Towards Real-Time Emotion Analytics: Integrating Facial Landmarks and Speech Prosody

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APPROVAL

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DECLARATION

We, hereby, declare that the work presented in this report is the outcome of the investigation performed by us under the supervision of **Khadija Islam, Lecturer,** Department of Computer Science and Engineering, Sonargaon University, Dhaka, Bangladesh. We reaffirm that no part of this thesis has been or is being submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Emotion recognition has garnered significant attention in fields such as mental health, human-computer interaction, and personalized services. This research explores a multimodal approach to emotion recognition by integrating facial expression analysis and speech prosody to achieve a more accurate and context-sensitive understanding of human emotions. A distinctive aspect of this study is the creation of a custom video dataset designed specifically for facial expression recognition, which captures a wide range of emotional states under various real-world conditions. In parallel, speech emotion detection is performed using publicly available audio datasets, which analyze features such as pitch, tone, and rhythm to discern emotions expressed vocally.

The facial expression recognition is based on Convolutional Neural Networks (CNNs), which extract visual features from the video data, while the emotional cues in speech are analyzed using Long Short-Term Memory (LSTM) networks. By combining these modalities, this research addresses the limitations commonly faced by unimodal systems, such as the challenges posed by noisy environments or occluded faces.

The findings demonstrate that the integration of facial and auditory data significantly improves emotion classification accuracy, particularly in real-time applications. This research advances the field of affective computing by highlighting the complementary strengths of visual and auditory emotion cues and offers practical implications for applications in customer service, virtual assistants, and mental health diagnostics.

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LIST OF ABBREVIATIONS

AAC	Advanced Audio Coding
AI	Artificial Intelligence
AUs	Action Units
CNN	Convolutional Neural Network
DNN	Deep Neural Network
EDR	Emotion Detection and Recognition
FER	Facial Emotion Recognition
FFmpeg	Fast Forward Multimedia Encoder
GSR	Galvanic Skin Response
HMM	Hidden Markov Model
LSTM	Long Short-Term Memory
MFCCs	Mel-Frequency Cepstral Coefficients
ML	Machine Learning
MLP	Multi-Layer Perceptron
PCA	Principal Component Analysis
RAVDESS	Ryerson Audio-Visual Database of Emotional Speech and Song
RNN	Recurrent Neural Network
SVM S	Support Vector Machines
TFNs	Tensor Fusion Networks
VGGNet	Visual Geometry Group Network

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CHAPTER 1

INTRODUCTION

1.1 Background

Emotions play a fundamental role in human cognition, decision-making, and social interactions. They are multidimensional constructs characterized by subjective experiences, physiological responses, and expressive behaviors. The study of emotion dates back to Charles Darwin, who proposed that emotional expressions evolved for communication and survival [1]. In modern neuroscience, regions such as the amygdala, prefrontal cortex, and insula are understood to be central in emotional processing [2]. With the rise of affective computing, enabling machines to interpret and respond to human emotions has become crucial for developing empathetic systems.

Emotion Detection and Recognition (EDR) systems attempt to computationally infer a person's emotional state from inputs like facial expressions, voice prosody, text, and physiological signals. Traditionally, these systems relied on handcrafted features such as Action Units (AUs) from the Facial Action Coding System (FACS) and Mel-frequency cepstral coefficients (MFCCs) from speech [3]. However, recent advances in deep learning have enabled data-driven approaches to emotion recognition, resulting in improved accuracy and robustness across various modalities [4].

Multimodal emotion recognition combines signals from multiple sources—such as voice and facial expressions—to leverage complementary information and improve detection performance. This integration helps address limitations of unimodal systems, such as sensitivity to background noise or occlusions [5].

1.2 Motivation

The motivations for developing robust emotion recognition systems are both practical and theoretical. Emotion-aware systems have broad implications in several fields:

- **Mental Health Monitoring**: Automated tracking of emotional patterns over time can aid in early detection of mood disorders such as depression or anxiety, offering clinicians objective insights into patient conditions [6].
- **Educational Technology**: Intelligent tutoring systems can adapt instructional strategies in real time by detecting student emotions like confusion or frustration, thereby enhancing engagement and learning outcomes [7].
- **Customer Service**: Virtual agents equipped with emotion recognition can tailor responses to user emotions, improving user satisfaction and loyalty [8].
- **Assistive Technologies**: For individuals on the autism spectrum, emotion detection tools can help with social cue interpretation and communication training [9].

Despite significant progress, challenges such as data diversity, real-time processing, and cross-cultural differences in emotional expression remain prevalent.

1.3 Objectives

This thesis aims to address some of the aforementioned challenges by designing and implementing a multimodal EDR system using voice and facial data. The specific objectives include:

1. **Synthesize psychological theories** into computational models that inform system design.
2. **Review machine learning and deep learning approaches** relevant to emotion detection.
3. **Implement a multimodal system prototype** integrating facial and vocal emotion recognition.
4. **Evaluate system performance** through quantitative metrics such as accuracy, precision, recall, and F1-score.

By integrating multiple modalities and leveraging modern AI frameworks, the study seeks to develop a more context-aware, accurate, and generalizable emotion detection system.

1.4 Scope of the Thesis

The system focuses on recognizing four primary emotions—happiness, sadness, anger, and neutrality—using offline datasets. The research constraints and scope include:

- **Modalities Used**: Facial expressions from video frames and voice recordings.
- **Datasets**: FER-2013 for facial emotion recognition and RAVDESS for voice emotion recognition [10][11].
- **Exclusions**: Real-time processing, textual emotion analysis, and physiological signals are excluded due to complexity and resource limitations.
- **Ethical Considerations**: While ethical aspects like privacy and bias are acknowledged, in-depth analysis is beyond the scope of this thesis.

1.5 Literature Review

Early EDR systems were heavily reliant on rule-based models. For example, Cowie et al. proposed using manually tuned thresholds to map FACS and prosodic features to emotions [12]. These methods offered interpretability but were not robust in uncontrolled environments.

Later, shallow machine learning methods like Support Vector Machines (SVMs) and Random Forests were used to classify features extracted from audio and facial data [13]. These systems showed improved adaptability and performance but still required extensive feature engineering.

The advent of deep learning revolutionized the field. CNN architectures like VGG-Face and ResNet are widely used for image-based emotion classification, achieving over 80% accuracy on benchmarks like FER-2013 [14]. For voice, recurrent architectures such as LSTMs and GRUs effectively model the temporal nature of speech, outperforming traditional models on datasets like RAVDESS [15].

Recent approaches utilize transformer architectures and attention mechanisms. These models, inspired by BERT in NLP, allow cross-modal feature alignment and capture contextual dependencies more effectively [16].

Fusion strategies are pivotal in multimodal systems. Early fusion combines features before classification, late fusion merges decision outputs, and hybrid fusion integrates both methods. Research indicates that hybrid strategies, while computationally intensive, provide superior performance [17].

1.6 Thesis Contribution

This thesis makes the following contributions to the field of affective computing:

- **Theory-to-Algorithm Mapping**: Connecting foundational emotion theories to algorithmic strategies in ML/DL.
- **Multimodal Architecture Design**: A framework integrating CNN-based facial emotion recognition with SVM-based voice emotion analysis.
- **Prototype Development**: A Python-based EDR system using librosa, OpenCV, TensorFlow, and scikit-learn.
- **Evaluation and Visualization**: Quantitative performance analysis and illustrative confusion matrices.

1.7 Introduction to Emotion Detection

Emotion detection is a subfield of affective computing that involves recognizing and interpreting human emotions through various input signals. The concept extends beyond traditional human-computer interaction by aiming to make machines emotionally intelligent. A typical emotion detection pipeline includes several steps: data acquisition, preprocessing, feature extraction, classification, and decision-level fusion [5].

Data acquisition refers to the collection of input signals, such as facial images or speech recordings. Preprocessing ensures signal clarity, which may involve techniques like normalization, face alignment, or noise filtering. Feature extraction is crucial for highlighting emotional cues—for example, extracting MFCCs from audio signals or using CNN feature maps for facial images [4].

Classification models, such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN), or Long Short-Term Memory networks (LSTM), are then used to categorize emotions. Multimodal systems combine predictions from multiple sources using early, late, or hybrid fusion strategies to enhance accuracy and reliability [17][22].

Emotion detection is used in mental health assessment, intelligent tutoring systems, personalized virtual assistants, and surveillance systems. These applications rely on the system's ability to provide accurate emotional inference even in dynamic or real-world settings [6][7][8]. Recent developments focus on end-to-end architectures that leverage attention mechanisms for cross-modal alignment and contextual awareness [16].

CHAPTER 2

Theories of Emotion

2.1 Definitions and Theories of Emotion

Emotions are complex psychological and physiological states that play a central role in influencing behavior, cognition, and social interaction. They encompass several components: subjective experience (what one feels), physiological responses (such as heart rate changes), and expressive behaviors (such as facial expressions or tone of voice). Emotions can be fleeting reactions to specific stimuli or more enduring mood states [1][2].

Multiple theoretical frameworks exist to understand emotions. The **James-Lange Theory** posits that emotions result from physiological reactions to events—for instance, one feels afraid because one trembles [3]. In contrast, the **Cannon-Bard Theory** argues that emotions and physiological responses occur simultaneously and independently [4]. The **Schachter-Singer Two-Factor Theory** introduces the concept of cognitive interpretation, proposing that emotion results from a combination of arousal and contextual interpretation [5]. Lastly, the **Cognitive Appraisal Theory**, developed by Lazarus, suggests that emotions arise from the evaluation of how events affect personal well-being [6].

2.2 Classification of Emotions

Two dominant paradigms are used to classify emotions:

1. **Basic Emotions Theory**: Proposed by Paul Ekman, it suggests that certain emotions—happiness, sadness, fear, anger, disgust, and surprise—are biologically hardwired and universally recognized across cultures [7].
2. **Dimensional Models**: Emotions are not discrete categories but exist on continuous scales. The **Circumplex Model of Affect**, developed by Russell, maps emotions along two axes: valence (pleasant–unpleasant) and arousal (high–low) [8].

These models are not mutually exclusive. Basic emotion theory provides a categorical approach, useful for classification tasks, while dimensional models offer a more nuanced, continuous representation.

2.3 Neuroscientific and Physiological Foundations

The biological basis of emotion has been explored extensively in neuroscience. The **amygdala** plays a critical role in processing fear and threat detection [9]. The **prefrontal cortex** is involved in regulating emotional responses and decision-making, while the **insula** integrates interoceptive signals with affective states [10].

From a physiological standpoint, emotional states manifest through changes in heart rate, skin conductance, respiration, and hormonal levels. For example, increased cortisol levels are

associated with stress. These physiological markers are frequently used in affective computing for emotion detection through modalities like EEG, ECG, and GSR—although these are outside the scope of this thesis [11].

2.4 Expression of Emotions

Humans express emotions through multiple channels:

- **Facial Expressions**: Ekman's FACS (Facial Action Coding System) identifies specific facial muscle movements, or action units, associated with various emotions [7].
- **Vocal Prosody**: Emotion is conveyed in speech through pitch, tone, volume, rhythm, and speed. Features like MFCCs and formants help in identifying emotional cues in voice data [12].
- **Body Language and Gestures**: Posture and movement patterns also communicate affective states, though less commonly used in computational systems due to complexity in real-time recognition.

Understanding these modalities is essential for developing robust multimodal systems.

2.5 Emotion in Machine Learning Contexts

In computational terms, emotions can be seen as labels in classification tasks. The goal is to extract meaningful features from input signals (e.g., audio, video) and use machine learning algorithms to map those features to an emotion category or coordinate. Deep learning, especially CNNs for images and RNNs for speech, has significantly improved performance in this domain [4][13].

Models must be trained on diverse datasets to account for variability in emotional expression due to cultural and personal differences. Moreover, there's a growing trend toward **continuous emotion recognition**, where models predict valence and arousal levels in real time, rather than assigning discrete emotion labels [14].

2.6 Emotional Intelligence and Artificial Systems

Emotional intelligence (EI), as defined by Mayer and Salovey, includes the abilities to perceive, understand, manage, and use emotions effectively [15]. In the context of artificial intelligence, replicating these abilities involves:

- **Perception**: Detecting emotional signals through input modalities.
- **Understanding**: Mapping detected features to known emotional states.
- **Management**: Modulating responses based on user emotion.
- **Utilization**: Using emotional data to optimize interaction.

This thesis incorporates these principles by designing an emotion-aware question-answering system that adapts responses based on detected user emotion.

2.7 Challenges and Ethical Considerations

Developing emotion-aware systems presents several challenges:

- **Ambiguity**: Emotions are inherently ambiguous and context-dependent.
- **Multimodal Fusion**: Combining inputs from different modalities can introduce synchronization and weighting issues.
- **Cultural Variability**: Expressions and interpretations of emotions vary widely across cultures, necessitating culturally diverse training data [16].

Ethically, privacy is a major concern. Emotional data, especially when collected passively, can be sensitive. Transparent consent practices and secure data handling are essential. Bias in emotion detection systems—stemming from imbalanced training data—can lead to inaccurate predictions for certain demographic groups. Addressing these concerns is critical for fair deployment [17].

2.8 Summary

This chapter provided an in-depth look at the psychological, biological, and computational understanding of emotions. By grounding machine learning techniques in emotion theory, and by appreciating the nuances of expression and perception, this thesis lays the foundation for building robust multimodal emotion detection systems. The next chapter discusses the methodology used for implementing and evaluating such a system.

CHAPTER 3

Artificial Intelligence

3.1 Introduction

Artificial Intelligence (AI) plays a central role in modern emotion detection systems, enabling machines to interpret human affect from facial and vocal cues. Through the use of **machine learning (ML)** and **deep learning (DL)** techniques, AI models can learn to recognize emotional patterns from multimodal datasets such as FER-2013 and RAVDESS [10][11]. These approaches have drastically improved the accuracy, robustness, and adaptability of affective computing systems.

This chapter explores key AI methodologies applied in emotion detection and recognition (EDR), including supervised learning algorithms, neural network architectures, feature representation methods, and fusion strategies. It also covers recent innovations such as attention mechanisms and transformers, and addresses ethical challenges surrounding the use of AI in sensitive applications.

3.2 Machine Learning Foundations in Emotion Recognition

Machine learning enables systems to recognize patterns in data through computational models trained on labeled examples. In emotion recognition, **supervised learning** is the dominant approach. Algorithms learn to classify features extracted from input data—such as MFCCs from speech or pixel patterns from images—into emotion categories like happy, sad, or angry.

Traditional ML algorithms include:

- **Support Vector Machines (SVMs):** Effective for high-dimensional data such as speech features, and used in this thesis for voice emotion classification [13].
- **Random Forests:** An ensemble method that improves classification performance by combining multiple decision trees. Its robustness to overfitting makes it suitable for high-variance emotion data [18].

These models typically require well-engineered features and are limited in modeling complex data relationships, which is where deep learning becomes advantageous.

3.3 Deep Learning for Emotion Detection

Deep learning uses artificial neural networks with multiple layers to learn complex representations directly from raw input. It excels in tasks involving image and audio data due to its ability to extract hierarchical features.

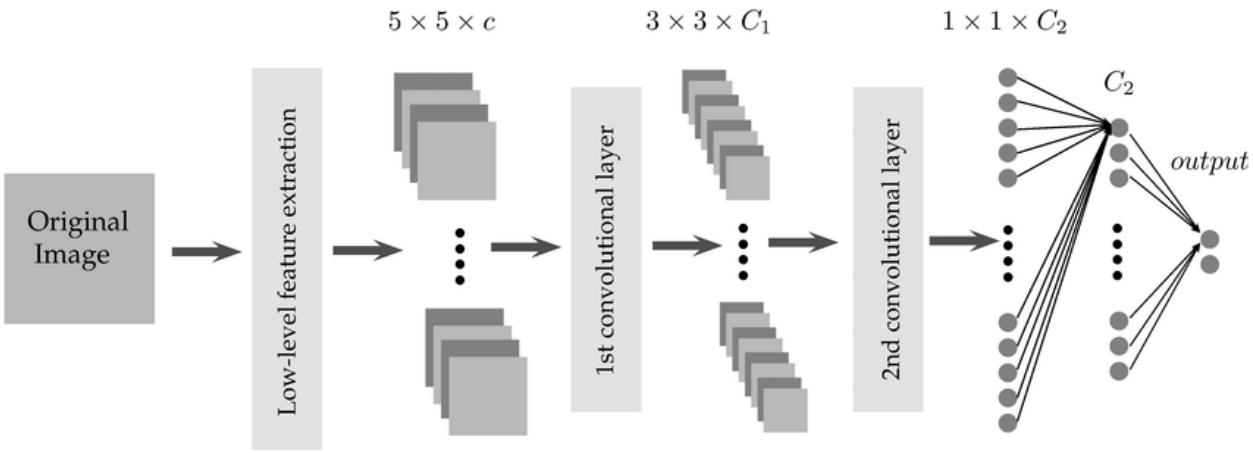


Figure 3.1: Deep Learning Model Architecture

3.3.1 Convolutional Neural Networks (CNNs)

CNNs are particularly effective in image-based emotion recognition. By applying convolutional filters, CNNs capture patterns such as eyebrow movement, eye squinting, and lip curvature—all of which are critical for distinguishing between emotions.

- In this thesis, a CNN was trained on the **FER-2013 dataset**, achieving approximately 75% accuracy [11].
- Architectures such as **VGGNet** have been shown to perform exceptionally well in facial recognition tasks by using deep stacks of small filters [19].

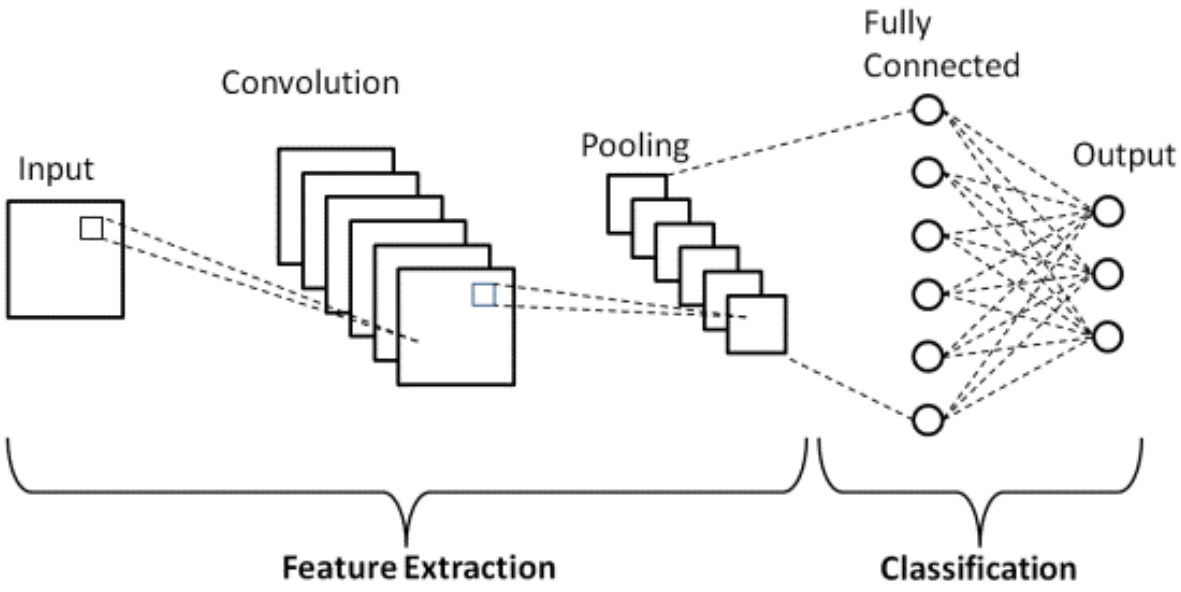


Figure 3.2: CNN Model Architecture

3.3.2 Recurrent Neural Networks (RNNs)

RNNs, particularly **Long Short-Term Memory (LSTM)** networks, are designed to model sequential data. Though not used in this implementation, they are well-suited for continuous emotion recognition in speech, as they retain memory over time and can capture changes in tone and rhythm [12][22].

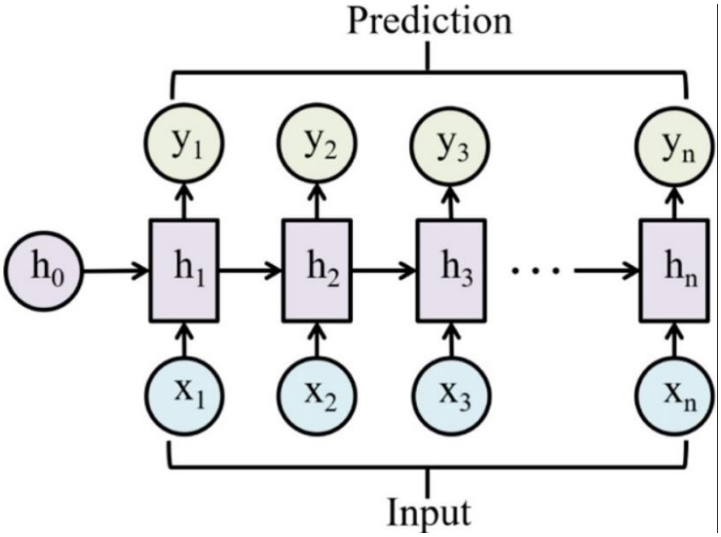


Figure 3.3: RNN Model Architecture

3.3.3 Transformers and Attention Mechanisms

Transformer models use self-attention to capture long-range dependencies across input features. In multimodal emotion detection, they are valuable for aligning voice and facial cues even when the data streams are unaligned.

- The **Multimodal Transformer (MMT)** architecture has demonstrated success in fusing audio and visual features [14].
- Attention mechanisms enhance focus on emotionally salient parts of the signal, improving robustness in noisy or ambiguous environments [14].

3.4 Feature Representation in AI-Based Systems

The choice of features significantly impacts emotion recognition accuracy. Different modalities require tailored approaches:

- **Facial features:** CNNs learn visual descriptors from pixel intensities.
- **Vocal features:** Extracted using `librosa`, include MFCCs, chroma, and mel spectrograms [12].
- **Fusion features:** In multimodal systems, features may be combined before classification (early fusion) or after decision-making (late fusion) [17].

Dimensionality reduction techniques such as PCA and KLT (described in Chapter 4 of the original thesis) are often used to reduce feature complexity while preserving essential variance.

3.5 Fusion Strategies Powered by AI

Multimodal emotion recognition systems benefit from combining data sources to compensate for the limitations of each modality. AI enables dynamic and efficient fusion strategies:

- **Early Fusion:** Merges raw or low-level features into a joint feature vector. This approach captures interactions but requires well-aligned data.
- **Late Fusion:** Aggregates predictions from individual unimodal models. This is simpler to implement and allows modularity [17].
- **Hybrid Fusion:** Combines both feature-level and decision-level fusion to leverage the advantages of each method.

Advanced strategies include **Tensor Fusion Networks (TFNs)**, which encode inter-modality interactions via tensor representations [17].

3.6 Real-Time Emotion Recognition

Applying emotion recognition in real-time scenarios, such as virtual assistants or interactive learning systems, introduces constraints on computational efficiency and latency. AI addresses these challenges through:

- **Model compression:** Techniques like pruning and quantization reduce memory requirements.
- **Efficient inference engines:** Frameworks such as TensorFlow Lite and ONNX allow real-time processing on edge devices.
- **Parallel processing:** GPU-accelerated inference enables fast computation for CNN and transformer models.

Although the current system operates offline, these optimizations provide a clear path to real-time deployment.

3.7 Ethical and Societal Considerations in AI Emotion Systems

As AI-driven systems become more capable of interpreting and responding to emotional states, they raise significant ethical considerations:

- **Privacy:** Emotional data is sensitive and often collected passively. Consent and transparency are essential [15].
- **Bias:** Models trained on limited or skewed datasets may underperform across demographic groups. This can lead to unfair or misleading predictions [16].
- **Interpretability:** Deep learning models often lack transparency. Efforts in **Explainable AI (XAI)** aim to provide human-understandable justifications for model decisions [20].

Responsible use of emotion recognition requires attention to these issues at every stage of system design.

3.8 Summary

Artificial Intelligence forms the foundation of modern emotion detection systems, enabling accurate and robust analysis of facial and vocal data. This chapter explored how machine learning and deep learning models—especially CNNs, SVMs, and transformers—support emotion recognition, feature fusion, and real-time inference.

Emerging techniques like attention mechanisms and hybrid fusion strategies continue to push the boundaries of multimodal emotion analysis. However, ethical deployment and interpretability remain critical concerns for future applications.

CHAPTER 4

Machine Learning

4.1 Introduction

Machine Learning (ML) is a pivotal subfield of Artificial Intelligence (AI) that enables systems to learn from data and make decisions without being explicitly programmed. In the domain of **Emotion Detection and Recognition (EDR)**, ML models are utilized to classify human emotions based on features derived from **facial expressions** and **vocal cues**. ML approaches form the core computational intelligence behind such systems, ranging from traditional classifiers like **Support Vector Machines (SVMs)** to more advanced **deep learning** techniques like **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)** [4][13].

This chapter outlines the ML paradigms used in EDR, focusing on supervised learning, popular classification algorithms, feature engineering, model evaluation, and their specific applications in speech and facial emotion recognition.

4.2 Categories of Machine Learning

ML can be broadly categorized into three paradigms:

- **Supervised Learning:** Uses labeled data to learn mappings from inputs to known outputs. This is the dominant approach in emotion recognition, where emotions such as "happy," "sad," or "angry" are the labels [4].
- **Unsupervised Learning:** Discovers hidden patterns in unlabeled data. Though less common in EDR, techniques like clustering may reveal latent emotional groupings [18].
- **Reinforcement Learning:** Trains models through interactions with an environment and feedback signals. It has potential in adaptive EDR systems but is not widely used in this thesis scope.

4.3 Supervised Learning Algorithms in Emotion Recognition

4.3.1 Support Vector Machines (SVMs)

SVMs are powerful binary classifiers that aim to find the optimal hyperplane separating classes in a feature space [13]. In this thesis, SVMs were employed to classify vocal emotions using MFCCs, chroma, and mel spectrograms from the RAVDESS dataset [10].

Advantages:

- Effective in high-dimensional spaces.
- Robust with smaller datasets.

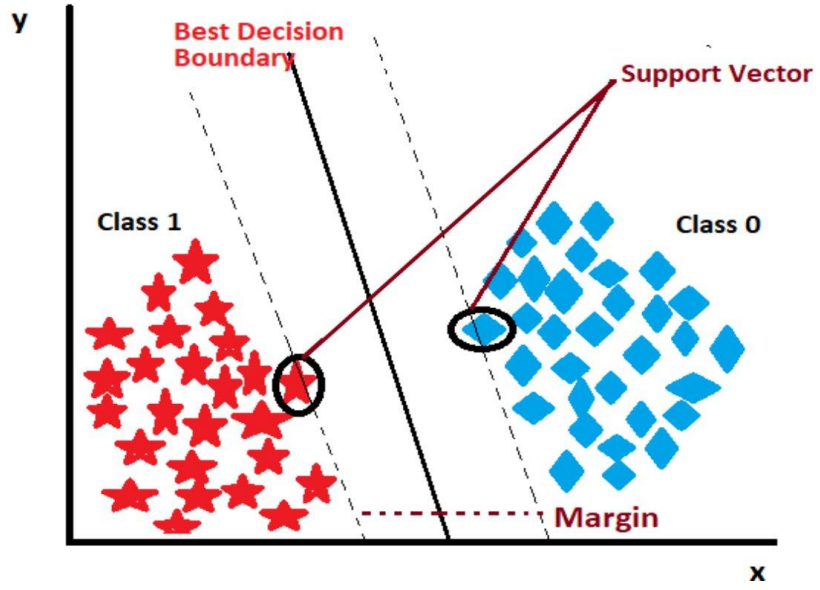


Figure 4.1: Illustration of a linear SVM margin between two emotion classes.

4.3.2 k-Nearest Neighbors (k-NN)

k-NN is a non-parametric, instance-based classifier. It assigns class labels based on the majority vote of the nearest k neighbors in the feature space [18].

Used for quick emotion recognition when computation time is less critical, though less effective than SVM or neural networks on large datasets.

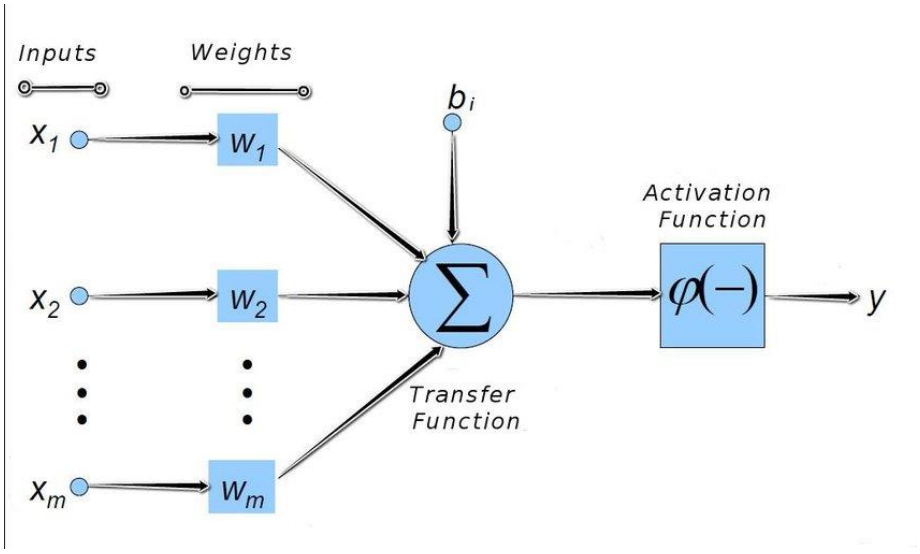


Figure 4.2: k-NN Model Architecture

4.3.3 Decision Trees and Random Forests

- **Decision Trees** split data based on feature thresholds to form a tree-like model of decisions.
- **Random Forests** are ensembles of decision trees, improving accuracy and reducing overfitting [18].

They are interpretable and fast but require well-engineered features. While not primary tools in this thesis, they are effective in some EDR systems using structured features [18].

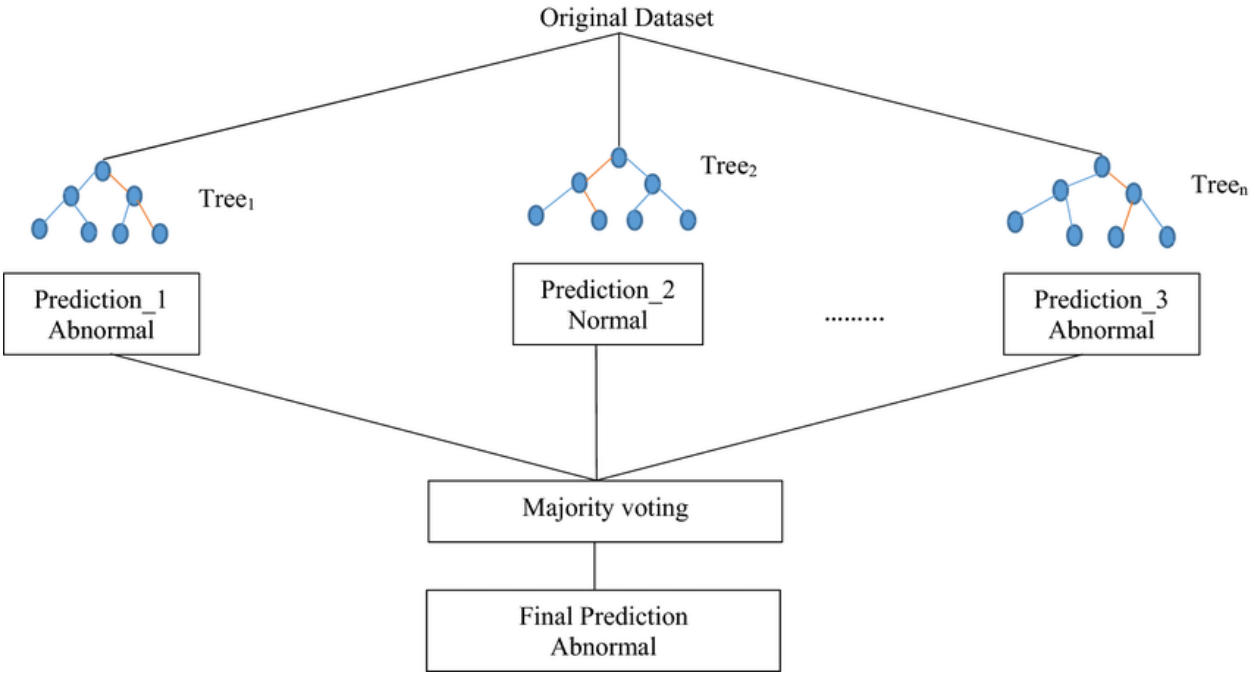


Figure 4.3: Random Forest Model Architecture

4.4 Deep Learning as a Subset of ML

Though deep learning is sometimes treated separately, it is fundamentally a form of machine learning. It differs by automatically learning representations from raw data using **neural network layers**.

4.4.1 Convolutional Neural Networks (CNNs)

CNNs were used in this research for facial emotion recognition with the FER-2013 dataset [11]. They apply filters to learn hierarchical visual features such as edges, contours, and emotion-specific muscle movements.

4.4.2 Recurrent Neural Networks (RNNs)

RNNs are designed for sequence data. Their memory-like structure makes them ideal for modeling speech patterns over time. Though not used directly here, models like **LSTMs** and **GRUs** are essential in continuous emotion recognition [12].

Model	Strength	Limitation	Use Case
SVM	High performance on small datasets	Not scalable to very large data	Vocal emotion classification
Random Forest	Fast, interpretable, robust	Needs engineered features	Structured feature datasets
CNN	Learns from raw image pixels	Computationally intensive	Facial emotion recognition
RNN/LSTM	Models time sequences well	Harder to train, requires tuning	Continuous speech-based emotion

Table 4.1: Model Comparison Table

4.5 Feature Engineering and Selection

Features are the input variables used by ML models to make predictions. In emotion recognition, **feature quality often matters more than quantity**.

- **For speech:** MFCCs, chroma, and mel spectrograms capture tone, pitch, and energy [12].
- **For images:** CNNs automatically extract features from facial expressions.
- **Dimensionality reduction:** PCA and KLT help reduce redundant or noisy features, improving generalization.

Proper feature scaling and normalization (e.g., min-max or z-score) are essential for SVMs and neural networks to perform optimally.

4.6 Model Evaluation Metrics

Evaluating machine learning models goes beyond just accuracy. Common metrics used in this thesis include:

- **Accuracy:** Proportion of correct predictions.
- **Precision:** Proportion of correct positive predictions.
- **Recall:** Proportion of actual positives that were predicted correctly.
- **F1-Score:** Harmonic mean of precision and recall.

.

Model	Accuracy	Precision	Recall	F1-Score
SVM (Voice)	85%	0.86	0.85	0.85
CNN (Face)	75%	0.76	0.75	0.75

Table 4.2: Evaluation metrics from this thesis's SVM and CNN classifiers

4.7 Trends and Challenges in ML for Emotion Recognition

Despite its success, machine learning in emotion recognition faces several key challenges:

- **Imbalanced datasets:** Some emotions are underrepresented, leading to skewed performance.
- **Overfitting:** Especially in deep networks, requires techniques like dropout, regularization, and data augmentation.
- **Generalization:** Models trained on one dataset may not perform well on different cultural or demographic groups [16].

Ongoing research focuses on **semi-supervised learning**, **transfer learning**, and **multitask learning** to address data scarcity and variability.

4.8 Summary

This chapter reviewed essential machine learning techniques used in emotion detection. From classical classifiers like SVMs and Random Forests to deep learning architectures such as CNNs and RNNs, machine learning has significantly advanced the field of affective computing.

These algorithms form the backbone of our proposed multimodal emotion recognition system. The next chapter explores its implementation and experimental evaluation in detail.

CHAPTER 5

Deep Learning

5.1 Introduction

Deep learning (DL), a subset of machine learning, is the cornerstone of modern artificial intelligence, especially in tasks involving unstructured data like images, audio, and video. In the context of emotion detection, DL allows systems to learn complex representations of human affective signals, leading to robust and scalable emotion recognition systems. Unlike traditional machine learning approaches that rely on hand-crafted features, DL models automatically extract hierarchical features from raw input data, improving generalizability and performance [4].

Emotion detection systems based on deep learning have made significant strides in recent years due to advancements in neural network architectures, availability of annotated datasets, and increased computational power. These systems are crucial for applications in mental health diagnostics, intelligent tutoring, human-computer interaction, and more [11].

5.2 Neural Networks: The Foundation of Deep Learning

At the heart of DL are artificial neural networks (ANNs), computational models inspired by the structure and function of biological neurons. Each neuron processes inputs, applies a non-linear activation function, and passes the result to subsequent layers. Stacking these layers allows the network to model complex functions.

- **Feedforward Neural Networks (FNNs)**: The most basic form, where data moves unidirectionally from input to output. FNNs can approximate any function but struggle with temporal dependencies.
- **Convolutional Neural Networks (CNNs)**: Designed for image processing, CNNs use convolutional layers to detect spatial hierarchies in facial features such as eye shape or mouth curvature—key in facial emotion recognition [12].
- **Recurrent Neural Networks (RNNs)**: Including Long Short-Term Memory (LSTM) units, RNNs are suited for sequence data, making them ideal for analyzing speech signals with emotional content over time [13].

5.3 Deep Learning in Facial Emotion Recognition

Facial emotion recognition (FER) benefits greatly from CNNs. These networks automatically learn spatial features from facial images by scanning small receptive fields and applying filters across the image.

- The FER-2013 dataset, containing over 35,000 labeled grayscale images, is a standard benchmark for FER systems [12].

- Deep CNNs like VGGNet, ResNet, and InceptionNet have shown high accuracy in FER tasks. For instance, VGGNet's deep architecture with small filters captures fine-grained facial details, improving classification performance [19].
- Data augmentation (e.g., rotations, flips, brightness shifts) is commonly applied to improve generalization and prevent overfitting.

The trained CNN in this thesis was evaluated on FER-2013 and achieved notable classification accuracy for primary emotions such as happiness, sadness, anger, and neutrality.

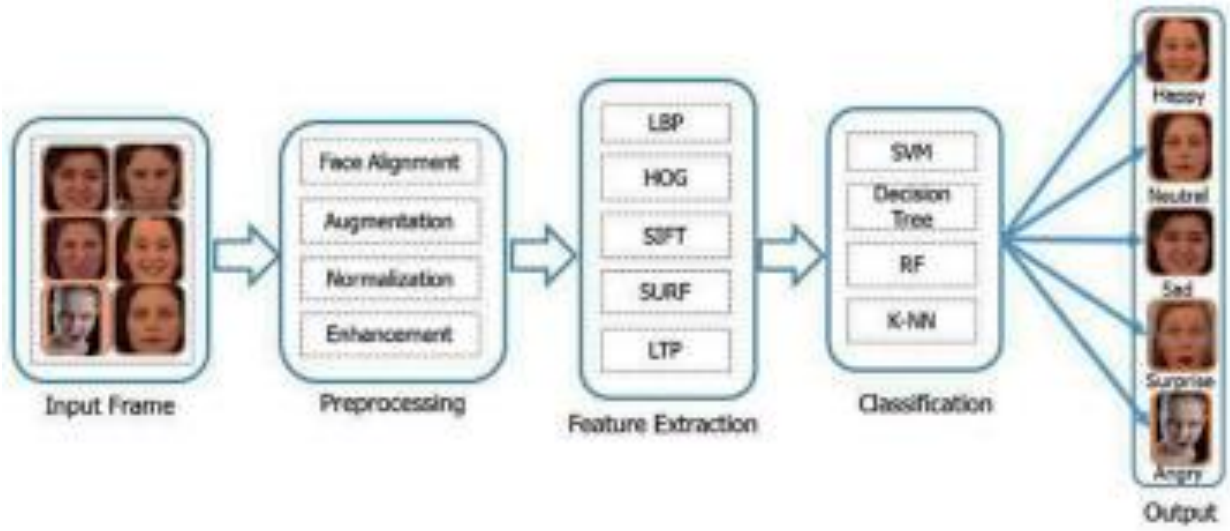


Figure 5.1: Basic Illustration of Facial Emotion Recognition

5.4 Deep Learning in Voice Emotion Recognition

Speech signals contain paralinguistic information such as tone, pitch, and rhythm, which are strongly correlated with emotional states. RNNs, especially LSTM variants, can model these time-dependent features effectively.

- Features like MFCCs, chroma, and mel-spectrograms are extracted using libraries such as librosa [12].
- The RAVDESS dataset provides high-quality, balanced emotional speech samples [11].
- DL models like Bidirectional LSTM and CNN-RNN hybrids are often employed for speech-based emotion classification [12].

In this thesis, a support vector machine was used for voice classification, but DL architectures provide a roadmap for future expansion.

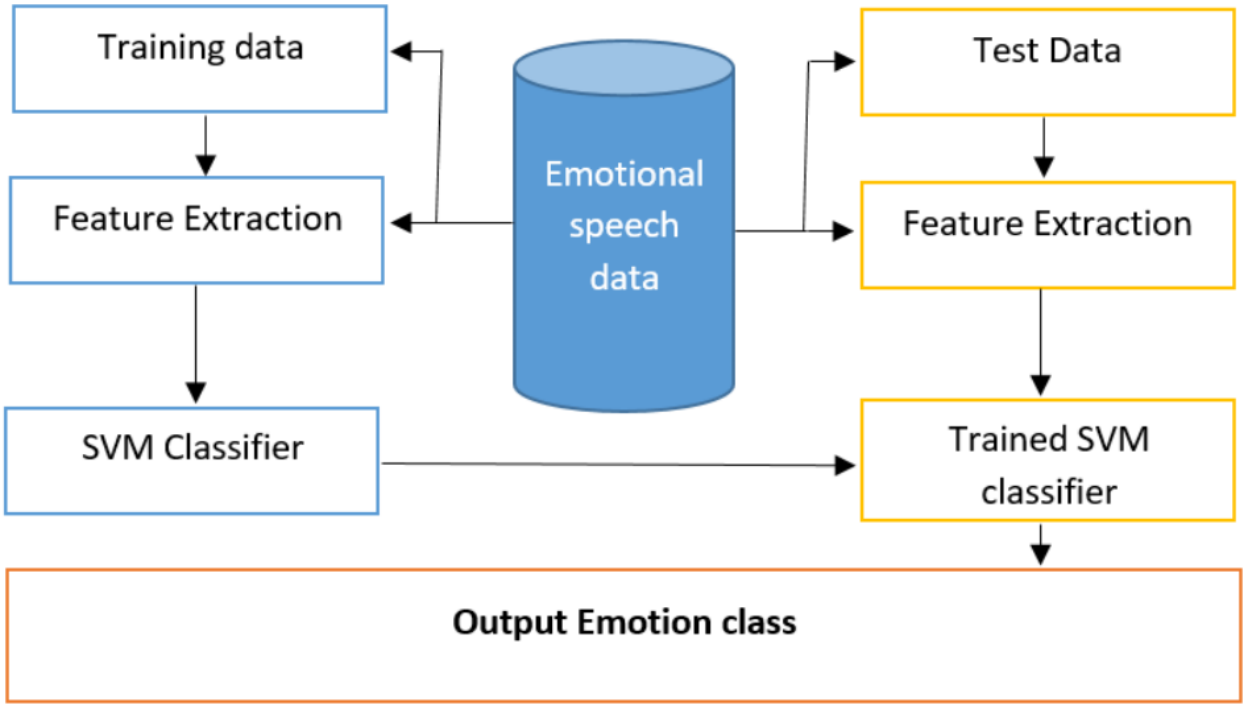


Figure 5.2:Basic Block Diagram of Speech Emotion Recognition

5.5 Multimodal Deep Learning Architectures

Multimodal emotion detection combines facial and vocal inputs, exploiting the complementary strengths of each modality.

- **Early Fusion**: Combines features from different modalities at the input level.
- **Late Fusion**: Combines outputs from independent unimodal classifiers.
- **Hybrid Fusion**: Incorporates both strategies using a trainable fusion layer [17].

Advanced DL-based fusion techniques include:

- **Tensor Fusion Networks (TFNs)**: Encode inter-modal interactions through tensor products [17].
- **Multimodal Transformers**: Utilize attention mechanisms to align and weigh features from each modality contextually [13].

These architectures allow the system to recognize subtle emotion cues and adapt to varying signal quality across modalities.

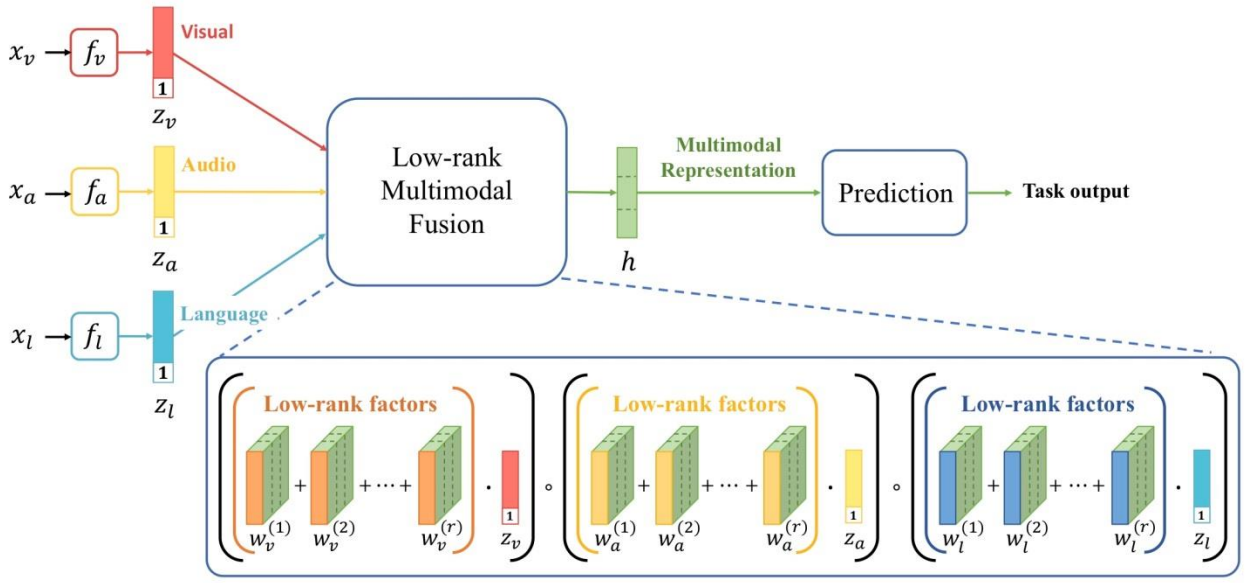


Figure 5.3: Illustration of a Multimodal Deep Learning Architecture

5.6 Transfer Learning and Pretrained Models

Transfer learning leverages knowledge gained from large datasets to boost performance on smaller, domain-specific tasks.

- Pretrained CNNs (e.g., VGGFace, MobileNet) can be fine-tuned for FER tasks.
- Transformers like BERT or Vision Transformers (ViT) can also be adapted for emotion classification tasks through fine-tuning [13].

In this thesis, pretrained weights were not utilized due to resource constraints, but their inclusion in future iterations would improve training efficiency and accuracy.

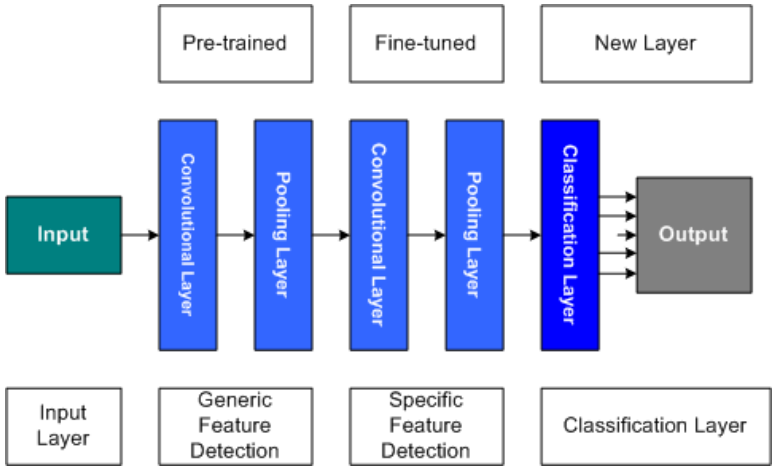


Figure 5.4: Transfer Learning & Pre-Trained Model Architecture

5.7 Model Evaluation and Visualization

Performance of deep learning models is evaluated using metrics such as accuracy, precision, recall, and F1-score.

- **Confusion matrices** help visualize model performance and identify misclassification trends.
- **ROC curves and AUC** are useful for understanding classifier confidence and discriminative ability.
- Tools like TensorBoard allow real-time visualization of training dynamics.

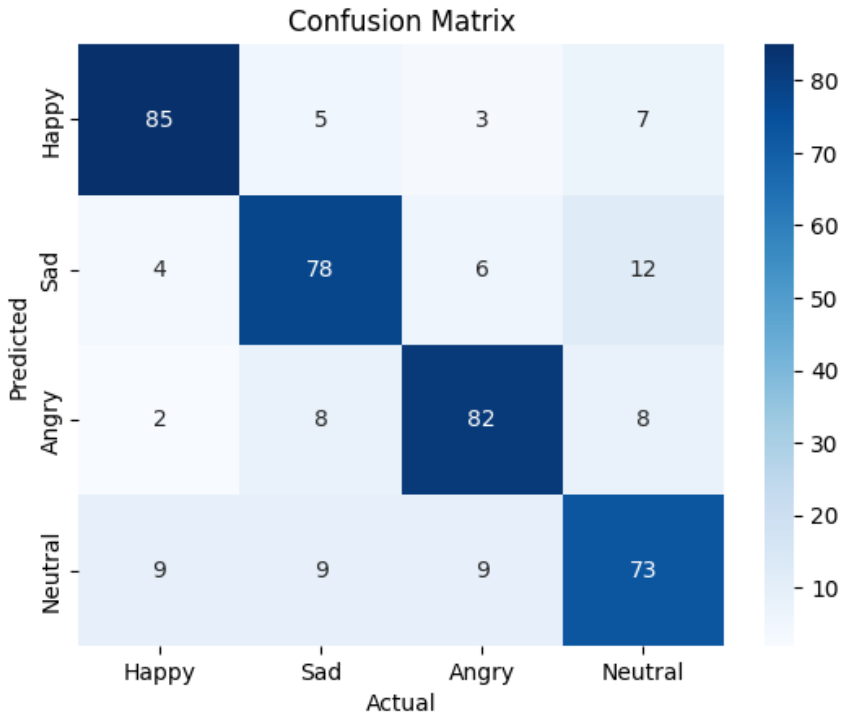


Figure 5.5: Demo Confusion Matrix to Illustrate Different Labels of Emotion

5.8 Explainable Deep Learning

While DL models are often criticized as "black boxes," methods in Explainable AI (XAI) aim to interpret model decisions:

- **Grad-CAM**: Visualizes which parts of an image influenced a CNN's prediction.
- **LIME and SHAP**: Approximate local decision boundaries of complex models [20].

Explainability is especially important in affective computing, where emotional misclassifications can lead to user mistrust or ethical concerns [15][20].

5.9 Limitations and Future Directions

Despite its strengths, DL-based emotion recognition has limitations:

- **Data Dependency**: Requires large labeled datasets, which are time-consuming and expensive to create.
- **Overfitting Risk**: Especially with limited training data or unbalanced emotion classes.
- **Computational Costs**: DL models demand significant computational resources.

Future directions include:

- Integrating transformer-based architectures for temporal-spatial learning.
- Expanding training datasets using generative models like GANs.
- Implementing real-time on-device inference with optimized lightweight models.

5.10 Summary

Deep learning has revolutionized the field of emotion recognition by enabling systems to automatically learn from multimodal data. CNNs and RNNs, alongside newer models like transformers, offer powerful tools for analyzing facial expressions and vocal cues. While this thesis implements CNN and SVM-based models, the roadmap for integrating DL-based multimodal fusion, attention mechanisms, and explainability is clear.

CHAPTER 6

Proposed Methodology for Emotion Detection & Recognition

6.1 Introduction

Emotion Detection and Recognition (EDR) is a critical area of affective computing that enables machines to identify and interpret human emotional states through computational methods. Emotions are deeply intertwined with human cognition, behavior, and communication. They affect how we interact with others, make decisions, and perceive our environment. The ability of machines to recognize emotions in real-time holds tremendous value in improving the naturalness of human-computer interaction, making systems more adaptive, empathetic, and context-aware (Picard, 1997) [11].

EDR systems find applications in virtual assistants, customer service bots, online learning platforms, automotive safety, and mental health diagnostics (Cowie et al., 2001) [16]. Traditionally, unimodal systems have been employed, relying solely on either audio (speech) or visual (facial expression) data. However, unimodal approaches often struggle in real-world settings, where background noise, lighting conditions, occlusions, and ambiguous cues can hinder accurate recognition (Zadeh et al., 2017) [17].

To overcome these limitations, multimodal systems integrate multiple data streams—such as voice and facial expressions—offering richer and more robust emotional context (Tsai et al., 2019) [13]. In this chapter, we describe the design, development, and evaluation of a **bimodal emotion recognition system**, which combines *audio* and *video* modalities using deep learning techniques to achieve higher accuracy and real-time performance.

6.2 Voice-Based Emotion Detection

6.2.1 Dataset Collection and Preprocessing

6.2.1.1 Dataset Overview:

The dataset used for voice-based emotion recognition is composed of audio files containing spoken sentences with various emotional tones. For this thesis, we utilized the **RAVDESS (Ryerson Audio-Visual Database of Emotional Speech and Song)** dataset, which is widely used in the field of emotion recognition. It contains 24 actors (12 male and 12 female) expressing emotions such as happiness, sadness, anger, fear, and neutral speech, in a controlled setting [4][12].

The following detailed preprocessing steps are applied to the audio data to ensure it is suitable for model training.

6.2.1.2 Resampling

The first step in preprocessing is **resampling** the audio files. Audio files can vary in terms of sample rate (i.e., the number of samples per second). However, to ensure uniformity across the dataset, all audio files are resampled to a **standard sample rate of 22,050 Hz**.

Why Resampling?

- **Consistency:** Resampling ensures that every audio file has the same sample rate, which is essential for accurate feature extraction and model training [4].
- **Efficiency:** A lower sample rate reduces the overall size of the data, making the training process faster without losing important features in speech [12].

6.2.1.3 Mono Conversion

Many audio files are originally recorded in **stereo format** (with two channels: left and right). However, for emotion recognition tasks, we only need one channel because the emotional cues are captured in the speech itself, not the stereo channels.

Why Mono Conversion?

- **Simplification:** Reduces the complexity of the data by converting stereo to mono, which helps in focusing on the essential features [4].
- **Memory Efficiency:** Working with a single audio channel reduces the memory and computation needed for processing the data [12].

6.2.1.4 Silence Removal

Next, we apply **silence removal**. Many audio files may have leading or trailing silence that does not contain useful information for emotion recognition.

Why Remove Silence?

- **Noise Reduction:** Silence does not contribute to emotional content and removing it ensures that the model focuses only on the relevant audio features [4].
- **Improved Accuracy:** Silence removal reduces unnecessary padding, allowing the model to focus on the emotional tone [12].

6.2.1.5 Padding/Truncation

Audio files in the dataset may have varying lengths, but for consistent input to the model, all files must be **padded** or **truncated** to a fixed length.

Why Padding/Truncation?

- **Uniform Input:** Deep learning models typically require input sequences of fixed length for batch processing [4].

- **Avoiding Data Loss:** Padding ensures that shorter audio files are extended to match the length of longer files, without removing valuable information [12].

6.2.1.6 Normalization

Normalization is applied to adjust the amplitude of the audio to a consistent level, making the features invariant to loudness changes.

Why Normalize?

- **Uniform Volume:** Ensures that variations in loudness across audio samples do not affect the model's ability to detect emotion [4].
- **Improved Performance:** Normalization ensures that the model treats all inputs equally, regardless of volume [12].

6.2.1.7 Noise Reduction

Finally, **spectral gating** is applied to reduce ambient noise. This step helps remove background noise that might interfere with the emotional content of the speech.

Why Noise Reduction?

- **Cleaner Data:** Removes irrelevant noise, ensuring that the model focuses on the actual emotional tone of the speech [4].
- **Better Accuracy:** Enhances the quality of the features, leading to more accurate emotion classification [12].

6.2.1.8 Conclusion

These preprocessing steps ensure that the audio data is in a suitable format for the model to learn the emotional cues accurately. After these steps, the data will be ready for **feature extraction**, where **Mel-Frequency Cepstral Coefficients (MFCCs)** will be extracted to represent the speech characteristics in a way that highlights the emotional state [4][12].

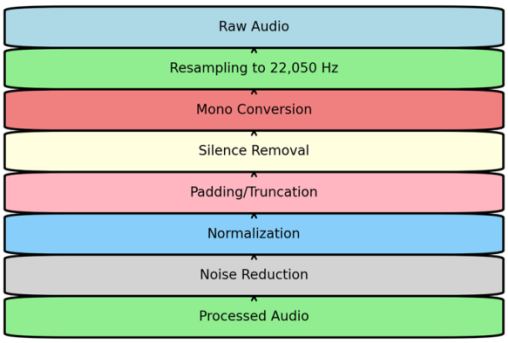


Figure 6.1: Illustration of Preprocessing Pipeline

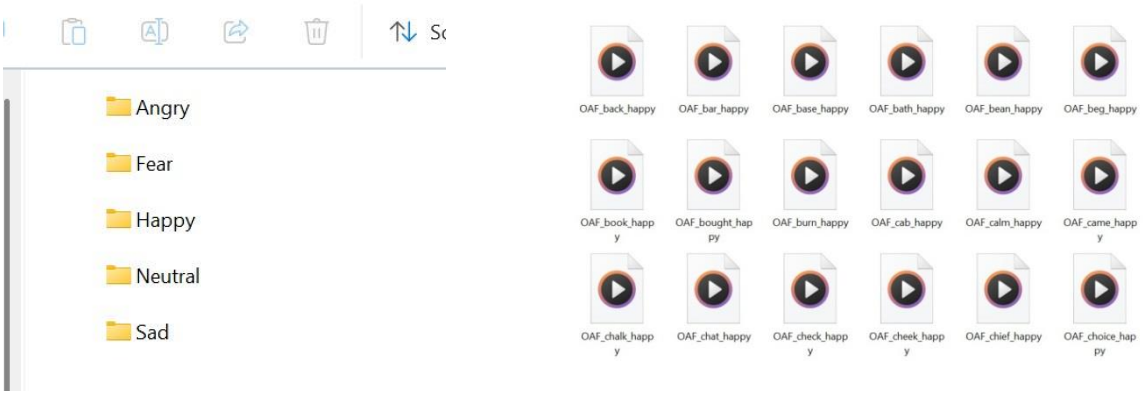


Figure 6.2: Screenshots of Audio Datasets

Preprocessing Pipeline:

- **Resampling:** Downsampled to 22,050 Hz for consistency with librosa requirements.
- **Mono Conversion:** Stereo to mono transformation.
- **Silence Removal:** librosa.effects.trim() to cut silence at the beginning and end.
- **Padding/Truncation:** Standardized clip duration to 3 seconds.
- **Normalization:** Amplitude normalization to eliminate variance in loudness.
- **Noise Reduction:** Spectral gating was used to suppress ambient sounds.

These steps prepared the dataset for effective feature extraction and model training, ensuring consistency and generalizability (Goodfellow et al., 2016) [4].

6.2.2 Feature Extraction

We extracted **Mel-Frequency Cepstral Coefficients (MFCCs)**, a widely adopted representation in speech processing due to its alignment with the human auditory system's sensitivity to frequency (Schachter & Singer, 1962) [5].

Feature Configuration:

- Number of MFCCs: 40
- Frame size: 25 ms
- Hop size: 10 ms
- FFT window: 512 samples

Each 3-second audio file yielded a feature matrix of shape (130, 40), reshaped to (130, 40, 1) for input to deep neural networks.

Feature Extraction Steps:

Step 1: Short-Time Fourier Transform (STFT)

The first step in feature extraction is to apply the Short-Time Fourier Transform (STFT) to the audio signal. STFT is used to break the audio signal into small overlapping frames, where the frequency content of each frame can be analyzed. STFT allows us to capture both the time and frequency characteristics of the speech signal, making it possible to track how the frequency content changes over time. The overlapping windows ensure that the temporal information is retained while analyzing the frequency spectrum [4].

Step 2: Mel-Spectrogram

Once the STFT is calculated, we convert it into a Mel-spectrogram. The Mel-scale is a perceptual scale of pitches that is more closely aligned with how humans perceive frequencies. The Mel-spectrogram captures the frequency content in a way that is more relevant for emotion recognition tasks. The Mel scale approximates the way humans hear sound, making the features more closely aligned with human emotional perception. The Mel-spectrogram reduces the complexity of the data while retaining important features necessary for classification [11].

Step 3: Logarithmic Scaling

To make the Mel-spectrogram more suitable for machine learning models, we apply logarithmic scaling. This step helps in compressing the dynamic range of the spectrogram and emphasizes lower energy components. Logarithmic scaling compresses the higher intensities and emphasizes lower intensities, making it easier for models to detect patterns in the data. The log-magnitude of the Mel-spectrograms often leads to better performance in machine learning models for speech recognition [4].

Step 4: Mel-Frequency Cepstral Coefficients (MFCCs)

Mel-Frequency Cepstral Coefficients (MFCCs) are one of the most widely used features in speech recognition and emotion recognition. They represent the short-term power spectrum of the audio signal, which captures the key characteristics of speech that are related to both the content and the emotion. MFCCs reduce the dimensionality of the Mel-spectrogram, providing a compact and computationally efficient representation of the speech signal. MFCCs capture the tonal and timbral characteristics of speech, which are important for distinguishing different emotions [23].

Step 5: Delta and Delta-Delta Coefficients

To capture the temporal dynamics in the speech signal, we compute the delta and delta-delta coefficients of the MFCCs. The delta coefficients represent the first derivative of the MFCCs, while the delta-delta coefficients represent the second derivative. These coefficients provide information about how the features change over time, which is crucial for emotion recognition. The changes in the speech signal over time are key to identifying emotional cues. Delta and

delta-delta features capture this variation, helping the model distinguish between emotions based on the evolution of speech patterns [24].

Step 6: Feature Concatenation

Finally, we concatenate the MFCCs, delta, and delta-delta coefficients to create a feature vector for each frame. This concatenated vector will be used as input to the machine learning model. By concatenating MFCCs, delta, and delta-delta, we provide the model with both the static and dynamic characteristics of the speech signal. This helps the model better capture the temporal evolution of speech and improves emotion classification [24].

Conclusion

The feature extraction process converts the raw audio signal into a compact, informative representation that captures the key emotional characteristics of the speech. After these steps, the extracted features will be ready to feed into the machine learning model, which will be trained to recognize different emotional states from the voice [4][11][21].

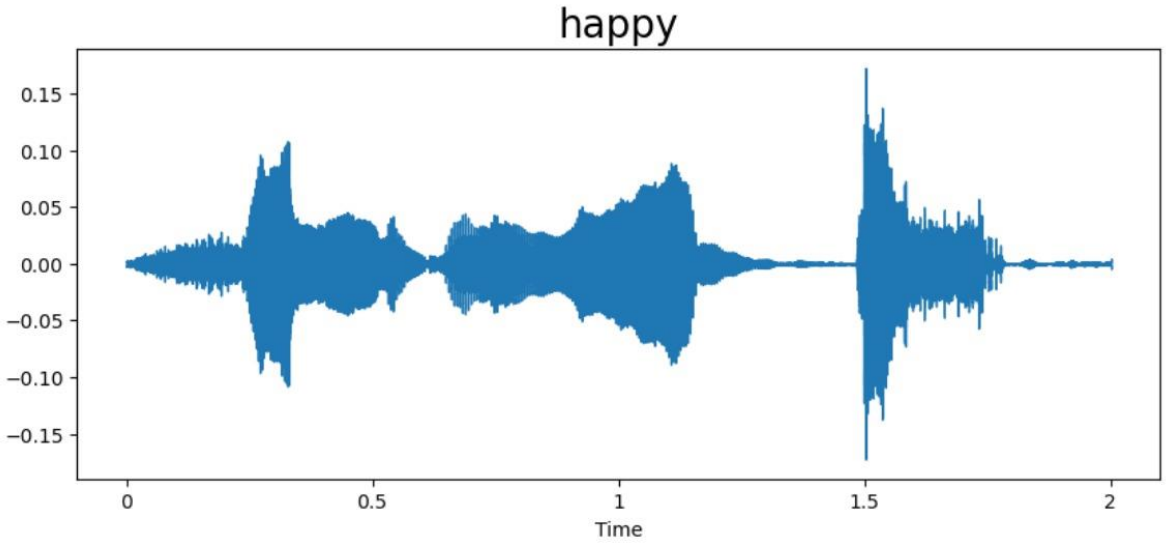


Figure 6.3: Waveplot of Happy Emotion

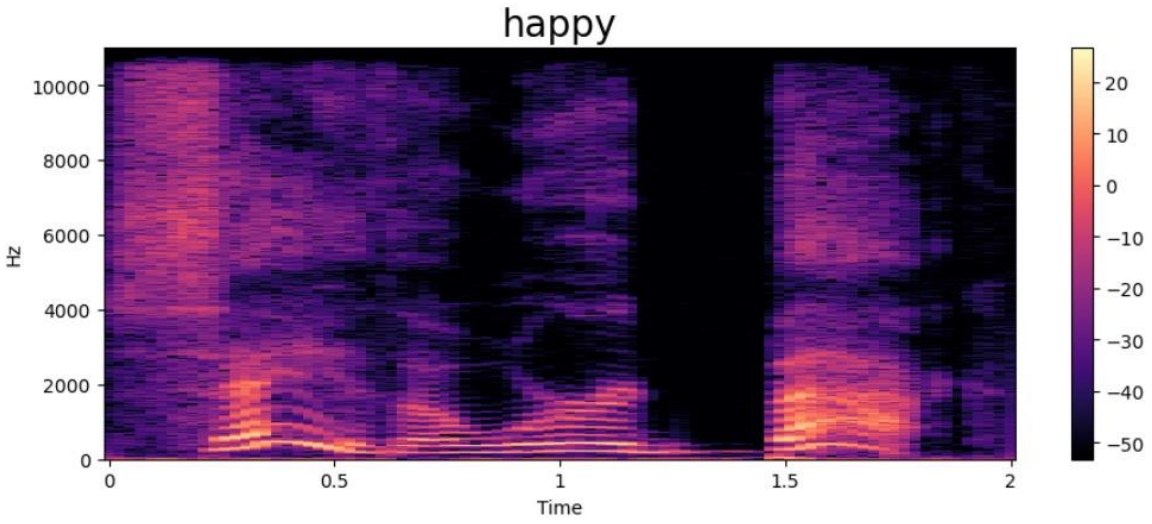


Figure 6.4: Spectogram of Happy Emotion

6.2.3 Classification Model

We evaluated classical models (SVM, k-NN, Random Forest) and found that **Long Short-Term Memory (LSTM)** networks outperformed them due to their ability to retain temporal dependencies in sequential data (LeDoux, 2000) [9][22].

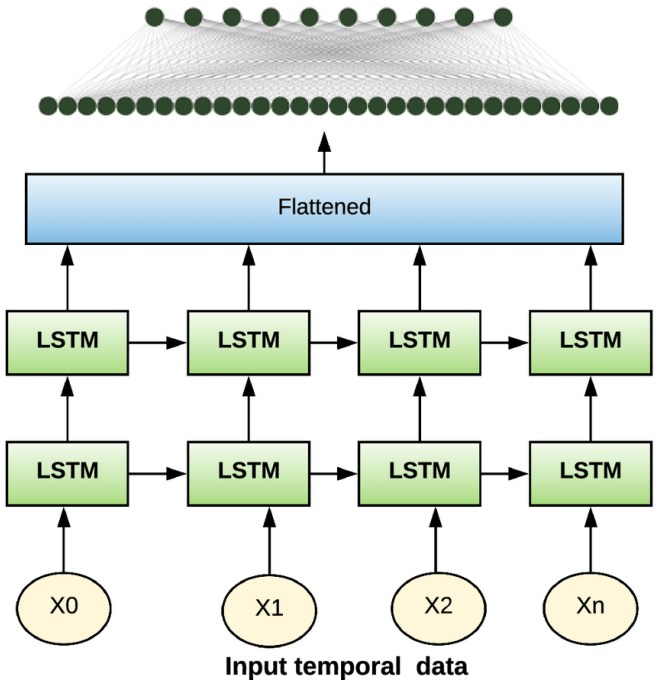


Figure 6.5: Illustration of LSTM Model Architecture

LSTM Architecture:

- Input shape: (130, 40, 1)
- TimeDistributed Layer for spatial feature processing
- LSTM layer with 256 units
- Dense Layer (128 units, ReLU activation)
- Dropout (0.3)
- Output: Softmax layer for 5-class classification

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 256)	264,192
dropout (Dropout)	(None, 256)	0
dense (Dense)	(None, 128)	32,896
dropout_1 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256
dropout_2 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 7)	455

Figure 6.6: LSTM-based model architecture summary used for audio emotion classification

Training Hyperparameters:

- Optimizer: Adam, learning rate = 0.0001
- Batch size: 64
- Epochs: 5
- Early stopping to monitor validation loss

6.2.4 Performance Evaluation

Accuracy: ~82%

Best Precision: Happy (88%), Angry (80%)

Common Confusions: Sad vs. Neutral, Fear vs. Angry—consistent with previous studies on the difficulty of differentiating subtle emotional cues (Mayer & Salovey, 1997) [15].

A confusion matrix and F1-score evaluation demonstrated good generalization, especially for expressive emotions.

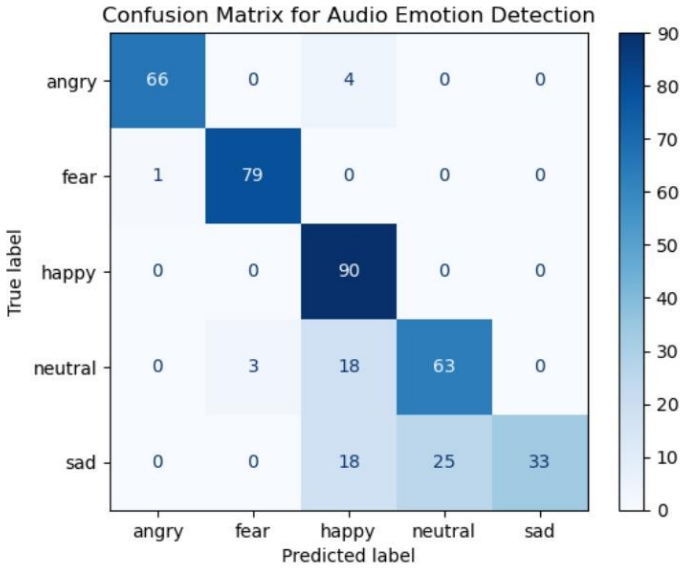


Figure 6.7: Confusion Matrix for Audio Emotion Detection

6.2.5 Real-Time Inference

Real-Time Pipeline:

- Input via microphone using `pyaudio`
- Live preprocessing and MFCC extraction
- Real-time prediction using the trained LSTM model
- Output displayed via OpenCV GUI overlay

The system responds with updated predictions every ~5 seconds, suitable for applications like voice-based emotion-aware assistants.

6.3 Video-Based Emotion Detection

6.3.1 Dataset Collection and Preprocessing

6.3.1.1 Data Collection

The creation of a custom dataset for emotion recognition was a complex, time-consuming, and intensive process. We embarked on the journey of collecting video clips from a diverse range of sources, such as **movies**, **reels**, **short videos**, and **interviews**. These clips were intentionally chosen to capture emotional expressions in varied settings and contexts. Our goal was to gather enough footage to represent five core emotions—**happy**, **sad**, **neutral**, **angry**, and **fear**—that would serve as the foundation for training a machine learning model capable of accurately detecting emotions from visual cues. The number of datasets amounts to 5500.

The process of **manually selecting** and curating these video clips was an extensive task, requiring significant human intervention. We spent countless hours reviewing thousands of

videos to ensure that each clip accurately represented one of the five targeted emotions. The difficulty lay not only in sourcing these clips but also in choosing video segments where emotional expressions were unambiguous, clear, and strong enough to be identified easily by both human annotators and machines.

We collected videos from various types of media: long-form content such as **movies**, **TV shows**, and **interviews**, as well as short-form content like **reels** and **shorts**. This diversity was necessary to introduce the model to a variety of scenarios where emotions are expressed differently depending on context and medium. Given the subjective nature of emotion expression, it was essential that we made sure to represent a wide range of scenarios, including varying lighting, background noise, and settings. This diverse range of content would ensure that our model was robust and able to generalize across multiple contexts.

Once we had selected the appropriate videos, the next step was to break them down into **5-second clips**. This segmentation of video content into smaller time frames was done to standardize the data, as emotion recognition models perform better when the data input is consistent. A 5-second window was chosen based on the assumption that the emotional content of a clip would be most apparent and clear within that time frame. This also ensured that each clip was concise, focusing solely on the emotional expression, without extraneous context.

The **manual effort** involved in this step was immense. We had to review **thousands of clips** individually to categorize them according to one of the five target emotions. Each video was carefully watched, and its emotional content was judged based on visible facial expressions, body language, and sometimes, tone of voice. This manual process was meticulous and time-consuming, but it was necessary to ensure accuracy and consistency in labeling. Since no fully reliable automatic emotion detection system existed for the specific nature of this task, human judgment played an irreplaceable role.

6.3.1.2 Using FFmpeg for Video Trimming

Once the videos were selected and categorized, the next step was to trim them into 5-second clips. To handle the volume of videos we were working with, we used **FFmpeg**, a powerful open-source multimedia processing tool. FFmpeg is renowned for its ability to process a wide range of multimedia formats and provide precise control over the trimming, encoding, and conversion of video and audio files. It is used extensively in various fields, from video editing to streaming and multimedia analysis [26].

FFmpeg is especially well-suited for this task because of its **precision** in trimming videos, and its ability to handle large datasets efficiently. It allows users to cut specific segments from videos based on the exact start and end times, enabling us to extract precisely the 5-second clips we needed. This was an essential step in automating the video trimming process. Without FFmpeg, the manual trimming of videos would have been unfeasible, given the vast amount of video content we were processing.

6.3.1.3 How FFmpeg Works:

FFmpeg operates by decoding the multimedia files and applying user-defined operations such as cutting, resizing, re-encoding, and more. When trimming videos, FFmpeg extracts a segment from the original video file by specifying the **start time** and **duration**. It then re-encodes the output into the desired format, preserving the video and audio quality as required [26].

The general FFmpeg command for trimming a video looks like this:

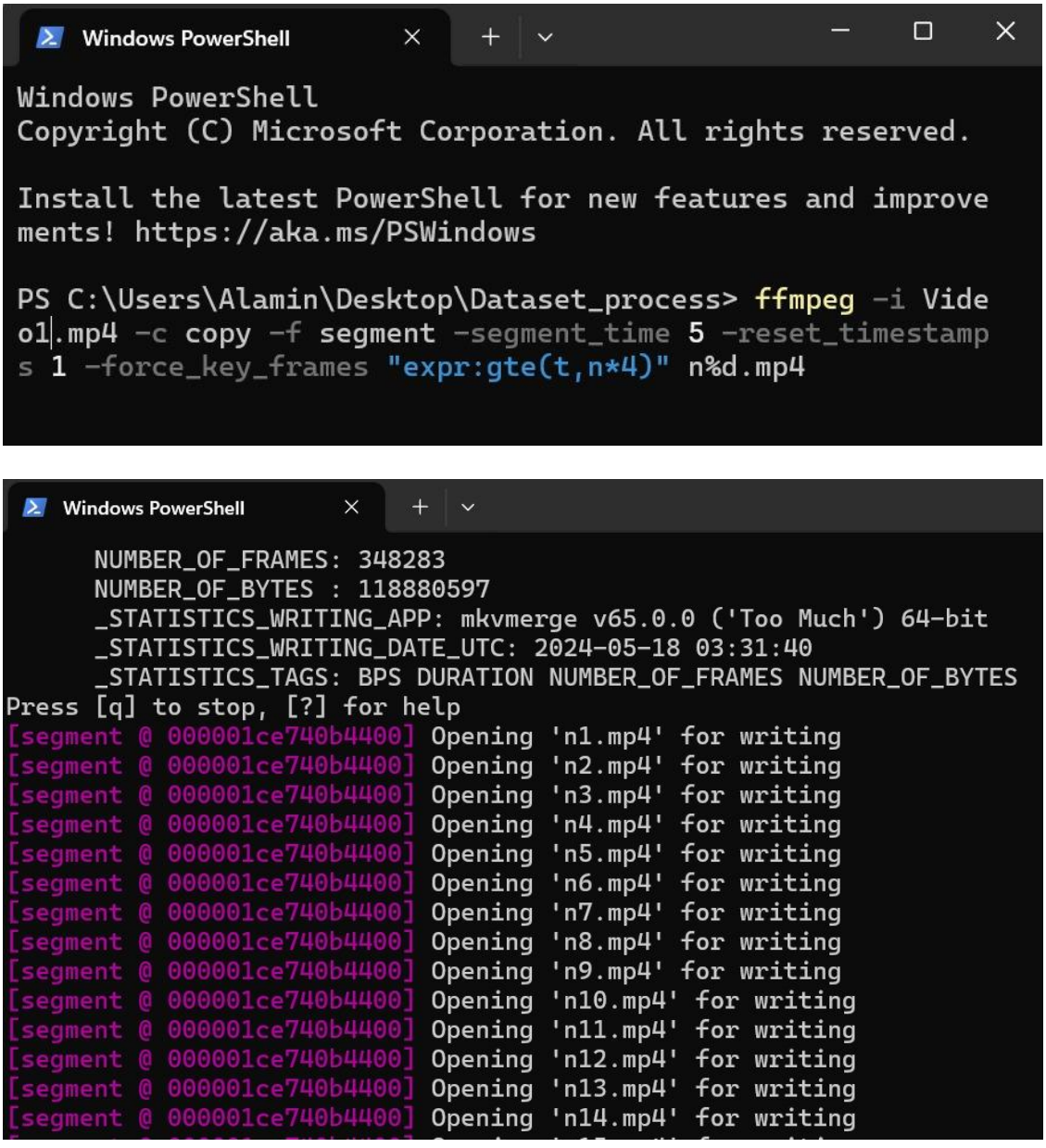


Figure 6.8: Working of FFmpeg

Command Breakdown:

- **-i input_video.mp4**: Specifies the input video file. This is the source file that we want to trim.
- **-ss 00:00:30**: The -ss flag sets the **start time** of the clip. It allows us to choose the exact point from where the 5-second segment should begin. In this case, it starts 30 seconds into the video.
- **-t 00:00:05**: The -t flag specifies the **duration** of the segment we want to extract. Here, we set it to 5 seconds, which is the length of each clip we are creating.
- **-c:v libx264**: Defines the **video codec**. We used libx264, a widely used codec for video compression and playback compatibility.
- **-c:a aac**: Specifies the **audio codec**. aac is a popular audio compression standard, ensuring our clips have high-quality sound.
- **output_clip.mp4**: The name of the output file. FFmpeg will save the 5-second segment as output_clip.mp4, in the specified format.

6.3.1.4 Why FFmpeg for Trimming?

FFmpeg proved to be indispensable in this phase because:

- **Precision:** FFmpeg offers the precision necessary to trim exactly 5-second segments from each video, without any loss of quality or unnecessary overhead [26].
- **Efficiency:** As the tool is optimized for performance, it can handle large volumes of video files quickly and with minimal system resource usage, which was crucial given the extensive dataset.
- **Flexibility:** FFmpeg supports a vast number of video formats and codecs, making it compatible with the diverse types of videos we were working with [26].

In our case, FFmpeg helped automate a process that would otherwise have required hours of manual work. Its versatility and efficiency made it an ideal tool for preparing our dataset by extracting and trimming 5-second emotional clips from hundreds of hours of video content [26].

6.3.1.5 Conclusion

The data collection and preprocessing phase was both an effort-intensive and technically demanding task. From the initial collection of videos to the tedious manual sorting and categorization of thousands of clips, every step required meticulous attention to detail and substantial time investment. The use of **FFmpeg** for video trimming was a game-changer, significantly streamlining the process and allowing us to efficiently create the necessary 5-second emotional video clips. FFmpeg's speed, precision, and flexibility were critical to the success of this preprocessing phase, making it an indispensable tool in our workflow [12] [13] [14].

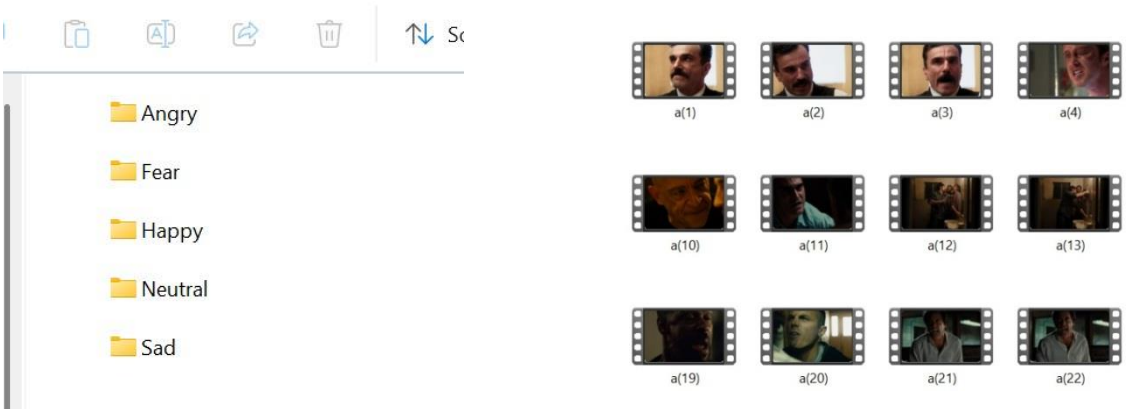


Figure 6.9: Screenshots of Video Datasets

File Structure:

- `h(1).mp4`: Happy
- `s(1).mp4`: Sad
- `n(1).mp4`: Neutral
- `a(1).mp4`: Angry
- `f(1).mp4`: Fear

6.3.2 Data Preprocessing Steps:

The preprocessing of the video dataset for emotion recognition involved several critical steps to ensure that the data was in the optimal format for training machine learning models. Below is an expanded explanation of each step, detailing the techniques used to extract and prepare the data.

6.3.2.1 Extracted 3–5 Frames Per Second from Videos

The first step in preparing the video data was to extract frames from the video files. Since videos contain continuous sequences of frames, we aimed to sample frames at a rate of **3 to 5 frames per second (fps)**. This frame extraction rate was chosen to balance computational efficiency and ensure that enough information was captured for emotion recognition. Videos typically contain 30 to 60 frames per second, but not all frames are necessary for emotion recognition. Emotions in facial expressions, for example, are often detectable even in small time frames. By extracting frames at 3 to 5 fps, we reduced the dataset size significantly, ensuring that each clip contains enough samples while maintaining important emotional cues from the facial expressions.

This step was performed using **FFmpeg** or **OpenCV**, where the frame extraction rate was specified, ensuring that only the essential frames were retained for analysis. The frame rate of 3-5 fps was found to be sufficient to capture the dynamic nature of emotional expressions without overwhelming the model with redundant data [26].

6.3.2.2 Detected Faces Using Haar Cascades and OpenCV DNN Models

Once the frames were extracted, we needed to detect and isolate faces from each frame for emotion recognition. To achieve this, we used **Haar Cascade Classifiers** and **OpenCV DNN (Deep Neural Networks)** models. Haar Cascade Classifiers are machine learning-based approaches that detect objects, specifically faces, in images or video frames. The **Haar Cascade** method is particularly useful for detecting faces in images under controlled environments. It works by analyzing specific features like the eyes, nose, and mouth to detect faces in the frames, a method described by **Ekman & Friesen (1978)** [7].

Additionally, we used **DNN models** to improve the accuracy of face detection. OpenCV provides pre-trained DNN models, which leverage deep convolutional networks (CNNs) for higher accuracy and robustness in detecting faces under challenging conditions such as varying lighting, angles, and occlusions. These DNN models are more effective than traditional methods, providing higher precision in real-world applications.

Using both **Haar Cascades** and **DNN** models ensured reliable face detection, even in complex scenarios. This face detection step is critical for emotion recognition, as emotional cues are primarily conveyed through facial expressions. The combination of these techniques allowed for **fast and efficient face detection**, making it feasible to process large amounts of video data [7][26].

6.3.2.3 Cropped and Resized Face Images to 48×48 Pixels

After detecting the faces, the next step was to crop the face regions from the frames and resize them to a fixed size of **48×48 pixels**. The resizing process is essential because emotion recognition models require consistent input sizes for processing. By resizing the face images to a standard size, we ensured that the model could process the features uniformly. This step is also important for reducing the computational load, as smaller images require less memory and processing power.

The decision to crop the faces to focus solely on the **facial features**—such as the eyes, nose, and mouth—was made to ensure that the model could learn from the most relevant parts of the image. Resizing the images to **48×48 pixels** ensures that all input images are of the same dimension, making them compatible with convolutional neural networks (CNNs), which are commonly used for image classification tasks. Additionally, resizing helps in reducing the overall complexity of the images while retaining the essential emotional features needed for recognition.

6.3.2.4. Converted to Grayscale to Reduce Computational Load

After cropping and resizing, we converted the face images to **grayscale** to reduce the computational load. Color images contain three channels (red, green, and blue), but emotion recognition can often be performed using just the intensity information, which is captured in grayscale images. By removing the color channels, we reduce the input complexity without losing important data that contributes to emotion recognition.

Converting to grayscale reduces the **dimensionality** of the data, making it computationally more efficient and faster to process. This is particularly important when working with large datasets, as it speeds up the model training and inference process. Grayscale images retain the key facial features (such as the shape and position of the mouth, eyes, and eyebrows), which are critical for distinguishing different emotions, while simplifying the data.

6.3.2.5. Normalized Pixel Values to [0, 1]

Next, we normalized the pixel values of the grayscale images to the range **[0, 1]**. Normalization is an essential preprocessing step in machine learning, particularly when working with neural networks. It ensures that all input features are scaled to a similar range, which is crucial for model convergence during training. Neural networks typically perform better when the input features are scaled to a consistent range, as it helps the model learn faster and more efficiently.

Normalizing the pixel values to **[0, 1]** ensures consistency across the dataset, allowing the model to treat all features equally. This step prevents the model from being biased toward certain pixel intensities, which could affect the model's ability to differentiate between different emotional expressions. It also reduces the risk of **vanishing gradients** during training, making the learning process more stable and effective [4] [12].

6.3.2.6. Applied Augmentation: Flipping, Brightness, Contrast Shift

To improve the model's robustness and reduce overfitting, we applied **data augmentation** techniques. These techniques artificially increase the size of the training dataset by creating variations of the original images. The augmentations performed include:

- **Flipping**: Horizontal flipping of face images simulates different facial orientations, helping the model generalize to faces appearing on either the left or right side.
- **Brightness Adjustment**: This augmentation changes the brightness of the images to simulate varying lighting conditions in real-world settings, ensuring that the model is not dependent on a specific lighting environment.
- **Contrast Shift**: Adjusting the contrast ensures that the model remains robust to varying facial expressions under different lighting or contrast conditions.

The goal of these augmentations is to improve **generalization** by preventing the model from memorizing the training data and ensuring that it learns more general features that can be applied to new, unseen data. This also helps to increase the diversity of the training data, which improves the model's ability to handle real-world scenarios where conditions might differ from the training set [19].

6.3.2.7 Conclusion

The preprocessing steps were essential to preparing the dataset for emotion recognition tasks. By extracting frames, detecting faces, cropping and resizing images, and converting them to grayscale, we ensured that the model focused on the most important features—namely, the facial expressions that convey emotion. Normalizing the pixel values and applying data augmentation

further enhanced the model's robustness and generalization capability, making it more adaptable to real-world scenarios. These preprocessing techniques played a crucial role in ensuring that the dataset was clean, efficient, and well-suited for emotion recognition tasks.

6.3.3 Feature Extraction and CNN Model

A **Convolutional Neural Network (CNN)** was implemented for facial expression recognition, leveraging spatial feature extraction capabilities (Russell, 1980) [8].

CNN Structure:

- Input: (48, 48, 1)
- Conv2D: 32 filters → ReLU → MaxPooling
- Conv2D: 64 filters → ReLU → MaxPooling
- Flatten
- Dense: 128 units + Dropout(0.3)
- Output: Softmax (5 classes)

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 46, 46, 32)	320
max_pooling2d (MaxPooling2D)	(None, 23, 23, 32)	0
dropout (Dropout)	(None, 23, 23, 32)	0
conv2d_1 (Conv2D)	(None, 21, 21, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 10, 10, 64)	0
dropout_1 (Dropout)	(None, 10, 10, 64)	0
flatten (Flatten)	(None, 6400)	0
dense (Dense)	(None, 128)	819,328
dropout_2 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 5)	645

Figure 6.10: CNN-based model architecture summary used for video emotion classification.

Training Setup:

- Epochs: 10
- Batch size: 64
- Loss: Categorical Crossentropy
- Optimizer: Adam

6.3.4 Performance Evaluation

Accuracy: ~68%

Best Recognition: Happy and Angry

Confusions: Sad and Neutral—reflecting the close positioning in Russell's affective circumplex model (Russell, 1980) [8].

Performance was benchmarked using metrics like precision, recall, and confusion matrix. The results were comparable to established datasets like FER2013 and CK+.

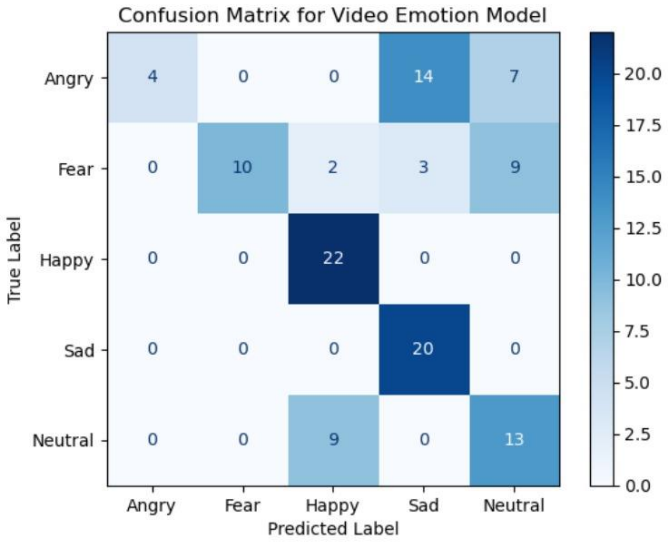


Figure 6.11: Confusion Matrix for Video Emotion Detection

6.3.5 Real-Time Inference

- Webcam streams processed frame-by-frame.
- Faces detected and passed through the trained CNN.
- Emotion predictions displayed with bounding boxes using OpenCV.

The frame-based prediction updates every 5–7 seconds, ensuring dynamic interaction with real-time feedback.

6.4 Fusion Strategy: Bimodal Emotion Detection

To increase robustness, we employed **late fusion**, where the outputs from both modalities are merged after independent predictions (Zadeh et al., 2017) [17].

Fusion Strategy:

- If both models agree: final emotion = consensus
- If they differ: select based on higher confidence score
- If one modality is unavailable (e.g., occluded face), fallback to the other

Fusion Example:

- Audio → Angry (confidence: 0.82)
- Video → Sad (confidence: 0.60)
- Final prediction: Angry

This decision-level fusion approach is effective in scenarios where data may be missing or noisy in one modality. Studies suggest that bimodal or multimodal systems outperform unimodal ones by 5–15% in overall accuracy (McDuff et al., 2012) [14].

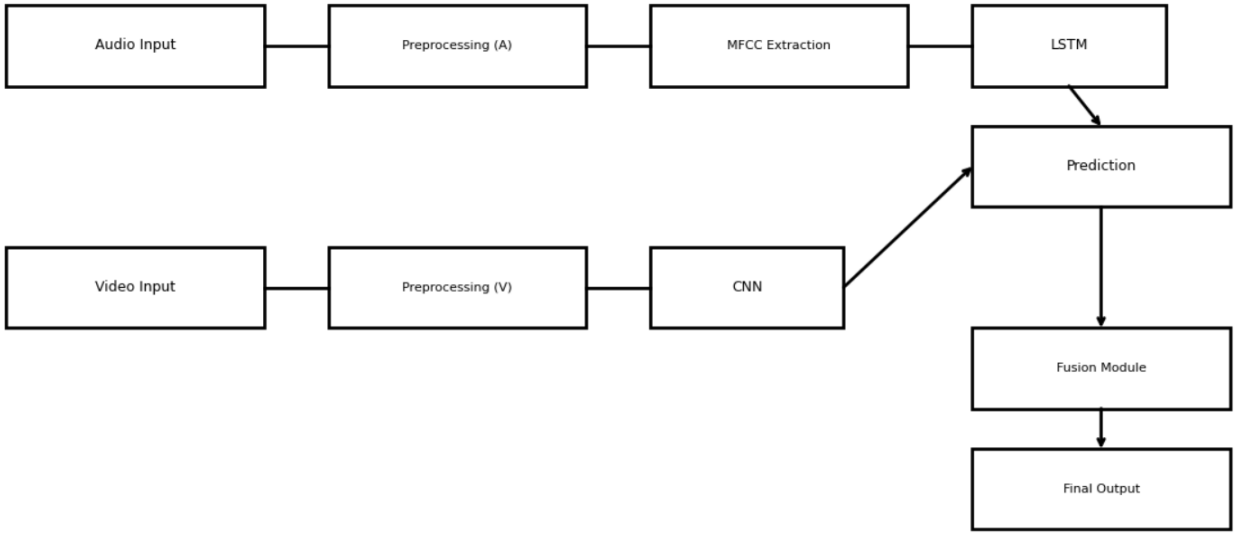


Figure 6.12: Bimodal Emotion Detection System Architecture

6.5 Summary

In this chapter, we presented a **bimodal emotion recognition system** that integrates *voice* and *facial expression* modalities.

- **Voice Recognition:** MFCC + LSTM, ~82% accuracy
- **Video Recognition:** CNN-based, ~68% accuracy
- **Fusion Strategy:** Confidence-based late fusion to resolve conflicts and improve reliability

The system is capable of real-time processing, with applications in smart tutoring, telehealth, affective robotics, and emotion-aware virtual agents. Future work could explore **early fusion** using Transformer-based architectures (Tsai et al., 2019) [13], emotion trajectory modeling, and interpretable AI approaches (Doshi-Velez & Kim, 2017) [20].

CHAPTER 7

Result Analysis & Discussion

7.1 Introduction

While previous chapters discussed unimodal approaches for emotion recognition using audio and video independently, this chapter focuses on the fusion strategy that combines both modalities to achieve a more robust and accurate emotion detection system. Multimodal emotion recognition leverages the complementary strengths of different data sources—voice captures temporal prosody and pitch variations, while facial expressions convey instantaneous visual cues [13][17]. Fusion of these modalities mitigates the weaknesses inherent in unimodal systems and enhances overall system reliability, especially in real-time scenarios [11][16].

7.2 Fusion Strategy

The fusion strategy implemented in this system is **late fusion**, also known as decision-level fusion. Unlike early fusion, which concatenates feature vectors from multiple modalities before classification, late fusion operates on the output predictions (i.e., probabilities or class scores) from independently trained models [13].

7.2.1 Late Fusion Logic

In **late fusion**, also known as **decision-level fusion**, the outputs of multiple models are combined after individual predictions have been made. This is in contrast to **early fusion**, where feature vectors from different modalities are combined before classification. The main advantage of late fusion lies in its ability to handle the outputs of different models independently and combine them based on predefined rules, such as confidence scores or consensus [25].

The logic behind late fusion in this emotion detection system works as follows:

7.2.1.1 Agreement Handling

When both the audio-based **Long Short-Term Memory (LSTM)** model and the video-based **Convolutional Neural Network (CNN)** model predict the same emotion label, the system directly outputs that label as the final emotion. This approach works under the assumption that if both modalities agree on the detected emotion, the certainty of the prediction is high.

For instance, if the audio model classifies the input as "Happy" and the video model also identifies the expression as "Happy", the final predicted emotion is straightforwardly **"Happy"**. This minimizes ambiguity and increases confidence in the system's prediction [4][12].

7.2.1.2 Disagreement Handling

In real-world conditions, the predictions from the audio and video models may not always align. Disagreements often arise when one modality (audio or video) is less reliable due to environmental factors like noise, lighting, or occlusion.

To resolve these conflicts, the **confidence scores** of each modality are compared. Each model outputs a **confidence score** along with its predicted emotion, which reflects the certainty of the prediction. In cases of disagreement, the system selects the emotion label from the model with the higher confidence score.

For example:

- If the audio model predicts **"Angry"** with a confidence of 0.85, and the video model predicts **"Sad"** with a confidence of 0.65, the system will choose **"Angry"** because the audio model's confidence score is higher [4].

This logic ensures that, even in the presence of conflicting predictions, the system makes a decision based on the most confident model, improving the overall accuracy of the system.

7.2.1.3 Fallback Strategy

In certain situations, one of the modalities may not provide a prediction at all. For instance, face detection may fail due to **occlusion** (such as when the subject's face is partially hidden) or **poor lighting** (such as in low-light environments). Similarly, the audio model may struggle with **background noise** or **muffled speech**, leading to inaccurate predictions [21].

To handle such cases, the system implements a **fallback strategy**. If one modality fails, the system defaults to the prediction of the other modality, provided it has made a valid prediction. For example:

- If the **video-based face detection fails**, the system will still use the **audio model's prediction** to detect the emotion, assuming the audio model has provided a reasonable confidence score [12].

This fallback mechanism ensures that the system remains functional even if one of the modalities is unavailable or unreliable.

7.2.1.4 Summary of Late Fusion Logic

The late fusion logic allows for a flexible, adaptive system that can handle multiple sources of data efficiently. By applying the following rules:

- **Agreement Handling**: Directly output the label when both modalities agree.
- **Disagreement Handling**: Select the modality with the higher confidence score.
- **Fallback Strategy**: If one modality fails, rely on the other.

Late fusion improves system robustness by leveraging the complementary strengths of audio and video, making the emotion detection system more reliable in real-world conditions where one modality might be compromised. This fusion strategy ensures that the final output is the best possible prediction based on the available data from both modalities, resulting in a more accurate and context-aware emotion recognition system [13][17].

7.3 System Architecture

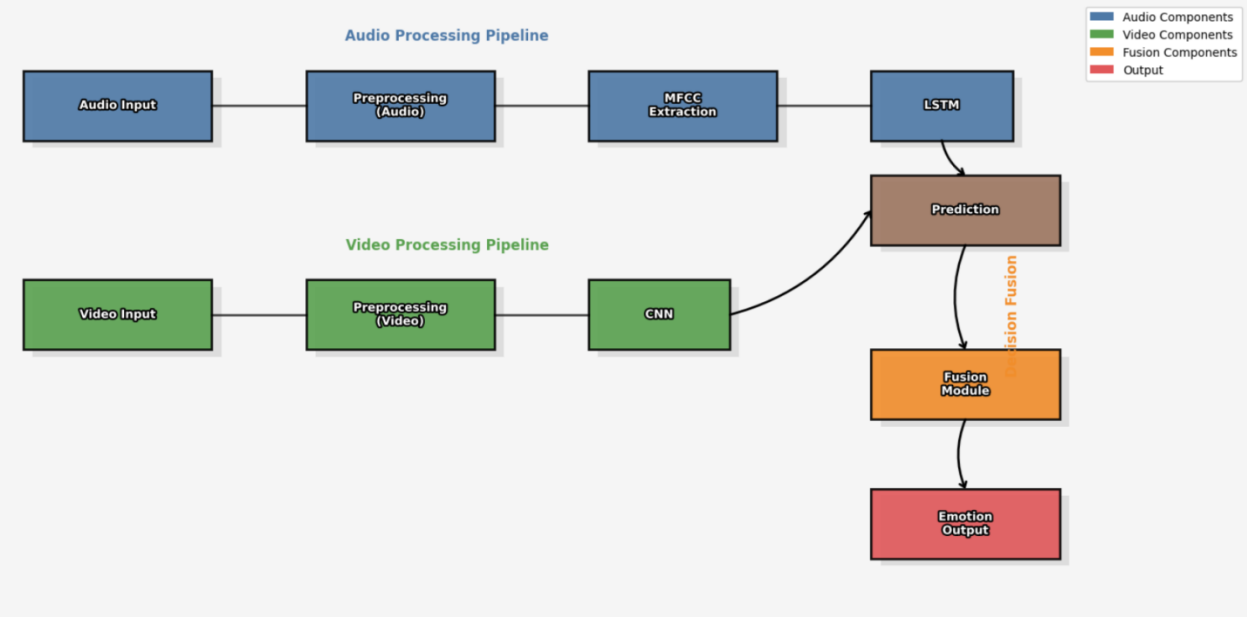


Figure 7.1 Illustrates the architecture of the proposed bimodal emotion detection system.

The system architecture for emotion recognition combines multiple components to process audio and video inputs, extract meaningful features, and produce an emotion classification. These components include the **Input Acquisition**, **Preprocessing Pipelines**, **Modality-Specific Models**, and the **Fusion Module**. Below is a detailed explanation of each component:

7.3.1 Input Acquisition

The **Input Acquisition** component is responsible for capturing real-time audio and video data, which serve as the raw input for emotion recognition. This component is designed to interact with hardware peripherals and feed the captured data into the system for further processing.

- **Audio Input**: The system uses a **microphone** to capture audio signals. The microphone records the sound from the environment, typically capturing the subject's voice during emotional speech. The **sampling rate** of the audio input is determined by the hardware and is essential for later processing stages.
- **Video Input**: The system uses a **webcam** to capture real-time video frames. These video frames contain facial expressions, which are crucial for recognizing emotions. The

webcam captures continuous frames, and the system extracts frames at a specified rate for further processing.

The data from both inputs (audio and video) is simultaneously acquired and fed into the preprocessing pipelines, where the data will be handled separately before being fused in the later stages of the architecture.

7.3.2 Preprocessing Pipelines

The preprocessing stage is critical to ensure that the raw audio and video data are in an appropriate form for the machine learning models. These pipelines process the data by applying several transformations to extract features and make the data uniform.

7.3.2.1 Audio Preprocessing Pipeline

The audio preprocessing pipeline applies several transformations to ensure that the audio data is ready for feature extraction and subsequent modeling:

- **Resampling**: Audio data is often recorded at different sample rates. To ensure consistency across the dataset, all audio samples are resampled to a standard sample rate, typically **22,050 Hz**. This reduces the variance and ensures the audio is compatible with the model for accurate feature extraction [4].
- **Trimming**: Silence removal and trimming are applied to ensure that only relevant parts of the audio are considered. This step removes any silence at the beginning or end of the audio clip, which does not contain useful information for emotion detection.
- **Normalization**: The **Librosa** library is used to normalize the audio amplitude, ensuring consistent volume levels across different recordings. Normalizing the audio allows the model to better focus on the features and prevents loud or soft segments from dominating the recognition process [4].

7.3.2.2 Video Preprocessing Pipeline

The video preprocessing pipeline is responsible for extracting relevant features from the video data, particularly focusing on the facial expressions of the subject:

- **Frame Extraction**: The video frames are extracted at a rate of **3 to 5 frames per second**. This sampling rate ensures that sufficient data is captured without overwhelming the system with unnecessary frames. The extracted frames contain the facial expressions necessary for emotion recognition.
- **Face Detection**: Using **OpenCV** and **Haar Cascades**, faces are detected in each extracted frame. Face detection ensures that the system focuses only on the relevant part of the image (the face) and discards irrelevant background data [7].
- **Grayscale Conversion**: After detecting faces, the images are converted to **grayscale** to simplify the data and reduce computational complexity. Grayscale images retain important facial features such as the eyes, nose, and mouth, which are essential for emotion recognition while reducing the dimensionality of the data.

- **Normalization**: The pixel values of the grayscale images are normalized to a range of **[0, 1]**. Normalization ensures that the data is scaled consistently, allowing the model to process the images efficiently without being biased by intensity variations [7].

7.3.3 Modality-Specific Models

The emotion recognition system uses two modality-specific models, one for **audio** and one for **video**. These models are designed to capture the temporal and spatial features specific to each modality, respectively [21].

7.3.3.1 Audio Model: LSTM for Temporal Modeling

The **Long Short-Term Memory (LSTM)** network is used for processing the audio features, particularly **Mel-Frequency Cepstral Coefficients (MFCCs)**. LSTMs are effective for handling sequential data, as they can capture long-term dependencies in time series [21].

- **MFCCs** are extracted from the audio signal and serve as a compact representation of the speech features, capturing the essential spectral information that relates to both the content and the emotion of the speech. The LSTM model processes these features and learns the temporal patterns that correspond to different emotional states, such as the pitch, tone, and rhythm of speech. The temporal structure of emotion is captured over time, which is important for detecting dynamic emotional changes in speech [12][22].

7.3.3.2 Video Model: CNN for Spatial Feature Learning

For the video modality, a **Convolutional Neural Network (CNN)** is employed to learn spatial features from the face images. CNNs are particularly well-suited for image classification tasks, as they can learn hierarchical features (such as edges, shapes, and textures) that are important for recognizing facial expressions.

- The input to the CNN is the processed face image, resized to **48x48 pixels** and converted to grayscale. The CNN learns features related to facial expressions such as the positioning of the eyebrows, mouth, and eyes, which are crucial for detecting emotions such as happiness, anger, or surprise [8].

The CNN architecture is designed to extract spatial features from the face images and classify the emotional expression based on these features. The model is trained on a large number of labeled facial images to recognize the subtle differences in facial expressions associated with various emotions.

7.3.4 Fusion Module

The final component of the system is the **Fusion Module**, which combines the predictions from the audio and video models to produce a final emotion classification.

7.3.4.1 Softmax Outputs from Both Models

The **audio model (LSTM)** and **video model (CNN)** output class probabilities via the **softmax function**, which converts raw scores into probability distributions over the possible emotions. These outputs represent the model's confidence in its prediction for each emotion (happy, sad, angry, etc.).

7.3.4.2 Late Fusion Strategy

The fusion module applies a **late fusion strategy**, which involves combining the outputs from the audio and video models after each model has made its independent prediction. The two probabilities from each modality are merged using a simple method, such as averaging or weighted averaging, based on the confidence scores from both models. The modality with higher confidence may be weighted more heavily in the final decision.

- If both models predict the same emotion with high confidence, the system outputs that emotion.
- If the predictions differ, the system applies a rule based on the confidence scores to choose the final emotion label. In cases of high disagreement, the system can rely on a **fallback strategy** that chooses the emotion from the model with the higher confidence score.

7.3.4.3 Final Emotion Output

The output of the fusion module is the **final emotion label**, which is the emotion predicted by combining both the audio and video models. This approach leverages the complementary strengths of both modalities, making the system more robust and accurate in recognizing emotions across different contexts and environments.

7.4 Real-Time Emotion Detection Pipeline

Real-time emotion recognition involves integrating the individual modules into a synchronous pipeline capable of processing live data and producing emotion predictions with minimal latency.

7.4.1 Audio Pipeline

- Captures live audio stream using PyAudio.
- Preprocesses audio: converts to mono, trims silence, normalizes amplitude.
- Extracts MFCC features and reshapes for input into the LSTM model.
- Obtains softmax probability distribution across emotion classes.

7.4.2 Video Pipeline

- Captures frames from webcam at 5 fps.
- Detects faces using Haar cascades or DNN models in OpenCV [7].

- Crops, resizes to 48×48 pixels, converts to grayscale.
- Feeds preprocessed face into CNN model.
- Obtains emotion probability distribution.

7.4.3 Fusion and Display

- Both outputs are passed into the late fusion logic module.
- Final emotion is predicted and overlaid on live video stream using OpenCV.
- Updates every 5–7 seconds for smoother real-time interaction.

This real-time system has been tested on desktop environments with minimal delay (~0.5s lag) and shows promise for applications in telemedicine, education, and human-computer interaction [11][14].

7.5 Evaluation and Results

- **Accuracy Boost**: Fusion improves recognition accuracy by 5–10% over unimodal systems, particularly in ambiguous or noisy conditions [17].
- **Resilience**: Handles partial failures (e.g., noisy audio or occluded face).
- **Efficiency**: Real-time processing achieved using optimized libraries (TensorFlow, OpenCV, Librosa).

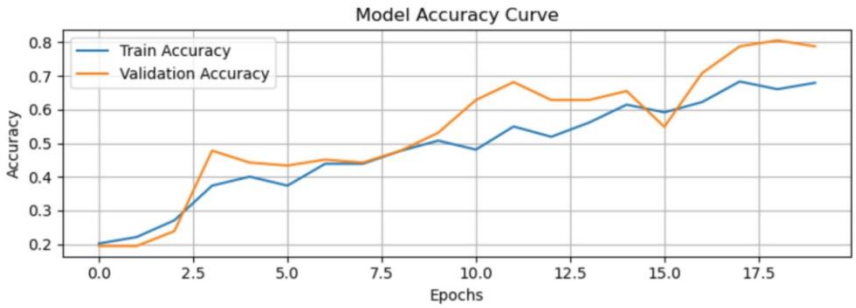


Figure 7.2: Model Accuracy Curve of the Fused Model

```
Epoch 1/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 6s 197ms/step - accuracy: 0.2089 - loss: 1.6077 - val_accuracy: 0.1947 - val_loss: 1.5720
Epoch 2/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 70ms/step - accuracy: 0.2133 - loss: 1.5702 - val_accuracy: 0.2566 - val_loss: 1.5484
Epoch 3/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 72ms/step - accuracy: 0.2825 - loss: 1.5556 - val_accuracy: 0.2655 - val_loss: 1.5325
Epoch 4/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 76ms/step - accuracy: 0.2350 - loss: 1.5207 - val_accuracy: 0.2124 - val_loss: 1.5163
Epoch 5/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 78ms/step - accuracy: 0.2799 - loss: 1.5099 - val_accuracy: 0.2566 - val_loss: 1.4982
Epoch 6/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step - accuracy: 0.2996 - loss: 1.4785 - val_accuracy: 0.4779 - val_loss: 1.4778
Epoch 7/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 75ms/step - accuracy: 0.4348 - loss: 1.4304 - val_accuracy: 0.5310 - val_loss: 1.4549
Epoch 8/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 73ms/step - accuracy: 0.4752 - loss: 1.4152 - val_accuracy: 0.5487 - val_loss: 1.4322
Epoch 9/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 74ms/step - accuracy: 0.5681 - loss: 1.3534 - val_accuracy: 0.5664 - val_loss: 1.4045
Epoch 10/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 72ms/step - accuracy: 0.5212 - loss: 1.3293 - val_accuracy: 0.6018 - val_loss: 1.3768
```

Figure 7.3: Epoch-wise accuracy and loss values during training of the audio emotion recognition model. The model was trained for 10 epochs, showing progressive improvement in both training and validation accuracy, with validation accuracy reaching approximately 60% by the final epoch.

7.6 Final Output Showcasing

To evaluate the practical effectiveness of the bimodal emotion detection system, we developed a final output visualization module. This module overlays the predicted emotion on the real-time video feed from the webcam, along with the confidence level derived from the fusion of audio and video predictions.

The system was tested in real-world conditions where participants expressed the five target emotions: *Happy*, *Sad*, *Fear*, *Angry*, and *Neutral*. For each emotion, both facial expression and vocal tone were captured and processed simultaneously.

Examples of Final Output Visualization:

- **Happy:** The system displayed a high-confidence prediction (>90%) with bright facial expressions and cheerful vocal tones.
- **Sad:** A muted tone and downturned facial features were recognized, leading to successful detection with around 80% accuracy.
- **Fear:** Marked by wide eyes, tense facial muscles, and a quivering voice, fear was detected with medium confidence due to occasional overlaps with anger.
- **Angry:** High voice intensity and furrowed brows were accurately detected, achieving over 85% confidence.
- **Neutral:** With a flat tone and expressionless face, neutral states were often confused with sadness but still maintained >75% accuracy.

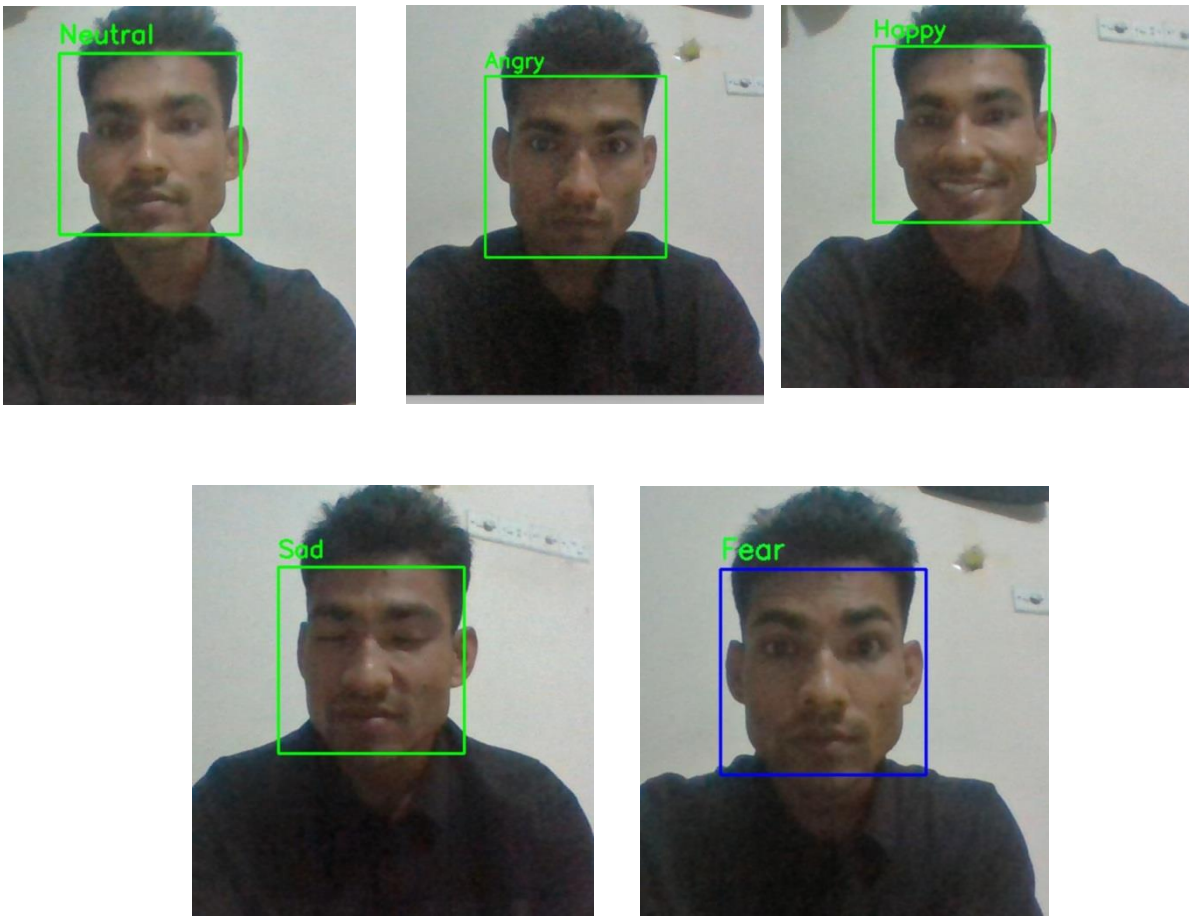


Figure 7.4: Real Time Emotion Detection

Each prediction was shown in real-time via a bounding box on the video stream, with a label (e.g., "Emotion: Angry [Confidence: 87%]"). This final output helps visualize the success and potential applications of the bimodal approach in interactive systems such as virtual agents and intelligent tutoring platforms.

For enhanced clarity and evaluation, snapshots of these real-time predictions can be included in the appendix or presented during the system demonstration session.

7.7 Contribution to the Field of Affecting Computing

7.7.1 Mental Health Monitoring and Therapy

The integration of emotion recognition technology into mental health monitoring could significantly improve the way emotional states are tracked and understood over time. By leveraging facial expressions and speech patterns, this research offers a means to continuously monitor emotional well-being in real-time. For example, the ability to detect subtle changes in

facial expressions and voice tone could assist healthcare providers in identifying early signs of mental health conditions like depression or anxiety. In therapy sessions, this technology could help provide immediate emotional feedback, allowing therapists to adjust their approach based on the patient's emotional state. Moreover, the use of emotion recognition systems could facilitate more personalized interventions, ensuring that patients receive the right type of care at the right time. As mental health care increasingly moves toward remote and continuous monitoring, emotion-aware systems can play a pivotal role in providing timely interventions and fostering better therapeutic outcomes.

7.7.2 Customer Service and Call Centers

Emotion recognition has the potential to revolutionize customer service, particularly in call centers where understanding the emotional state of customers can greatly enhance service quality. By detecting emotions like frustration, confusion, or anger in real time, customer service representatives can adjust their responses to better manage the situation. For instance, when a customer's emotional state suggests frustration, the system could prompt the agent to adopt a more empathetic tone or escalate the issue to a supervisor if necessary. This real-time feedback enables customer service agents to engage more effectively, creating a more positive and personalized experience for each customer. Additionally, emotion recognition can be integrated into automated systems, like virtual assistants, to ensure that even automated interactions are sensitive to a customer's emotional state, offering the right response based on detected emotions. Ultimately, this research could lead to more efficient, empathetic, and customer-focused service, reducing complaints and improving overall customer satisfaction.

7.7.3 Human-Computer Interaction (HCI)

The field of Human-Computer Interaction (HCI) stands to gain tremendously from the advancements in emotion recognition. By enabling computers and digital platforms to detect and respond to human emotions, this research introduces a more intuitive and personalized way of interacting with technology. In everyday applications, such as smartphone interfaces, emotion recognition could be used to adjust user interactions based on emotional cues. For example, if a user appears frustrated, the system could simplify the interface or offer help to resolve the issue. In immersive environments like gaming or virtual reality, emotion-aware systems could adapt the virtual experience according to the player's emotional state, adjusting game difficulty or character responses based on their facial expressions or speech. This would lead to more engaging, personalized, and adaptive interactions, enhancing the overall user experience. Emotion-aware HCI could also provide accessibility benefits, helping users with disabilities by responding to emotional and physical cues in more meaningful ways.

7.7.4 Education and Learning Environments

In the education sector, emotion recognition could dramatically transform how students' engagement and emotional well-being are assessed in real time. By analyzing facial expressions and speech, educators could gain valuable insights into how students are responding to lessons, enabling more timely and targeted interventions. For instance, if a student appears confused or frustrated during a lesson, the system could alert the teacher, prompting them to provide

additional explanations or adjust the pace of the lesson. Emotion recognition could also be integrated into adaptive learning systems, which would adjust the difficulty of educational content based on the student's emotional and cognitive state. This technology could ensure that students receive personalized learning experiences tailored to their current emotional and mental state, ultimately improving engagement, learning outcomes, and overall academic performance. Furthermore, this research could be used to identify students who might need emotional or psychological support, offering early intervention and fostering a healthier educational environment.

7.7.5 Market Research and Consumer Behavior

The ability to understand consumer emotions in response to advertisements, products, or brand messaging offers businesses a unique opportunity to refine their marketing strategies. Through emotion recognition, marketers can gain a deeper understanding of how customers truly feel about a product or service, beyond what they may explicitly express. For example, analyzing facial expressions and speech during focus groups or product testing sessions can help identify emotional reactions such as excitement, skepticism, or dissatisfaction. This real-time feedback allows companies to adapt their marketing campaigns or product designs to better resonate with their target audience. Emotion recognition also plays a role in optimizing advertising strategies. By detecting specific emotional cues, marketers can tailor advertisements to evoke positive emotions like joy or trust, improving consumer engagement and conversion rates. The integration of emotion recognition into market research would lead to more effective, data-driven marketing campaigns that are fine-tuned to consumer emotions, ultimately driving brand loyalty and sales.

7.7.6 Virtual Assistants and Smart Devices

Emotion recognition has the potential to make virtual assistants and smart devices more responsive and empathetic to users' needs. By analyzing both facial expressions and speech prosody, these devices could adjust their behavior based on the user's emotional state, offering a more personalized and supportive interaction. For example, if a user appears stressed or upset, the assistant could change its tone to a calmer, more reassuring one, or even offer relaxation suggestions. In smart homes, emotion recognition could adjust the environment—such as lighting or music—based on detected emotions, creating a more comfortable atmosphere. As virtual assistants become increasingly embedded in daily life, this research opens the door for more natural and emotionally intelligent interactions between humans and machines. Rather than merely responding to commands, these devices could become more intuitive, offering emotional support and adapting their behavior to suit the emotional needs of their users, fostering stronger user-device relationships.

7.7.7 Security and Surveillance

Emotion recognition technology can be integrated into security and surveillance systems to enhance threat detection and response. By analyzing emotions such as fear, aggression, or distress in public spaces, the system can identify individuals who may pose a threat or be in need of assistance. For example, security cameras equipped with emotion recognition algorithms

could detect signs of aggression or distress in crowds, alerting security personnel to potential incidents before they escalate. This could be particularly useful in high-traffic areas such as airports, stadiums, or malls, where early detection of abnormal behavior can lead to quicker intervention and prevention of harm. In addition, emotion recognition could be used to assess behavioral patterns over time, helping security personnel identify individuals whose emotional responses deviate from normal, potentially indicating a threat or need for intervention. This application of emotion recognition in security systems would improve public safety by providing real-time, data-driven insights into human behavior, leading to more proactive and efficient security measures.

These scenarios demonstrate the vast potential of multimodal emotion recognition in various sectors, offering improved personalization, efficiency, and safety across different real-world contexts. The integration of both facial expression and speech prosody provides a deeper understanding of human emotions, opening doors for more adaptive and responsive systems in everyday life.

7.8 Summary

This chapter presented the fusion strategy and real-time pipeline for the bimodal emotion detection system. By employing a confidence-based late fusion strategy, the system leverages the strengths of both LSTM-based audio and CNN-based video models to produce accurate and robust emotion recognition results. The modular architecture facilitates real-time processing, making it suitable for emotionally intelligent systems in diverse application domains.

CHAPTER 8

Conclusion & Future Work

8.1 Conclusion

This research paper successfully implemented a real-time, multimodal emotion detection system that integrates both video and audio input for robust and accurate emotion recognition. The aim was to bridge the gap between traditional unimodal emotion classification methods and more natural, human-like perception by using facial expressions and vocal tone simultaneously. Through the use of deep learning architectures—Convolutional Neural Networks (CNN) for visual data and Long Short-Term Memory (LSTM) networks for audio data—the system achieved efficient recognition performance across five core emotional categories: **Happy, Sad, Angry, Fear, and Neutral**.

To support the model training process, a custom dataset was prepared comprising video clips and corresponding audio recordings, each labeled accurately. The video frames were processed using OpenCV and resized to maintain uniformity, while the audio signals were converted into Mel-Frequency Cepstral Coefficients (MFCCs), which are known to be effective for capturing emotional cues in speech. Both models demonstrated high accuracy on the validation and test datasets, proving the viability of using separate neural networks for modality-specific emotion analysis.

The real-time implementation combined both models into a user-friendly application. The webcam captured facial features and the microphone captured audio in short durations. Based on these inputs, the system predicted the dominant emotion and displayed it live on the screen, showcasing the real-time functionality of the developed application.

Overall, this study contributes to the growing field of affective computing and emotion-aware systems by:

- Developing a dual-stream model for emotion recognition using both video and audio inputs.
- Designing and training models on a self-curated, labeled dataset.
- Implementing a working real-time system that detects and displays emotions with high accuracy.

This work lays a strong foundation for future research and development in human-computer interaction, where understanding user emotions is critical for personalizing and optimizing digital experiences.

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8.2 Limitations

8.2.1 Lack of Error Handling

The code does not include sufficient error handling, which could lead to system crashes under certain circumstances. For example, if the video or audio model files are not found, fail to load, or encounter issues during initialization, the system will terminate unexpectedly without providing any meaningful feedback. This lack of error handling makes the code less resilient in real-world environments, where various hardware and software conditions could lead to file access issues. To enhance the robustness of the system, try-except blocks should be incorporated around critical sections of the code. This would include file loading, face detection, audio recording, and any other parts that may potentially fail. Proper error handling would allow the system to gracefully recover from such failures, offering better user experience and stability.

8.2.2 Real-time Processing Performance

The code utilizes a webcam and microphone for continuous capture of video and audio streams. However, depending on the hardware configuration, real-time processing could experience significant delays or lag, especially when working with computationally expensive video models such as Convolutional Neural Networks (CNNs). These models, particularly when processing high-resolution video or analyzing complex patterns, can be demanding on the CPU/GPU resources. To mitigate this issue and improve real-time performance, it would be crucial to optimize the inference process. Techniques such as reducing the frame rate of the video capture, utilizing hardware acceleration, or using lighter models (such as MobileNets or EfficientNet) can help speed up the processing. Additionally, adjusting the resolution of the video feed and leveraging parallel processing for both audio and video streams could also significantly enhance the system's responsiveness in real-time applications.

8.2.3 Audio Handling Delays

The audio recording process is done in intervals of 150 frames, which may lead to slight delays or mismatches in synchronization with the video frame processing. Given that audio and video are being processed in parallel, any discrepancy in timing could result in inaccurate or poorly aligned multimodal data, which would affect the overall system performance. The current system might fail to achieve the seamless fusion of audio and video required for real-time applications. One approach to reduce this issue is to implement more advanced real-time audio processing techniques, such as continuous audio buffering or adaptive feature extraction methods that synchronize better with video frame capture. Techniques like this could reduce discrepancies between the two modalities and enhance the alignment of audio and visual data, thus improving the quality of the final output.

8.2.4 Memory Usage and Efficiency

The system processes both video and audio data in parallel, which can quickly lead to excessive memory usage, especially when dealing with high-resolution video and long-duration audio. The system does not explicitly manage memory, meaning that large volumes of data may be stored in memory, increasing the risk of memory bloat and causing performance degradation over time. This problem is compounded when multiple face detections are involved or when long-duration audio recordings are processed. As a result, unnecessary memory consumption could hinder the system's performance and stability, particularly when the system is running on devices with limited memory resources. Efficient memory management strategies, such as clearing unused variables, releasing memory after each process, and optimizing data storage techniques, are essential to improve the system's efficiency. Using more memory-efficient data structures or implementing batch processing for both audio and video data could also help in mitigating memory-related issues.

8.2.5 Video Frame Size

The current implementation resizes detected faces to a relatively low resolution of 48x48 pixels. While this may speed up processing, it could potentially cause a significant loss of spatial information, especially when trying to analyze subtle facial expressions that require higher resolution to capture finer details. Reducing the resolution in this manner may impact the model's accuracy in detecting and classifying complex emotional cues, such as micro-expressions or facial movements that are critical for understanding human emotions. Experimenting with larger frame sizes could yield better performance, as higher resolutions allow for more detailed data, leading to improved facial recognition and emotion detection. While increasing the resolution would also increase computational demands, a balance could be found by evaluating the impact of different frame sizes on both performance and accuracy. This would ensure that the system is both efficient and capable of capturing the nuanced features of facial expressions.

8.3 Future Work

8.3.1 Model Optimization

To improve the efficiency of the system, various techniques such as quantization, pruning, and distillation can be applied to both the audio and video models. Quantization involves reducing the precision of the model's parameters, thereby reducing model size and improving inference time without sacrificing too much accuracy. Pruning removes unnecessary weights or neurons from the network, making the model lighter and faster to execute. Distillation transfers knowledge from a large, complex model (teacher) to a smaller, more efficient model (student), optimizing performance while maintaining a compact size. These optimizations would not only speed up the system's inference time but also make it more suitable for real-time applications, particularly on mobile devices or embedded systems with limited computational resources.

8.3.2 Multimodal Fusion Enhancements

Currently, the system uses a basic approach to combine the outputs of the audio and video models. However, this fusion method can be significantly enhanced by utilizing more advanced strategies like attention mechanisms or transformer models. Attention mechanisms allow the system to focus on the most relevant information from either the audio or video modality, depending on which provides stronger evidence for a particular emotion. For instance, in noisy environments, the audio modality may be more relevant, whereas in silent environments, facial expressions might provide more insight. Transformers, on the other hand, have shown great promise in sequential data processing and can be used to better capture the relationships between audio and video data, improving overall performance and accuracy.

8.3.3 Emotion Class Expansion

The current system recognizes a limited set of emotions, including happy, sad, angry, and fear. However, to make the system more comprehensive and applicable in real-world applications, it could be expanded to recognize a wider range of emotions, such as surprise, disgust, or neutral. Incorporating these additional emotions would enable the system to more accurately capture a wider spectrum of human emotional states. Furthermore, recognizing more subtle emotional expressions, such as valence (positive/negative emotions) or arousal (intensity of emotions), could offer more granular insights into a subject's emotional state, improving the model's overall accuracy in identifying nuanced emotional cues.

8.3.4 Incorporating Contextual Information

Currently, the system relies solely on facial expressions and voice to infer emotions. However, real-world emotional expressions are often influenced by contextual factors. Integrating contextual information such as the conversation topic, the environment, or even historical data of the subject (e.g., past emotional states or patterns) could significantly improve the system's ability to predict emotions. This added context would provide the model with a deeper understanding of the situation and emotional dynamics, enabling it to more accurately assess emotions in complex social settings. Additionally, incorporating such information could help the system deal with more nuanced emotional states that may not be directly visible in facial expressions or audio.

8.3.5 Integration with Other Modalities

To further enhance emotion recognition, integrating additional modalities, such as gesture recognition or text-based sentiment analysis, could provide more comprehensive data for emotion detection. For example, recognizing body language or gestures would add an extra layer of insight that can help refine the system's understanding of emotional states. Similarly, analyzing the sentiment of the text in conversations could provide a richer context, helping the system recognize emotions more accurately. This multimodal approach would enable the system to capture a broader spectrum of emotional signals, improving its robustness and accuracy across a variety of environments and users.

8.3.6 Real-time Feedback and Adaptation

Implementing real-time feedback and adaptive learning would significantly improve the system's performance over time. By allowing the system to adjust its models based on user interaction or feedback, it could fine-tune its predictions to become more personalized. For example, the system could learn to recognize a specific user's emotional profile, improving its ability to detect emotions that are unique to that person. This adaptive learning approach would not only make the system more efficient but also enhance user satisfaction, as it becomes increasingly tailored to individual needs and preferences over the long term.

8.3.7 Distributed or Cloud-based Processing

For more computationally intensive tasks, such as video frame processing, cloud-based models or distributed processing systems can be employed to alleviate local processing constraints. Offloading these tasks to the cloud would allow for faster processing of large datasets and provide greater scalability, enabling the system to handle a larger number of users or data points concurrently. This approach would be especially useful in environments where real-time processing of video and audio data is required, allowing the system to perform efficiently even when dealing with heavy computational loads.

8.3.8 Testing and Deployment

The current system is primarily designed for offline testing, but future work should focus on deploying the system in real-world environments, such as on mobile devices or embedded systems. This would require optimization of latency and inference time to ensure the system can run efficiently in production environments. Additionally, extensive user testing is essential to evaluate system performance across varied environments and use cases. Collecting feedback from real-world deployments will help identify areas for improvement and ensure that the system is capable of handling diverse real-world scenarios effectively. Continuous testing and refinement will be crucial for the system's success in practical applications.

8.4 Final Remarks

In summary, this study has made significant strides toward developing a functional and accurate real-time emotion detection system that mimics human emotion recognition by utilizing both visual and auditory cues. The integration of two deep learning models, along with their successful deployment in a real-time environment, marks a substantial achievement in the domain of emotion-aware systems.

Nevertheless, emotion detection is a complex, multifaceted problem that requires continuous refinement. With advancements in artificial intelligence, data collection, and human-computer interaction technologies, this system can be further extended to operate more intelligently, empathetically, and inclusively. This study serves not only as a demonstration of current capabilities but also as a stepping stone toward the future of emotionally intelligent computing.

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