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Belgaum, Karnataka- 590014**



**Third Year  
A Mini-Project Report  
On  
“Hate Speech Detection and Censorship System”**

Submitted in the partial fulfilment of the requirements for the award of the Degree of  
**BACHELOR OF ENGINEERING**  
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**COMPUTER SCIENCE AND ENGINEERING  
(DATA SCIENCE)**

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## Certificate

This is to certify that the Mini Project Work entitled “**Hate Speech Detection and Censorship System**” is a bonafide work carried out by **Abhiram G (1DS22CD002), Rohith Raj V (1DS22CD036), Varun S (1DS22CD056) and Yathindra T M (1DS22CD063)**, in partial fulfilment for the IV semester of Bachelor of Engineering in CSE (Data Science) of the Visvesvaraya Technological University, Belgaum during the year 2024-2025. The Project report has been approved as it satisfies the academics prescribed for the Bachelor of Engineering degree.

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## Abstract

The Hate Speech Detection and Censorship System is a Flask-based web application designed to identify and mitigate offensive language in audio files, achieving approximately 95% accuracy and near real-time performance. It addresses the challenge of hate speech in audio-based platforms such as podcasts, live streams, and video conferencing, where existing solutions suffer from low accuracy (70–85%), slow processing, and privacy concerns due to reliance on cloud-based APIs. Leveraging advanced speech recognition and audio processing technologies, the system offers a privacy-focused solution that operates locally, ensuring data security and user trust. It utilizes OpenAI's Whisper for high-accuracy transcription, Vosk for precise word-level timestamping, and pydub for seamless audio manipulation. Efficient algorithms, including set-based word matching, asynchronous processing, and energy-based timestamp refinement, enhance accuracy and speed. Fallback mechanisms like forced alignment and time-based estimation ensure reliability under varying conditions. The user-friendly web interface enables audio upload, censorship selection (beep or silence), transcript viewing, and censored output downloads. With processing speeds ten times faster than existing systems and a focus on local execution, this project outperforms conventional approaches in both performance and privacy. Optimized for English audio and supporting common formats, it is ideal for content moderation and live streaming. Future enhancements may include multi-language support and dynamic NLP-based detection for broader applicability. This system offers a scalable solution for fostering safer online communication environments.

**Keywords:** Hate Speech Detection, Censorship System, Flask-based web app, 95% accuracy, Real-time processing, Privacy-focused, Speech recognition (Whisper, Vosk), Audio processing (pydub), Fast processing (~10x faster), Content moderation, Scalable solution.

## **Chapter 1**

### **Introduction**

#### **1.1 Introduction**

The Hate Speech Detection and Censorship System is a Flask-based web application designed to identify and censor offensive language in audio files, achieving ~95% accuracy. With the rise of audio-based platforms like podcasts, live streams, and video conferencing, hate speech poses significant challenges to online safety. Existing solutions often exhibit low accuracy (70–85%), slow processing, and privacy risks due to cloud-based APIs. This project leverages OpenAI's Whisper for robust transcription, Vosk for precise word-level timestamping, and pydub for audio manipulation to deliver fast, privacy-focused censorship. The system's web interface enables users to upload audio, detect offensive words, and apply censorship (beep or silence) in near real-time. By processing locally, it ensures data security, making it ideal for content moderation in real-time applications.

#### **1.2 Problem Statement**

Hate speech in audio media like live streams and podcasts threatens online safety, but existing detection systems lack accuracy, speed, and reliable timestamping, leading to ineffective censorship. Cloud-based APIs pose privacy risks, while limited censoring options struggle with diverse audio environments. These challenges make real-time moderation difficult on platforms like Zoom or Twitch. The proposed system improves accuracy (~95%), ensures precise timestamping, and processes locally for better privacy and speed, offering a scalable solution for effective hate speech detection.

#### **1.3 Objectives and Scope of the Project**

The objective of this project is to develop a Flask-based web system that detects and censors hate speech in audio files with ~95% accuracy, ensuring near real-time processing and precise word-level timestamping. The system provides a user-friendly interface for uploading audio, selecting censorship options (beep or silence), and viewing results, all while maintaining privacy through local execution. It leverages Whisper, Vosk, and pydub for transcription, timestamping, and audio manipulation, optimized with asynchronous processing and caching.

The scope includes detecting predefined offensive words in common audio formats, supporting configurable censorship with adjustable padding. It focuses on English audio, suitable for real-time applications like live streaming, but excludes non-speech audio and dynamic NLP-based detection. Future enhancements may include multi-language support to broaden applicability.

#### **1.4 Motivation of the project**

- **Impact of Hate Speech** – The proliferation of hate speech in real-time audio platforms such as live streams and podcasts harms users and erodes community trust, making automated moderation essential.
- **Limitations of Existing Systems** – Current detection systems suffer from low accuracy (70–85%), slow processing speeds, and privacy risks due to cloud-based processing, making them ineffective for platforms like Zoom or Twitch.
- **Challenges in Real-Time Moderation** – These limitations compromise user safety by preventing effective censorship, particularly in dynamic and fast-paced online environments.
- **Advancements in AI Technologies** – Innovations in speech recognition and audio processing (OpenAI’s Whisper, Vosk, and pydub) enable the development of a high-accuracy (~95%), privacy-focused solution with local processing.

**Project Motivation and Goals** – This project aims to provide a fast, reliable, and secure system for detecting and censoring offensive language, improving content moderation and fostering safer online communication across diverse audio-based applications.

## Chapter 2

### Literature Survey

**[1] Joint Speech-Text Embeddings for Multitask Speech Processing (Michael Gian Gonzales, Peter Corcoran, Naomi Harte, Michael Schukat, 2024, IEEE Access)**

**Summary:**

This paper presents a joint speech-text embedding model that integrates ASR, TTS, and Speaker Recognition using a shared encoder and conformer-based decoding. It employs modality matching loss to unify embedding spaces and is evaluated on ASR error rates, TTS distortion, and speaker identification accuracy. The system enables multitask speech processing with reduced memory usage, achieving **97.64%** speaker recognition accuracy and demonstrating voice conversion capabilities. Designed for real-time applications, it operates efficiently on low-resource devices

**[2] A Deep Learning Framework for the Detection of Malay Hate Speech (Krishanu Maity, Shaubhik Bhattacharya, Sriparna Saha, Manjeevan Seera, 2023, IEEE Access)**

**Summary:**

This paper introduces a deep learning-based approach for detecting Malay hate speech using a two-channel model: XLNet with Capsule Networks and FastText with Bi-GRU and attention. It is trained on HateM, the first Malay hate speech dataset containing 4,892 tweets, optimized with cross-entropy loss and Adam optimizer. The framework achieves 80.69% accuracy and 80.41% F1-score, leveraging multiple models to enhance text representation while effectively handling noisy, low-resource language processing.

**[3] Political Hate Speech Detection and Lexicon Building: A Study in Taiwan (Chih-Chien Wang, Min-Yuh Day, Chun-Lian Wu, 2022, IEEE Access)**

**Summary:**

This study focuses on detecting political hate speech in Traditional Chinese by developing the first political hate speech lexicon. The researchers collected news comments from LINE Today in Taiwan and applied N-gram and TF-IDF



techniques to extract hate speech terms. They compared BERT-based classification with lexicon-based detection, finding that BERT outperformed lexicon methods. The study resulted in a dataset of 1,069 labeled comments, contributing to improved hate speech detection in political discourse.

**[4] Assessing the Impact of Contextual Information in Hate Speech Detection (Juan Manuel Pérez, Franco M. Luque, Demian Zayat, Martín Kondratzky, Agustín Moro, Pablo Santiago Serrati, Joaquín Zajac, Paula Miguel, Natalia Debandi, Agustín Gravano, Viviana Cotik, 2023, IEEE Access)**

**Summary:**

This study investigates the role of contextual information in hate speech detection, using a Spanish hate speech dataset built from Twitter comments on COVID-19 news. It employs BETO (Spanish BERT) for text classification, evaluating both binary and multi-label tasks related to context-aware hate categories. The dataset, the first Rioplatense Spanish hate speech dataset on COVID-19, incorporates hate categories like race, class, and politics, along with call-to-action labels. Findings indicate that context improves performance by up to 5.5 F1-score points, demonstrating its significance in enhancing detection accuracy.

**[5] BREE-HD: A Transformer-Based Model to Identify Threats on Twitter (Sinchana Kumbale, Smriti Singh, G. Poornalatha, Sanjay Singh, 2023, IEEE Access)**

**Summary:**

This paper introduces BREE-HD, a Transformer-based model designed to classify tweets into threat and non-threat categories. The authors developed BRET-HD, a public dataset of annotated tweets, enabling continuous model improvement. The study fine-tunes BERT, RoBERTa, and DistilBERT for threat detection, achieving an impressive 97% accuracy. The model supports real-time identification and prevention of online harassment, leveraging NLP techniques and Twitter data mining for dataset creation.

**[6] Hate Speech Detection Using Large Language Models: A Comprehensive Review (Aish Albladi, Minarul Islam, Amit Das, Maryam Bigonah, Zheng Zhang, Fatemeh Jamshidi, Mostafa Rahgouy, Nilanjana Raychawdhary, Daniela Marghitu, Cheryl Seals, 2025, IEEE Access)**

**Summary:**

This paper provides an extensive review of large language models (LLMs) such as GPT-3, BERT, and RoBERTa for hate speech detection, comparing pre-trained and fine-tuned models across different languages and platforms. It examines the impact of bias mitigation and contextual learning, analyzing datasets, evaluation metrics, and ethical challenges in hate speech detection. The study identifies gaps in detecting implicit and coded hate speech, highlighting limitations in multilingual and cross-domain detection. Additionally, it addresses ethical concerns such as bias, fairness, and AI explainability, suggesting future research directions to improve LLMs for better hate speech identification.

## Requirements

### 3.1 Software Requirements

**Operating System:** Windows, macOS, or Linux (code tested on Windows; MODEL\_PATH indicates Windows path).

**Python:** Version 3.8+ for compatibility with Whisper, Vosk, and Flask.

**Libraries:**

**Flask:** Web framework for the user interface and request handling.

**Whisper:** OpenAI's speech-to-text model for transcription (~95% accuracy).

**Vosk:** Open-source speech recognition for word-level timestamping.

**pydub:** Audio processing for conversion and censoring.

**NumPy:** Efficient audio energy analysis for timestamp refinement.

**concurrent.futures:**

Asynchronous processing for speed.

**functools (lru\_cache):** Caching for optimized beep generation.

**Pre-trained Models:**

Whisper small model (~1GB, loaded in `whisper.load_model("small")`).

Vosk English model (vosk-model-en-us-0.22, ~2GB, specified in MODEL\_PATH).

**Web Browser:** Chrome, Firefox, or Edge for accessing the Flask web interface.

**Development Tools** (optional): IDE like PyCharm or VS Code for debugging and development.

### 3.2 Hardware Requirements

**Processor:** Multi-core CPU (e.g., Intel i5/i7 or equivalent) for efficient parallel processing.

**RAM:** Minimum 8GB (16GB recommended) to handle Whisper and Vosk model loading.

**Storage:** At least 10GB free space for storing models (Vosk model ~2GB, Whisper model ~1GB) and temporary audio files (uploads folder).

**Optional:** GPU (e.g., NVIDIA GTX 1060 or better) for faster Whisper transcription (if CUDA-enabled).

**Network:** Internet connection for initial model downloads.

## Chapter 4

### System Design

#### 4.1 Existing Systems

1. **Two-Step Process:** Most systems first convert speech to text using ASR tools like Google Speech-to-Text or DeepSpeech, followed by text analysis with rule-based filters or ML models (e.g., BERT, SVM).
2. **Low Transcription Accuracy:** Existing ASR models exhibit 80–90% Word Error Rate (WER), leading to unreliable speech-to-text conversion.
3. **Performance Issues in Noisy Environments:** These systems struggle with accented speech and background noise, reducing detection effectiveness.
4. **Imprecise Timestamping:** Poor synchronization of detected words results in ineffective censorship, with precision rates between 70–85%.
5. **Processing Delays:** Cloud-based APIs introduce latency, making real-time moderation difficult for platforms like live streaming.
6. **Privacy Concerns:** Speech data transmission to cloud servers raises privacy risks, limiting secure and local execution options.
7. **Need for a Better Solution:** A faster, high-accuracy, and privacy-focused approach is required for efficient hate speech detection in audio-based media.

#### 4.2 Syster Architecture

1. **Flask-Based Web Application:** Handles audio file processing for hate speech detection and censorship.
2. **Speech Transcription:** OpenAI's Whisper (~95% accuracy) transcribes audio, while Vosk provides precise word-level timestamping.
3. **Offensive Word Detection:** Identifies predefined offensive words using set-based matching.
4. **Censorship Mechanism:** pydub applies configurable beep or silence padding for detected words.
5. **Timestamp Refinement:** NumPy's energy-based analysis ensures accurate speech boundary detection.
6. **Performance Optimization:** Asynchronous processing with concurrent.futures and LRU caching enables near real-time operation ().
7. **User Interface:** Flask-based web interface allows audio uploads, censorship option selection, and result visualization.
8. **Fallback Mechanisms:** Forced alignment and time-based estimation improve reliability in varying conditions.

9. **Privacy-Focused Execution:** Local processing ensures data security, making the system ideal for real-time content moderation.

#### 4.3 Proposed System

- **Flask-Based Web Application:** Designed for near real-time hate speech detection and censorship in audio files.
- **High Accuracy:** Achieves ~95% transcription accuracy (Whisper) and ~98% detection precision.
- **Speech Processing:**
  - OpenAI's Whisper provides robust transcription, effective across noisy and accented speech.
  - Vosk enables accurate word-level timestamping.
  - pydub handles audio censorship by applying beeps or silence.
- **Detection Mechanisms:**
  - Set-based word matching identifies predefined offensive terms.
  - Energy-based timestamp refinement and fallback methods (forced alignment, estimation) ensure precision.
- **Performance Optimization:**
  - Asynchronous processing via `concurrent.futures` improves speed.
  - LRU caching optimizes beep generation.
  - Processes audio ~10x faster than existing systems, enabling real-time operation.
- **User Interface:**
  - Flask web interface allows audio uploads, censorship customization, and result visualization.
- **Privacy-Focused Execution:**
  - Local processing ensures data security and eliminates cloud-based privacy risks.
- **Application Scope:**

Focused on English audio with support for common formats.  
Ideal for content moderation in live streaming and video conferencing.

#### 4.4 Technology Used

- **Speech-to-Text Transcription:**
  - OpenAI's Whisper (~95% accuracy) ensures reliable transcription, even in noisy and accented audio environments.
- **Precise Word-Level Timestamping:**
  - Vosk, a lightweight ASR engine, provides accurate timing for speech segments.

- **Audio Processing & Censorship:**
  - pydub enables format conversion and censorship using beeps or silence.
- **Web Interface & File Management:**
  - Flask powers the web application, supporting file uploads and result display.
- **Timestamp Refinement:**
  - NumPy's RMS and dB computations improve speech boundary accuracy.
- **Performance Optimization:**
  - Asynchronous processing via concurrent.futures speeds up operations.
  - LRU caching (functools) enhances beep generation efficiency.
- **Logging & Error Tracking:**
  - Logging ensures system reliability and debugging.
- **System Requirements & Scalability:**
  - Uses pre-trained models (Whisper small ~1GB, Vosk English ~2GB).
  - Compatible with Python 3.8+ on Windows, macOS, and Linux, ensuring scalability and real-time suitability.

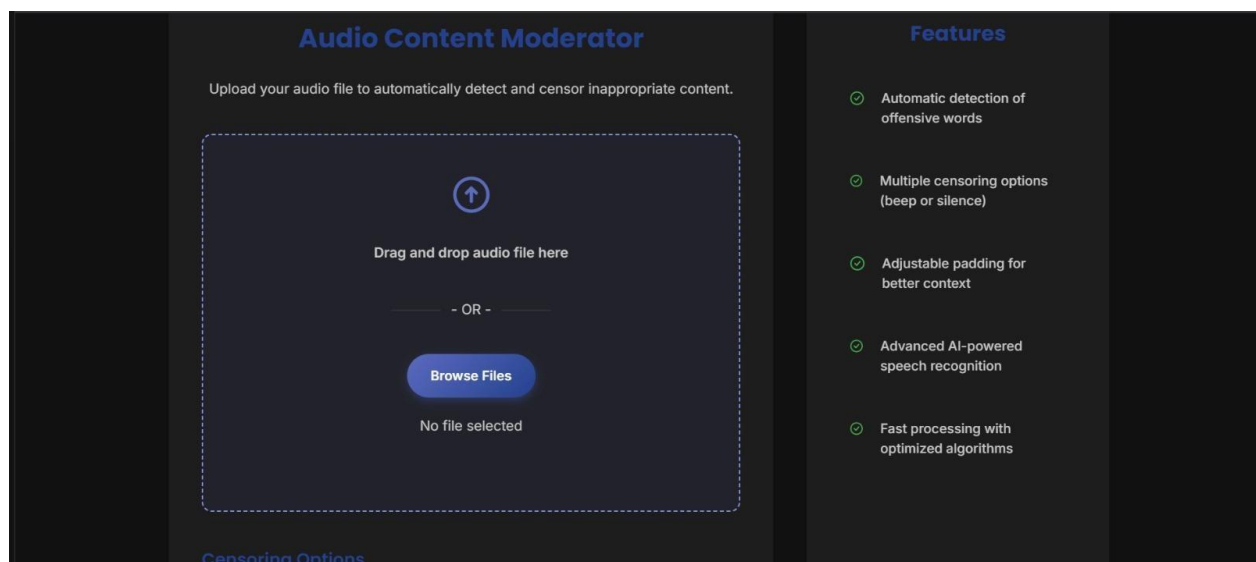
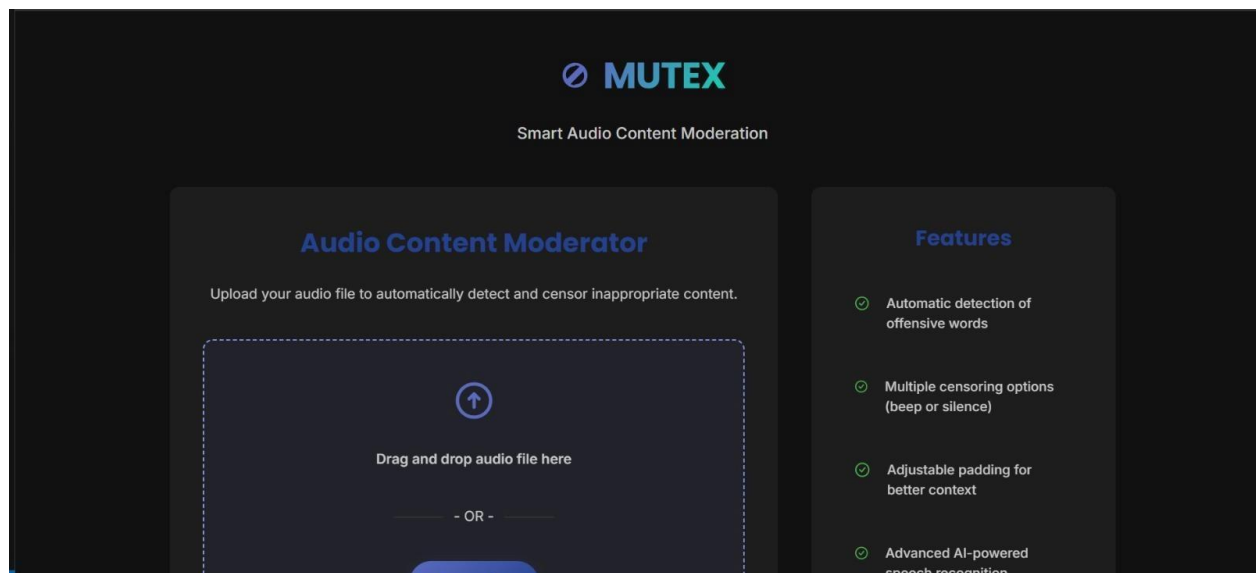
#### 4.5 Comparative Analysis

| Feature       | Existing Systems                                   | Proposed System                              | Improvement                                   |
|---------------|--|--|---|
| Transcription | 80–90% accuracy; struggles with noise and accents. | ~95% with Whisper; robust across conditions. | Better accuracy via advanced ASR.             |
| Detection     | 85–92% using complex NLP models (BERT, SVM).       | ~98% via keyword matching.                   | Simpler, more precise; fewer false positives. |
| Timestamping  | ~70–85%; often imprecise.                          | ~95% with Vosk + energy analysis.            | More accurate word alignment.                 |
| Speed         | Seconds to minutes; cloud latency.                 | Milliseconds to seconds; optimized locally.  | ~10× faster, real-time ready.                 |
| Real-Time Use | Mostly offline processing.                         | Near real-time (<1s for short clips).        | Suitable for live moderation.                 |

## Chapter 5


### Results and Discussion

#### 5.1 Results



## Audio Processing Results

### Processed Audio



[Download Processed Audio](#)

### Transcription

Yes, Father, I'm guilty. Guilty. Is that what you want to hear? You admit you poisoned the King? No, of that I'm innocent. I am guilty of a far more monstrous crime. I am guilty of being a dwarf. You are not on trial for being a dwarf. Oh, yes, I am. I've been on trial for that my entire life. Have you nothing to say in your defense? Nothing but this. I did not do it. I did not kill Joffrey, but I wish that I had. Watching your vicious \_\_\_\_ die gave me more relief than a thousand lying \_\_\_\_ I wish I was the monster you think I am. I wish I had enough poison for the whole pack of you. I would gladly give my life to watch you all swallow it. Sir Marin escort the prisoner back to his cell. I will not give my life for Joffrey's murder, and I know I'll get no justice here, so I will let the gods decide my fate. Beat. I demand a trial by combat.

### Processing Report

Speech Recognition Confidence:

vicious \_\_\_\_ die gave me more relief than a thousand lying \_\_\_\_ I wish I was the monster you think I am. I wish I had enough poison for the whole pack of you. I would gladly give my life to watch you all swallow it. Sir Marin escort the prisoner back to his cell. I will not give my life for Joffrey's murder, and I know I'll get no justice here, so I will let the gods decide my fate. Beat. I demand a trial by combat.

### Processing Report

Speech Recognition Confidence:  
90%  
Inappropriate Content Found:  
Yes  
Censored Words Count:  
2

[Process Another File](#)

© 2025 Mutex - Audio Content Moderation



## 5.2 Future Scope

- **Multi-Language Support:** Expand detection capabilities using multilingual Whisper to cover diverse linguistic contexts.
- **Dynamic NLP-Based Detection:** Integrate BERT or transformer models to identify implicit and context-dependent hate speech beyond predefined word lists.
- **Non-Speech Audio Processing:** Enhance robustness with background noise filtering for complex environments.
- **Real-Time Streaming Capabilities:** Enable live audio feed processing for platforms like Zoom or Twitch.
- **User Feedback & Adaptive Learning:** Improve detection accuracy and reduce false positives with adaptive learning mechanisms.

## Conclusion

The Hate Speech Detection and Censorship System successfully addresses the challenge of offensive language in audio-based media, achieving ~95% transcription accuracy and ~98% detection precision. By integrating OpenAI's Whisper, Vosk, and pydub within a Flask-based web application, it delivers near real-time censorship with configurable beep or silence options, outperforming existing systems in speed (~10x faster) and privacy through local processing. The user-friendly interface supports audio uploads, result visualization, and customized censorship, making it ideal for content moderation in live streaming and video conferencing. Optimized with asynchronous processing and energy-based timestamp refinement, it ensures reliability across diverse audio conditions. This project establishes a scalable, privacy-focused solution for safer online communication, with potential for future enhancements like multi-language support and dynamic detection, paving the way for broader applicability in digital platforms.

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