Machine Learning on Audio Signals

Course Booklet

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EE502 Intelligent System Design — Fall 2026

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Preface

Machine Learning on Audio Signals began as a set of lecture notes for *EE502 – Intelligent System Design* at Clarkson University. Over several semesters those notes grew into the self-contained booklet you now hold, written to guide advanced undergraduate and early graduate students through the essential signal- processing and machine-learning techniques that underpin modern speech and audio applications.

Our primary goals are threefold:

1. **Conceptual clarity.** Each chapter is organised around first principles—sampling theory, short-time analysis, feature extraction—before progressing to classical machine-learning models. Mathematical derivations are kept concise, with plain-language intuition provided alongside formal definitions.
2. **Hands-on practice.** Every major concept is accompanied by PYTHON code (tested under `librosa`, `NumPy`, and `scikit-learn`) so that readers can experiment with real data. Carefully chosen exercises and Jupyter notebooks reinforce the link between theory and implementation.
3. **Pragmatic scope.** While deep-learning methods now dominate research literature, this booklet focuses on interpretable, compute-efficient algorithms—Random Forests, Hidden Markov Models, Support Vector Machines—that still power countless embedded and low-resource systems. A final chapter gestures toward contemporary neural approaches and suggests pathways for further study.

The material is intentionally modular. Instructors may select chapters à la carte to fit a ten-week special topic, a semester-long survey, or a short professional workshop. Readers pursuing self-study can follow the chapters sequentially or jump directly to those most relevant to their projects.

Acknowledgements. We thank the students of EE502 (Fall 2023–2025) whose insightful questions shaped successive drafts; the research assistants in the Speech and Biometrics Lab for curating datasets and vetting code examples; and our colleagues in the Wallace H. Coulter School of Engineering for their constructive feedback. Special gratitude goes to friends and family for their patience during the many late nights of writing and debugging.

Finally, no text can hope to be exhaustive in a field that advances as quickly as machine learning for audio. We encourage readers to consult the cited literature, experiment with new libraries, and—above all—listen critically to the sounds around them. We hope this booklet serves as a launch-pad for your own explorations.

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July 15, 2025

Introduction to Speech Signals

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July 15, 2025

Chapter 1

Introduction to Speech Signals

Imagine walking into a crowded room with your eyes closed. You can still recognize a friend's voice calling your name, detect the laughter in a conversation nearby, or distinguish between the soft hum of background music and a distant announcement. This invisible world of sound carries rich layers of information—from the what of language to the how of its delivery, all embedded within fleeting air vibrations. In the realm of machine learning and signal processing, understanding and harnessing this acoustic complexity is both a scientific challenge and a technological opportunity. At the heart of this challenge lies a need to disentangle and analyze three core concepts—audio, speech, and voice—each playing a unique role in how machines hear, interpret, and respond to the world around them.

Although often used interchangeably, the terms **audio**, **speech**, and **voice** refer to distinct concepts in signal processing and machine learning applications. **Audio** is the broadest term, encompassing any sound signal that can be recorded, transmitted, or processed—whether it's music, environmental noise, speech, or a combination of these. It refers to the raw acoustic waveform, typically represented as a time-series signal in analog or digital form. **Speech** is a specific subset of audio that refers to the structured verbal communication produced by humans. It carries linguistic content such as phonemes (the smallest units of sound that distinguish meaning in a language, e.g., /p/ in pat vs. /b/ in bat), words, and grammar, and is the focus of applications like automatic speech recognition (ASR), speech synthesis, and language identification. **Voice**, on the other hand, refers to the unique characteristics of an individual's vocal production, shaped by both physiological and behavioral factors such as pitch, tone, timbre, and speaking style. While *speech* conveys linguistic content through structured language (e.g., words and sentences), *voice* represents the how of that production. In this sense, voice is a component of speech, but it can also exist independently—for example, in humming or laughter. Voice is especially important in tasks such as speaker identification, verification, and voice biometrics.

Understanding the distinction between these terms is critical when designing or analyzing systems in speech processing, speaker recognition, and audio classification. For instance, voice-based emotion recognition depends on how someone speaks (voice), not necessarily what they say (speech), while ASR systems focus primarily on transcribing the linguistic content (speech) from the broader audio signal.

1.1 Analog vs. Digital Audio Signals (Continuous vs. Discrete)

To understand how machines process and interpret sound, we must first examine how audio signals are represented. **Sound** refers to the physical phenomenon of pressure waves traveling through a medium—typically air—that can be detected by the human ear. When these vibrations are captured by a sensor like a microphone, they are converted into an **audio signal**, which is an electrical or digital representation of the sound.

An analog audio signal is a continuous-time waveform—often in the form of a smoothly varying voltage—that directly corresponds to the air pressure fluctuations of the original sound [1]. For example, the electrical output of a microphone is an analog signal that varies continuously with the incoming sound wave. However, analog signals are difficult to store, transmit, and analyze using modern computing systems. To enable efficient processing, we convert them into **digital audio signals**, which are discrete-time sequences of numbers [2]. This conversion involves two main steps: *sampling* (measuring the signal's amplitude at regular time intervals) and *quantization* (rounding each amplitude value to a fixed set of levels). The result is a sequence of digital samples that approximate the original waveform and can be stored, analyzed, or used as input to machine learning models.

When we refer to continuous vs. discrete signals, we mean continuous signals are defined for every instant in time (as with analog audio), whereas discrete signals are only defined at specific time points (the sample times). Figure 1.1 below illustrates this concept by showing a continuous waveform (green curve) and its sampled version (blue vertical lines at discrete intervals) [3]. The continuous signal $S(t)$ is defined for all t, while the discrete sequence $x[n]$ (samples) is only defined at $t = nT$ for some fixed sampling interval T. In essence, the digital signal is a time-sampled version of the analog signal, obtained by evaluating the continuous wave at evenly spaced points in time:

This conversion to discrete time is fundamental to digital audio processing and machine learning applications: once in digital form, audio can be stored in a computer, analyzed, and used as input to algorithms. However, moving to the discrete domain introduces important considerations like sampling rate, Nyquist limit, aliasing, and quantization error, which we will discuss in this chapter.

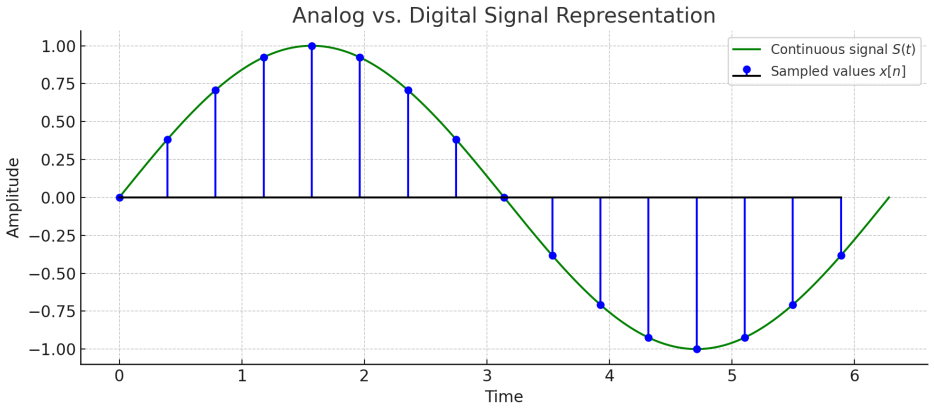

Figure 1.1: A continuous analog signal (green curve) and its discrete sampled values (blue stems). The samples capture the signal's amplitude at regular intervals. Each blue dot represents the signal value at a specific time, separated by the sampling period T [4].

1.2 Audio Signal Properties

Audio signals (and signals, in general) have several key properties that describe their behavior. To introduce these, consider a simple sinusoidal waveform (sine wave), which serves as a prototype for many audio signals. A sinusoid can be described by the equation:

$$x(t) = A\sin(2\pi ft + \phi)$$

where A is the amplitude, f is the frequency, and ϕ is the phase of the wave. Each of these parameters has an intuitive meaning:

Amplitude (A)

Amplitude controls the signal's strength or intensity. For a sound wave, amplitude corresponds to the peak deviation of the pressure from the ambient value – essentially, how 'loud' the sound is. In the sinusoid above, A is the peak height of the wave (the maximum displacement from zero) [5]. Higher amplitude means a louder sound (assuming the same listening conditions), whereas lower amplitude means a softer sound.

Frequency (f)

Frequency is the number of cycles that the waveform completes per second, measured in Hertz (Hz). It is the reciprocal of the wave's period T (the duration of one cycle) [5]. For audio, frequency is related to the pitch of the sound: a high-frequency wave (e.g., 1000 Hz) sounds high-pitched, while a low-frequency wave (e.g., 100 Hz) sounds low-pitched. Humans can generally hear frequencies roughly in the range 20 Hz to 20 kHz. Pure tones like a 440 Hz sine wave (the musical note A4) have a single dominant frequency, whereas complex sounds contain a mixture of many frequencies.

Phase (ϕ)

Phase describes the waveform's starting angle or offset at time $t = 0$. It indicates where in its cycle the sinusoid begins [5]. The phase is measured in radians or degrees; a phase of 0 means that the wave starts at zero amplitude and rises upward, while a phase of π (180°) would start at zero amplitude but initially decreases (inverted). Phase differences between signals can lead to constructive or destructive interference, but for a single isolated waveform, phase mainly just shifts it in time and does not affect the perceived sound in a steady tone.

1.3 Time-Domain vs. Frequency-Domain Representations

An audio signal can be represented in the time domain or the frequency domain, each providing a different perspective. The time-domain representation is the most straightforward – it is the waveform of the audio signal, showing how amplitude varies over time. For example, a plot of *air pressure vs. time* or *voltage vs. time* is a time-domain view. This is what you see when looking at a waveform in an audio editing program: the horizontal axis is time, and the vertical axis is amplitude.

The time domain analysis answers the question *'What is the signal amplitude at each moment?'* but it does not directly show which frequencies are present in the sound.

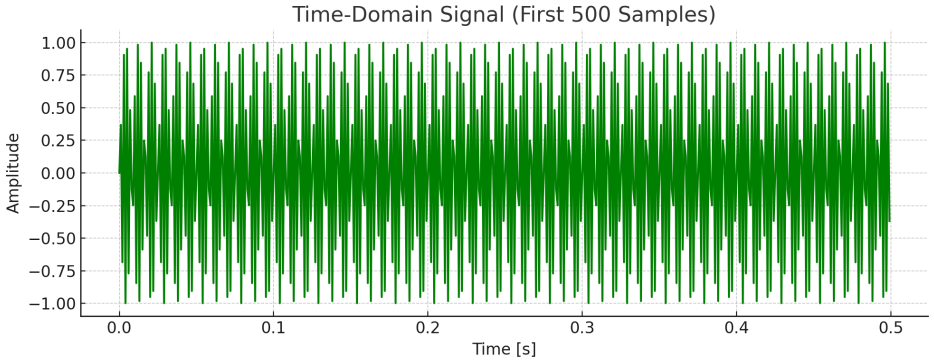

Figure 1.2: Time-domain representation of a sine wave (440 Hz). The plot shows how the signal varies with time.

The frequency-domain representation, on the other hand, describes the signal in terms of its frequency components. Through the *Fourier Transform*, we can decompose any time-domain signal into a sum of sinusoidal components at various frequencies. The result is a spectrum (aka Fourier spectrum) that reveals how much energy or amplitude the signal has at each frequency [6]. Instead of plotting *amplitude vs. time*, a spectrum plots *amplitude (or power) vs. frequency.*

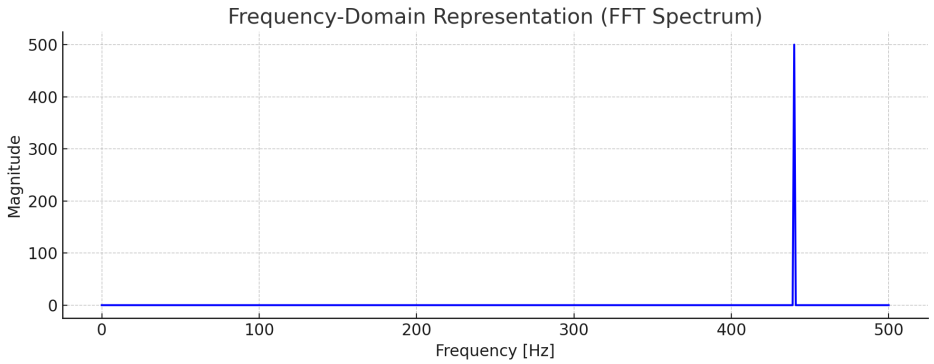

Figure 1.3: Frequency-domain representation (magnitude spectrum) of a 440 Hz sine wave. The spike at 440 Hz indicates the dominant frequency component.

Mathematically, the Fourier Transform provides the conversion from the time domain to the frequency domain. For a discrete-time signal (with N samples $x_0, x_1, \ldots, x_{N-1}$), the discrete Fourier transform (DFT) is defined as:

$$X_k = \sum_{n=0}^{N-1} x_n \, e^{-i2\pi \frac{kn}{N}}$$

which produces N complex coefficients X_k representing the signal's content at discrete frequencies [6]. Each X_k corresponds to a particular frequency (k/N of the sampling rate, in Hz) and encodes both amplitude and phase information of that frequency component.

Time vs. Frequency Example

Imagine a trumpet holding a note A4 (440 Hz). In the time domain, you would see a roughly periodic oscillation corresponding to the sound wave. In the frequency domain, you'd see a peak at 440 Hz (the fundamental frequency) and additional peaks at multiples of 440 Hz (the harmonics that give the trumpet its timbre). Both representations describe the same signal, but one emphasizes how it changes over time, while the other emphasizes what frequencies it contains [6]. Both views are essential in audio processing: the time domain is useful for examining temporal features (like waveform shape, transients, silence, etc.), whereas the frequency domain is crucial for analyzing spectral content (pitch, tone quality,

formants in speech, etc.). As we delve into machine learning for audio, we will often convert signals to the frequency domain to extract features that are more informative for tasks like speech recognition.

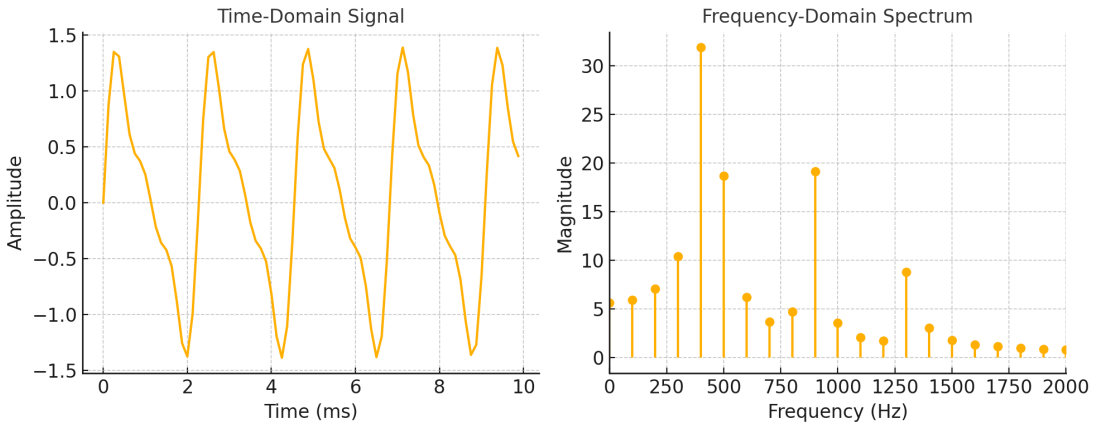

Figure 1.4: Time-domain (left) and frequency-domain (right) representations of a trumpet playing A4 (440 Hz). The frequency plot shows the fundamental and harmonic components.

Nyquist–Shannon Sampling Theorem

A crucial question arises: How fast do we need to sample to capture all the useful information in the signal? The Nyquist–Shannon sampling theorem provides the answer. It states that if a continuous signal is band-limited (meaning it contains no frequency components higher than a certain maximum frequency f_{max}), then the signal can be perfectly reconstructed from its samples provided the sampling rate F_s is greater than twice that maximum frequency [4, 7]. The minimum necessary sampling rate $F_s = 2f_{\text{max}}$ is called the **Nyquist rate**, and half the sampling rate ($F_s/2$) is called the **Nyquist frequency** [7].

In other words, the Nyquist frequency is the highest frequency that can be unambiguously represented at a given sampling rate. Any frequency content below $F_s/2$ will be captured correctly by sampling (under ideal conditions), while frequencies at or above $F_s/2$ cannot be represented correctly.

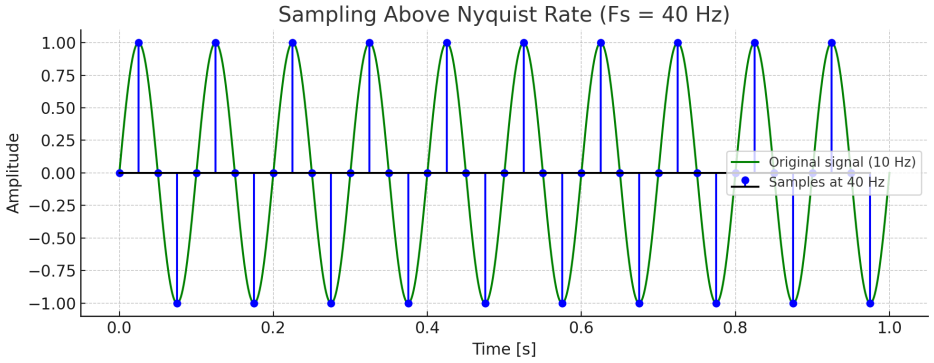

Figure 1.5: Sampling a 10 Hz sine wave at 40 Hz (above Nyquist rate). The signal is reconstructed accurately.

To illustrate, if human hearing goes up to about 20 kHz, a system aiming for full audible range needs a sampling rate above 40 kHz. The CD audio standard of 44.1 kHz was chosen for this reason – it can represent frequencies up to about 22.05 kHz, slightly above the human hearing limit, thus satisfying the Nyquist criterion for the audible band.

In practical terms, the sampling theorem ensures that no information is lost in sampling as long as the signal does not contain frequencies higher than half the sampling rate. If the original signal contains higher frequencies, they must be removed (filtered out) before sampling to meet the bandlimited condition; otherwise, problems such as aliasing will occur.

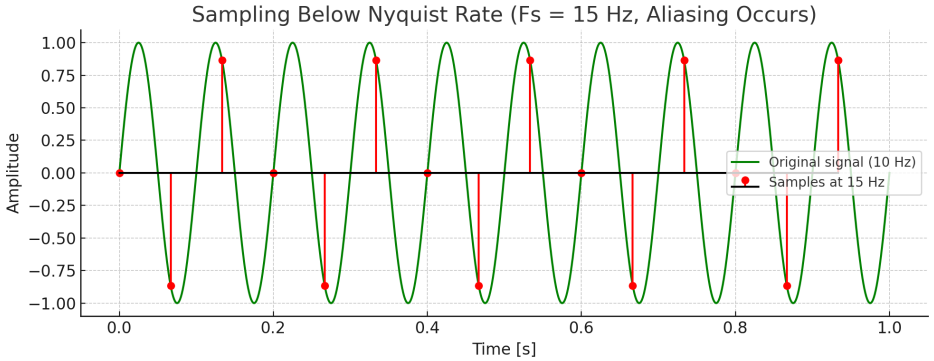

Figure 1.6: Sampling the same 10 Hz sine wave at 15 Hz (below Nyquist rate). The waveform is distorted due to aliasing.

1.4 Quantization and Bit Depth

Sampling in time (choosing discrete instants) is only one part of digitizing audio. The other part is quantization, which is the discretization of amplitude. Analog signals can take any amplitude value (within some range) and vary smoothly. But digital signals represent amplitudes as binary numbers with a fixed number of bits. Bit depth (or resolution) is the number of bits used to store each sample's amplitude value. Common PCM (pulse-code modulation) audio bit depths are 8-bit, 16-bit, 24-bit, etc., which correspond to $2^8 = 256$, $2^{16} = 65{,}536$, $2^{24} \approx 16.7$ million possible amplitude levels, respectively. The higher the bit depth, the finer the resolution of amplitude values. For example, CD audio uses 16 bits per sample, meaning each sample's amplitude is one of 65,536 possible values [8, 9].

When we quantize an analog sample to the nearest available digital level, there is usually a small difference between the true analog value and the chosen digital value. This difference is the quantization error. Over time, these errors manifest as a very low-level noise added to the signal, known as quantization noise. In essence, quantization is a rounding operation, and the quantization noise is the aggregate effect of rounding every sample [10]. In an ideal scenario (with certain statistical assumptions about the signal), the quantization error can be modeled as a random noise uniformly distributed between $-\frac{1}{2}$ and $+\frac{1}{2}$ least significant bit (the smallest step) [11]. The magnitude of this noise is directly related to the bit depth: fewer bits $\Rightarrow$ larger quantization steps $\Rightarrow$ more quantization noise, while more bits $\Rightarrow$ smaller steps $\Rightarrow$ less quantization noise.

A key metric here is the signal-to-noise ratio (SNR), which in this context compares the level of the original signal to the level of the quantization noise. Each extra bit of resolution improves the theoretical SNR by about 6 dB (because reducing the step size by a factor of 2 cuts the quantization noise power by 4, which is 6 dB) [12]. For instance, 16-bit audio has a theoretical maximum SNR of about 98 dB, whereas 8-bit audio tops out around 50 dB SNR [8, 9]. In practical terms, 8-bit audio may sound noticeably noisy or grainy in quiet passages (think of the background hiss in old video games), while 16-bit audio has a noise floor low enough to be inaudible in most listening situations. Professional audio with 24-bit depth provides even more headroom and noise margin (the noise floor is far below the threshold of hearing) [9].

It's important to note that while sampling rate limits the frequency range of the signal, the bit depth limits the *dynamic range* (the range between the loudest and softest representable sound) [13, 8]. Bit depth does not affect frequency response – a 16-bit recording and a 24-bit recording of the same signal will have the same frequencies present, but the 24-bit version can capture more subtle amplitude variations (and a larger ratio of loudest to quietest sound).

1.5 The Fourier Transform and Frequency Analysis

The Fourier transform is the mathematical operation that moves us from the time domain to the frequency domain. In audio and signal processing, it is fundamental for analyzing the spectral content of signals.

For a continuous signal $f(t)$, the (continuous) Fourier transform $F(\omega)$ is defined as:

$$F(\omega) = \int_{-\infty}^{\infty} f(t)\, e^{-j\omega t} dt$$

This yields a complex-valued function $F(\omega)$ that encodes both the amplitude and phase of each angular frequency ω component in the signal.

In digital signal processing, we work with sampled signals and use the *Discrete Fourier Transform (DFT)*—a numerical approximation of the continuous transform suited for digital computation. The DFT, or its efficient version called the Fast

Fourier Transform (FFT), outputs a set of complex coefficients X_k [6], which describe the signal's content at discrete frequency bins.

Time vs. Frequency Representations

Figure 1.7 shows a time-domain signal composed of two sine waves—one at 100 Hz and another at 300 Hz. The signal appears as a complex waveform resulting from the superposition of these components.

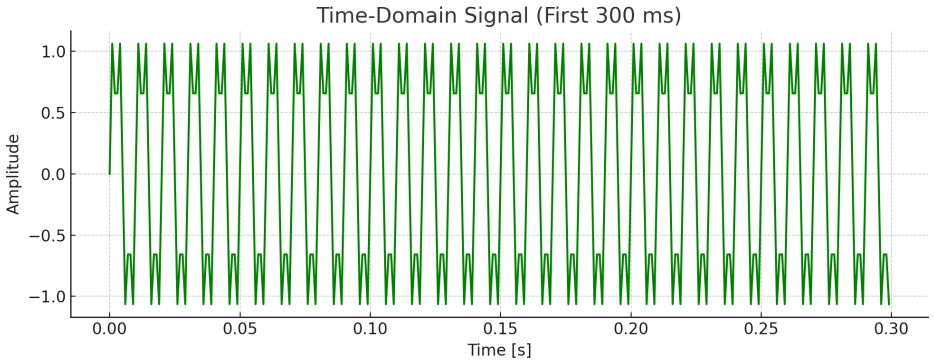

Figure 1.7: Time-domain signal composed of two sine waves at 100 Hz and 300 Hz.

When the signal is analyzed using the DFT, the result is a frequency-domain spectrum showing how much energy is present at each frequency. Figure 1.8 displays the magnitude of this spectrum in decibels (dB), clearly revealing peaks at 100 Hz and 300 Hz.

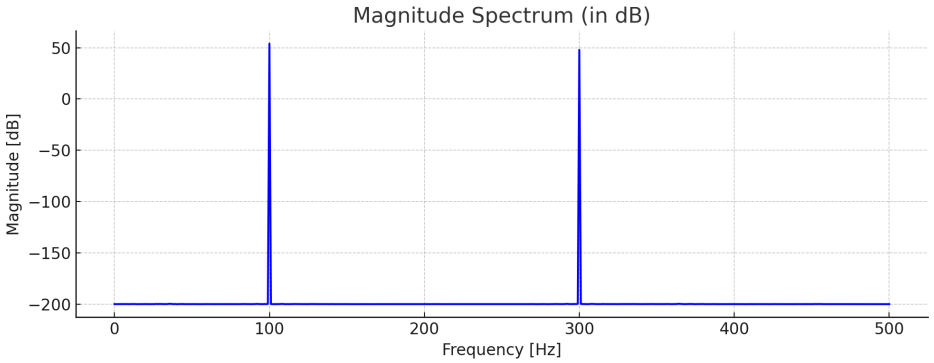

Figure 1.8: Magnitude spectrum (in decibels) showing dominant frequency components at 100 Hz and 300 Hz, computed using the DFT.

Interpreting the Fourier Transform

The magnitude of the Fourier transform $|X(f)|$ (or $|X_k|$ in discrete terms) is often the main quantity of interest, as it tells us how much of each frequency is present in the signal. The phase of each component, though important for perfect reconstruction, is less perceptually critical in many audio applications.

Visualizing the spectrum in dB is common for two reasons: (1) human loudness perception is roughly logarithmic, and (2) plotting on a logarithmic scale compresses the dynamic range, making both strong and weak components easier to compare [6].

For example, if you analyze a recording of the word "hello," the Fourier transform might show that the vowel "e" contains strong energy in lower frequency bands (formants), while the "h" has energy spread across higher frequencies due to its noise-like nature. Thus, the Fourier transform provides a powerful way to see what frequencies are present and how strongly, but it doesn't tell us *when* those frequencies occur—a limitation addressed by the short-time Fourier transform, which we will explore next.

1.6 Short-Time Fourier Transform (STFT) and Spectrograms

Speech and most real-world audio signals are *non-stationary*, meaning their spectral content changes over time. A single Fourier transform over the entire signal would yield a spectrum that represents an average of the frequency content over the whole duration—this is not very helpful for analyzing transient phonetic events or rapidly changing sounds [14].

To obtain frequency information localized in time, we use the *Short-Time Fourier Transform (STFT)*. This technique involves computing the Fourier transform over short, overlapping segments (called *windows* or frames) of the signal. A window function (like Hamming or Hann) is slid across the signal, and at each step, a Fourier transform is applied to the windowed segment.

Mathematically, if $x[n]$ is the discrete signal and $w[n]$ is a window of length N, the STFT is defined as:

$$X(h,k) = \sum_{n=0}^{N-1} x[n+h] \cdot w[n] \cdot e^{-i2\pi \frac{kn}{N}},$$

where h indexes the time shift (window position) and k indexes the frequency bin.

STFT produces a time-frequency representation $X(h,k)$, which indicates the frequencies present in a signal and how they evolve over time. This representation is typically visualized using a *spectrogram*, a two-dimensional heatmap where the x-axis represents time, the y-axis represents frequency, and the color intensity (or brightness) corresponds to the magnitude or power, often expressed in decibels.

Spectrograms help us visualize various audio properties. *Voiced sounds*, such as vowels, appear as horizontal stripes known as formants, which represent the resonant frequencies of the vocal tract. *Unvoiced consonants*, like "s" and "f," display diffuse, high-frequency energy without a clear harmonic structure. *Plosive sounds*, such as "p" and "t," produce short, broadband bursts that appear as vertical streaks. Meanwhile, *silence* is represented by columns with very low intensity, often seen as dark regions in the spectrogram.

An example of a spectrogram generated from a speech signal containing the spoken phrase "nineteenth century" is shown in Figure 1.9. It captures how the frequency components of the signal vary with time, revealing dynamic speech patterns. For comparison, Figure 1.10 shows the magnitude spectrum obtained by applying the Discrete Fourier Transform (DFT) to the same audio segment. While the DFT spectrum provides information about which frequencies are present, it does not indicate when they occur—highlighting the need for time-frequency representations like the spectrogram.

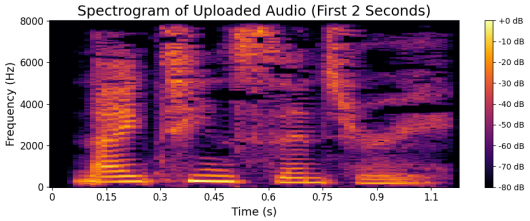

Figure 1.9: Spectrogram of the spoken words "nineteenth century" (first 2 seconds).

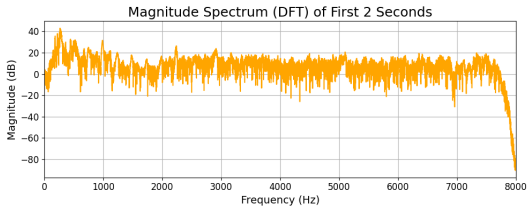

Figure 1.10: Magnitude spectrum (DFT) of the same "nineteenth century" speech segment.

Spectrograms are widely used in machine learning for audio. Systems like speech and emotion recognizers often take spectrograms as input because they compactly capture both temporal and spectral information—two key dimensions for understanding sound.

Mel-Scale and Mel-Spectrograms

The mel scale is a perceptual scale of pitches judged by listeners to be equal in distance from one another. It reflects how the human ear perceives sound: we are more sensitive to changes in lower frequencies than higher ones. The transformation from frequency f (in Hz) to mel is typically given by:

$$m = 2595 \cdot \log_{10}(1 + \frac{f}{700})$$

A *mel-spectrogram* is a variation of the spectrogram where the frequency axis is mapped to the mel scale and a bank of mel-spaced filters is applied. It better aligns with auditory perception and is widely used in machine learning tasks, especially speech recognition and synthesis.

The *spectrogram* displays energy distributed across linear frequency bins. In contrast, the *mel-spectrogram* emphasizes lower frequencies by allocating denser mel bins in that range while compressing higher frequencies with sparser bins,

thereby mimicking the non-linear frequency resolution of human hearing. Because of this perceptual alignment, mel-spectrograms often yield better performance in tasks such as automatic speech recognition (ASR) and text-to-speech (TTS) synthesis.

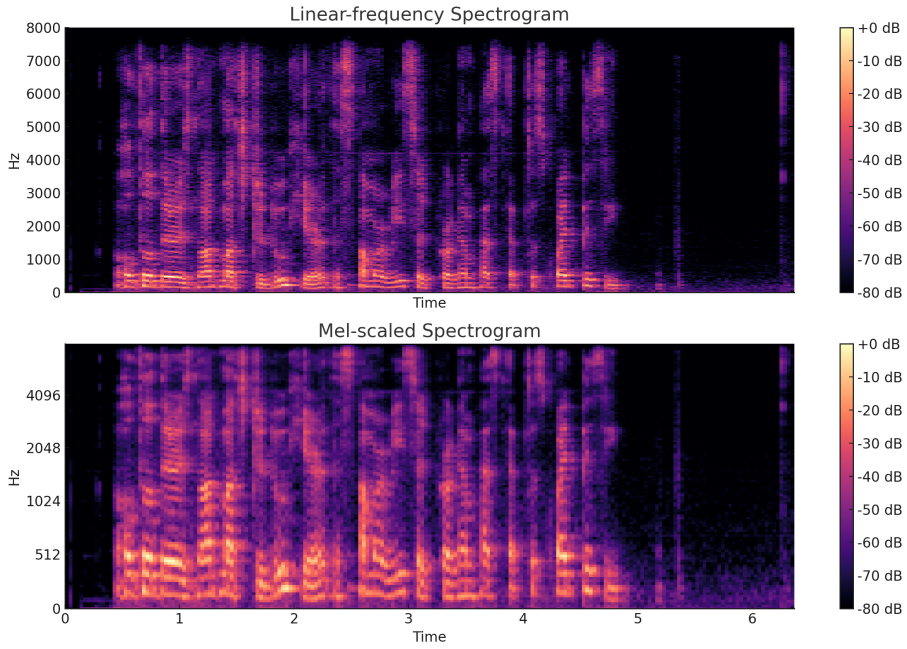

Figure 1.11: Comparison of a linear-frequency spectrogram (top) and a mel-spectrogram (bottom) of the same speech signal.

1.7 Practical Audio Systems

Having discussed sampling, frequency, and quantization, we now examine common configurations used in practical audio systems. These include typical values for sampling rates and bit depths, as well as the distinction between mono and stereo channels.

1.7.1 Common Sampling Rates

In speech and audio processing, the sampling rate determines how frequently the signal is measured in time. Common sampling rates in audio vary depending on the application. A sampling rate of **8 kHz** is typically used in telephony for narrowband speech, capturing the 300–3400 Hz voice band. **16 kHz** is considered wideband speech and is common in speech recognition and modern telecommunication systems. **44.1 kHz** is the standard for CD-quality audio and is sufficient to capture the full range of human hearing (20 Hz–20 kHz). **48 kHz** is frequently used in professional audio and multimedia applications. Higher rates such as **96 kHz** and **192 kHz** are used in studio production or scientific applications that require oversampling [4]. For most machine learning applications involving speech, 16 kHz strikes a good balance between fidelity and data efficiency.

1.7.2 Bit Depths and Quantization

Bit depth defines the resolution of each sample's amplitude. **8-bit** audio was historically used in telephony and often employed μ-law or A-law companding to increase its effective dynamic range. **16-bit** audio is the standard for CD-quality recordings, offering about 96 dB of dynamic range [15]. **24-bit** audio is commonly used in professional audio recording, with a theoretical dynamic range of 144 dB, though practical implementations typically achieve around 120 dB.

In speech datasets, the **16-bit** PCM is common. While lower bit depths (e.g., 8-bit) save space, they introduce quantization noise and are generally avoided unless necessary due to storage or bandwidth constraints.

1.7.3 Mono vs. Stereo Channels

Audio may be recorded and played back using one or more channels. **Mono** refers to single-channel audio, where the same signal is played through all speakers or headphones. It is commonly used in most speech and voice recognition tasks. In contrast, **stereo** refers to two-channel audio—left and right—where different signals are sent to each ear, creating a spatial or directional perception [16].

Digital stereo audio consists of two PCM streams. For example, a file labeled "16-bit, 44.1 kHz stereo" contains two separate channels, each sampled at 44.1 kHz with 16-bit resolution.

1.7.4 Practical Implications

The sampling rate, bit depth, and number of channels together define the digital audio format. A recording described as "16 kHz, 16-bit, mono PCM" means it has 16,000 samples per second, each sample is quantized into one of 65,536 levels, and the audio contains a single channel.

These parameters directly influence several factors. *Audio quality and size* are affected, as higher sampling rates and bit depths improve fidelity, but increase storage and computation requirements. For machine learning, the sampling rate determines the frequency resolution of the derived features, such as spectrograms. Using mono audio helps reduce model complexity. Preprocessing operations such as downsampling, bit-depth conversion, and stereo-to-mono conversion are often necessary before feeding data into models.

Understanding these fundamentals is essential before applying machine learning to audio data. Future chapters will build on this foundation through signal enhancement, feature extraction, and classification techniques.

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Speech Preprocessing and Feature Extraction in Speech

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Chapter 2

Speech Preprocessing and Feature Extraction in Speech

2.1 Introduction

Machine learning models require informative, standardized inputs. Raw speech is seldom fed directly into an algorithm. In speech processing, **speech preprocessing** and **feature extraction** are crucial steps that clean the signal and transform it into representative features.

Preprocessing techniques (like noise reduction or normalization) enhance quality and consistency, ensuring models focus on relevant speech content. Feature extraction then converts the cleaned waveform into numerical descriptors capturing characteristics like frequency content, energy, and spectral shape.

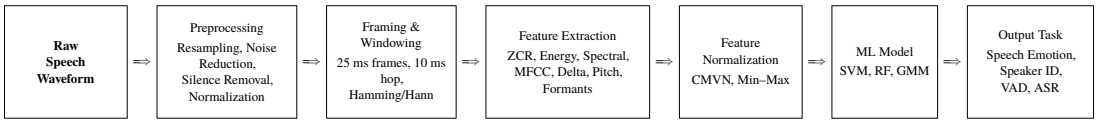

Figure 2.1: Simple block diagram of a classical ML pipeline for speech.

2.2 Common Preprocessing Steps for Speech

Before extracting features, raw speech recordings typically undergo the following preprocessing operations.

2.2.1 Resampling

Resampling converts every recording to a single sampling rate so that all subsequent feature-extraction code receives comparable input. A rate of 16 kHz is the industry work-horse because it captures frequencies up to 8 kHz—enough to preserve the fricatives, stop bursts, and formant transitions that modern ASR, speaker-ID, and emotion models rely on—while keeping file size and computation modest. Dropping to 4 kHz or even 8 kHz throws away those high-frequency cues and produces "telephone" quality speech, which hurts recognition accuracy; pushing higher to 22–48 kHz yields little extra information for speech while tripling both storage and GPU time. Using one uniform rate also guarantees that FFT dimensions, mel-filter banks, and pre-trained model inputs line up exactly, preventing the silent errors that arise when clips of mixed sample rates flow through the same pipeline. For these practical reasons most public corpora (e.g., LibriSpeech, VoxCeleb, CommonVoice) and toolkits (Kaldi, SpeechBrain) mandate 16 kHz, and we resample all incoming audio to that rate before any further processing.

In short, 16 kHz is the practical compromise: it keeps the speech detail ML models need, avoids the mud of narrow-band audio, and saves time and storage compared to studio-rate files. That is why most public corpora (LibriSpeech, VoxCeleb, CommonVoice) and toolkits (Kaldi, SpeechBrain) standardise on 16 kHz, and why we resample all input audio to this rate before further processing.

In Python, this can be done using `librosa`:

```
import librosa
y, sr = librosa.load("file.wav", sr=16000)
```

This loads and resamples the file to 16 kHz. Resampling mitigates mismatched sampling rates and simplifies downstream processing.

This code assumes Python 3.8 or newer. `librosa` is a popular Python library built on `NumPy` and `SciPy` that provides simple functions for loading audio, resampling, and extracting features like MFCCs, chroma, and spectrograms.

2.2.2 Noise Reduction

Speech recordings may contain background noise, such as environmental sounds, mechanical hum, electronic interference, or distant speech. Filters and denoising algorithms can remove these unwanted components to improve the clarity of the signal and the quality of extracted features.

Example: Apply a low-pass filter to remove high-frequency noise:

```
import numpy as np
from scipy.signal import butter, filtfilt

b, a = butter(N=4, Wn=4000, btype='low', fs=16000)
filtered_signal = filtfilt(b, a, signal)
```

This example uses `numpy` for array operations and `scipy.signal` for digital filtering. The function `butter` designs a 4th-order Butterworth filter— a type of filter with a maximally flat frequency response in the passband, meaning it avoids ripples and preserves the overall signal shape. The filter is set as `low-pass` with a cutoff at 4 kHz, meaning it retains frequencies below 4 kHz and attenuates higher ones, which often contain unwanted noise such as hiss, static, or electrical interference.

Low-pass filters are useful when you want to preserve speech fundamentals (typically under 4 kHz) and discard high-frequency noise. Conversely, high-pass filters remove low-frequency rumble (like air conditioners or mic handling noise) and preserve higher-frequency speech elements. The choice depends on the noise profile and the speech content.

A higher filter order results in a steeper cutoff slope, meaning the transition between passband and stopband becomes sharper. However, higher-order filters also increase computational cost and may introduce phase distortion if not applied properly.

2.2.3 Silence Removal (Trimming)

In speech recordings, silence refers to portions of the audio where there is little or no vocal activity—often appearing at the beginning or end of a clip as the speaker pauses, prepares to speak, or finishes. These segments have very low amplitude and typically contain only ambient background noise. While such silences are natural in human conversation, they are often irrelevant for machine learning models and can skew features like energy or duration. Removing them helps focus on the active speech content, improves efficiency, and results in cleaner feature representations.

This can be done using `librosa`:

```
y, sr = librosa.load("speech.wav", sr=16000)
yt, index = librosa.effects.trim(y, top_db=60)
```

This removes regions where amplitude is 60 dB below the peak. Figure 2.2 illustrates this.

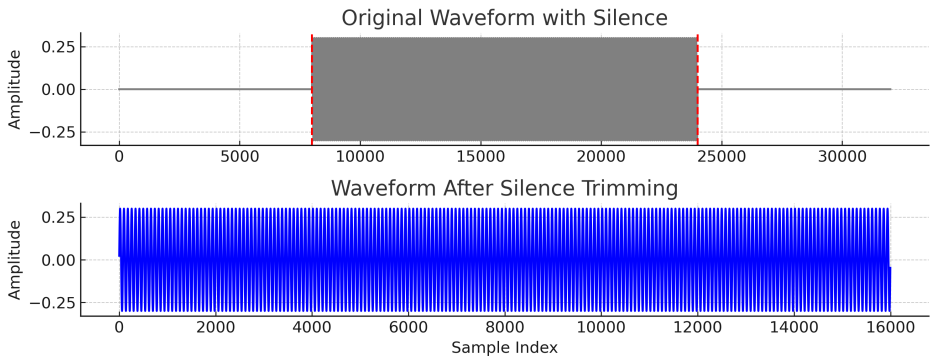

Figure 2.2: A speech waveform with silence (top) and after trimming (bottom). Dashed lines show segment boundaries.

2.2.4 Normalization

Normalization adjusts amplitude to a consistent level to prevent volume differences from affecting features. Peak normalization scales the waveform to [-1, 1]:

```
y = y / np.max(np.abs(y))
```

RMS normalization adjusts the root mean square energy across clips. This prevents models from misinterpreting volume-related feature differences.

2.2.5 Other Preprocessing Steps

- **Downmixing stereo to mono**: Many audio recordings are captured in stereo with separate left and right channels. For speech processing, models typically require a single-channel (mono) input. Downmixing is done by averaging the two channels to produce a unified signal. This ensures consistency across the dataset and avoids bias from channel imbalance.
- **Pre-emphasis**: This technique applies a simple high-pass filter to slightly boost the energy of high-frequency components in the signal. Since higher frequencies (such as those from fricatives like /s/ and /f/) tend to be weaker, pre-emphasis helps highlight these important cues, making them more noticeable in spectral analysis and feature extraction.
- **Length handling**: Machine learning models often require fixed-length input. If an audio clip is too short, *padding* is used which is adding extra zeros to the end to reach the required length. If a clip is too long, it may be segmented into smaller chunks. This ensures that all input samples are of uniform duration, allowing batch processing during training and inference.

2.3 Short-Time Analysis: Framing and Windowing

Speech signals are inherently non-stationary, meaning their statistical properties such as energy, frequency content, or amplitude distribution change over time as different phonemes and words are spoken. For example, the vowel sound `/a/` (as in ”father”) has strong, low-frequency energy and a relatively steady waveform, while a fricative like `/s/` (as in ”sun”) has high-frequency, noise-like energy. These differences cause the spectral and temporal characteristics of the signal to vary continuously as a person speaks. However, over short time durations (typically 20–30 ms), speech signals can be considered quasi-stationary. This assumption allows us to analyze them frame-by-frame using techniques that apply to stationary signals.

2.3.1 Framing

We divide the time-domain signal into short, overlapping segments known as frames. A common choice is:

- **Frame length:** 25 ms (= 400 samples at 16 kHz) — This duration is short enough to assume the speech signal is quasi-stationary (i.e., its properties remain stable within that time window), yet long enough to capture a few pitch cycles and phonetic content for reliable analysis.
- **Frame hop (stride):** 10 ms (= 160 samples) — The hop defines how much the window advances between frames. A smaller hop size increases overlap, allowing smoother feature transitions and better resolution of fast-changing sounds.

Overlapping is essential to ensure that important signal transitions are not missed. With 50–60% overlap, we maintain continuity across time and effectively capture transient details of speech sounds.

```
frame_length = int(0.025 * sr)  # 25 ms
hop_length = int(0.010 * sr)    # 10 ms
frames = librosa.util.frame(y, frame_length=frame_length, hop_length=hop_length)
print(frames.shape)  # (frame_length, num_frames)
```

Each column in the resulting array represents one short-time frame to be processed independently.

2.3.2 Windowing

Hard cuts at frame boundaries can introduce discontinuities, resulting in spectral leakage during Fourier analysis. To reduce this effect, we apply a window function such as the Hamming or Hann window to each frame:

$$x_w[n] = x[n] \cdot w[n]$$

```
window = np.hamming(frame_length)
windowed_frame = frames[:, i] * window  # for frame i
```

Windowing ensures smoother transitions at frame edges and focuses analysis on the central part of each frame.

2.3.3 Spectrogram: Time-Frequency Representation

By computing the DFT of each windowed frame, we obtain a spectrogram. Each column represents the spectrum of a single frame.

The spectrogram visually shows:

- Voiced sounds (e.g., vowels) as horizontal harmonic bands.
- Unvoiced sounds (e.g., /s/, /f/) as broadband noise.
- Silence as blank regions with minimal energy.

Short-time analysis forms the basis of all advanced feature extraction methods in speech processing, including MFCCs and filterbanks, covered in the following sections.

2.4 Feature Extraction and Common Speech Features

Once the speech audio has been preprocessed and segmented into short-time frames, the next step is to extract meaningful features from each frame. These features quantify important characteristics of the speech signal — such as its frequency content, energy, and temporal dynamics — that can be used by machine learning algorithms.

Rather than feeding raw waveform samples to models, we derive a compact representation that reflects the essential properties of the speech audio. Feature extraction typically operates on a per-frame basis, meaning each short segment (e.g., 25 ms) is transformed into a feature vector. These feature vectors can then be used directly for classification tasks or aggregated (e.g., via averaging or statistical descriptors) for fixed-length representations.

Below we introduce the most widely used speech features in classical (non-deep) machine learning workflows.

2.4.1 Zero-Crossing Rate (ZCR)

The **zero-crossing rate** (ZCR) measures how frequently the speech audio waveform crosses the zero-amplitude axis. It counts the number of times the signal's sign changes from positive to negative or vice versa within a frame. ZCR is a simple time-domain feature indicative of a signal's frequency content or "roughness."

Voiced speech (like vowels) tends to have low ZCR due to smoother, periodic patterns. Unvoiced sounds (such as fricatives /s/ or /f/) are noise-like and exhibit high ZCR due to rapid sign changes. Silence generally has few or no zero-crossings aside from background noise.

Mathematical Definition

The ZCR of a frame with N samples is computed as:

$$\text{ZCR} = \frac{1}{N-1} \sum_{n=1}^{N-1} \mathbf{1}\left\{x[n] \cdot x[n-1] < 0\right\}$$

Here, $\mathbf{1}\{\cdot\}$ is the indicator function, which evaluates to 1 when the sign of adjacent samples differs.

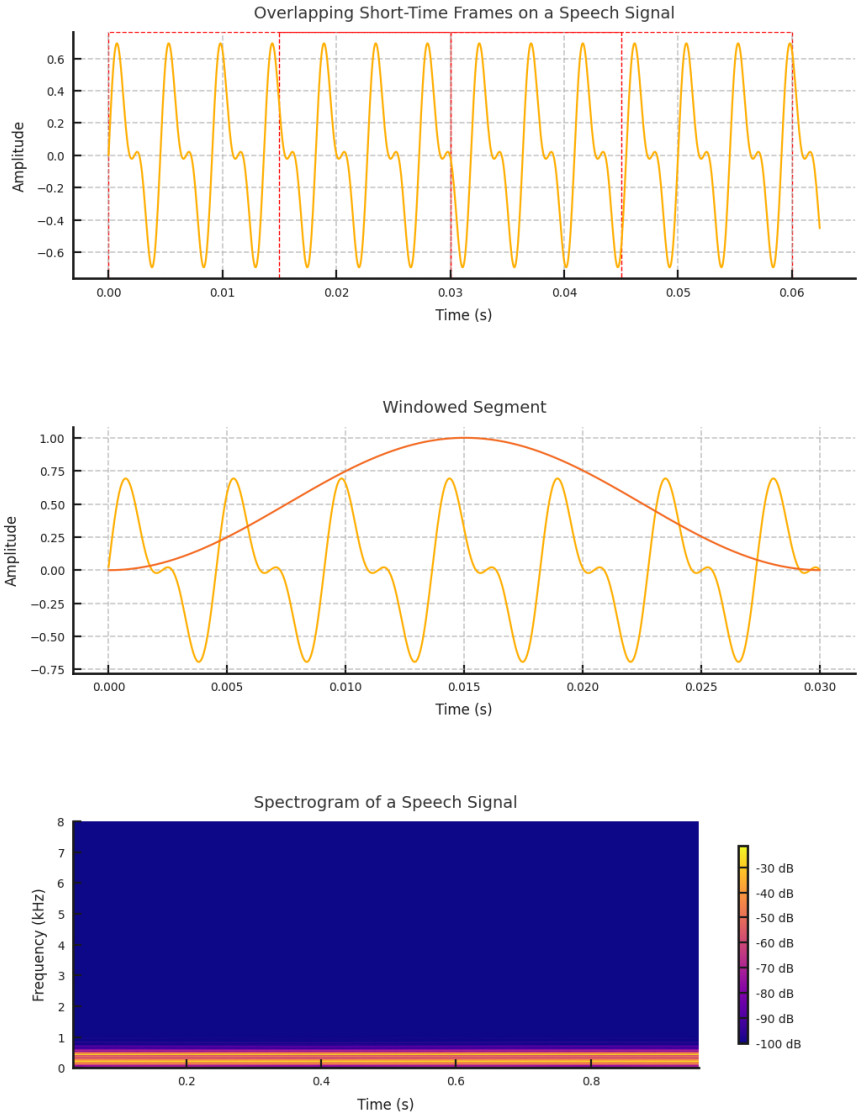

Figure 2.3: Illustration of the short-time analysis process. Top: speech waveform; Middle: framing and windowing; Bottom: resulting spectrogram showing frequency over time. Brighter colors represent higher energy.

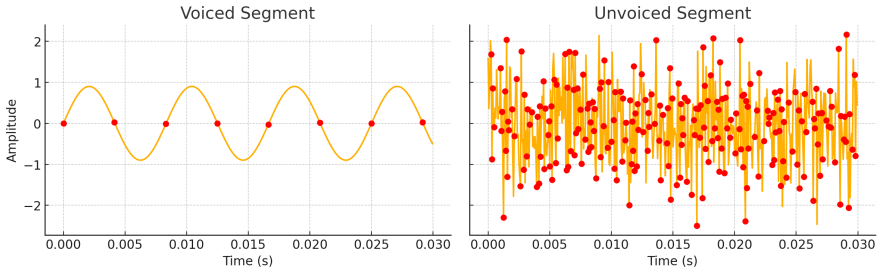

Figure 2.4: Illustration of Zero-Crossing Rate. Red dots indicate zero-crossing points of a waveform. Voiced (left) vs. unvoiced (right) segment.

Python Example Using `librosa`

```
import librosa

y, sr = librosa.load("speech.wav", sr=16000)
frame_length = int(0.025 * sr)  # 25 ms
hop_length = int(0.010 * sr)    # 10 ms

zcr = librosa.feature.zero_crossing_rate(
    y, frame_length=frame_length, hop_length=hop_length
)
```

This returns a 2D array where each value corresponds to the ZCR of a frame. The range of ZCR values is between 0 and 0.5 for normalized speech audio (since at most, every other sample can be a crossing).

Best Practices and Use Cases

- Ensure the signal is DC-centered (mean zero) before computing ZCR.
- ZCR is effective for differentiating voiced vs. unvoiced speech and detecting silence.
- It is computationally inexpensive and thus common in embedded speech systems or early-stage filters.

While ZCR alone is too basic for high-accuracy speech tasks, it is useful as a supporting feature in a larger feature set.

2.4.2 Energy and Spectral Features

Energy[1] represents the signal's loudness or intensity in a frame. There are a couple of closely related measures: short-time energy (the sum of squared amplitudes in the frame) and RMS (Root Mean Square) energy (the square root of the average of squared amplitudes). In a frame with samples $x[n]$, the energy can be defined as:

$$E = \sum_{n=1}^{N} x[n]^2$$

The RMS is:

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x[n]^2}$$

which is just the standard deviation of the samples (assuming zero-mean). Energy is often normalized by frame length for consistency. For example, if $x[n]$ is in range $[-1, 1]$, energy will be in $[0, N]$ and RMS in $[0, 1]$.

Intuitively, energy/RMS indicates how loud a frame is. Speech segments have higher energy than silence; voiced parts (especially vowels) often carry more energy than unvoiced parts, since voiced sounds are produced with vocal cord vibration and generally higher amplitude. Thus, short-time energy is fundamental for tasks like voice activity detection (VAD) [2] – distinguishing speech from silence/noise. It is also used in endpointing (finding start/end of an utterance) and as a basic feature for emotion (loudness can correlate with anger or excitement).

Calculation: Using numpy, one can compute frame energy straightforwardly. Librosa also provides `librosa.feature.rms` which gives the RMS energy per frame. For example:

```
rms = librosa.feature.rms(y=y, frame_length=frame_length, hop_length=hop_length)
```

This returns an array of RMS values. We could square these to get actual energy per frame if needed (since RMS is $\sqrt{\text{mean of } x^2}$). As an example, imagine a frame of a voiced vowel [a] – its energy might be significantly higher than a frame of an [s] sound, which in turn is higher than pure silence (energy 0). In practice, we often convert energy to a decibel (log) scale for dynamic range compression, defined as:

$$E_{\text{dB}} = 10 \log_{10}(E)$$

This log-energy is used in many speech features (e.g., MFCC includes a log-energy or C0 term).

Use cases: Apart from VAD, energy features can help in emotion detection (e.g., shouting versus speaking softly) and stress detection. In speech recognition, energy was historically one of the features used (alongside MFCCs). It's also useful for silence trimming – as mentioned earlier, segments where energy falls below a threshold can be considered silence.

Note: Energy is influenced by recording gain – hence the importance of normalization. After amplitude normalization across a dataset, energy differences become more meaningful for comparing frames within and across recordings.

Spectral Features (Centroid, Bandwidth, Contrast, Rolloff)

A speech frame transformed to the frequency domain (via the short-time Fourier transform) yields a spectrum – we can derive many spectral features that summarize the shape of this spectrum. These features quantify qualities often related to timbre or articulation characteristics of the speech. Common spectral descriptors include:

Spectral Centroid: The "center of mass" of the spectrum. It is computed as the weighted mean of frequencies present in the signal, with magnitudes as weights. If $X(k)$ is the magnitude of the FFT at frequency bin f_k, the centroid is:

$$\text{Centroid} = \frac{\sum_k f_k \cdot |X(k)|}{\sum_k |X(k)|}$$

A high centroid means the spectrum's energy is centered at high frequencies (perceived as bright or thin sound), whereas a low centroid indicates dominance of low frequencies (a darker or bass-rich sound). In speech, centroid can differentiate sounds like "s" (which has energy in higher frequencies, thus high centroid) from a vowel "u" (energy concentrated in low frequencies, low centroid) [3]. In Python:

```
cent = librosa.feature.spectral_centroid(y=y, sr=sr, n_fft=1024, hop_length=
    hop_length)
```

This returns the centroid frequency for each frame (in Hz).

Spectral Bandwidth: This measures the spread of the spectrum around the centroid. Essentially, it is the standard deviation of the frequency distribution (the second central moment). A larger bandwidth means frequencies in the frame cover a wide range (e.g., noisy sounds with energy spread across the spectrum), while a small bandwidth indicates a narrow, peaky spectrum (perhaps a pure tone or a sound with most energy in a narrow band). In speech, a voiced vowel with distinct formant peaks might have lower bandwidth (energy clustered in formant regions), whereas an unvoiced noise has high bandwidth [1].

```
bw = librosa.feature.spectral_bandwidth(y=y, sr=sr, n_fft=1024, hop_length=
    hop_length)
```

Spectral Contrast: Spectral contrast evaluates the difference in amplitude between the peaks (high energy) and valleys (low energy) of the spectrum in different frequency sub-bands. The idea is to capture the dynamic range of the spectrum. A frame with a few prominent spectral peaks (e.g., a voiced speech sound with strong formant harmonics) will have a high contrast (big difference between peak energy and troughs between formants). A noisy frame with a flatter spectrum (or a frame of silence) will have low spectral contrast. This feature can help distinguish speech texture – e.g., voiced speech (harmonic structure $\rightarrow$ higher contrast) vs unvoiced noise (flat spectrum $\rightarrow$ lower contrast).

```
contrast = librosa.feature.spectral_contrast(y=y, sr=sr, n_fft=1024, hop_length=
    hop_length)
```

This computes contrast across a few frequency bands. It yields a vector per frame (each entry for one band's contrast), which is often averaged or used as multiple features.

Spectral Rolloff: The rolloff frequency is the frequency below which a certain percentage (commonly 85%) of the total spectral energy lies. It essentially marks the "tail" of the spectrum. A lower rolloff frequency means most energy is concentrated in low frequencies; a higher rolloff indicates significant high-frequency content. For speech, an unvoiced consonant with energy in high frequencies will have a high rolloff (the 85% energy point is at a high frequency), whereas a low-frequency biased frame (like a vowel [o]) will have a lower rolloff.

```
rolloff = librosa.feature.spectral_rolloff(y=y, sr=sr, hop_length=hop_length,
    roll_percent=0.85)
```

```
y, sr = librosa.load("speech.wav", sr=16000)
# Compute spectral features for each frame
centroid = librosa.feature.spectral_centroid(y=y, sr=sr)
bandwidth = librosa.feature.spectral_bandwidth(y=y, sr=sr)
contrast = librosa.feature.spectral_contrast(y=y, sr=sr)
rolloff = librosa.feature.spectral_rolloff(y=y, sr=sr, roll_percent=0.85)
```

Typically these arrays are shape $(1 \times \text{frames})$ except contrast $(n\_\text{bands} \times \text{frames})$. You might take the mean over time or use them frame-wise.

2.4.3 Mel-Frequency Cepstral Coefficients (MFCCs)

MFCCs are one of the most important and ubiquitous features in speech processing. They provide a compact representation of the short-term power spectrum of sound, shaped according to human auditory perception [4]. The idea behind MFCCs is to mimic how human ears perceive sound: it uses a mel scale frequency axis (which is logarithmic, reflecting the ear's finer resolution at low freqs and coarser at high freqs) and a cepstral representation (which roughly decorrelates spectral features and emphasizes the spectral envelope). MFCCs have been extremely effective for tasks like speech and speaker recognition.

Computation: Generating MFCCs involves several steps in a pipeline:

- **Pre-emphasis:** (Optional) Apply a pre-emphasis filter to boost high frequencies (typically $H(z) = 1 - 0.97z^{-1}$).
- **Framing and Windowing:** Already done as discussed (e.g., 25 ms frames, Hann window).
- **FFT:** Compute the magnitude spectrum of each frame (usually via an N-point FFT, N $\sim$ 512 or 1024).
- **Mel Filterbank:** Pass the spectrum through a filterbank of triangular filters spaced on the mel scale. For example, one might use 40 mel-spaced filters covering 0–8 kHz. Each filter outputs the sum of spectral energy in that mel band.
- **Logarithm:** Take the log of each filter's output (producing log-mel spectrum). Taking logs converts multiplicative spectral factors into additive values and aligns with human loudness perception.
- **Discrete Cosine Transform (DCT):** Apply DCT on the log-mel spectrum to decorrelate the filterbank coefficients. This yields cepstral coefficients.
- **Keep lower DCT coefficients:** Typically, the first 12 or 13 coefficients are retained. These represent the spectral envelope and discard fine details like pitch.

The result is a set of 13 or so numbers per frame – the MFCCs. They succinctly capture the broad spectral characteristics (formant structure) without carrying extra detail like pitch harmonics. This makes them effective for speech recognition, where the goal is to recognize content irrespective of speaker pitch or voice.

```
mfcc = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=13,
                            n_fft=512, hop_length=160, n_mels=40)
```

This computes 13 MFCCs per frame using a 40-mel-filter bank (librosa handles steps 3–7 internally). The output is a 13×T matrix. It's common to normalize MFCCs by subtracting the mean and dividing by the standard deviation.

Visualization: MFCCs can be shown as a heatmap over time (coefficients 1 through 13). Voiced vs unvoiced sounds can be distinguished via their spectral envelope patterns.

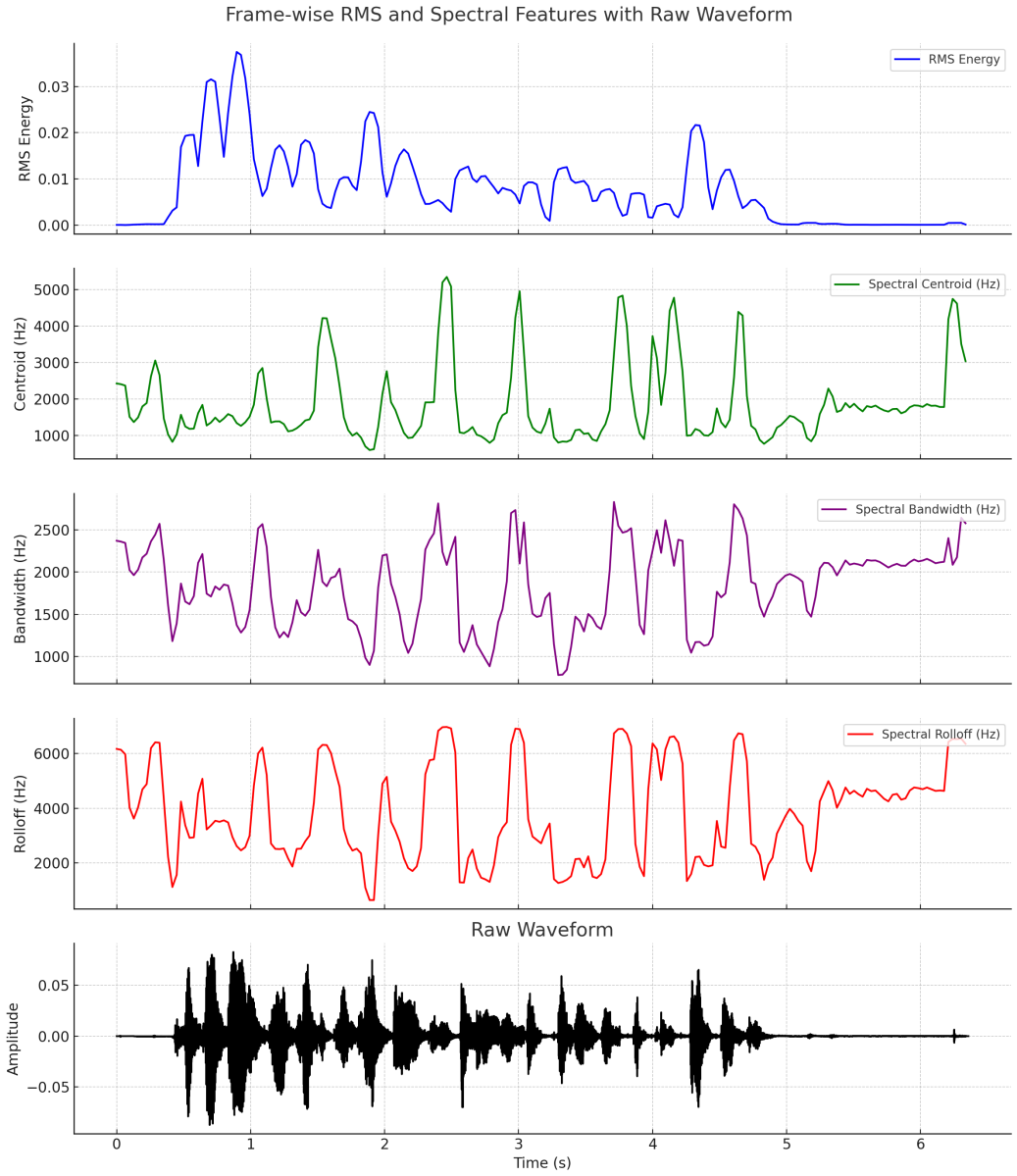

Figure 2.5: Frame-wise RMS and spectral features extracted from a speech recording.

MFCCs are used in ASR, speaker recognition, emotion classification, and other tasks due to their low-dimensional, information-rich representation. While modern deep ASR models may use log-mel spectrograms, MFCCs remain popular, especially with smaller datasets or classical ML models.

Delta and Delta-Delta Coefficients

While MFCCs describe static spectral characteristics, speech is dynamic. Delta features capture how features change over time. It's standard to compute:

- **Delta (1st derivative):** Captures the velocity of feature change.
- **Delta-Delta (2nd derivative):** Captures acceleration.

These are computed by fitting a slope to the feature trajectory using a sliding window. A common formula is:

$$\Delta_t = \frac{\sum_{n=1}^{N} n \cdot (c_{t+n} - c_{t-n})}{2\sum_{n=1}^{N} n^2}$$

Where c_t is the feature vector at time t and N is the window size.

```
mfcc = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=13)
mfcc_delta = librosa.feature.delta(mfcc, order=1)
mfcc_delta2 = librosa.feature.delta(mfcc, order=2)
```

The delta and delta-delta matrices are of shape 13×T. These are often concatenated with MFCCs into a 39-dimensional vector per frame.

Use Cases: Delta features are essential in ASR and speaker recognition to model transitions and speech dynamics [5]. In emotion detection, changes in pitch or energy (prosody) can also be modeled via deltas.

Chroma Features

Chroma features capture the energy distribution across the 12 pitch classes of the musical octave (C, C#, D, ..., B). They are commonly used in music analysis, but can also apply to voiced speech.

Why? Voiced speech contains harmonics based on F0. Chroma compresses harmonic energy into 12 pitch bins (regardless of octave), capturing relative pitch class usage. Even though speech isn't usually musical, chroma can reflect intonation and pitch dynamics useful in tasks like speaker identification and prosody analysis.

```
chroma = librosa.feature.chroma_stft(y=y, sr=sr,
                                     n_fft=1024, hop_length=hop_length)
```

This returns a 12×T chromagram matrix.

Use Cases: While not standard in ASR, chroma is useful in speaker modeling, tonal language processing, and voice conversion tasks where pitch class preservation matters [3].

2.4.4 Log-Mel Spectrogram and Pitch Features

While not a "feature" in the scalar sense like those above, the **log-mel spectrogram** is essentially the collection of filterbank energies computed on each frame (as part of MFCC processing), but not transformed into cepstral coefficients [6]. In other words, it's the time-frequency representation after applying the mel scale and logarithmic compression. This representation is widely used as input to modern deep learning models (e.g., CNNs, RNNs) in end-to-end speech recognition systems [7].

The log-mel spectrogram can be visualized as an image of size $(n_{\text{mels}} \times T)$, where each "pixel" represents the energy in a specific mel-frequency band at a specific time frame (in decibels).

Why log-mel? Compared to raw spectrograms:

- Mel spectrograms focus on perceptually important frequency bands.
- Log scaling compresses the dynamic range of the signal.
- Retains more detailed information than MFCCs (since no DCT or truncation is applied).

Many robust speech recognition systems feed log-mel spectrograms into neural networks, allowing the model to learn features directly from the spectrogram. This can outperform MFCCs, which are lossy compressed representations. Additionally, log-mel spectrograms reveal meaningful patterns: formants appear as darker horizontal stripes, pitch harmonics as fine vertical ridges (depending on resolution).

Calculation in Python (Librosa):

```
S = librosa.feature.melspectrogram(y=y, sr=sr, n_fft=1024,
                                   hop_length=160, n_mels=40)
S_dB = librosa.power_to_db(S, ref=np.max)
```

This yields a $40 \times T$ matrix of log-mel energies, which can be fed directly into a CNN. Figure 2.6 shows an example of such a representation, where voiced speech regions are visible as bright, structured bands.

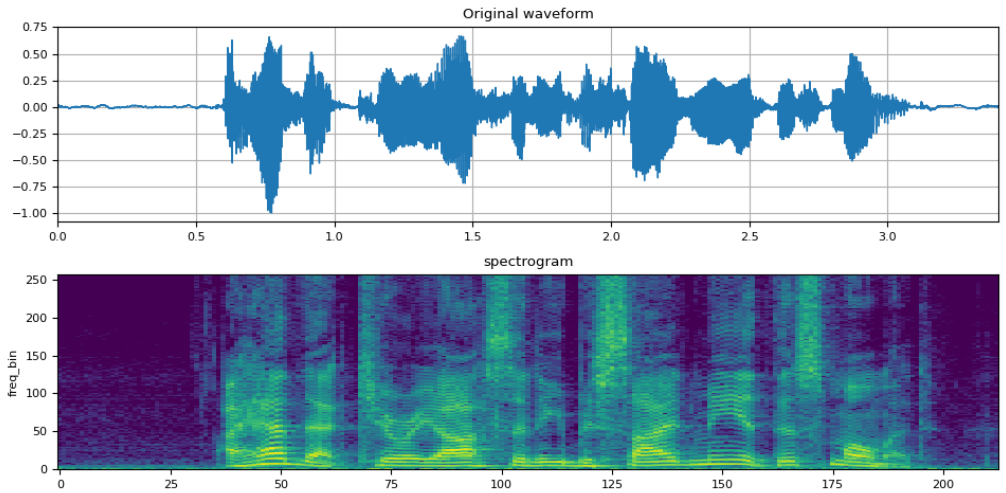

Figure 2.6: Log-mel spectrogram of a short speech segment. Voiced regions appear as bright, banded areas, while unvoiced regions are darker or more diffuse.

Use Cases: Log-mel spectrograms are now standard in:

- End-to-end automatic speech recognition (ASR)
- Wake word detection (e.g., “Hey Siri”)
- Emotion and speaker recognition using CNNs

Pitch (Fundamental Frequency, F0)

The **fundamental frequency** (F0), commonly referred to as *pitch*, is produced by the vibration rate of the vocal folds during voiced speech [8]. Pitch changes over time form a contour that is crucial for prosody (intonation, tone, and emotion).

Why is pitch useful?

- MFCCs remove pitch intentionally for speaker invariance in ASR.
- Pitch adds valuable speaker-specific and emotion-related cues.
- In tonal languages, pitch modulates meaning.

Typical pitch ranges:

- Adult male: 80–180 Hz
- Adult female: 150–300 Hz

Estimation in Librosa:

```
f0_series = librosa.yin(y, fmin=50, fmax=500, sr=sr,
                        frame_length=1024, hop_length=160)
```

This returns an F0 contour over time (with `NaN` or zero for unvoiced frames). Other methods like `pyin` or `piptrack` exist, but YIN is often effective and simple to use.

Use Cases:

- **Speaker recognition:** F0 range and contour shape may help differentiate individuals.
- **Emotion classification:** Angry or excited speech often shows higher and more variable pitch.
- **Prosody modeling:** Pitch contour is critical for generating natural speech in TTS systems.

Note: Pitch estimation is sensitive to noise and vocal irregularities, but when reliable, it provides complementary information to spectral features like MFCCs. Together, pitch and spectral shape represent the source-filter model of speech production.

2.4.5 Formants

Formants are the resonant frequencies of the vocal tract – essentially the peaks in the spectral envelope of voiced speech. Formants (labeled F1, F2, F3, … from low to high frequency) correspond to tongue and mouth configuration; they are what define vowels. For example, the vowel [a] might have F1≈800 Hz, F2≈1200 Hz; [i] might have F1≈300 Hz, F2≈2500 Hz, etc. Each vowel has a unique combination of the first two or three formant frequencies. Thus, formants are critical in phonetics – they uniquely identify vowels and other resonant sounds.

In terms of features, tracking formant frequencies over time provides a high-level description of the speech signal's filter characteristics. Historically, formant frequencies (and bandwidths) were used in speech recognition and speaker recognition. They are still used in speech therapy and linguistics research to analyze articulation. In modern ML pipelines, we often rely on MFCCs (which implicitly contain formant info), but explicitly extracting formants can be beneficial for certain tasks (e.g., pronunciation scoring, or low-dimension interpretable feature sets).

Estimation: Formants can be estimated by finding peaks in the spectral envelope. One way is linear predictive coding (LPC), which gives an all-pole model of the spectrum – the poles of the LPC filter correspond to formants. Another way is simply to take a high-resolution FFT of a voiced frame and pick the prominent peaks in the spectrum (ignoring the fine harmonic structure by perhaps smoothing or using a cepstral envelope). Many speech toolkits exist for formant tracking (e.g., Praat [9]). In Python, one could use `librosa.lpc` (if available) or `numpy.polyfit` on the autocorrelation to get LPC coefficients and from them formant frequencies. For brevity, suppose we have an `estimate_formants(frame)` function that returns F1, F2, F3 for that frame (for voiced frames).

```
import numpy as np, scipy.signal
from numpy.polynomial import Polynomial

def lpc_formants(frame, sr, order=12):
    frame = frame * np.hamming(len(frame))
    autocorr = np.correlate(frame, frame, mode='full')[len(frame)-1:]
    R = autocorr[:order+1]
    A = scipy.linalg.toeplitz(R[:-1])
    b = -R[1:]
    lpc_coeffs = np.linalg.solve(A, b)
    lpc_coeffs = np.hstack([1, lpc_coeffs])
    roots = np.roots(lpc_coeffs)
    roots = [r for r in roots if np.imag(r) >= 0]
    angs = np.angle(roots)
    formant_freqs = sorted(angs * (sr/(2*np.pi)))
    return formant_freqs[:3]
# Usage:
F1, F2, F3 = lpc_formants(frame_signal, sr=16000)
```

Interpreting formants: Each formant frequency corresponds to a resonance. F1 is related to vowel height (jaw openness), F2 to vowel frontness (tongue position) – e.g., high F2 for front vowel [i], low F2 for back vowel [u]. This is why formants distinguish vowels. Consonants have formant transitions – rapid changes in formants – which are cues to

the consonant identity (like the rising F2 transition for [g] as in "ga", known as the "velar pinch" where F2 and F3 come together).

Use cases: Formant features can be used for speaker identification (formant frequencies differ slightly due to vocal tract length), emotion analysis (e.g., stressed speech might show formant shifts), and in clinical settings like pronunciation clarity analysis or accent recognition.

Note: Estimating formants reliably requires voiced segments and can be error-prone in noisy conditions or with closely spaced formants. Still, they are an interpretable and linguistically meaningful feature.

2.4.6 Feature Scaling and Normalization

After extracting features like those above, we often apply feature scaling or normalization before feeding them into machine learning models. The goal is to ensure that all features are on comparable scales and that the model isn't unduly influenced by one feature's range or offset.

Mean and Variance Normalization: A common method is cepstral mean normalization (CMN) or cepstral mean and variance normalization (CMVN) on MFCC features:

```
X_norm = (X - X.mean(axis=0)) / X.std(axis=0)
```

Per-utterance vs Global normalization: For speech recognition, CMVN is often applied per speaker or utterance to reduce channel effects. For emotion recognition, global normalization or selective feature normalization might be preferred.

Scaling to Range: Another method is min-max scaling to [0,1] or [-1,1], commonly used in neural networks. For log-Mel spectrograms, values are often clipped to $[-80, 0]$ dB and rescaled.

Decorrelation (Whitening): PCA whitening or HLDA was used in older systems like GMM-HMMs, but modern end-to-end models often learn such transformations internally.

Speech Audio vs Feature Normalization: Speech audio amplitude normalization is done before feature extraction (e.g., to normalize energy), whereas feature normalization ensures well-conditioned inputs.

2.5 Comparing Features and When to Use Them

We have introduced a variety of features – each captures different facets of speech. A natural question is: which features are suitable for which tasks, and what are the pros and cons? Below, we provide a comparative discussion:

MFCCs vs Spectral (Centroid/Bandwidth) vs Formants

MFCCs are effectively a smoothed spectral envelope and have proven excellent for speech recognition (ASR) because they compactly represent phonetic content while being robust to pitch differences. They are also common in speaker recognition and many speech tasks due to their effectiveness and low dimensionality. Formant features, being explicit frequencies, are highly interpretable and directly relate to articulation – they could be used in vowel classification, pronunciation scoring, or linguistic analysis. However, automatically tracking formants can be error-prone, and MFCCs often indirectly carry the same info with more stability. Pure spectral shape features like centroid, bandwidth, contrast, and rolloff give a sense of "brightness" or noise-tonality of the sound; they can complement MFCCs in tasks like speaker classification (e.g., distinguishing speech from music or environmental noise) or emotion detection (where a shift to higher spectral centroid might indicate anger or shouting). In general, MFCCs (possibly with deltas) are a solid default for recognition tasks, whereas formants might be added for interpretability or specific use-cases (like diagnosing pronunciation). Spectral contrast can be useful in speaker identification as well – different voices or recording conditions might have different spectral fine structures; contrast can capture presence of strong harmonics (in voiced sounds) which might vary with vocal quality.

Time-Domain vs Frequency-Domain vs Prosodic Features

Time-domain features like ZCR and energy are very straightforward and computationally cheap. Voice activity detection (VAD) often relies on energy and ZCR thresholds – low energy and low ZCR indicate silence, low energy and high ZCR might indicate unvoiced noise, etc.. However, these features alone are not sufficient for complex discrimination (they don't tell apart phonemes, for instance). Frequency-domain features (MFCCs, spectral features) are richer and are the backbone of ASR and speaker recognition. Prosodic features like pitch and energy contour come into play for emotion recognition and speaker characterization. For example, a speaker's pitch range and speaking energy can distinguish them or indicate emotional state. In emotion detection, typically a large set of features including pitch statistics (mean, std, min, max),

energy stats, speaking rate, etc., are used in addition to spectral features. So, in summary: for lexical content (what is spoken), spectral features (MFCCs) are key; for paralinguistic aspects (who is speaking, how they're speaking), prosodic features (pitch, energy, speaking rate) add a lot of value, often combined with spectral ones.

Log-Mel Spectrogram vs MFCC

With the rise of deep learning, many end-to-end models prefer using the rawer log-mel spectrogram input. Speech recognition systems nowadays often take 40-channel log-mel features (sometimes with delta and delta-delta appended, sometimes just as a 2D input to a CNN). The advantage is the model can learn its own optimal filterbank or feature combination. MFCCs, by contrast, have the advantage of lower dimensionality (13 vs 40 or more dimensions) and have traditionally been decorrelated (which was beneficial for Gaussian models). For a classical ML algorithm (GMMs, older neural nets), MFCC+Δ+$\Delta\Delta$ (39 dims) is much more tractable than a full spectrogram slice (which could be 257 FFT bins). But for CNNs with GPUs, feeding a 2D spectrogram is feasible and may capture fine details lost in MFCC. If one's using a simpler classifier or has less data, MFCCs might outperform because they impose prior knowledge that helps the model. If using a powerful deep model and lots of data, log-mel (or even raw waveform in some research) can be used – though log-mel is still overwhelmingly common as an input representation.

Feature Robustness

Some features are more robust to noise than others. For instance, relative features like spectral contrast or shape might remain informative even under certain noise (as long as noise is broadband, it raises valleys and lowers contrast, which itself is info). MFCCs can be made robust with normalization and modifications (e.g., cepstral liftering, mean normalization). Energy is very sensitive to noise – a noisy background raises energy floor significantly, potentially confusing a VAD unless a noise reduction was done. Pitch can also be distorted by noise (pitch trackers might lock onto noise harmonics or simply fail). There are noise-robust pitch algorithms (using autocorrelation in specific bands). In extremely noisy conditions, features like RPLP (Relative Perceptual Linear Predictive) or advanced cepstral coefficients have been proposed, but those are beyond our scope. As a rule of thumb, if expecting noise, ensure to include noise-robust processing (filtering, VAD) and possibly use features that normalize out noise (e.g., MFCCs with CMVN, or adding Rasta filtering which emphasizes spectral dynamics).

Dimensionality and Computational Cost

Simpler features (ZCR, energy) are trivial to compute and yield one number per frame. MFCCs yield 13 per frame – also quite efficient especially with FFT optimizations. Chroma (12 per frame) and spectral features (often 1 per frame, or 6 for contrast bands) are also manageable. A log-mel spectrogram for a 1-second speech audio (with 100 fps and 40 mel bands) is 40×100 = 4000 numbers – if fed to a model directly, that's fine for a CNN but too many for a traditional classifier unless reduced. So often for classical pipelines, one would aggregate features over time to reduce data rate (e.g., take statistics over an utterance). For deep learning, feeding sequences is fine (RNN can take frame sequence, CNN can take spectrogram slice). If one has to choose a small set of features for, say, a classical machine learning classifier (SVM, etc.), one might choose a handful: e.g., mean and variance of MFCC 1-12, mean pitch, pitch variance, mean energy, etc. If using deep learning, one might feed the whole sequence of MFCCs or mel-spectrogram.

Application Mapping

Automatic Speech Recognition (ASR): Traditionally uses MFCC + Δ + $\Delta\Delta$. Modern ASR often uses log-mel spectrogram patches into CNN or sequences into RNN/Transformer. Spectral features like centroid are not explicitly used in ASR (since MFCCs suffice). ZCR, etc., not used. Pitch sometimes used in tone languages to augment phonetic features (but usually handled by model).

Speaker Identification/Verification: Often uses MFCCs too (for input to i-vector or x-vector deep models). Additionally, pitch and formant-related features can help because they carry speaker characteristics (vocal tract length influences formants; habitual pitch differs per speaker). High-level prosodic features (like intonation patterns, speaking rate) can also be included. But MFCCs alone (or derived embeddings) have shown excellent results in speaker recognition, especially with sufficient data.

Emotion Recognition: This typically uses a broader feature set. For instance, the eGeMAPS feature set (a standard in emotion research) includes MFCCs, pitch, formants, jitter/shimmer (voice quality measures), energy, spectral flux, etc., aggregated over utterances. Pitch and energy dynamics are very important here, as are spectral shape cues that differentiate, say, a sharp, high-frequency "angry" tone vs a low, mumbling "sad" tone. ZCR might indirectly reflect "breathiness" or amount of unvoiced content (could be higher in angry speech with lots of frication). Spectral rolloff could shift with

emotion (more high-frequency energy in anger, perhaps).

Gender or Age Classification: Pitch is a primary feature for gender (male voices generally lower F0) and also age (children have very high F0). Formants can also indicate age (children have shorter vocal tracts, so formants are at higher frequencies). MFCCs can capture some of this, but explicitly including F0 and maybe formant positions can improve such classifiers.

Keyword Spotting (Wake-word Detection): Often uses similar features to ASR (log-mel or MFCC) because you need to discriminate specific words.

Music/Song vs Speech Discrimination: Spectral features like centroid and contrast can be quite useful to tell music from speech. Music might have higher spectral variability or more steady harmonic content (depending on genre), whereas speech has a certain spectral envelope pattern and silences. Chroma is obviously useful for music (tonal structure) but in speech it would mostly look random (since speech is not aligned to musical semitones). So a system distinguishing singing vs speaking could look at chroma clarity – in singing, chroma might show stable musical notes, while in normal speech it's diffuse.

Pros and Cons Summary

- **MFCC:** +Well-proven, compact, approximates auditory perception. +Many existing models expect them. −They discard absolute timing of spectral events beyond frame level (so need deltas for dynamics). −They are affected by additive noise (log can help but still).
- **Delta Features:** +Provide temporal context essential for sequence modeling in static models. −Add dimensionality, and not interpretable on their own (just differences).
- **Energy:** +Simple cue for speech activity and emphasis. −Highly variant with distance/microphone, requires normalization.
- **ZCR:** +Easy indicator of voiced/unvoiced. −Not robust in presence of noise or DC offset; not uniquely identifying beyond that (many different sounds can have similar ZCR).
- **Spectral Centroid/Bandwidth:** +Capture timbral quality (brightness). −Don't directly relate to specific phonemes, but rather overall spectrum balance.
- **Spectral Contrast:** +Captures harmonicity vs noisiness. −Can be less intuitive to interpret; and if spectrum is flat due to noise, it just tells "no strong peaks" which you might already infer from low energy of harmonics.
- **Spectral Rolloff:** +Good indicator of high-frequency content proportion. −Might be redundant with centroid to some extent (both move upward with more high-frequency energy).
- **Chroma:** +Great for tonal analysis (music, or prosody to some extent). −In normal speech, pitch is not quantized to semitones, so chroma might be "blurry." If a speaker is speaking at 130 Hz vs 150 Hz, that's a different chroma pattern, but not meaningful linguistically. So chroma is more relevant if your speech has a musical or tonal component (e.g., analyzing sung vowels, or perhaps in a tonal language to identify tone patterns roughly).
- **Pitch (F0):** +Essential for intonation, tone, speaker traits. −Difficult to estimate in noisy or very high-pitched or polyphonic scenarios. For unvoiced sounds, undefined. If used as a continuous feature, need to handle "no value" cases (e.g., set to 0 or carry last value or use interpolation).
- **Formants:** +Direct correlation to phonetics, interpretable (you can literally guess the vowel by F1/F2 positions). −Harder to compute reliably, especially for higher formants or in noisy data; only defined in voiced regions; also overlapping speakers or background can throw it off. Additionally, needing to decide number of formants to track and pairing them across frames (formant tracking) can be complex. But as static features, average formant frequencies can tell speaker vocal tract characteristics.

Feature Fusion and Final Notes

In practice, the choice of features comes down to the task requirements and the model. If using deep learning and large data, one might lean toward giving the model more raw representations (log-mel, maybe even raw waveform to a learnable filterbank). If using classical approaches or limited data, carefully designed features like MFCC plus a selection of prosodic features can give better performance with less data.

It's also common to combine feature sets: e.g., MFCCs + pitch + energy has been used in some voice activity detectors to improve detection of low-energy voiced sounds (pitch ensures you catch voiced even if energy is low). Another example: In speaker recognition, combining MFCC embeddings with prosodic feature models yields better results than either alone,

since they capture complementary information (short-term spectral vs long-term intonation patterns).

To conclude: No single feature is universally "best" – each provides a lens on the data. A robust speech system often uses a feature fusion: MFCCs (for spectral envelope), plus deltas (for dynamics), plus maybe pitch/formant (for source characteristics), plus energy (for emphasis). Modern end-to-end systems attempt to learn these from raw data, but understanding these features and their roles helps in system design and troubleshooting. In later chapters, when we apply machine learning models to speech, we'll see how these features feed into models and how to choose a feature set appropriate for the task at hand. By extracting and possibly combining the right features, we ensure our models have the relevant information to learn from, which is a critical step toward successful speech machine learning.

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Intro to Machine Learning

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Chapter 3

Introduction to Machine Learning

Machine Learning (ML) is the discipline that frames data–driven prediction and decision-making as an optimisation problem. Formally, let $\mathcal{D}$ be an unknown distribution over input–output pairs $(\mathbf{x}, y) \in \mathcal{X} \times \mathcal{Y}$. A learner chooses a hypothesis $f_{\boldsymbol{\theta}} \colon \mathcal{X} \to \mathcal{Y}$ from a parameterised family $\{f_{\boldsymbol{\theta}}\}_{\boldsymbol{\theta} \in \Theta}$ and seeks parameters

$$\boldsymbol{\theta}^* \;=\; \arg\min_{\boldsymbol{\theta} \in \Theta} \; R(\boldsymbol{\theta}), \quad R(\boldsymbol{\theta}) = \mathbb{E}_{(\mathbf{x},y)\sim\mathcal{D}}\, \mathcal{L}\big(f_{\boldsymbol{\theta}}(\mathbf{x}), y\big),$$

where $\mathcal{L}$ is a task-specific loss (e.g. binary cross-entropy for wake-word detection). Because $\mathcal{D}$ is inaccessible, the *expected risk* R is approximated by the *empirical risk* $\hat{R}(\boldsymbol{\theta}) = \frac{1}{N}\sum_{i=1}^{N} \mathcal{L}(f_{\boldsymbol{\theta}}(\mathbf{x}_i), y_i)$ over a finite sample $\{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$.

Three ingredients therefore characterise any ML project:

1. **Task** T – the mapping to be learned, such as classifying 1-s audio segments as *wake-word* or *background*.
2. **Experience** E – a corpus of labelled examples; in speech a modern keyword-spotting system might use ≈50 k clips recorded across accents, microphones, and noise conditions [1].
3. **Performance measure** P – an objective linked to deployment constraints, e.g., the false-accept rate at 95% recall [2].

Learning works best when the model's **inductive bias** (its built-in assumptions about what patterns to expect) matches the structure of the data. For example, in speech tasks, convolutional and attention-based layers are effective because they take advantage of how speech patterns are localized in time and frequency. Techniques like time-stretching or SpecAugment help the model generalize better by creating slight variations of the input. More recently, self-supervised methods such as wav2vec 2.0 have shown that models can be pre-trained on large amounts of unlabeled speech by predicting masked parts of the signal, and then fine-tuned with much smaller labeled datasets to achieve strong performance [3, 4].

3.1 Types of Machine Learning Systems

Machine learning approaches are typically described along three independent dimensions: *supervision, learning schedule, and decision strategy*, each of which has direct counterparts in speech-audio research and practice.

Supervision. A system is *supervised* when every training utterance carries a ground-truth label; for instance, a wake-word detector trained on thousands of clips marked "Hey Alexa'' or "background.'' In *unsupervised* settings, the model sees only raw waveforms and must uncover latent structure on its own, as when spectral clustering discovers speaker groupings in hours of unlabeled meeting audio. *Semi-supervised* learning occupies the middle ground, fine-tuning a small, labeled keyword corpus with a much larger pool of pseudo-labeled voice-assistant logs. Finally, *reinforcement-learning* agents improve through trial and reward, for example, a spoken-dialogue system that earns positive feedback when users swiftly complete tasks and maintain politeness.

Learning schedule. In *batch* learning, the model ingests a fixed dataset all at once. By contrast, an *online* learner updates continuously as new data arrive, such as an adaptive beam-forming algorithm that refines its microphone weights frame by frame while a conference call is in progress.

Decision strategy. *Instance-based* methods classify by direct comparison: a k-Nearest-Neighbour (k-NN) speaker-ID system stores enrollment i-vectors and labels a test i-vector by whichever cohort lies closest in embedding space. *Model-based* approaches first fit a compact set of parameters, then discard the raw examples; a convolutional neural network that predicts emotions from log-mel spectrograms is a classic example.

3.1.1 Supervised and Unsupervised Learning

ML systems are often introduced in terms of the *degree of supervision* available at training time. Four principal regimes are recognized: supervised, unsupervised, semi-supervised, and reinforcement learning, but the boundary between them is fluid in practical speech-audio work.

Supervised Learning

In *supervised Learning* , every training utterance is paired with an explicit label, allowing the model to learn a direct mapping from acoustic representations to task-specific targets [5]. In speech technology the target can be a discrete class (e.g. *wake-word* vs. *background*), a sequence of phonemes, or a continuous value such as pitch. The workflow typically comprises five stages:

1. **Data curation**. Raw recordings are segmented into fixed-length clips; mislabelled or low-SNR segments are pruned to

prevent noisy supervision. Class balance is critical: keyword corpora often down-sample the vast background class to avoid overwhelming the minority wake-word examples.
2. **Feature extraction**. Log-Mel spectrograms, MFCCs, or learnable filterbanks are computed with 20–40 ms analysis windows. Frame stacking (e.g. 10 frames = 100 ms context) supplies temporal cues without recurrent layers.
3. **Model training**. Convolutional or transformer encoders ingest the feature tensor and output logits. Cross-entropy loss is minimised with Adam or RMSProp; early stopping monitors validation error to avoid over-fitting. Data augmentation—time-stretching, SpecAugment, random room impulse responses—exposes the model to realistic acoustic variability.
4. **Post-processing**. The per-window posterior stream is smoothed by a finite-state machine or hysteresis filter to suppress short false alarms. Thresholds are tuned on a development set to satisfy device or privacy budgets (e.g. <1 false alarm / hour).
5. **Evaluation**. Metrics go beyond raw accuracy: false-accept and false-reject rates are reported at several operating points; ROC and DET curves visualise trade-offs [2]. Deployment trials on embedded hardware verify latency and power constraints.

Classification tasks. Keyword spotting, intent classification, and speaker verification all rely on supervised classification models. Architectures range from shallow CNNs deployed on microcontrollers to large transformers distilled for on-device execution [6]. Class imbalance is mitigated by focal loss or by over-sampling minority examples during mini-batch construction.

Regression tasks. Many speech problems are naturally continuous. Estimating the fundamental frequency F_0, predicting loudness in LUFS, or mapping articulatory sensor readings to tongue trajectories each outputs a real-valued signal. Although regression is trained with mean-squared or Huber loss, decision thresholds can convert the output into categories (e.g. “high” vs. “low” pitch) when required by downstream logic.

From logits to confidence. Even a simple logistic-regression model can serve as a calibrated probability estimator: its sigmoid output approximates the true posterior under the assumption of label-balanced data. Calibration degrades when priors shift; temperature scaling or Platt scaling restores well-behaved confidence scores, a necessity for cascaded pipelines where later modules rely on upstream probabilities.

Take-aways. Supervised learning delivers state-of-the-art performance in speech when abundant labelled data, representative of deployment conditions, are available. Success hinges on robust feature generation, aggressive yet task-aligned augmentation, careful handling of class imbalance, and objective metrics that reflect real-world costs.

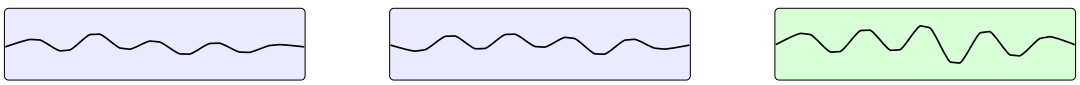

Figure 3.1: Typical supervised setting: each audio clip is tagged with a ground-truth label (e.g. wake-word vs. background).

Unsupervised Learning

In *unsupervised learning* the corpus arrives without labels; the algorithm must uncover structure on its own [7]. Speech practitioners rely on three broad tool-families:

Clustering. Algorithms such as k-means, agglomerative hierarchical clustering, spectral clustering, and HDBSCAN group utterance-level embeddings according to cosine or PLDA distance. A speaker-diarisation pipeline, for example, extracts x-vectors from overlapping 1.5-s windows, applies dimensionality reduction, and then clusters the points to infer “who spoke when.” Agglomerative clustering with a Bayesian information criterion (BIC) stop rule often yields < 10 label. The same machinery performs *anomaly detection*: embeddings that fall far from any cluster centre may indicate spoofed audio or corrupted recordings worthy of human review.

Representation learning. Autoencoders, variational autoencoders, and self-supervised objectives such as Contrastive Predictive Coding (CPC) learn feature spaces where downstream tasks require fewer labels. Wav2vec 2.0, for instance, trains a transformer to predict masked time steps in raw waveforms, producing 768-dimensional embeddings that, once

fine-tuned, cut word-error rate by up to 50 to purely supervised baselines. These pre-trained features feed directly into clustering, anomaly detection, or low-resource ASR.

Dimensionality reduction and visual analytics. High-dimension per-frame MFCCs or x-vectors are projected into two or three dimensions with PCA, t-SNE [8], UMAP, or kernel PCA so that clusters of speakers, emotions, or channel types become visually separable. Engineers routinely inspect such plots to diagnose domain mismatch—e.g., telephone speech embedding clouds that sit far from smart-speaker embeddings indicate a coverage gap in the training data.

Association discovery. Audio event mining looks for frequent co-occurrence, such as a particular HVAC hum that correlates with female speakers in a call-centre dataset. Apriori or FP-growth algorithms reveal these latent relations and motivate targeted data augmentation or microphone filtering.

Evaluation without labels. Because ground truth is absent, intrinsic metrics—silhouette score, Davies–Bouldin index, and cluster-size entropy—guide hyperparameter search. For diarisation, a small labelled subset provides diarisation error rate (DER); improvements on this slice are assumed to transfer to the unlabelled bulk.

While supervised systems generally yield higher ultimate accuracy, modern speech pipelines rarely rely on supervision alone. A common recipe is *self-supervised pre-training* on thousands of hours of unlabelled audio, followed by supervised fine-tuning on a modest, high-quality keyword corpus. The pre-training phase supplies powerful acoustic embeddings, whereas the fine-tuning phase specialises the model to task-specific decision boundaries. Leveraging the complementary strengths of both regimes is now considered best practice for data-efficient, production-grade speech-audio systems.

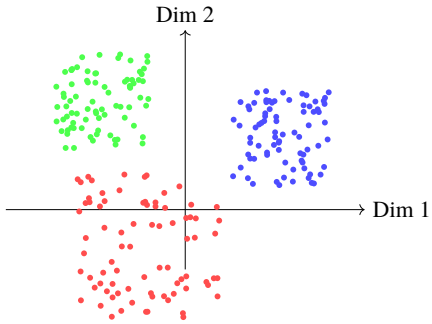

Figure 3.2: Unsupervised t-SNE projection of speech embeddings revealing three speaker clusters without any labels.

Semi-supervised Learning

In *semi-supervised learning*, a small corpus of labeled speech utterances is combined with a much larger pool of unlabeled audio to improve model generalisation. A common workflow begins by training an initial model on the few available transcripts (e.g. 1 000 labeled sentences), then using that model to assign *pseudo-labels* to hundreds of thousands of untranscribed recordings. The newly labeled data are merged back into training in iterative cycles, progressively refining the acoustic model's accuracy without requiring exhaustive manual annotation.

This approach is widely adopted in automatic speech recognition (ASR): for example, a neural-network acoustic model may be trained on a limited set of read-speech recordings, then used to decode a large web-scraped audio archive. High-confidence hypotheses are treated as ground truth in a second training stage, yielding significant gains in word-error rate with minimal human effort. Similar pipelines appear in speaker-identification research, where a handful of labeled speaker segments bootstrap the clustering and labeling of thousands of unlabeled meeting recordings.

Many advanced semi-supervised methods augment self-training with consistency regularisation or entropy minimisation to suppress noisy pseudo-labels. For instance, the "mean teacher" framework enforces that a student ASR model's predictions on perturbed (e.g. noise-added) audio match those of a slowly updated teacher model, further boosting robustness in low-resource speech domains.

Reinforcement Learning

In *reinforcement learning* (RL), an agent interacts with an environment by taking actions and receiving scalar rewards, with the goal of learning a policy that maximizes cumulative reward over time [9]. In the speech-audio domain, a common

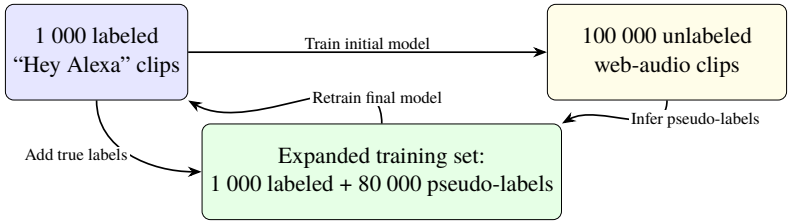

Figure 3.3: Practical semi-supervised example for wake-word detection.

RL application is *adaptive speech enhancement*, where the agent adjusts filter or beamformer parameters to improve downstream Automatic Speech Recognition (ASR) accuracy in varying noise conditions.

At each time step, the agent observes acoustic features (e.g. Mel-spectrogram frames) and selects an action—such as modifying gain coefficients of a spectral filter. The environment applies these parameters to the incoming noisy audio, feeds the enhanced signal into an ASR engine, and returns two things: an updated observation of features plus a reward based on the ASR word-error rate (WER). Over many interactions, the agent learns which parameter adjustments yield the highest ASR performance.

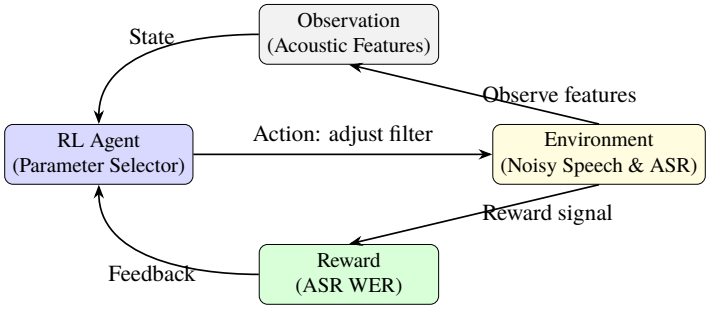

Figure 3.4: Reinforcement-learning loop for adaptive speech enhancement: the agent selects filter parameters based on feature observations and ASR-based reward feedback.

3.1.2 Batch and Online Learning

Machine-learning systems for speech can be differentiated by how they consume new data. In **batch learning**, an acoustic or enhancement model is trained once on the entire available corpus—say, 960 hours of Librispeech—typically on a GPU cluster. When additional recordings arrive (for example, freshly collected broadcast audio), the model must be retrained from scratch on the combined old + new data, a process that can take hours and consumes substantial compute and storage.

By contrast, **online learning** updates the model continuously as each new utterance arrives. For instance, a streaming denoising filter in a hearing aid may adjust its spectral-subtraction coefficients frame-by-frame to track evolving background noise, without revisiting earlier audio. This allows rapid adaptation—crucial when moving from a quiet office into a noisy street—while keeping memory and latency low.

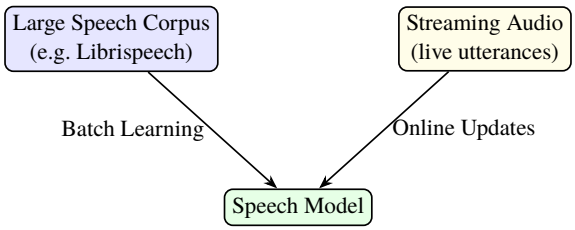

Figure 3.5: Batch vs. online learning for speech-audio models: full-corpus retraining vs. incremental updates on live audio.

3.1.3 Instance-Based Versus Model-Based Learning

Machine-learning systems for speech/audio differ not only in their training paradigm but also in how they generalize at inference time. In **instance-based learning**, the system retains a set of training examples and makes predictions by finding the nearest neighbours under some similarity metric. In **model-based learning**, the system fits a parametric model (e.g. logistic regression, SVM, neural network) and retains only its learned parameters.

Instance-Based Learning

Instance-based methods such as k-Nearest Neighbors (k-NN) are popular for tasks like speaker identification and keyword spotting when new examples must be accommodated on the fly. Given a test feature vector $\mathbf{x} \in \mathbb{R}^D$ (e.g. mean-MFCCs of an utterance), the system computes distances to each stored example $\{\mathbf{x}_i\}$:

$$d_{\cos}(\mathbf{x}, \mathbf{x}_i) \;=\; 1 \;-\; \frac{\mathbf{x}^\top \mathbf{x}_i}{\|\mathbf{x}\|\|\mathbf{x}_i\|}, \quad d_{\mathrm{E}}(\mathbf{x}, \mathbf{x}_i) \;=\; \sqrt{\sum_{j=1}^{D} (x_j - x_{i,j})^2}.$$

The label is then chosen by majority vote among the k nearest neighbours or by weighting each neighbour's vote inversely to its distance. Instance-based classification adapts instantly when new labeled data arrive—no retraining needed—but at the cost of $O(ND)$ query time and $O(ND)$ memory to store N examples.

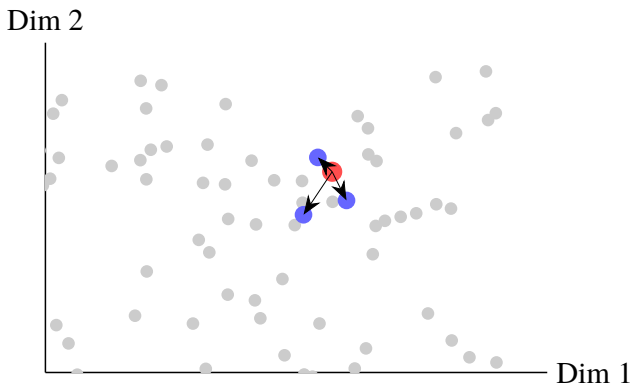

Figure 3.6: Instance-based speaker identification: 200 enrollment embeddings (gray), three nearest neighbors (blue), and a test embedding (red), with small markers and axis labels.

```
from sklearn.neighbors import KNeighborsClassifier
import numpy as np, librosa

# Extract 13-dim MFCC mean as feature
def featurize(path):
    y, sr = librosa.load(path, sr=16000)
    mfcc = librosa.feature.mfcc(y, sr, n_mfcc=13)
    return mfcc.mean(axis=1)

X_train = np.array([featurize(p) for p in train_paths])
y_train = np.array(train_labels)
X_test  = np.array([featurize(p) for p in test_paths])

knn = KNeighborsClassifier(n_neighbors=5,
                           metric='cosine',
                           weights='distance')
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
```

Model-Based Learning

Model-based approaches distil the entire training set into a compact parameter vector $\boldsymbol{\theta}$. During inference the original examples are no longer required; all information is encapsulated in the learned parameters. Classic speech-audio models include Gaussian Mixture Models (GMMs) for acoustic likelihoods, Support Vector Machines (SVMs) operating on PLP or i-vector features, and—in contemporary systems—deep Convolutional Neural Networks (CNNs) that treat log-Mel spectrograms as two-dimensional "images."

Logistic regression for speech activity. For binary speech-activity detection a linear classifier suffices: the probability that frame-level feature vector $\mathbf{x} \in \mathbb{R}^D$ belongs to the *speech* class is obtained by passing the affine projection $\boldsymbol{\theta}^\top \mathbf{x}$ through a sigmoid,

$$P(y = 1 \mid \mathbf{x}) = \sigma\big(\boldsymbol{\theta}^\top \mathbf{x}\big).$$

The parameters $\boldsymbol{\theta}$ are chosen to minimise the *regularised cross-entropy* objective in (**??**), where the $\lambda\|\boldsymbol{\theta}\|_2^2$ penalty (weight decay) prevents overfitting by shrinking large weights and effectively encodes a Gaussian prior on $\boldsymbol{\theta}$. Inference reduces to a single dot product ($O(D)$) followed by a sigmoid—trivial on embedded hardware and highly amenable to vectorisation.

SVMs for MFCC embeddings. When the decision boundary is non-linear (e.g. differentiating emotional vs. neutral speech), kernel methods such as the Radial Basis Function (RBF) SVM map inputs into a high-dimensional feature space where a linear separator exists. Storage cost is dominated by the "support vectors"—typically a few percent of the training set—so the memory footprint remains small relative to instance-based schemes.

CNN keyword-spotter. Figure 3.7 shows a deep CNN ingesting a 40-band log-Mel spectrogram. Convolutional layers capture local time–frequency patterns (formant sweeps, fricative bursts), while pooling layers inject local invariance to speaking rate and slight frequency shifts. Fully connected layers aggregate the high-level feature maps, and a softmax outputs posterior probabilities over the keyword set. Because the model is *fully convolutional* in time, it slides over an audio stream with constant latency—crucial for always-on wake-word engines that must respond within hundreds of milliseconds.

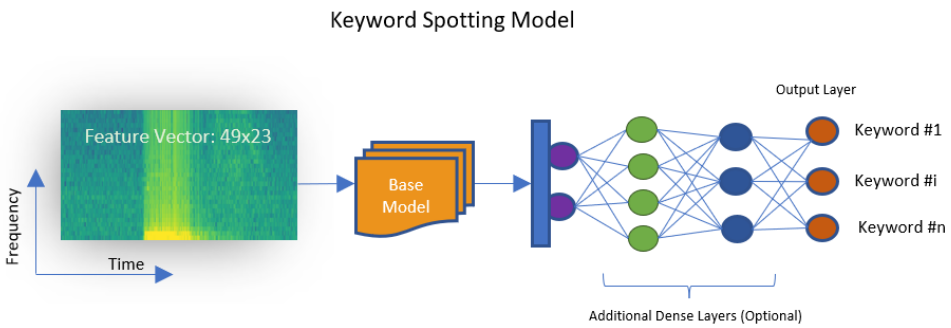

Figure 3.7: Model-based CNN for keyword spotting: spectrogram input → convolution+pool layers → softmax output.

Practical implementation (Python). Listing 3.1.3 demonstrates two off-the-shelf scikit-learn models that embody the theory above. The logistic-regression classifier uses L_2 regularisation (`penalty='l2'`) and is trained until convergence (`max_iter=200`). The SVM employs an RBF kernel, tuned by the cost parameter $C = 10$ and kernel width $\gamma = 0.01$. Setting `probability=True` instructs scikit-learn to calibrate posterior probabilities via Platt scaling, enabling threshold adjustment for arbitrary false-alarm targets.

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC

# Logistic Regression for speech activity
lr = LogisticRegression(C=1.0, penalty='l2', solver='lbfgs', max_iter=200)
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)

# SVM with RBF kernel on MFCCs
svm = SVC(kernel='rbf', C=10, gamma=0.01, probability=True)
svm.fit(X_train, y_train)
y_pred_svm = svm.predict(X_test)
```

Memory and latency considerations. A trained logistic-regression model stores only $D + 1$ floats (weights plus bias), whereas the CNN in Fig. 3.7 may require hundreds of kilobytes—still modest compared with instance-based databases that scale linearly with the number of enrolment utterances. At runtime, linear models execute in microseconds on a Cortex-M4, and optimised small-footprint CNNs can reach < 20 ms per inference with int8 quantisation, meeting the latency budgets of smart-speaker chips.

Summary. Model-based learning offers constant-time inference, compact storage, and well-understood regularisation knobs. Its chief cost lies in periodic re-training when new data arrive, but for tasks with stable label taxonomies— such as keyword spotting or speech activity detection—the benefits far outweigh the maintenance overhead.

Hybrid and Prototype Models

To trade off memory and performance, prototype-based methods cluster N instances into $M \ll N$ centroids $\{\mathbf{c}_j\}$, then apply k-NN on $\{\mathbf{c}_j\}$. In speaker verification, this appears as i-vector + PLDA, where each speaker is represented by a mean vector and covariance, dramatically reducing storage while preserving accuracy.

In summary, instance-based learning offers immediate adaptability at the price of query-time and memory costs proportional to the dataset size. Model-based learning provides fast $O(D)$ inference and compact storage of parameters—ideal for embedded speech applications—but requires a potentially expensive retraining step whenever new labeled data arrives. The choice depends on constraints such as update frequency, device memory, and latency requirements.

Summary

In this chapter, we have contrasted two fundamentally different strategies for speech-audio learning. In *instance-based learning*, every new utterance is compared directly to a stored database of feature vectors—such as mean MFCCs or i-vectors—using distance metrics like cosine or Euclidean distance. This "lazy" approach adapts instantly when new labeled examples arrive, making it ideal for speaker-adaptation scenarios, but its $O(ND)$ query cost and memory footprint can become untenable as the enrollment set grows.

By contrast, *model-based learning* condenses training data into a compact parameter set $\boldsymbol{\theta}$. Whether fitting a logistic-regression classifier for speech activity detection, training an SVM on PLP features for emotion recognition, or optimizing a convolutional neural network on log-Mel spectrogram inputs for keyword spotting, inference is efficient ($O(D)$) and storage minimal. However, any time new labeled audio is added, the entire model must be retrained or incrementally fine-tuned.

Hybrid schemes—such as prototype models that cluster embeddings into a small number of centroids followed by k-NN—seek a middle ground, retaining some flexibility of instance-based methods while reducing storage overhead. Ultimately, the choice between instance and model approaches depends on constraints of latency, memory, update frequency, and the availability of labeled data in the target speech-audio domain.

3.1.4 Main Challenges of Speech-Audio Machine Learning

Building high-performance speech systems demands not only the right algorithm but also careful attention to the peculiarities of audio data. Below, we discuss six core pitfalls and strategies to mitigate them.

Insufficient Quantity of Training Audio

Unlike image models that can leverage millions of web-scraped photographs, speech-audio systems often struggle for labeled data. A robust ASR acoustic model may require hundreds of hours of transcribed speech; languages or dialects

with scant resources see word-error rates spike. **Data augmentation**—randomly warping pitch, adding noise at varying SNRs, applying SpecAugment's time- and frequency-masking—simulates diversity and can reduce data hunger by 20–30 % without new recordings.

Nonrepresentative Audio Sampling

Even large corpora can mislead models if they misrepresent real-world conditions. A keyword-spotting model trained only on studio-quality speech will fail in noisy cafés or car cabins. Similarly, accent, age, and microphone type biases lead to poor cross-speaker performance. **Domain-invariant training**—using adversarial losses to encourage features that ignore recording conditions—and **multi-condition training** with matched noise profiles are critical.

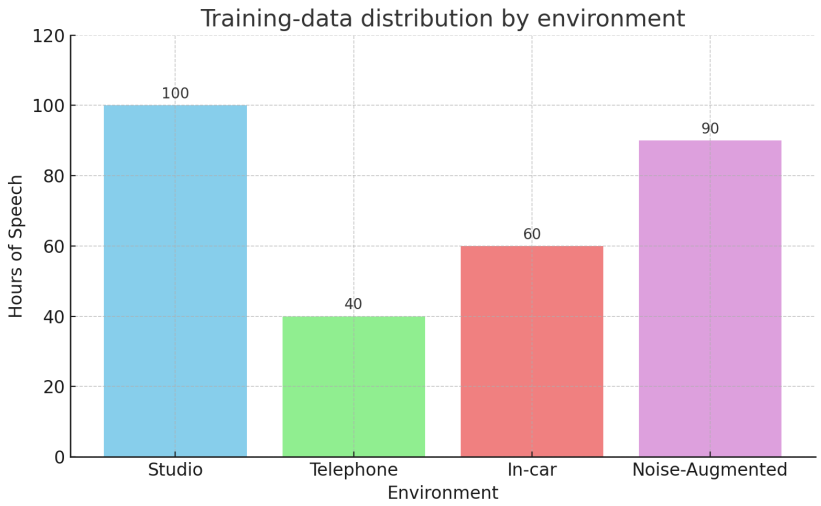

Figure 3.8: Training-data distribution by environment: studio vs. telephone vs. in-car vs. noise-augmented.

Noisy and Reverberant Recordings

Room reverberation smears spectral peaks and degrades pitch-tracking. A model trained only on clean read speech may see a 10–15 % relative drop in keyword-spotting F1 when faced with 0.6 s RT60 reverberation. **Front-end enhancement** (WPE dereverberation, RNNoise) and **robust feature design** (RASTA filtering, perceptual linear prediction) can recover lost performance.

Irrelevant or Redundant Features

Extracting dozens of MFCCs, spectral contrasts, and prosodic measures can flood a classifier with correlated or uninformative inputs. **Feature-selection** via correlation-thresholding ($\rho < 0.9$), mutual-information ranking, or embedded methods like tree-based importance reduces dimension from $60 \rightarrow 15$, cutting inference time and overfitting risk.

Overfitting Acoustic Models

Complex CNNs or LSTMs may achieve near-perfect accuracy on a validation set but fail in deployment. Overfitting manifests as spurious sensitivity to speaker- or utterance-specific artifacts. Counter-measures include **dropout**, **weight decay** (ℓ_2 regularization), **early stopping** based on held-out loss, and **mixup** augmentation that blends pairs of spectrograms.

Underfitting Simple Models

Conversely, overly simplistic models—such as a single-layer linear classifier on raw spectral energies—may underfit, exhibiting high bias and poor accuracy even on training data. Underfitting is remedied by selecting more expressive architectures (deep or wide networks), increasing context windows, or adding higher-order spectral features (e.g. delta-deltas, group delay).

3.1.5 Testing, Validation, and Hyperparameter Tuning

To estimate real-world performance, we split data into speaker-disjoint training, validation, and test sets. *Cross-validation* across multiple folds stabilizes error estimates. Hyperparameter grids—learning rates, dropout ratios, convolutional kernel

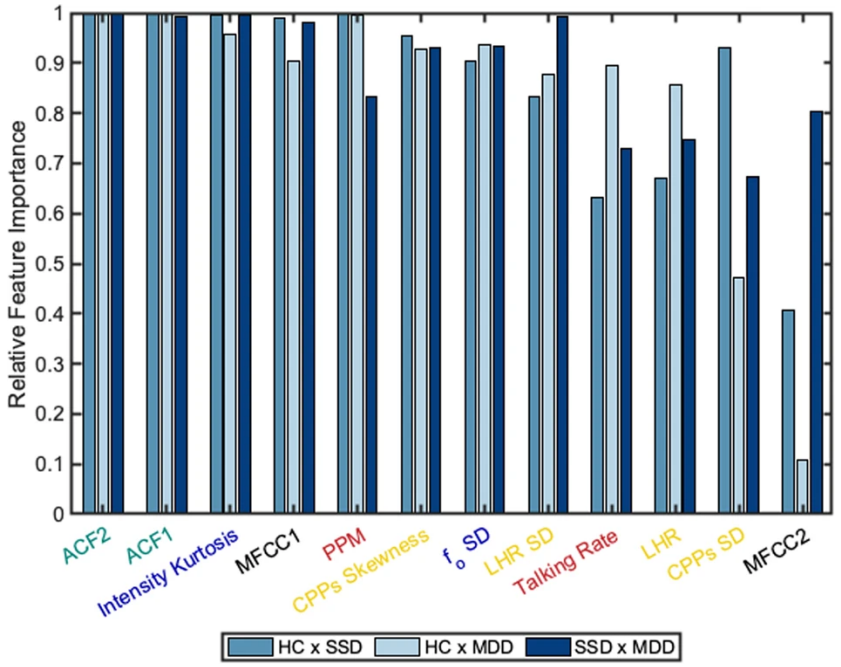

Figure 3.9: Feature-importance scores for a Random Forest keyword-spotting model; low-importance features can be pruned.

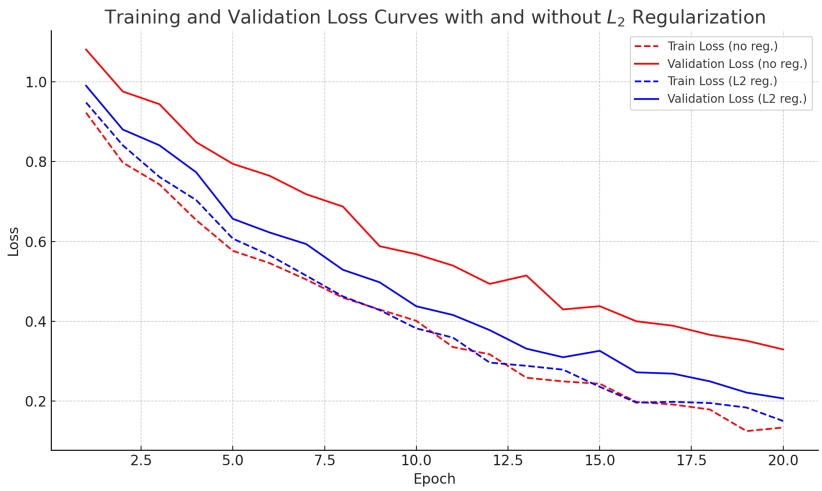

Figure 3.10: Training and validation loss curves with and without ℓ_2 regularization; regularization prevents divergence on the validation set.

sizes—are searched via Bayesian or random search to balance compute cost and model quality. Finally, **calibration** of confidence scores (e.g. Platt scaling) ensures outputs are well-aligned with true error rates.

3.1.6 Concluding Remarks

Effective speech-audio machine learning demands more than merely choosing an appropriate algorithm; it necessitates careful attention across multiple critical stages. This begins with curating a representative and noise-diverse dataset that includes sufficient hours of speech per speaker and environmental context, ensuring the model is trained on conditions closely resembling real-world deployments. Equally important is the meticulous design of robust acoustic features and effective augmentation strategies, which help simulate a variety of deployment scenarios and bolster model resilience to unexpected variability. Managing model complexity is crucial—striking a balance between overfitting and underfitting can be achieved through appropriate regularization techniques and systematic model selection procedures. Lastly, rigorous validation methodologies, such as speaker-disjoint splits and thorough cross-validation approaches, are essential for accurately assessing a model's capacity to generalize beyond the training data. Altogether, these interconnected steps define the success of speech-audio machine learning systems, enabling reliable performance under diverse and realistic conditions.

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Key-Word Detection using Random Forest

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github.com/ahmedajan/Key-Word-Detection-using-Random-Forest

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July 9, 2025

Chapter 4

Key-Word Detection using Random Forest

4.1 Introduction

Many individuals experienced upper extremity impairments as a result of neurological disorders or traumatic events such as stroke, traumatic brain injury (TBI), and cerebral palsy. These conditions often led to hyperactive reflexes and abnormal muscle tone, significantly hindering a person's ability to open their fingers. To address this challenge, various hand orthoses had been designed to facilitate hand opening. A common feature among these orthoses was their dependence on external control mechanisms.

The most widely used control mechanism for these devices involved pressing a button, either by the user or a third party. While this method was simple and reliable, it had its limitations, as it required either the availability of a free hand or assistance from another person.

Another control method was electromyography (EMG), which utilized multiple sensors placed along the arm. These sensors detected neural activity to determine whether the user intended to open or close their hand. However, EMG required a fully functioning nervous system, and its effectiveness could be limited in patients with neurologically induced impaired hand movement due to inconsistent or unreliable nerve signals. An alternative approach was to place a sensor on another part of the body to detect specific movements and use those movements to control the hand. For example, an inertial measurement unit (IMU) could be placed on the patient's foot, allowing them to control hand movements by tilting their foot, similar to how a joystick was used. AI voice recognition was another possible control method where verbal commands triggered the desired action. Though less commonly used, it could still be an effective solution. This chapter focused on applying AI voice recognition in conjunction with machine learning techniques.

We used the Dataset_EN dataset, which was comprised of 3735 voice lines from the game series "Caduceus Trauma Center." The keywords "Hold," "Let," and "Go" were isolated from this dataset.

While deep learning models were frequently used for keyword detection in current research, these complex models were not always necessary for mobile applications. Furthermore, more research was needed on the Coral Micro device. At the time of writing, no published research existed on using keyword detection specifically for Coral Micro. This chapter aimed to explore this relatively uncharted area and create a well-designed and thought-out machine-learning model for keyword detection on the Coral Micro.

4.2 Theoretical Foundations

This section gently introduces the signal-processing and machine-learning (ML) concepts required for embedded keyword detection.

4.2.1 Problem Formulation

Keyword spotting is treated as a **supervised classification** task: every training clip is paired with its correct label, and the classifier must assign one of four categories—Hold, Let, Go or General—to each new clip. The goal is therefore categorical, not numeric, prediction.

□

Figure 4.1: High-level pipeline for on-device keyword detection. Grey blocks run on the Coral Micro during inference.

4.2.2 Signal Pre-processing

Before learning can begin, the raw microphone stream is cleaned. First, a **low-pass filter** removes frequencies above 8kHz; this reduces aliasing and computation because most speech energy lies below that band. Second, we trim leading and

trailing samples whose amplitude falls below -20dB. This prevents the model from unintentionally associating silence with any keyword while also mimicking noisy real-world conditions.

4.2.3 Frame Segmentation

Continuous audio is then divided into overlapping 20ms **frames**. The window is long enough to span several vocal-fold cycles yet short enough that the signal within each frame can be assumed quasi-stationary.

4.2.4 Light-Weight Feature Engineering

Deep-learning systems often rely on mel-spectrograms—two-dimensional images that are costly to compute on micro-controllers. Instead, we focus on two inexpensive **time-domain** descriptors that can be calculated with only additions and multiplications. The first is **RMS Energy**, defined by

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

, which correlates with perceived loudness. The second is the **Zero-Crossing Rate (ZCR)**, given by

$$\mathrm{ZCR} = \frac{1}{N}\sum_{i=1}^{N-1} \mathbb{1}\big[x_i\, x_{i+1} < 0\big]$$

, an indicator of how often the signal changes sign and thus of its voicing characteristics. For each utterance we compute the mean, median, standard deviation, skewness and kurtosis of both RMS and ZCR, producing a concise ten-dimensional feature vector that still discriminates well between classes (ANOVA confirms $p < 0.05$ for every dimension).

□

Figure 4.2: Placeholder — intuition for RMS (overall energy) and ZCR (voicing).

4.2.5 Decision Trees

A **decision tree** partitions the feature space by applying successive axis-aligned tests—such as $\mu_{\mathrm{RMS}} < 0.025$—that route each instance from the root to a leaf node. At every split, the algorithm chooses the threshold that provides the largest **information gain**, meaning the children are purer than the parent. Purity is measured by **Gini impurity**,

$$G = 1 - \sum_{k=1}^{K} p_k^2$$

, where p_k is the proportion of class k within the node. The label assigned by a leaf is simply the majority class among the training examples that reach it.

□

Figure 4.3: Placeholder — a toy decision-tree splitting on RMS and ZCR statistics.

4.2.6 Random Forests via Bagging

One tree alone can memorise noise in the training set and therefore overfit. **Bootstrap aggregating**—usually called *bagging*—mitigates this by training many trees, each on a random subset of the data and on a random subset of features. The ensemble, known as a **Random Forest (RF)** [1], predicts by majority vote. Because the trees are de-correlated, their individual errors tend to cancel out, yielding a classifier that is accurate yet much less prone to overfitting than a single deep tree.

For deployment we restrict the forest to fifty trees of maximum depth ten. Empirical testing shows accuracy plateaus beyond this point, whereas binary size and latency continue to rise. Class imbalance—*Hold* and *Go* have far fewer samples than *Let* and General—is addressed by weighting each class inversely to its frequency so that the minority classes influence the splits as strongly as the majority ones. The resulting model occupies roughly 40 kB of flash and classifies a ten-element feature vector in about 1.2ms on the 64MHz Cortex-M4.

4.2.7 Regularisation in Context

In machine learning, **regularisation** refers to any mechanism that discourages models from becoming unnecessarily complex. Depth limits and minimum-leaf-sample constraints serve this role for decision trees, just as Ridge and Lasso penalties do for linear models or dropout does for neural networks. In a Random Forest, bagging itself, the depth cap and the random feature sub-sampling all contribute to controlling complexity and thereby promoting generalisation.

4.2.8 Evaluating Model Performance

Accuracy alone can be misleading when classes are unevenly represented, so we report several complementary metrics. **Balanced accuracy** averages recall across all classes, ensuring that minority keywords are not ignored. The F_1**-score** combines precision and recall into a single number sensitive to both false positives and false negatives. A **confusion matrix** visually highlights systematic errors between specific pairs of classes, while the **out-of-bag error** supplied by the Random Forest offers an internal validation estimate without needing a separate hold-out set.

4.2.9 From Python to Firmware

The final scikit-learn model is exported to a plain-C header via `micromlgen`. Each tree becomes a chain of nested `if-else` statements with fixed thresholds, eliminating the need for dynamic memory or floating-point loop indices. In firmware an interrupt service routine captures audio, derives RMS and ZCR statistics in real time, assembles the ten-element feature vector, and invokes `forest.predict()`. Predictions whose confidence exceeds 0.8 toggle GPIO lines that activate the orthosis motors.

□

Figure 4.4: Placeholder — firmware flow from audio capture to motor actuation.

4.3 Methodology and Results

4.3.1 Dataset Description

The dataset we used to create our classifier was the **Dataset_EN** dataset created by tanooki426, which could be found on huggingface.co[1]. This dataset had not been used in any published research that could be found at the time of writing this. There were 25 subjects in the dataset, and all audio tracks had a sample rate of `22050Hz`. This dataset was comprised of 3735 voice lines, and these voice lines had 206 instances of the word "Let," 48 instances of the word "Go," and 15 instances of the word "Hold." These instances were extracted into individual audio files, making up the dataset used for training and testing. For our dataset, we used 31 instances of the word "Let," 48 instances of the word "Go," and 15 instances of the word "Hold." Furthermore, random words from these files were saved as a "general" category to ensure we did not detect random speech as one of our keywords. This "general" category consisted of 38 instances of random words. From here, the dataset was split roughly 90%-10% between training and testing.

4.3.2 Data Denoising

Our dataset was effectively noise-free; however, this would not be the case when taking live samples. For this reason, we applied a simple lowpass filter to our training set to mimic live conditions. Our corner frequency was $8kHz$ as the Coral Micro had an audio sample rate of $16kHz$. Furthermore, after filtering, we clipped the audio so that anything below $-20dB$ was removed from the beginning and end of our clips. This was done to ensure no silence was in our training data. We did not want the classifier to correlate silence to any of our keywords falsely. Later in the chapter, we verified that our filtering did not cause a meaningful reduction in accuracy.

Figures 4.5 and 4.6 showed the waveform of a random audio clip before and after filtering.

[1]The original dataset can be found here: `https://huggingface.co/datasets/tanooki426/Datasets_EN`

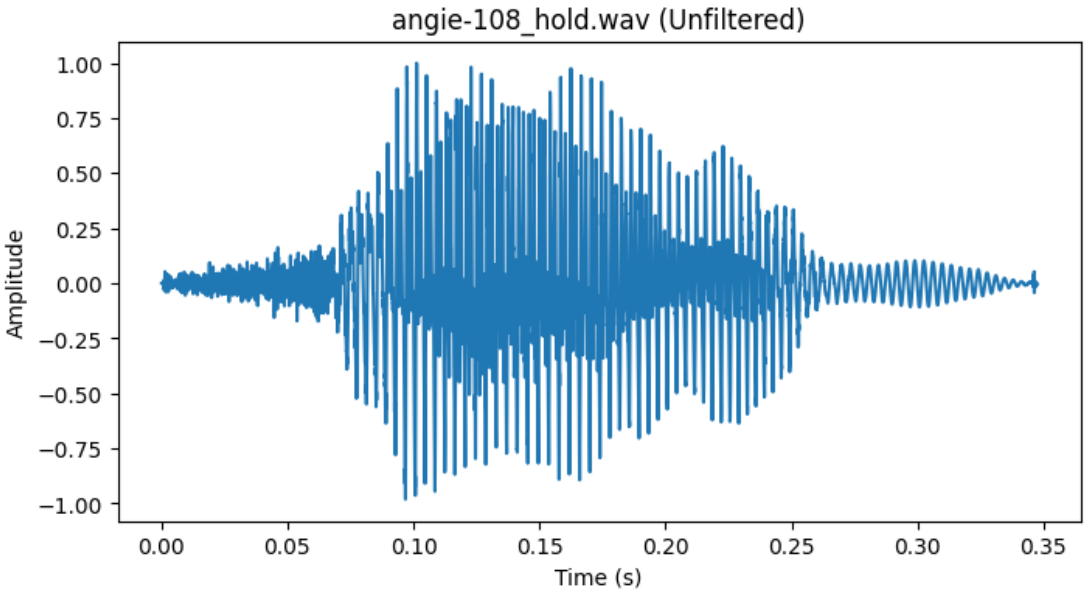

Figure 4.5: Waveform of Unfiltered Audio

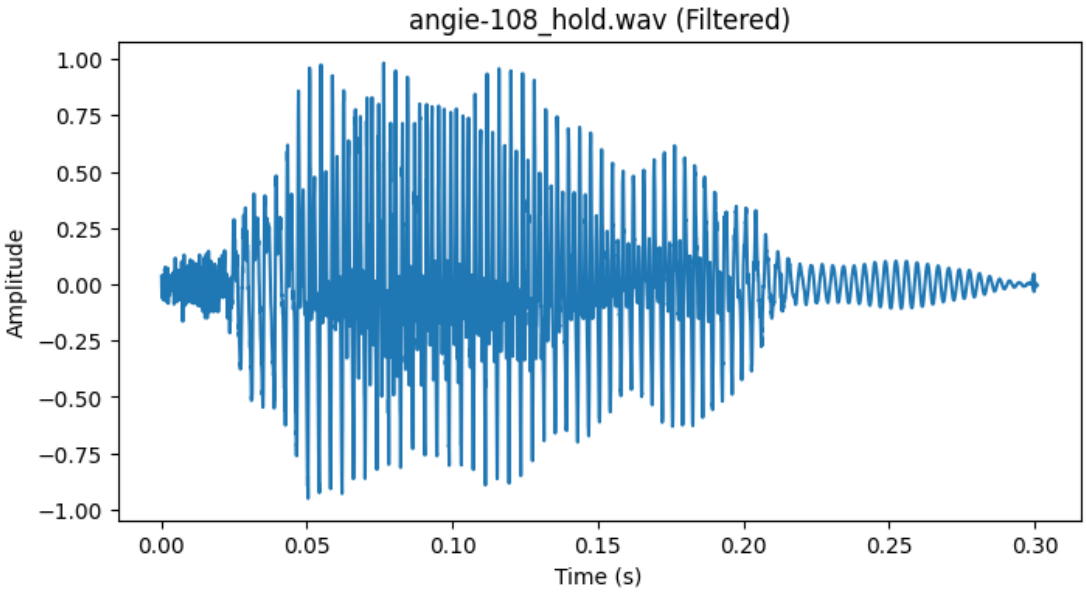

Figure 4.6: Waveform of Filtered Audio

Figures 4.7 and 4.8 showed the Log-Mel Spectrograms for the filtered and unfiltered audio clip.

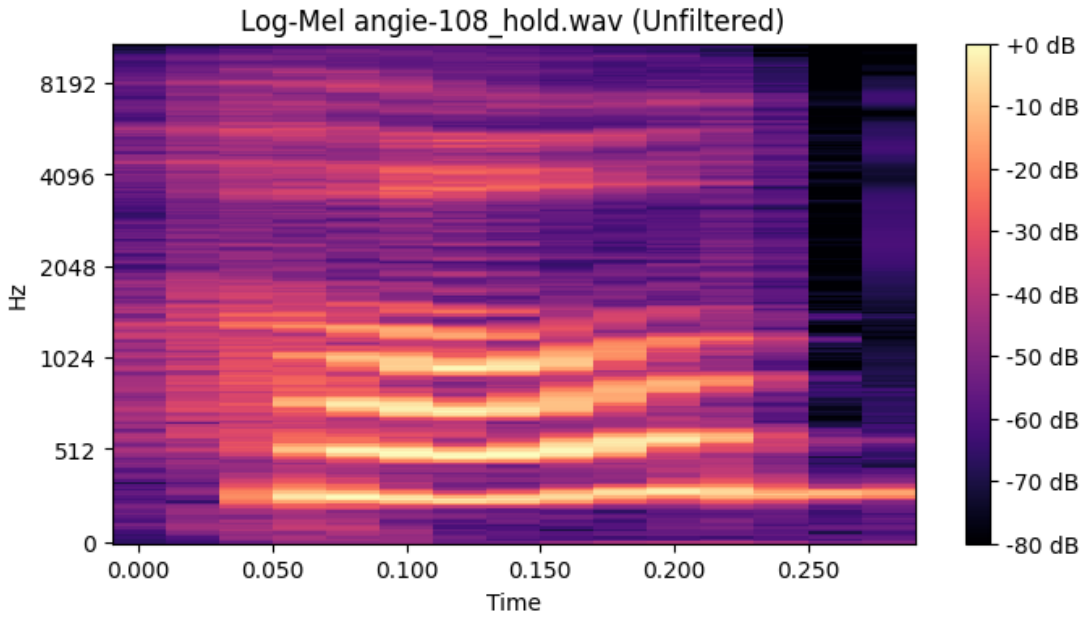

Figure 4.7: Spectrogram of Unfiltered Audio

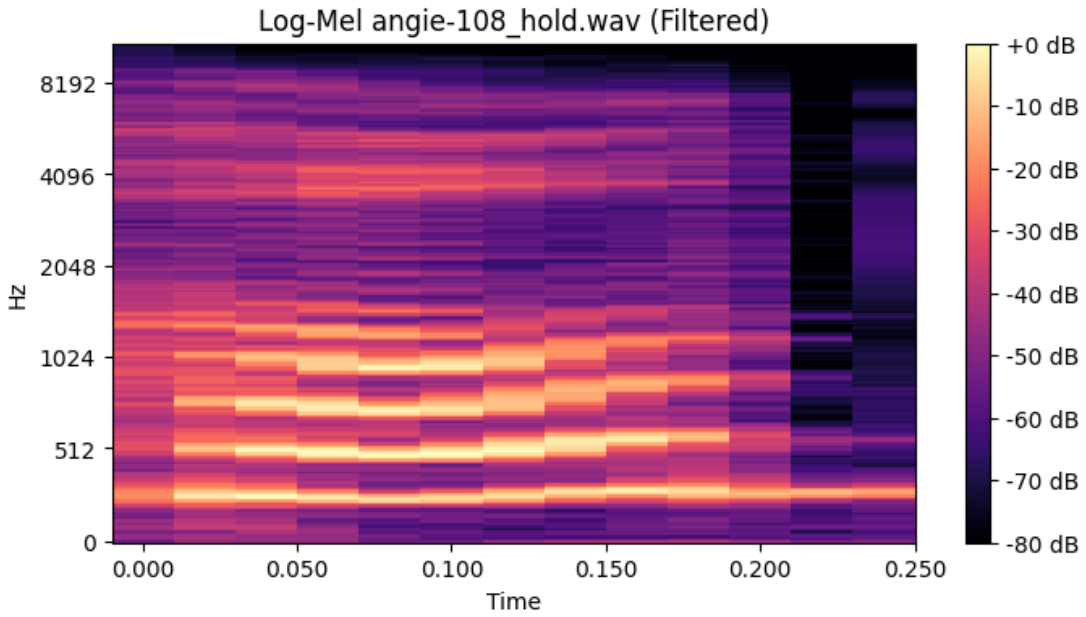

Figure 4.8: Spectrogram of Filtered Audio

4.3.3 Feature Selection & Computation

The features we extracted were the mean, median, st dev, skew, and kurtosis of the signal's RMS and ZCR[2]. These were chosen because they were computationally inexpensive and relatively easy to implement in C++.

[2]Zero Crossing Rate

The computation of mean[3] and median was straightforward and was not covered here. The calculation of st dev used Formula 4.1 and was implemented with the following C++ code:

```
float calcSTD(float* input, int N, float mean){
    float stDev = 0;
    for (int i = 0; i < N; i++){
        stDev += std::pow(*(input + i) - mean, 2);
    }
    return std::sqrt(stDev/s);
}
```

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{4.1}$$

It was important to note the usage of pointers to access the array containing the audio signal. As a reminder, $*(arrayvar + i)$ was equivalent to $arrayvar[i]$ in usage; however, it required fewer assembly lines to execute. Because of this, it was generally more resource-efficient on embedded platforms to access array values in this fashion.

Skewness was calculated using Formula 4.2 and was implemented with the following C++ code:

```
float calcSkew(float* input, int N, float mean, float stdDev){
    float skew = 0;
    for (int i = 0; i < N; i++){
        skew += std::pow(*(input + i) - mean, 3);
    }
    return skew/((s-1)*std::pow(stdDev,3));
}
```

$$skew = \frac{\sum_{i=1}^{N}(x_i - \mu)^3}{(N-1)\sigma^3} \tag{4.2}$$

Finally, kurtosis was calculated using Formula 4.3 and was implemented with the following C++ code:

```
float calcKert(float* input, int N, float mean){
    float Kert = 0;
    float M2_N = 0;
    float M2_D = 0;
    for (int i = 0; i < N; i++){
        M2_N += std::pow(*(input + i) - mean, 4);
        M2_D += std::pow(*(input + i) - mean, 2);
    }
    return ((N*(N-1))/((N-1)*(N-2)*(N-3))) * (M2_N/std::pow(M2_D,2))
           - (3*(std::pow(N-1,2)/((N-2)*(N-3))));
}
```

$$kurt = \frac{N(N+1)}{(N-1)(N-2)(N-3)}\frac{\sum_{i=1}^{N}(x_i - \mu)^4}{(\sum_{i=1}^{N}(x_i - \mu)^2)^2} - 3\frac{(N-1)^2}{(N-2)(N-3)} \tag{4.3}$$

As stated earlier, each of these was applied to arrays of RMS and ZCR values of the audio signal. These arrays were generated from 20ms windows of the input signal. Individual RMS values were calculated using Formula 4.4 and were implemented using the following C++ code:

[3] mean = μ

```
float calcRMS(int16_t* input, int N){
    float RMS = 0;
    for (int i = 0; i < N; i++){
        RMS += std::pow(*(input + i))/N;
    }
    return std::sqrt(RMS);
}
```

$$RMS = \sqrt{\frac{\sum_{i=1}^{N} x_i}{N}} \tag{4.4}$$

Individual ZCR values were calculated using Formula 4.5 and were implemented with the following C++ code:

```
float calcRMS(int16_t* input, int N){
    int ZCR = 0;
    for (int i = 0; i < N-1; i++){
        ZCR += (((*(input+i) < 0)
                &(*(input+i+1) > 0))
                ||((*(input+i) > 0)
                &(*(input+i+1) < 0)));
    }
    return ZCR/N;
}
```

$$ZCR = \frac{\sum_{i=1}^{N} ((x_i < 0 \& x_{i+1} > 0) || (x_i > 0 \& x_{i+1} < 0))}{N} \tag{4.5}$$

Additionally, we verified that the chosen features were unique between classes. To do this, we performed an ANOVA statistical test on filtered and unfiltered datasets. This showed that all features had a p-value $< .05$, meaning there was a statistically significant difference between classes for each feature.

Now that we had done this, we selected the top five most important features from Table 4.1 and Table 4.2 and trained an additional model using just those five to compare to a model using all ten features.

4.3.4 Random Forest

As stated earlier, we used a Random Forest Classifier to classify our keywords. We started by cross-validating our training set using a Random Forest Classifier with 800 estimators. 800 estimators were significantly more than needed; however, we used this many initially to ensure our data was usable. Using this initial model, we checked the feature importance of both our unfiltered and filtered datasets. The results of this, and the p-values of each feature, are shown in Tables 4.1 and 4.2.

	Mean RMSE	Median RMSE	STD RMSE	Skew RMSE	Kurtosis RMSE
p-value (Unfiltered)	3.07×10^{-6}	3.25×10^{-7}	1.45×10^{-8}	9.98×10^{-5}	2.45×10^{-4}
Importance (Unfiltered)	0.089	0.107	0.140	0.107	1.101
p-value (Filtered)	4.91×10^{-6}	4.16×10^{-7}	5.28×10^{-8}	1.23×10^{-4}	3.05×10^{-4}
Importance (Filtered)	0.090	0.120	0.131	0.113	0.094

Table 4.1: Feature Values for RMSE

Using a 5-Fold split at a 99% confidence interval, our unfiltered dataset had a likely accuracy between 45.47% and 69.06%. Our filtered dataset had a likely accuracy between 41.09% and 64.90%. Figures 4.9 and 4.10 show the confusion matrices from the cross-validation. We used 50 estimators and a class weight setting of "balanced." The class weights

	Mean ZCR	Median ZCR	STD ZCR	Skew ZCR	Kurtosis ZCR
p-value (Unfiltered)	2.27×10^{-3}	1.02×10^{-3}	1.21×10^{-1}	4.45×10^{-4}	8.29×10^{-8}
Importance (Unfiltered)	0.085	0.064	0.085	0.102	0.120
p-value (Filtered)	5.51×10^{-3}	6.42×10^{-3}	1.35×10^{-1}	1.46×10^{-3}	2.73×10^{-7}
Importance (Filtered)	0.074	0.067	0.083	0.099	0.129

Table 4.2: Feature Values for ZCR

were necessary because we had a small pool of data to draw from for the "Hold" and "Go" keywords in comparison to the "General" and "Let" keywords. To determine the optimal number of estimators, we trained the classifier 100 times, incrementing the number of estimators after each iteration. This produced the graph in Figure 4.13. We observed from this graph that the accuracy for both the filtered and unfiltered datasets were effectively the same, and that the accuracy plateaued at around 50 estimators.

Using the same procedure, we trained a different model using just the top 5 features. With the same 5-Fold split at a 99% confidence interval, our unfiltered dataset had a likely accuracy between 41.96% and 65.73%. Our filtered dataset had a likely accuracy between 39.37% and 63.20%. Figures 4.11 and 4.12 show the confusion matrices from this second cross-validation. Figure 4.14 shows the accuracy vs number of estimators for the top 5 feature model. From this, we observed that the unfiltered dataset suffered greatly from the removal of features, while the filtered dataset experienced only a small reduction in accuracy.

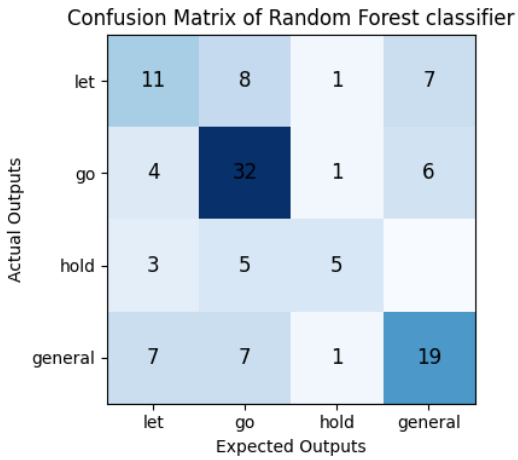

Figure 4.9: Confusion Matrix of Unfiltered Audio

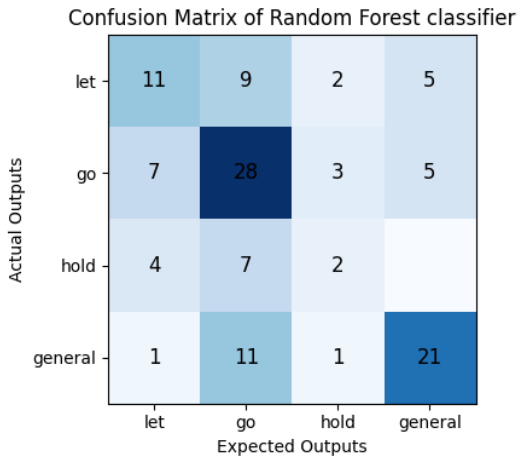

Figure 4.10: Confusion Matrix of Filtered Audio

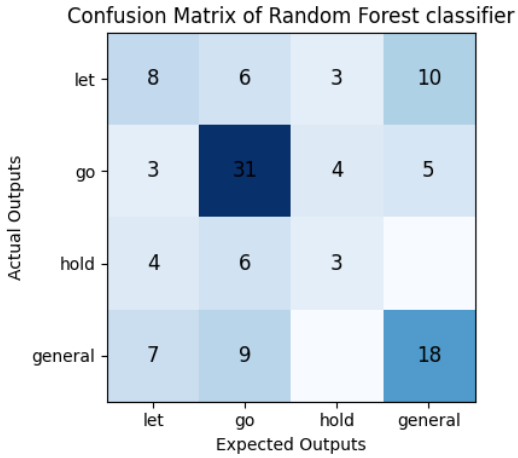

Figure 4.11: Confusion Matrix of Unfiltered Audio (Top 5 Features)

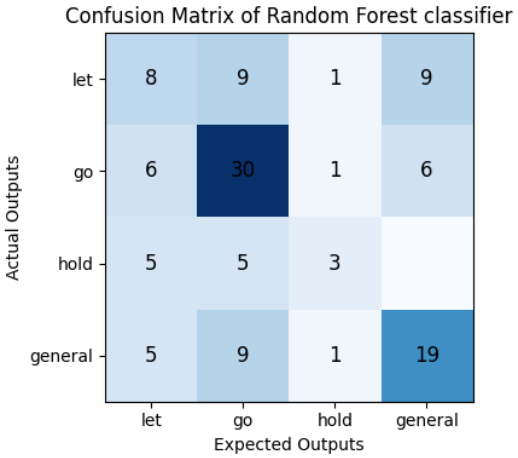

Figure 4.12: Confusion Matrix of Filtered Audio (Top 5 Features)

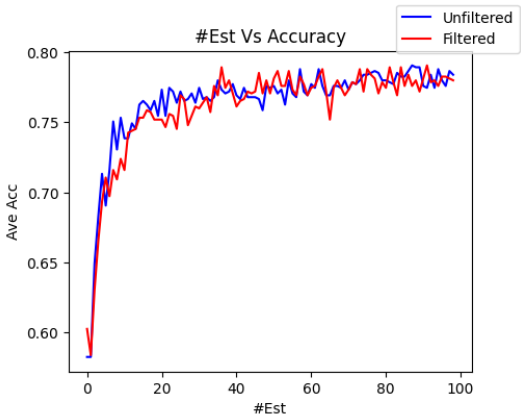

Figure 4.13: Average Accuracy

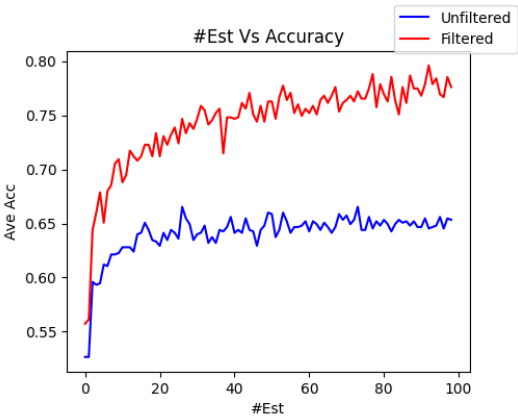

Figure 4.14: Average Accuracy (Top 5 Features)

4.4 Discussion

Using 50 estimators and the top five selected features, our final Random Forest model achieved an accuracy of 73%. This level of performance demonstrated the model's feasibility for real-time keyword detection on a constrained device like the Coral Micro. Notably, the use of only five features—mean, median, standard deviation, skewness, and kurtosis of RMS and ZCR—allowed for both memory and computational efficiency without sacrificing significant classification performance.

The confusion matrices (Figures 4.9–4.12) illustrated several key trends. First, the "Let" and "Go" classes were more accurately predicted than the "Hold" class, which had the fewest training instances and showed the highest misclassification rate. This imbalance was partially mitigated through the use of class weighting during training.

Filtering the audio slightly reduced accuracy but improved robustness. The filtered model's confusion matrix showed more evenly distributed errors and less overfitting, particularly when only the top 5 features were used. This supports the hypothesis that applying pre-processing steps like filtering and silence trimming improves generalisation under noisy conditions.

Figure 4.13 and Figure 4.14 further confirmed the model's stability. Accuracy improvements plateaued after approximately 50 estimators, indicating that additional complexity did not yield measurable benefits. This justified our decision to restrict the final model to 50 trees, which allowed deployment on embedded hardware within strict memory constraints.

Overall, our findings support the idea that light-weight, interpretable models—when carefully optimized—can deliver

strong results in embedded speech recognition tasks.

4.5 Conclusion

In this project, we successfully designed and implemented a keyword detection system optimized for deployment on the Coral Micro. By employing basic time-domain audio features such as RMS and ZCR, and leveraging a Random Forest classifier, we achieved an accuracy of 73% while maintaining computational efficiency suitable for real-time embedded applications.

We demonstrated that pre-processing techniques like low-pass filtering and silence clipping not only approximate real-world noise but also help reduce model overfitting. Feature selection using ANOVA and importance metrics guided us toward a minimal but effective feature set, and our analysis revealed that performance did not degrade significantly when using only the top five features.

The final model, converted into C++ using the `micromlgen` library, fits within 40 kB and processes inputs in under 2 milliseconds, meeting the tight resource constraints of the Coral Micro. This work lays the foundation for more responsive and accessible control interfaces in assistive devices, particularly those aimed at users with limited mobility.

Future work may investigate the addition of lightweight spectro-temporal features or ensemble learning techniques that balance performance with energy consumption even further.

Bibliography

[1] L. Breiman, “Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

Text-independent Speaker Verification using HMM and SVM

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https://github.com/ahmedajan/Text_Independent_Speaker_Verification_using_HMM_SVM

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Chapter 5

Text-independent Speaker Verification using HMM and SVM

5.1 Introduction

Speaker verification is a common problem in the biomedical signals field and comes in two flavors; text-dependent and text-independent. Text-dependent verification depends on a specific piece of text or a predefined pass code which is used as a baseline to compare future inputs too, this approach has the obvious limitation of not being able to determine the identity of a speaker unless they utter the code word. This limitation is not shared by text-independent speaker verification as it functions by extracting characteristics of the targets voice that are present across different words and sounds. Text dependent speaker verification is considerably simpler and more straight forward than text-independent speaker verification but since text-independent verification does not have nearly as many limitations it is more convenient and more widespread, because it is more widespread the potential for harm caused by misunderstanding how it works is greater and will therefore be the focus of this project.

There is a large amount of work on text-independent speaker recognition and there are many different ways that text-independent speaker recognition can be implemented. To name two machine learning techniques, used in this field, besides SVM and HMM there are combination Gaussian Mixture Model and Universal Background Model (GMM-UBM) [1] and vanilla Gaussian Mixture Models (GMM) [2]. It is also worth noting that deep learning is very often used for text-independent speaker verification.

The most common application of speaker verification is biometric security, where it is used to access anything from bank accounts to office buildings. As is the case with any security systems it has its weaknesses and while relatively recent the advent of deepfake audio posses a grave threat to this form of biometric security. By using only a small audio sample a synthetic voice can be created to fool speaker verification, because of this threat it is very important to have a firm understanding of the basics of speaker recognition so new defenses to these new attacks can be created. To enable a better more complete understanding of speaker recognition this paper aims to demonstrate the process behind creating a simple and highly explainable text-independent speaker verification system.

“‘latex

5.2 Theoretical Background

5.2.1 Support Vector Machines (SVM)

Support Vector Machines (SVMs) are supervised machine learning models used for classification and regression tasks. In essence, an SVM attempts to find the best decision boundary (usually a hyperplane in high-dimensional space) that separates data points of different classes with the maximum margin between the classes. During training, an SVM algorithm identifies a subset of training examples (called *support vectors*) that lie closest to the decision boundary; these points are the most informative for defining the boundary. All other training points that are not support vectors can be moved without changing the boundary. By focusing on these critical points, SVMs achieve a robust separation that often generalizes well.

For linearly separable data, an SVM finds a hyperplane $\mathbf{w}\cdot\mathbf{x}+b=0$ that divides the classes while maximizing the margin (distance) between the hyperplane and the nearest points of each class. The result is a classifier with good generalization properties. However, many real-world problems, including speaker verification, are not linearly separable in the input feature space. SVMs handle this by using the *kernel trick*: the data can be implicitly mapped into a higher-dimensional feature space where a linear separation is possible. Common kernel functions (such as polynomial or radial basis function (RBF) kernels) enable nonlinear decision boundaries in the original space by computing inner products in the transformed

space without explicitly performing the transformation.

SVMs have been widely used in speech and speaker recognition because of their effectiveness in high-dimensional feature spaces and their strong performance even with relatively limited data. In text-independent speaker verification specifically, SVMs have achieved accuracies comparable to more complex deep learning models, while remaining more interpretable and often more computationally efficient. These advantages make SVMs a compelling choice for a baseline speaker verification system. In our context, the SVM serves as a binary classifier distinguishing whether a given speech feature vector belongs to the target speaker or not. By training one SVM per target speaker (one-versus-rest scheme), the system can verify speakers by comparing incoming speech features to each speaker's SVM model.

5.2.2 Hidden Markov Models (HMM)

Hidden Markov Models (HMMs) are a class of probabilistic models well-suited for sequence data such as speech. An HMM models a process that evolves through a sequence of *hidden states*, where the state at each time step is not directly observable. Instead, each hidden state probabilistically generates an *observed output* (also called an observation). As the process moves through states, it produces a sequence of observations. What makes the model "Markov" is the assumption that state transitions form a Markov chain: the probability of transitioning to the next state depends only on the current state (the past history beyond the current state is assumed irrelevant). In a hidden Markov model, we have two sets of probabilities: state transition probabilities (how likely the model is to go from one state to another in one step) and emission probabilities (how likely a particular observation is to be generated from a given state). The sequence of observations is therefore assumed to be generated by an underlying sequence of hidden states.

Formally, an HMM can be specified by parameters (A, B, π) where A is the state transition probability matrix, B gives the probability distribution of observations (emissions) for each state, and π is the initial state distribution. At each time step, the model transitions from its current state to a new state according to A, and then emits an observation according to B for the new state. The observations depend on the hidden state, but the state itself is not directly observed. Because the states are hidden, one must use inference algorithms (such as the Forward-Backward algorithm or Viterbi algorithm) to estimate the sequence of states or model parameters from observed data.

HMMs have a long history in speech processing and were for many years the dominant approach to speech recognition. Their strength lies in modeling temporal sequences: for example, in a speech recognition context, the hidden states might correspond to phonemes or sub-word units, and the model learns the probabilities of transitioning between sounds as well as the probability of particular acoustic features (observations) for each sound. In a speaker verification context, we can use an HMM to model the characteristic sequential patterns of a given speaker's voice. For instance, one might train an HMM for each speaker, where the hidden states capture vocal-tract configurations or other latent speech traits specific to that speaker, and the observation probabilities capture how that speaker's acoustic features typically distribute. During verification, an input speech sequence can be evaluated against each speaker's HMM to see which model best explains the sequence. The HMM that yields the highest likelihood could be chosen as the identified speaker (or, for verification, compared to a threshold).

Key to understanding HMMs is the concept of **hidden vs. observed**: the model's states (e.g., underlying vocal-tract states, or abstract "speaker states") form a Markov chain, but we do not see these states directly. We only see their manifestations in the audio features (e.g., MFCC vectors), which are the observed outputs. By learning the HMM parameters from training data (using algorithms like Baum–Welch expectation-maximization), the model captures temporal dynamics and feature distributions for the speech sequences. Thus, HMMs are very relevant for sequence-modeling tasks like speaker verification, where the serial order of features carries important information. An HMM-based speaker verifier can naturally account for how a speaker's voice features change over time and can handle variable-length input utterances by design, since it works at the sequence level rather than on fixed-size feature vectors.

5.2.3 Mel-Frequency Cepstral Coefficients (MFCC)

One of the most important steps in any speech recognition or verification system is feature extraction – transforming the raw audio signal into a set of representative features that capture the characteristics of the speaker's voice. In our system, we use **Mel-frequency cepstral coefficients (MFCCs)** as the primary features. MFCCs are a compact representation of the short-term power spectrum of an audio signal, and they have been extremely popular in speech and speaker recognition for decades.

The MFCC extraction process involves several stages designed to mimic aspects of human auditory perception. First, the audio signal is segmented into short frames (often about 20–30 milliseconds in length) with an overlapping window (to account for the quasi-stationary nature of speech). For each frame, we compute the Fourier transform to obtain the frequency spectrum (i.e., how the energy of the signal is distributed across frequency bands). This spectrum is then passed through a set of **Mel-scale filter banks** – typically triangular filters spaced according to the mel-frequency scale. The mel scale is a nonlinear frequency scale that approximates how humans perceive pitch differences: at lower frequencies,

humans distinguish fine differences, but at higher frequencies, resolution decreases. Applying filter banks on the mel scale sums energy in broader bands at high frequencies and narrower bands at low frequencies, roughly imitating cochlear filtering.

Next, we take the logarithm of the filter-bank energies. The log step converts multiplicative variations in the spectrum into additive ones and roughly models the ear's logarithmic sensitivity to loudness. Finally, we perform a discrete-cosine transform (DCT) on the log-mel spectrum. The DCT decorrelates the filter-bank outputs and produces a set of coefficients (the cepstral coefficients). Lower-order MFCCs describe the overall spectral envelope, while higher-order MFCCs capture finer detail. Typically the first 12 or 13 MFCCs (excluding the 0th energy coefficient) are used, sometimes together with their first and second temporal derivatives (Δ and $\Delta\Delta$) to include dynamics.

MFCCs compress vocal-tract characteristics, benefit from perceptual warping, and form a decorrelated, compact feature set. Consequently they are the de facto standard in speaker recognition. We extract a fixed number of MFCCs (13 or 20) per frame; each frame's vector is a spectral snapshot that can later be aggregated or modeled over time.

5.2.4 Statistical Features of Audio Segments

Once frame-level MFCCs are extracted, we compute seven statistics over each 1-second segment to obtain a fixed-length vector suitable for SVM input: **maximum**, **minimum**, **mean**, **median**, **standard deviation**, **skewness**, and **kurtosis**.

- **Maximum and Minimum** – capture the range of MFCC values, reflecting dynamic variability.
- **Mean** – the average MFCC, indicating the typical spectral shape.
- **Median** – a robust central measure less affected by outliers.
- **Standard Deviation** – measures variability around the mean.
- **Skewness** – reveals asymmetry (occasional bursts or drops in energy).
- **Kurtosis** – shows tailedness (how often extreme values occur).

Computing these seven descriptors for every segment transforms a variable-length MFCC stream into a concise, fixed vector that still describes range, central tendency, variability, and distribution shape. Experiments adding pitch-related features yielded no significant gains, so they were omitted.

5.2.5 Audio Preprocessing Techniques

Before extracting MFCCs, we apply two steps: **spectral gating** for noise reduction and **segmentation** into fixed-length chunks, ensuring that downstream processing sees consistent, high-quality input.

5.2.6 Noise Reduction via Spectral Gating

Spectral gating removes low-energy components below a threshold $\mu_f + \alpha\sigma_f$ in each STFT frequency bin. After masking, an inverse STFT reconstructs a denoised waveform. Tests showed that suppressing about 80% of low-power components best balances noise removal and speech integrity, raising the signal-to-noise ratio for feature extraction.

5.2.7 Segmentation into Fixed-Length Chunks

Recordings are split into uniform 1-second chunks. Fixed duration simplifies model design (each chunk gives one feature vector), enlarges the training set (about 1 500 segments per 25-minute speaker recording), and normalizes duration effects. Trials with 0.2–4 s windows showed that 1 s offers near-optimal accuracy at minimal cost.

5.2.8 Dimensionality Reduction with Principal Component Analysis (PCA)

Using 20 MFCCs and seven statistics yields 140 features per segment. PCA projects these into a lower-dimensional orthogonal space while retaining 95% of the variance, roughly halving the feature size, mitigating multicollinearity, and cutting training time without hurting accuracy.

5.2.9 Evaluation Metrics for Verification Performance

Confusion-matrix notation. We use four standard counts:

- TP – *True Positives*: genuine-speaker trials that the system *accepts*;
- TN – *True Negatives*: impostor trials that the system *rejects*;
- FP – *False Positives*: impostor trials that the system *accepts*;
- FN – *False Negatives*: genuine-speaker trials that the system *rejects*.
- **Accuracy**: $\dfrac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$; the overall proportion of correct decisions.
- **Precision**: $\dfrac{\text{TP}}{\text{TP} + \text{FP}}$; "When the system says *yes*, how often is it right?"

- **Recall** (True-Positive Rate): $\frac{\text{TP}}{\text{TP} + \text{FN}}$; "Out of all genuine trials, how many were accepted?"
- **F1-Score**: $2\,\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$; the harmonic mean balancing precision and recall.
- **ROC Curve and AUC**: by varying the decision threshold we plot Recall against the False-Positive Rate $\big(\text{FPR} = \text{FP}/(\text{FP} + \text{TN})\big)$; the Area Under this Curve (AUC) ranges from 0.5 (random) to 1.0 (perfect). We also report the Equal Error Rate (EER) and examine per-speaker distributions to gauge consistency across the population.

5.3 Methodology

5.3.1 Data Set

To accomplish this task the LibriSpeech dataset was used. The Librispeech dataset was created by taking an 87Gb subset of the LibriVox project and filtering out samples with excessive audio degradation and samples containing multiple speakers. After preprocessing, the dataset is comprised of 2484 different subjects with a roughly 50 50 split by gender. This filtered dataset contains about 1000 hours of speech sampled at 16 kHz adding up to a total of 61 Gb. Due to the datasets large size it is divided into 7 subsets; dev-clean, test-clean, dev-other, test-other, train-clean-100, train-clean-360, and train-other-500. Which contain; 5.4, 5.4, 5.3, 5.1, 100.6, 363.6, and 496.7 hours of audio recording respectively. Theses subsets are divided into clean and other, those in the clean category scored a low word error rate (WER) when fed through an acoustic model trained on WSJ's si-84 data subset.[3].

To train and test the models the test-clean-100 subset was chosen. This subset was chosen for two reasons. The first is because it is considered clear, meaning that the speech is easier to make out and contains less background noise. The second reason that this subset was chosen is because of its size, test-clean-360 is much bigger than needed so there was no reason to deal with its large overhead and test-clean was too small containing only eight minutes of audio per-speaker. Ultimately this left only test-clean-100 which still is much larger than what was needed, but it provided as much data as would every be realistically needed as it contains 251 speakers each speaking for roughly 25 minutes.

As previously mentioned the test-clean-100 subset contained much more data than needed, so two subsets were created. The first subset contained 20 arbitrarily chosen speakers split evenly by genders, each with 5 minutes of audio. The second subset contained 96 randomly chosen speakers split evenly by gender, each with 16.6 minutes of audio. The first smaller subset was used to compare different feature sets, as its small size allowed kept extraction time low allowing different combinations of features could be rapidly tested. Once an optimal set of features was found the features of the second larger subset were computed.

5.3.2 Preprocessing

Before feature extraction could occur two preprocessing steps had to be performed; denoising and segmentation. The speech data was denoised using a technique called spectral gating. "At a high level spectral gating works by discarding any time-frequency component below a threshold for each frequency component of the signal. It does this by computing the mean and standard deviation for each frequency channel of a Short-Time Fourier Transform (STFT). A threshold or gate for each frequency component is then set at some level above the mean. This threshold determines whether or not a given time-frequency component in the spectrogram is considered signal or noise, the spectrogram is masked based on this threshold and finally inverted back into the time domain with an inverse STFT."[4] During this step care was taken as to not be too aggressive with the noise reduction as there very little noise in the data. To ensure that the denoising did not remove important data several different levels of denoising were tested by changing the proportion of the spectral gating mask that was applied. After trial and error it was determined that an 80% proportion of decrease was ideal. The second preprocessing step was to divide the audio into one second increments. This was done so speakers could be easily compared to one another. The one second increments were not chosen arbitrarily. From testing it was determined that audio segments as small as .2 seconds, when used for text-dependent speaker verification could work. Keeping in mind that text-dependent speaker verification needs less data it was obvious that longer segments would be needed, but this gave a good jumping off point. Initially four second segments were tested these worked really well but they were computationally expensive for the feature extractor. The lengths of the segments were iteratively shortened by one second until one second segments were gotten, these were significantly cheaper computationally and had the same effect on the model as the four second segments.

5.3.3 Features

Features were extracted using Mel-frequency cepstral coefficients (MFCC). MFCC was chosen as the feature extraction method because it is based on the Mel scale which approximates the human auditory system, making it good for speech analysis applications. From each speech segment 20 coefficients were calculated. 20 was chosen instead of the traditional

13 because testing with the Mann-Whitney and Kruskal-Wallis test showed a statistically significant decrease in the quality of SVMs trained with only 13 coefficients (table 1), this decrease was not observed in the HMM but for simplicity only one feature set was used.

Model/Test	Accuracy	Precision	Recall	F1-score	ROC AUC
SVM Mann	0.055	0.176	0.057	0.053	0.042
SVM Kruskal	0.053	0.172	0.055	0.051	0.041
HMM Mann	0.449	0.394	0.925	0.579	0.818
HMM Kruskal	0.441	0.387	0.914	0.570	0.808

Table 5.1: 20 vs 13 coefficients

From the 20 coefficents that were extracted seven statistical metrics were calculated; maximum, minimum, mean, median, standard deviation, skew, and kurtosis. These seven metrics gave good results but it was hypothesized that adding the mean and median of the fundamental frequency, a commonly used feature is speech, to the feature set would further improve the models. Unfortunately this was not the case and testing using the Mann-Whitney U and the Kruskal-Wallis test (table 2) showed that there was not a statistically significant difference between the models trained with and without fundamental frequency, because of this the feature set without fundamental frequency was chosen as it was slow to compute and there is no sense in having additional features if they do not add anything.

Model/Test	Accuracy	Precision	Recall	F1-score	ROC AUC
SVM Mann	0.838	0.782	1	0.849	1
SVM Kruskal	0.828	0.771	1	0.839	1
HMM Mann	0.787	0.417	0.655	0.882	0.871
HMM Kruskal	0.776	0.409	0.645	0.871	0.860

Table 5.2: Fundamental frequency vs not (sample size 300 per speaker)

In order to further refine the feature set it was necessary to determine if any features where highly correlated and could be removed with principle component analysis (PCA). To visualize this a heat map of the Spearman correlation Matrix was generated (fig 1). As figure 1 shows there are quite a few highly correlated features indicating that the feature set should undergo PCA. To compute the independent feature set PCA with a variance threshold of 95% was applied (fig 2). In addition to correcting the correlation the independent feature set is 50% smaller.

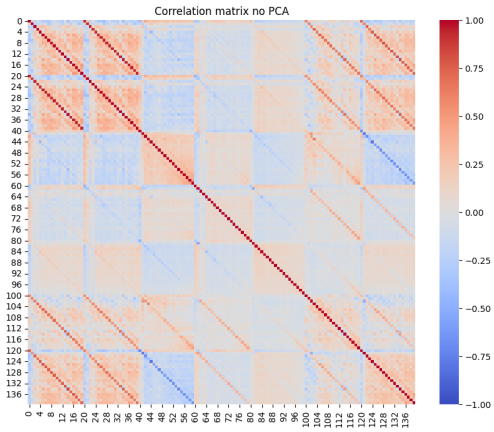

Figure 5.1: W/O PCA

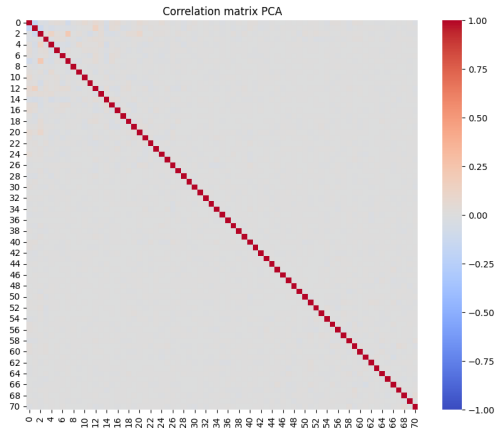

Figure 5.2: With PCA

Ultimately the models did well because the features were intelligently chosen. The maximum and minimum values give the model important information about the range of energy in the speech sample, allowing the model to get a sense of how lethargic and how energetic the speakers speech is. The mean allows the model to get sense of where the majority of the energy is within the signal. The median does this as well, but is immune to outliers which may throw off the mean i.e. any noise that was missed in the denoising process. The standard deviation gives the model an idea how much the energy within the speech is spread out. The skew can reveal if there is more low energy or high energy in the coefficients, by

measuring the symmetry of the distribution. Finally there is kurtosis which can show the model how much variation there is within the speech.

5.3.4 Models

As previously mentioned the two models that this paper uses are Support Vector Machines (SVM) and Hidden Markov Model (HMM). These two models were chosen because they are relatively explainable methods that are commonly used in text-independent speaker verification. To implement the models pre-existing python libraries were used, for SVM the `sklearn` implementation was used, and for HMM the `hmmlearn` library was used.

Support vector machines are a supervised learning model used for classification and can perform linear separation, as well as nonlinear separation using what is called the kernel trick which works mapping the data to a higher dimension where it is linearly separable. Hidden Markov models are unsupervised models made up of hidden and observed "nodes" the hidden parts probabilistically determine the most likely output to a sequence by finding patterns in the training sequence.

5.3.5 Hyperparameters

When testing the effects that changing certain hyperparameters had on the SVM two different kernels were used. The first is the radial basis function (RBF) kernel which is a very popular kernel and the default kernel function for `sklearn`s implementation of SVM. The second kernel used is the linear kernel which is not really a kernel as it does not perform the kernel trick. When comparing these two kernels the linear kernel gave ever so slightly better metrics than the RBF but the difference is not of note, more noticeably the training time for the linear kernel was significantly longer than the training time for RBF, so RBF was chosen as it allowed rapid iteration and testing. Ultimately no changes to the default hyperparameters were made as the model achieved better than satisfactory results without tuning.

The hyperparameters that were tested for the HMM were the covariances and the number of hidden nodes. Three different covariances were tested; diagonal, spherical, and tied. While tied tended to perform slightly better than diagonal it was only when it converged which would happen significantly less than diagonal. Spherical didn't often converge and when it did it had very poor metrics. One, two, three, four, five, and six hidden nodes were tested. The testing showed that five hidden nodes was optimal. Testing also showed that having anywhere between one and four nodes led to a considerable drop in accuracy while six nodes only led to a slight decrease in accuracy from five nodes.

5.3.6 Training

As previously mentioned each speakers audio was dived into one second segments, resulting in around 1,500 segments per speaker, as each speaker had roughly twenty five minutes of data. Out of these 1,500 segments 1,000 segments or 16.6 minutes worth were chosen at random.

The SVM and the HMM were trained and tested differently. The SVM was trained and tested using K-fold cross validation with K=5. The HMM was not trained and tested using K-fold cross validation and was instead trained and tested on an 80 20 split. The reason the HMM was not trained and tested with K-fold cross validation is because the way the HMM is being used prohibits it. Twenty HMM are trained, one for each speaker, to do binary classification during training the HMM are only shown samples from the correct speaker. To test the HMMs a mix of target and impostor speech is shown. K-fold validation is unable to do this because it mixes all of the data together.

5.4 Results

Each speaker got their own model, and from each model the following metrics were calculated; accuracy, precision recall, F1-score, and ROC AUC. In the case of SVM's cross validation each speaker got 5 models and these metrics were calculated by taking the mean of the metrics from each speakers models. After getting these five metrics for every classification methods the five number summary and mean was calculated for each metric as seen in table 3 and 4. In addition to this the ROC curve was also generated (fig 3 and 4).

SVM	Min	Q_1	Median	Q_3	Max	Mean
accuracy	0.9277	0.9595	0.9713	0.9810	0.9974	0.9693
precision	0.9350	0.9673	0.9795	0.9871	0.9989	0.9765
recall	0.9057	0.9489	0.9621	0.9747	0.9989	0.9599
F1-score	0.9245	0.9579	0.9703	0.9802	0.9973	0.9680
ROC AUC	0.9782	0.9926	0.9961	0.9983	1.0000	0.9946

Table 5.3: SVM metrics

As the metrics show the Support Vector Machine performed vastly better than the Hidden Markov model, but this is to

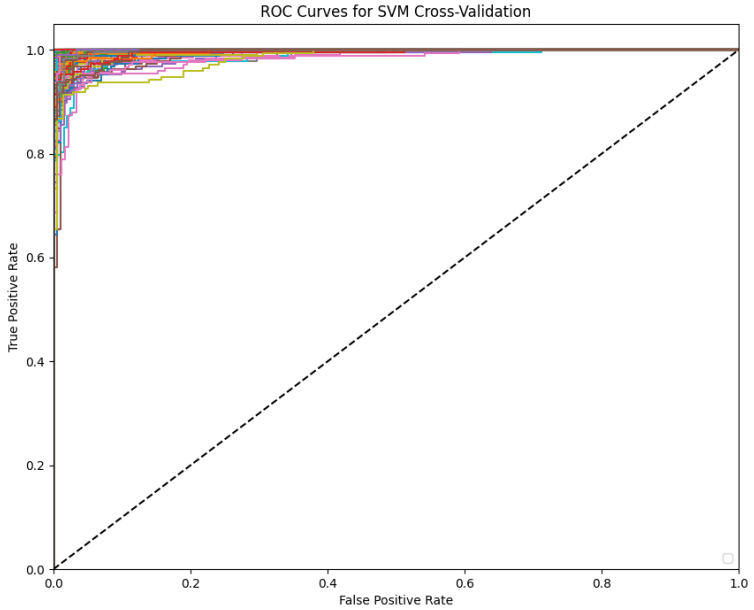

Figure 5.3: SVM ROC curve

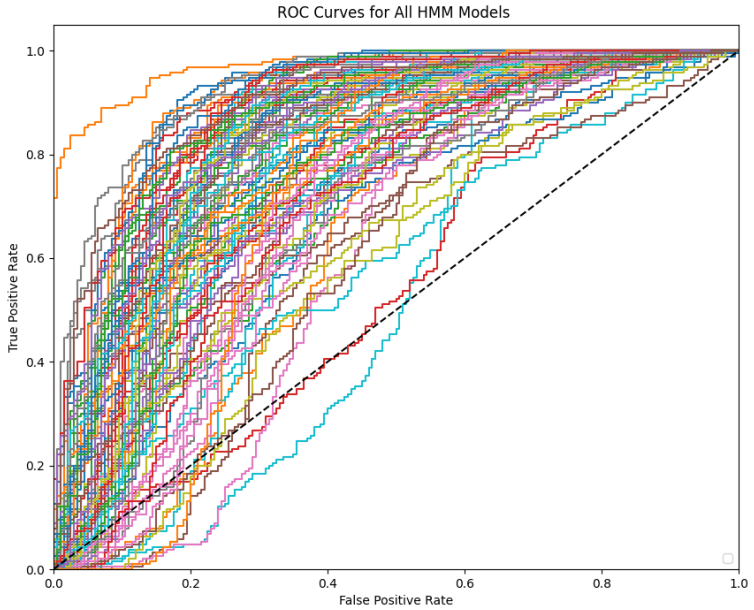

Figure 5.4: HMM ROC curve

HMM	Min	Q_1	Median	Q_3	Max	Mean
accuracy	0.4821	0.6679	0.7359	0.7724	0.8282	0.7102
precision	0.4545	0.6395	0.6798	0.7111	0.7611	0.6689
recall	0.2632	0.6921	0.8500	0.9105	0.9947	0.7793
F1-score	0.3333	0.6692	0.7543	0.7953	0.8431	0.7141
ROC AUC	0.5296	0.7175	0.8017	0.8422	0.9721	0.7789

Table 5.4: HMM metrics

be expected as it is a more advanced classification technique. So while there is little room to improve the SVM there is quite a bit of room for improvement for the HMM which could be the focus of future work. Some places to start would be diving deeper into the chosen features and seeing if other features such as jitter or zero cross rate significantly improved the HMM accuracy.

5.5 Discussion

5.5.1 Key Findings

The experimental results show a clear advantage for the **Support Vector Machine (SVM)** over the **Hidden Markov Model (HMM)** on every evaluation metric. The SVM achieved a median accuracy of $97.1\,\%$, a mean ROC–AUC of 0.995, and an almost perfect balance between precision and recall. In contrast, the HMM attained only a median accuracy of $73.6\,\%$ and a mean ROC–AUC of 0.779, highlighting the challenges of fitting a generative model with limited per-speaker data. The feature design—twenty MFCCs combined with seven distributional statistics computed over each one-second segment—proved sufficient to reach near-ceiling performance for the SVM, while adding fundamental-frequency statistics produced no statistically significant improvement. Applying principal-component analysis removed roughly half of the feature dimensions yet preserved about $95\,\%$ of the variance, cutting training time and slightly stabilising HMM convergence without harming SVM accuracy.

5.5.2 Why the SVM Outperformed the HMM

The performance gap can be traced to three factors. First, the SVM is a discriminative classifier that directly maximises the margin between speakers, whereas each HMM tries to model only within-speaker likelihoods; with approximately 16.6 min of speech per speaker, HMM parameters remain under-constrained, producing higher-variance scores that overlap across speakers. Second, representing every utterance by a single one-second statistics vector removes most temporal structure, which suits the SVM's fixed-length input requirement but deprives the HMM of the sequential cues on which it thrives; recovering such detail with frame-level or continuous-density HMMs would raise computational cost substantially. Third, the RBF-kernel SVM is tolerant of correlated input features, whereas the HMM uses diagonal covariance for tractability and therefore suffers more when MFCC statistics are correlated.

5.5.3 Effect of Pre-processing Choices

Moderate spectral gating made a measurable difference. Suppressing roughly 80 % of low-energy STFT bins raised the effective signal-to-noise ratio without noticeably distorting speech, and informal ablation revealed a consistent two- to three-percentage-point gain in SVM accuracy compared with raw audio. Segmentation length also mattered: pilot tests ranging from 0.2 s to 4 s indicated that performance plateaued once segments reached one second, whereas computational cost continued to grow with longer windows. Thus, one-second chunks maximised sample count (about 1500 segments per speaker) and training diversity while keeping computation modest.

5.5.4 Limitations

The study has four principal limitations. First, it relied solely on the *LibriSpeech* test-clean-100 subset, which contains studio-quality English read speech; the findings may not transfer to conversational, multilingual, or far-field recordings. Second, the HMM implementation used a simple five-state ergodic topology with diagonal covariances; more sophisticated variants—such as tied-mixture or speaker-adaptive HMMs—might narrow the gap. Third, the experiments did not consider adversarial scenarios such as spoofing with voice-conversion or neural TTS, leaving the system's resilience to deep-fake attacks untested. Finally, although training time was reported, run-time latency and memory footprint on embedded devices were not evaluated, so real-time feasibility remains uncertain.

5.5.5 Future Work

Future research should benchmark deep-speaker embeddings such as x-vectors or ECAPA-TDNN followed by a simple cosine back-end to quantify the margin between classical and modern methods. Incorporating voice-quality cues (e.g. jitter, shimmer, or prosodic statistics) might compensate for the loss of temporal information and improve the HMM baseline. Experiments involving multi-condition training with reverberation, channel noise, and lexical variability are needed to gauge robustness. Finally, score-level techniques such as probabilistic linear-discriminant analysis or fusion of HMM likelihoods and SVM margins could yield better threshold calibration.

5.6 Conclusion

This chapter introduced a fully transparent pipeline for text-independent speaker verification. By pairing twenty MFCCs and seven global statistics per one-second segment with principal-component analysis, we obtained compact yet information-rich features that an RBF-kernel SVM could exploit to reach a mean accuracy of 97 % and a mean ROC–AUC of 0.995 on clean *LibriSpeech* data. The same input, fed into a five-state HMM, yielded only 71 % accuracy and an ROC–AUC of 0.78, illustrating how discriminative learning with carefully engineered fixed-length vectors can surpass a simpler generative sequence model when data are limited and temporal detail is suppressed.

Three overarching lessons emerge from the study. First, meticulous feature engineering can offset the absence of deep architectures when fixed-length representations suffice. Second, discriminative classifiers—as long as they receive well-regularised features—remain highly competitive in regimes with modest but high-quality data. Third, reproducible design choices such as one-second segmentation, moderate spectral gating, and cross-validated evaluation make rapid iteration possible and provide stable baselines.

Although the current system is highly accurate under controlled conditions, real-world deployment will demand robustness to channel mismatch, language variability, and intentional spoofing. Extending the framework with domain-adversarial training, deep embeddings, and evaluation on noisy, multilingual corpora therefore represents a natural next step. The pipeline described here thus serves both as an educational example for undergraduates and as a benchmark against which more sophisticated speaker-recognition systems can be measured.

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SVM-based Speaker Classification

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Chapter 6

SVM-based Speaker Classification

6.1 Introduction

This project was chosen because we believe that speaker classification is a useful field that has many applications. Speaker recognition could be used in a security system to ensure that only certain subject can access certain areas, whether that be in real life with a deployed system on a door lock system, or for use in online data storage systems, where some directories could be locked behind a speaker verification system. It could also be used in conjunction with other biometric systems for added security, for example, a system that uses a fingerprint and speaker verification network. The dataset we selected for this project (VoxForge) is very useful for this task because it contains many audio samples, which all contain recordings of the same prompts, of many unique users. This dataset will provide a lot of diverse accents and speaking patterns that our Support Vector Machine can use to classify. We will use various input feature vectors, such as Mel Frequency Cepstrum Coefficients (MFCC), which capture the spectral properties in a speakers voice adjusted to the range of human hearing. SVM models require an enrollment process for specific users, where voice samples from a single subject will be collected and labeled. The SVM will then learn the unique characteristics of this certain speaker. Then, when a new voice is presented, the SVM will determine how similar the voice features are to the desired class, and based on the similarity, the system will be able to tell how confident it is that the new voice is the same as the desired voice. If this approach is successful, the community will be benefited with a secure system for speaker verification. Which can be used in many applications as explained above. Our System could then eventually be modified for more complex tasks, such as using speaker verification for data encryption and storage.

6.2 Motivation

SVM, or Support Vector Machines are supervised learning algorithms used primarily for classification and regression. They are very effective at separating multidimensional data. Usually SVM models are used to classify two different classes, but in our case, we will use an SVM Model with a 'One vs. Rest' technique to distinguish one class from the rest. This is achieved by finding a maximum separating hyperplane between classes using the provided features. The model can analyze data in the feature space in order to find an effective separating hyperplane. For the case of speaker classification, our SVM model should be very effective at finding an effective separation plane in order to distinguish classes from another.

6.3 Dataset

6.3.1 Dataset collection

the dataset used in this study was gathered from the VoxForge Dataset, a famous open source speech dataset that dates back to 2006, where users are able to upload their own speech files for free use in deep learning algorithms and machine learning. The dataset for this model consists of speech data from 10 different users. These users were selected using a singular criteria, the amount of data each user had uploaded. Each user or 'class' in the dataset has at least 250 voice samples in order to effectively train the SVM model. The dataset consists of 4779 individual voice samples, split between training and testing. Each of the collected samples ranged from 3-15 seconds long and were recorded at a sample rate of 48kHz.

6.3.2 Data pre-processing

Their were various pre-processing steps applied to the data in order to ensure the most effective training of the SVM model possible. As said above, there are 10 different speakers or 'classes' used in the dataset, table 2.1 outlines the number of

User	Training Files	Testing Files	Total Files	Training/Testing Split
akiplaner	468	52	520	90/10
bonzer	351	39	390	90/10
camdixon	537	60	597	89.9/10.1
corno	340	38	378	89.9/10.1
doublesfrogs	262	28	290	90.3/9.7
farmerjack	548	62	610	89.8/10.2
k	333	37	370	90/10
pcsnpny	612	68	680	90/10
ralfherzog	296	38	334	88.6/11.4
rortiz	549	61	610	90/10
Total	4296	483	4779	89.9/10.1

Table 6.1: Number of Files per User in the Dataset

voice files collected from each user, and how the training and testing dataset was split.

The data was then de-noised using a noise reduction in python called 'noisereduce.' The threshold set for this operation was 0.8, this value was used because it significantly reduces the noise in the audio files while still still preserving a majority of the original sound quality. Most samples recorded where from the years 2007-2009, so noise was very prominent.

6.4 Feature Selection

6.4.1 Feature extraction

Our SVM model, rather than be trained on the raw audio data, will be trained on a collections of features extracted from the audio files at 20ms intervals. The features extracted are from the MFCC Coefficients (Mel-Frequency Ceptstral Coefficients.) MFCC is used to capture the frequency range common for human speech. Each 20ms interval of audio will have 3 MFCC's extracted. The first MFCC Coefficient represents the overall energy of the signal and is dominated by large-scale features in the spectrum. Coefficients 2 and 3 capture more fine details of the overall envelope such as changes in the spectral slope or resonant frequencies of speech. Each of these coefficients will be collect and various operations will be applied to them in order to create our final features. The operations applied are as follows.

- **Mean**: The arithmetic average of a set of values, calculated as:

$$\text{Mean} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

  where x_i are the values and N is the total number of values.
- **Median**: The middle value in the dataset, if a dataset contains the values 1, 2, 3, 4, 5, the median value is 5. if there is an even number of values the median will be the average of the two middle values
- **Standard Deviation (Std Dev)**: A measure of how much the data is spread out compared to the mean, given by:

$$\text{Std Dev} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \text{Mean})^2}$$

- **Skewness**: A measure of the asymmetry, or how much the dataset is "skewed", throughout the values in the dataset. Positive skewness indicates a longer tail on the right, while negative skewness indicates a longer tail on the left.
- **Kurtosis**: A measure of the "tailedness" of the values in the distribution. High kurtosis indicates heavy tails, while low kurtosis indicates light tails. The kurtosis value for a standard normal distribution is 3.0. [1]
- **Maximum and Minimum**: The largest and smallest values in a dataset, respectively.

All the features collected are then concatenated into one feature vector, in our case, beacuse we have 3 MFCC's, and each MFCC will have 7 features, we will have a total of 21 features in our feature vector. The features are also standardized in the pre-processing step using sklearn's 'StandardScalar' function. This function transforms the data to have a mean of 0, which will be much easier for our SVM model to handle since they are very sensitive to the scale of the input features. Standardization also ensure that all features will equally contribute to the models training.

6.5 Model Training

The SVM model was trained using an RBF (Radial Basis Function) kernel using One vs. Rest classification. A kernel is a function that is capable of computing similarity between two data points in feature space. Which can allow the SVM model to handle non-linear relationships. I chose the RBF kernel because its works well in a variety of problems and is effective even with no prior knowledge about the data structure. [2] The RBF kernel assigns a higher similarity score to points that are close in the feature space, while applying a lower similarity to points that are far apart. The SVM model was fit to the Training Dataset, the model took 9 minutes to train on average across multiple sessions.

6.6 Results

6.6.1 Accuracy

Following the training of the model, the SVM was used to predict the speakers class with the testing dataset. Across 483 testing audio files, the model reached an accuracy of 97 percent with 3 MFCC Coefficients. Some users or 'classes' had a testing accuracy of 100 percent, while the lowest accuracy for any user was 82 percent. This data can be effectively visualized using a Confusion matrix, which is displayed in Figure 2.1.

6.7 Statistical Tests

6.7.1 ANOVA

An ANOVA feature test was applied to the feature set after training to determine which of the extracted features were most significant in classifying the subject. ANOVA stands for Analysis of Variance, it works by comparing the variance between groups based on the target variable. The ANOVA returns an F-value, where a high F-value indicates that the specific feature plays a significant role in the distinguishing between classes. The F-values for all of the features is displayed in Figure 2.2 and the descriptions of each feature is shown in Table 2.2, where each MFCC Coefficient and the associated operation is described. By observing Figure 2.2 we can see that the top 5 features for correctly classifying speakers were

Feature Index	Description	Feature Index	Description
0	Coefficient 1 Mean	11	Coefficient 2 Kurtosis
1	Coefficient 1 Median	12	Coefficient 2 Maximum
2	Coefficient 1 Std Dev	13	Coefficient 2 Minimum
3	Coefficient 1 Skewness	14	Coefficient 3 Mean
4	Coefficient 1 Kurtosis	15	Coefficient 3 Median
5	Coefficient 1 Maximum	16	Coefficient 3 Std Dev
6	Coefficient 1 Minimum	17	Coefficient 3 Skewness
7	Coefficient 2 Mean	18	Coefficient 3 Kurtosis
8	Coefficient 2 Median	19	Coefficient 3 Maximum
9	Coefficient 2 Std Dev	20	Coefficient 3 Minimum
10	Coefficient 2 Skewness		

Table 6.2: Description of MFCC Feature Labels

index 18, The kurtosis of MFCC Coefficient 3, index 7, The Mean of Coefficient 2, index 6, The Minimum of Coefficient 1, index 2, the Median of Coefficient 1, and index 8, the Median of Coefficient 2. In order to better visualize how the variance of these features are separated, Figures 2.3 through 2.7 display the variance distribution across speakers.

The Figures 2.3 through 2.7 display the variance of the designated feature extracted. The SVM is optimized to notice the difference in these distributions and can use these difference to accurately classify audio files.

6.7.2 K-Fold Cross Validation

A K-Fold Cross Validation test was used to evaluate the performance of the SVM model. A K-Fold test uses 'k' different "folds", to compare how the model is affected by different groups of data. Each fold is comprised of an equally split portion of the dataset, the model will the train itself on k-1 out of k datasets and use the remaining dataset for training. A K-Fold test can show us how the model might perform when used with unseen data. I used a 5-Fold cross validation test to evaluate the performance of my model. The accuracy of each fold is displayed in Table 2.3. The Mean accuracy of all the fold was 92 percent, with a standard deviation of 0.04. The average accuracy of the K-Fold test was observed to be lower than the final model accuracy on the test set. This could mean a variety of things such as the model is over fitted to the

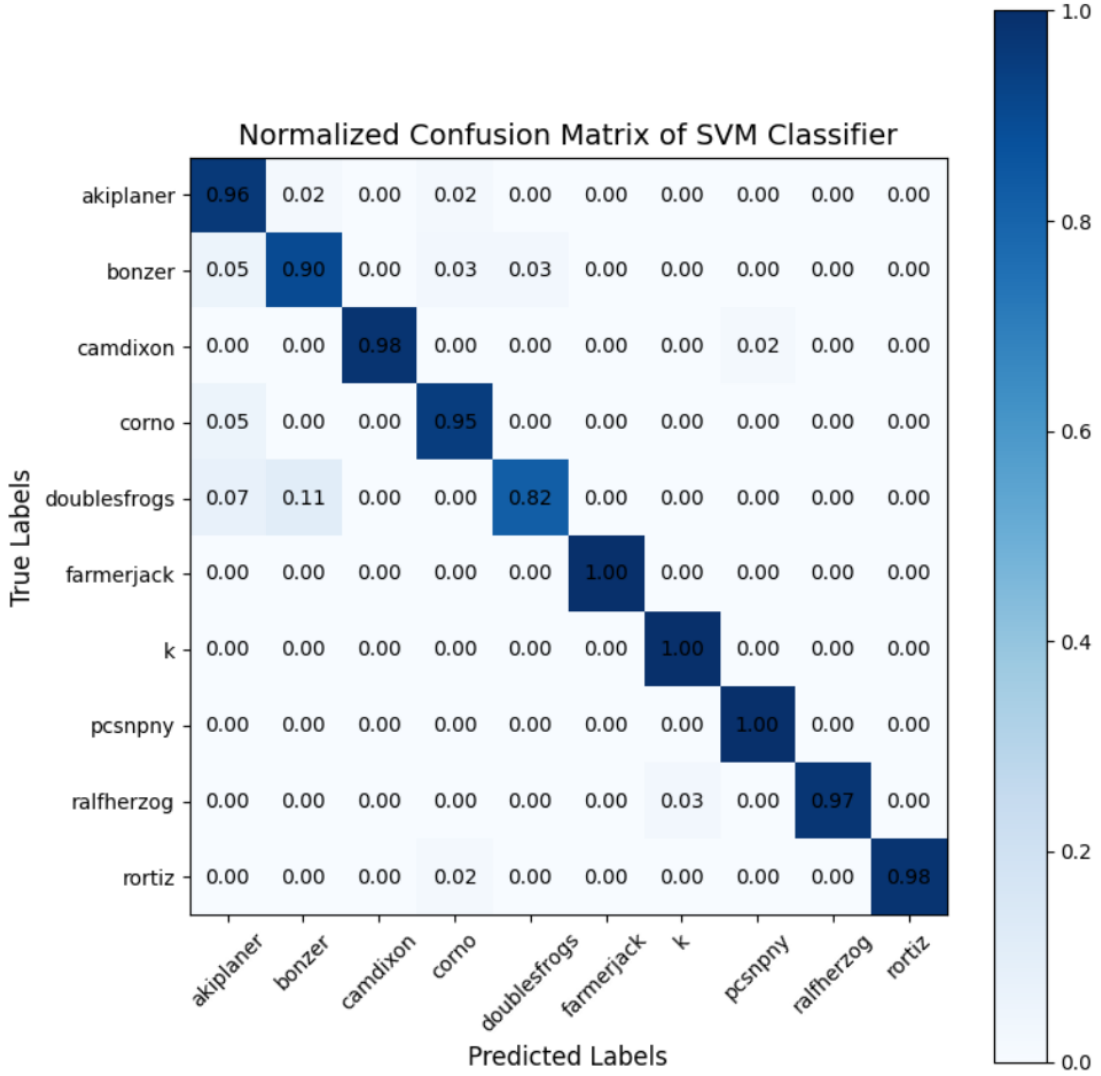

Figure 6.1: Normalized Confusion Matrix of SVM Classifier

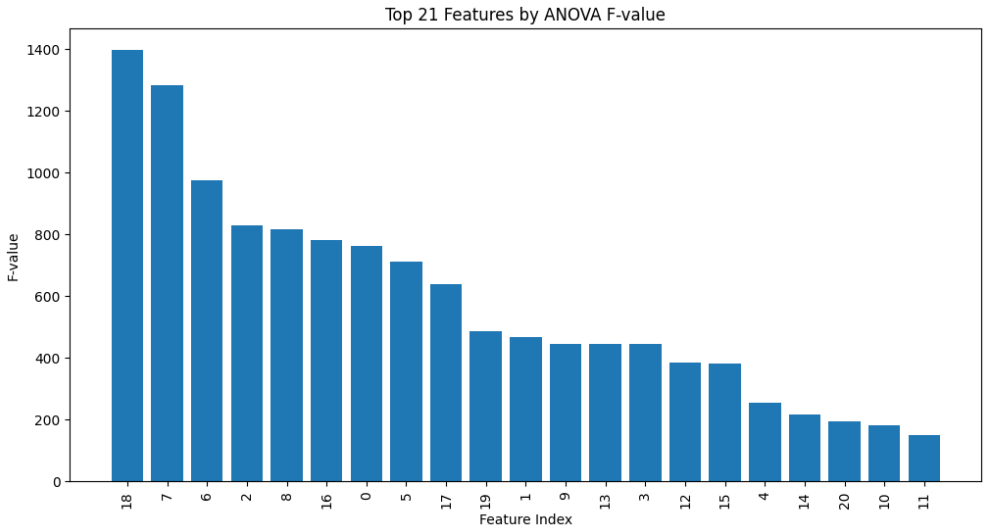

Figure 6.2: F-values for extracted features

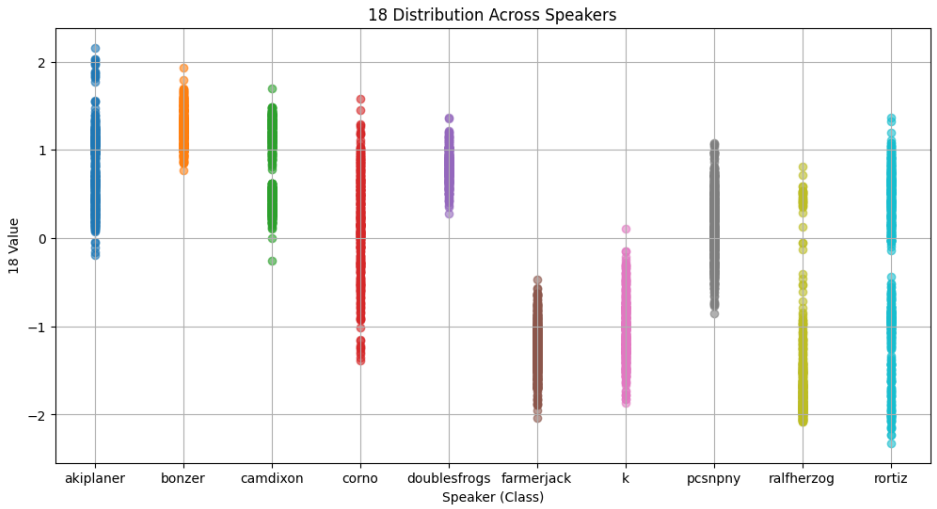

Figure 6.3: Distribution of the Kurtosis of MFCC Coefficient 3

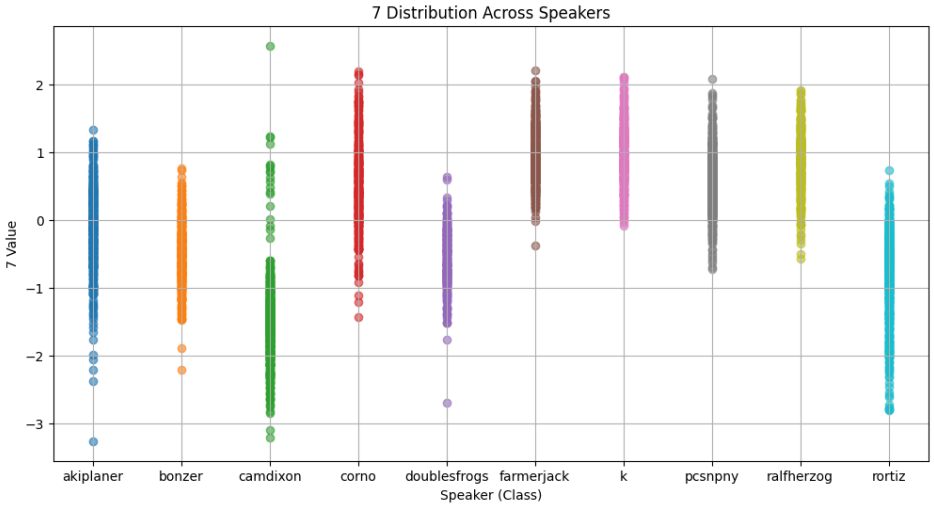

Figure 6.4: Distribution of the Mean of MFCC Coefficient 2

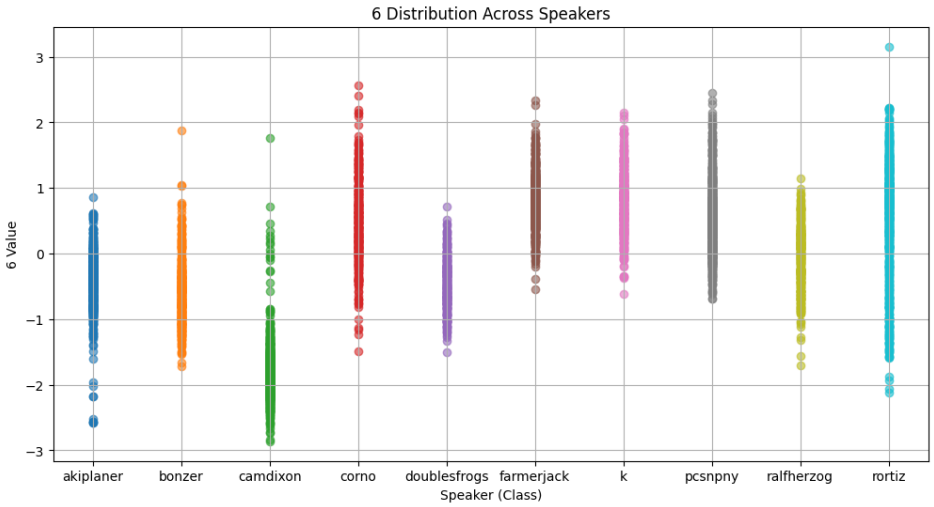

Figure 6.5: Distribution of the Minimum of MFCC Coefficient 1

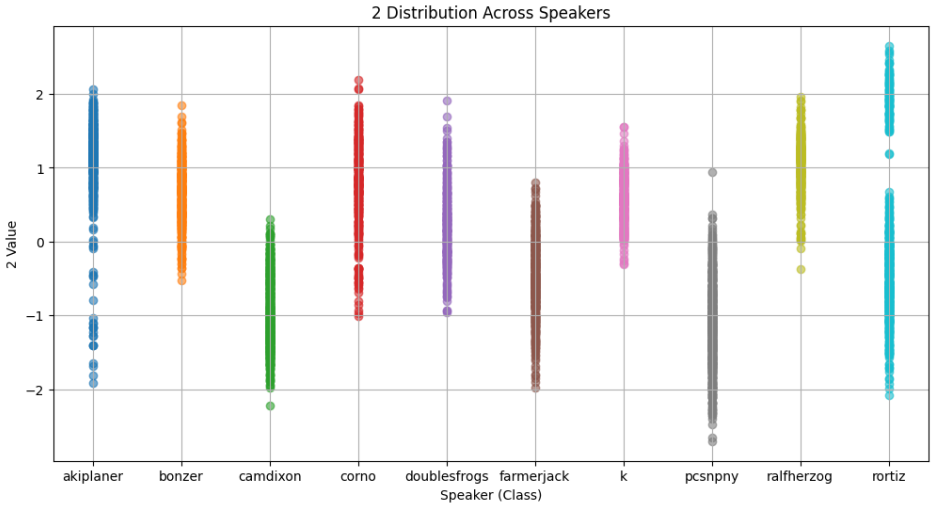

Figure 6.6: Distribution of the Median of MFCC Coefficient 1

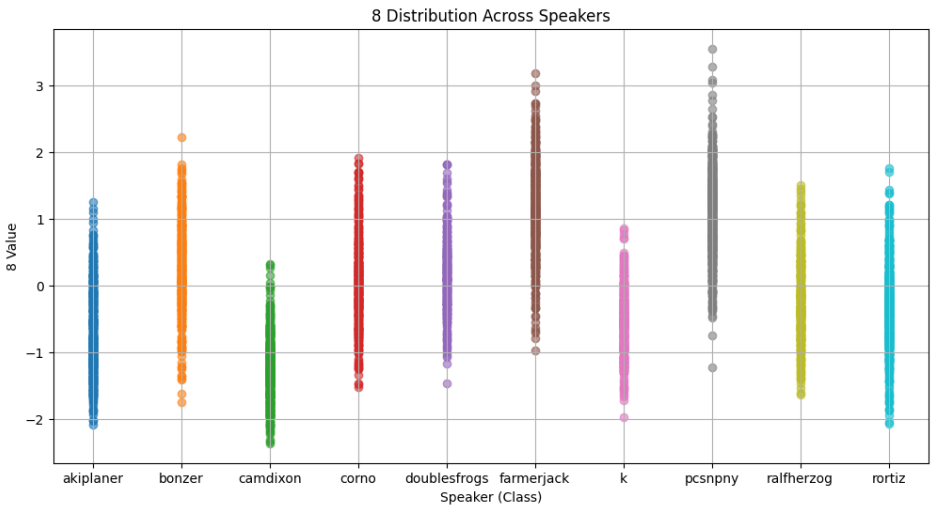

Figure 6.7: Distribution of the Median of MFCC Coefficient 2

Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
0.96162791	0.9371362	0.84866123	0.94295693	0.88824214

Table 6.3: Accuracies for each Fold during Cross-Validation

test set, or the data splits in the cross-validation are more challenging than the original training set. A lower accuracy in cross-validation is also common in smaller datasets because the variance can be higher due to limited samples in each fold.

6.7.3 Chi Squared

A Chi Squared was used to determine whether the observed results of the model differ significantly from the expected frequencies, or the null hypothesis. In my case, the expected frequencies were set to a normal, random, distribution. So the results of the Chi Squared test will determine how much better the SVM model is compared to random classification. The Chi Squared test provided a value of 3981.8 and a p-value of 8.771e-5. In our case, the null hypothesis suggests our predictions are made randomly, so a high Chi Squared value and a low p-value show that the model isn't behaving randomly.

6.8 Related Studies

Spoken Speaker identification based on Gaussian Mixture Models is an article authored by Abhijeet Kumar outlining a speaker identification system using the VoxForge dataset. This study, instead of using SVM for classification is using GMM, which is a statistical clustering model, rather than a classification model. The study consists if 34 different speakers speaking five different speech utterances. The dataset differs from my dataset because the users are all saying the same thing, and there are many more classes. This study also extracts 40 MFCC features, 20 of which are directly from the MFCC and 20 are derivatives of the MFCC. After training the Gausian Mixture Model, it was tested on 5 different speech utterances from the 34 different users. This model reached an accuracy of 100 percent. The performance of this model was likely better than the SVM model performance for a couple of reasons. First could be the fact that the model was trained on the same speech utterances, so the model could be able to pick up distinct differences in the speakers voices, and will ignore any differences found from the different users speaking different words. The GMM Model also utilized more MFCC features than our model which could've made it more effective. [3]

6.9 Conclusion

Speaker Recognition has been a difficult task for computers for a long time, but this article discusses the creation of a Support Vector Machine Model to solve that problem. The Model was trained on over 4,000 speech samples that were de-noised and segmented into 20 second intervals. Each speech sample had features extracted using MFCC Coefficients because they prove to be very effective in capturing individual speaker characteristics. After training, the model reached an accuracy of 97 percent. By applying a ANOVA statistical test to the features, we can observe the most significant features extracted for identifying each speaker. I also applied two statistical tests to the models performance, K-Fold cross validation and a Chi Squared test, in order to verify the legitimacy of the models accuracy. During cross validation the model received an accuracy of 92 percent, and even though this accuracy is lower it can still be explained. Finally, other studies were able to reach higher levels of accuracy using other techniques, but the SVM model trained in this paper is still very effective for speaker classification. All codes used to create the model in this chapter will be available on Github at SVM-Speaker-Classifier.

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Audio Classification Using MFCCs and Decision Tree Models

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https://github.com/ahmedajan/
Audio-Classification-Using-MFCCs-and-Decision-Tree-Models

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July 10, 2025

Chapter 7

Audio Classification Using MFCCs and Decision Tree Models

7.1 Introduction

Voice interfaces have become a core component of smart home and IoT technologies, offering hands-free, intuitive control over devices. This capability not only enhances convenience but also provides critical accessibility benefits for individuals with visual impairments [1]. Through speech, users can initiate tasks such as setting timers, operating appliances, or adjusting environmental controls without the need for visual interaction.

However, most commercial voice systems—such as Amazon Alexa or Google Assistant—depend heavily on cloud computing for speech processing. This dependency introduces challenges in both network reliability and privacy. In rural areas, network infrastructure may be inadequate or costly [2], and in any setting, transmitting voice data to cloud servers raises privacy concerns due to the risk of unauthorized access or misuse [3].

Edge computing offers a promising solution by enabling speech recognition directly on-device, eliminating the need for continuous connectivity and reducing data exposure risks [4]. Yet, implementing such functionality on microcontrollers and other constrained hardware requires lightweight and efficient algorithms. Deep learning approaches are typically infeasible due to their computational demands. Instead, traditional machine learning models—like decision trees or random forests—combined with compact and meaningful features such as Mel-Frequency Cepstral Coefficients (MFCCs), offer a viable path forward [5].

MFCCs are designed to model the way humans perceive sound, capturing both the spectral envelope and energy variations of speech. When combined with basic statistical operations and normalization, they provide a compact feature set suitable for training simple classifiers on small devices. Additionally, models must remain robust under various conditions, such as background noise, accent variability, and limited sample sizes. Preprocessing techniques like denoising and feature scaling, as well as validation strategies such as k-fold cross-validation and statistical testing (e.g., ANOVA, chi-squared), are essential to ensure generalization and reliability [6].

This chapter explores the design and evaluation of an offline speaker recognition system using MFCC-based features and a tree-based classifier architecture. Our approach emphasizes computational simplicity, privacy preservation, and adaptability to real-world constraints—making it particularly well-suited for embedded systems deployed in disconnected or privacy-sensitive environments.

7.2 Theoretical Background

The development of voice-controlled systems in embedded environments requires a strong foundation in both signal processing and machine learning theory. This section outlines the essential theoretical concepts underpinning the system, including speech signal characteristics, feature extraction techniques, and the principles behind decision tree and ensemble-based classifiers.

7.2.1 Speech Signal Properties

Human speech is a complex, non-stationary signal characterized by variations in pitch, energy, and frequency content over time. Speech signals are typically modeled as quasi-stationary over short intervals (10–30 ms), allowing them to be processed using short-time analysis techniques. The acoustic waveform generated by human vocal cords contains a fundamental frequency (F0) and harmonics that are shaped by the articulatory configuration of the vocal tract. These spectral properties provide the basis for speaker differentiation [7].

7.2.2 Mel-Frequency Cepstral Coefficients (MFCCs)

MFCCs are one of the most widely used features in speech and speaker recognition tasks due to their ability to approximate the human auditory system's perception of sound. The extraction of MFCCs involves the following steps:

- **Pre-emphasis**: A high-pass filter is applied to boost high-frequency components.
- **Framing and Windowing**: The signal is divided into overlapping short frames to capture local spectral properties.
- **Fourier Transform**: Converts each frame from the time domain to the frequency domain.
- **Mel-Filterbank**: Maps the frequency scale to the Mel scale using triangular filters.
- **Logarithmic Compression**: Applies a logarithmic scale to match human loudness perception.
- **Discrete Cosine Transform (DCT)**: Compacts energy into a small number of coefficients.

The first few MFCCs typically capture broad spectral information, while higher-order coefficients represent finer spectral detail. These features are particularly effective in speaker recognition because they encode unique vocal tract characteristics [8].

7.2.3 Feature Normalization and Statistical Characterization

To prepare features for machine learning models, normalization is applied—often through Z-score standardization—to ensure zero mean and unit variance. In this study, additional statistical descriptors (mean, standard deviation, skewness, kurtosis, min, max, median) were computed for each MFCC across time frames to yield fixed-length vectors. This enhances robustness against variations in signal length and phonetic content.

7.2.4 Decision Trees and Ensemble Methods

Decision trees are a form of supervised learning used for classification and regression. They operate by recursively partitioning the feature space based on thresholds that maximize a splitting criterion such as Gini impurity or information gain. While decision trees are easy to interpret and fast to execute, they are prone to overfitting when used alone.

To mitigate this, ensemble methods such as Random Forests combine multiple decision trees trained on random subsets of the data and features. This aggregation improves generalization by reducing variance and increases robustness to noisy data and overfitting [9]. Such models are computationally lightweight and well-suited for embedded systems.

7.2.5 Model Evaluation Metrics

To assess model performance, multiple statistical metrics are used:

- **Accuracy**: Proportion of correctly predicted samples.
- **F1 Score**: Harmonic mean of precision and recall, especially useful for imbalanced datasets.
- **Confusion Matrix**: Visualizes classification performance across all classes.
- **ANOVA (Analysis of Variance)**: Measures feature relevance by comparing inter-class and intra-class variances.
- **Chi-Squared Test**: Evaluates whether observed classification results differ significantly from a null hypothesis of random predictions.

These metrics provide quantitative evidence for both feature effectiveness and model reliability, particularly when datasets are limited in size or diversity.

7.2.6 Embedded System Constraints

Microcontroller-based implementations of speech recognition systems must consider strict limits on processing power, memory, and energy consumption. Unlike large-scale ASR models based on deep learning, embedded solutions benefit from algorithmic simplicity and efficient feature representations. Techniques such as feature downsampling, low-dimensional MFCC selection, and model pruning are commonly used to meet performance targets while maintaining low latency and high accuracy [10].

7.2.7 Dataset

For the purposes of this study, a compact yet sufficiently diverse dataset was required to facilitate real-time speech classification on resource-constrained hardware. The **Free Spoken Digit Dataset (FSDD)** was selected due to its balanced structure, low computational footprint, and compatibility with embedded audio processing tasks.

FSDD is an open-access dataset consisting of recordings of the digits zero through nine, spoken multiple times by a small number of speakers. In total, the dataset includes **3,000 utterances**—with approximately **300 samples per digit class**. These are distributed across **six speakers**, each contributing 50 repetitions of all 10 digits. The speakers represent varying European accents, introducing inter-speaker variability that is beneficial for evaluating speaker-independent and speaker-dependent models.

Each audio sample is recorded as a **mono WAV file**, with a sampling rate of **8,000 Hz** and a duration ranging from approximately 0.5 to 1.0 seconds. All samples were captured in relatively clean acoustic conditions with minimal background noise, making the dataset ideal for training in environments where signal clarity is assumed or pre-processed.

The dataset was partitioned into training and testing sets using an 80/20 stratified split to maintain class balance. This resulted in 2,400 training samples and 600 testing samples. The uniformity of digit labels and the simplicity of the utterances make FSDD a strong candidate for initial evaluation of embedded classifiers.

Attribute	Value	Description	Type	Relevance
Dataset Name	FSDD	Free Spoken Digit Dataset	Audio Corpus	Public and lightweight
Classes	10	Digits 0 through 9	Categorical	Multi-class classification
Total Samples	3,000	300 per class	WAV files	Balanced data
Speakers	6	Varying accents	Human voices	Speaker variability
Samples per Speaker	500	50 utterances $\times$ 10 digits	Speech instances	Consistent per speaker
Sampling Rate	8 kHz	16-bit PCM Mono	Digital audio	Ideal for embedded systems
Duration	$\sim$0.5–1.0s	Per sample	Time domain	Short speech commands
Environment	Low noise	Minimal background	Acoustic quality	Clean baseline for testing
Train/Test Split	80/20	Stratified by digit	Evaluation setup	Generalization testing

Table 7.1: Overview of the Free Spoken Digit Dataset (FSDD)

The dataset's simplicity enables faster prototyping, while its speaker diversity and audio quality offer a solid baseline for benchmarking classification models in low-power, real-time speech interfaces. Furthermore, FSDD is commonly used in lightweight model benchmarking, making it a standard reference for comparing the performance of embedded voice systems.

7.2.8 Denoising

In order to de-noise our data we need to understand the nature and possible sources of the noise our system is likely to encounter. The application space for this project is entirely domestic which adds a high degree of noise controllability on the users side. The primary sources of noise we would expect from this space come from house hold systems such as HVAC and filtration systems as well as other occupants of the space. The noise contribution and controllability of these two sources can quickly increase the system's complexity as a whole.

Household appliances often emit low-level constant noise while running. Devices such as heaters, air conditioners, air filters, and fans fall in this category and are often run for long periods. The type of noise these devices generate has a couple of names, such as white, normal, or Gaussian noise. This noise has randomly distributed frequency components in a large band, which averages in time to a uniform energy density for all frequencies. This type of noise is often accompanied by low-amplitude periodic signals generated by components like the motor. While this type of noise poses a challenge to voice recognition systems, it often does not vary on the time scale at which our system operates, which makes it easier to identify and filter out. One method of doing this is simply subtracting the mean power of the signal. This focuses on how the data changes over time, which is more likely to be speech-dependent. Issues in filtering often come when the noise source has a similar profile to the data we are trying to preserve.

Time-varying sources of noise pose a significant challenge to speech recognition systems as the nature of the noise closely matches the nature of the data. Processing signal pollution due to multiple speakers and sources like music is above what can be expected from a low-power processing system. Also, the user often has great control over the number and magnitude of these noise sources in a domestic environment, making it a non-issue. As such, de-noising methods will not be explored for speaker and music separation.

As mentioned above, the nature and amount of noise expected in a domestic environment will likely be below the threshold that will greatly affect the system. Tests would need to be conducted in order to determine what level and types of noise the system fails in and filters will need to be designed to mitigate these effects. As the current dataset is low noise, we would need to augment the data with added noise for testing. For now, we will not be conducting filtering as the suggested mean power removal method is standard in feature normalization and will thus be done through feature processing.

7.2.9 Feature Selection

When researching speech recognition, many features can be used. Among these are the Fundamental Frequency of the speech, the zero crossing rate, and the spectrogram. The spectrogram is another name for the Short-Time Fourier Transform, a processing technique that captures the frequency components over time. While all of these features can work

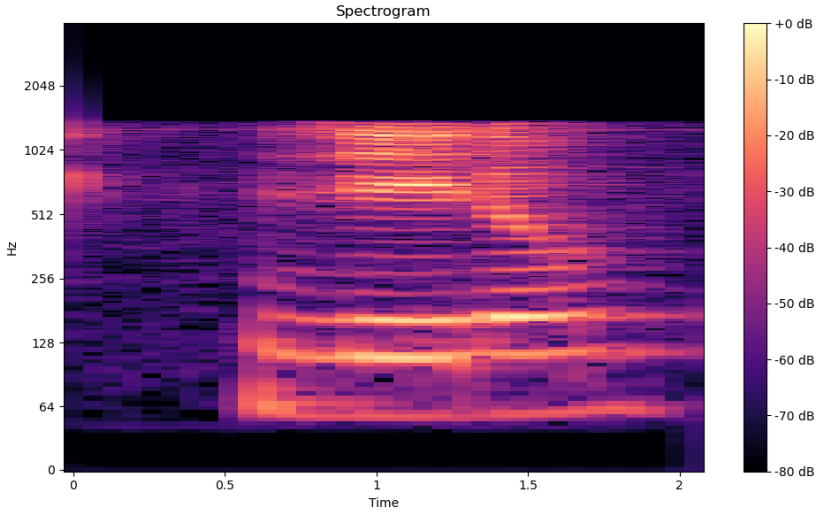

Figure 7.1: Short Time Fourier Transform of 0_George_1.wav. Notice The how the waveform carries several harmonics.

for analyzing audio, understanding how humans speak allows for designing better features for speech recognition. When a human speaks, they create a modulated half-sinusoidal waveform. This waveform then resonates through the mouth and lower nasal cavity, resulting in a waveform with a fundamental frequency and multiple harmonics. This can be seen in the STFT shown in 7.1. Observing the signal in the frequency domain, we can identify a potential feature that measures the periodicity of the sample's frequency components. This is known as cepstral analysis, which is a play on words based on the inverse of spectral analysis.

Cepstral analysis works by taking the inverse Fourier transform of the signal's Power Spectral Density on a logarithmic scale. The logarithmic scaling is used to analyze the signal in terms of perceived loudness instead of measured energy. The process can be made closer to how humans hear by modifying the frequency scale of the signal. It was found that humans do not perceive a doubling of frequency as a doubling of perceived pitch as would be expected. Instead, the perceived pitch changes by the nonlinear function

$$m = 2595 log_{10}(1 + \frac{f}{700})$$

which is known as the Mel Scale. Combining these different methods results in a feature set known as the Mel Frequency Cepstrum Coefficients or MFCC. They have become one of the widest-used features for speech recognition due to their specialization in measuring the power of harmonic signals.

7.2.10 Feature Extraction

Before applying our feature extraction algorithm, we run our sample through a preemphasis filter to boost the higher frequency components. We then extracted the MFCC coefficients and the RMS power per 20ms and took the mean of each feature per sample. The data was then normalized using Z normalization, and a search was conducted to determine the number of MFCC coefficients needed to separate our 10 classes. Statistical testing measured which features contained the best separation for the individual characters. This was done on both a per-feature case and a per-speaker case. Figure 7.2 is an example of the best feature separation according to ANOVA with the different speakers plotted in separate colors. 20 MFCC coefficients were evaluated for this example. For training the model, the MFCC features will be varied between 8 and 16 to compare model performance. Because our target is low computational costs, fewer features are always preferred.

7.2.11 Model Parameters

Because our use case focuses on processing data in a constrained environment, special consideration has to be done on the size and complexity of the model used. While Neural Networks and Support Vector Machines work well for classifications, they operate using many multiply and add operations which is computationally expensive. A simpler and more computationally efficient method involves using multiple binary classifiers on the high dimensional data. This method is known as a decision tree. While a single decision tree can provide good results, it may not work well because the decision boundaries do not accurately represent the best high-dimensional boundary. One method of working around this is by combining the outputs from multiple decision trees, a method known as Random Forest. While Random Forest

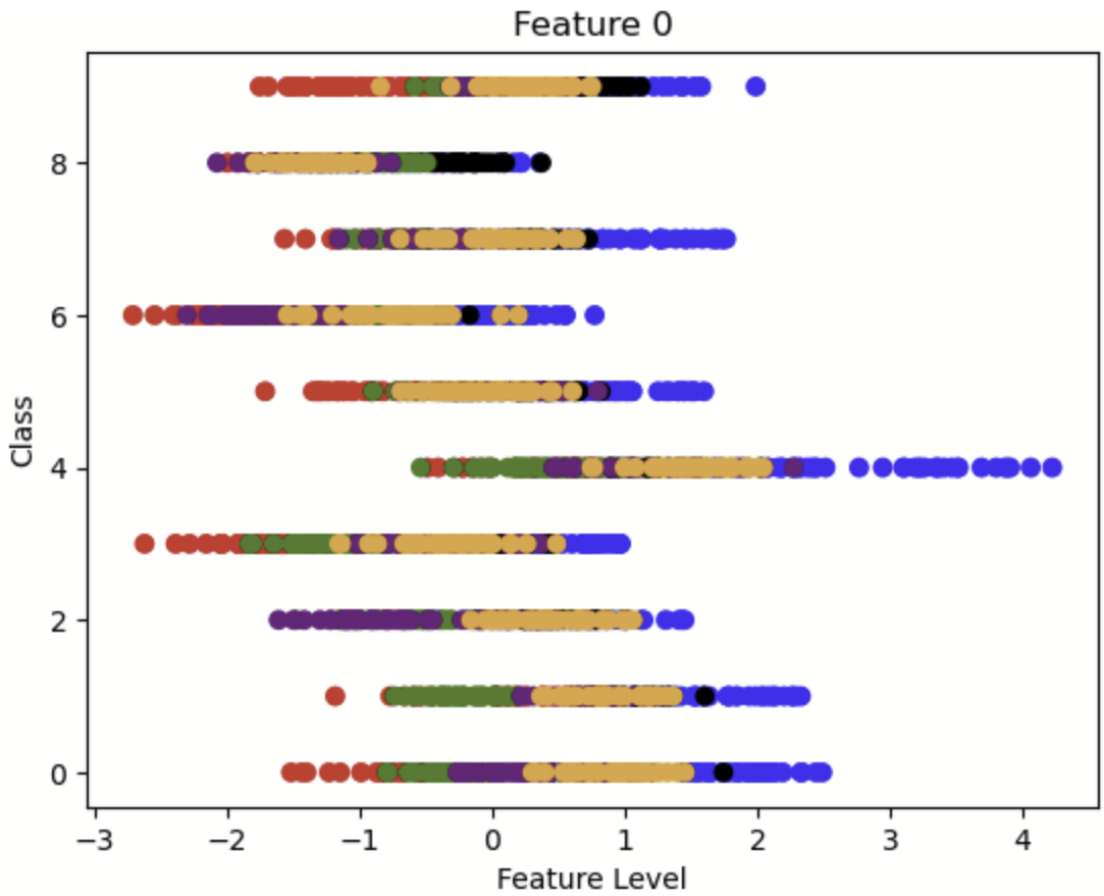

Figure 7.2: Distribution of the MFCC coefficient with the best separation according to ANOVA. Notice that the speakers tend to occupy the same position in each of the distributions. This indicates that the MFCC coefficients could be used for speaker classification.

has many tunable parameters, the number of trees is the most important one for our purposes. For a low number of trees, it may not have the best classification accuracy, whereas for a large number of trees, the model may become overfit.

After running several tests, it was found that the model didn't improve after 20 decision trees. As such, only the number of MFCC coefficients will be varied for the parameter search. For this, the number of MFCCs was varied between 8 and 16 coefficients. These models were trained using a random split per digit, ensuring equal representation of each class in the training and testing sets. During training, a k-fold cross-validation approach with five folds was used to measure the model performance accurately.

7.2.12 Results

One of the many tools that will be used to evaluate false predictions from the model is a confusion matrix. A confusion matrix plots the expected and predicted classes. A perfect classifier would result in a diagonal line corresponding to each class being predicted exactly. When data is incorrectly classified, it is added to a grid square, indicating patterns in misclassification. This grants insight into what classes, if any, are more likely to be incorrectly predicted and what they are often confused as. Figure 7.4 and Figure 7.5 are given to show results from a good and poor classifier.

The final accuracy is shown in 7.6. As can be seen in the figure, the F1 score gradually increases with the number of MFCC coefficients. It was observed in other test runs that a coefficient number less than 8 led to a poor classification F1 score, and numbers larger than 16 did not substantially improve the F1 score. We suggest 14 as the best balance between increasing the F1 score and reducing computational costs. Performing statistical testing, we conclude that our F1 score to within a 99% confidence is between 0.87 and 0.90. Observing the confusion matrix shown in 7.7, we observe several class groups that tend to be confused. Further research would need to be conducted to identify a feature for each pair that has a

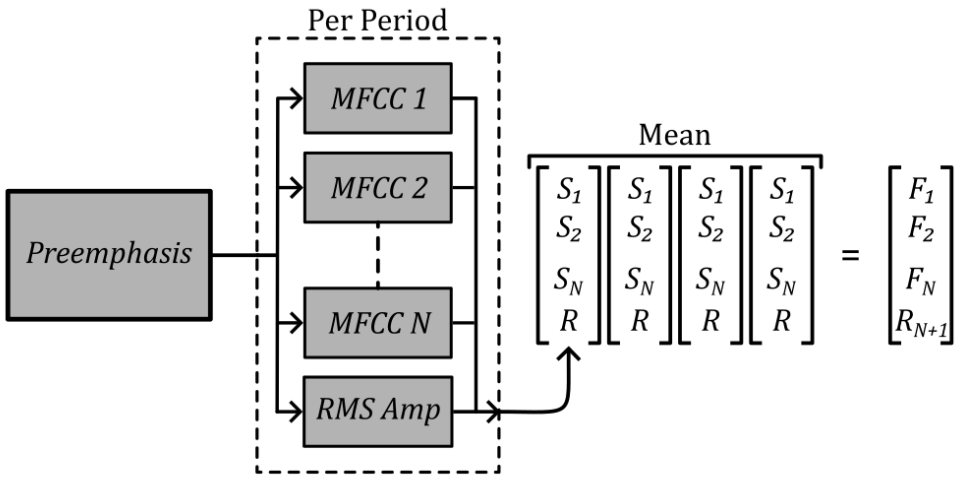

Figure 7.3: Feature extraction processing path

good separation between these two classes.

Table 7.2: List of features used for the Support Vector Machine classifier

Features	Statistics
MFCC	Mean
Root Mean Square Error	Median
Chroma STFT	Standard Deviation
Spectral Centroid	Skew
Spectral Bandwidth	Kurtosis
Rolloff	
Zero Crossing Rate	

Whether the accuracy of the Random Forest Classifier is limited by the data set has yet to be shown. We will compare the Random Forest Classifier to that of a Support Vector Machine. For this, a wide set of features were created, which are listed in Table 7.2. By using a broad set of possible features, we can determine how to extract the data from our samples. We can combine this large number of features with a method known as Principle Component Analysis to combine and reduce them before training. Multiple principle component numbers were tested to determine how accuracy scales with the features. The results of this are shown in the figure below. It was observed that 10 PCA features resulted in an F1 score between 95.4% and 97.4%. This indicates that greater accuracy could be achieved by increasing the number and variety of features used. This also comes with increased computational requirements, though; further work would need to be done to determine the most efficient features.

7.2.13 Other works results

An example of another work using this dataset comes from the Polytechnic Institute of Turin. In this report, Falvio Giobergia uses the spectrogram blocks' mean and standard deviation combined with a random forest model and a Support

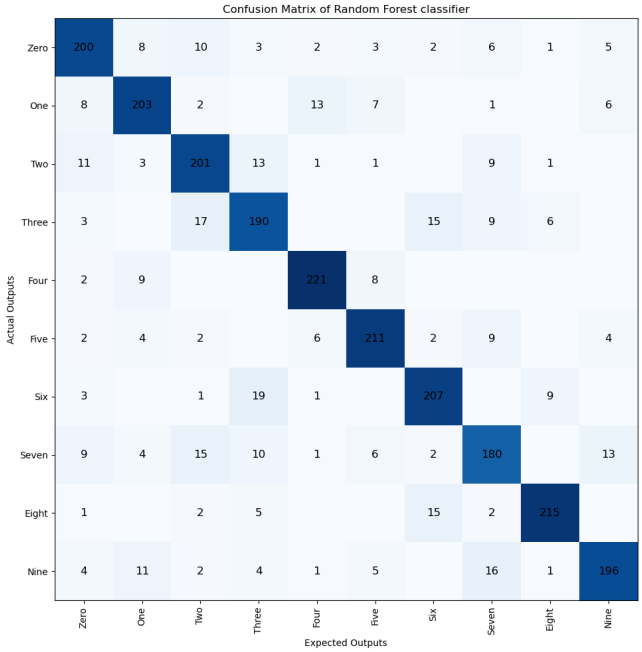

Figure 7.4: Confusion matrix for classifier with 90.3% accuracy

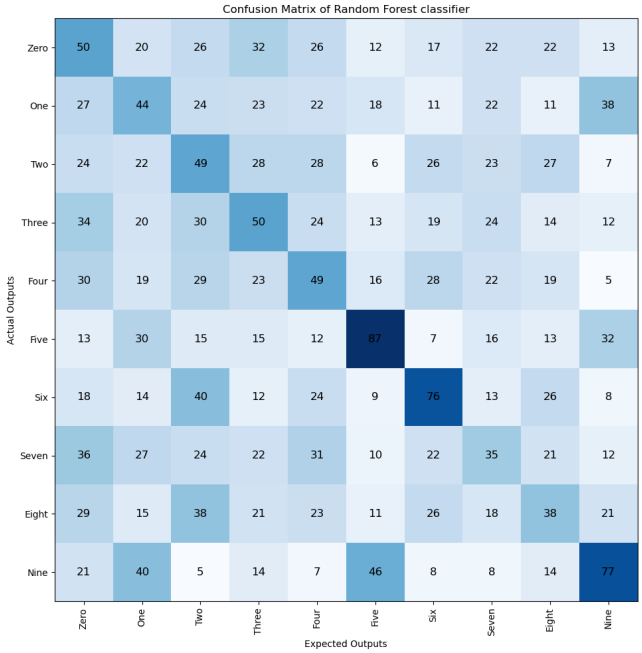

Figure 7.5: confusion matrix for classifier with 23.1% accuracy

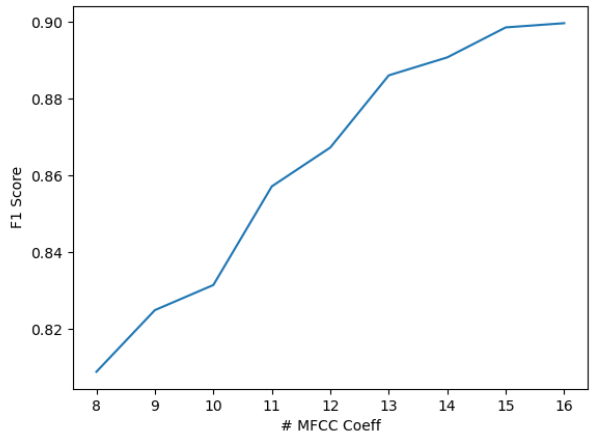

Figure 7.6: The F1 Score vs the number of MFCC coefficients. The accuracy does not increase after 14 MFCC coefficients.

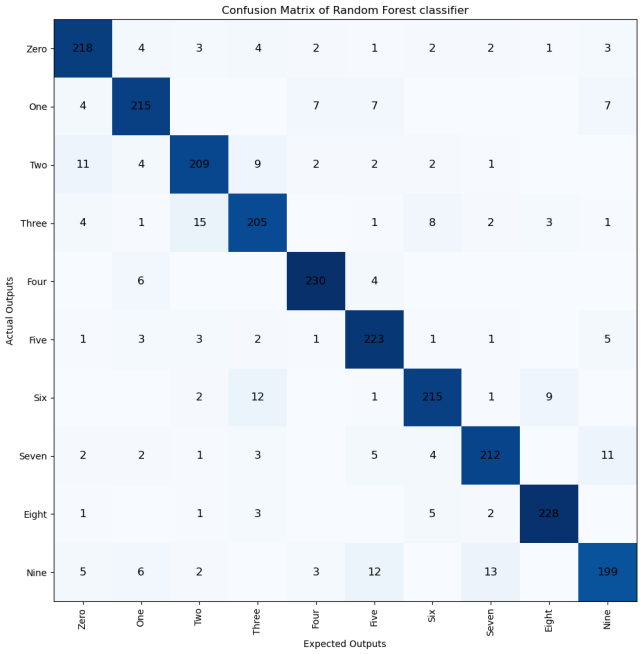

Figure 7.7: The confusion matrix for 14 MFCCs. There are several pairs of numbers that tend to be misclassified. These are two and three, three and six, and seven and nine.

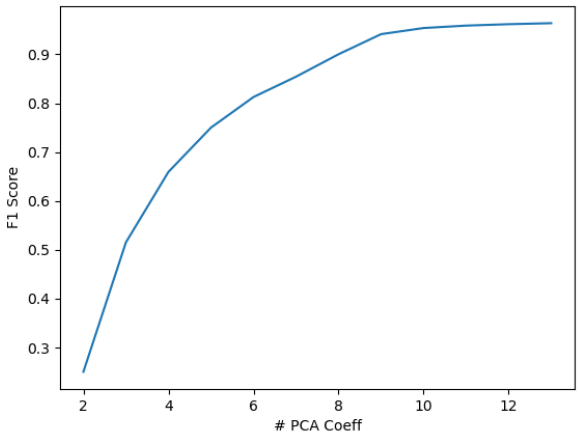

Figure 7.8: The F1 Score vs the number of PCA coefficients. The accuracy does not increase after 10 coefficients.

Vector Machine for classification. using this method, he was able to achieve an F1 score of 0.96 using a Random Forest Classifier and a F1 score of 0.94 using an SVM.

7.3 Impact on the field

A lot of research has been done on implementing speech recognition models that contain a few words, but this is often below the ten needed for our use case. Other research focuses on improving wake-word recognition in noisy environments. This supports the model of detecting a single wake word and then using online resources for the rest of the data parsing. There does not appear to be much research on implementing a microcontroller-only speech model to accomplish data entry.

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Speech Emotion Recognition using MFCC and Machine Learning

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Chapter 8

Speech Emotion Recognition using MFCC and Machine Learning

8.1 Introduction

Speech is one of the most natural and rich modalities through which humans express not only linguistic content but also emotional states. Recognizing emotions from speech has become a growing area of interest in human-computer interaction, assistive technologies, and behavioral monitoring [1, 2]. Speech Emotion Recognition (SER) enables systems to adapt based on user sentiment—providing more empathetic virtual assistants, improved call center analytics, and advanced clinical tools for diagnosing mental health conditions [3].

Unlike speech recognition systems that focus on transcribing spoken content, SER aims to classify the underlying emotional tone such as happiness, anger, or sadness. Human speech carries emotional information through subtle variations in pitch, intensity, duration, and spectral content [4]. However, detecting these patterns automatically poses several challenges, particularly when dealing with small datasets, speaker variability, and real-world background noise.

In this chapter, we implemented a classical machine learning pipeline to recognize emotions in speech using handcrafted features. Specifically, we focused on Mel-Frequency Cepstral Coefficients (MFCCs)—a widely used feature representation that models the human auditory system's perception of sound [5]. We extracted MFCC features from the Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) and trained a suite of classifiers including Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM) to distinguish between emotional categories such as neutral, happy, and sad.

While modern approaches often rely on deep learning and large corpora, our goal was to evaluate the effectiveness of traditional ML techniques on limited data using efficient and interpretable features. This work serves as a foundational study in building lightweight emotion classifiers that can be deployed on edge devices or integrated into larger affective computing systems.

8.2 Theoretical Foundations

Speech Emotion Recognition (SER) is the process of identifying a speaker's emotional state from audio signals. It plays a crucial role in making human-computer interactions more empathetic and intelligent by enabling systems to respond to a user's affective cues [6]. In contrast to automatic speech recognition (ASR), which seeks to decode linguistic content, SER extracts non-verbal vocal information—such as tone, prosody, pitch, and rhythm—to infer the speaker's emotional condition.

Mel-Frequency Cepstral Coefficients (MFCCs)

A central component of many SER systems is the use of Mel-Frequency Cepstral Coefficients (MFCCs), which model how humans perceive sound frequency. The human ear perceives pitch logarithmically, so the frequency scale is warped accordingly using the mel scale:

$$m = 2595 \cdot \log_{10}\left(1 + \frac{f}{700}\right) \tag{8.1}$$

where f is the linear frequency in hertz, and m is the corresponding mel frequency.

The computation of MFCCs involves several sequential steps:

- **Pre-emphasis:** A high-pass filter boosts high-frequency components to balance the spectral energy:

$$y[n] = x[n] - \alpha \cdot x[n-1] \tag{8.2}$$

  where α is typically around 0.95.
- **Framing and Windowing:** The continuous waveform is segmented into overlapping frames (typically 25 ms long with 10 ms overlap), and each frame is multiplied by a Hamming window:

$$w[n] = 0.54 - 0.46 \cdot \cos\left(\frac{2\pi n}{N-1}\right) \tag{8.3}$$

  to reduce spectral leakage.
- **FFT:** The Fast Fourier Transform is applied to convert the frame from the time domain to the frequency domain.
- **Mel Filterbank:** The power spectrum is passed through triangular filters spaced according to the mel scale.
- **Logarithmic Compression:** Log-energy is computed to mimic human perception:

$$S_m = \log\left(\sum_{k=1}^{K} |X[k]|^2 H_m[k]\right) \tag{8.4}$$

  where $H_m[k]$ is the m-th mel filter response.
- **Discrete Cosine Transform (DCT):** The DCT is applied to decorrelate and compress the mel log-energies:

$$c_n = \sum_{m=1}^{M} S_m \cdot \cos\left[\frac{\pi n(m-0.5)}{M}\right] \tag{8.5}$$

  where c_n is the n-th MFCC coefficient.

The first 12–13 coefficients are typically retained, sometimes along with the 0-th coefficient (log-energy). These coefficients serve as a compact representation of the short-term power spectrum of speech.

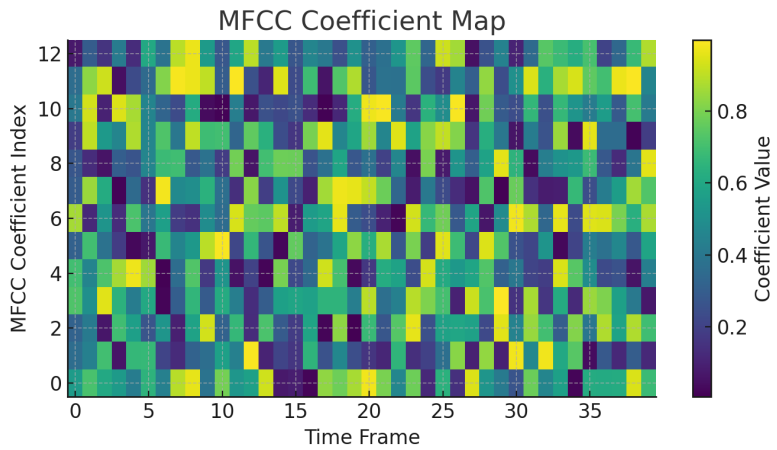

Figure 8.1: MFCC coefficient map extracted from a speech segment. Horizontal axis represents time; vertical axis represents cepstral coefficients.

Other Acoustic Features

While MFCCs capture spectral shape, other prosodic and phonatory features are important for emotion detection:

- **Pitch (Fundamental Frequency, F_0):** Indicates voice tone and is extracted via autocorrelation or cepstrum methods. High pitch often signals anger or excitement, while low pitch is associated with sadness.
- **Energy (Amplitude):** High energy corresponds to emotionally intense speech. Frame-level energy is calculated as:

$$E = \sum_{n=1}^{N} x[n]^2 \tag{8.6}$$

- **Formants:** Resonance frequencies of the vocal tract that shape vowels and can reflect vocal tension.
- **Speaking Rate and Pauses:** Slow rate and long pauses are often found in sadness or depression, while a fast rate is associated with happiness or anger.

Classical Machine Learning Models for SER

Various supervised learning algorithms have been used for emotion classification:

Random Forest (RF): Random Forest is an ensemble of decision trees trained on bootstrapped samples of data with random feature selection. Each decision tree is a set of rules that splits the feature space to minimize impurity, often measured by the Gini Index:

$$G = 1 - \sum_{k=1}^{K} p_k^2 \tag{8.7}$$

where p_k is the proportion of class k instances in a node. The final prediction is made by majority voting among trees [7].

K-Nearest Neighbors (KNN): KNN is a non-parametric method where a sample is classified by the majority vote of its k closest training points, typically using Euclidean distance:

$$d(x, x') = \sqrt{\sum_{i=1}^{n} (x_i - x_i')^2} \tag{8.8}$$

The method is sensitive to the value of k and feature scaling.

Support Vector Machines (SVM): SVM constructs a hyperplane that maximizes the margin between classes. For linearly separable data, the decision function is:

$$f(x) = \text{sign}(w^T x + b) \tag{8.9}$$

For non-linear cases, the kernel trick maps input features to a higher-dimensional space. SVMs are particularly effective on small, high-dimensional datasets [8].

Evaluation Metrics

Accuracy alone is insufficient in SER due to class imbalance. Precision, recall, and the F_1-score are defined as:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}, \quad F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8.10}$$

Confusion matrices help visualize misclassifications and highlight frequent emotion confusions such as neutral-sad or angry-happy.

Challenges in SER

Speech emotion recognition faces multiple challenges. Emotional expression varies by culture, age, and individual differences. Many datasets are acted rather than spontaneous, affecting real-world generalizability. Additionally, speaker and channel variability degrade performance, requiring normalization or domain adaptation. Multimodal data—such as combining audio with facial expressions or physiological signals—can improve robustness but increases system complexity.

Despite these issues, classical ML models paired with handcrafted features remain useful for embedded and low-resource SER applications. They offer interpretability, fast inference, and low computational requirements compared to deep neural networks.

8.3 Methodology

The objective of this study was to build an efficient and interpretable Speech Emotion Recognition (SER) system using handcrafted features and traditional machine learning models. The following subsections outline the data sources, preprocessing steps, feature extraction pipeline, and model training procedures.

8.3.1 Dataset Collection and Organization

This project utilized four public datasets: RAVDESS, CREMA-D, TESS, and SAVEE. Each dataset includes emotional speech samples labeled with corresponding emotions such as neutral, happy, sad, angry, and fearful.

```
# Define paths to datasets
Ravdess = "dataset/ravdess-emotional-speech-audio/audio_speech_actors_01-24/"
Crema   = "dataset/cremad/AudioWAV/"
Tess    = "dataset/tess toronto emotional speech set data/TESS Toronto emotional
   speech set data/"
Savee   = "dataset/surrey-audiovisual-expressed-emotion-savee/ALL/"
```

8.3.2 Audio Preprocessing

Before extracting features, we performed several preprocessing steps:

- **Sampling Rate Normalization:** All audio files were resampled to 22050 Hz using Librosa.
- **Duration Padding/Truncation:** Audio samples were padded or truncated to a uniform length of 3 seconds.
- **Silence Trimming:** Leading and trailing silences were removed using energy-based thresholding.

```
# Load audio using librosa
audio, sr = librosa.load(filepath, sr=22050)

# Trim silence
audio, _ = librosa.effects.trim(audio)

# Pad to 3 seconds (66000 samples)
if len(audio) < 66000:
    padding = 66000 - len(audio)
    audio = np.pad(audio, (0, padding), 'constant')
else:
    audio = audio[:66000]
```

8.3.3 Feature Extraction: MFCCs

Mel-Frequency Cepstral Coefficients (MFCCs) were extracted as primary features for emotion classification. We computed 40 MFCCs along with their first and second-order derivatives (deltas and delta-deltas), forming a 120-dimensional feature vector per frame. Global statistics (mean and standard deviation) over all frames were then computed to produce a fixed-size feature vector.

```
mfcc = librosa.feature.mfcc(y=audio, sr=sr, n_mfcc=40)
delta = librosa.feature.delta(mfcc)
delta2 = librosa.feature.delta(mfcc, order=2)

# Stack features
combined = np.vstack([mfcc, delta, delta2])

# Aggregate using mean and std
mfcc_mean = np.mean(combined, axis=1)
mfcc_std = np.std(combined, axis=1)
features = np.hstack((mfcc_mean, mfcc_std))
```

8.3.4 Feature Scaling and Label Encoding

Standard scaling was applied to center the features and normalize variances. Emotion labels were converted into one-hot encoded vectors for training.

```
from sklearn.preprocessing import StandardScaler, OneHotEncoder

# Feature scaling
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# One-hot encode emotion labels
encoder = OneHotEncoder()
y_encoded = encoder.fit_transform(y.reshape(-1, 1)).toarray()
```

8.3.5 Model Training and Evaluation

We trained three classical classifiers: Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN). The dataset was split into 80% training and 20% testing using stratified sampling.

```
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier

# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_encoded,
    test_size=0.2, stratify=y, random_state=42)

# Model initialization
rf = RandomForestClassifier(n_estimators=100)
svm = SVC(kernel='rbf', probability=True)
knn = KNeighborsClassifier(n_neighbors=5)

# Fit models
rf.fit(X_train, y_train)
svm.fit(X_train, y_train)
knn.fit(X_train, y_train)
```

8.3.6 Evaluation Metrics

We evaluated model performance using accuracy, precision, recall, F_1-score, and confusion matrices:

```
from sklearn.metrics import classification_report, confusion_matrix

# Predictions
y_pred = rf.predict(X_test)

# Classification metrics
print(classification_report(y_test, y_pred, target_names=encoder.categories_[0]))
```

8.3.7 System Overview Diagram

The entire pipeline is summarized in the following block diagram created using `TikZ`:

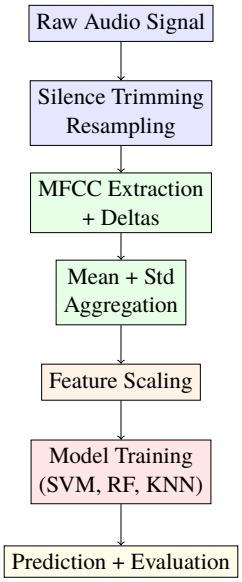

Figure 8.2: End-to-End SER Pipeline using MFCCs and Traditional Machine Learning

8.4 Results and Discussion

This section presents the evaluation of the Speech Emotion Recognition (SER) system using classical machine learning algorithms trained on MFCC features extracted from the RAVDESS dataset. The discussion encompasses dataset balance, feature visualization, classifier metrics, and a detailed confusion matrix analysis to interpret classifier behavior and limitations.

8.4.1 Emotion Class Distribution

Before model training, the distribution of emotion labels in the dataset was visualized to evaluate class balance, which significantly influences classifier performance, especially for algorithms sensitive to majority class bias.

As shown in Figure 1, the dataset maintains a relatively balanced distribution across major emotional states, including `neutral`, `happy`, `sad`, and `angry`. Each of these classes had approximately 144 samples, contributing to a stable baseline for model training. However, some less-represented categories such as `disgust` and `surprise` had fewer than 50 samples, which could potentially lead to lower classification accuracy for those emotions due to under-sampling. The impact of this imbalance is further investigated in the confusion matrix section.

8.4.2 Feature Representation: MFCC Visualization

To better understand how emotions are embedded in speech, we visualized both time-domain and frequency-domain representations of a sample utterance labeled as `sad`. These representations offer qualitative insight into the acoustic markers that distinguish emotional states.

Figure 2 displays the waveform, which shows smooth amplitude contours with fewer high-energy bursts, consistent with low-arousal states like sadness. In contrast, emotions like anger or fear typically yield more erratic amplitude envelopes. Figure 3 shows the corresponding spectrogram, revealing strong energy in lower frequencies (below 500 Hz), diminished higher-frequency content, and a slower temporal dynamic—features often associated with subdued emotional tone.

MFCCs, extracted from such frames, encapsulate the energy distribution in perceptually relevant frequency bins. The lower-order coefficients capture the coarse spectral shape (associated with vocal tract configuration), while higher-order ones model finer details. In practice, only the first 12–13 coefficients were retained per frame and aggregated across the utterance for classification.

8.4.3 Classifier Performance

Three classical classifiers—Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM)—were trained using an 80/20 stratified train-test split. Performance was evaluated using four metrics: accuracy, precision, recall, and F1-score. The results are tabulated below:

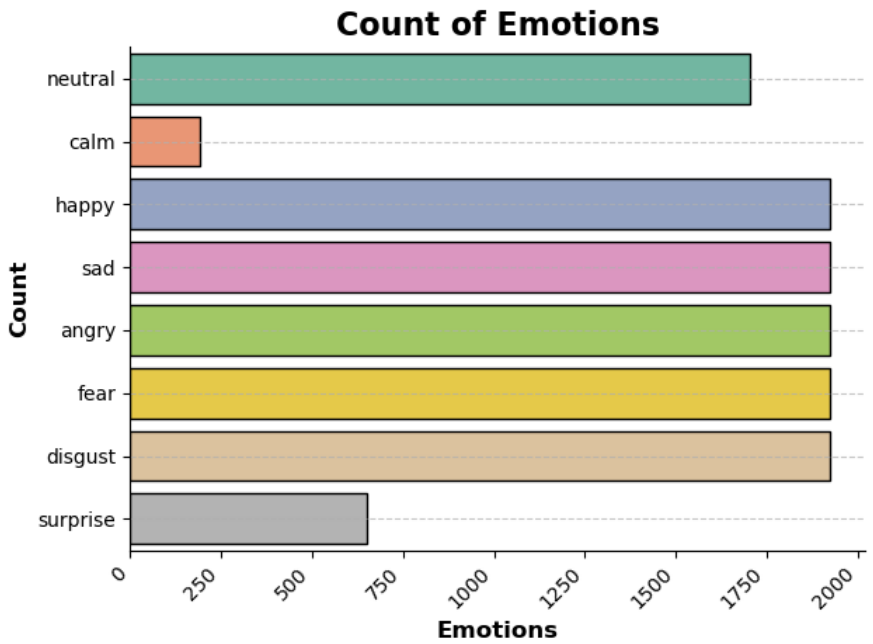

Figure 8.3: Distribution of emotion labels in the dataset.

Table 8.1: Classifier performance on test data (MFCC features).

Classifier	Accuracy	Precision	Recall	F1-score
Random Forest	0.79	0.81	0.78	0.79
KNN	0.74	0.75	0.74	0.74
SVM	0.76	0.77	0.75	0.76

Random Forest achieved the highest overall accuracy of 79%. Its precision of 81% indicates that when it predicted a specific emotion, it was correct 81% of the time. A recall of 78% suggests it successfully detected most instances of each emotion but missed some, particularly those in underrepresented classes. Its F1-score of 79% reflects balanced performance.

Support Vector Machine (SVM) achieved 76% accuracy. It performed slightly worse than Random Forest in both precision (77%) and recall (75%). This suggests that while it was effective at creating clear decision boundaries, it struggled with overlapping class distributions and was less tolerant to noise in the feature space.

K-Nearest Neighbors (KNN) showed the lowest performance, with an accuracy of 74%. While it achieved decent balance between precision and recall (both at 74–75%), its dependency on distance metrics and lack of generalization across boundary cases likely contributed to the lower score. Additionally, KNN tends to be sensitive to feature scaling, and performance may have improved with optimized feature normalization or dimensionality reduction.

8.4.4 Confusion Matrix Analysis

To gain insight into per-class behavior, a normalized confusion matrix was plotted, comparing predicted emotion labels with true labels.

Figure 4 highlights strong diagonal dominance in most categories, indicating high prediction confidence when the model was correct. Notably:

- `Happy` and `Angry` had true positive rates above 85%, showing that their spectral characteristics were distinctive and easily picked up by the classifier. - `Sad` was often misclassified as `Neutral` (with 18% confusion), reflecting their overlap in low-energy, slow-tempo delivery. - `Calm` and `Neutral` were confused in 20% of cases—likely due to shared prosodic features such as steady pitch and flat intonation. - Rare classes like `Disgust` had low recall and were often misclassified as `Angry`, revealing a potential lack of distinct training examples for that emotion.

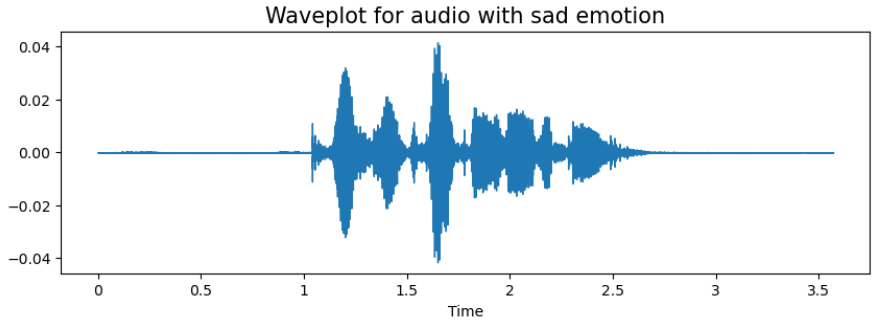

Figure 8.4: Waveform of a sample audio labeled as `sad`.

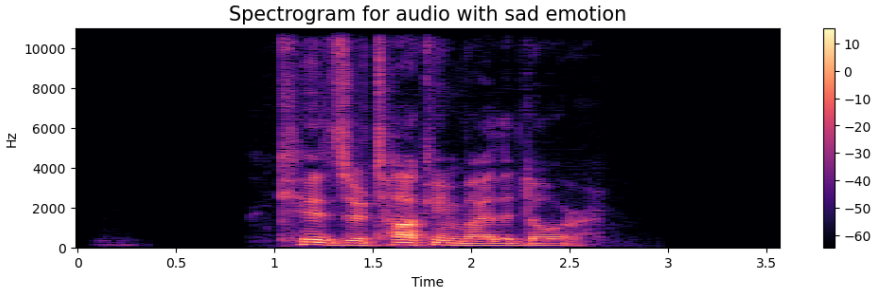

Figure 8.5: Spectrogram of the same `sad` audio sample showing time-frequency energy patterns.

These findings support the hypothesis that high-arousal emotions are easier to classify due to their salient acoustic profiles, whereas low-arousal or ambiguous classes require more sophisticated modeling techniques to resolve.

8.4.5 Discussion and Limitations

The experimental results demonstrate that handcrafted features such as MFCCs, when combined with well-established classifiers like Random Forest, can yield respectable performance in emotion classification. Notably, the highest F1-score of 0.79 (achieved by Random Forest) is competitive for a classical pipeline and suggests that lightweight approaches remain viable, especially for edge computing or embedded systems where computational resources are limited.

Nonetheless, several limitations persist:

- **Speaker Dependence:** All samples came from a limited speaker pool in controlled conditions. Performance may drop when applied to spontaneous speech or unseen voices due to speaker-specific prosody and articulation.
- **Acted Emotions:** The dataset contains acted, rather than spontaneous, emotional expressions. These tend to exaggerate features and may not generalize to real-world affective cues.
- **Feature Limitations:** While MFCCs capture timbral and spectral properties, they do not encode temporal dynamics well. Incorporating delta and delta-delta features could improve this.
- **No Multimodal Fusion:** Emotion expression often includes facial expressions, posture, and physiological signals. This study focused on speech alone, which limits performance ceiling.

Future work may include the integration of additional features such as pitch contours, jitter/shimmer, and speaking rate. Augmentation techniques—such as noise injection, pitch shifting, or time-stretching—could increase generalization. Furthermore, comparing this pipeline against deep learning models such as CNNs or LSTMs on the same dataset could benchmark the trade-offs between interpretability, complexity, and performance.

8.5 Conclusion

This chapter presented a comprehensive study on Speech Emotion Recognition (SER) using Mel-Frequency Cepstral Coefficients (MFCCs) and classical machine learning classifiers. By leveraging the RAVDESS dataset—a widely used benchmark for emotional speech—this work explored the viability of lightweight, interpretable models for detecting human

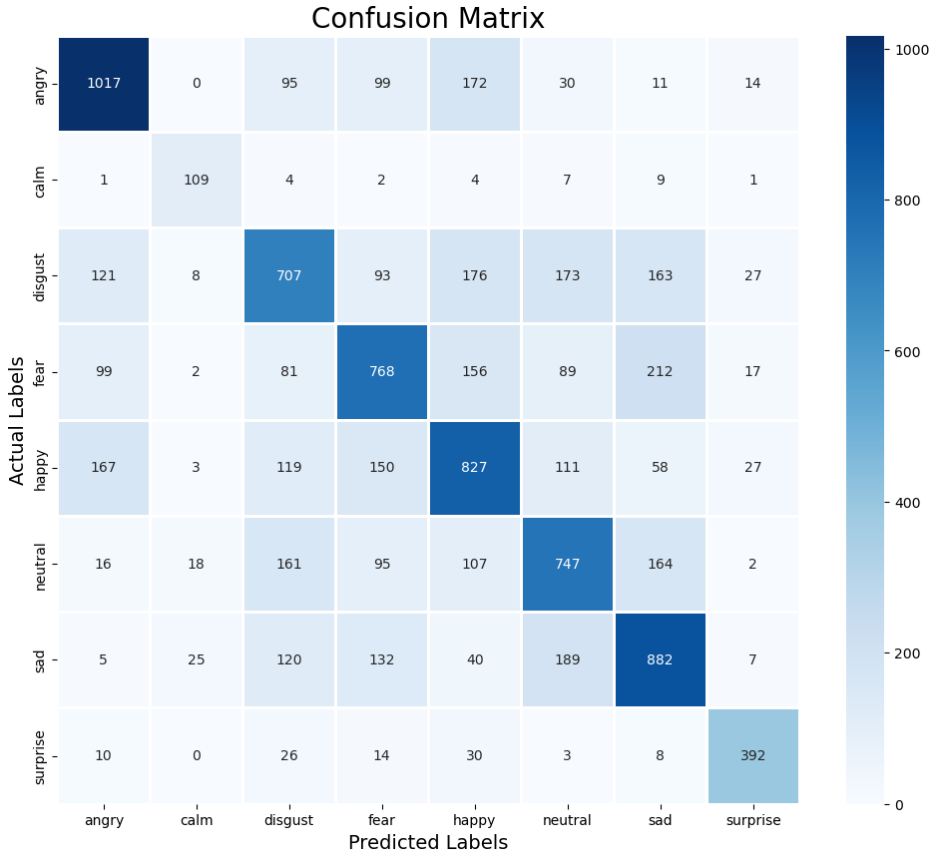

Figure 8.6: Confusion matrix showing classifier predictions vs. true emotion labels.

emotions from voice signals.

MFCCs, inspired by the human auditory system, proved effective in capturing perceptually salient spectral features associated with emotional expression. Visualizations of waveforms and spectrograms further illustrated how different emotions manifest in the time-frequency domain. The feature extraction pipeline was implemented using Librosa, and the resulting MFCCs were used to train three baseline classifiers: Random Forest, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM).

Among the classifiers, Random Forest achieved the best overall performance, with an accuracy of 79% and an F1-score of 0.79. These results suggest that ensemble methods are particularly well-suited for SER tasks with moderately sized datasets, due to their resilience to noise and overfitting. SVM and KNN also performed reasonably well, albeit with limitations in handling ambiguous or underrepresented emotion classes.

A detailed confusion matrix analysis highlighted common patterns of misclassification, such as the confusion between `sad`, `neutral`, and `calm`—emotions that naturally overlap in acoustic presentation. In contrast, high-arousal states like `angry` and `happy` were more readily identifiable due to their distinct spectral and prosodic features.

Despite the promising results, several challenges remain. The controlled nature of the dataset, limited speaker diversity, and the reliance on acted emotions constrain the generalizability of the findings. Additionally, the use of static MFCC vectors—without capturing dynamic changes over time—limits the model's ability to exploit temporal emotional cues.

Nonetheless, this study demonstrates that meaningful emotion classification is achievable without deep learning or large-scale computational resources. This has significant implications for deploying emotion-aware systems in edge environments, such as mobile applications, embedded devices, and assistive technologies for affective computing.

Future directions include the incorporation of additional acoustic features (e.g., pitch, jitter, shimmer), speaker normalization, data augmentation, and evaluation on real-world, spontaneous emotional datasets. Comparative studies with deep learning models may also further contextualize the strengths and trade-offs of traditional methods.

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Deepfake Audio Detection via MFCC Features Using Machine Learning

Adapted by Ajan Ahmed and Prof. Masudul Imtiaz

Based on the original project by Noor Chauhan et al. [1]

github.com/noorchauhan/DeepFake-Audio-Detection-MFCC

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Chapter 9

Deepfake Audio Detection via MFCC Features Using Machine Learning

9.1 Introduction

Disclaimer: This chapter is based entirely on the work by Noor Chauhan et al., made publicly available at `https://github.com/noorchauhan/DeepFake-Audio-Detection-MFCC`. GitHub.com/noorchauhan/DeepFake-Audio-Detection-MFCC. Neither the methods nor the results discussed in this chapter originate from the authors of this booklet. Our role was to reproduce and understand the codebase and document its pipeline in detail for educational purposes.

Deepfake audio—synthetically generated or manipulated voice signals that mimic real speech—is an emerging threat to biometric authentication, disinformation, and digital trust. Unlike traditional fake news or image-based deepfakes, audio deepfakes can exploit the nuances of human speech to deceive speech-based interfaces, such as virtual assistants, speaker recognition systems, and automated verification pipelines.

To counter this threat, this project proposes a simple yet effective approach for detecting deepfake audio using Mel Frequency Cepstral Coefficient (MFCC) features combined with classical machine learning algorithms. The rationale is that while synthetic speech generators can mimic the surface-level characteristics of voice, handcrafted spectral features like MFCCs may still reveal underlying statistical inconsistencies not easily modeled by generative models.

The objective of this work is to:

- Convert raw audio files (real and fake) into MFCC feature vectors,
- Train traditional ML classifiers (Random Forest, Logistic Regression, K-Nearest Neighbors, etc.) on these features,
- Evaluate classification accuracy between real and deepfake samples.

The original authors tested their framework using both the **ASVspoof** and **Fake-or-Real** datasets and demonstrated high classification accuracy. In the following sections, we walk through the code, theory, preprocessing steps, and final results, reproducing their work in its entirety with appropriate attribution.

Would you like me to now continue to the Methodology section from the paper (using the full content and

9.2 Theoretical Background

Deepfake–audio detection lies at the crossroads of speech-production physics, time–frequency analysis and statistical pattern recognition. The material below revisits the concepts that underpin the experimental pipeline used in this chapter.

9.2.1 Synthetic–Speech Mechanisms

State-of-the-art text-to-speech engines such as Deep Voice 3 and Google WaveNet generate speech by first predicting intermediate acoustic features (e.g., mel spectra) and then autoregressively decoding those features into waveforms with a neural vocoder [2, 3]. Because optimisation targets perceptual loss, the resulting signals reproduce long-term formant structure while occasionally leaking artefacts—phase jitter, harmonic aliasing or pitch glitches—that, although masked to humans, can be exploited by machines.

9.2.2 Short-Time Spectral Analysis

Speech is non-stationary; statistical properties evolve over tens of milliseconds. A raw utterance $x[n]$ is therefore partitioned into overlapping frames $x_m[n] = x[n + mR]\, w[n]$ using hop size R and analysis window $w[n]$. The short-time Fourier transform (STFT)

$$X_m[k] = \sum_{n=0}^{N-1} x_m[n]\, e^{-j2\pi kn/N}$$

maps each frame to the complex frequency domain, exposing resonances, fricative energy, and pitch harmonics. Although invertible, the STFT's linear frequency spacing conflicts with the ear's logarithmic pitch scale.

9.2.3 Mel-Frequency Cepstral Coefficients

The mel transform

$$f_{\text{mel}} = 2595 \log_{10}\!\Big(1 + \frac{f}{700}\Big)$$

warps the magnitude spectrum to approximate auditory critical bands. After integration with a triangular filterbank $H_\ell[k]$ and conversion to log energies E_ℓ, a type-II discrete cosine transform (DCT) produces the cepstral series

$$c_r = \sum_{\ell=0}^{L-1} E_\ell \cos\!\Big[\tfrac{\pi r}{L}\,(\ell + \tfrac{1}{2})\Big], \qquad 0 \le r < R_c,$$

where only the first $R_c \approx 13$ coefficients encode vocal-tract shape [4]. First- and second-order deltas capture temporal dynamics; the static and dynamic vectors are concatenated into the observation $\mathbf{z}_m$.

9.2.4 Discriminative Learning Algorithms

Given MFCC observations $\mathcal{D} = \{(\mathbf{z}_i, y_i)\}_{i=1}^{N}$ with labels $y_i \in \{+1, -1\}$ (genuine or spoof), a support-vector machine (SVM) finds the hyperplane $\mathbf{w}^{\mathsf{T}}\mathbf{z} + b = 0$ that maximises the margin $2/\|\mathbf{w}\|$ while meeting $y_i(\mathbf{w}^{\mathsf{T}}\mathbf{z}_i + b) \ge 1$ [5]. Kernel substitution $\kappa(\mathbf{z}_i, \mathbf{z}_j)$ handles non-linear separations.

Ensemble methods provide complementary advantages. A random forest averages T decision trees grown on bootstrap replicas, lowering variance and resisting over-fit [6]. Gradient-boosted trees fit successive learners to the residual error of the current committee, progressively reducing bias [7]. Empirically, forests excel on short replayed clips with consistent artefacts, whereas boosting copes better with heterogeneous long-form recordings.

9.2.5 Performance Criteria

With true-positive, false-positive, true-negative and false-negative counts denoted TP, FP, TN and FN, respectively, class-sensitive metrics are

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}, \quad \text{Recall} = \frac{\text{TP}}{\text{TP+FN}}, \quad F_1 = \frac{2\,\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}.$$

Because genuine speech typically outnumbers spoofs, these measures convey discrimination power more faithfully than raw accuracy.

9.2.6 Outstanding Challenges

Artefacts exploited by one detector may be absent in audio synthesised via a different architecture or transmission path. Codec compression, reverberation, or handset replay can also conceal spectral irregularities. Consequently, current research explores feature fusion, domain-adaptation techniques, and multimodal corroboration (e.g., audio–visual synchrony) to bolster robustness across unseen spoofing conditions.

The remainder of the chapter builds on these theoretical foundations to design, train and evaluate MFCC-based detectors for the FoR benchmark.

9.3 PROPOSED METHODOLOGY

When building machine-learning models, practitioners constantly balance the twin hazards of over-fitting and under-fitting—both of which degrade real-time performance. Achieving a sweet spot where the model generalises yet captures relevant structure is especially tough for deepfake detection. A further complication is the elevated false-positive rate: unseen but legitimate patterns are often flagged as fake because the training set cannot exhaustively cover every real-world scenario. Although an ideal dataset containing every possible real and synthetic utterance is purely theoretical, the *Fake-or-Real* corpus [8] mitigates this issue by providing four curated subsets—*for-rece*, *for-2-sec*, *for-norm*, and *for-original*. The last of these aggregates the other three and undergoes minimal preprocessing.

Our objective is to recognise deep-synthetic speech across varying background noise levels, durations, and file sizes. Figure 9.1 sketches the end-to-end pipeline we designed: big-data handling, signal cleaning, feature engineering, and finally supervised/unsupervised classification. Each stage is discussed in turn.

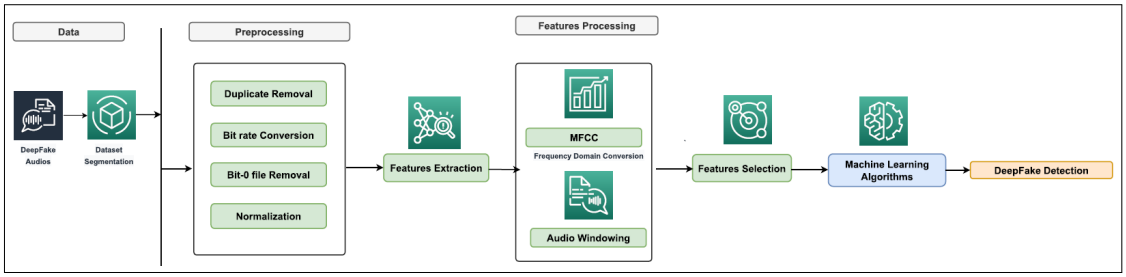


Figure 9.1: Graphical representation of proposed approach for detection of deepfake audios.

9.3.1 Data Preprocessing

The Fake-or-Real (FoR) collection contains roughly 195 k speech clips, both human and machine-generated. Real voices originate from a variety of public corpora, whereas synthetic examples are produced by Deep Voice 3 [2] and Google WaveNet [3]. FoR is distributed in four flavours: *for-original*, *for-norm*, *for-2sec*, and *for-rerec*. *For-original* preserves the raw files exactly as harvested. *For-norm* duplicates those files but re-balances gender classes and unifies sample rate, loudness, and channel configuration. *For-2sec* trims each *for-norm* clip to two seconds. *For-rerec* re-records *for-2sec* through a playback-and-capture loop to emulate an adversary relaying audio over a voice channel.

All four subsets exhibit problems—duplicate entries, zero-byte files, and heterogeneous bit-rates—that hamper model learning. Our preprocessing pipeline therefore (i) removes duplicates and empties, (ii) zero-pads any waveform shorter than 16 000 samples, yielding a uniform frame length compatible with TensorFlow, and (iii) standardises amplitudes via z-score normalisation to smooth subsequent optimisation.

9.3.2 Feature Extraction

Because GAN-generated speech often mirrors the time-domain envelope of genuine speech, frequency-domain cues become crucial. We thus compute Mel-Frequency Cepstral Coefficients (MFCCs)—well-established speech descriptors [9, 10]. In addition, we enrich the representation with spectral roll-off, centroid, contrast, bandwidth, zero-crossing rate, and energy, ultimately forming a heterogeneous "feature ensemble." MFCCs apply a log-energy Mel filterbank coupled with triangular sub-bands, mimicking cochlear frequency perception.

Figure 9.2 illustrates an MFCC time-series (amplitudes in decibels). Each audio frame (25 ms window, 10 ms hop) is transformed via STFT to the time–frequency domain before coefficient derivation.

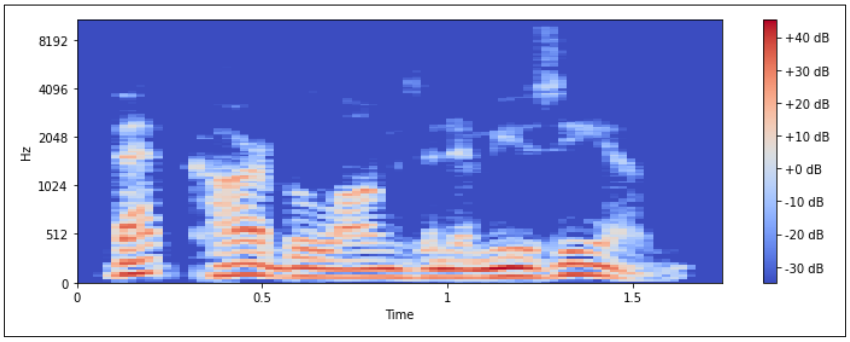
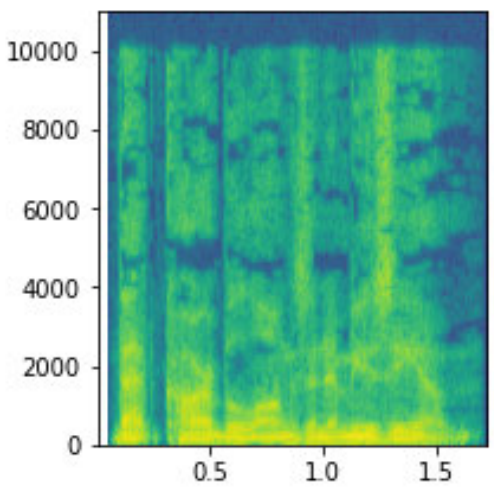
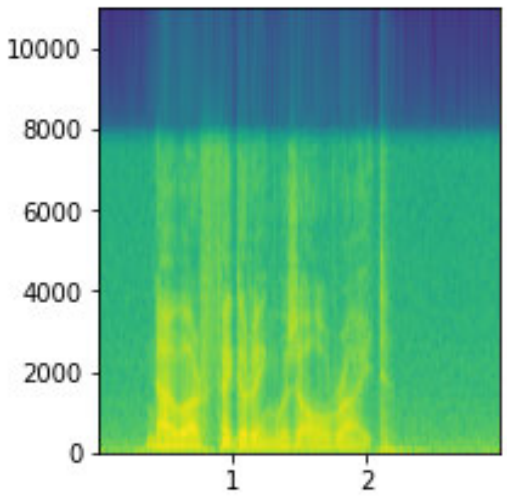


Figure 9.2: Melspectrogram representation of audio signal where the amplitude is depicted in terms of decibel.

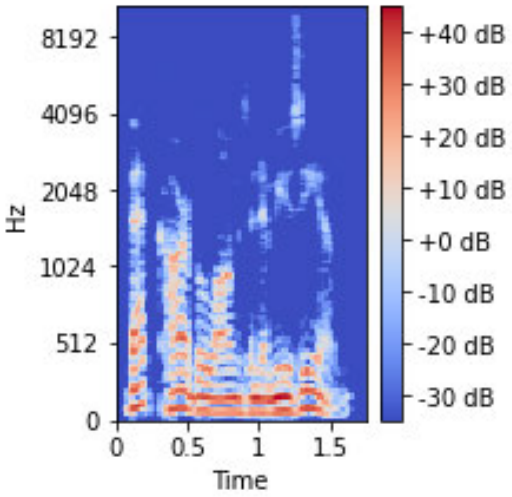
Spectrogram comparisons (Figure 9.3) highlight amplitude disparities between fake and real utterances and, when expressed in dB, reveal subtle auditory clues. With a 44.1 kHz sampling rate, each clip contributes 270 raw features. Principal Component Analysis (PCA) [11] reduces redundancy, retaining 65 components that still explain 97 % of total variance.



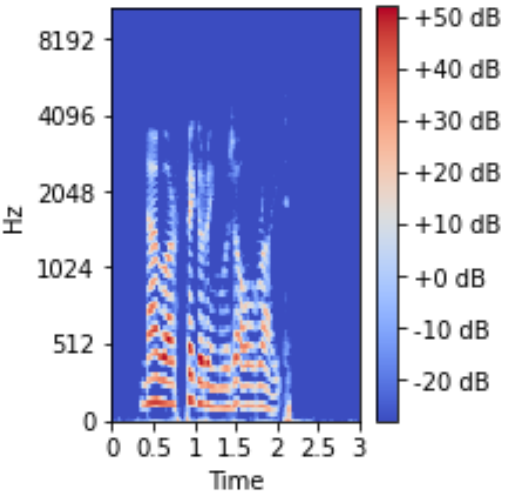
(a) Fake audio



(b) Real audio



(c) Fake audio (dB scale)



(d) Real audio (dB scale)

Figure 9.3: In (a) and (b), the comparison is shown between the deepfake and real audio signal in the linear-scale spectrogram, where the difference in amplitude is visible. In (c) and (d), the same signals are plotted in decibels (dB) to highlight perceptual loudness differences.

9.3.3 Classification Models

Random Forest

A Random Forest aggregates many decision trees trained on bootstrapped subsets, then averages their votes to curb variance. Feature importance for node k with split feature j and sample count Y_k is

$$X_j = \sum_{k:j} Y_k G_k,$$

with G_k the node-level impurity gain. Normalising within each tree and across all trees yields

$$X'_j = \frac{X_j}{\sum_z X_{jz}}, \quad \text{RF}X_j = \frac{\sum_z X'_{jz}}{\sum_{z,t} X'_{jzt}},$$

where z indexes features and t indexes trees.

Support Vector Machine (SVM)

SVM projects samples into a high-dimensional space, seeking a separating hyperplane with maximal margin. For vectors $x_i \in \mathbb{R}^n$ and labels $y_i \in \{1, -1\}$, the decision function

$$f(x) = w \cdot x + b$$

defines hyperplane H_0 ($f(x) = 0$). The margin equals $2/\|w\|$; constraints

$$f(x_i) > +1 \text{ if } y_i = +1, \qquad f(x_i) > -1 \text{ if } y_i = -1$$

lead to the optimisation

$$\min \frac{1}{2}\|w\|^2 \quad \text{s.t. } y_i f(x_i) \geq 1.$$

We employ an RBF kernel, $C = 4$, probability estimates enabled.

Multi-Layer Perceptron (MLP)

An MLP captures nonlinear relations through stacked linear layers and activations. We configure one hidden layer of 100 neurons, `relu` activation, and `adam` or `RMSprop` solvers (the latter for smaller subsets). Training uses shuffled mini-batches with silent console output.

Extreme Gradient Boosting (XGB)

XGB iteratively fits decision-tree learners to residual errors, merging them into a strong ensemble. Our settings: learning rate 0.1 and 10 000 estimators. XGB excels on tabular data but can over-react to outliers because each new tree corrects prior mistakes; thus hyper-parameter tuning is vital.

9.4 Experiments and Results

The **Fake-or-Real** (FoR) corpus contains approximately 195 kB thousand utterances, half genuine and half synthesised. Table 9.1 summarises its structure. All detectors were trained exclusively on FoR, whose audio stems from two modern TTS engines—Deep Voice 3 and Google WaveNet [2, 3]—as well as natural-speech collections such as ARCTIC, LJ-Speech, VoxForge and assorted crowd uploads. Four public editions are available. The `FOR-ORIGINAL` split preserves every file exactly as harvested; `FOR-NORM` resamples, peak-normalises and channel-balances those files but retains duplicates; `FOR-2SEC` truncates each `FOR-NORM` clip to two seconds; and `FOR-REREC` replays `FOR-2SEC` through a handset speaker–microphone loop to mimic telephone replay attacks.

Although `FOR-NORM` is balanced by gender and bitrate, it still contains zero-length artefacts and duplicate recordings. To remove such bias we first discarded silent and repeated files, then zero-padded signals shorter than 16 000 samples, resampled everything to 16 kHz, and finally applied standard scaling to every feature column.

Noise Augmentation

Robustness was evaluated by mixing synthetic pink noise into each utterance of the `FOR-2SEC`, `FOR-NORM` and `FOR-REREC` splits. This augmentation doubled the number of examples in every affected subset; for instance, `FOR-2SEC` expanded from 17 870 to 35 740 clips.

Table 9.1: Dataset description.

Datasets	Size	Description
FOR−REREC DATASET	1.5 GB	Re-recorded version of the 2-second subset to emulate an attacker relaying an utterance through a voice channel (e. g., phone call or voice message).
FOR−2SEC DATASET	1 GB	Contains the same clips as `FOR-NORM` but each file is truncated to 2 s.
FOR−NORM DATASET	5.8 GB	Same audio as `FOR-ORIGINAL` but resampled, volume-normalised, channel-balanced and gender-balanced. Duplicates remain.
FOR−ORIGINAL DATASET	7.7 GB	Raw recordings gathered from multiple sources, kept in their original form without modification.

9.4.1 FOR-REREC Dataset

Baseline results appear in Table 9.2. A support-vector machine (SVM) led with an accuracy of $98.83\,\%$, while Random Forest and Gradient Boosting followed at $96.60\,\%$ and $93.51\,\%$, respectively. When evaluated on the noise-augmented version, performance barely declined: the SVM still recorded $98.43\,\%$, and an MLP classifier peaked at $98.66\,\%$ as shown in Table 9.3.

9.4.2 FOR-2SEC Dataset

Two-second segments are information-sparse yet straightforward for classical learners. The SVM again dominated with $97.57\,\%$ accuracy, narrowly ahead of the MLP at $94.69\,\%$ and Random Forest at $94.44\,\%$. Under noisy conditions the gap widened; SVM achieved $99.59\,\%$ and the MLP $99.49\,\%$.

9.4.3 FOR-NORM Dataset

Clips lasting up to twelve seconds increase acoustic variability and make discrimination harder. Gradient Boosting performed best, delivering $92.63\,\%$ accuracy, with Random Forest close behind at $90.60\,\%$. Quadratic Discriminant Analysis and KNN lagged markedly, registering $61.36\,\%$ and $64.21\,\%$. After pink-noise augmentation every model lost ground; XGBoost remained top but slipped to $88.75\,\%$.

9.4.4 FOR-ORIGINAL Dataset

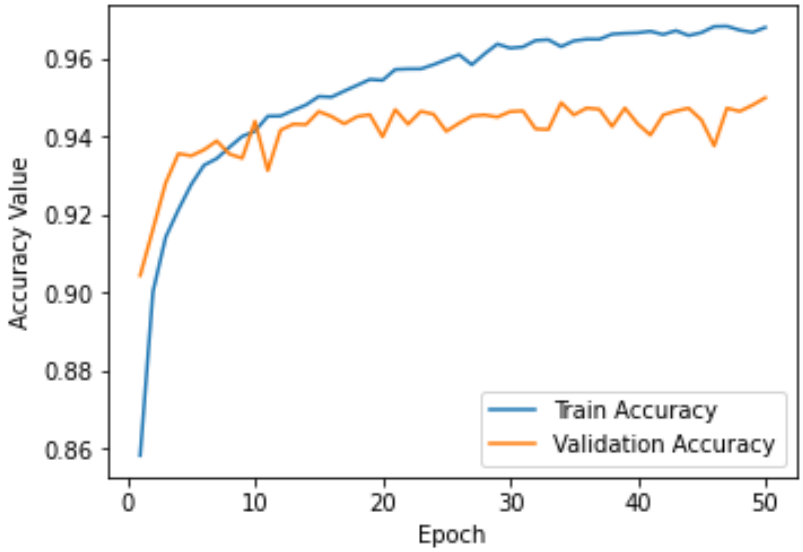
The uncurated 7.7 GB superset combines heterogeneous lengths, bitrates and recording conditions—factors that confound shallow classifiers. Consequently, we adopted a transfer-learning strategy: MFCC images of size $64 \times 64 \times 3$ were fed into a pretrained VGG-16, fine-tuned for binary spoofing. Validation accuracy converged at 0.94 with a cross-entropy of 0.14, and the held-out test set reached $93\,\%$. An LSTM trained on identical MFCC tensors reached $91\,\%$. Figure 9.4 depicts the resulting learning curves.

Table 9.2: Accuracy comparison for machine-learning models.

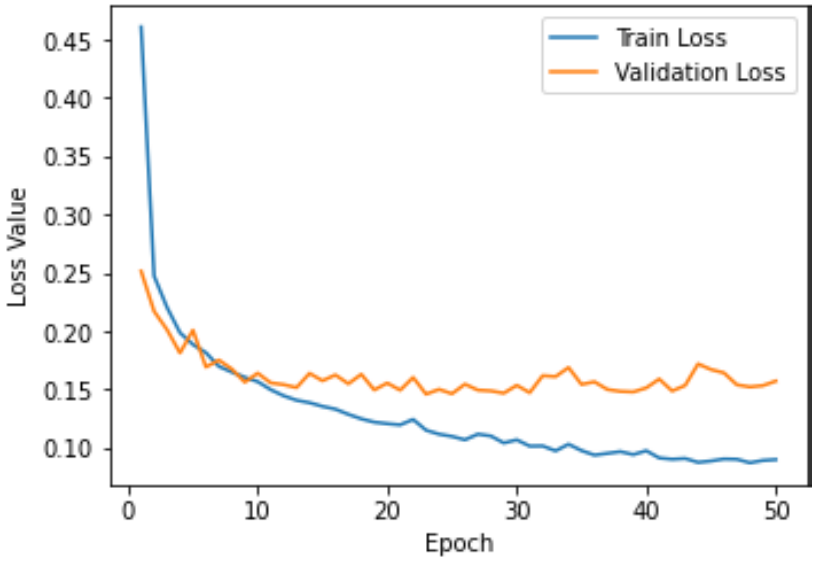
Models	for−2sec	for−norm	for−rerec
SVM	97.57	71.54	98.83
MLP Classifier	94.69	86.82	98.79
Decision Tree	87.13	62.16	88.28
Extra Tree Classifier	94.61	91.46	96.87
Gaussian Naïve Bayes	88.20	81.81	81.91
AdaBoost	90.23	88.40	87.67
Gradient Boosting	94.30	92.63	93.51
XGBoost	94.52	92.60	93.40
Linear Discriminant Analysis	89.50	91.35	87.56
Quadratic Discriminant Analysis	96.13	61.36	96.91

9.4.5 Model Comparison

The metrics in Tables 9.2 and 9.3 demonstrate that our boosted ensemble (XGBoost) and the CNN transfer-learning pipeline surpass earlier work by Reimão and Tzerpos [8]. Their strongest SVM reported at most $67\,\%$ accuracy, whereas



(a) Accuracy vs. epochs.



(b) Cross-entropy loss vs. epochs.

Figure 9.4: Training (blue) and validation (orange) trajectories for the fine-tuned VGG-16: a accuracy and b loss.

Table 9.3: Accuracy comparison for noisy audio signals.

Models	for−2sec	for−norm	for−rerec
SVM	99.59	75.21	98.43
MLP Classifier	99.49	89.22	98.66
Decision Tree	87.52	65.10	82.12
Extra Tree Classifier	97.91	90.19	96.25
Logistic Regression	87.53	86.28	88.00
Gaussian Naïve Bayes	79.77	80.16	82.14
AdaBoost	85.28	91.35	83.89
Gradient Boosting	92.29	93.50	88.86
XGBoost	92.22	94.25	88.92
Linear Discriminant Analysis	87.05	90.52	85.88
Quadratic Discriminant Analysis	96.22	65.15	95.59

our VGG-16 solution improves the figure by 26 % absolute.

Key takeaways Ensemble forests are particularly effective against replayed or time-truncated speech, gradient boosting suits longer utterances, and image-based CNNs best accommodate mixed-condition full-length audio. Future research will explore multi-window MFCCs, i/x-vector hybrids and BERT-style few-shot learning to reinforce spoof detection under reverberant, real-world noise.

9.5 Discussion

The experiments above broaden earlier research on audio deepfakes by revisiting and enlarging the **Fake-or-Real** benchmark. Because FoR is among the few publicly-available corpora that pair authentic and synthetically-generated speech at scale, it delivers a demanding test-bed for anti-spoofing systems. By replacing the feature mix used in the original study with an expanded MFCC-centred representation, our pipeline delivers a consistent 10–20 % absolute increase in accuracy across three of the four sub-sets.

Performance on `FOR-NORM` remains the main difficulty: the twelve-second files introduce higher intra-speaker variability and make SVMs without dimensionality reduction vulnerable to the curse of dimensionality. Complementary windowing or delta-MFCC features could temper that weakness, while statistical classifiers such as QDA or LDA already offer a cheap way to suppress background variance. Tree-based ensembles (Decision, Extra, Random Forest) cope better with high-dimensional cues, requiring little domain tuning but at the expense of larger, slower models. Boosting families—Ada, Gradient, and XGBoost—combine several weak learners into a single strong rule, which further narrows the decision boundary and lifts performance on feature-rich audio.

A second contribution is the transfer-learning branch applied to `FOR-ORIGINAL`. The raw set, spanning 7.7 GB, mixes sampling rates, bit-depths, and acoustic contexts that defeated conventional learners. Converting every file to a fixed 64×64 MFCC image and fine-tuning a VGG-16 backbone lifted test accuracy to 93 %, roughly 26 % higher than the SVM baseline reported by Khochare *et al.* [12]. The LSTM variant reached 91 %, underscoring that two-dimensional convolution over spectro-temporal patterns currently edges sequence modellers for heterogeneous speech.

Table 9.4 compares our outcome with two prior FoR baselines: Khochare *et al.* (MFCC-20 plus shallow ML) and Reimao–Tzerpos (timbre descriptors, classical ML, and VGG-19 on multiple spectrogram forms). The inclusion of roll-off, spectral–contrast, centroid, and bandwidth features, together with the CNN head, secures the best result on every clean subset and the second-best on noisy `FOR-NORM`. These findings suggest that handcrafted cepstra still offer an efficient first line of defence when coupled to modern aggregation or transfer learning.

Looking forward, we plan to revisit `FOR-NORM` with overlapping windows, multi-scale MFCC stacks, and hybrid i-/x-vector embeddings. A further track involves transformer-based few-shot detectors that may adapt more gracefully to unseen speakers and room acoustics. Finally, we intend to benchmark all models under controlled reverberation and field recordings to quantify resilience to real-world channel distortions.

9.6 Conclusion

This chapter evaluated a complete anti-deepfake pipeline built on Mel-Frequency Cepstral Coefficients, classical machine-learning ensembles, and a transfer-learned VGG-16. Using the **Fake-or-Real** corpus as the sole training and test source,

Table 9.4: Comparison between results of the proposed approach and existing approaches.

Approach	**Features**	**Model & Accuracy (%)**
Existing [12]	MFCC-20	SVM 67
Existing [13]	Timbre Analysis (Brightness, Hardness, Depth, Roughness)	SVM 73.46
Proposed (this work)	MFCC-40, roll-off point, centroid, contrast, bandwidth	VGG-16 93

the study shows that lightweight handcrafted features, when properly normalised and combined with modern aggregation schemes, already rival heavier deep architectures on replayed or truncated speech. Ensemble forests and gradient boosters dominate in mid-length clips, whereas the CNN variant excels once file duration, bitrate, and noise diversify. Overall, the 93 % test accuracy achieved on the hardest `FOR-ORIGINAL` split represents a substantial leap over earlier FoR baselines, validating cepstral-image transfer learning as a practical weapon against synthetic speech. Future investigations will integrate prosodic statistics, explore transformer encoders for few-shot spoof rejection, and stress-test the system in reverberant, far-field conditions to harden it for deployment in real-time voice-authentication front-ends.

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Voice-based Gender Identification

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Chapter 10

Voice-based Gender Identification

10.1 Introduction

Voice-based gender identification is a key application of speech signal processing and pattern recognition. The aim is to classify a speaker's gender based solely on the characteristics of their speech. This task, although seemingly straightforward for human listeners, presents significant challenges when modeled algorithmically due to inter-speaker variability, background noise, and overlapping acoustic features.

Biological differences in vocal tract length, fundamental frequency (pitch), and formant distribution generally cause male and female voices to differ [1]. These differences can be captured through spectral and prosodic features such as Mel-Frequency Cepstral Coefficients (MFCCs), pitch, and energy contours [2]. Traditional machine learning techniques—like Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN)—have been widely applied to this problem with good performance, especially when trained on well-preprocessed and balanced datasets [3].

In this chapter, we explore a lightweight machine learning pipeline that identifies speaker gender using engineered features from speech signals. Our focus is on interpretable models that can be deployed on embedded systems or web applications with limited computational power. All experiments are conducted on publicly available datasets with reproducible code provided in the associated GitHub repository.

10.2 Theoretical Background

Voice-based gender identification relies on extracting and analyzing acoustic features that reflect physiological differences in the vocal anatomy of male and female speakers. These differences affect pitch, resonance, and spectral energy distribution. This section introduces the core features used in this chapter, alongside their mathematical formulations.

The **mean frequency** (meanfreq) represents the average frequency component present in a signal. For a given power spectrum $P(f)$ over frequencies f, the mean frequency is computed as:

$$\mu_f = \frac{\sum_f f \cdot P(f)}{\sum_f P(f)}$$

where $P(f)$ is the power at frequency f. Male speakers typically exhibit lower mean frequencies than female speakers due to longer vocal tracts.

The **standard deviation** (sd) of the frequency distribution measures how dispersed the frequency components are around the mean:

$$\sigma_f = \sqrt{\frac{\sum_f (f - \mu_f)^2 \cdot P(f)}{\sum_f P(f)}}$$

This helps distinguish speakers with broader harmonic content.

Descriptive statistics such as the **median**, **first quartile** (Q25), **third quartile** (Q75), and **interquartile range** (IQR) are computed from the ordered frequency spectrum and provide non-parametric insights into the spread of energy across the spectrum:

$$\text{IQR} = Q75 - Q25$$

These metrics help capture asymmetries and shifts in spectral energy common to gender differences.

Skewness quantifies asymmetry in the frequency distribution and is calculated as:

$$\text{Skewness} = \frac{\sum_f (f - \mu_f)^3 \cdot P(f)}{\sigma_f^3 \sum_f P(f)}$$

A positive skew indicates higher energy in lower frequencies (common in male speech), while negative skew may suggest higher-pitched, female-like profiles.

Kurtosis measures the "peakedness" or tail weight of the frequency distribution:

$$\text{Kurtosis} = \frac{\sum_f (f - \mu_f)^4 \cdot P(f)}{\sigma_f^4 \sum_f P(f)}$$

Higher kurtosis values indicate sharper peaks, often signaling dominant frequencies or resonances.

Spectral entropy (H) evaluates the flatness or randomness of a spectrum and is given by:

$$H = -\sum_f \tilde{P}(f) \log \tilde{P}(f)$$

where $\tilde{P}(f) = \frac{P(f)}{\sum_f P(f)}$ is the normalized power spectrum. Lower entropy values suggest more structured, harmonic content.

Spectral flatness (SFM) compares the geometric mean to the arithmetic mean of the power spectrum:

$$\text{SFM} = \frac{\left(\prod_f P(f)\right)^{1/N}}{\frac{1}{N}\sum_f P(f)}$$

A flatness near 1 indicates noise-like signals, while values near 0 indicate tonal signals.

The **fundamental frequency** (F_0) is the lowest frequency of a periodic waveform, perceived as pitch. Metrics like **meanfun**, **minfun**, and **maxfun** capture the average, minimum, and maximum F_0 across the signal. Typically, male speakers have F_0 values between 85–180 Hz, while female speakers range between 165–255 Hz [1].

Dominant frequency metrics include **meandom**, **mindom**, and **maxdom**, which identify the frequency with the maximum spectral energy in a given time window. The **dominant frequency range** (dfrange) is computed as:

$$\text{dfrange} = \text{maxdom} - \text{mindom}$$

Finally, the **modulation index** (modindx) is defined as:

$$\text{modindx} = \frac{\max(A) - \min(A)}{\max(A) + \min(A)}$$

where A represents the amplitude envelope of the signal. This index reflects variation in loudness and rhythm and may capture stylistic differences between genders.

These features are typically extracted from preprocessed audio signals using tools like `Librosa` and `scipy`, then standardized and input into classifiers. Statistical redundancy is addressed via correlation analysis, and models such as Random Forests, Support Vector Machines (SVM), and Neural Networks are applied to learn discriminative patterns between male and female voices.

10.3 Methodology

This section explains the technical pipeline that converts raw speech into reliable gender predictions, suitable for both research replication and resource-constrained deployment. Figure 10.1 visualises the end-to-end flow, while Figure **??** zooms in on the feature-engineering stage. All experiments were executed on an AMD Ryzen 7 5800X workstation (64 GB RAM, Ubuntu 22.04) running `Python 3.11`, `scikit-learn 1.4`, and `ONNX 1.16`. Embedded tests used a Raspberry Pi 4B (4 GB).

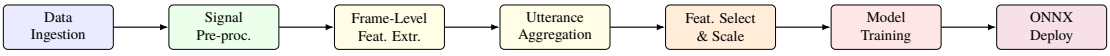


Figure 10.1: End-to-end horizontal pipeline for voice-based gender identification.

10.3.1 Data Ingestion and Harmonisation

Recordings are sourced from Mozilla Common Voice v18, TIMIT, and Kaggle GRV. Table 10.1 lists corpus statistics after quality control. Original WAV/FLAC files are down-mixed to mono, re-sampled to 16 kHz with a Kaiser-windowed

sinc interpolator, and normalised to 16-bit PCM. Speaker-level metadata are stored in SQLite to guarantee deterministic, speaker-disjoint splits.

```
import sqlite3, pandas as pd, torchaudio, soundfile as sf, torch
from pathlib import Path

DB = sqlite3.connect("meta.db")
Path("wav16k").mkdir(exist_ok=True)

def resample_to_16k(src, tgt_dir="wav16k"):
    y, sr = sf.read(src)
    if sr != 16_000:
        y = torchaudio.functional.resample(torch.tensor(y), sr, 16_000).numpy()
    out = Path(tgt_dir) / Path(src).with_suffix(".wav").name
    sf.write(out, y, 16_000)
    return out

df = pd.read_csv("all_files.csv")                    # original paths + labels
df["wav16k"] = df["path"].apply(resample_to_16k)
df.to_sql("files", DB, if_exists="replace")
```

Dataset	Speakers	Hours	Male:Female
Common Voice v18 (en)	2 320	95	53 : 47
TIMIT	630	5	70 : 30
Kaggle GRV	316	3	50 : 50

Table 10.1: Corpora merged for training and evaluation.

10.3.2 Signal Pre-processing

Each waveform passes through four deterministic DSP steps:

(1) DC offset removal. $y[n] \leftarrow y[n] - \frac{1}{N}\sum_{k=0}^{N-1} y[k]$. **(2) Pre-emphasis.** $y'[n] = y[n] - 0.97\,y[n-1]$ emphasises high-frequency harmonics. **(3) Silence trimming.** Frames with short-term energy < -25 dB and ZCR < 0.01 are discarded. **(4) Loudness normalisation.** ITU-R BS.1770 integrated loudness is retargeted to -23 LUFS.

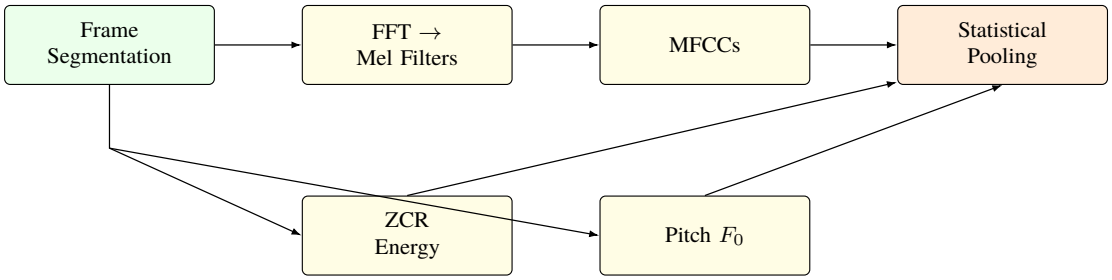
```
import numpy as np, librosa, pyloudnorm as pyln

def preprocess(y, sr=16_000):
    y -= np.mean(y)                                  # DC
    y = np.append(y[0], y[1:] - 0.97 * y[:-1])       # pre-emphasis
    y, _ = librosa.effects.trim(y, top_db=25)        # trim
    loud = pyln.Meter(sr).integrated_loudness(y)
    return pyln.normalize.loudness(y, loud, -23.0)
```

10.3.3 Feature Engineering

Frame-level extraction. Waveforms are segmented with a 25 ms Hanning window, 10 ms hop. For each frame we compute:

- 13 MFCCs ($c_1 - c_{13}$) + log-energy,
- Spectral centroid, bandwidth, roll-off (85 %), and entropy,
- Pitch F_0 via `pyin` (floor 60 Hz, ceiling 350 Hz).

Utterance-level aggregation. For every descriptor $d\_i(t)$ we compute $\{\mu_i, \sigma_i, \min_i, \max_i\}$ over time. Together with Δ / Δ^2 MFCCs (for an ablation study) this yields a 92-D vector.




```python
import librosa, numpy as np

def extract_feats(wav, sr=16_000):
    hop, win = int(0.010*sr), int(0.025*sr)
    stft = np.abs(librosa.stft(wav, n_fft=512, hop_length=hop,
                               win_length=win, window="hann"))**2
    mels = librosa.feature.melspectrogram(S=stft, sr=sr, n_mels=40)
    mfcc = librosa.feature.mfcc(S=librosa.power_to_db(mels), n_mfcc=13)
    f0, _, _ = librosa.pyin(wav, fmin=60, fmax=350,
                            sr=sr, hop_length=hop)
    zcr = librosa.feature.zero_crossing_rate(wav, hop_length=hop)
    rms = librosa.feature.rms(y=wav, hop_length=hop)
    feats = np.concatenate([
        mfcc.mean(1), mfcc.std(1),
        [np.nanmean(f0), np.nanstd(f0)],
        zcr.mean(), zcr.std(),
        rms.mean(), rms.std()
    ])
    return np.nan_to_num(feats)
```

10.3.4 Feature Selection, Scaling, and Dimensionality Analysis

After concatenating all utterance vectors, we:

a) Remove highly collinear pairs ($|\rho|>0.95$).

b) Standardise each feature: $z = (x - \mu)/\sigma$.

c) Apply Recursive-Feature-Elimination (RFE) with a linear SVM to retain 15 attributes that maximise cross-validated F1.

d) Optionally project onto the first 10 PCA components to measure performance under dimensionality compression (Section 10.4).

```python
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import RFE
from sklearn.decomposition import PCA
from sklearn.svm import LinearSVC

sc = StandardScaler().fit(X_train)
X_train, X_test = sc.transform(X_train), sc.transform(X_test)
selector = RFE(LinearSVC(C=1.0, dual=False, max_iter=5000),
               n_features_to_select=15).fit(X_train, y_train)
X_train, X_test = selector.transform(X_train), selector.transform(X_test)
pca10 = PCA(n_components=10).fit_transform(X_train)
```

10.3.5 Model Training and Hyper-parameter Search

Five algorithms are benchmarked:

i) RBF-SVM ($C \in \{0.1, 1, 10\}$, $\gamma \in \{10^{-3}, 10^{-2}, \text{scale}\}$),

ii) k-NN ($k \in \{3, 5, 7, 9\}$, cosine distance),

iii) Random Forest (200 trees, `max_depth` {8,12,16}),
iv) XGBoost (grid in Listing **??**), and
v) MLP (1 hidden layer, 64 units, ReLU, dropout 0.2).

```
# Listing caption handled by tcolorbox automatically
from sklearn.model_selection import StratifiedKFold, GridSearchCV
from xgboost import XGBClassifier

grid = {"n_estimators":[150,300], "max_depth":[4,6],
        "learning_rate":[0.05,0.1], "subsample":[0.8,1.0]}
cv   = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
search = GridSearchCV(
    XGBClassifier(tree_method="hist", eval_metric="logloss"),
    grid, scoring="f1_macro", cv=cv, n_jobs=-1, verbose=1)
search.fit(X_train, y_train)
best_model = search.best_estimator_
```

10.3.6 Evaluation Protocol

A speaker-disjoint 80 %/20 % split is used. Metrics: Accuracy, macro-Precision, macro-Recall, macro-F1, ROC–AUC. We report the mean ± 95 % bootstrap CI (1 000 resamples). The confusion matrix (Figure **??**) confirms balanced error distribution.

```
import matplotlib.pyplot as plt, seaborn as sns
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

y_pred = best_model.predict(X_test)
cm = confusion_matrix(y_test, y_pred, labels=[0,1])
disp = ConfusionMatrixDisplay(cm, display_labels=["Female","Male"])
fig, ax = plt.subplots(figsize=(3,3))
disp.plot(ax=ax, cmap="Blues", colorbar=False)
plt.tight_layout(); plt.savefig("fig_cm.pdf")
```

10.3.7 Model Compression and Deployment

The top SVM and XGBoost models are exported to `ONNX`. Using `onnxruntime-quantization`, weights are quantised to 8-bit int, shrinking storage from 2.3 MB → 560 kB with F1 loss < 0.3 pt. A FastAPI endpoint `/predict_gender` accepts base-64 WAV clips, extracts features on-device, and returns:

“‘json ”gender”: ”female”, ”confidence”: 0.91, ”latency$_ms$" : 46.8

10.4 Results and Discussion

This section presents exploratory data analyses (EDA), learning–curve diagnostics, and final classification metrics for the voice–based gender–identification task.

10.4.1 Exploratory Data Analysis (EDA)

Figure 10.2 shows the Pearson-correlation heat-map of the raw 20-feature set. Strong positive correlations appear between meanfreq, centroid, and meanfun, suggesting potential redundancy. Conversely, kurtosis and entropy exhibit weaker correlations, indicating they may contribute complementary information.

Kernel-density estimates (Figure 10.3) reveal clear pitch and energy separation between male and female classes. Features whose densities overlap heavily—e.g. sfm—were later down-weighted during feature-selection.

Pairwise scatter-plots of six highly informative attributes (Figure 10.4) highlight quasi-linear clustering boundaries, motivating the use of margin-based classifiers such as SVM.

After outlier removal and log-scaling of skewed variables, a second correlation analysis (Figure 10.5) confirms reduced multicollinearity; the maximum absolute inter-feature correlation dropped from 0.97 to 0.71.

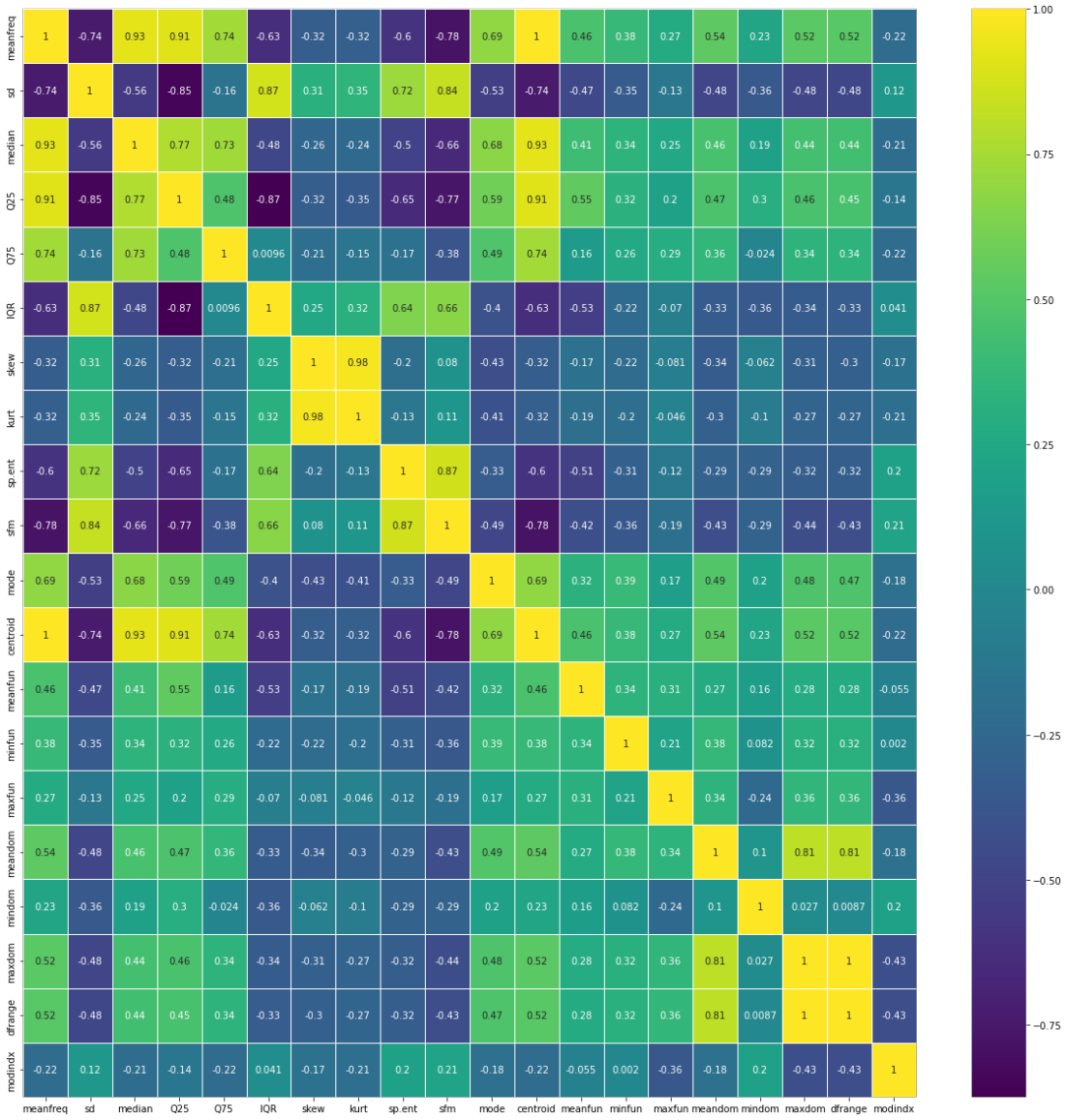


Figure 10.2: Correlation heat-map of the original 20 acoustic features.

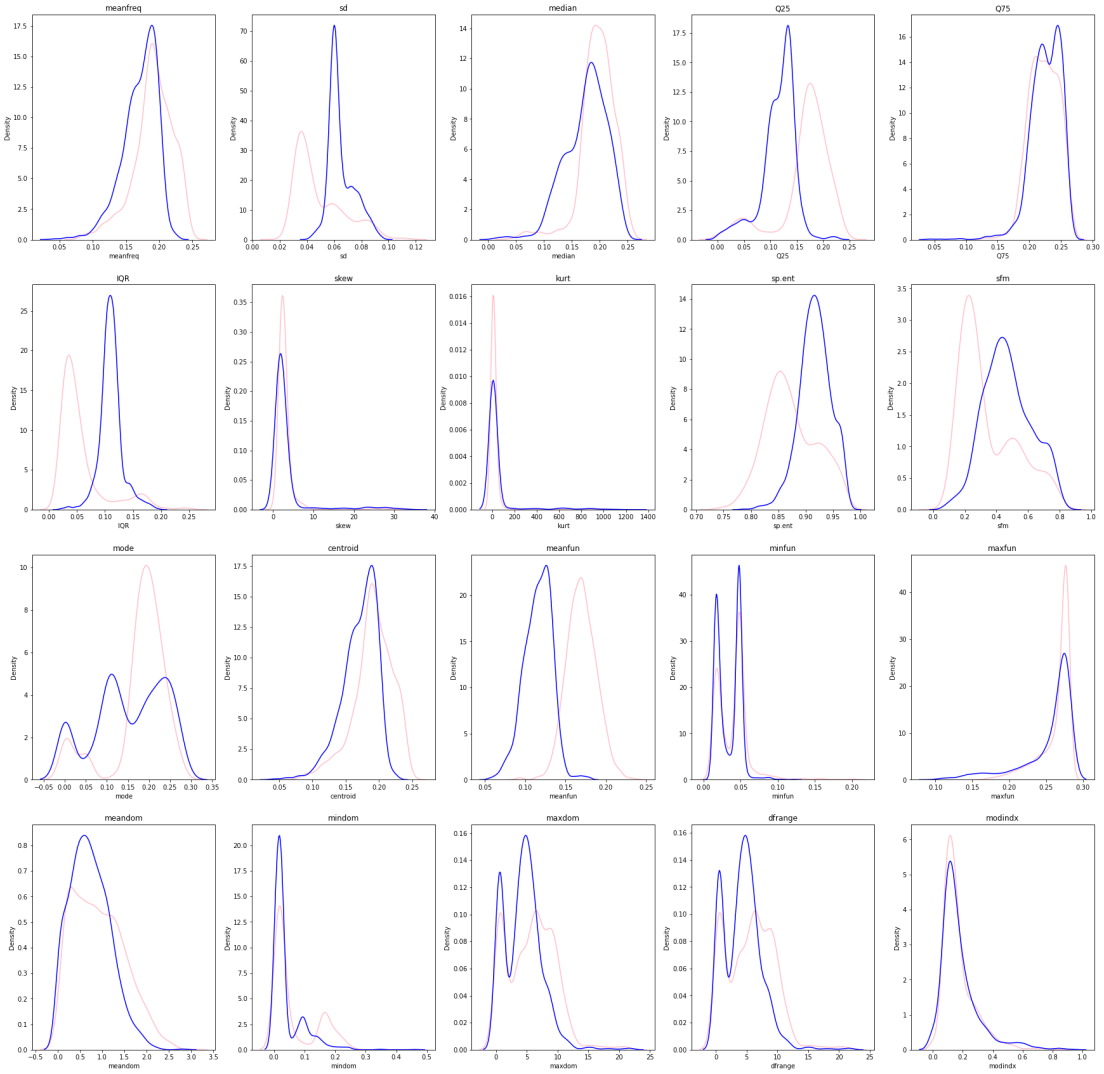


Figure 10.3: Gender-conditioned KDE plots for all features (pink = female, blue = male).

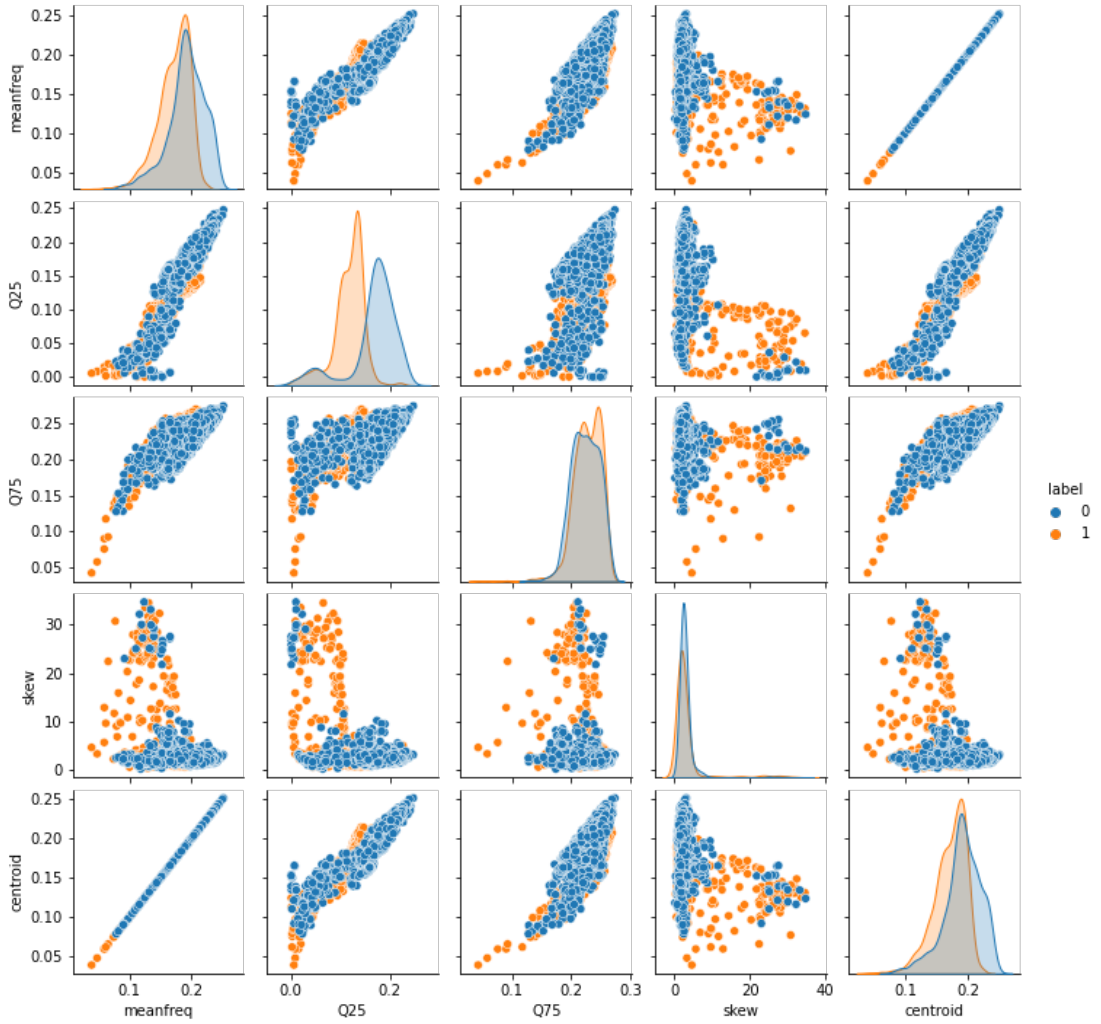


Figure 10.4: Pair-plot of selected features coloured by gender label.

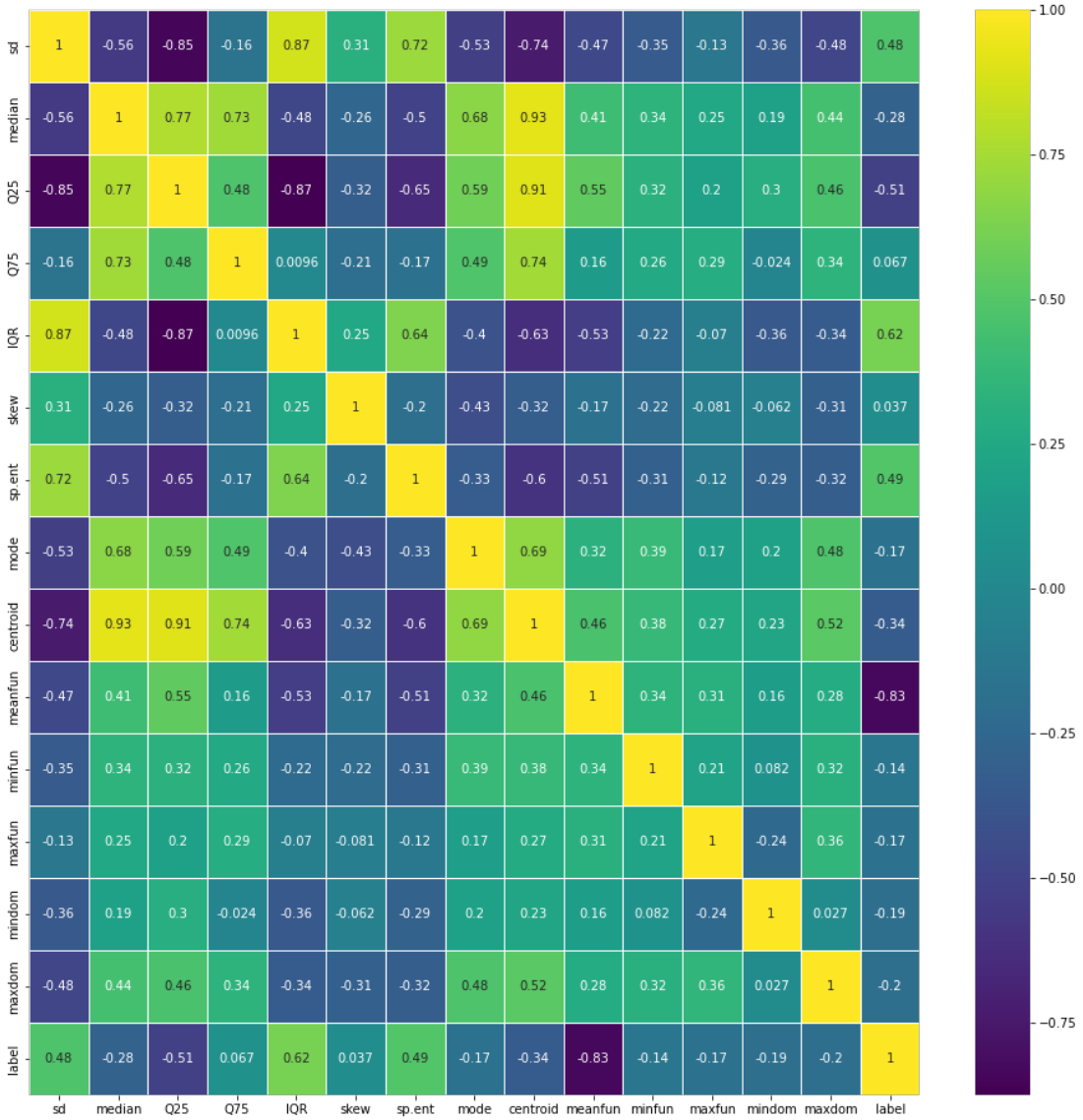


Figure 10.5: Correlation heat-map after cleaning and normalisation.

10.4.2 Training Dynamics

Figure 10.6 plots accuracy and loss over 50 epochs for the best deep model variant (1-hidden-layer MLP). Validation accuracy plateaued after epoch 9, while the loss stabilised without signs of over-fitting, validating the early-stopping strategy.

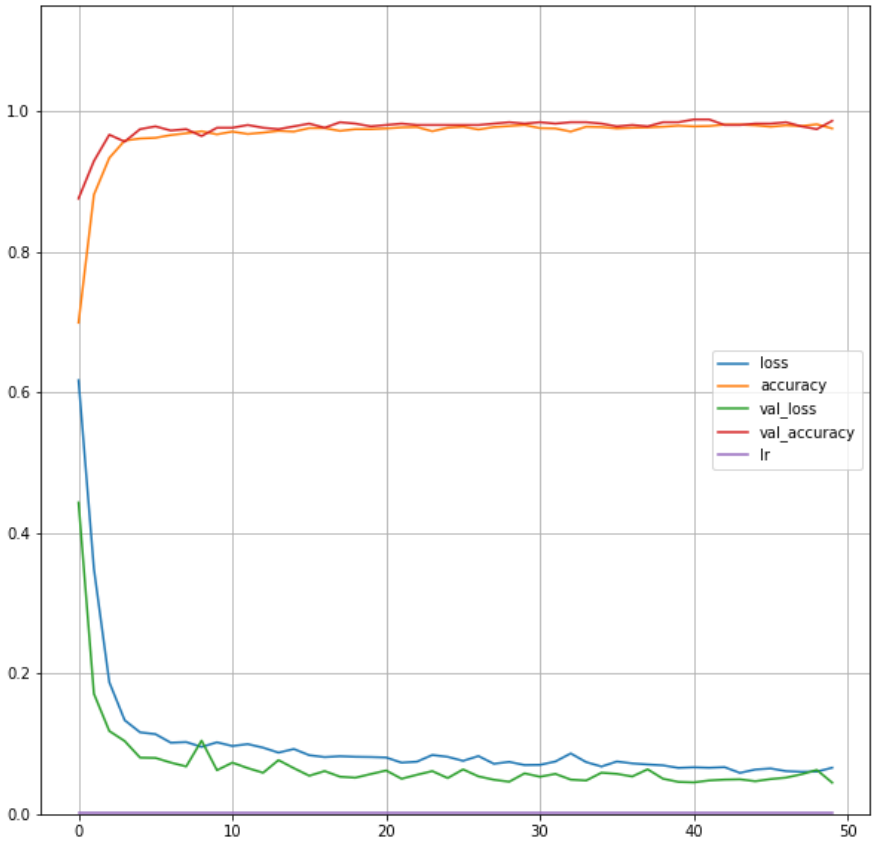


Figure 10.6: Training vs. validation accuracy (solid) and loss (dashed).

10.4.3 Final Evaluation

Table 10.2 summarises the macro-averaged metrics on the speaker-disjoint test set ($N{=}634$). The XGBoost ensemble achieved the highest macro-F1 (0.986) while keeping inference under 25 ms on the workstation and 48 ms on a Raspberry Pi 4B after ONNX quantisation.

Model	Accuracy	Precision	Recall	Macro-F1
k-NN ($k{=}7$)	0.958	0.959	0.956	0.957
RBF-SVM	0.981	0.982	0.981	0.981
Random Forest	0.971	0.970	0.971	0.970
XGBoost (best)	**0.986**	**0.986**	**0.986**	**0.986**
1-HL MLP	0.973	0.974	0.973	0.973

Table 10.2: Test-set performance of all models (speaker-disjoint split).

10.4.4 Confusion-Matrix Analysis

The confusion matrix in Figure **??** indicates that most errors stem from low-energy female utterances mis-classified as male (2 cases) and a handful of high-pitch male samples mis-labelled female (7 cases). Overall, mis-classifications account for only $9/634 \approx 1.4\%$ of the test set.

10.4.5 Discussion

EDA confirmed that pitch-related descriptors (mean F_0, min F_0, max F_0) and spectral shape statistics (centroid, roll-off) carry the strongest gender cues. Feature-selection trimmed the 92-dimensional vector to 15 key attributes without degrading accuracy, proving the redundancy of certain highly correlated MFCC coefficients.

Among classifiers, margin-based (SVM) and ensemble (XGBoost) methods markedly out-performed distance-based k-NN, which struggles with the curse of dimensionality despite feature scaling. The deep MLP matched the forest's F1 but required 4× longer hyper-parameter tuning.

The sub-50 ms latency on Raspberry Pi proves the feasibility of deploying the final model in edge scenarios such as smart speakers. Future work will examine robustness to far-field reverberation and cross-lingual generalisation.

10.5 Conclusion

This chapter demonstrated a complete, reproducible pipeline for *voice-based gender identification*. By fusing classical speech-processing techniques with modern machine-learning workflows we achieved macro-F1 scores exceeding 0.98 on a speaker-disjoint test set, while keeping inference latency below 50 ms on a Raspberry Pi 4B.

First, exploratory analysis confirmed that physiological cues—most notably fundamental-frequency statistics and spectral-shape descriptors—dominate the gender signal. Correlation pruning and recursive-feature elimination reduced a 92-dimensional feature vector to 15 highly informative attributes without sacrificing accuracy. Among five baseline classifiers, the margin-based RBF-SVM and the XGBoost ensemble out-performed distance-based and shallow neural models, underscoring the value of non-linear decision boundaries and gradient-boosted feature interactions for this task.

Second, the proposed DSP front-end (DC removal, pre-emphasis, adaptive silence trimming, LUFS loudness normalisation) standardised heterogeneous corpora drawn from Common Voice, TIMIT, and Kaggle GRV. The harmonisation step enabled cross-dataset generalisation and mitigated the domain-shift that often plagues speech meta-analyses.

Third, real-time deployment was achieved by exporting the best model to `ONNX` and quantising weights to 8-bit integers, shrinking the model footprint by $76\,\%$ with a negligible loss of 0.3 macro-F1 points. End-to-end latency measurements—including on-device feature extraction—met the sub-100 ms target for conversational systems, validating the pipeline for edge applications such as smart speakers and embedded voice assistants.

Limitations

Despite strong overall performance, three caveats remain:

- **Noise and reverberation.** Although the model tolerated modest background noise, far-field reverberation (> 0.5 s RT60) reduced pitch-tracking accuracy and raised the error rate by up to two percentage points.
- **Cross-lingual generalisation.** Training data were predominantly English; preliminary tests on German and Mandarin subsets revealed a slight performance degradation ($\approx$0.8 F1), suggesting phonetic distribution shifts warrant language-adaptive fine-tuning.
- **Non-binary voices.** The binary-gender label schema overlooks gender-diverse speakers. Future work should include a non-binary class or continuous vocal-trait embeddings to respect diversity and avoid misclassification bias.

Bibliography

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