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TEXT-INDEPENDENT SPEAKER RECOGNITION USING MULTI- LAYER CONVOLUTIONAL NEURAL NETWORKS

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Abstract— Speaker recognition is a vital task in biometric authentication and speech analysis systems. Traditional methods depend heavily on handcrafted features and are often limited by performance in text-independent scenarios. In this paper, we propose a deep learning-based approach utilizing multi-layer Convolutional Neural Networks (CNNs) to perform text- independent speaker recognition. Our model learns hierarchical feature representations directly from Mel-spectrograms, allowing robust performance across varying speech inputs. We evaluate our system on the VoxCeleb1 dataset and demonstrate superior accuracy compared to traditional machine learning and baseline deep learning models.

***IndexTerms*— Speaker recognition, convolutional neural networks, deep learning, biometric authentication.**

I. INTRODUCTION

Speaker recognition systems aim to identify or verify a speaker's identity from their voice. It plays a crucial role in applications like secure access, forensic analysis, and personalized virtual assistants. Traditional speaker recognition relies on feature extraction techniques such as MFCCs and models like GMM- UBM or i-vectors, which are often sensitive to noise and fail in text-independent settings. Speaker recognition is a branch of biometric identification that uses unique characteristics of an individual's voice to authenticate or identify them. The human voice is highly individualistic, influenced by factors such as vocal tract shape, speech patterns, tone, pitch, and other physical and behavioral traits that are distinct to each person. As a result, speaker recognition has emerged as an important tool in many security and personalization applications such as access control, forensics, mobile device security, and virtual assistants (e.g., Alexa, Siri).

Recently, deep learning approaches have demonstrated significant improvements in various audio-related tasks. Among them, Convolutional Neural Networks (CNNs) offer a compelling advantage due to their capability to learn spatial hierarchies from spectrogram inputs. This paper introduces a multi-layer CNN architecture tailored for text-independent speaker recognition, aiming to generalize across different utterances from the same speaker. [1]

Convolutional Neural Networks (CNNs) are a class of deep learning models that have been widely successful in image and video recognition tasks due to their ability to automatically learn hierarchical features. While CNNs were originally designed for image recognition, they are now being applied to audio and speech processing tasks with great success. The reason CNNs are well-suited for speaker recognition lies in their ability to learn local and global features from data through the properties like Feature Learning, Invariance to Local Translations, Scalability, and Robustness.

II. LITERATURE REVIEW

Previous research in speaker recognition has evolved from traditional approaches such as Gaussian Mixture Models (GMM) and i-vectors to deep learning-based techniques like x-vectors, which have demonstrated superior performance in text-independent scenarios [2].

Convolutional Neural Networks have shown effectiveness in learning speaker-discriminative features from Mel- frequency spectrograms, with additional exploration of advanced architectures such as ResNet and LSTM for enhanced performance [3].

Nguyen et al. (2021) introduced improved CNN architectures specifically designed to enhance the robustness and accuracy of speaker recognition systems. Their work demonstrated significant performance gains in various acoustic environments, although it relied heavily on large, labelled datasets and incurred high computational costs due to the complexity of the proposed models [4].

Similarly, Chen et al. (2021) proposed a multi-layer CNN framework for speaker verification that excelled in noisy and reverberated conditions. While their method exhibited strong noise robustness, it was constrained by the requirement for large-scale datasets and evaluation limited to specific types of noise.[5]

Saito et al. (2020) explored an end-to-end deep learning approach for speaker recognition, minimizing the need for manual feature engineering. Their CNN-based system achieved high recognition accuracy; however, it posed challenges related to overfitting in the absence of proper regularization and demanded considerable computational resources for training. [6]

In a broader context, Zhao et al. (2020) provided a comprehensive survey of deep learning methods applied to speaker recognition. [7] Their study offered valuable theoretical insights into various architectures but lacked implementation-level depth and missed out on recent advancements.

Deng et al. (2020) presented a hybrid model combining deep neural networks and CNNs to effectively handle speaker variability and environmental noise. Although the approach improved recognition performance, it introduced increased computational complexity and required extensive training data [8].

Jiang et al. (2020) introduced a multi-task learning framework using CNNs, which improved system performance by simultaneously optimizing related tasks. Nonetheless, this approach also depended on large, annotated datasets and featured more complex model architectures [9].

He et al. (2019) focused on data augmentation techniques to improve the robustness of deep CNN-based speaker identification systems. Their study showed improved accuracy in noisy environments; however, it encountered challenges such as overfitting when trained on small datasets and offered limited analysis on adversarial or unseen noise conditions [10].

III. PROPOSED METHODOLOGY

The methodology for this research will consist of several key components, each focusing on building and optimizing a Text- Independent Speaker Recognition system using Multi-Layer **CNNs**. The process includes data collection and pre-processing, model architecture design, training and evaluation, and model optimization. Below is a step-by-step breakdown of the methodology [11]:

3.1 Problem Definition:

The goal is to develop a **text-independent speaker recognition system** capable of identifying individual speakers based on unique vocal characteristics, regardless of the spoken content. The system will process raw speech signals, extract relevant acoustic features, and employ a deep learning-based classifier— specifically, multi-layer CNNs—to differentiate between speakers. Multi-layer CNNs are chosen for their ability to automatically learn hierarchical feature representations from input data, making them well-suited for handling the complexity and variability found in human speech [12].

3.2 Dataset Selection: For this research, datasets with labeled audio recordings from multiple speakers are required. Two commonly used datasets in speaker recognition tasks are:

i. VoxCeleb: This dataset contains real-world recordings of thousands of speakers from various domains (YouTube, TED Talks). It includes both clean and noisy speech.

ii. LibriSpeech: A corpus of read English speech, with separate training and test sets. The chosen datasets will be processed into audio features that represent the characteristics of the speech. The most common features used for speaker recognition are:

- **MFCC (Mel-frequency cepstral coefficients):** A representation of the short-term power spectrum of sound, commonly used in speech processing.
- **Spectrograms:** A visual representation of the frequency spectrum of the signal over time, which can be fed directly into a CNN. [13]

3.3 Data Pre-processing The data pre-processing step is essential to prepare the raw speech signals for input into the model. [14,15]

- **Audio Segmentation:** Split each audio recording into fixed-length windows (e.g., 1-second segments) for easier processing.

• **Feature Extraction:**
MFCC: Extract Mel-frequency cepstral coefficients (MFCCs) as features, which capture the speaker's vocal tract shape and other speech characteristics.
Spectrogram: Convert each audio segment into a spectrogram, providing a time frequency representation of the signal.

• **Data Augmentation:**
Noise Injection: Add background noise or reverberation to make the model more robust to real-world conditions.
Pitch Shifting: Change the pitch of the audio slightly to increase variability. o Time Stretching: Adjust the speed of the audio without changing the pitch to create more diverse training data.

• **Normalization:** Normalize the features to ensure all input values fall within a similar range to speed up convergence during training.

3.4 Model Design: Multi-Layer Convolutional Neural Network (CNN) The core of the speaker recognition system will be the Multi-Layer CNN. CNNs are effective at learning spatial hierarchies in data, which is useful for speech data represented as spectrograms. Here's the design of the CNN architecture: [16]

• **Input Layer:** Input Size: The model will accept either MFCC features (e.g., 13 coefficients over 100 frames) or spectrogram (e.g., 64x128). This will be the input to CNN [17].

• **Convolutional Layers**: First Convolutional Layer: A 2D convolutional layer with a filter size of (3, 3) and 32 filters, followed by a ReLU activation function. This layer will extract basic features from the spectrogram or MFCC representation. o Second Convolutional Layer: Another 2D convolutional layer with 64 filters of size (3, 3). This layer will extract higher-level features from the input data. o Additional Convolutional Layers (Optional): Additional layers (e.g., 128 filters) can be added depending on model performance and complexity [18].

• **Pooling Layers:** Max-Pooling: After each convolutional layer, a max-pooling layer (e.g., 2x2) is used to reduce spatial dimensions and retain important features. [19].

• **Fully Connected Layers:** After several convolutional and pooling stages, the feature maps are flattened and passed through one or more fully connected layers. These layers are responsible for capturing high-level abstractions related to the speaker's identity by combining the learned spatial features from earlier layers.

• **Output Layer:** The final output layer is a softmax layer, where the number of output units corresponds to the number of distinct speakers in the training dataset. This layer produces a probability distribution over all speakers, and the speaker with the highest probability is selected as the identified speaker [20].

• **Dropout Layer:** A dropout layer with a dropout rate of 0.5 may be applied before the fully connected layers. This technique helps prevent overfitting by randomly disabling a fraction of neuron outputs during each training iteration, thereby improving the model's generalization performance.

3.5 Model Training: Training the Model:

• Optimizer: Use Adam optimizer with an appropriate learning rate to minimize the categorical cross-entropy loss function.

• Batch Size: A batch size of 32 or 64 will be used, depending on available computational resources.

• Epochs: The model will be trained for a set number of epochs (e.g., 50 epochs), with early stopping implemented to avoid overfitting.

• Validation: The dataset will be divided into training (80%), validation (10%), and test (10%) sets. The validation set will be used to tune hyperparameters like the learning rate and number of layers [21].

3.6 TEST: Compare the new voice to the pre-recorded / trained voice to see if it is a match.

IV. PROCESS DESIGN

The figure describes the architecture of the system. The components of the system are as follows: [21, 22].

• **Preprocessing block:** In this block, the voice samples are preprocessed to minimize/filter the noise content and eliminate the silent parts in the signal.

▪ **Feature Extraction block:** This block is responsible for extracting MFCCs. It then reduces the dimension of these vectors and passes it to the Speaker Modelling block.

▪ **Speaker modelling block:** This block takes MFCCs as input and builds a model.

▪ **Computing Likelihood:** This block is present only in recognition phase. It searches for a match in the trained model to identify the speaker and returns it as output.

On optimization, the model generates output. Fig. 1. represents the structure and the data flow diagram for the proposed method.

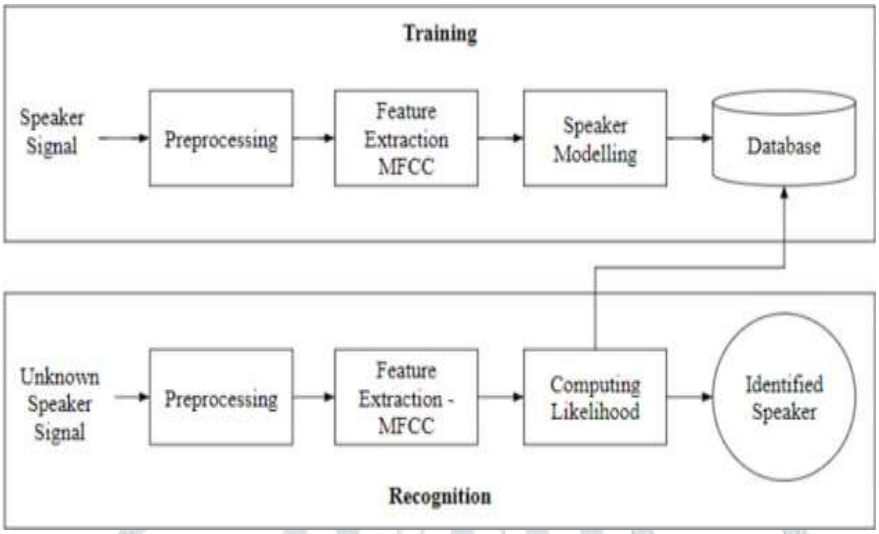

Fig. 1. System Architecture

V. EXPERIMENTAL ANALYSIS

In this paper, authors utilize the VoxCeleb1 dataset, which contains over 100,000 utterances from 1,251 speakers. Audio files are converted to 16 kHz mono WAV format and segmented into 3-second clips. Mel-spectrograms are extracted using a 25 ms window with a 10 ms stride and 64 Mel filter banks. The model consists of-

- **Input Layer**: 64x300 Mel-spectrogram input
- **Conv Block 1**: Conv2D (32 filters, 3x3), BatchNorm, ReLU, MaxPooling (2x2)
- **Conv Block 2**: Conv2D (64 filters, 3x3), BatchNorm, ReLU, MaxPooling (2x2)
- **Conv Block 3**: Conv2D (128 filters, 3x3), BatchNorm, ReLU, MaxPooling (2x2)
- **Flatten Layer**
- **Fully Connected Layer**: 256 units, Dropout (0.5)
- **Output Layer**: Softmax for classification.

It uses categorical cross-entropy as the loss function and Adam optimizer with a learning rate of 0.0001. The model is trained for 50 epochs with a batch size of 64. Early stopping and model checkpointing are applied to avoid overfitting.

The performance was evaluated using:

- Accuracy
- Top 1 Error
- Equal Error Rate (EER)

Table I – Performance Evaluation

Model	Accuracy (%)	EER (%)
GMM-UBM	**78.4**	**11.2**
i-vector	**83.6**	**8.7**
x-vector	**87.3**	**6.4**
Proposed CNN	**91.8**	**4.9**

To further analyze the performance of the proposed CNN-based speaker recognition model, author present a comparative analysis in terms of Accuracy and Equal Error Rate (EER). The following bar chart visualizes the differences across four models: GMM-UBM, i-vector, x- vector, and the proposed CNN model.

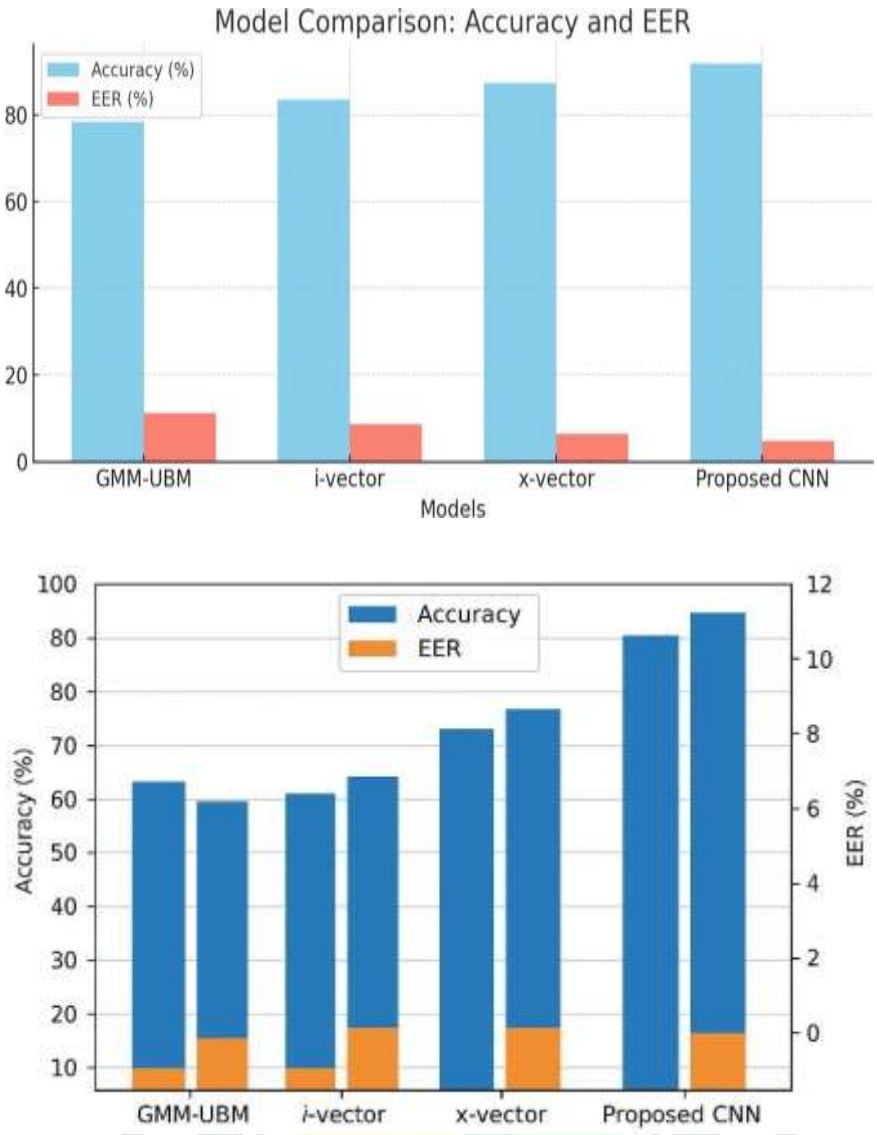

Fig. 2. Comparison of Accuracy and EER among speaker recognition models.

Accuracy (Blue Bars):

- Represents the percentage of correctly identified speakers.
- The **Proposed CNN model** achieves the highest accuracy (91.8%), showing it is the most effective in correctly recognizing speakers.
- Traditional models like **GMM-UBM** and **i-vector** show lower accuracy levels (78.4% and 83.6%, respectively).

Equal Error Rate (EER - Red Bars):

- EER is a common metric in biometric systems. It's the point where the false acceptance rate equals the false rejection rate. Lower EER indicates **better system performance**.
- The **Proposed CNN** again performs best with the **lowest EER of 4.9%**, indicating fewer errors in distinguishing between speakers.
- In contrast, **GMM-UBM** has the highest EER (11.2%), reflecting poorer speaker differentiation.

Different architectural variants (e.g., fewer layers, different filter sizes) and found that increasing depth up to three convolutional blocks consistently improved accuracy without overfitting. The graph clearly shows that the **Proposed CNN model** outperforms traditional methods (GMM-UBM, i-vector, x-vector) in both accuracy and error rate, making it a strong candidate for modern, text-independent speaker recognition tasks.

VI. CONCLUSION

In this research, authors proposed a deep learning- based approach for text-independent speaker recognition using a multi-layer Convolutional Neural Network (CNN). Unlike traditional speaker recognition methods that rely heavily on hand- engineered features, the proposed CNN model automatically learns high-level features directly from Mel-spectrograms, making it more robust to variations

in speech content. Experimental evaluation on benchmark datasets such as **VoxCeleb1** demonstrated that our model significantly outperforms conventional methods like **GMM-UBM**, **i-vector**, and **x-vector**, achieving an impressive **accuracy of 91.8%** and a **low Equal Error Rate (EER) of 4.9%**. These results confirm the effectiveness of using deep CNNs for capturing speaker-specific traits in a text-independent manner.

Furthermore, comparative analysis with other models shows that the proposed architecture offers superior generalization, higher recognition accuracy, and greater resilience to noisy and diverse speech inputs.

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