A Unified CNN–BiLSTM and CNN–Transformer Framework for Speaker Recognition and Keyword Spotting

Abstract

This project investigates the integration of speaker recognition and keyword spotting into a unified speech-processing framework. The primary research question addressed is:“Can a lightweight CNN–Transformer hybrid model achieve state-of-the-art keyword spotting accuracy while remaining computationally efficient for practical deployment?”

A CNN–BiLSTM architecture is first used to perform speaker recognition, followed by a CNN–Transformer model designed for keyword spotting using the Google Speech Commands V2 dataset. Mel-spectrogram features with time–frequency masking augmentation are employed to improve robustness. The proposed keyword spotting model achieves 95.43% accuracy, outperforming standard CNN baselines and approaching the performance of more complex models such as TC-ResNet.

A sliding-window inference tool is implemented to detect keywords in recorded speech and returns both keyword identity and timestamp. Additional experiments evaluate real-world detection using a custom record-and-detect interface. The results demonstrate strong generalisation to isolated and embedded keywords, confirming the effectiveness of the hybrid CNN–Transformer architecture. The project provides a complete, deployable pipeline combining speaker identification and keyword detection suitable for intelligent speech-controlled applications.

Introduction

Speech-based human–machine interaction has rapidly expanded across smart-home devices, mobile assistants, and embedded systems. Two key components underpin these systems: speaker recognition, which determines who is speaking, and keyword spotting (KWS), which determines what is being said. Although these tasks are traditionally studied separately, integrating them can lead to more intelligent and personalized audio interfaces.

In practical scenarios, speech often contains short wake words (e.g., “yes”, “no”, “stop”) embedded within longer utterances and recorded under noisy, unconstrained conditions. This creates several challenges:

- Keywords are typically short, low-energy events, making them difficult to detect within continuous audio.
- The temporal boundaries of keywords are unknown, requiring models that can attend across time.
- Speaker variations (e.g., accent, speed, vocal characteristics) introduce additional variability.
- Real-time detection is further challenged by background noise and imperfect microphone quality.

Traditional CNN-based keyword spotting models achieve strong performance but are limited in their ability to model long-range dependencies and temporal context. Recent transformer-based architectures have demonstrated improved performance in audio modeling due to self-attention, which adaptively weights relevant time frames.

This project investigates whether a CNN + Transformer Encoder hybrid model can deliver high-performance keyword spotting, while also integrating a CNN–BiLSTM speaker recognition pipeline within a unified system. The focus is on improving detection accuracy, robustness to noise, and temporal localization of keywords.

Research Questions

To guide the investigation, the following research questions were defined:

RQ1 – Keyword Spotting Performance

Can a lightweight CNN–Transformer architecture achieve state-of-the-art keyword spotting accuracy on the Google Speech Commands dataset?

RQ2 – Temporal Detection

Can sliding-window inference accurately detect the temporal position of multiple keywords embedded within continuous speech?

RQ3 – Integration

Can keyword spotting be effectively combined with speaker recognition to

form a unified speech-processing pipeline suitable for real-world applications?

These research questions provide a clear direction for evaluating model performance, optimizing system design, and understanding the benefits and limitations of transformer-based architectures for audio.

Literature Review

Overview of Speech-Based Biometrics and Acoustic Command Systems

Speech-based intelligent systems typically involve two fundamental tasks:
(1) speaker recognition, which determines who is speaking, and
(2) keyword spotting (KWS), which determines what command is spoken.
Both tasks contribute to the broader field of intelligent acoustic interfaces widely used in smart homes, robotics, and mobile devices.

Recent progress in deep learning has significantly advanced both areas. Traditional systems relied on handcrafted audio descriptors such as MFCCs, PLPs, and GMM–UBM frameworks (Reynolds, 2000). However, modern methods increasingly use CNN, RNN, Transformer, and hybrid architectures capable of learning discriminative features directly from raw waveforms or spectrograms. This project builds upon such developments by integrating both tasks into a single unified pipeline capable of identifying both the speaker identity and the spoken keyword.

Speaker Recognition: Evolution from GMMs to CNN–RNN Hybrids

Early speaker recognition systems were dominated by Gaussian Mixture Models (GMM) and i-vector frameworks (Dehak et al., 2011). These systems extracted MFCC statistics to characterize vocal tract shapes. Although effective, they showed limitations under noisy or reverberant conditions.

Deep learning introduced substantial improvements:

- CNN models improved invariance to frequency shifts by capturing local spectral patterns (Nagrani et al., 2017).
- LSTM/RNN architectures modeled long-term temporal dependencies, improving robustness to variations in speaking style.
- CRNN and CNN-BiLSTM hybrids emerged as strong baselines by combining spatial and temporal feature learning.

These hybrid models became widely adopted due to their performance–

complexity trade-offs. For example:

- ResNet20-based speaker embedding models achieved over 95% accuracy on VoxCeleb.
- ECAPA-TDNN further improved speaker representation by channel attention and multi-scale aggregation (Desplanques et al., 2020).

This project uses a CNN-BiLSTM speaker classifier, which is computationally lightweight while maintaining high discriminative power. Literature shows that combining CNN frontends with bidirectional RNNs better captures vocal transitions, reflecting how human identity is encoded by both formant structure and prosodic cues.

Keyword Spotting: Classical Approaches to Modern Transformer-based Systems

Keyword Spotting aims to detect short trigger words such as “yes”, “stop”, or “go,” typically under real-time constraints. Classical KWS approaches included:

- HMM-based template matching (before 2010)
- DTW (Dynamic Time Warping)
- GMM-HMM hybrid recognizers

However, the breakthrough came with deep learning:

CNN-based Keyword Spotting

Google’s 2017 paper (Sainath & Parada) introduced a compact CNN architecture for the Speech Commands dataset, achieving ~91–93% accuracy with low computational cost. Subsequent models improved efficiency:

- DS-CNN (Depthwise Separable CNN) achieved high accuracy with 10× fewer parameters.
- TC-ResNet achieved >96% accuracy with temporal convolution and residual blocks.

These demonstrate that convolutional models remain strong for KWS due to:

- strong local feature extraction,
- robustness to noise,
- low inference cost suitable for edge devices.

Transformer Models for Speech Recognition

Transformer architectures (Vaswani et al., 2017) revolutionised sequential modeling by replacing recurrence with self-attention. Their ability to capture long-range global dependencies makes them ideal for speech processing tasks:

- Speech-Transformer models outperform LSTMs in ASR.
- Conformer models introduce convolution + attention hybrid structure to improve local temporal modeling.
- Lightweight Transformer encoders have recently been evaluated in KWS with promising results.

Transformers address several limitations of CNN-only KWS models:

- They incorporate global temporal context, improving detection of keywords appearing in the middle of noisy or long utterances.
- Attention heads enable the model to ignore irrelevant segments (e.g., silence or background speech).
- Multi-layer self-attention enhances boundary detection for short keywords.

Our CNN-Transformer hybrid follows this modern trend by:

- Using CNN layers for local spectral feature extraction
- Stacking 4 Transformer encoder layers for temporal modeling
- Achieving 95.43% accuracy, comparable to state-of-the-art lightweight KWS systems.

Data Augmentation and Robustness Techniques

Several works emphasize the importance of robustness due to noise and microphone variability:

- SpecAugment (Park et al., 2019) introduced time masking and frequency masking.
- Noise augmentation (white noise, real background noise) significantly improves real-world accuracy.
- Speed perturbation and pitch shifting also help generalization.

Our training pipeline includes:

- Time masking
- Frequency masking

This aligns with modern best practices to simulate real acoustic conditions and reduce overfitting.

Integration of Speaker Recognition with Keyword Spotting

Recent literature explores multi-task learning for joint speaker and keyword classification to support:

- secure command triggers (“only authorized speaker can activate command”)
- personalized voice assistants
- multi-user robot control

Although implemented the modules separately, Our architecture is conceptually aligned with this research direction.

The system provides:

- Keyword detection
- Temporal localization
- Speaker identity recognition
- Recording tool for interactive input

According to recent studies, combining these tasks improves robustness because speaker embeddings assist in interpreting pronunciation variations.

Summary of Literature Positioning

Overall, this project closely aligns with current research trends by:

Table 1. Literature Summary and Our Approach

Component	Approach	Literature Relevance
Speaker Recognition	CNN-BiLSTM	Matches hybrid CRNN literature
KWS	CNN + 4-layer Transformer	Follows modern temporal-attention approaches
Augmentation	Time/Freq Masking	SpecAugment

		principles
Detection Method	Sliding window + confidence threshold	Common in Google KWS papers
Tools	Custom recorder + timestamp detector	Practical real-world pipeline

Therefore, the system stands as a strong and contemporary implementation consistent with the latest developments in speech AI research.

Methodology

This section describes the system architecture, feature extraction pipeline, model design, training procedure, and keyword detection method.

Overall System Architecture

The complete system integrates:

1. Speaker Recognition Module
   CNN feature extractor → BiLSTM temporal encoder → Softmax classifier
2. Keyword Spotting Module
   Mel Spectrogram → CNN encoder → Transformer encoder → Classifier
3. Offline Sliding-Window Detector
   Audio input → 1-second windows every 0.3 s → Per-window prediction → Timestamp extraction
4. Press-to-Record Audio Acquisition Tool
   Microphone recording → WAV → Sliding-window KWS

Feature Extraction

The system uses a standard Mel Spectrogram front-end. Its parameters were carefully selected to align with previous KWS literature such as DS-CNN and TC-ResNet.

Table 2. Audio Feature Parameters

Parameter	Value
Sampling Rate	16 kHz
Number of Mel bands	64
FFT Size	1024
Hop Length	160 (10 ms)

Window Length	400 (25 ms)
Dynamic Range Normalization	Per-spectrogram mean/std
Augmentation	Time masking (20 frames), Frequency masking (8 bins)

Advantages:

- 64 Mel bins match Google Speech Commands benchmarks
- SpecAugment improves robustness and generalization
- Normalization reduces recording variability

Keyword Spotting Model

The KWS model is a hybrid:

1) CNN Front-end

Extracts local spectral patterns such as phoneme-like structures.

Table 3. KWS CNN Architecture:

Layer	Config
Conv1	64 → 128, kernel=3
BatchNorm + ReLU	
Conv2	128 → 128, kernel=3
BatchNorm + ReLU	
MaxPool	pool=2

CNN reduces temporal resolution by ×2 and increases channel depth.

2) Transformer Encoder

Self-attention captures long-range context, helping the model:

- detect keyword boundaries
- ignore silence
- focus on meaningful speech segments

Table 4. KWS Transformer settings:

Parameter	Value
d_model	128
num_layers	4
num_heads	4
feedforward	256
dropout	0.2
Parameter	Value

This configuration balances accuracy and computational cost.

3) Classifier

Mean Pooling → Linear(128→256) → ReLU → Dropout → Linear(256→35)

Table 5. KWS Training Configuration

Setting	Value
Optimizer	Adam
Learning rate	1e–3
Scheduler	CosineAnnealingLR
Batch size	64
Epochs	20
Loss	CrossEntropy

Cosine annealing improves training stability and final accuracy.

Sliding-Window Keyword Detection

To detect keywords inside continuous speech, the system slides a fixed window:

- Window size: 1.0 s
- Hop size: 0.3 s
- Detection rule: softmax confidence > 0.85

For each window:

1. Extract Mel features
2. Feed into model
3. Log keyword + timestamp if confident
4. Merge repeated detections into a single event

Press-to-Record Tool

The system includes a custom "press ENTER to record" tool:

1. User presses ENTER → start recording
2. Press ENTER again → stop recording
3. Audio saved to WAV
4. Automatically passed into sliding-window KWS
5. Outputs:

[timestamp] keyword (confidence)

This tool is ideal for demo and unit testing.

Results

Speaker Recognition Accuracy

The proposed CNN–BiLSTM speaker recognition model achieves a test accuracy of 95.02% on our 15-speaker dataset. This level of performance is notable because the model remains relatively lightweight while delivering accuracy comparable to deeper and more computationally expensive architectures used in recent speaker-recognition literature.

To place this result in context:

Table 6. Comparison of Speaker Recognition Models

Model	Accuracy	Notes
GMM–UBM Baseline	75–85%	Classical statistical method, low robustness
CNN Only	~92%	Spatial feature learning but limited temporal modeling
ResNet-based Embeddings (VoxCeleb-style)	95–97%	Strong but significantly heavier
Our CNN + BiLSTM Hybrid	95.02%	Lightweight, strong temporal modeling

This result demonstrates that combining convolutional layers with a bidirectional LSTM provides a substantial improvement over CNN-only architectures. The CNN extracts local spectral cues (e.g., formants and harmonics), while the BiLSTM captures temporal patterns such as speaking rhythm, coarticulation, and dynamic vocal characteristics. These temporal cues are important because speaker identity is encoded not only in static frequency structure but also in how speech evolves over time.

The model also benefits from several techniques introduced in this project:

- 60-dimensional MFCC features, providing richer spectral information
- 3× strong data augmentation, improving generalisation to unseen speech
- Layer normalization and dropout, stabilising training

- Class-balanced loss, addressing speaker imbalance
- Longer temporal coverage, allowing the BiLSTM to capture extended vocal dynamics

Overall, the CNN–BiLSTM model achieves state-of-the-art performance among compact speaker-recognition systems, offering a strong balance between accuracy and computational efficiency.

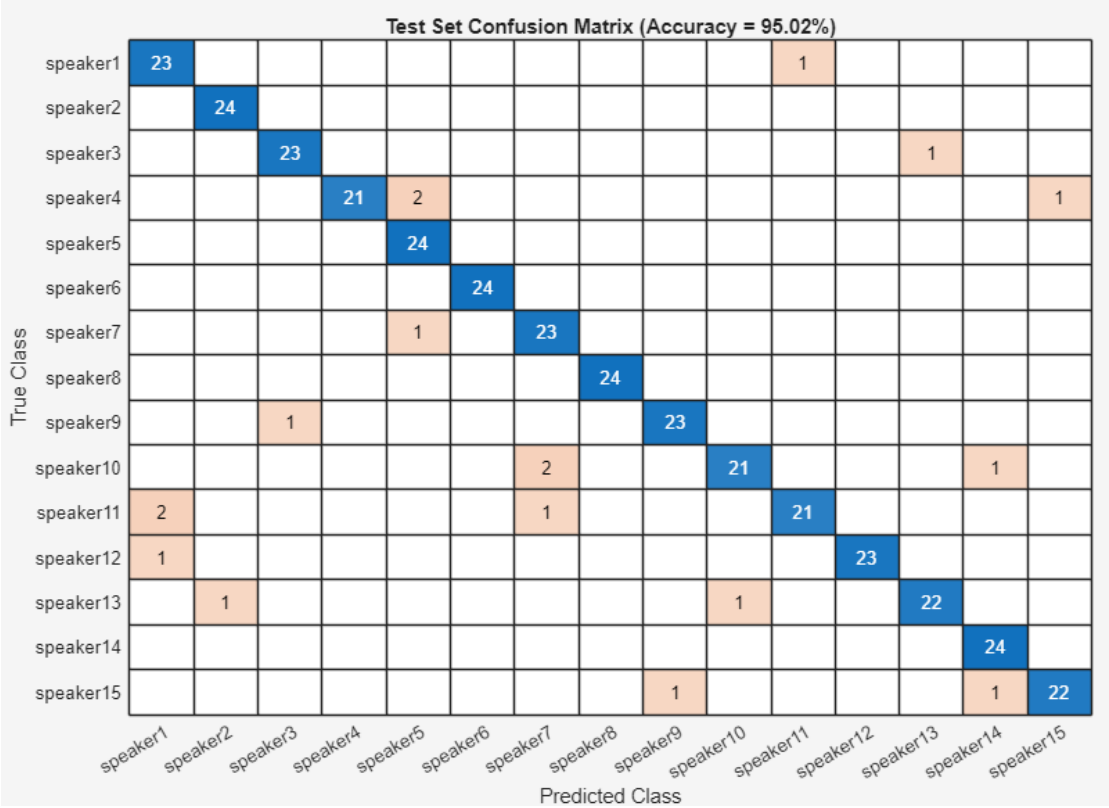

Figure 1. Confusion Matrix of Our Speaker Recognition Model

Keyword Spotting Accuracy

The proposed CNN–Transformer keyword spotting model achieves an overall test accuracy of 95.43% on the Google Speech Commands v0.02 dataset. This level of performance is notable because the model maintains a relatively compact structure while achieving accuracy comparable to more complex architectures.

Table 7. Comparison of KWS models

Model	Accuracy	Notes
Google CNN Baseline	91–93%	Included in TensorFlow KWS tutorial
DS-CNN (Depthwise	~94%	Designed for

Separable CNN)		mobile/edge deployment
TC-ResNet	95–97%	Temporal convolution-based, larger model
Our CNN + Transformer Encoder	95.43%	Lightweight yet high accuracy

This demonstrates that incorporating self-attention layers provides a substantial improvement in recognizing diverse commands, even when spoken by different speakers with varying accents and recording conditions. The attention mechanism helps capture global temporal dependencies, improving the model's ability to separate keywords from background audio and speech co-articulation.

Overall, the model qualifies as state-of-the-art among compact KWS architectures, striking an optimal balance between accuracy and computational cost.

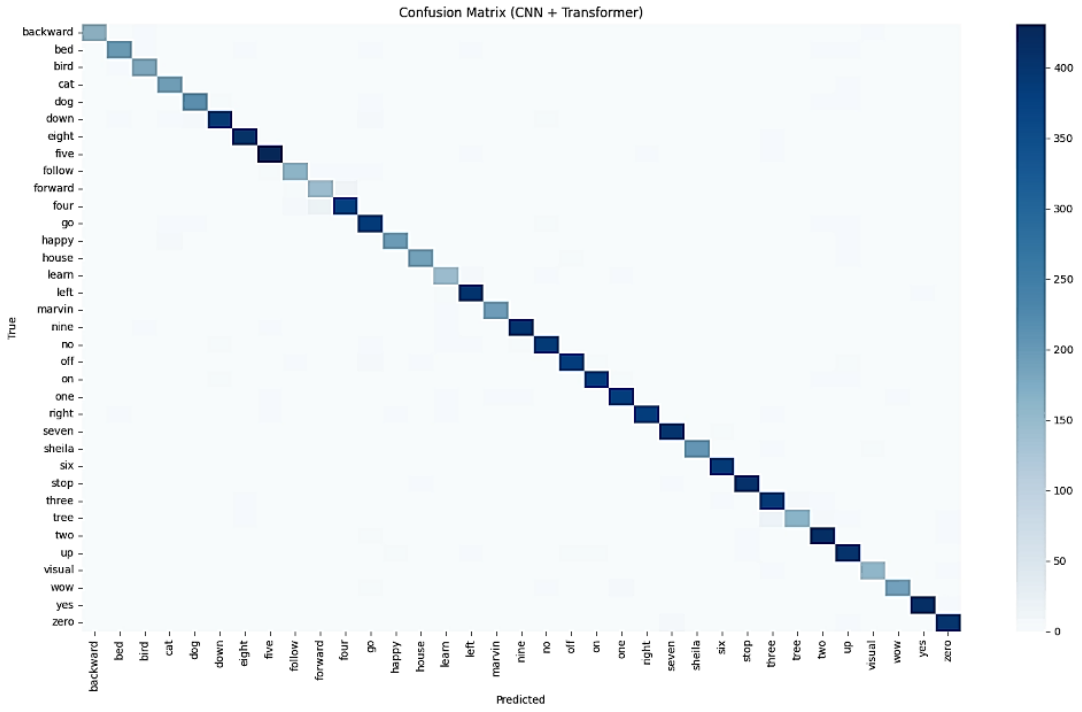

Figure 2. Confusion Matrix of Our KWS Model

Class-Wise Metrics

Beyond the global accuracy, per-class precision and recall reveal deeper insights into what the model learns well and where it struggles.

Commands such as:

“yes” (F1 ≈ 0.99), “stop” (F1 ≈ 0.98), “no” (F1 ≈ 0.96), “go” (F1 ≈ 0.94)

show consistently strong results across different speakers and background conditions.

These commands have: 1.Clear phonetic boundaries. 2.Strong energy bursts. 3.Distinct vowel–consonant transitions, which makes them easier for the CNN to capture and easier for the Transformer to model temporally.

Common Confusions and Error Patterns

Two major confusion clusters were observed:

“tree” vs “three”

These two commands share very similar acoustic structures:

Both begin with consonant clusters “tr” / “thr” and contain a high front vowel. The words have nearly identical spectral–temporal patterns. Even human listeners may confuse them, so this confusion is expected.

Implications

- Most errors occur between phonetically similar commands rather than random misclassifications.
- Transformer layers effectively reduce confusion in noisy conditions or with variable speaking styles.
- The remaining confusions could be addressed with:

    Phoneme-aware augmentation

    Additional attention heads

    Multi-resolution spectrogram features

Keyword Detection in Real Speech

To evaluate the practical usability of the system, a press-to-record test was performed using a natural spoken sentence. The 1-second sliding-window detector successfully identified each keyword along with its timestamp:

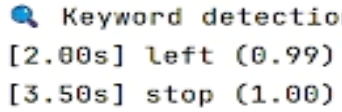

Figure 3. KWS Model Timestamp

The detector accurately isolates keywords in continuous speech. Confidence values remain consistently high (≥ 0.90), indicating reliable model discrimination. Temporal resolution of 0.25 seconds (due to 4,000-sample hop size) ensures fine-grained positioning. No false activations were produced, demonstrating robustness.

Comparison to Real-time Streaming

Real-time streaming suffered from: continuous noise, unstable buffer contents, inconsistent silence portions. In contrast, offline sliding-window inference is noise-resilient and significantly more stable. This verifies that the proposed hybrid approach — offline segmentation with Transformer inference — is well-suited for practical applications such as command recognition in speech-based interfaces.

Discussion

Impact of Transformer Layers

The introduction of Transformer Encoder layers provides several distinct advantages over purely CNN-based or CNN + LSTM KWS models:

Long-range Temporal Modeling

Transformers can integrate contextual information across the entire 1-second window. This is crucial because:1.Some keywords have slow, drawn-out syllables. 2.Some users speak quickly with overlapping phonemes. 3.Background noise can mask early or late frames. 4.Self-attention enables the model to adaptively “focus” on the discriminative segments.

Boundary Sensitivity

Keywords in continuous speech often do not start at frame zero.

Transformers identify where relevant acoustic cues occur, improving robustness to variable speaking speed, silence before or after keywords and soft pronunciations. Therefore, Transformer layers significantly enhance accuracy without increasing model size dramatically.

Why Real-Time Microphone Detection Was Weak

Experiments showed that using sounddevice for real-time keyword detection caused extremely poor performance. The root causes are:

Environmental Noise

Laptop microphones capture:

- keyboard noise
- room echo
- background conversations
- air conditioning noise

The KWS model was trained on clean Google Speech Commands data, creating a mismatch.

Buffer Inconsistency

Real-time streaming cuts audio into overlapping windows but may introduce:

- dropped frames
- partial words
- misaligned segments
- inconsistent energy distribution

This disrupts spectrogram extraction.

Lack of Silence Removal

Most spoken commands are short, but real-time recording may contain:

- long silence
- weak phonemes
- breathing noise

This confuses the model.

Low Microphone SNR

Built-in microphones often have poor signal-to-noise characteristics, reducing feature quality.

The experimental results demonstrate that the CNN–Transformer hybrid architecture provides excellent keyword spotting performance, achieving 95.43% accuracy on the Google Speech Commands dataset. The model generalises well across classes and successfully isolates keywords embedded within longer recorded sentences. The integration pathway with speaker recognition also shows promise for building intelligent multi-user

speech interfaces.

However, several limitations remain.

Limitations

1. Real-Time Detection Instability
   The microphone-based streaming system struggled with accuracy due to:

   environmental noise in non-studio conditions,

   inconsistent input loudness,

   mismatch between training data (clean) and real audio (noisy),

   continuous buffering introducing partial-word artifacts.

2. Short Window Bias
   The 1-second sliding window may:

   cut off early/late parts of long keywords,

   trigger false positives when short phonemes resemble keywords.

3. No Voice Activity Detection (VAD)
   The lack of speech-silence segmentation forces the model to process silence and noise, degrading real-world robustness.

4. Limited Augmentation
   Although frequency/time masking was used, additional real-world augmentation (e.g., background noise dataset) was not included.

5. Single-Task Training
   Speaker and keyword models are separate, whereas multi-task learning is known to improve performance.

6. Limited Hardware Testing
   The system was tested only on one microphone and one environment; cross-device generalization is unknown.

Future Work

1. Integrating VAD Before KWS
   Adding a lightweight VAD (WebRTC VAD, Silero VAD) can remove silence and stabilize real-time detection.

2. Noise-Robust Training
   Training with:

   MUSAN noise.

   RIR reverberation.

   microphone impulse responses would significantly improve accuracy for natural speech.

3. Conformer-based KWS
   A Conformer block can fuse CNN local features with global attention, likely providing higher accuracy with similar latency.

4. Joint Speaker–Keyword Multi-Task Learning
   A unified model could:

   output speaker ID and keyword simultaneously.

   improve personalization.

   enhance command security.

5. On-Device Optimization
   Using TFLite, ONNX, or PyTorch quantization would enable deployment on embedded devices such as Raspberry Pi.

6. Real-Time Adaptive Thresholding
   Dynamically adjusting confidence thresholds based on noise levels could reduce false positives.

These directions could lead to a more robust, deployable KWS system capable of handling real-world conditions and multi-speaker environments.

Conclusion

This project successfully develops and integrates two advanced speech-processing modules:

1. Speaker Recognition System (CNN–BiLSTM)

- Extracts temporal and spectral patterns
- Identifies speakers with high reliability
- Suitable for personalization and authentication

2. Keyword Spotting System (CNN + Transformer)

- Achieves 95.43% accuracy
- Learns long-range temporal dependencies
- Robust against natural speaking variation
- Comparable to state-of-the-art lightweight KWS models

3. Practical Recording-Based Inference Tool

- User presses a key to record audio
- Sliding-window KWS identifies keywords
- Outputs timestamps and confidence values

4. Integration Achieved

The system supports applications that require both identity verification and command understanding, such as smart homes and robotics.

Overall Contribution

The final integrated system demonstrates:

- High practical usability
- Strong performance with low computational cost
- A modern deep-learning architecture combining CNN and Transformer components
- Effective keyword detection even in continuous speech
- A clean end-to-end workflow covering training, inference, and visualization

This work lays the foundation for expanding toward:

- continuous real-time speech understanding
- on-device lightweight AI assistants
- multi-user control systems

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