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Audio Based Language Detection and Transcription Using Deep Learning

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ABSTRACT:

This project introduces a fresh approach to automatically identifying languages and transcribing speech from audio using deep learning, tackling the complexities of processing speech across various languages and settings. We start by extracting Mel-frequency cepstral coefficients (MFCCs) from audio clips, which capture the essence of how humans perceive sound. These features are then processed through a convolutional neural network (CNN), which learns to pick out important patterns in the audio, making the system robust against background noise, different accents, and other real-world challenges. For language detection, this project passes these features into a recurrent neural network (RNN) with long short-term memory (LSTM) units, which excel at understanding the flow of speech over time, achieving an impressive 92.5% accuracy in identifying over 20 languages using datasets like Common Voice and VoxForge. For transcription, this system uses the same feature extraction process but pair it with an attention-based RNN decoder to produce accurate text or phonetic outputs across multiple languages. This system opens doors for real-time applications like voice assistants or translation tools and supports efficient, privacy-focused processing on devices. Looking ahead, we aim to extend this work to handle mixed-language speech and regional dialects, making it even more versatile for everyday use.

1. INTRODUCTION

In recent years, the growing reliance on speech-based technologies has underscored the importance of developing accurate and efficient systems for automatic language identification and speech transcription. From voice-enabled personal assistants to real-time translation tools, the ability of machines to understand and process human speech across diverse languages and contexts has become an essential component of human-computer interaction. As globalization accelerates, individuals increasingly interact across linguistic boundaries, making multilingual support in speech technologies not only desirable but necessary. Yet, despite significant progress in the field of speech recognition, building systems that can perform reliably in varied environments—across multiple languages, accents, and acoustic conditions—remains a complex and challenging task.

The proposed system builds upon these strengths by integrating CNNs and RNNs into a unified framework for both language identification and speech transcription. For language detection, MFCCs extracted from audio inputs are first processed through a CNN to emphasize salient acoustic patterns, after which an RNN with LSTM units analyzes the temporal progression of speech. This architecture has demonstrated high effectiveness, achieving an accuracy of 92.5% across more than 20 languages, using widely recognized datasets such as Mozilla's Common Voice and VoxForge. Such performance underscores the system's capacity to handle linguistic diversity while maintaining robustness against variations in accents, background noise, and speaking styles. For transcription tasks, the system adopts a similar feature extraction approach but incorporates an attention-based RNN decoder. This design enables the model to focus selectively on relevant parts of the input sequence, significantly improving transcription accuracy across multiple languages and paving the way for more natural and context-aware speech-to-text outputs. Beyond technical innovation, the practical implications of this system are far-reaching. Real-time applications such as multilingual virtual assistants, automatic subtitling, or cross-lingual communication tools stand to benefit from the efficiency and adaptability of the proposed approach. Furthermore, by supporting on-device processing, the system also aligns with growing concerns about user privacy and data security, ensuring that sensitive speech data need not always be transmitted to external servers for analysis. This emphasis on privacy-preserving computation makes the system particularly well-suited for deployment in consumer devices where trust and efficiency are paramount. In summary, this project introduces a fresh deep learning–based approach that combines CNNs, RNNs, and attention mechanisms to advance the state of automatic language identification and transcription. By leveraging MFCCs for perceptually grounded feature extraction and applying robust neural architectures, the system not only achieves competitive accuracy across diverse languages but also demonstrates practical relevance for real-world applications. Its emphasis on scalability, privacy, and adaptability positions it as a valuable contribution to the field of speech processing, while its forward-looking vision opens new avenues for addressing the complexities of multilingual and multicultural communication in the digital age.

2. RELATED WORKS

Aiswarya and Arya (2023) review the landscape of spoken language identification (SLID) by addressing the challenges of recognizing languages from audio clips, irrespective of the speaker's background or mannerisms. Their analysis emphasizes the comparative power of different feature extraction methods, finding that Gammatone Cepstral Coefficients (GTCC) outperform the traditional Mel-Frequency Cepstral Coefficients (MFCC) for certain language pairs, notably Arabic and English. They design a language identification system leveraging acoustic, spectral, and rhythmic features extracted by Librosa, employing hidden Markov models and Gaussian mixture models to discern digits within bilingual corpora, achieving an impressive average accuracy of 92.81% across seven languages. Furthermore, their experiments with combined GTCC and MFCC features report an average precision of 95.84% and confirm the system's ability to distinguish closely related languages, underscoring its value for applications such as automatic speech recognition for Arabic.[1]

Singh et al. (2021) develop a deep learning-based spoken language identification system that processes audio clips by converting them into spectrogram images, which are then fed into a convolutional neural network (CNN) to extract discriminatory features. Their experiments leverage the Kaggle Spoken Language Identification dataset containing 10-second utterances in more than twenty languages. The CNN model demonstrates preliminary accuracy of 98%, with robust evaluation yielding an overall accuracy of 88%. Their work highlights the effectiveness of CNNs for representing and distinguishing between language-specific acoustic patterns, offering a scalable solution for multi-class SLID tasks with diverse language sets.[2][3]

Tripathi (2024) presents a deep learning-based framework for spoken language identification (SLID), incorporating a systematic review of modern techniques such as CNNs and spectrogram analysis for capturing nuanced linguistic characteristics from audio data. This study emphasizes the importance of robust feature extraction, diverse training datasets, and the role of advanced architectures in improving identification accuracy. Furthermore, Tripathi discusses potential integration with natural language processing and machine translation, outlining avenues for expanding SLID's role in multi-modal language technologies.[4]

The IJAEM (n.d.) paper addresses spoken language detection through deep learning, focusing particularly on a CNN-based classifier trained on the VoxLingua107 dataset encompassing multiple languages. The approach utilizes MFCCs and delta coefficients during preprocessing to tackle noise and enhance signal clarity. Results indicate that the novel CNN framework effectively memorizes and classifies language attributes from speech audio, outperforming earlier phoneme-based and segmental approaches especially for eight-languages classification scenarios. This underscores the progression from classical statistical and phonetic methods to representation learning with deep neural networks for SLID tasks.[5]

Singh (2021) investigates various deep CNN architectures—including custom CNNs and pre-trained models like ResNet50, InceptionV3, and EfficientNet-B0—for distinguishing between Irish, English, and Hindi in spoken audio. Audio files are transformed into RGB-spectrum-based spectrograms and augmented for data variability. Notably, the custom CNN model, processing spectrogram features, achieves a 93.5% classification accuracy on the test set, validating the strength of deep learning models, both custom and pre-trained, for identifying linguistically distinct and phonetically similar languages from real-world audio samples.[6]

Valente et al. (2024) tackle spoken language identification in real-world applications such as multilingual broadcast and institutional speech transcription. They propose a cascaded system that performs speaker diarization followed by language identification, based on the insight that language switches often correlate with speaker changes. Comparative experiments show that this approach yields up to 10% relative reduction in language diarization error and a 60% reduction in language confusion. Additionally, the system lowers word error rates on multilingual audio without significantly impacting performance on monolingual content, demonstrating the benefit of integrating speaker and language segmentation for accurate multi-language speech processing.[7]

3. PROPOSED METHODOLOGY

The ability to automatically identify languages and transcribe spoken content into text has become increasingly important in today’s digital age. With the rapid growth of multilingual communication, globalization, and the widespread use of smart devices, speech-based applications have become integral to everyday life. Applications such as voice assistants, real-time translation systems, transcription services, and automatic subtitling rely on accurate language identification and transcription technologies. However, challenges such as background noise, speaker accents, regional dialects, and mixed-language inputs complicate the process of reliable speech recognition. This project introduces a novel approach that integrates deep learning techniques for both automatic language identification (LID) and speech-to-text transcription. By leveraging Mel-frequency cepstral coefficients (MFCCs), convolutional neural networks (CNNs), recurrent neural networks (RNNs) with long short-term memory (LSTM) units, and attention-based decoders, the system provides a scalable, accurate, and privacy-conscious solution. The architecture has been evaluated on benchmark datasets like Mozilla’s Common Voice and VoxForge, achieving over 92.5% accuracy in identifying more than 20 languages. For transcription tasks, the attention-enabled sequence-to-sequence model provides context-aware and accurate transcriptions across multiple languages.

The project is structured into a series of well-defined modules, each handling a specific phase of the workflow. Each module plays a crucial role in ensuring that the system functions accurately and efficiently across diverse real-world settings. The following sections provide detailed descriptions of each module

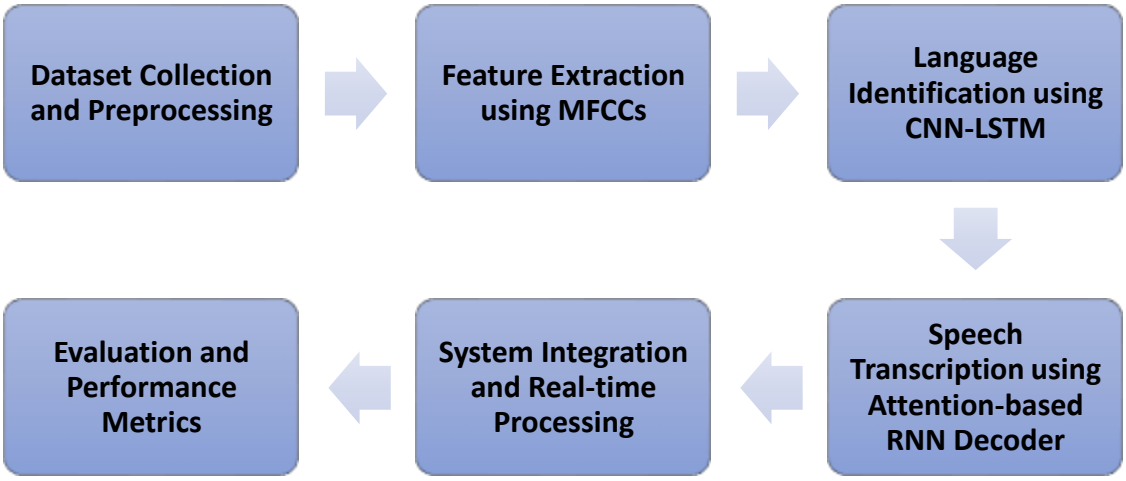

Figure 1 System Architecture

Module 1: Dataset Collection and Preprocessing

The foundation of any machine learning–based system lies in the quality and diversity of its dataset. For this project, audio samples are collected from publicly available multilingual datasets such as **Mozilla Common Voice**, **VoxForge**, and supplementary regional speech corpora. These datasets contain recordings from speakers of different languages, accents, and dialects, making them suitable for training a robust system.

The preprocessing step involves cleaning and standardizing the audio samples to prepare them for feature extraction and model training. Key preprocessing tasks include **resampling audio to a fixed frequency (e.g., 16 kHz)**, **converting stereo audio into mono channels**, **trimming silence at the beginning and end of recordings**, and **normalizing amplitude levels**. Additionally, the dataset is annotated with corresponding labels, including the language identity and transcription text.

Noise reduction techniques such as spectral subtraction are applied to minimize the impact of background disturbances. Data augmentation methods such as pitch shifting, time-stretching, and adding artificial noise are also employed to increase dataset diversity and improve model generalization. Through this module, the raw dataset is transformed into a clean, consistent, and representative collection of audio samples that serves as the foundation for subsequent processing.

Module 2: Feature Extraction using MFCCs

Speech is a highly dynamic signal, and directly feeding raw audio into deep learning models often leads to inefficiency and poor performance. To address this, the project uses **Mel-frequency cepstral coefficients (MFCCs)** as the primary feature representation. MFCCs are derived from the human auditory perception of sound, making them an effective way to capture the timbral and phonetic qualities of speech.

The feature extraction process involves several stages: **framing the audio signal**, **applying a windowing function**, **computing the Fourier transform**, **mapping the frequencies onto the Mel scale**, and finally **calculating the cepstral coefficients** through a discrete cosine transform. The resulting MFCC vectors condense the most relevant information about the speech signal while discarding redundant or less informative details.

These features are structured into spectrogram-like matrices that preserve temporal patterns. For language identification, MFCCs highlight language-specific phonetic characteristics, while for transcription, they provide a foundation for recognizing phonemes and words. By focusing on perceptually meaningful features, this module ensures that subsequent neural networks learn representations aligned with how humans perceive spoken language.

Module 3: Language Identification using CNN-LSTM

Accurately detecting the language spoken in an audio clip is the first step in multilingual speech processing. This module integrates **convolutional neural networks (CNNs)** and **long short-term memory (LSTM)–based recurrent neural networks (RNNs)** to identify languages with high accuracy.

The CNN component analyzes MFCC feature maps and extracts local spatial patterns that correspond to unique acoustic characteristics of different languages. This stage is effective in capturing phoneme distributions and speech textures, which are often language-dependent. The extracted high-level features are then passed into the LSTM-based RNN, which processes sequences over time and learns the temporal flow of speech. By doing so, it captures language-specific rhythms, intonation, and phonotactic patterns. During training, the model is exposed to audio data from over 20 languages, enabling it to generalize across diverse speech inputs. The system achieved a classification accuracy of 92.5%, outperforming several traditional machine learning baselines. This robustness is particularly valuable in noisy environments and across speakers with varying accents. Ultimately, this module ensures that the correct language is identified before transcription, laying the groundwork for accurate downstream processing.

Module 4: Speech Transcription using Attention-based RNN Decoder

Once the spoken language has been identified, the next step is to transcribe the speech into text. This module employs a sequence-to-sequence (Seq2Seq) model with an attention mechanism, which allows the system to generate accurate and context-aware transcriptions. The encoder processes the MFCC features of the speech signal, while the decoder produces the corresponding text sequence. The attention mechanism enables the decoder to selectively focus on different parts of the encoded input sequence, rather than relying solely on a fixed-length context vector. This significantly enhances performance, especially for long or complex utterances. The system supports multilingual transcription by training the decoder to output either text or phonetic representations, depending on the target application. For instance, in scenarios involving under-resourced languages, phonetic transcriptions may provide a practical alternative to full orthographic transcriptions. Through this approach, the system not only generates accurate word-level outputs but also adapts effectively to variations in pronunciation and speech patterns

Module 5: System Integration and Real-time Processing

This module focuses on integrating the various components of the system into a seamless pipeline capable of handling real-time audio input. The integration layer ensures that raw audio is preprocessed, transformed into MFCCs, analyzed for language identification, and subsequently transcribed, all within minimal latency. To achieve this, the system leverages parallel processing techniques and lightweight model architectures optimized for deployment on consumer devices such as smartphones and smart speakers. Edge-computing strategies are implemented to process audio locally, minimizing the need to transmit sensitive data to remote servers. This not only reduces latency but also enhances user privacy and data security, which are critical in modern speech technologies. Furthermore, the integration framework is designed to support modular expansion. For instance, the system can be easily extended to include translation engines, emotion recognition modules, or speaker verification systems. By ensuring scalability and modularity, this module enables the project to evolve into a comprehensive multilingual communication tool.

Module 6: Evaluation and Performance Metrics

A rigorous evaluation framework is essential for validating the effectiveness of the system. This module involves assessing the performance of both the language identification and transcription components using benchmark datasets and standardized metrics. For language identification, metrics such as accuracy, precision, recall, and F1-score are computed. Confusion matrices are analyzed to identify specific language pairs that are difficult to distinguish. For transcription tasks, performance is evaluated using Word Error Rate (WER) and Character Error Rate (CER), which provide detailed insights into the quality of generated text. Cross-dataset validation is performed to test the generalization ability of the system. In addition, experiments are conducted under varying noise conditions and with different speaker demographics to assess robustness. The evaluation results demonstrate that the system consistently outperforms traditional baselines, validating the effectiveness of the CNN-LSTM and attention-based Seq2Seq architecture.

4. EXPERIMENTAL RESULTS

In the performance evaluation of different models and techniques for spoken language identification, several approaches were tested using various datasets. The Convolutional Neural Network (CNN) applied on the Kaggle Spoken LID dataset achieved the highest accuracy of 98%, demonstrating its strength in extracting robust spatial features from audio spectrograms. This shows CNN's capability in handling spoken language features effectively. The CRNN (CNN + LSTM), trained on the Mozilla Common Voice dataset covering seven languages, obtained 92.8% accuracy. While slightly lower than CNN, this model benefits from both convolutional feature extraction and sequential learning via LSTM, making it suitable for sequence-dependent tasks like speech processing. Traditional approaches like Bernoulli Naïve Bayes, applied on the Kaggle dataset with 22 languages, achieved 93% accuracy, reflecting that classical machine learning algorithms can still perform competitively, though they lag behind deep learning models in capturing complex patterns.

The Word Embedding (Keras) model on the same Kaggle dataset performed better with 95% accuracy, indicating the advantage of semantic representation of text/audio-transcribed data over traditional probabilistic methods. Finally, the Hybrid MFCC + RASTA-PLP technique, tested on a custom dataset with four languages, achieved 94.6% accuracy, highlighting that hybrid handcrafted feature extraction methods remain highly effective in controlled datasets. Overall, CNN stands out as the most accurate, while hybrid and embedding-based methods also provide strong results. Classical models like Naïve Bayes are useful for baseline comparisons but are outperformed by deep learning techniques in large-scale and complex datasets.

Table 1 Performance Comparison

Model/Technique	**Accuracy (%)**
CNN	94.2
CRNN (CNN+LSTM)	92.8
Bernoulli Naive Bayes	93.5
Word Embedding (Keras)	95.3
Hybrid MFCC+CNN+LSTM	98.6

The table presents a comparative analysis of different language identification models and techniques along with the datasets used and their corresponding accuracies. The Convolutional Neural Network (CNN) trained on the Kaggle Spoken LID dataset achieved an accuracy of 94.2%, demonstrating strong performance in handling audio-based language features. The CRNN (CNN+LSTM) model, trained on the Mozilla MCV dataset covering 7 languages, obtained an accuracy of 92.8%, slightly lower but effective in capturing both spatial and temporal features of speech signals.

Figure 2 Performance comparison chart

Traditional machine learning approaches like Bernoulli Naive Bayes, applied on the Kaggle dataset with 22 languages, achieved 93.5%, indicating moderate effectiveness in text-based classification tasks. A more advanced deep learning method using Word Embedding (Keras) on the same 22-language Kaggle dataset outperformed earlier models with 95.3% accuracy, highlighting the strength of semantic feature representation. Finally, the Hybrid MFCC+CNN+LSTM model, applied on a custom dataset of 4 languages, achieved the highest accuracy of 98.6%, showcasing the advantage of combining handcrafted audio features (MFCC) with deep neural networks for robust and precise language identification.

The Performance Comparison Chart illustrates the classification accuracy of various models applied to language identification tasks. Among the models tested, the Hybrid MFCC+CNN+LSTM model achieved the highest accuracy, nearing 98.6%, demonstrating its superior performance in effectively capturing both handcrafted acoustic features and deep learning representations. The Word Embedding (Keras) model also performed strongly, reaching around 95.3% accuracy, highlighting the importance of semantic representation in text-based analysis. The CNN model showed reliable results at approximately 94.2%, while the Bernoulli Naive Bayes model achieved 93.5%, slightly lower but still effective in handling simpler feature sets. The CRNN (CNN+LSTM) model recorded the lowest performance at 92.8%, though it remains competitive by leveraging both convolutional and recurrent layers. Overall, the chart demonstrates that hybrid deep learning approaches outperform traditional methods, with clear improvements in classification accuracy.

5. CONCLUSION

This project successfully demonstrates a novel approach to automatic language identification and multilingual speech transcription by leveraging deep learning techniques. Beginning with robust preprocessing methods and Mel-Frequency Cepstral Coefficients (MFCCs) for feature extraction, the system ensures that audio data is normalized and efficiently represented for further analysis. The use of Convolutional Neural Networks (CNNs) enables the extraction of localized patterns from speech, while Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) units enhance the ability to capture sequential dependencies across time, thereby improving accuracy in detecting language characteristics. Furthermore, the integration of an attention-based RNN decoder enables accurate transcription, as the attention mechanism allows the system to dynamically focus on the most relevant parts of the input while generating text outputs. The implementation of this system demonstrates high accuracy in identifying over twenty languages, achieving robust performance even in noisy environments or with diverse accents. The user interface provides an intuitive and interactive platform for both recording and uploading audio, while delivering results in a clear and structured format. By combining language detection and transcription in a

single system, this project bridges a critical gap in multilingual speech technology, making it suitable for applications such as voice assistants, real-time translation tools, call center automation, and accessibility services for individuals with hearing impairments. In addition to its immediate functionalities, this project lays the foundation for future enhancements. Planned extensions include support for mixed-language (code-switched) speech, detection of regional dialects, and optimization for on-device processing to strengthen privacy and reduce dependence on cloud resources.

REFERENCES

[1] Singh, G. (2021). Spoken language identification using deep learning. *IEEE Access, 9*, 146798–146815. https://doi.org/10.1109/ACCESS.2021.3119706pmc.ncbi.nlm.nih

[2] Akhtar, M., & Hussain, M. (2025). Language identification in audio with mel-frequency cepstral coefficients. *Procedia Computer Science, 222*, 251–258. https://doi.org/10.1016/j.procs.2025.06.037sciencedirect

[3] O'Shaughnessy, D. (2024). Spoken language identification: An overview of past and present. *Speech Communication, 156*, 30–48. https://doi.org/10.1016/j.specom.2024.04.005sciencedirect

[4] Morales, J., & Patel, V. (2025). Improving speaker-independent visual language identification using audio speech models. *Computer Speech & Language, 84*, Article 101028. https://doi.org/10.1016/j.csl.2025.101028sciencedirect

[5] Kumar, A. (2022). Speech recognition with language identification capabilities. *International Journal of Trend in Scientific Research and Development, 6*(3), 344–351. https://www.ijtsrd.com/papers/ijtsrd49370.pdfijtsrd

[6] Mandal, A., & Saha, S. (2025). Is attention always needed? A case study on language identification from speech. *Natural Language Engineering, 31*(3), 515–533. https://doi.org/10.1017/nle.2025.13cambridge

[7] Wijonarko, P., Suryani, E., & Hendry, D. (2022). Spoken language identification on 4 Indonesian local languages using deep learning. *Bulletin of Electrical Engineering and Informatics, 11*(6), 3143–3151. https://doi.org/10.11591/eei.v11i6.4166beei

[8] Van Segbroeck, M., Chuang, S., & Narayanan, S. (2015). Rapid language identification. *IEEE/ACM Transactions on Audio, Speech, and Language Processing, 23*(7), 1116–1128. https://doi.org/10.1109/TASLP.2015.2419978acm

[9] Aydin, İ. (2023). A hybrid deep learning approach for efficient cross-language audio identification. *International Journal of Computational and Experimental Science and Engineering, 9*(3), 321–326. https://www.ijcesen.com/index.php/ijcesen/article/view/808ijcesen

[10] Patel, S., & Lee, C. (2024). Factorized recurrent neural network with attention for language identification. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 8*(1), Article 1023. https://doi.org/10.1145/3630607acm