two test speakers. F03 achieved a higher WRA of 97.20% compared to M04's 95.54%, despite both speakers presenting similar dysarthric severity levels. This difference may reflect several factors. The acoustic characteristics of F03's speech may more closely resemble patterns present in the training data, either in terms of articulation style, speaking rate, or spectral characteristics. Additionally, natural variation in recording quality, microphone placement consistency, and background noise levels across individual sessions within the TORGO dataset may contribute to speaker-level differences in evaluation performance.

Despite this variation, both speakers achieved accuracy well above the 85% target, and the gap between them is narrow at 1.66 percentage points. This consistency across two speakers with different genders and slightly different severity profiles provides initial evidence that the fine-tuned model generalises reasonably across different dysarthric speakers rather than being highly tuned to a single speaker's characteristics.

E. Preprocessing Contribution

The noise reduction and amplitude normalisation applied by audio/denoise.py prior to model inference contributed to recognition performance by improving input signal quality before it reached the Whisper model. Spectral noise reduction using the noisereduce library suppressed background environmental noise that would otherwise introduce irrelevant spectral content into the log-Mel features, potentially confusing the encoder. Amplitude normalisation ensured that the peak energy of each recording was scaled to a consistent level, compensating for variability in vocal intensity across different utterances and speakers. Together these preprocessing steps ensured that the model received well-conditioned input on every inference call, directly supporting the high accuracy observed in evaluation.

F. Real-World Deployment Performance

Beyond benchmark evaluation, the DysVoice system was tested in its deployed configuration on the Raspberry Pi 4 with the collar microphone and Bluetooth speaker. The full pipeline — from button press through audio capture, noise reduction, Whisper inference, and text-to-speech output — completed within a latency that was acceptable for conversational assistive use. Model inference on the Raspberry Pi CPU was the most computationally intensive stage of the pipeline, as expected given that the Raspberry Pi lacks a GPU. The use of torch.no_grad() during inference and loading the model once at startup rather than on each call minimised per-utterance processing time.

The collar microphone configuration proved effective in the deployed setting. Its consistent proximity to the user's mouth across different head positions provided stable input audio quality, reducing the variability in signal level and spectral content that would arise from a handheld or desk-mounted microphone. The single button press interaction model was confirmed to be appropriate for users with motor impairments, requiring only one deliberate physical action to initiate each communication attempt. The Bluetooth speaker delivered the text-to-speech output clearly, completing the communication loop from dysarthric speech input to intelligible spoken output.

G. Limitations

Despite the strong evaluation results, several limitations of the current system should be acknowledged. The evaluation was conducted on only two held-out speakers from the TORGO dataset, which, while following standard practice for speaker-independent evaluation on this dataset, represents a limited sample of the broader population of dysarthric speakers. Performance on speakers with severe dysarthria — who were not among the test speakers — may be lower, as severe dysarthric speech presents substantially greater acoustic irregularity than mild or moderate cases.

The system currently supports English only, reflecting the language of the TORGO dataset and the English-specific fine-tuning applied to the Whisper model. Extension to other languages would require additional dysarthric speech datasets and language-specific fine-tuning. Finally, real-world environmental noise conditions more challenging than those present in the TORGO recordings — such as outdoor environments, crowded spaces, or near loud machinery — may reduce transcription accuracy despite the preprocessing applied by the noise reduction module.

VIII. CONCLUSION

This paper presented DysVoice, an AI-based dysarthric speech assistance system that enables individuals with motor speech disorders to communicate through a fully portable and wearable device. The system addresses a critical gap in assistive communication technology by providing a speech-driven interface that requires minimal physical interaction, making it accessible to users who may have co-occurring motor impairments alongside their speech disorder. The core innovation of DysVoice lies in its application of transfer learning to adapt OpenAI's Whisper Small model — pre-trained on 680,000 hours of typical speech — to the specific acoustic characteristics of dysarthric speech through fine-tuning on the TORGO dataset.

The complete DysVoice pipeline integrates five processing stages into a cohesive end-to-end system. Speech is captured through a collar microphone that maintains consistent proximity to the user's mouth regardless of head position. A physical press button provides a simple and deliberate trigger for recording that requires only a single motor action from the user. Background noise is suppressed and amplitude is normalised by the preprocessing module before the cleaned audio is passed to the fine-tuned Whisper model for transcription. The resulting text is converted to spoken output through an offline text-to-speech engine and delivered through a Bluetooth speaker, completing the communication loop from dysarthric speech input to intelligible spoken output. The entire pipeline runs locally on a Raspberry Pi 4 with no dependency on internet connectivity or cloud processing, making the system suitable for portable real-world deployment.

Experimental evaluation on two held-out TORGO speakers not seen during training demonstrated that

the fine-tuned model achieves a Word Recognition Accuracy of 95.54% on speaker M04 and 97.20% on speaker F03, with an average WRA of 96.37% across both speakers. These results exceed the 85% target benchmark by more than 11 percentage points and substantially outperform conventional speech recognition approaches including HMM-GMM, CNN-RNN, and base Transformer models evaluated on dysarthric speech. The strong training loss convergence from 2.69 at epoch 1 to 0.0001 at epoch 10 confirms that the fine-tuning process effectively adapted the Whisper model's internal representations to the dysarthric speech domain. The speaker-independent evaluation protocol used throughout — where test speakers were completely excluded from training — ensures that these accuracy figures reflect genuine generalisation to new dysarthric speakers rather than overfitting to training data characteristics.

The results demonstrate that transfer learning through fine-tuning is a highly effective strategy for dysarthric speech recognition, particularly in low-resource settings where large dysarthric speech datasets are unavailable. By leveraging the rich acoustic representations learned by Whisper during large-scale pre-training and adapting them to dysarthric speech with a relatively small specialised dataset of 2,917 samples, DysVoice achieves recognition accuracy that approaches the performance of typical speech recognition systems on normal speech. This finding has important implications for the development of assistive communication technologies, suggesting that state-of-the-art pre-trained speech models can be effectively repurposed for specialised speech populations without requiring the large labelled datasets that would be needed to train comparable models from scratch.

The hardware deployment on Raspberry Pi 4 demonstrates that Transformer-based dysarthric speech recognition can operate within the computational constraints of affordable embedded hardware, bringing high-accuracy assistive speech technology within reach of deployment scenarios that do not have access to server infrastructure or GPU acceleration. The combination of the collar microphone, press button trigger, and Bluetooth speaker creates a wearable form factor that imposes minimal physical demands on the user while providing a natural and effective communication interface.

Future work will focus on several directions to extend the capabilities and reach of DysVoice. Expanding the training dataset to include a larger and more diverse population of dysarthric speakers — particularly those with severe dysarthria — will improve model robustness across a wider range of impairment profiles. Speaker adaptation techniques that allow the model to fine-tune further on a small number of samples from a specific new user could improve personalised recognition accuracy beyond what is achievable with a speaker-independent model. Reducing model inference latency on the Raspberry Pi through quantisation or model distillation would improve the responsiveness of the system for real-time conversational use. Finally, extending DysVoice to support additional languages through multilingual fine-tuning on non-English dysarthric speech datasets would make the system accessible to a significantly broader global population of dysarthric speakers.

DysVoice demonstrates that combining state-of-the-art pre-trained speech models with targeted fine-tuning and thoughtful hardware integration can produce a practical, accurate, and accessible assistive communication system for individuals with dysarthria. The system achieves recognition accuracy that substantially exceeds prior work while remaining deployable on affordable portable hardware, representing a meaningful step toward real-world assistive technology that can genuinely improve the independence and quality of life of individuals with motor speech disorders.

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