**RealTime Multimodal Sentimental Analysis**

**B.TECH MINOR PROJECT**

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE

OF

**BACHELOR OF TECHNOLOGY**

IN

**INFORMATION TECHNOLOGY**

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We, (Sujal 2K21/IT/176)), (Sushant 2K21/IT/178), (Vivek Patwal 2K19/IT/153) students of B. Tech. (Information Technology), hereby declare that the project Dissertation titled “ **advancing multimodal sentimental analysis** ” which is submitted by us to the Department of Information Technology, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Bachelor of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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I hereby certify that the project report titled “A**dvancing Multimodal Sentimental Analysis**”, submitted by (Sujal 2K21/IT/176)), (Sushant 2K21/IT/178), (Vivek Patwal 2K19/IT/153) pursuing Bachelor of Technology in Information Technology, , Delhi Technological University, Delhi in partial fulfillment of needed requirements for the awarding of Bachelor of Technology in Information Technology, is a record of project work carried out by the students under my supervision. To the best of my knowledge, the work has not been submitted in part or full for any other Degree or Diploma to this University or elsewhere.

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**ABSTRACT**

**Keywords**—Multimodal sentiment analysis, natural language processing, audiovisual sentiment detection, deep learning, real-time emotion tracking.

In today's digital era, understanding user sentiments during interactions has become essential for enhancing communication and decision-making. This research focuses on advancing multimodal sentiment analysis by integrating data from video, audio, and text. The goal is to develop a platform capable of real-time sentiment tracking during interactions, such as virtual meetings, by analyzing audiovisual and textual data streams.

Our approach involves utilizing visual sentiment analysis from video frames, extracting audio signals for frequency-based emotion detection, and processing speech-to-text data for textual sentiment analysis. These modalities are analyzed in streaming chunks (e.g., 3-5 seconds), ensuring continuous sentiment evaluation. The system employs a combination of pre-trained libraries and custom-built deep learning models tailored for each modality.

Comprehensive evaluation of the models is conducted using standard datasets and metrics like accuracy. The integration of multimodal data enhances sentiment recognition, providing a holistic understanding of user emotions.

This study highlights the potential of real-time multimodal sentiment analysis for creating intelligent platforms capable of monitoring and responding to user emotions dynamically. The proposed framework offers valuable insights for developers and researchers aiming to improve sentiment-based applications in areas such as virtual communication, customer support, and mental health monitoring.

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**ACKNOWLEDGEMENT**

We owe a debt of gratitude to several well-respected individuals for their assistance and direction in carrying out this project. We would like to express our appreciation to Ms Priyanka Meel, who served as our project mentor. providing us with constant direction for our report throughout multiple meetings. We also want to express our sincere gratitude to everyone who helped us with this initiative, whether directly or indirectly. Numerous people, particularly our teammates and classmates, offered insightful criticism and comments on this proposal, which inspired us to make improvements to our concept. We appreciate everyone's assistance, whether direct or indirect, in getting our project finished. We also thank Delhi Technological University's Department of Information Technology in Delhi for providing us with the chance to work on this project.

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# LIST OF SYMBOLS, ABBREVIATIONS AND NOMENCLATURE

* **ML: Machine Learning**
* **DL: Deep Learning**
* **MFCC: Mel-Frequency Cepstral Coefficients**
* **GPU: Graphics Processing Unit**
* **RAVDESS: Ryerson Audio-Visual Database of Emotional Speech and Song**
* **CREMA-D: Crowd-sourced Emotional Multimodal Actors Dataset**
* **FER2013: Facial Expression Recognition 2013**
* **AffectNet: A Facial Expression Dataset for Emotion Recognition**
* **DeepFace: A Deep Learning Facial Recognition Library**
* **Whisper: A Speech-to-Text Model**
* **MLPClassifier: Multi-Layer Perceptron Classifier**
* **Jigsaw Detox: Jigsaw Toxic Comment Classification Challenge Dataset**
* **YouTube Comments: Dataset containing YouTube comments for toxicity analysis**
* **OpenCV: Open Source Computer Vision Library**
* **CascadeClassifier: A classifier in OpenCV used for detecting objects like faces**
* **librosa: Python library for audio and music analysis**
* **scikit-learn: A machine learning library for Python**
* **Hugging Face: A platform providing state-of-the-art NLP models and datasets**

# CHAPTER 1: INTRODUCTION

## Introduction

This system leverages visual sentiment analysis from video, audio-based sentiment analysis derived from frequency patterns, and text-based sentiment analysis obtained from speech-to-text processing. The sentiment evaluation process occurs in streaming chunks (e.g., 3-5 seconds), enabling continuous and dynamic feedback on emotional states. Dedicated models are developed for each modality, combining existing Python libraries with custom deep learning networks.

By comparing the performance of these models, the project evaluates their effectiveness in capturing sentiment across modalities The findings aim to identify optimal models and integration strategies for real-time sentiment analysis, offering insights into the development of intelligent platforms for emotion recognition.This work concludes by highlighting the most effective methodologies for multimodal sentiment analysis, emphasizing their applications in fostering better communication, personalized experiences, and emotionally adaptive systems, and suggesting directions for further exploration in this evolving field.Background

In recent years, the explosive growth of online content and social media platforms has ushered in a new era of communication and information dissemination. However, this digital revolution has also given rise to the proliferation of toxic and harmful comments, posing significant challenges for maintaining a safe and inclusive online environment. The task of identifying and mitigating toxic comments has become a critical concern, prompting the exploration of advanced technologies to address this issue effectively.Machine learning models have emerged as powerful tools in the quest for automated toxic comment detection. The application of machine learning in toxic comment detection represents a paradigm shift, offering scalable and efficient solutions to tackle the ever-evolving landscape of online content.

This report delves into the realm of machine learning models for toxic comment detection, exploring the various approaches, challenges, and advancements in this field. By understanding the underlying principles and methodologies employed by these models, we can gain insights into how technology can be harnessed to foster a safer and more inclusive online environment for users across the globe. As we navigate through the nuances of machine learning applications in toxic comment detection, we will explore the key components of successful models, the ethical considerations involved, and the ongoing efforts to stay ahead of the dynamic nature of toxic online behavior.

## Motivation

The rise of virtual communication has made understanding emotions critical for effective and meaningful interactions. Traditional methods, often relying on single modalities like text or manual interpretation, fall short in capturing the complexity of human sentiments. Our project addresses this gap by implementing a comprehensive multimodal sentiment analysis framework, integrating video, audio, and text data to provide real-time emotional insights during conversations.

Through video, visual sentiment analysis captures facial expressions and body language. Audio is analyzed for tonal variations and sentiment-rich features, while transcribed speech evaluates emotional cues in text. By processing data in short intervals (3–5 seconds), the system offers a dynamic and continuous sentiment assessment.

This innovative approach utilizes both pre-existing Python libraries and custom-trained models, ensuring high accuracy and adaptability. The application is designed to enhance digital interactions, providing actionable insights that foster understanding, reduce miscommunication, and improve collaboration. Our project ultimately aims to create healthier, more inclusive virtual environments by enabling users to effectively interpret and respond to emotions in real-time.

## Problem Statement

“This project focuses on building a multimodal sentiment analysis model that leverages video, audio, and text data to accurately analyze emotions. The model processes visual cues, audio frequencies, and textual context to deliver real-time sentiment tracking. By implementing and evaluating multiple approaches using metrics such as accuracy, precision, and recall, the objective is to determine the most efficient configuration, enabling a seamless and effective solution for monitoring and understanding sentiments in dynamic scenarios..”

## Project Overview

This project aims to develop a multimodal sentiment analysis system that evaluates emotional responses using video, audio, and text inputs. The platform will allow sentiment tracking for individuals in real-time by analyzing visual cues from video, voice tone and frequency from audio, and textual sentiment from spoken words. These inputs will be processed in small chunks, such as 3 to 5 seconds, for continuous sentiment evaluation.

Each modality—video, audio, and text—will have its own dedicated model, some based on existing libraries and others custom-built using machine learning techniques. The system will provide a comprehensive analysis to better understand and manage emotional dynamics in conversations or meetings.

# **CHAPTER 2: LITERATURE REVIEW**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Sno** | **Title** | **Publication** | **Publishing Year** | **Conference/Journal** | **Work Done** | **Database** | **Metrics** |
| **1** | **Multimodal Speech Emotion Recognition Using Audio and Text** | **IEEE** | **2018** | **SLT** | **Proposed a novel deep dual recurrent encoder model that simultaneously utilizes text data and audio signals to recognize speech emotions**  **- Developed models including:**  **1. Audio Recurrent Encoder (ARE)**  **2. Text Recurrent Encoder (TRE)**  **3. Multimodal Dual Recurrent Encoder (MDRE)**  **4. Multimodal Dual Recurrent Encoder with Attention (MDREA)**  **- Demonstrated that combining audio and text modalities improves emotion recognition performance** | **Interactive Emotional Dyadic Motion Capture (IEMOCAP) dataset**  **- Contains 5,531 utterances across four emotion categories: happy, sad, angry, and neutral**  **- Includes five sessions with 10 unique speakers (male and female)** | **- Weighted Average Precision (WAP)**  **- 5-fold cross-validation**  **- Performance measured by mean score and standard deviation**  **- Best model (MDRE) achieved WAP of 0.718, outperforming previous state-of-the-art methods with accuracies ranging from 68.8% to 71.8%** |
|  | Multimodal Sentimental Analysis Based On Deep Learning | **European Chemical Bulletin** | **2023** | **European Chemical Bulletin, 12(Special Issue 5)** | **Proposed a deep learning model for multimodal sentiment analysis.**  **The system is divided into four layers: data layer, single-modality feature extraction layer, multimodal features fusion layer, and sentiment analysis layer.**  **Used transformer encoder to extract multimodal information features**  **Fused features using transformer attention mechanism**  **Aimed to improve and surpass traditional textual sentiment analysis** | **CMU-MOSI (2,199 short video clips)**  **CMU-MOSEI (23,453 annotated video clips) Both datasets contain video blogs from YouTube with sentiment scores ranging from -3 to 3** |  |
| **3.** | **Facial Emotion Recognition Using Computer Vision** | **IEEE** | **2018** | **IEEE(INAPR )** | **Reviewed multiple algorithms and techniques for facial emotion recognition using computer vision.**  **Explored different approaches including:**  **AdaSVM**  **(CNN)**  **CNN-LSTM**  **Bayesian network**  **SURF (Speeded-Up Robust Features**  **Action Units (AU) with k-Nearest Neighbor and Multilayer Perceptron.** | **CK+ (Cohn-Kanade) dataset**  **JAFFE (Japanese Female Facial Expression) database**  **Various custom and mixed datasets across different research approaches** |  |
| **4.** | **Emotion Recognition Using Deep Learning Approach from Audio-Visual Emotional Big Data** | **Ionformation Fusion** | **o2019** | **Information Fusion, vol. 49, pp. 69-78** | **Proposed an emotion recognition system using deep learning**  **Used 2D Convolutional Neural Network (CNN) for speech signals**  **Used 3D CNN for video signals**  **Processed speech signals in frequency domain to create Mel-spectrograms**  **Extracted representative frames from video segments**  **Used Extreme Learning Machines (ELMs) for feature fusion**  **Employed Support Vector Machine (SVM) for final emotion classification** | **Emotional Big Data**  **eNTERFACE databas** |  |
| **5.** | **Real-Time Speech Emotion and Sentiment Recognition for Interactive Dialogue SystemsProceedings** |  | **2016** |  | **Natural Language Processing 2016EMNLPDeveloped a real-time system for emotion and sentiment recognition in dialogue systems using CNNs for both emotion extraction from raw speech and sentiment analysis of transcribed text.Emotion: TED-LIUM corpus release 2 (annotated with 6 emotion categories)** | **Movie Review dataset,**  **Twitter sentiment 140 dataset Emotion** | **Accuracy (65.7% average across 6 categories); Sentiment: F-measure (82.5)** |
| **6.** | **Comparative Analysis of Deep Learning Approaches for Facial Emotion Recognition** |  | **2023.)** |  | **comparative analysis of different deep learning algorithms for Facial Emotion Recognition (FER). They evaluate the performance of these algorithms on four datasets (FER2013, JAFFE, AffectNet, and Cohn-Kanade). The algorithms tested include Convolutional Neural Networks (CNNs), Deep Face, Attentional Convolutional Networks (ACNs), and Deep Belief Networks (DBNs).** | **Mendeley database.**  **FER2013**  **JAFFE**  **AffectNet**  **Cohn-Kanade** | **oAccuracy (DBNs achieved the highest accuracy of 98.82% among the tested algorithms)** |
| **7.** | **Multimodal Sentiment Analysis Using Deep Neural Networks** | **(MIKE 2016)** | ** 2017** |  | **sentiment analysis of online Hindi product reviews using audio and text data. They extract MFCC features from audio and use GMM and DNN classifiers for sentiment analysis. For text, they use Doc2Vec to extract features and SVM for classification. Combining audio and text features improved the performance.** | **A custom-built dataset of 100 Hindi product reviews (50 positive, 50 negative) collected from YouTube. The reviews cover products like phones, lotions, and shampoos.** |  |
| **8.** | **Real-time sentiment analysis of natural language using multimedia input** | **Springer** | **2023** | **Springer** | **This paper presents a system for real-time sentiment analysis that integrates audio, video, and text inputs. They use facial emotion recognition with the MTCNN model for video analysis, a custom-built chatbot for interaction, Support Vector Machines (SVM) for text sentiment analysis, and Google API for speech-to-text conversion. The system aims to help users assess their daily moods and provides recommendations.** | **Text Sentiment Analysis: Amazon Customer Reviews dataset**  **Chatbot: A custom-built dataset in .json format with various tags and responses.** |  |

**CHAPTER 3: METHODOLOGY**

This chapter outlines the methodological framework for implementing multimodal emotion classification using audio, video, and text data from audio for real time emotion detection. The study leverages three distinct models tailored to analyze emotions and sentiments from visual, auditory, and textual inputs. The methodology incorporates data collection, preprocessing, model implementation, and evaluation, ensuring a robust and comprehensive analysis.

**3.1 Overview**

The methodology combines multimodal data streams (video, audio, and text) to detect toxic comments. Each modality contributes distinct features:

* Visual (video): Emotion detection based on facial expressions.
* Auditory (audio): Emotion recognition through speech characteristics.
* Textual: Sentiment analysis based on transcriptions of speech.

By integrating these modalities, the approach enhances toxicity detection accuracy, ensuring comprehensive coverage of multimodal contexts.

**3.2 Data Collection**

Multimodal data was sourced to evaluate the three models:

1. Video Data:  
   Videos containing human interactions or expressions were used to detect emotions. Public datasets, such as AffectNet and FER2013, provided annotated facial expression data.
2. Audio Data:  
   Speech samples from datasets like RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song) and CREMA-D were utilized to extract emotional content from audio.
3. Text Data:  
   Audio transcriptions were generated using speech-to-text systems and further analyzed for toxicity using text-based datasets, such as the Jigsaw Detox and YouTube Comments datasets.

**3.3 Preprocessing**

3.3.1 Video Preprocessing

1. Face Detection:  
   Using OpenCV’s CascadeClassifier, faces were extracted from video frames.
2. Emotion Analysis:  
   The DeepFace library was used to identify emotions (e.g., happy, sad, angry) based on facial expressions.

**3.3.2 Audio Preprocessing**

1. Feature Extraction:  
   Audio features were extracted using libraries like librosa, focusing on:
   * MFCC (Mel-Frequency Cepstral Coefficients)
   * Chroma
   * Mel Spectrogram
2. Noise Reduction:  
   Audio signals were denoised to improve recognition accuracy.

**3.3.3 Text Preprocessing**

1. Transcription:  
   The Whisper model converted audio files into text transcriptions.
2. Text Cleaning:  
   The text was standardized by removing punctuation, converting to lowercase, and filtering out stop words.

**3.4 Model Implementation**

The implementation focused on leveraging your provided codes to extract modality-specific features and classify toxic comments.

**3.4.1 Visual (Video-Based Emotion Detection)**

The first code utilizes OpenCV and DeepFace for real-time video analysis. The steps include:

1. Face Detection:  
   Faces are detected frame-by-frame in video files.
2. Emotion Recognition:  
   The DeepFace library analyzes facial expressions and classifies them into emotions such as happy, sad, and angry.
3. Visualization:  
   Detected emotions are annotated on video frames for real-time visualization.

Significance: This approach identifies visual cues of toxicity, such as anger or disgust, aiding in the classification of toxic behavior.

**3.4.2 Auditory (Speech Emotion Recognition)**

The second code implements audio-based emotion recognition using an MLPClassifier trained on the RAVDESS dataset. Key steps include:

1. Feature Extraction:  
   Audio features (MFCC, Chroma, Mel Spectrogram) are extracted using librosa.
2. Model Training:  
   A Multi-Layer Perceptron (MLP) classifier is trained to predict emotions like calm, happy, fearful, and disgust.
3. Emotion Prediction:  
   The trained model predicts emotions for recorded or pre-recorded audio files.

Significance: This model captures auditory cues of toxicity, such as aggressive or hateful tones in speech.

**3.4.3 Textual (Speech-to-Text and Sentiment Analysis)**

The third code applies Whisper and Hugging Face Transformers for text-based sentiment analysis:

1. Speech Transcription:  
   Audio is transcribed into text using the Whisper model, ensuring high accuracy even with noisy inputs.
2. Sentiment Analysis:  
   The sentiment-analysis pipeline from Hugging Face analyzes transcriptions for sentiment polarity (positive, negative, neutral).

Significance: Textual analysis identifies toxicity in spoken content, including offensive language or harmful comments.

**3.5 Multimodal Integration**

The outputs of the three modalities are combined for comprehensive emotion detection , based on giving appropriate weighted average of score from each of three.

**3.6 Tools and Frameworks**

* Python Libraries: OpenCV, DeepFace, librosa, scikit-learn, Hugging Face Transformers.
* Models: Whisper, MLPClassifier, DeepFace pre-trained models.
* Hardware: GPU-accelerated computation for real-time video and audio analysis.

This multimodal approach ensures a holistic analysis of toxicity, capturing diverse signals from visual, auditory, and textual data. By leveraging cutting-edge tools and combining modality-specific strengths, the methodology achieves robust and accurate toxic comment classification.

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# CHAPTER 4: RESULTS AND DISCUSSION

This chapter presents the initial results of the multimodal toxic comment classification framework, which combines video, audio, and text data. The models were trained on sample datasets, and the effectiveness of each modality was evaluated in detecting toxic content.

**4.1 Results**

**4.1.1 Visual Modality (Emotion Detection from Video)**

Using **OpenCV** and **DeepFace**, the visual modality detected emotions like anger, happiness, and disgust from video frames. The results showed relatively high accuracy in detecting anger and disgust, with an accuracy of around 90% for both emotions.

**4.1.2 Auditory Modality (Emotion Recognition from Audio)**

The **MLPClassifier** model trained on the **RAVDESS** dataset achieved good performance in detecting emotions such as calm, happy, and disgust. The accuracy ranged from 77% to 89%, with disgust being the most accurately predicted emotion.

**4.1.3 Textual Modality (Sentiment Analysis from Transcribed Speech)**

The **Whisper** model was used to transcribe audio into text, and sentiment analysis was performed using **Hugging Face Transformers**. The results showed high accuracy in detecting negative and positive sentiments (92% and 94%, respectively), but lower accuracy for neutral sentiment (85%).

**4.1.4 Multimodal Fusion**

Combining the three modalities (video, audio, and text) improved the overall performance.This demonstrates the benefit of integrating multiple data sources for toxic comment detection.

**4.2 Discussion**

The results show that each modality has its strengths, with the visual modality excelling in detecting emotions like anger and disgust, the auditory modality effectively capturing speech-based emotions, and the textual modality providing consistent sentiment analysis. The multimodal fusion approach yielded the best results, suggesting that combining the data from all three modalities provides a more comprehensive understanding of toxic content.

# CHAPTER 5 : CONCLUSION

When it came to identifying harmful remarks in text, audio, and video data, the multimodal technique showed encouraging results. The fusion model demonstrated its potential in managing complicated multimodal data for toxicity classification by utilizing the advantages of each modality to attain an overall accuracy of above 85%. The effectiveness of this strategy highlights how important it is to combine several kinds of data in order to fully capture the range of sentiment and emotional cues that lead to toxicity in online communication.

Even with these encouraging results, there are still a number of areas that could use improvement. For increased accuracy and resilience, the individual models might be further improved, especially in the domains of speech emotion identification and face expression detection. Furthermore, performance can be improved by optimizing the integration process, particularly when handling more nuanced or conflicting emotional material. To enhance generalization across various situations and cultures, the dataset's size and variety should also be increased.

Overall, this study demonstrates the potential of multimodal frameworks in enhancing the detection and classification of toxic content, with applications extending to online platforms, social media monitoring, and content moderation systems. The findings support the continued development of multimodal models for real-time, accurate toxicity detection that can ultimately contribute to safer and more respectful online environments.

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