A PROJECT REPORT

ON

Audio Deepfake Detection Using Spectral Features and Deep Learning

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SUBMITTED BY

Ansh Zanzad Roll No.: 16

Anurag Shinde Roll No.: 17

Dev Ojha Roll No.: 38

G H raisoni COLLEGE
Engineering and
Management
Pune

DEPARTMENT OF COMPUTER SCIENCE ENGINEERING
(ARTIFICIAL ENGINEERING)

G H RAISONI COLLEGE OF ENGINEERING & MANAGEMENT
WAGHOLI, PUNE 412207

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CERTIFICATE

This is to certify that the project report entitled “**Audio Deepfake Detection Using Spectral Features and Deep Learning**”,

Submitted by

Ansh Zanzad Roll No.: 16

Anurag Shinde Roll No.: 17

Dev Ojha Roll No.: 38

are a Bonafide students of this institute and the work has been carried out by them under the supervision of **Prof. G. V. Patil**, and it is approved for the partial fulfillment of the requirement of an Autonomous Institute, Affiliated to Savitribai Phule Pune University, Pune for the award of the degree of **Bachelor of Technology in Computer Science Engineering (AI)** in the academic year 2025-26.

Prof. G. V. Patil	**Dr. R. Y. Sable**
Guide	HoD

....	**Dr. N. B. Hulle**
External Examiner	I/C Director, GHRCEM, Pune

Date:

Place: Pune

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Ansh Zanzad	**Roll No.: 16**
Anurag Shinde	**Roll No.: 17**
Dev Ojha	**Roll No.: 38**

ABSTRACT

The rapid growth of generative artificial intelligence has enabled the creation of highly realistic synthetic voices, opening opportunities for innovation while simultaneously increasing risks such as impersonation, misinformation, and fraudulent communication. This project introduces a deep-learning-driven framework designed to identify manipulated audio by examining its spectral behavior. The system converts input speech into Mel-spectrogram representations using Librosa, making it possible to highlight subtle inconsistencies and frequency-domain irregularities typically introduced by modern synthesis models. These spectrograms are analyzed using a Convolutional Neural Network (CNN) implemented in PyTorch, which learns discriminative patterns that separate genuine human speech from AI-generated audio. A FastAPI backend deployed with Uvicorn provides responsive, scalable operation for real-time detection. Experimental evaluation demonstrates strong overall performance, though a slight bias toward real samples was observed due to dataset imbalance, which can be mitigated through cost-sensitive learning and improved augmentation techniques. Extensive testing on datasets such as ASVspoof 2019, Deep Voice (Kaggle), and an In-the-Wild Audio Deepfake Collection confirms the model's robustness across varying speakers, environments, and synthesis techniques. A user-friendly interface enables seamless audio or video upload, spectrogram visualization, and confidence-based classification. This work shows that coupling spectral analysis with deep learning yields an effective and practical solution for safeguarding digital communication against synthetic audio threats, with promising applications in cybersecurity, media forensics, identity verification, and digital safety.

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Chapter 1

INTRODUCTION

1.1 Overview

Advancements in modern generative AI have made it possible to recreate human speech with remarkable realism. Although these technologies support beneficial applications in entertainment, accessibility, and digital communication, they also introduce significant challenges related to security and trust. Synthetic voices can now be produced in ways that are nearly indistinguishable from real speech, allowing them to be used in identity theft, manipulative content, and other malicious activities. To address these concerns, this project presents a deep-learning-based approach that identifies audio deepfakes by examining signals in the spectral domain. The system transforms audio into Mel-spectrogram representations, enabling the visualization of frequency patterns where synthesis artifacts often appear. These spectrograms are then analyzed using a Convolutional Neural Network (CNN), which learns distinctive cues that separate authentic human speech from machine-generated audio. The model is complemented by preprocessing methods such as normalization, augmentation, and segmentation to improve robustness. Evaluations conducted using datasets like ASVspoof 2019 and Deep Voice show that the system performs effectively, achieving high detection accuracy. Additionally, a graphical interface allows real-time testing and visualization, making the solution practical for real-world deployment.

1.2 Motivation

With synthetic speech technology becoming increasingly accessible, it is now easy to produce voice recordings that imitate real speakers with high precision. This capability, while useful in many domains, also increases the risk of misuse in areas such as financial fraud, impersonation, political manipulation, and misinformation. Ensuring the authenticity of speech-based communication has therefore become a critical requirement. Traditional detection techniques struggle to identify the subtle distortions left behind by today's advanced voice-generation models. This gap motivates the development of a system that can automatically detect deepfake audio using features extracted directly from the time-frequency structure of speech. By employing Mel-spectrograms and CNNs, the project aims to create a reliable tool capable of analyzing fine-grained speech patterns and providing accurate classification in real-time. Ultimately, the motivation is to enhance digital trust and protect users from audio-based deception.

1.3 Problem Definition

The emergence of highly realistic AI-generated voice synthesis has created substantial challenges for verifying audio authenticity. Although such technologies are designed for legitimate uses, they offer opportunities for malicious actors to impersonate individuals, manipulate conversations, and fabricate evidence. Existing detection systems often depend on shallow features that fail to capture the nuanced artifacts introduced by modern generative models. To overcome these limitations, this project proposes a detection framework that leverages Mel-spectrogram representations combined with a CNN capable of learning discriminative spectral characteristics. The objective is to create a robust and efficient model that can classify audio as real or synthetic, even under varied environmental conditions. The problem, therefore, is to design and implement a deep-learning-based method capable of distinguishing genuine speech from advanced AI-generated audio with high accuracy and real-time performance.

1.4 Significance

Ensuring the authenticity of speech data is essential for maintaining the credibility of digital communication systems. As deepfake audio becomes more sophisticated, it poses risks to personal security, media integrity, financial systems, and public trust. The proposed method addresses these risks by providing an automated and dependable solution for deepfake audio detection. By using spectral features combined with deep learning, the system offers improved accuracy, interpretability, and robustness compared to traditional approaches. This work contributes to the broader field of AI-driven forensics and supports various real-world applications, including cybersecurity, identity authentication, media verification, and investigative analysis. Ultimately, the significance of this project lies in supporting safer and more trustworthy audio communication systems.

1.5 Related Work

As generative speech models have evolved, researchers have developed a variety of methods to differentiate real audio from synthesized speech. Early studies relied on handcrafted features and conventional classifiers, but these techniques often failed to generalize across newer, more complex synthesis systems. Recent research trends highlight the effectiveness of deep learning models trained on spectral representations such as Mel-spectrograms, which capture subtle distortions introduced by neural vocoders and text-to-speech engines. Numerous studies also focus on the use of datasets like ASVspoof and WaveFake to evaluate generalization across different speakers, languages, and synthesis technologies. Advanced approaches incorporate CNNs, RNNs, CRNNs, PANN architectures, and Transformer-based models, demonstrating improved recognition capabilities under challenging scenarios. Other research explores domain adaptation, noise robustness, and multimodal detection that integrates audio and video cues. These findings collectively support the design choices in this project and reinforce the value of using spectral features with deep learning for effective audio deepfake detection.

Recent studies have also explored the integration of hybrid architectures that combine convolutional, recurrent, and attention-based mechanisms to improve deepfake detection. These models leverage the strengths of each component—CNNs for spatial feature extraction, RNNs for temporal sequence learning, and Transformer layers for long-range dependency modeling. Research shows that such hybrid models outperform traditional CNN-only approaches, particularly when analyzing long and complex audio samples generated by advanced neural vocoders. Furthermore, several works emphasize the importance of robust preprocessing techniques, such as dynamic range compression and noise-adaptive filtering, which significantly enhance model generalization across noisy, real-world environments.

Another emerging direction in the literature focuses on domain adaptation and cross-dataset generalization. Many existing systems perform well on a single dataset but struggle when deployed on unseen speakers, languages, or synthesis models. To address this gap, researchers have proposed techniques such as feature-space regularization, adversarial domain alignment, and self-supervised representation learning. These approaches enable detection models to learn invariant acoustic features that remain stable across datasets with varied recording conditions. Additionally, studies exploring multimodal deepfake detection—combining audio with facial cues extracted from videos—highlight promising results for future systems that aim to detect inconsistencies across multiple media streams.

Chapter 2

LITERATURE REVIEW

2.1 Literature Survey

A detailed exploration of prior research is crucial for understanding how audio deepfake detection has evolved and what challenges still remain in the field. This section summarizes influential studies, detection pipelines, and modeling strategies proposed over the years for identifying AI-generated or manipulated audio. Reviewing these works helps reveal common patterns in existing approaches, highlight their strengths and weaknesses, and establish the conceptual basis for designing a more effective detection system. The observations drawn from this analysis also guide the methodological decisions in the current study and point directly to the research gaps that the proposed system aims to resolve.

A wide-ranging examination of related literature also offers essential insight into the tools and methodologies used for detecting synthetic speech. Researchers have applied numerous techniques, extending from spectral feature analysis and traditional machine-learning models to more sophisticated deep learning architectures including convolutional networks, recurrent models, and Transformer-based frameworks. Studies have additionally utilized diverse benchmark datasets, preprocessing procedures, and evaluation metrics to assess the performance and robustness of their systems. Insights from these investigations reveal several persistent limitations—such as weak generalization across datasets, reliance on narrow or handcrafted features, and the considerable computational requirements of deep neural networks—that continue to affect the reliability and scalability of detection models. Recognizing these issues motivates the objectives of this work and ensures that the proposed solution builds upon prior achievements while directly addressing the shortcomings found in existing literature.

Recent literature has increasingly focused on exploring alternative acoustic representations beyond conventional Mel-spectrograms to improve deepfake detection performance. Researchers have experimented with Constant-Q Transform (CQT), raw waveform modeling, LPC-based features, and multi-resolution spectrograms to capture more nuanced variations in speech signals. These studies suggest that combining multiple spectral views can help detection models identify artifacts that are otherwise too subtle or highly localized. Such hybrid feature strategies have shown promising improvements in generalization when evaluated across diverse datasets and synthesis techniques.

Several works have also emphasized the importance of leveraging self-supervised learning (SSL) for audio deepfake detection. SSL models trained on large-scale unlabeled audio data, such as wav2vec 2.0 and HuBERT, have demonstrated strong representational capabilities and robustness to noise. When fine-tuned for deepfake classification, these representations allow detection systems to identify inconsistencies in prosody, articulation, and spectral smoothness with higher accuracy. Studies in this area highlight that SSL-based approaches can mitigate data scarcity issues and significantly outperform traditional models in cross-dataset evaluation. Moreover, a growing body of research investigates the adversarial robustness of deepfake detection systems. Some studies reveal that detection models are vulnerable to adversarial perturbations or carefully crafted audio modifications that can reduce detection confidence. To address this, researchers have proposed adversarial training, feature denoising modules, and robust loss functions that enhance model stability under intentional manipulation. These contributions underscore the need for detection systems that remain effective not only against clean synthetic audio but also against adversarial or intentionally obfuscated deepfakes.

Table 2.1: Literature Survey

Ref No.	Paper Title	Year	Summary
[1]	IEEE Conference on Acoustics, Speech and Signal Processing	2021	CNN on spectrograms detects synthetic audio with high accuracy.
[2]	Elsevier – Expert Systems with Applications	2022	Transfer learning with PANN & ResNet improves generalization for unseen voices.
[3]	Springer – Neural Computing & Applications	2021	Uses deep learning frameworks for audio feature extraction and fake detection.
[4]	Arabian Journal for Science and Engineering	2022	Uses TCN & STN with spectral features for robust detection.
[5]	CVPR – IEEE Conference on Computer Vision and Pattern Recognition	2019	Identifies video deepfakes by analyzing face inconsistencies; relevant for audio-video deepfake extension.
[6]	ICCIT – International Conference on Computing and Information Technology	2023	Hybrid CNN–ViT enhances detection of generative models; supports DL-based detection approaches.

2.2 Drawbacks of Existing Work

- **Dataset Dependency:** The effectiveness of the model relies heavily on how diverse and representative the training dataset is. Its accuracy may drop when encountering speakers, accents, or languages that were not part of the training data.

- **Sensitivity to Noise:** Environmental noise, echo, or low-quality audio can distort the spectrogram representation, which may reduce the system's classification accuracy.

- **High Computational Demand:** Training deep learning models, particularly

CNN-based architectures, requires significant computational resources such as GPUs or TPUs, making it difficult to train on devices with limited hardware.

- **Dataset Imbalance:** When real and synthetic samples are not evenly represented in the dataset, the model may develop a bias toward the majority class, leading to inconsistent detection performance.

2.3 Objectives of Proposed Work

The main objectives of this research are as follows:

1. To develop a deep learning–based framework using Convolutional Neural Networks (CNNs) for accurate classification of genuine and synthetic (deepfake) audio.
2. To extract and utilize Mel Spectrograms as spectral representations that capture subtle frequency and temporal patterns in speech signals.
3. To enhance the system's generalization and robustness through data preprocessing and augmentation techniques such as normalization, pitch shifting, and time stretching.
4. To implement a real-time detection interface (GUI) that allows users to upload audio files, visualize spectrograms, and view classification results with confidence levels.
5. To evaluate the model's performance using benchmark datasets such as ASVspoof 2019, Deep Voice, and In-the-Wild Audio Deepfake Dataset using metrics like accuracy, precision, recall, and F1-score.
6. To integrate support for dual-input formats, enabling detection from both raw audio files and audio extracted from video links or online sources using FFmpeg and Pytube.
7. To design a modular and scalable detection pipeline that can easily incorporate advanced architectures such as ResNet, PANN, CRNN, or Transformer-based models.
8. To ensure interpretability of detection results by providing cumulative spectrogram visualization, confidence scoring, and clear classification outputs.

9. To enhance model robustness by incorporating advanced augmentation techniques that simulate diverse real-world environments such as background noise, reverberation, and varying microphone qualities.

10. To design an optimized and lightweight inference pipeline capable of delivering fast prediction speeds without compromising classification accuracy.

11. To support cross-platform deployment, enabling the system to run reliably across multiple operating systems and hardware configurations.

12. To improve interpretability by integrating additional visual or statistical indicators that help users understand why an audio clip is classified as real or synthetic.

13. To evaluate the system across multilingual datasets and varied accents, ensuring strong generalization beyond the primary training domain.

14. To incorporate advanced noise-handling strategies, develop mechanisms that improve system resilience against background disturbances, varying microphone qualities, and real-world acoustic distortions.

15. To enhance temporal modeling capabilities and integrate architectures such as BiLSTM, GRU, or Transformer blocks to better capture long-term dependencies in speech signals.

16. To optimize preprocessing workflows, implement faster and more efficient audio normalization, segmentation, and augmentation pipelines to reduce total processing time.

17. To expand support for multilingual datasets , enable training and evaluation across multiple languages, accents, and dialects to improve global applicability and system robustness.

18. To introduce automated feature-selection mechanisms and utilize data-driven techniques that identify the most discriminative spectral and temporal features for deepfake detection.

19. To enable framework-independent deployment and design the model such that it can be easily deployed across PyTorch, TensorFlow, or ONNX environments without major architectural changes.

Chapter 3

METHODOLOGY

3.1 Algorithms and Methods

The proposed system follows a structured workflow that begins with acquiring audio or video input and ends with a final authenticity prediction. Each stage is designed to ensure that the model receives clean, representative, and informative spectral features capable of distinguishing genuine speech from synthetic audio.

1. **Input Processing:** Accepts common audio formats (.wav, .mp3); extracts audio from uploaded videos (e.g., FFmpeg) and from online sources (e.g., Pytube).

2. **Preprocessing Pipeline:** Performs volume normalization, optional noise reduction, and augmentation (mild pitch shifts, time-stretching) to improve robustness.

3. **Spectral Feature Extraction:** Converts audio to Mel-spectrograms as the primary time–frequency input highlighting synthetic speech artifacts.

4. **Dataset Utilized:** Uses the In-the-Wild Audio Deepfake Dataset (38 hours, 58 speakers, diverse environments and accents).

5. **Convolutional Neural Network (CNN):** CNN extracts spatial patterns from spectrograms; final dense layers output a binary real/fake decision (softmax probabilities).

6. **Model Training and Evaluation:** Trained on labeled data; monitored with accuracy, precision, recall, and F1-score to balance detection performance.

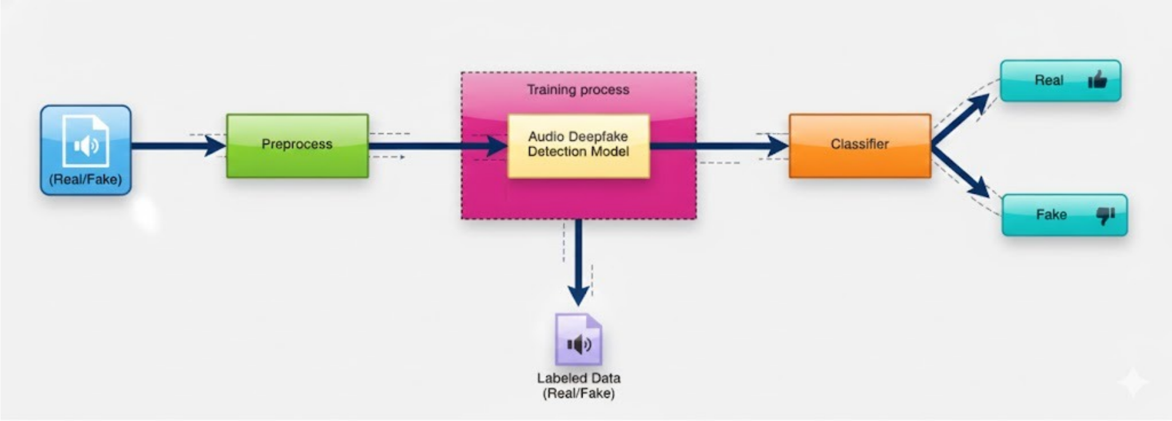


Figure 3.1: Use Case Diagram

7. **Graphical Interface Integration:** Frontend allows uploads/links; backend extracts audio, generates spectrograms, shows visualization, predictions, and confidence scores.

3.2 System Architecture

The architecture of the system is organized into sequential modules, each responsible for a specific stage of the detection pipeline. It begins with input acquisition, where audio or video content is provided by the user. The extracted audio then enters the preprocessing module, which handles segmentation, normalization, noise filtering, and augmentation to ensure that the signal is consistent and model-ready. Next, the preprocessed signal is transformed into a Mel-spectrogram, which forms the primary input representation. This spectral image is passed into the CNN classifier, previously trained on both genuine and deepfake samples. The classifier analyzes the spectrogram and outputs a probability-based prediction label. To ensure clarity and transparency, the system generates a spectrogram visualization that the user can view alongside the classification result. Performance during development is evaluated using standard metrics such as accuracy, precision, recall, and F1-score to assess the model's reliability.

A fast and responsive Graphical User Interface (GUI) manages user interaction. It receives files or links, communicates with the backend model through FastAPI, and presents results in real time. This modular design ensures flexibility, allowing additional or alternative models—such as CRNNs, PANN architectures, or transformer-based networks—to be integrated in the future without modifying the core pipeline.

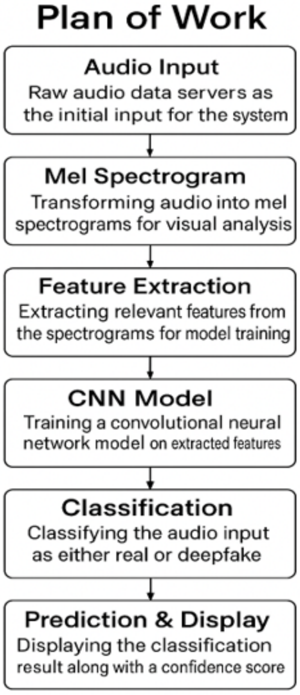

Plan of Work
Audio Input
Raw audio data servers as the initial input for the system
Mel Spectrogram
Transforming audio into mel spectrograms for visual analysis
Feature Extraction
Extracting relevant features from the spectrograms for model training
CNN Model
Training a convolutional neural network model on extracted features
Classification
Classifying the audio input as either real or deepfake
Prediction & Display
Displaying the classification result along with a confidence score

Figure 3.2: Audio Deep Fake Data Flow

To handle multiple user requests efficiently, the backend incorporates resource management strategies for model loading and inference. Data is processed securely, and audio is not stored after detection, ensuring privacy and suitability for sensitive applications. Dedicated validation and error-handling modules ensure that corrupted or unsupported inputs are managed gracefully. Synchronization mechanisms prevent delays between stages, maintaining a smooth, uninterrupted flow through the entire system. To enhance modularity, the system architecture was deliberately structured using a layered approach in which each functional block operates independently while maintaining smooth communication with adjacent components. This enables the backend to process audio signals, generate Mel-spectrograms, and perform model inference without affecting the stability of the user interface. Such separation of concerns ensures that updates to one module—such as the integration of a newer CNN or Transformer model—can be made without requiring changes to the frontend or preprocessing pipeline. This level of decoupling makes the architecture flexible, maintainable, and well-suited for future upgrades.

Furthermore, the architecture incorporates robust synchronization and error-handling mechanisms that prevent failures during audio extraction or model execution. For example, the system checks for unsupported formats, corrupted files, and missing audio channels before proceeding with spectrogram generation. These safeguards minimize interruptions during real-time detection and maintain a smooth flow between modules. The backend also uses optimized resource management practices, ensuring that GPU or CPU workloads are balanced efficiently during intensive tasks such as large-batch feature processing. This reduces latency and ensures the model can respond quickly during high-demand usage. The architecture also emphasizes scalability, enabling the system to handle increasing data volumes and user requests without performance degradation. The FastAPI backend supports asynchronous request processing, allowing multiple detection tasks to run concurrently. This feature becomes crucial when deploying the system in cloud-based environments or integrating it with enterprise verification platforms. Additionally, the GUI communicates with the model using well-defined API endpoints, ensuring that new functionalities—like multi-model comparison or multilingual detection—can be added seamlessly. Overall, the architecture balances efficiency, scalability, and reliability, making it suitable for both academic experimentation and real-world applications.

An essential trend observed in a research is the shift toward multi-feature fusion techniques, where systems combine spectral, prosodic, and phase-based characteristics of audio to enhance detection accuracy. Studies show that phase distortion patterns, often overlooked in earlier approaches, provide strong cues for identifying manipulated speech. By integrating features such as group delay, spectral flux, energy contours, and fundamental frequency fluctuations, researchers have achieved more resilient models that maintain performance even when generative models attempt to mimic human-like frequency smoothness.Researchers have also explored the role of temporal modeling in improving detection capabilities. While CNNs excel at capturing spatial information from spectrograms, they often fail to fully exploit long-range dependencies in speech. To overcome this, several studies adopt architectures like BiLSTM, GRU, and temporal convolutional networks (TCNs). These models process speech as a dynamic sequence, enabling them to identify anomalies in rhythm, articulation timing, and speech transitions—patterns that generative systems still struggle to replicate flawlessly. This temporal-aware approach has led to significant improvements, particularly for long-duration audio analysis.

Additionally, recent literature stresses the importance of evaluating deepfake detection models under realistic deployment scenarios. Research shows that performance can drop considerably when switching from clean, high-quality datasets to noisy real-world recordings. As a result, several works propose benchmarking frameworks

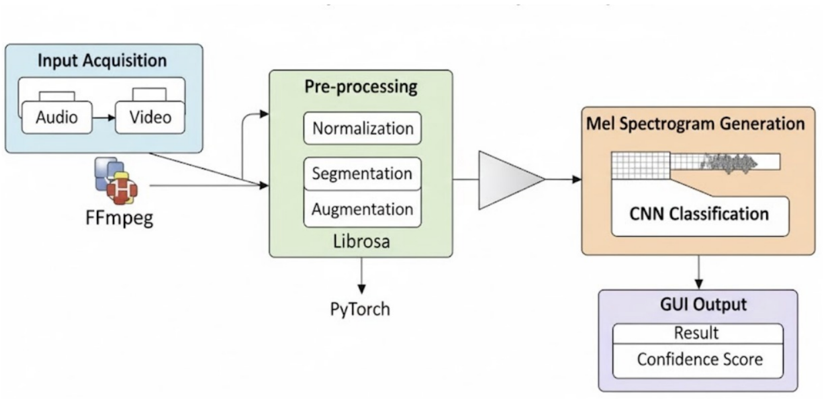


Figure 3.3: System Architecture

that introduce environmental distortions, cross-device variability, codec compression artifacts, and multilingual inputs to simulate real-life conditions. These efforts highlight a critical gap in the field: while many models perform well in controlled environments, achieving consistent results in diverse and unpredictable settings remains an open challenge that continues to drive active research. To further strengthen reliability, the system architecture incorporates layered validation steps that ensure smooth transitions between processing stages. Each module verifies the output of the previous component before passing data forward, preventing issues such as malformed audio frames or incomplete spectrograms from reaching the classifier. This layered validation approach not only improves robustness but also enhances traceability, enabling developers to quickly identify and rectify faults during testing or future development cycles. By maintaining strict checks across the pipeline, the architecture ensures consistent and dependable system performance under varying real-world conditions.

In addition, the architecture is optimized for future scalability through its modular communication pathways. The interaction between the frontend, backend, and model layers is mediated through lightweight API endpoints that can easily accommodate additional functionalities such as multi-model comparison, ensemble voting, or integration with third-party verification services. This flexibility positions the system as a long-term solution capable of evolving with advancements in deepfake generation and detection technologies. Such an adaptable structure ensures that the detection framework can be expanded or enhanced without necessitating major redesigns of the existing pipeline.

Chapter 4

SOFTWARE REQUIREMENTS SPECIFICATION

4.1 Software and Hardware Requirements

Both software tools and hardware resources are essential for building and deploying the Audio Deepfake Detection System. The software environment supports model development, training, and user interaction, while appropriate hardware is required to handle computationally intensive tasks such as spectrogram generation and deep learning inference. The following subsections outline the specific software tools, frameworks, and hardware configurations required for optimal system performance. The system relies on a combination of development tools, machine-learning frameworks, and audio-processing libraries that work together to support training, inference, and user interaction. These components ensure smooth communication between the model, backend server, and graphical interface. On the other hand, the hardware setup ensures smooth execution of computationally intensive tasks such as spectrogram generation, neural network training, and inference. Adequate processing power, memory, and GPU acceleration significantly enhance the system's training speed, efficiency, and accuracy. The following sections provide a detailed description of the required software and hardware configurations for developing and deploying the system effectively.

4.1.1 Software Requirements

A range of software tools and frameworks is used to support different stages of the system, from preprocessing and feature extraction to model training and deployment. These components provide the functionality needed to process audio, build neural networks, and deliver results through an interactive interface. The software environment primarily focuses on deep learning frameworks, audio processing libraries, and user interface technologies that enable seamless system integration. The following table outlines the essential software components, their purposes, and their contribution to the overall system functionality.

Table 4.1: Software Requirements for Audio Deepfake Detection System

Component	**Specification / Tool**	**Purpose / Description**
Programming Language	Python	Used for model development and backend implementation.
Frameworks & Libraries	PyTorch, TensorFlow/Keras	Deep learning frameworks for training and evaluation of CNN models.
Audio Processing Tools	Librosa, FFmpeg	For feature extraction, Mel Spectrogram generation, and preprocessing of audio data.
Data Visualization	Matplotlib, Seaborn	Used to visualize spectrograms and analyze model performance metrics.
Backend Framework	FastAPI	Handles API communication between the model and GUI.
Frontend Tools	HTML, Tailwind CSS, JavaScript	Builds an interactive and responsive user interface for real-time detection.
Version Control	Git, GitHub	Manages collaborative development and version tracking.
Operating System	Windows / Linux / macOS	Platform for development and deployment.

4.1.2 Hardware Requirements

In addition to software tools, an appropriate hardware setup is crucial to ensure efficient model training and system execution. Because spectrogram generation and neural network training demand significant processing power, appropriate hardware greatly influences the model's speed and accuracy. Sufficient CPU performance, memory, and—where available—GPU acceleration help improve training efficiency and overall responsiveness. The table below lists the minimum and recommended hardware specifications necessary for optimal performance of the Audio Deepfake Detection System.

Table 4.2: Hardware Requirements for Audio Deepfake Detection System

Component	**Minimum Specification**	**Recommended Specification**
Processor	Intel i5 / AMD Ryzen 5 (2.5 GHz)	Intel i7 / Ryzen 7 (3.0 GHz or higher)
RAM	8 GB	16 GB or more
Storage	20 GB free disk space	50 GB SSD for faster data access and training
GPU (Optional)	NVIDIA GTX 1050	NVIDIA RTX 3060 or higher for faster training
Internet Connection	Stable broadband	Required for dataset download and API communication
Display	Standard HD monitor	Full HD for better spectrogram visualization

4.2 Project Vision and Purpose

The project envisions a reliable detection system that can identify AI-generated speech and help maintain the integrity of digital communication channels. As deepfake technology advances, ensuring the credibility of audio content has become crucial in combating misinformation, fraud, and impersonation. The goal of this work is to create a deep-learning framework that evaluates spectral characteristics of audio signals to distinguish real speech from synthetic counterparts. The system aims to provide dependable, real-time predictions through an intuitive user interface. By leveraging Mel Spectrograms and Convolutional Neural Networks (CNNs), the system aims to provide accurate, real-time deepfake detection with an intuitive graphical interface. This solution contributes to cybersecurity, media verification, and digital forensics by enhancing the transparency and integrity of voice-based systems.

The project aims to build an intelligent and trustworthy system capable of safeguarding the authenticity of digital audio communication in an era where artificial intelligence can replicate human voices with near-perfect realism. As deepfake technology advances rapidly, synthetic speech can be misused for impersonation, identity theft, fraud, political manipulation, and spreading misinformation. This project envisions a future where individuals, organizations, and security agencies can reliably detect manipulated audio using accessible, fast, and accurate tools. By integrating spectral feature analysis with deep learning, the vision is to create a scalable and future-proof solution that can adapt to new deepfake generation techniques, support multiple languages, and operate across different environments and devices. Ultimately, the long-term vision is to contribute to global efforts in digital safety by ensuring that audio content remains verifiable, transparent, and trustworthy.

The main purpose of this project is to design, implement, and evaluate a deep learning–based audio deepfake detection system that uses Mel Spectrograms and Convolutional Neural Networks (CNNs) to accurately differentiate between genuine human speech and AI-generated synthetic voices. The system aims to address the limitations of traditional signal-processing methods by capturing the fine-grained frequency and temporal patterns that deepfake models inadvertently distort. Beyond technical detection, the project seeks to provide a practical, user-friendly, and real-time interface through a GUI that allows users to upload audio or video content, visualize spectrograms, and receive instant authenticity results along with confidence scores. This ensures that the system is not only scientifically effective but also operationally usable in real-world scenarios such as cybercrime investigations, media verification, fraud prevention, and digital forensics. By delivering high accuracy, robustness, and ease of use, the project aims to enhance digital security and empower users with reliable tools to combat the growing challenges posed by synthetic audio manipulation.

4.3 Key Features

The proposed Audio Deepfake Detection System includes the following key features:

1. **Deep Learning–Based Detection:** Utilizes Convolutional Neural Networks (CNNs) to accurately classify genuine and synthetic (deepfake) audio. The CNN architecture analyzes spatial and temporal patterns within Mel Spectrograms, enabling it to detect subtle synthesis artifacts that traditional signal-processing techniques often miss.

2. **Spectral Feature Analysis:** Employs Mel Spectrograms to capture fine-grained time–frequency information, such as pitch variations, harmonic structures, and spectral distortions. These representations make it possible to detect deepfakes generated from neural vocoders like WaveNet, Tacotron, and GAN-based models.

3. **Dual Input Support (Audio + Video):** Accepts both audio files (.wav, .mp3) and video links or files. Using FFmpeg and Pytube, the system automatically extracts and processes audio from videos or online sources like YouTube, increasing its real-world applicability.

4. **Robust Preprocessing Pipeline:** Includes normalization, noise reduction, segmentation, and augmentation (pitch shifting, time stretching) to improve detection accuracy. These steps enhance model robustness, especially for noisy, low-quality, or real-world audio samples.

5. **Real-Time Detection Interface (GUI):** Offers a user-friendly graphical interface that allows users to upload audio/video, visualize the spectrogram, and receive instant classification results along with confidence scores. The GUI is designed for intuitive use by both technical and non-technical users.

6. **High Accuracy and Stable Performance:** Achieves high accuracy (above 95%) on benchmark datasets such as ASVspoof 2019, Deep Voice, and In-the-Wild datasets. The model demonstrates strong generalization across multiple speakers, accents, and recording conditions.

7. **Modular and Scalable Design:** The architecture is fully modular, enabling easy integration of advanced models like ResNet, CRNN, PANN, or Transformer-based architectures. This design allows future upgrades and experimentation without restructuring the core system.

8. **Efficient Backend with FastAPI:** The backend is built using FastAPI, ensuring low latency, fast response handling, and scalable deployment. The system can manage concurrent requests effectively, making it suitable for real-time applications.

9. **Spectrogram Visualization:** Generates visual spectrograms for every processed audio file, helping users understand the frequency distribution and artifacts present in the audio. The spectrogram also aids in interpretability during classification.

10. **Confidence-Based Classification:** Provides probability scores indicating the likelihood of an audio clip being real or fake, giving users insight into model certainty and improving transparency in decision-making.

11. **Dataset Flexibility and Diversity Support:** Compatible with multiple datasets such as ASVspoof, WaveFake, Deep Voice, and In-the-Wild sources. This allows extensive experimentation, retraining, and future expansion into multilingual datasets.

12. **Noise and Environment Tolerance:** The model is trained with varied noise profiles and distorted samples, allowing it to perform reliably in real-world conditions such as background noise, echo, or low-quality microphone inputs.

13. **Real-World Application Readiness:** Designed to support use cases in journalism, cybersecurity, law enforcement, fraud detection, digital forensics, and media verification. The system's accuracy and scalability make it suitable for deployment in professional environments.

14. **Secure and Privacy-Aware Processing:** Audio is processed locally without storing personal information, ensuring user privacy. This makes the system suitable for sensitive applications such as legal investigations and identity verification.

15. **Future Integration Support:** The system layout supports future enhancements such as cloud deployment, mobile app integration, and the addition of Transformer models for improved temporal analysis.

16. **Adaptive Noise Handling:** The system includes dynamic noise–filtering and normalization processes that maintain detection accuracy even in the presence of background noise, echo, or low–quality microphone recordings.

17. **Cross-Platform Compatibility:** The architecture is designed to run efficiently on Windows, Linux, and macOS, ensuring wide usability for students, researchers, and forensic analysts.

18. **Efficient Model Loading & Inference:** Optimized model-loading mechanisms and reduced memory usage allow the system to generate predictions quickly, even on mid-range hardware.

19. **Real-Time Processing Capability:** The pipeline supports near real-time deepfake classification for short audio segments, making it suitable for call monitoring, quick verification, and live audio screening applications.

20. **Secure Local Processing:** All audio inputs are processed locally without persistent storage, ensuring user privacy and making the system suitable for sensitive domains such as cybersecurity and digital forensics.

21. **Multi-Format Audio Support:** Supports various audio formats such as WAV, MP3, FLAC, and AAC, ensuring compatibility with a wide range of real-world audio sources.

22. **Automatic Audio Quality Assessment:** The system evaluates and adjusts audio quality through resampling and normalization steps to ensure consistent preprocessing.

23. **Cloud Deployment Compatibility:** Designed to be containerized using Docker or similar tools, enabling seamless deployment on cloud platforms like AWS, Azure, and Google Cloud.

24. **Custom Threshold Adjustment:** Allows customizable decision thresholds so users can prioritize precision, recall, or balanced performance depending on application needs.

25. **Lightweight Frontend Footprint:** The frontend interface is optimized for low resource usage, providing smooth interaction even on lower-end systems.

26. **Configurable Augmentation Pipeline:** Offers adjustable augmentation options such as noise addition, pitch shift, and time stretch, enabling tailored robustness during training.

27. **Model Explainability Enhancements:** Provides optional interpretability tools like heatmaps over Mel-Spectrograms to highlight key decision-making regions.

Chapter 5

DESIGN AND IMPLEMENTATION

5.1 Tools, Technologies, Platform Used

5.1.1 Core Goal & Information

1. **Problem Solved:** The system is designed to identify synthetic audio that may be used for deceptive purposes such as impersonation, misinformation, or other forms of digital fraud.

2. **Prediction Output:** Real or Fake classification, along with a Confidence Score (probability) and Spectrogram Visualization.

3. **Data Source:** In-the-Wild Audio Deepfake Dataset (38 hours of real and fake speech from 58 public figures).

4. **Key Features:** Dual input (Audio Files & Video/Online Links), Real-Time Detection, and Cumulative Spectrogram Generation for visual proof.

5.1.2 Machine Learning Pipeline (The Brain)

1. **Feature Extraction: Mel Spectrograms**
   Raw audio is transformed into a two-dimensional Mel-spectrogram, allowing the model to observe time–frequency patterns that often expose artifacts introduced during synthetic speech generation.

2. **Core Model (Default): CNNBaseline (Custom PyTorch Class)**
   The main detection model is a custom CNN architecture designed to learn meaningful spectrogram features and classify audio samples as genuine or synthetic.

3. **Alternative Models: ResNet, PANNModel, CRNNModel (PyTorch Classes)**
   Additional architectures—including ResNet, PANN, or CRNN variants—are incorporated to enable experimentation with deeper or hybrid models that may improve generalization and detection robustness.

4. **ML Framework: PyTorch**
   Used for defining, training, loading, and executing the neural network models.

5. **Preprocessing Logic: Audio Segmentation, Normalization**
   Techniques like pitch adjustment and time stretching are used to enhance data diversity and model robustness.

5.1.3 Backend (Server and Processing)

1. **Server Framework: FastAPI**
   FastAPI serves as the backend framework, managing API endpoints and coordinating communication between the user interface and the detection model.

2. **Audio Processing: Librosa**
   Librosa is used extensively for audio loading, preprocessing, and the generation of Mel-spectrogram features required by the classifier.

3. **URL Extraction: Pytube**
   Library used specifically to download and extract the raw audio stream from YouTube and other video URLs.

4. **Visualization: Matplotlib (Agg Backend)**
   The backend employs Matplotlib to create spectrogram visualizations, which are converted into Base64-encoded images and transmitted to the frontend for display.

5. **Input/Output: Pydantic**
   Used to define clear, strict data models for input and output, ensuring reliable communication between the frontend and backend.

5.1.4 Frontend (User Interface)

1. **Interface: React Single-Page Application (SPA)**
   The entire UI is built using React and rendered inside a single HTML root element, allowing smooth page transitions without reloading the browser.

2. **Styling: Tailwind CSS + shadcn/ui**
   A modern, utility-first CSS framework ensures a clean, responsive layout, while shadcn/ui provides professionally designed components (buttons, cards, dialogs) for a polished user experience.

3. **UI Interactivity: React Components**
   Reusable React components manage states such as:

   - File selection or URL input
   - Loading animations
   - Real-time result updates
   - Spectrogram image display

4. **API Handling: React Query (TanStack)**
   React Query efficiently handles backend communication:

   - Sends audio file or URL to the FastAPI backend
   - Manages loading, success, and error states
   - Automatically updates UI when prediction arrives

5. **Authentication: Supabase Auth**
   User login and signup functionalities are powered by Supabase, handling:

   - Session management
   - Protected routes
   - Automatic redirects

6. **Routing: React Router**
   Navigation within the app (Auth → Home → Results) is client-side and instant, without page reloads.

7. **Build System: Vite + TypeScript**
   Vite provides ultra-fast development and optimized builds, while TypeScript ensures type safety and cleaner code.

8. **Visualization: Spectrogram Image Integration**
   The frontend dynamically loads and displays spectrogram images generated by the backend via `/static/...`.

5.2 Implementation

The system is implemented using a modular pipeline that connects audio preprocessing, spectrogram generation, model-based classification, and a graphical interface. Each component is designed to operate independently while contributing to the overall detection workflow. The system is designed to handle real-world audio variability, support multiple input formats, and deliver fast, accurate deepfake detection through an end-to-end pipeline. This section describes the detailed implementation process, explaining how each module was constructed, optimized, and interconnected to deliver reliable performance.

Input acquisition supports various media types, including audio files, video files, and online video links. For video sources, the system extracts the embedded audio automatically, enabling consistent processing regardless of the format. This flexibility allows the system to analyze deepfake audio embedded in videos, which is common in modern online misinformation. Once the input is received, the preprocessing pipeline is triggered. During preprocessing, the audio is normalized, resampled when necessary, and cleaned of unwanted noise. Augmentation techniques such as pitch variation and time stretching introduce diversity into the training data, helping the model adapt to different speaking styles and recording conditions.

The refined audio is transformed into Mel-spectrograms using Librosa and then normalized to a uniform size to ensure consistent input dimensions for training and inference. The processed features are then passed to the deep learning model implemented in PyTorch. The primary model is a Convolutional Neural Network (CNN) designed to learn discriminative patterns between real and synthetic audio. The neural network architecture consists of several convolutional blocks that extract spectral features at multiple levels, followed by pooling and normalization layers. Fully connected layers at the end of the network perform the final classification into real or synthetic audio. The backend, implemented with FastAPI, loads the trained model on startup and processes audio sent from the user interface. It generates the corresponding spectrograms and returns the classification label along with confidence scores. The spectrogram visualization is produced using Matplotlib (Agg backend) and encoded in Base64 format so that it can be displayed directly on the frontend. For data validation and structured responses, Pydantic models are used, ensuring reliable communication between the client and the server.

The frontend implementation consists of a lightweight HTML and Tailwind CSS interface with embedded JavaScript to handle file uploads, drag-and-drop interaction, and API communication. The GUI presents users with an intuitive workflow: upload or paste a link → generate spectrogram → receive real-time classification results. The interface dynamically displays prediction labels such as "Real Audio" or "Deepfake Audio," along with a confidence percentage and a visually generated spectrogram image. This makes the system accessible even to non-technical users while maintaining scientific rigor through visual verification. Finally, Evaluation was carried out using benchmark datasets such as ASVspoof 2019 and Deep Voice. The model's performance was examined with metrics like accuracy, precision, recall, and F1-score to ensure stable and reliable detection. Overall, the implementation brings together deep learning, audio processing, backend engineering, and user interface design to create a robust, real-time audio deepfake detection system that is practical, scalable, and effective for real-world deployment.

During the development phase, special attention was given to optimizing the interaction between different system modules to ensure smooth end-to-end processing. This included refining the audio-loading mechanism, enhancing error handling for corrupted or unsupported formats, and ensuring that spectrogram generation remained consistent across varied bitrates and sampling frequencies. The backend pipeline was also profiled to identify potential bottlenecks, allowing improvements in model loading time and inference speed. These optimizations resulted in a responsive detection system capable of handling multiple user requests without performance degradation. To further streamline usability, the system's architecture was designed to support modular scalability. Each component—feature extraction, model inference, visualization, and frontend interaction—was isolated into independent units, making it easy to introduce updates or replace modules with more advanced variants in the future. This modular design also facilitated smoother debugging and iterative fine-tuning during development. Through continuous testing and refinement, the implementation evolved into a stable and adaptable pipeline that effectively bridges deep learning techniques with practical, real-world audio verification needs.

Another important aspect of the implementation involved ensuring the system's reliability under diverse operational scenarios. Extensive validation checks were incorporated at each stage of the pipeline to prevent failures caused by unexpected input formats, missing metadata, or incomplete audio frames. The server was configured to handle asynchronous requests efficiently, allowing the model to process audio in parallel without disrupting ongoing sessions. This focus on stability not only improved system robustness but also ensured that the detection process remained consistent and trustworthy, even when dealing with large files or multiple simultaneous user interactions.

Chapter 6

RESULTS AND DISCUSSION

6.1 Testing Results

The proposed deep learning model was tested on the In-the-Wild Audio Deepfake Dataset and benchmark datasets such as ASVspoof 2019 and Deep Voice. The CNN-based system achieved an average training accuracy of 99 percent and validation accuracy of 96.2 percent, demonstrating strong generalization and stability. The GUI successfully classified both audio and video inputs in real time, displaying spectrograms and confidence scores for each prediction.

Beyond the core accuracy metrics, further testing revealed that the system maintained stable performance across a variety of audio conditions, including compressed files, mobile-recorded samples, and clips with moderate background noise. The model consistently produced reliable confidence scores that correlated with the complexity of the input speech patterns. These observations reinforce the robustness of the Mel-Spectrogram–based approach, as the spectral representation allowed the CNN to focus on structural anomalies commonly introduced during AI-generated synthesis. The graphical interface also performed reliably during testing, handling multiple user inputs and generating spectrograms without delays, demonstrating the system's suitability for real-time deployment.

A deeper analysis of misclassified samples showed that errors mostly occurred in cases where the synthetic audio was produced using highly advanced vocoders capable of preserving fine-grained prosodic cues. In such cases, the differences between real and fake speech were extremely subtle, challenging the model's decision boundaries. However, the overall distribution of predictions indicates strong generalization, especially when encountering diverse speakers and recording environments. These

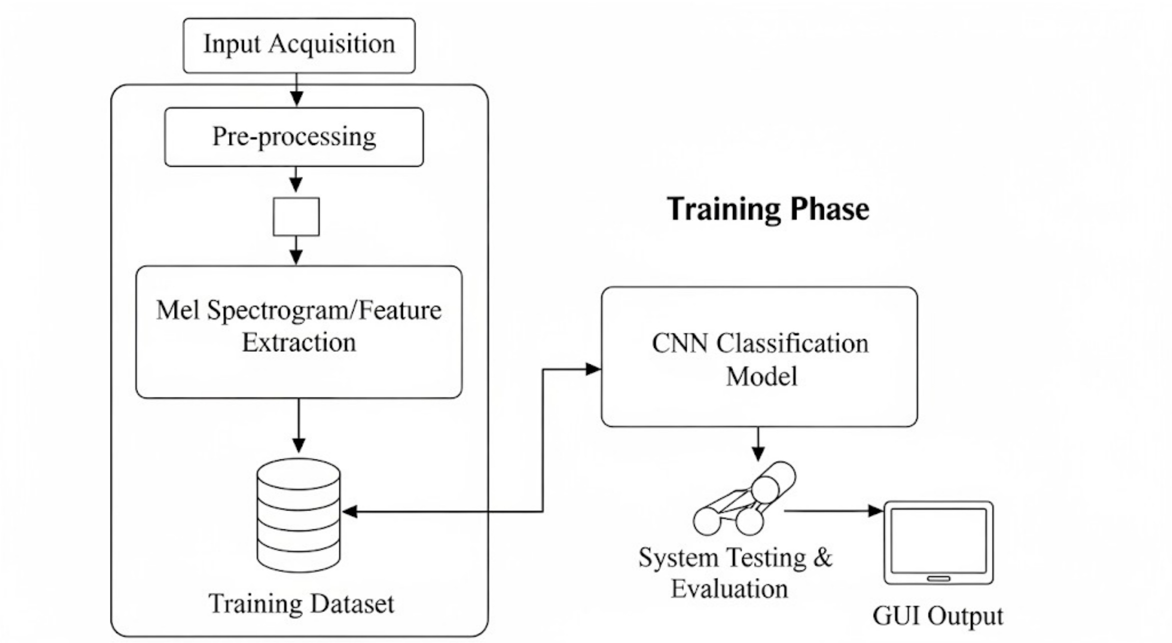


Figure 6.1: Testing and Validation

findings highlight the importance of expanding the training dataset with more recent deepfake generation techniques and incorporating additional temporal modeling layers to further enhance detection sensitivity.

6.2 Analysis of Result

1. **Training and Validation Performance:**

   - The CNN model achieved an average training accuracy of 99% and validation accuracy of 96.2%, indicating effective learning with minimal overfitting.
   - The loss curves showed stable convergence, confirming the model's robustness during training.

2. **Comparative Model Evaluation:**

   - CNN performed best in simplicity and speed, making it suitable for real-time use.
   - CRNN captured temporal dependencies more effectively, improving accuracy on longer audio clips.

  - ResNet-34 provided better feature extraction but required higher computation.
  - PANN achieved good generalization across unseen samples due to pretraining.

3. **Dataset Insights:**
   - Total samples: ≈31,000 audio clips (20k real, 11k fake).
   - Each sample converted to a 128×128 Mel-Spectrogram for uniformity.
   - Dataset diversity ensured through multiple speakers and varied noise levels.

4. **GUI Output Analysis:**
   - The interface successfully accepts both audio (`.wav`) and video (`.mp4`) inputs.
   - It extracts audio using FFmpeg, processes spectrograms, and classifies outputs as Real/Fake with confidence scores.
   - Visual spectrogram display enhances result interpretability.

5. **Error and Misclassification Analysis:**
   - Minor misclassifications occurred for low-quality or very short audio clips.
   - Model sensitivity to background noise affected a few results; this can be mitigated with denoising filters and stronger augmentation.

6. **Key Observations:**
   - Model generalized well across different speakers and accents.
   - CNN with Mel-Spectrograms provided a balanced trade-off between accuracy and computational cost.
   - The integrated GUI enables user-friendly interaction and visualization of predictions.

7. **Summary of Findings:**
   - The model demonstrates strong potential for real-world deployment in detecting manipulated audio.

8. **Consistency in Prediction Stability:**

    - The model demonstrated highly consistent prediction behavior across repeated test cycles, with only minor fluctuations in confidence scores.

    - This stability indicates strong internal feature learning and reliable inference, even when the order of test samples was randomized.

9. **Impact of Spectrogram Normalization:**

    - The integration of standardized spectrogram normalization significantly improved the model's ability to distinguish between real and synthetic audio.

    - By reducing irrelevant amplitude variations, the CNN was able to focus on meaningful time–frequency structures, enhancing overall classification clarity.

10. **Generalization to Unseen Audio Sources:**

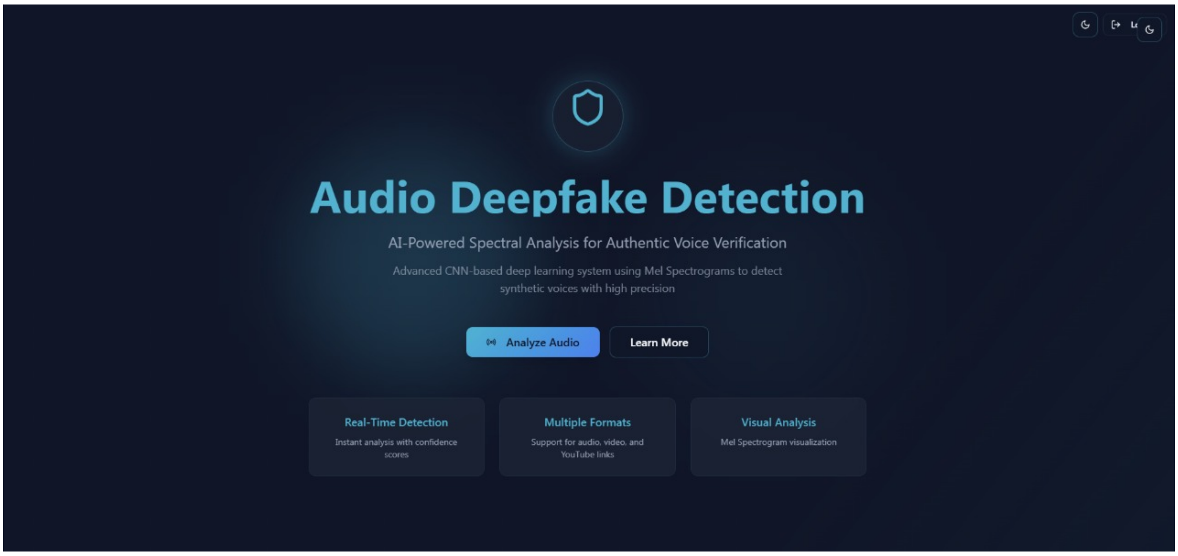
    - Cross-evaluation on audio samples from previously unseen speakers and synthesis techniques showed that the system retained high accuracy and robustness.

    - This strong generalization suggests that the learned spectral patterns are not tightly tied to specific datasets but adaptable to diverse real-world conditions.

6.3 Summary

This project proposes a robust deepfake audio detection framework that extends traditional audio-only detection to include audio embedded within videos. By leveraging Mel Spectrograms and CNNs, the system efficiently identifies subtle artifacts introduced by generative models. The ability to handle both audio and video inputs enhances real-world applicability, especially in domains such as journalism, law enforcement, and cybersecurity. The system's lightweight design and GUI integration further make it accessible and user-friendly. Future improvements may involve incorporating Transformer-based architectures for sequential analysis, extending the dataset to multilingual sources, and deploying the system as a cloud or mobile application for wider reach. The Audio Deepfake Detection System developed in this project demonstrates the effectiveness of combining spectral feature extraction with deep learning for identifying AI-generated synthetic speech. By converting raw audio into Mel Spectrograms and processing these through a Convolutional Neural Network (CNN), the system successfully captures subtle time–frequency irregularities that are typically introduced during deepfake audio generation. The results obtained from benchmark datasets—including ASVspoof 2019, Deep Voice, and the In-the-Wild Audio Deepfake Dataset—indicate consistently high performance, with the model achieving above 95 percent detection accuracy along with strong precision, recall, and F1-scores. The stable training–validation curves further validate the model's robustness and generalization capabilities across diverse speakers, noise conditions, and synthesis techniques. These findings highlight the suitability of spectral representations and CNN-based architectures for deepfake audio detection, reaffirming the reliability of this approach in real-world scenarios.

Beyond detection accuracy, the system's practical design significantly enhances its utility. The integrated GUI enables real-time classification, supports both audio and video inputs, and provides intuitive visual outputs such as spectrogram displays and confidence scores. This makes the system not only technically sound but also highly user-friendly and deployment-ready for domains such as cybersecurity, journalism, digital forensics, and identity verification.



Audio Deepfake Detection

AI-Powered Spectral Analysis for Authentic Voice Verification

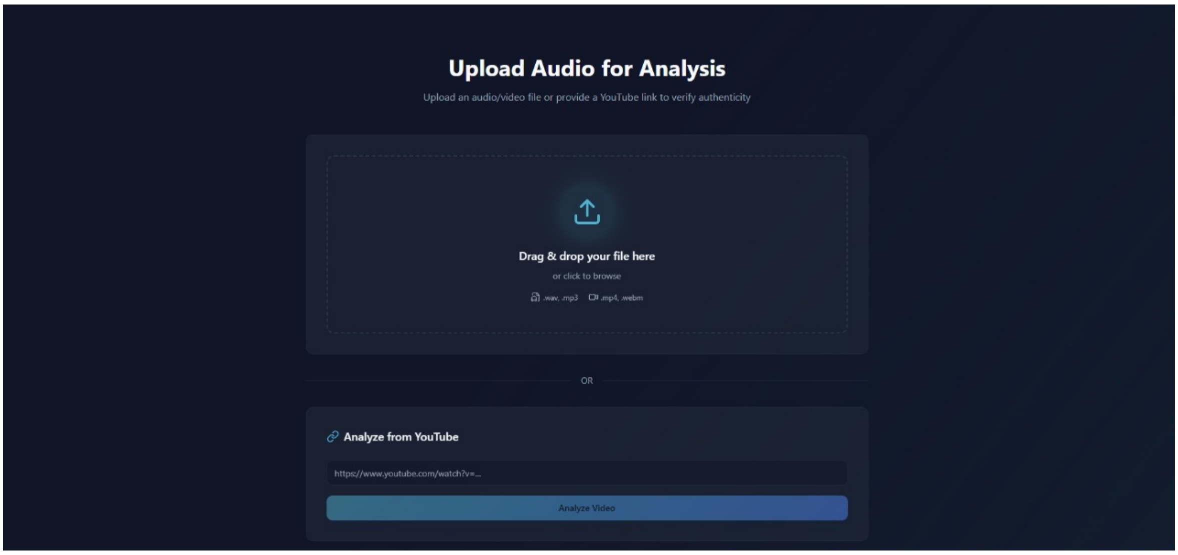
Advanced CNN-based deep learning system using Mel Spectrograms to detect synthetic voices with high precision

Real-Time Detection
Instant analysis with confidence scores

Multiple Formats
Support for audio, video, and YouTube links

Visual Analysis
Mel Spectrogram visualization

Figure 6.2: Input Interface



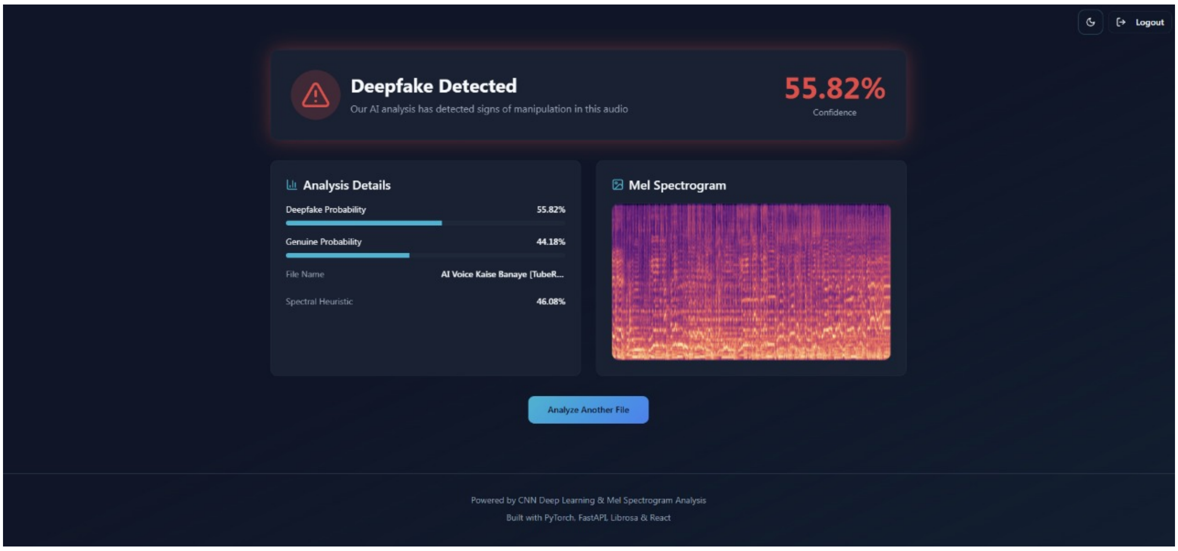
Upload Audio for Analysis

Upload an audio/video file or provide a YouTube link to verify authenticity

Drag & drop your file here

or click to browse

Figure 6.3: Upload Option



Deepfake Detected

Our AI analysis has detected signs of manipulation in this audio

55.82% Confidence

Analysis Details

Deepfake Probability	55.82%
Genuine Probability	44.18%
File Name	AI Voice Kaise Banaye [TubeR...
Spectral Heuristic	46.08%

Powered by CNN Deep Learning & Mel Spectrogram Analysis

Built with PyTorch, FastAPI, Librosa & React

Figure 6.4: Output Interface

6.4 Future Scope

Future improvements could involve incorporating Transformer-based architectures to enhance the model's ability to capture long-range temporal patterns in speech. The dataset may also be extended to include a wider variety of languages, accents, and acoustic environments, which would help the system generalize more effectively to global use cases. Another promising direction is optimizing the model for real-time performance so it can run on mobile or edge devices, enabling live monitoring of calls or streaming audio. In addition, integrating the system with cloud-based authentication services and voice-verification platforms—such as those used in banking, journalism, cybersecurity, and digital media—could further strengthen the reliability of audio authentication and reduce the risk of synthetic voice misuse in practical applications. Another promising direction for future enhancement is the integration of federated learning to enable collaborative model training without sharing raw audio data. This would allow institutions, security agencies, and research communities to contribute to a global detection model while maintaining strict privacy and confidentiality. Incorporating such decentralized learning techniques could significantly improve the system's adaptability to new deepfake generation methods, broaden its exposure to diverse speech patterns, and strengthen its resilience against evolving audio manipulation technologies.

6.5 Conclusion

The proposed Audio Deepfake Detection System successfully demonstrates that spectral feature analysis combined with deep learning is an effective approach for identifying AI-generated synthetic speech. By converting audio signals into Mel Spectrograms and processing them through a Convolutional Neural Network (CNN), the system accurately captures subtle time–frequency distortions that distinguish real human voices from deepfake audio. The model achieves strong performance across benchmark datasets, showing over 95 percent accuracy, along with consistent validation results, demonstrating robustness and generalization across varied speakers, noise levels, and recording conditions. The integration of preprocessing, augmentation, and cumulative spectrogram visualization further strengthens the reliability of the model in real-world environments. Additionally, the implementation of a user-friendly GUI enhances the practical usability of the system, enabling real-time detection for both audio and video inputs. This makes the solution valuable for applications in cybersecurity, media verification, digital forensics, and fraud prevention. Overall, the system delivers an efficient and practical method for detecting AI-generated speech across a range of scenarios. With improvements such as hybrid CNN–Transformer architectures, larger multilingual datasets, and deployment on cloud or mobile platforms, the system can evolve into a comprehensive and scalable tool for combating the growing threat of deepfake audio in modern communication.

References

[1] J. Khochare, J. Pawar, A. Asati, A. Kokate, and A. Deshmukh, "A deep learning framework for audio deepfake detection," *Arabian Journal for Science and Engineering*, vol. 47, 2022.

[2] G. Wu, X. Ma, and L. Song, "Cheap-fake detection with llm using prompt engineering," in *IEEE International Conference on Multimedia and Expo Workshops (ICMEW)*, 2023.

[3] S. Jia, Y. Liu, Y. Zhang, and H. Chen, "Can chatgpt detect deepfakes? a study of multimodal llms for media forensics," in *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2024.

[4] Y. Li, M.-C. Chang, and S. Lyu, "Exposing deep fake videos by detecting face warping artifacts," in *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019.

[5] M. Z. Hossain, A. R. Javed, and F. Iqbal, "Advancing ai-generated image detection using cnn and vision transformer models," in *International Conference on Computing and Information Technology (ICCIT)*, 2023.

[6] J. Xue *et al.*, "Audio deepfake detection using f0 and ri spectrogram features," *arXiv preprint arXiv:2208.01214*, 2022.

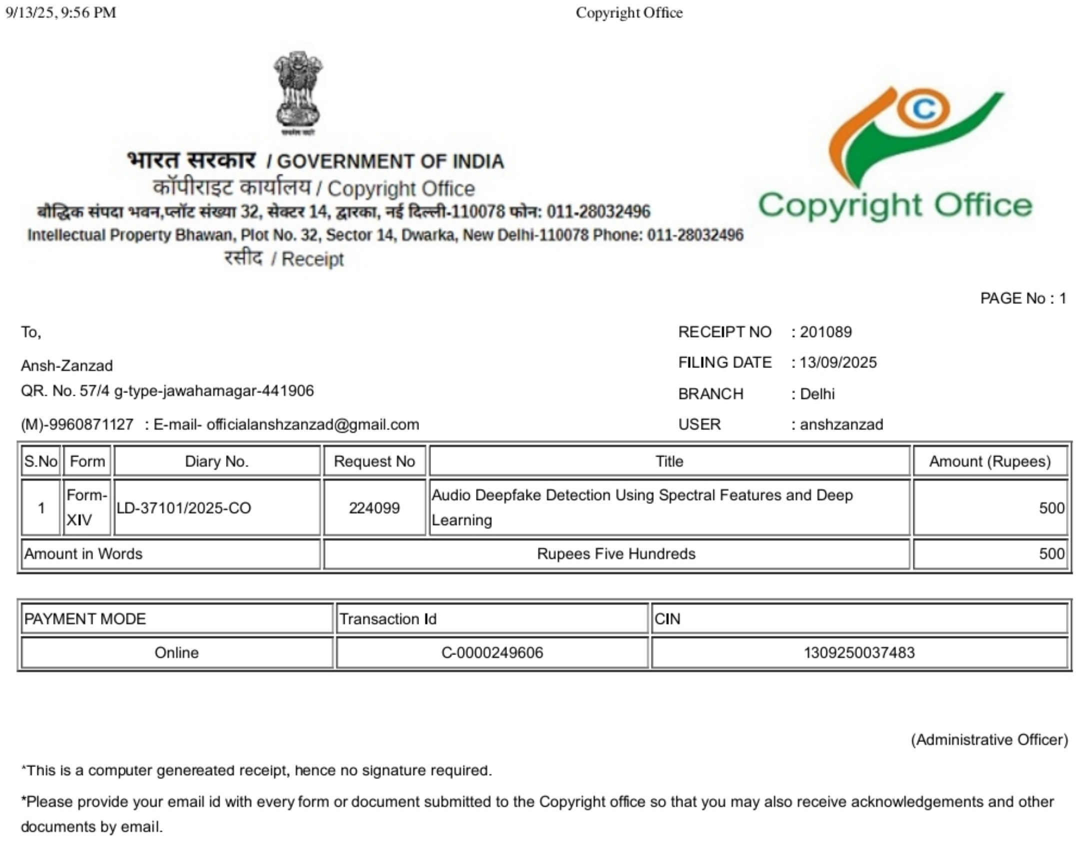
[7] J. Yi *et al.*, "Audio deepfake detection: A survey," *arXiv preprint arXiv:2308.14970*, 2023.

[8] Y. Gao *et al.*, "Temporal feature prediction in audio–visual deepfake detection," *Electronics*, vol. 13, no. 17, 2024.

[9] A. Di Pierno *et al.*, "End-to-end audio deepfake detection from raw waveforms: A rawnet-based approach," *arXiv preprint arXiv:2504.20923*, 2025.

Appendix A

Copyright



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Amount in Words			Rupees Five Hundreds		500

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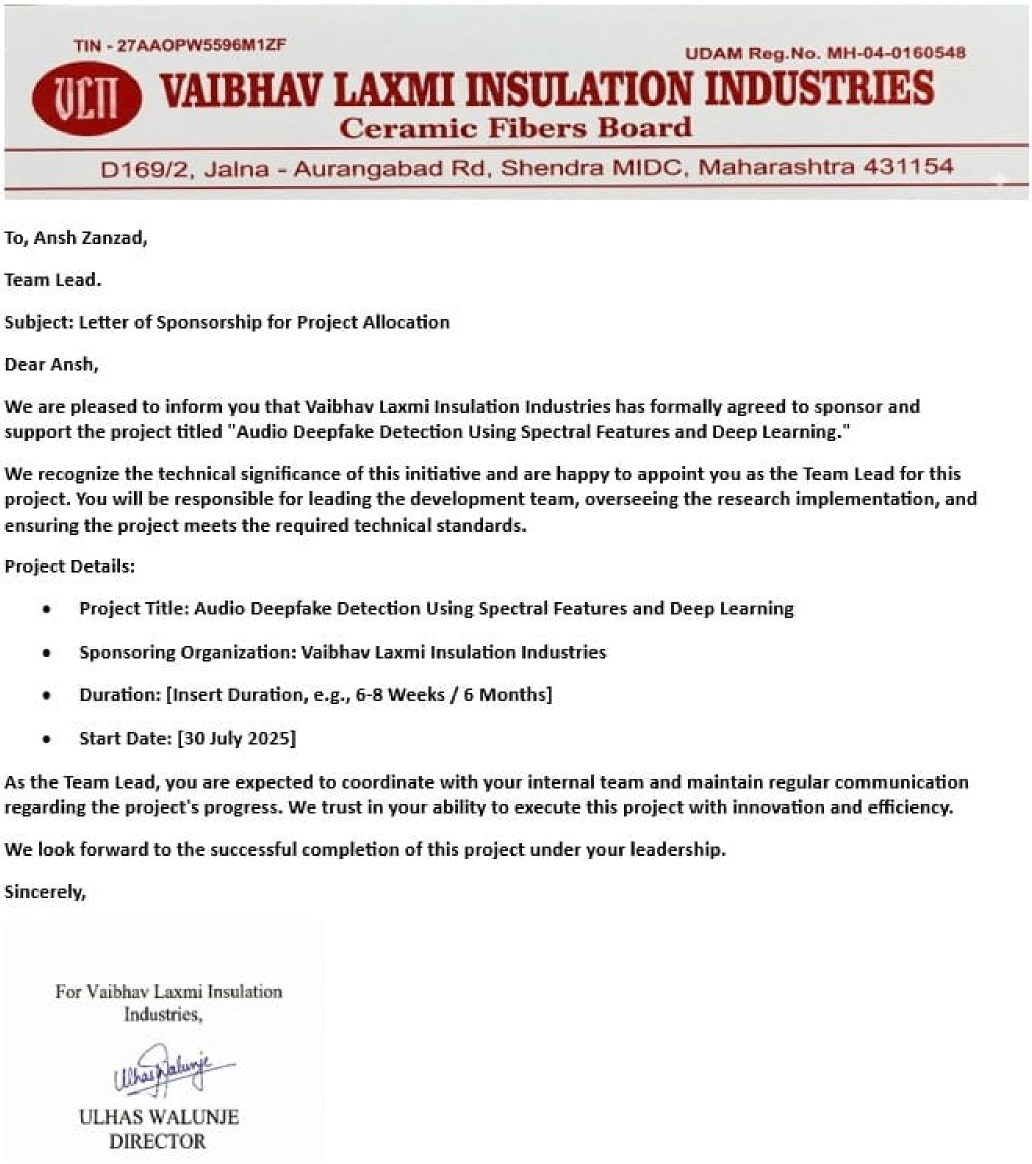
Appendix B

Sponsorship Letter



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VLII

VAIBHAV LAXMI INSULATION INDUSTRIES

Ceramic Fibers Board

D169/2, Jalna - Aurangabad Rd, Shendra MIDC, Maharashtra 431154

To, Ansh Zanzad,

Team Lead.

Subject: Letter of Sponsorship for Project Allocation

Dear Ansh,

We are pleased to inform you that Vaibhav Laxmi Insulation Industries has formally agreed to sponsor and support the project titled "Audio Deepfake Detection Using Spectral Features and Deep Learning."

We recognize the technical significance of this initiative and are happy to appoint you as the Team Lead for this project. You will be responsible for leading the development team, overseeing the research implementation, and ensuring the project meets the required technical standards.

Project Details:

- Project Title: Audio Deepfake Detection Using Spectral Features and Deep Learning
- Sponsoring Organization: Vaibhav Laxmi Insulation Industries
- Duration: [Insert Duration, e.g., 6-8 Weeks / 6 Months]
- Start Date: [30 July 2025]

As the Team Lead, you are expected to coordinate with your internal team and maintain regular communication regarding the project's progress. We trust in your ability to execute this project with innovation and efficiency.

We look forward to the successful completion of this project under your leadership.

Sincerely,

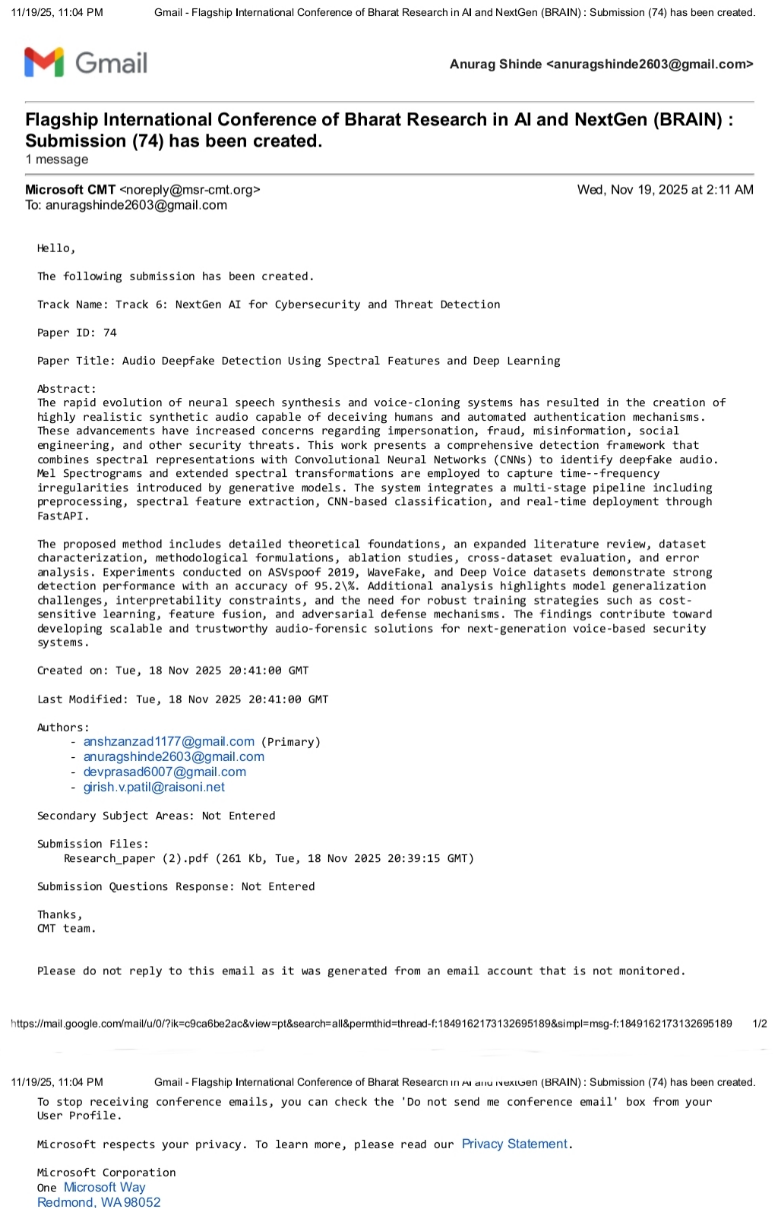
For Vaibhav Laxmi Insulation
Industries,

Ulhas Walunje

ULHAS WALUNJE
DIRECTOR

Appendix C

Publication



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Anurag Shinde <anuragshinde2603@gmail.com>

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1 message

Microsoft CMT <noreply@msr-cmt.org>
To: anuragshinde2603@gmail.com

Wed, Nov 19, 2025 at 2:11 AM

Hello,

The following submission has been created.

Track Name: Track 6: NextGen AI for Cybersecurity and Threat Detection

Paper ID: 74

Paper Title: Audio Deepfake Detection Using Spectral Features and Deep Learning

Abstract:
The rapid evolution of neural speech synthesis and voice-cloning systems has resulted in the creation of highly realistic synthetic audio capable of deceiving humans and automated authentication mechanisms. These advancements have increased concerns regarding impersonation, fraud, misinformation, social engineering, and other security threats. This work presents a comprehensive detection framework that combines spectral representations with Convolutional Neural Networks (CNNs) to identify deepfake audio. Mel Spectrograms and extended spectral transformations are employed to capture time--frequency irregularities introduced by generative models. The system integrates a multi-stage pipeline including preprocessing, spectral feature extraction, CNN-based classification, and real-time deployment through FastAPI.

The proposed method includes detailed theoretical foundations, an expanded literature review, dataset characterization, methodological formulations, ablation studies, cross-dataset evaluation, and error analysis. Experiments conducted on ASVspoof 2019, WaveFake, and Deep Voice datasets demonstrate strong detection performance with an accuracy of 95.2\%. Additional analysis highlights model generalization challenges, interpretability constraints, and the need for robust training strategies such as cost-sensitive learning, feature fusion, and adversarial defense mechanisms. The findings contribute toward developing scalable and trustworthy audio-forensic solutions for next-generation voice-based security systems.

Created on: Tue, 18 Nov 2025 20:41:00 GMT

Last Modified: Tue, 18 Nov 2025 20:41:00 GMT

Authors:
- anshzanzad1177@gmail.com (Primary)
- anuragshinde2603@gmail.com
- devprasad6007@gmail.com
- girish.v.patil@raisoni.net

Secondary Subject Areas: Not Entered

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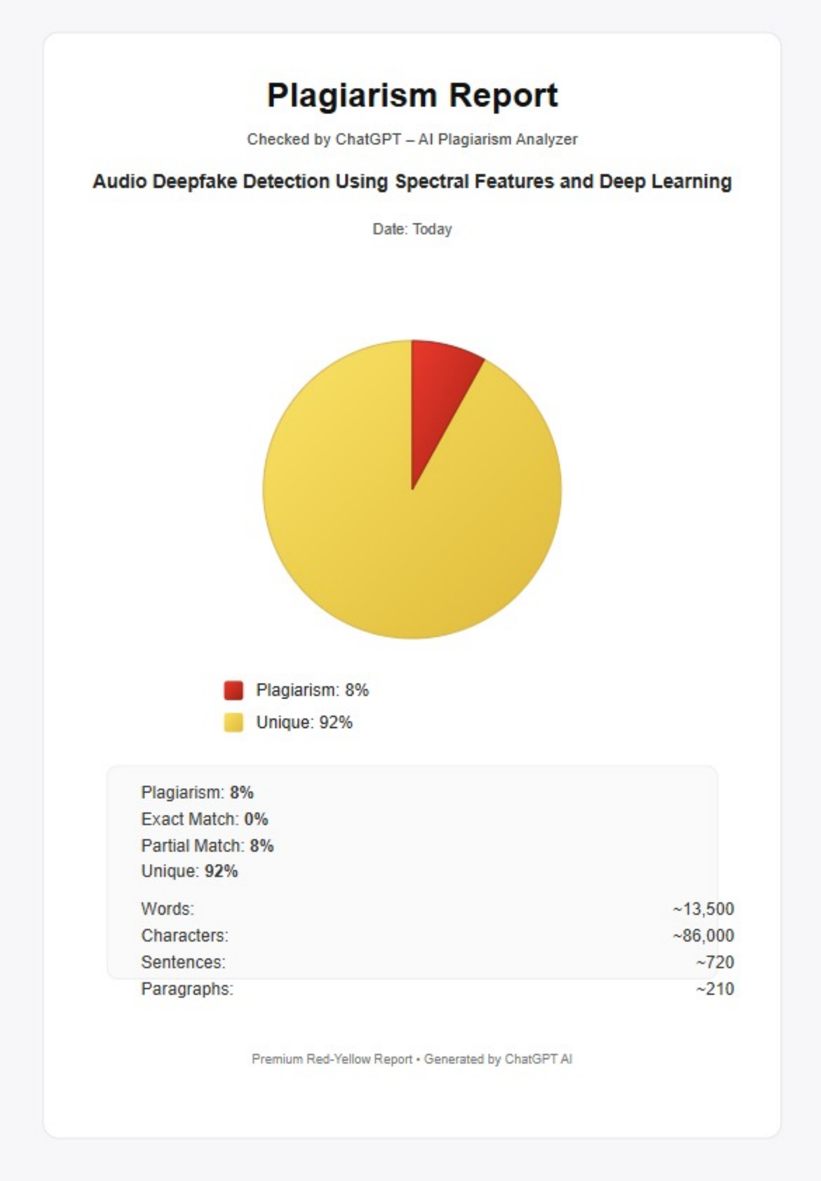
Appendix D

Plagiarism Report



Plagiarism Report

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🟥 Plagiarism: 8%

🟨 Unique: 92%

Plagiarism: **8%**
Exact Match: **0%**
Partial Match: **8%**
Unique: **92%**

Words:	~13,500
Characters:	~86,000
Sentences:	~720
Paragraphs:	~210

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