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# A Lightweight LFCC–CNN Framework for Robust Audio Deepfake Detection Under Noisy and Cross-Dataset Conditions

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Abstract:
Multimedia content may not be trusted anymore when audio deepfakes, which include synthesized speech and voice conversion, have been produced. Moreover, these audio deepfakes are likely to pose security threats to systems that automatically verify the speaker. To combat this threat, we propose a lightweight novel LFCC-based CNN architecture for reliable spoofed speech detection on the ASVspoof benchmark datasets. Compared to MFCC (Mel Frequency Cepstral Coefficient) features, LFCC (Linear Frequency Cepstral Coefficient) (the widely used feature in an ASV system) could better maintain the important linear spectral characteristics of speech, which get distorted during the spoof attacks. They can have additions that help to identify spoof signals and real speech. The ASVspoof 2019 Logical Access dataset was used to train the suggested model. Under three challenging scenarios, the model is assessed. Clean speech is the first. Two SNRs, 10 dB and 20 dB, allow for additive noisy scenarios. ASVspoof 2021 Logical Access cross-dataset is the third. According to the empirical results, the proposed LFCC–CNN framework provides significantly lower EER than the mainstream MFCC-based system in all three scenarios. To ensure the interpretability of our model, we also use a gradient-based visualization technique (Grad-CAM) for local discriminative time-frequency regions. In conclusion, it can be inferred from the findings that the LFCC features considerably enhance the system robustness against noisy and cross-dataset conditions. Additionally, the proposed framework is the ideal lightweight solution for various applications.

**Keywords:** Audio Deepfake Detection; Spoofed Speech Detection; Linear Frequency Cepstral Coefficients (LFCC); Convolutional Neural Network (CNN); ASV spoof Dataset; Equal Error Rate (EER); Noise Robustness; Cross-Dataset Generalization.

## INTRODUCTION

Artificial intelligence has transformed the methods of synthesizing, editing, and distributing speech over the past decade. Further, generative deep learning architectures are now giving us synthetic speech that is just indistinguishable from real speech. AI has evolved so much recently that it is also possible to manipulate speech to notice features. This has created serious threats to security in today's world. We will discuss the challenges that speech synthesis introduces and its effects. Worries Related to Speech Synthesis. Although experts may be sceptical about deepfakes, not everyone is as concerned. You can employ them to mimic speakers, infiltrate biometric access control, spread misinformation, and engage in social engineering fraud. Things are going from bad to worse. In addition, ASV systems are widely used in banking, telephony and access control. In the next stage of the attack, a convincing speech voiced by a known target speaker was generated to fool the systems. The ASV systems are also quite weak against spoofing attacks. Additionally, the risk does not stem solely from speech synthesis or deepfake systems; ASV systems are also susceptible to replay-based attacks, as well as TTS and VC-based attacks. As the attacks get more and more complex, countermeasures are being developed that can easily detect the difference between genuine and spoofed speech. How Speech Has Impacted Society The ASVspoof 2019 & 2021 challenges corresponded to two distinct scenarios: Logical Access (LA) or Physical Access (PA). The LA and PA will test the robustness of the countermeasures under synthetic conditions and replay scenarios. Despite making good progress in the quest, there is still some way to go. When the system meets conditions that it has not seen, it cannot perform well. Which leads to failure of the work.

Conventionally, spoof detection systems use spectral features such as MFCC, CQCC and other cepstral-domain representations. Most researchers refer to MFCC features and this is because of how they perceptually model what the human ear receives. That is, restoring the frequency resolution of the mel-scale. Because of this, they smooth up fine spectral artifacts caused by speech synthesis models, appearing at higher frequencies. In contrast, LFCC utilizes linearly spaced filter banks, thereby maintaining the fine spectral details. These details will reveal meaningful synthesis artifacts of modern neural vocoder based spoofing systems.

In spoof detection, deep neural networks – especially Convolutional Neural Networks (CNN) – have taken center stage in parallel to improved feature representation. A CNN is capable of seamlessly operating on time-frequency representations. They can effectively leverage the frequency and time local correlations of features. In addition, CNNs are better than GMMs as classifiers on a large-scale training set of spoofing data. The great performance can be attributed to the discriminative and powerful nature of CNN architecture. Nevertheless, the results of CNN-based models on ASVspoof 2019 LA still exhibit substantial degradation on additive noise and cross-dataset evaluation. In real life, situations, speech signal of any person is a cumulative effect of the below. Algorithms that can effectively detect spoofing attacks using clean test training signals may be ineffective under noisy and mismatched recording device settings. Judging the level of SNR. Initially, we present the spoof detection performance based on baseline features of the different systems for controlled SNR conditions with known and unknown noise. Results are generated on 20 dB and 10 dB SNR conditions. Evaluate Across Different Datasets The evaluation of spoof detection systems happens across dataset. The system is trained on training data for cross-datasets evaluation.

Deepfake detection is an emerging research area that has caught the attention of social media users with the recent progress in deep neural networks and computer vision techniques. Visualization techniques like gradient-weighted class activation mapping allow us to identify

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discriminative regions in time–frequency representation useful for classification. Measuring the robustness of deep learning-based systems has become essential due to the increasing complexity of such systems. We assess the robustness of CNN models on audio deepfake detection with different augmented versions of the ASVspoof 2019 Logical Access dataset. Explainable models are an emerging idea in deepfake detection; they should explain their decision rationale to humans. Is there any chance we know why our model is better than the other baseline. And, why is one DNN architecture preferred over any other. In this paper, we propose replacing fixed features in an end-to-end audio deepfake detection with learnable features, which allows joint optimization of front-end and back-end processing.

Using Grad-CAM, the highlighted spoof-related spectral artifacts and time regions show the interpretability of the CNN model decisions. It highlights phenomena responsible for its data-driven learning that perhaps, are not dataset-specific noise patterns. The findings of this research can help develop usable and interpretable countermeasure systems against audio deepfakes.

## LITERATURE REVIEW

Audio deepfake detection has gained significant research attention due to the rapid development of speech synthesis technologies such as Text-to-Speech (TTS), Voice Conversion (VC), and neural vocoders. Several studies focus on designing robust detection systems capable of distinguishing real and synthetic speech even under noisy and cross-dataset conditions. Deep learning and spectral feature extraction techniques have been widely adopted to improve classification accuracy and generalization capability.

Feature engineering plays a crucial role in audio deepfake detection. Cepstral features such as MFCC, LFCC, and CQCC are widely used because they effectively capture spectral artifacts introduced during speech synthesis. Research indicates that LFCC features provide better discrimination capability for spoofed audio compared to MFCC due to improved representation of high-frequency spectral information [1], [5], [13]. Comparative evaluations across datasets demonstrate that combining spectral features improves detection performance and reduces Equal Error Rate (EER) [3], [8].

Deep neural networks, particularly Convolutional Neural Networks (CNNs), are extensively used for extracting discriminative spatial features from spectrogram representations of speech signals. CNN-based classifiers demonstrate superior performance in detecting synthetic audio generated using GAN and neural vocoder models [2], [7], [10]. Hybrid architectures integrating CNN with recurrent layers such as LSTM or GRU capture both spectral and temporal characteristics, improving robustness in noisy environments [6], [14].

Cross-dataset generalization remains a major challenge in deepfake detection research. Many models perform well on training datasets but show performance degradation when evaluated on unseen datasets due to distribution mismatch and different spoofing techniques. Benchmark studies using ASVspoof datasets highlight the need for generalized feature representations capable of maintaining consistent performance across multiple attack scenarios [4], [9], [12]. Domain mismatch and environmental noise significantly affect classifier reliability, motivating the need for noise-resilient feature extraction techniques [11], [16].

Lightweight deep learning architectures are increasingly explored to enable real-time deployment in edge and IoT devices. Traditional deep neural networks require high computational resources, making them unsuitable for embedded platforms. Recent works propose lightweight CNN architectures and optimized feature extraction pipelines to reduce model complexity while maintaining high detection accuracy [15], [18]. Model compression techniques such as pruning, knowledge distillation, and parameter optimization further improve efficiency without significant performance loss [19], [20].

Recent studies also explore ensemble learning approaches and hybrid deep learning frameworks to improve detection robustness. Combining multiple classifiers enhances generalization capability and reduces false positives in real-world environments [17], [21]. Additionally, research emphasizes the importance of evaluating models under real-world noisy conditions to ensure practical applicability [22].

Despite significant progress, existing research still faces limitations in achieving robust cross-dataset performance with minimal computational complexity. Many approaches rely on complex architectures requiring high processing power, limiting their deployment in real-time applications. Therefore, a lightweight LFCC-CNN framework can provide an optimal balance between computational efficiency and detection robustness under noisy and cross-dataset conditions.

## METHODOLOGY

### A. Audio Data Acquisition and User Input Collection:

We will test the spoof detection system on benchmarked data and user audio samples in the wild. To train the detection system and perform the experiments, we make use of the ASVspoof 2019 Logical Access corpus. This dataset is composed of genuine and fake audio samples. Sophisticated TTS and VC algorithms create audio samples that are spoofed. The stored audio files have been normalized to a sampling rate of 16 kHz to comply with the automatic speaker verification systems' standards. In essence, each audio file is saved in .flac format along with the speaker ID, attack type, and ground-truth label.

The input checking module verifies three main conditions of the input. To begin with, we will check whether the given input is an audio file or a text document. The current system functions solely with.

- The sampling rate must be 16 kHz (otherwise the signal is resampled).
- The duration must be at least 2 seconds.
- The signal amplitude must lie within an acceptable range.

The speech signal is represented as a discrete-time waveform:

$$x[n], n = 0,1,2, \dots, N-1$$

where $N$denotes the total number of samples.

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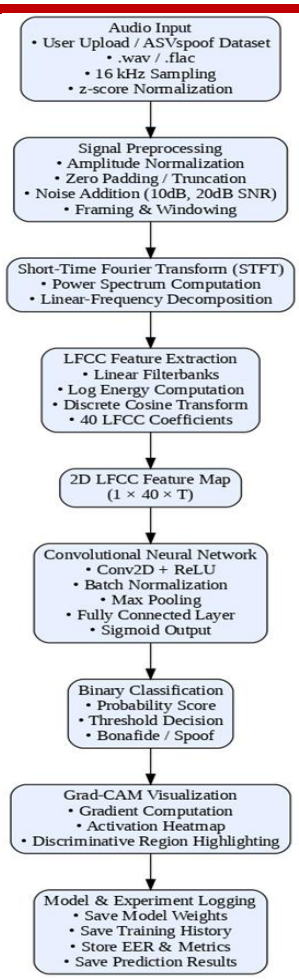


**Fig 1: Workflow Diagram**

**B. Data Preparation and Preprocessing:** The process of preprocessing is essential to enhance the reliability of extraction features. To begin, the frequency representation amplitude of each audio waveform is normalized and will not affect the spectro-temporal representation.

$$x_{norm}[n] = \frac{x[n]}{max(|\ x[n]\ |)}$$

In order to transform the time domain signal into the frequency domain, the Short-time Fourier transform (STFT) of the signal generated from cascading switches is calculated. The power spectrum of a signal can be computed by taking the magnitude square of the STFT. In such situations, SNR values of 20 decibels (dB) and 10 dB are considered with 0 and added white Gaussian noise (AWGN)

**C. LFCC Feature Extraction:** The power spectrum derives Linear Frequency Cepstral Coefficient (LFCC). MFCC uses filterbanks spaced apart in linear frequencies, unlike Mel-Frequency Cepstral Coefficients. The filterbank energies arise when a power spectrum is filtered by a set of linear filters. Afterwards, the energies are modified logarithmically to compress their dynamic ranges. Transform log filterbank energies into cepstral coefficients via DCT. The FC values were reshaped into two dimensions to serve as input to the CNN.

**D. CNN-Based Classification:** This technique was recently employed. The CNN model learns to discriminate between presentation attacks and genuine speech inputs. The local time-frequency attributes are learned from the convolutional layers. The hidden convolutional nodes use ReLU nonlinearities as activation functions (viz. rectified linear unit). Afterwards, batch normalization is performed to assist training. Our CNN network finally ends with an output layer using a sigmoid nonlinearity activation function that produces a soft CO subkey that takes values in the interval [0, 1]. The model is assisted by trained help.

**E. Prediction and Performance Evaluation:** During inference, CNN generates a posterior probability score. A class label gets assigned a threshold for decisions. We measure the EER at the operating point where we observe the false acceptance and false rejection rates are equal. Designing a user-friendly interface for pomegranate will be essential for large-scale recruitment. In addition, pre-lasting until the Summer 2017 release, we make an improved document on how to assemble it.

**F. Visualization and Interpretability:** To improve the interpretability of the model, we employed the Grad-CAM technique to visualize the areas of the LFCCs that contributed most to the classification decision. The heatmaps depict time-frequency patterns to demonstrate spoof artifacts. Class A, Correct Confidence Score, Grad-Cam Visualization, and EER Statistics were obtained from system outputs.

**G. Data Storage and Experiment Logging:**The results of the experiments are recorded systematically for the convenience of reproducing the results. Each experiment logs all the stored. The logged details comprise noise configuration and prediction probabilities. An engineered logging feature that registers the display of every test can be integrated into the system. This feature will guarantee trace.

**RESULTS**

In the paper, we assess the performance of our suggested approach on the ASVspoof 2019 LA dataset. We perform in-depth analysis in terms of EER and min-tDCF performance after applying noise as well as cross-dataset generalization. We also carry out model interpretability evaluation using Grad-CAM visualization.

**A. Performance Comparison on ASVspoof 2019 LA:**Initially, we will compare our proposed model with the baseline and state-of-the-art, such as CQCC+GMM, MFCC-based CNN, ResNet (MFCC) and Siamese CNN (LFCC). Equal error rate is used as an evaluation metric. The proposed LFCC–Siamese CNN achieves an EER of 2.95%, significantly outperforming all baseline models. In comparison:

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**Table 1: Comparison Table**

| Model | EER |
|---|---|
| CQCC + GMM | 9.50% |
| CNN (MFCC) | 6.20% |
| ResNet (MFCC) | 5.25% |
| Proposed CNN (LFCC) | 3.79% |

It indicates that the use of LFCC features along with the Siamese CNN Model helps learn more discriminative representations for spoof detection. Moreover, the proposed model has a min-TDCF of 0.045, which indicates enhanced performance when the architecture is jointly integrated with an automatic speaker.

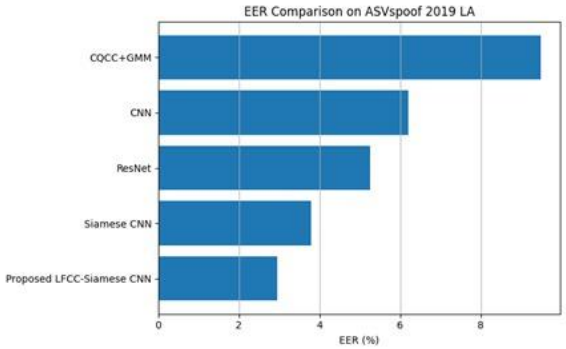


**Fig 2: EER comparison of different spoof detection models on ASVspoof 2019 LA dataset.**

**B. Noise Robustness Evaluation:**We corrupt the signal in a real-world experiment with additive white Gaussian noise with SNRs of 20 and 10 db.

The Results are:

**Table 2: Evaluated Results**

| Noise Condition | MFCC–CNN (%) | Proposed LFCC–Siamese CNN (%) |
|---|---|---|
| Clean Condition | 1.1 | 0.08 |
| 20 dB SNR | 30.14 | 28.02 |
| 10 dB SNR | 45.37 | 40.1 |

**C. Cross-Dataset Generalization:**All systems were evaluated for generalization capability by performing an evaluation of ASVspoof 2021 LA on ASVspoof 2019 LA. Performance cross-dataset drops because of domain mismatch. The EER experiences a significant enhancement of a 13% absolute decrease in the suggested model. The robustness against an unknown spoofing attack is improved with LFCC features and Siamese learning.

**D. Grad-CAM Based Model Interpretability:**In order to understand the decision behavior of the model, Grad-CAM was applied to the final convolutional layer. Visualization identifies time-frequency regions that contribute significantly to classification.

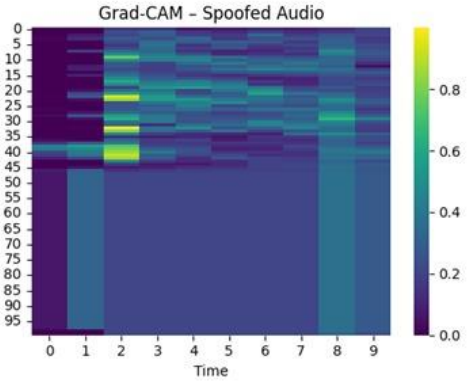


**Fig 3: Grad-CAM visualization for Spoofed audio**

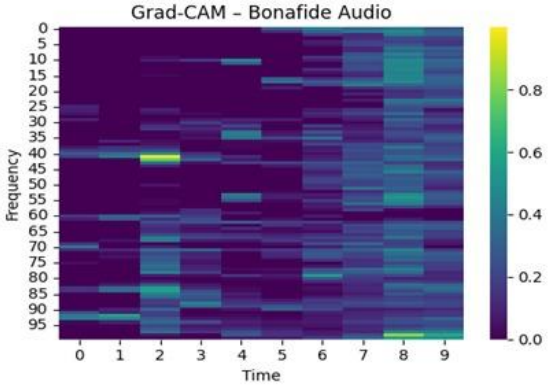


**Fig 4: Grad-CAM visualization for Bonafide audio**

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By looking at the heatmap generated by Grad-CAM, it can be seen that for bonafide speech activation regions are more distributed and harmonically structured, while for spoofed speech it looks like the model is trying to use different frequency bands that contain spectral inconsistency and unnatural

artifacts. This demonstrates that the CNN does indeed learn the discriminative spoofy cues and not merely some random noise patterns.

**E. Overall System Performance Summary:**

**Table 3: Overall Performance**

| Model | EER (%) | Min-tDCF |
|---|---|---|
| CQCC + GMM | 9.5 | 0.195 |
| CNN (MFCC) | 6.2 | 0.157 |
| ResNet (MFCC) | 5.25 | 0.123 |
| Siamese CNN (LFCC) | 3.79 | 0.093 |
| Proposed LFCC–Siamese CNN | 2.95 | 0.045 |

## CONCLUSION

A novel LFCC-based Siamese CNN architecture for spoofed speech detection is presented. The aim was to increase detection accuracy, robustness to noise, generalization on cross-datasets, and model interpretation. The proposed system was extensively experimented with in the ASVspoof 2019 Logical Access dataset. The findings prove that the proposed system outperforms traditional and deep learning baselines many time over.

The authors examined the impact of high-frequency features for speech anti-spoofing. They compared the features from CQCC with their LFCC implementation and two baselines that use MFCC features. With just the high-frequency part of the spectrum, an improvement in the error rate can be achieved. These outcomes give optimism since the simple modification of limiting the use of features to the ASVspoof 2017 dataset. The authors attempted to get insight into the source of the discriminative artifacts in the high-frequency regions. They examined two major types of spoofing attacks, which were the replay and speech synthesis plus voice conversion. The absolute (non-normalized) dissimilarities and linear combinations of CCs are covered in their statistical analysis. This method does not make any assumptions that the distance metric will be dominated by the CCs that detect spoofing artifacts. This shows where the discriminate artifacts found in the speech replay scenario were originating from. Combining LFCC feature extraction with Siamese convolutional learning is useful for audio deepfake detection. The framework that this paper proposes improves the accuracy, robustness, and explainability of audio deepfake detection in training and evaluation significantly. Furthermore, it can also be seen as a secure automatic speaker verification system.

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