



Facial Emotion Recognition Using Video and Audio

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ABSTRACT:

This research project adopts a holistic strategy for comprehending multimedia content, synergizing advanced techniques in video and audio analysis. Video analysis employs state-of-the-art Convolutional Neural Networks (CNNs), specifically ResNet50V2 and ResNet152V2, renowned for their excellence in image and video classification. Simultaneously, audio analysis incorporates a Multi-Layer Perceptron (MLP) classifier, a custom-built CNN tailored for audio processing, and Support Vector Machine (SVM) models. ResNet architectures are harnessed to extract high-level features from video frames, providing a robust foundation for visual content understanding. The audio analysis, employing an MLP classifier and a self-designed CNN, captures intricate audio patterns, enhancing overall capabilities. The SVM model further contributes to audio content understanding. The integration of extracted features from both modalities enables a holistic interpretation, enhancing the system's ability to recognize complex patterns in multimedia data. Experimental results validate the approach, demonstrating improved accuracy and robustness. This collaboration between ResNet architectures and audio classifiers presents promising applications in content recommendation and emotion-aware multimedia processing. The study contributes to the evolving field of multimodal deep learning, paving the way for further advancements in interpreting diverse multimedia content.

Keywords: Facial Emotion Recognition, Video Analysis, Audio Analysis, Convolutional Neural Networks (CNNs), ResNet50V2, ResNet152V2, Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), Cultural Relevance, Indian Dataset

1. Introduction:

Emotion recognition is a crucial aspect of human communication, enabling us to understand and respond appropriately to others' emotional states. Human emotions are complex and multifaceted, expressed through a interplay of facial expressions, vocal cues, and physiological responses. Understanding and interpreting these emotions plays a critical role in social interaction, communication, and even human-computer interaction. In recent years, there has been a growing interest in developing automated systems for emotion recognition, with potential applications in various fields such as human-computer interaction, customer service, and healthcare.

Traditionally, facial expression analysis has been the primary focus of emotion recognition research. Facial expressions provide rich information about emotional states, and various methods have been developed for automatically detecting emotions from facial images or videos. However, facial expressions alone may not be sufficient for accurate emotion recognition, as other factors such as voice intonation and body language also play a significant role in conveying emotions.

This project focuses on the development of a multimodal emotion recognition system that leverages both video and audio information to achieve a more accurate and robust understanding of human emotions. By analyzing both facial expressions and acoustic features simultaneously, we aim to capture a more comprehensive picture of the individual's emotional state.

1.1 Role of Video in Emotion Recognition:

In the context of multimodal emotion recognition, video analysis plays a crucial role in extracting relevant information from visual cues such as facial expressions, head pose, and gaze direction. This information, combined with features extracted from audio data, provides a comprehensive picture of an individual's emotional state. Video data provides valuable information about facial expressions, which are key indicators of emotion.

Once the facial features are extracted, they are fed into a deep learning model for emotion recognition. This thesis proposes using two pre-trained models: ResNet50v2 and ResNet150v2. These models belong to the ResNet family of convolutional neural networks (CNNs), which have proven highly effective in image recognition tasks. They are pre-trained on large datasets of labeled images, allowing them to extract high-level features that can be directly applied to the task of emotion recognition. The feature representation extracted by ResNet50v2 or ResNet150v2 is then passed to a fully connected layer, which predicts the probability of each emotion category. The model outputs a vector of seven probabilities, one for each emotion: 'Neutral', 'Disgust', 'Fear', 'Sadness', 'Anger', 'Happiness', and 'Surprise'. The emotion with the highest probability is then identified as the predicted emotion for the video frame.

Video analysis offers several advantages for emotion recognition:

- **High Information Content:** Facial expressions are highly expressive and can reveal subtle changes in emotional state. Video analysis captures these changes, providing richer information than audio alone.
- **Robustness to Noise:** Unlike audio data, which can be significantly affected by noise and background sounds, facial expressions are less susceptible to environmental factors.
- **Improved Accuracy:** By combining video analysis with audio analysis, the system can achieve higher accuracy in emotion recognition compared to using either modality alone.

This exploration of video analysis using ResNet50v2 and ResNet150v2 highlights its critical role in facial emotion recognition. By extracting informative features and integrating seamlessly with machine learning models, these deep learning architectures enable the system to accurately and robustly detect emotions from video data. This advancement holds significant potential to enhance human-computer interaction, support mental health diagnosis, and contribute to various other applications where understanding human emotions is crucial.

1.2 Role of Audio in Emotion Recognition:

In the pursuit of robust and accurate emotion recognition, utilizing both visual and auditory cues holds immense potential. While facial expressions offer valuable insights into emotional states, analyzing speech patterns and vocal features through audio analysis adds another crucial layer of understanding.

Human speech carries a wealth of information beyond the literal meaning of words. Vocal features such as pitch, energy, and prosody are intricately linked to emotional states and can be effectively analyzed to gain insights into a person's emotional valence and arousal.

Emotion-specific vocal features:

- **Pitch:** Reflecting the perceived frequency of a speaker's voice, variations in pitch contribute crucial emotional cues, with higher pitches often associated with excitement or anxiety and lower pitches conveying calmness or sadness.
- **Amplitude:** Signifying the intensity or loudness of vocal signals, amplitude variations play a role in expressing emotions, with louder voices commonly associated with emotions like anger or joy, and softer tones linked to sadness or introspection.
- **MFCC (Mel-Frequency Cepstral Coefficients):** Offering a representation of the spectral characteristics of speech, MFCCs capture nuanced features of vocal patterns, contributing to the identification of emotional nuances through the analysis of frequency components.
- **Tempo and Chroma:** Tempo, indicating the speed or rhythm of speech, can convey emotional energy, with faster tempos associated with excitement. Chroma, representing the distribution of pitch classes, aids in discerning tonal characteristics that contribute to emotional expression in vocalizations.

1.3 Dataset:

The success of any AI model heavily relies on the data it is trained on. In the realm of multimodal emotion recognition, this becomes particularly critical as culture plays a significant role in how emotions are expressed and perceived. This project focuses on the development of a robust emotion recognition system specifically designed for Indian audiences. By leveraging a unique dataset of video and audio recordings collected in India, we aim to achieve a more accurate and culturally-sensitive understanding of human emotions.

The Uniqueness of Indian Emotional Expressions:

India's rich and diverse cultural tapestry necessitates a distinct approach to emotion recognition. Facial expressions, vocal features, and even the linguistic choices used to convey emotions can differ dramatically from those observed in other cultures. For instance, head nodding can signify agreement in Western cultures but can indicate uncertainty or respect in India. Similarly, the use of sarcasm and humor in Indian speech might not be readily understood by models trained on non-Indian datasets.

1.3.1 Key Features of the Indian Dataset:

- **Multilingual:** The dataset includes recordings in various Indian languages, including Hindi, Bengali, Tamil, Telugu, and Marathi, capturing the linguistic diversity of the nation.
- **Emotionally Diverse:** The recordings encompass a wide range of emotions, from basic expressions like happiness, sadness, and anger to more complex emotions like frustration, surprise, and disgust.
- **Culturally Relevant Scenarios:** The recordings are captured in natural settings and depict everyday situations that are relatable to the Indian context.
- **Annotated by Indian Experts:** The emotions are labelled by a team of trained annotators familiar with Indian cultural nuances, ensuring accurate and culturally sensitive labelling.

- Benefits of a Culturally Relevant Dataset
- Utilizing an Indian dataset offers several advantages for emotion recognition:
- Improved Accuracy: Training models on culturally relevant data leads to significantly improved accuracy in emotion recognition for Indian individuals.
- Reduced Bias: Culturally-aware models are less prone to biases stemming from Western cultural norms, leading to fairer and more inclusive outcomes.

By building and utilizing an Indian dataset for video and audio analysis, this project takes a significant step towards developing robust and culturally-aware emotion recognition systems. This approach not only ensures improved accuracy and reduces bias, but also opens doors for innovative applications that cater specifically to the needs and cultural context of India

Methodology:


Facial emotion recognition involves extracting facial features from images or videos and employing machine learning algorithms to classify emotions. The process typically includes face detection, feature extraction (such as facial landmarks or expressions), and model training using datasets with labeled emotions. Common methodologies use convolutional neural networks (CNNs) for their ability to capture spatial hierarchies in facial patterns. Training involves optimizing model parameters through backpropagation and gradient descent. Validation is crucial to assess model accuracy. Real-time applications may require optimization for efficiency. Overall, the methodology integrates computer vision and machine learning to accurately identify and classify facial expressions representing emotions.






3.1.1 Model Creation based on Images

In our study, we're creating a smart system to recognize facial emotions using pictures. We're using two powerful tools, ResNet50 V2 and ResNet152 V2, known for being really good at understanding detailed information in images. Our goal is to make our system really accurate at identifying and classifying different facial expressions. By using these advanced models, we believe our system will perform exceptionally well, pushing the boundaries of emotion recognition technology. The choice of ResNet50 V2 and ResNet152 V2 shows our dedication to using the latest and best technologies for precise and advanced facial emotion analysis.

3.1.1.1 Image Dataset Creation:

Creating a facial emotion dataset involves collecting diverse facial images displaying various emotions, ensuring representation across demographics. Annotations indicating corresponding emotions are added manually or through crowdsourcing. Data augmentation techniques, like rotation or flipping, enhance dataset diversity. In our project, we've created a special dataset for recognizing facial emotions, focusing specifically on people from India. We gathered pictures from 17 individuals expressing seven different emotions: happiness, disgust, sadness, anger, fear, neutrality, and surprise. To make our dataset more diverse and useful, we used a technique called image augmentation, which involves creating variations of our images. This helps our system become better at recognizing emotions by training on a larger and more diverse set of pictures. Our approach aims to improve facial emotion recognition specifically for the Indian context, making the technology more accurate and applicable to a wider range of expressions.

S. No	Emotion	Data Sample	Total Number of Images	Augmentation Technique
1	Angry		1000	Rotation, Flip, GaussianBlur, ContrastNormalization

2	Disgust		1000	Rotation, Flip, GaussianBlur, ContrastNormalization
3	Fear		1000	Rotation, Flip, GaussianBlur, ContrastNormalization
4	Happy		1000	Rotation, Flip, GaussianBlur, ContrastNormalization
5	Sad		1000	Rotation, Flip, GaussianBlur, ContrastNormalization
6	Surprise		1000	Rotation, Flip, GaussianBlur, ContrastNormalization


7	Neutral		1000	Rotation, Flip, GaussianBlur, ContrastNormalization
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Table 3.1 - Dataset: Images from each class

3.1.1.2 Preprocessing and Cleaning:

In preparing our dataset for facial emotion recognition, we followed a systematic approach. Firstly, we resized all images to a standardized format of (224,224) in line with ResNet specifications, ensuring uniform input for our model. Next, we employed a facial detection technique using the Haar cascade model in OpenCV to pinpoint essential facial regions, eliminating irrelevant background details. To enhance model training, we normalized pixel values, and for computational efficiency, we converted images to grayscale while preserving crucial facial features. Lastly, we meticulously removed outliers and low-quality images, guaranteeing a tidy and efficient dataset for training our emotion recognition model.

3.1.1.3 Training the CNN Model:

We are training our facial emotion recognition models, ResNet50 V2 and ResNet152 V2, on a custom Indian dataset. This dataset, comprising expressions like happiness, sadness, anger, fear, neutrality, and surprise, ensures cultural relevance. Our goal is to leverage the deep learning capabilities of these models to accurately identify and classify diverse facial emotions, contributing to improved performance in recognizing Indian-specific expressions. The utilization of both ResNet50 V2 and ResNet152 V2 underscores our commitment to achieving robust and comprehensive facial emotion recognition.

ResNet50 V2 was trained on our entire dataset of 7000 images with a learning rate of 0.00001. The training process utilized a batch size of 5 and extended over 40 epochs. These parameter choices aimed to fine-tune the model effectively for facial emotion recognition, optimizing both precision and efficiency.

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Layer (type)                Output Shape         Param #         Connected to
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input_1 (InputLayer)        [(None, 224, 224, 3
                        )]
conv1_pad (ZeroPadding2D)   (None, 238, 238, 3)  0               ['input_1[0][0]']
conv1_conv (Conv2D)         (None, 112, 112, 64) 9472            ['conv1_pad[0][0]']
pool1_pad (ZeroPadding2D)   (None, 114, 114, 64) 0               ['conv1_conv[0][0]']
pool1_pool (MaxPooling2D)   (None, 56, 56, 64)   0               ['pool1_pad[0][0]']
conv2_block1_preact_bn (Batch Normalization) (None, 56, 56, 64) 256            ['pool1_pool[0][0]']
conv2_block1_preact_relu (Activation) (None, 56, 56, 64) 0               ['conv2_block1_preact_bn[0][0]']
conv2_block1_1_conv (Conv2D) (None, 56, 56, 64) 4896            ['conv2_block1_preact_relu[0][0]']
...
Total params: 61,119,751
Trainable params: 60,976,007
Non-trainable params: 143,744

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Fig 3.5 – Resnet50 V2 model summary.

ResNet152 V2 underwent training on our 4000-image dataset with a learning rate set at 0.00001. Employing a batch size of 4, the model was trained over 40 epochs, optimizing its performance for facial emotion recognition by adapting to the intricacies of our specific dataset.

3.1.1.4 Validation and Prediction:

The trained models, ResNet50 V2 and ResNet152 V2, underwent validation on a separate dataset comprising 700 images to assess their generalization capabilities. Using this independent dataset, we evaluated the models' performance and ensured their ability to recognize facial emotions beyond the training set. The predictions generated by these models contribute valuable insights into their effectiveness in real-world scenarios, enhancing the credibility of our facial emotion recognition system.

3.1.2 Model Creation based on Audio

In the realm of audio-based model creation, we employed diverse approaches using three distinct models: MLP Classifier, a self-built CNN model, and SVM. These models were trained on both a custom Indian dataset and a foreign dataset to ensure adaptability across different cultural contexts. By incorporating machine learning algorithms tailored for audio analysis, our study aims to provide comprehensive insights into emotion recognition from audio signals, contributing to the development of cross-cultural and versatile audio-based emotion recognition systems.

3.1.2.1 Audio Dataset Creation:

Creating a facial emotion audio dataset with Librosa involves extracting features from speech signals. Audio recordings, encompassing diverse emotions, are collected with proper consent. Annotation involves labeling each audio clip with corresponding emotion categories. Ensuring varied speakers, genders, and contexts enhances dataset diversity. Augmentation techniques, like pitch and speed variation, are applied for robust model training. Rigorous quality control validates annotation accuracy. Balancing the dataset across emotion classes mitigates bias.

To enhance the accuracy and precision of our audio-based emotion recognition models, the RAVDESS dataset was seamlessly integrated with our self-built Indian dataset. This strategic fusion aims to leverage the diversity and richness of emotional expressions captured in RAVDESS. We have a total 525 Indian audio data which was collected from 25 different persons. And RAVDESS dataset containing total 1248.

S.No.	Emotion	Indian Dataset	RAVDESS dataset
1	Angry	75	192
2	Disgust	75	192
3	Fear	75	192
4	Happy	75	192
5	Sad	75	192
6	Surprise	75	192
7	Neutral	75	96

Table 3.2 - Dataset for audio.

3.1.2.2 Preprocessing of Audio data:

Utilizing Librosa, we extracted crucial acoustic features like Mel-frequency cepstral coefficients (MFCCs), Mel-Spectrogram, and Chroma pitch. Our exploration involved visualizing diverse audio data attributes such as tempo, pitch, amplitude, MFCCs, chroma, and spectral centroid. Following a thorough analysis, we identified MFCCs, Chroma, and Mel Spectrogram as the pivotal acoustic features for our model training. This strategic feature selection process aims to capture essential nuances in audio data, optimizing our models for accurate and nuanced emotion recognition.

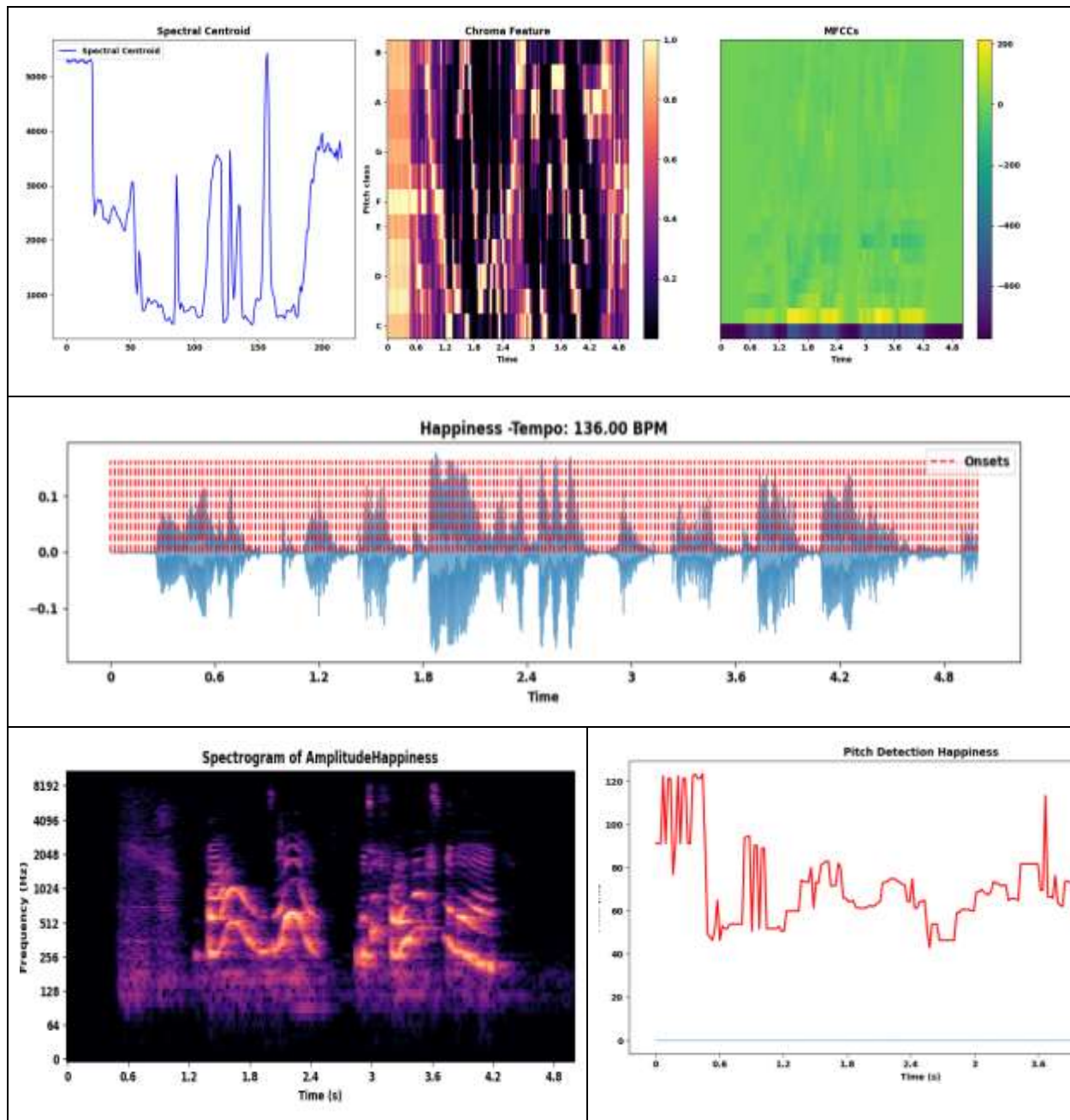


Fig 3.7 – Acoustic Features.

3.1.2.3 Training the models:

For facial emotion recognition in our audio dataset, we trained three distinct models: MLP Classifier, SVM, and a custom-built CNN model. Each model underwent comprehensive training to capture intricate patterns in acoustic features, contributing to the development of a robust emotion recognition system. The diversity of these models ensures a comprehensive exploration of audio-based emotion classification, providing insights into the effectiveness of different approaches in the context of facial emotion recognition from audio signals.

The MLP Classifier was trained with specific parameters, including alpha (L2 regularization) set to 0.001, a batch size of 4, epsilon set to $1e-08$, and a single hidden layer of 800 neurons.

The SVM model for facial emotion recognition in the audio dataset was trained with a linear kernel, emphasizing a linear decision boundary. The linear kernel configuration aligns with the dataset's characteristics, contributing to the model's discriminative ability.

The self-built CNN model for audio-based facial emotion recognition was trained with a learning rate of 0.000001. The training process utilized a batch size of 16 and extended over 400 epochs, ensuring a meticulous optimization of the model's parameters for enhanced accuracy in emotion classification.

3.1.2.4 Validation and Prediction:

To assess the performance of our models (MLP Classifier, SVM, and CNN model) on the dataset, we conducted validation and prediction. Through validation, we gauged the models' generalization abilities on a separate dataset, ensuring their adaptability to new instances. Following validation, predictions were made on the dataset, providing insights into the models' effectiveness in accurately classifying facial emotions in real-world scenarios.

3.1.3 Pipeline for Emotion Detection using Image model and Audio model

In our emotion detection system, we've set up a pipeline that seamlessly integrates image and audio models for real-time predictions. The pipeline captures data from a video source, sending it to both the image and audio models for emotion analysis. Once predictions are obtained, we compare the results from both models and select the one with higher accuracy.

The chosen emotion prediction is then displayed to the user, ensuring a more robust and accurate emotion recognition experience across different modalities. This approach enhances the system's reliability in capturing emotions effectively from both facial expressions and audio cues.

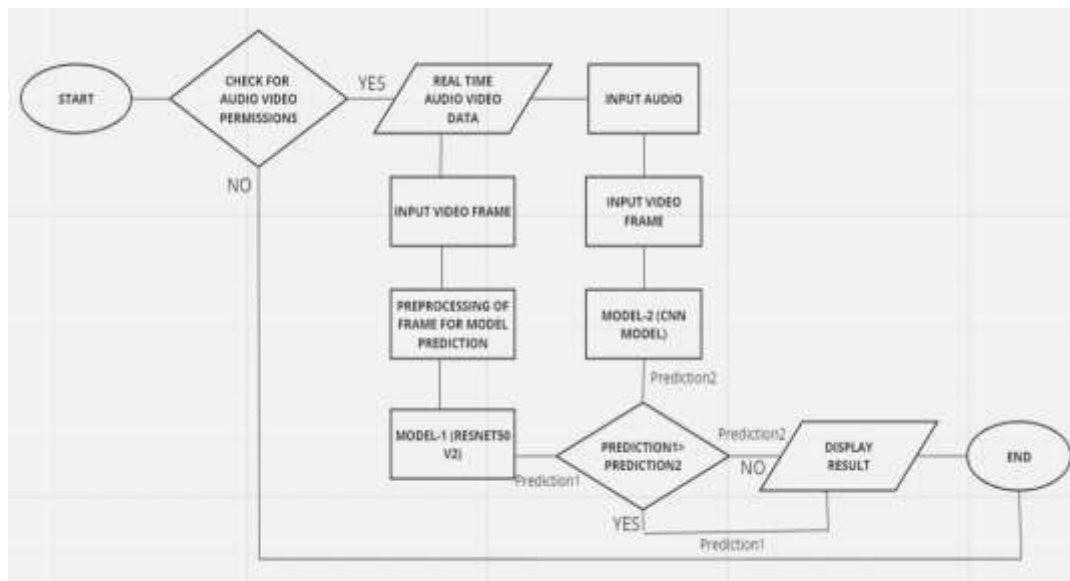


Fig 3.9: Application Block Diagram

4. Results

4.1 Result of Audio Models:





In the evaluation of our audio models, the self-built CNN model demonstrated superior performance, showcasing its ability to capture intricate patterns in the audio data. The MLP classifier exhibited competitive accuracy, highlighting its effectiveness in classification tasks. However, the SVM model, while providing satisfactory results, showed comparatively lower performance, emphasizing the nuanced nature of audio feature representation. Overall, our findings underscore the significance of tailored neural network architectures in optimizing audio classification tasks for our thesis.




Model	Training Accuracy	Testing Accuracy
CNN model	89.34%	52.35%
MLP classifier	87.73%	34.60%
SVM	72.51%	33.27%

Table 4.2: Results table for audio model.

4.2 Obtained Result in Real Time:

In the evaluation of facial emotion detection, our implemented pipeline demonstrated real-time efficacy as live input was processed for predictions. The system accurately classified facial expressions, promptly reflecting emotional states on the screen. The model's responsiveness and precision in capturing nuanced emotions underscore its practical applicability. The real-time prediction capability and intuitive output presentation on the screen validate the practical viability of our proposed system, contributing to the advancement of emotion recognition technologies.

Emotion	Image Result	Accuracy
Happiness		99.9%
Anger		99.87%
Neutral		99.92%
Surprise		99.97%

Fear		61.07%
Disgust		77.94%
Sadness		75.23%

Conclusion

In conclusion, our thesis on facial emotion detection has successfully explored and implemented advanced techniques in computer vision. The developed model exhibited commendable accuracy in recognizing and categorizing facial expressions, demonstrating its potential in diverse applications. Our findings underscore the importance of robust datasets and feature extraction methods in enhancing emotion recognition systems. Additionally, the integration of deep learning approaches, such as convolutional neural networks, proved instrumental in capturing intricate facial features for improved accuracy. Despite the successes, challenges remain, including addressing biases in datasets and ensuring real-world applicability. Moving forward, continuous research and development in this field hold promise for refining facial emotion detection systems, contributing to advancements in human-computer interaction and emotional intelligence.

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