Speaker Verification

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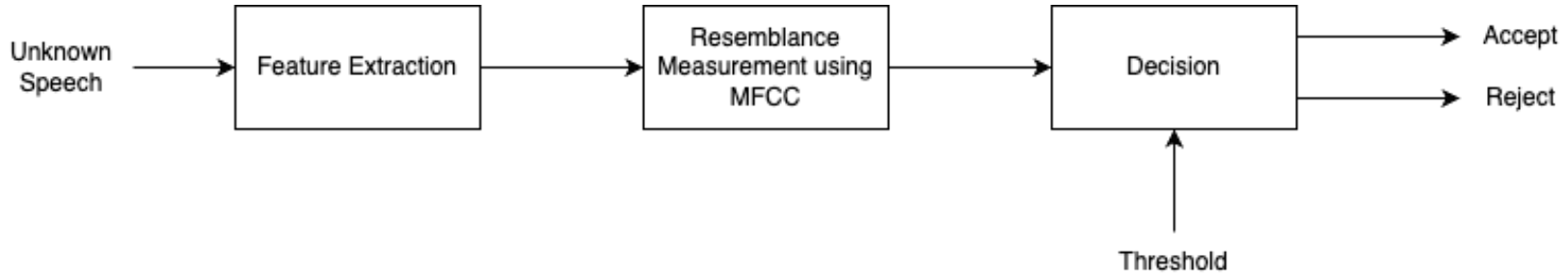
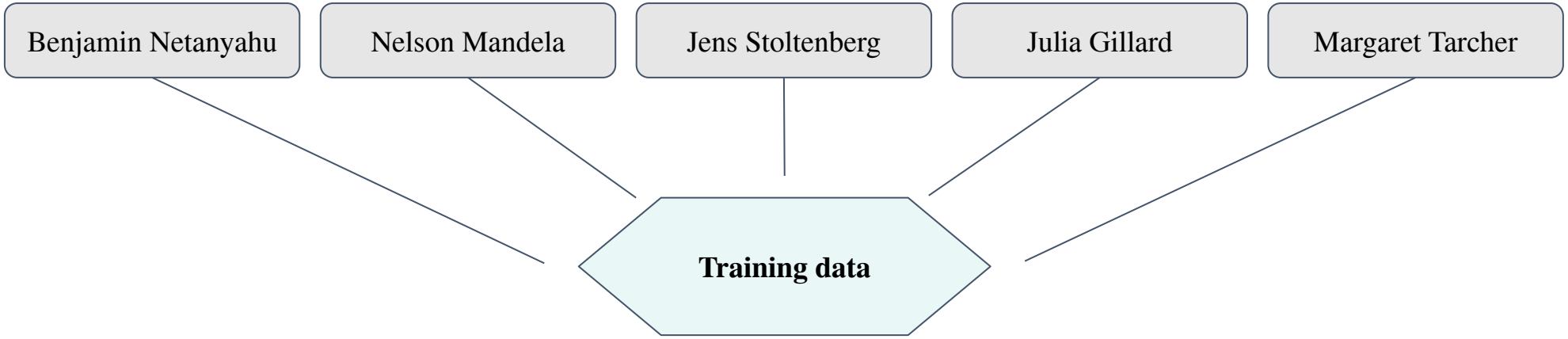
Problem Statement

- Speech recognition facilitates identity verification and access control, enabling voice-activated services. Our task focuses on Speaker Recognition, analyzing speeches by five leaders: Benjamin Netanyahu, Jens Stoltenberg, Julia Gillard, Margaret Thatcher, and Nelson Mandela.
- The challenge lies in applying Mel-Frequency Cepstral Coefficients (MFCC) and Gaussian Mixture Model (GMM) techniques to accurately identify speakers in the dataset. This contributes to the progress of speaker recognition technology, with applications in diverse fields, including security and accessibility for individuals with physical challenges.



About the Dataset

1. There are **5 speakers**, and each of their speeches has been divided into 1500 audio chunks (0.wav to 1500.wav), each lasting for **1 second** at a sample rate of 16000.



2. The **background_noise folder** consists of audio recordings that aren't speeches but capture various ambient sounds present in and around the speaker's environment, like laughter or applause from the audience. Within the **other** folder, there are additional types of noise present, such as pink noise, among others.

Exploratory Data Analysis

1. Data preprocessing :

At first, background noise was segmented into one-second chunks and integrated with speech audio using additive mixing. There is background noise in 2 folders, having audio files of different lengths. We have made one-second noise clips from the original audio file, with the same sampling rate as that of the speech files.

2. Use of ZCR over RMS for silence removal :

Utilizing Zero Crossing Rate (ZCR) thresholds instead of Root Mean Square (RMS) is crucial for accurate silence elimination in noise preprocessing. ZCR excels in distinguishing silent intervals by capturing variations in signal frequency, making it more effective than RMS. Unlike RMS, ZCR's sensitivity to signal changes ensures precise identification of speech segments, enhancing the quality of the dataset for subsequent speaker recognition tasks.

Speaker	**ZCR variance Threshold**
Benjamin Netanyahu	425
Jens Stoltenberg	500
Julia Gillard	700
Margaret Tarcher	300
Nelson Mandela	650

Methodology and Feature Extraction

3. Feature Extraction:

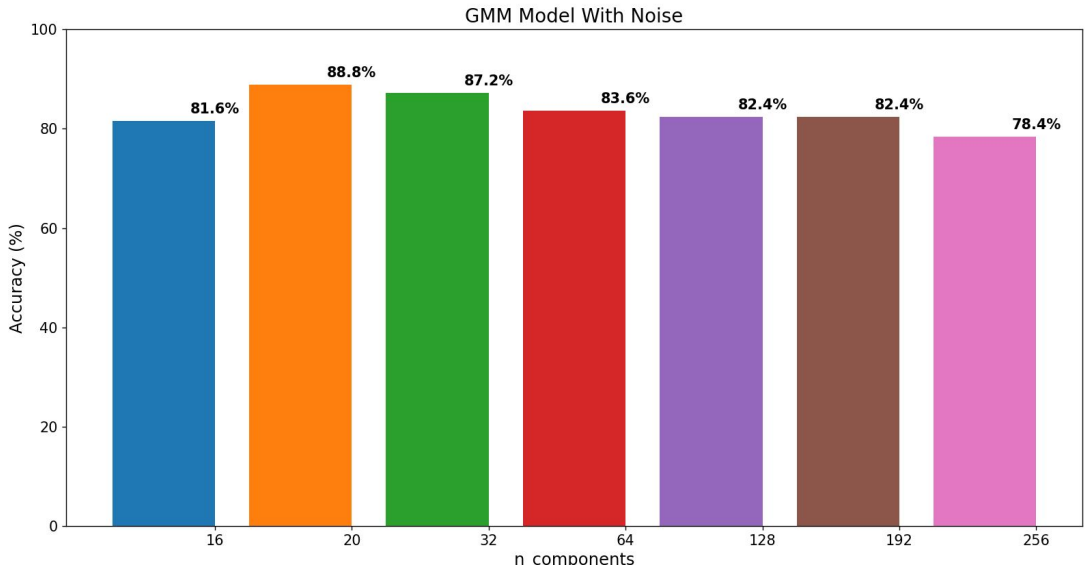
- Feature extraction involved MFCC, delta, and delta2 from audio files, supplemented by explorations of ZCR mean, ZCR variance, RMS energy, scaling, LPC, and PLP. Despite the diverse feature considerations, ZCR mean and ZCR variance exhibited limited effectiveness, while RMS, scaling, LPC, and PLP resulted in reduced accuracy, emphasizing the prominence of MFCC-based features.
- Normalization using dBFS is essential for maintaining consistent loudness across diverse audio samples. By adjusting each audio file to a target dBFS level, such as -16 dBFS, variations in loudness are standardized. This ensures a uniform and comparable representation of audio features, crucial for accurate and reliable analyses in applications like speaker recognition.

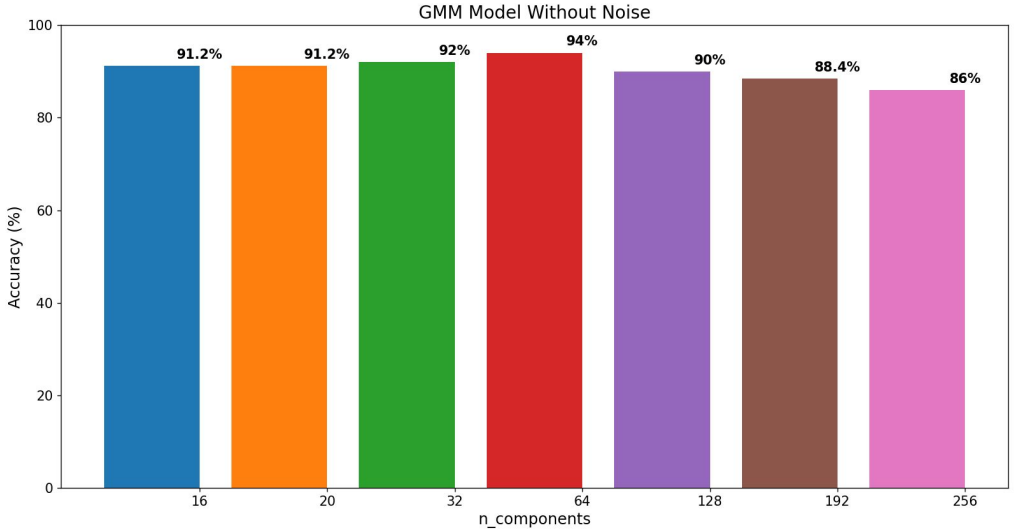
4. Model Training

- Utilizing a Gaussian Mixture Model (GMM) for speaker identification, the model underwent training with varying numbers of components (16, 20, 32, 64, 128, 192, 256) for MFCC, delta, and delta2 features. This comprehensive approach aimed to identify the optimal model configuration for accurate speaker recognition.

Results

- Among the evaluated configurations, training the Gaussian Mixture Model (GMM) **with Noise** with **n_components = 20** yielded the highest accuracy, achieving an impressive **88.8%.**



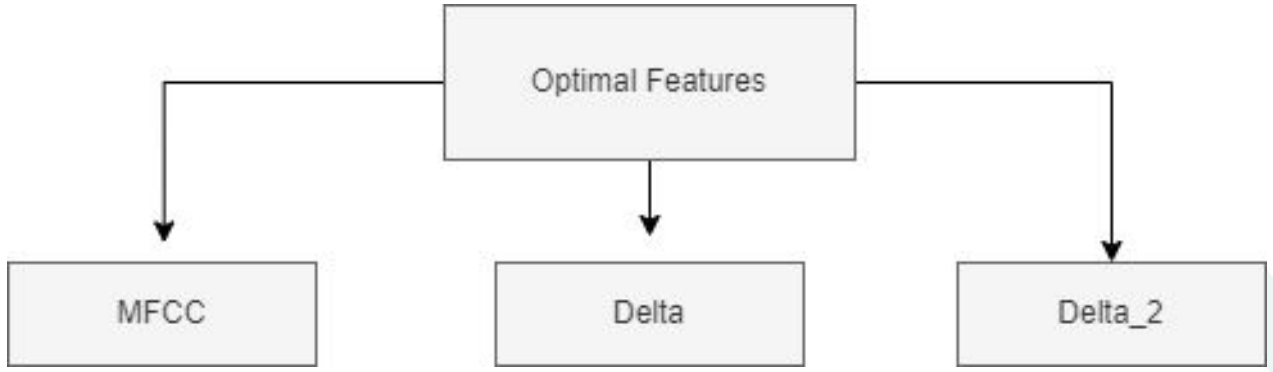


- Among the evaluated configurations, training the Gaussian Mixture Model (GMM) **without Noise** with **n_components = 64** yielded the highest accuracy, achieving an impressive **94%.**

Conclusion

- The experimentation revealed that despite exploring various features, including RMS, ZCR variance, ZCR mean, log energy, delta log energy, LPC, PLP, MFCC, delta, and delta2, the trio of **MFCC, delta, and delta2** emerged as the most effective for achieving high accuracy in speaker recognition.

- These features demonstrated their sufficiency in capturing distinctive speaker characteristics, underscoring their robustness and practicality in the task, simplifying the computational complexity without compromising accuracy.



Comparison with Existing Analysis

- **Gaussian Mixture Models (GMM)** with Mel Frequency Cepstral Coefficients (MFCC), delta, and delta2 have proven to be a robust and well-established method for text-independent speaker recognition. In scenarios where there is no prior knowledge of the spoken content, GMMs have emerged as the most successful likelihood function.

- In contrast, text-dependent speaker recognition scenarios benefit from incorporating additional temporal knowledge using **hidden Markov models (HMMs)** as likelihood functions. In these cases, where there is a strong prior knowledge of the spoken text, HMMs can enhance the modeling of temporal dependencies in speech, potentially improving performance

- **Likelihood Ratio Interpretation:** Utilizes LPCC, LPC, and MFCC features to calculate the probability ratio of aural differences between questioned and sample voices.
- **I-vector Technique:** Condenses GMM supervector means into a low-dimensional form, vulnerable to voice disguise, VoIP, and channel mismatch effects.

- **Support Vector Machine (SVM):** Employs SVM classifiers for pattern recognition in speaker verification, demonstrating reported recognition rates.
- **Neural Networks and Deep Learning:** Encompasses architectures like MLP, CNN, and DNN, featuring the x-vector for deep speaker embedding and achieving low Equal Error Rates (EER) in experiments.