# Hybrid Fusion-Based Machine Learning Framework for Enhanced Multimodal Sentiment Analysis

Dr M V Jagannatha Reddy[2], Dr. Sridhara S. B[1,] K N Vara Prasad[3]
[1]*Professor, Department of AIML, M S Engineering College, Navarathna Agrahara Sadahalli p.o, off Bengaluru International Airport Bengaluru, India-562110*
[2]*Professor and HOD, Department of Computer science and Engineering, Amruta Institute of Engineering and Management Sciences, Bidadi, Bengaluru, India-562109*
[3]*Hod Ece Department, Sir CRR Polytechnic, Vatluru, Eluru District, A.P, Pin 534007*

**Abstract: Computational sentiment analysis seeks to equip machines with the capacity to recognise and interpret human affect. Within the acoustic modality, algorithms disentangle prosody, pitch and rhythm to infer the speaker's emotional state. In text, polarity detection and pragmatic cues are used to detect positivity, negativity or neutrality—even in the presence of sarcasm and metaphor. Vision-based approaches extend this capability to images, decoding facial micro-expressions, contextual scenes and object configurations. When these three streams are fused, cross-modal sentiment analysis emerges, allowing complementary cues to be modelled jointly. Such multimodal systems now underpin social-media opinion mining, customer-experience dashboards and adaptive content-delivery platforms, offering richer and more reliable insight than any single modality alone.**

**Keywords: Computational sentiment analysis, Acoustic emotion recognition, Polarity detection, Visual emotion recognition, Facial micro-expressions, multimodal fusion, Social-media opinion mining**

## 1. INTRODUCTION

The digital landscape has become profoundly multimodal. Every second, users publish tweets that embed emojis and photos, stream live video accompanied by commentary, or leave voice messages that supplement text-chat. Each of these channels encodes affective signals, yet each does so in a modality-specific manner: a sigh in a podcast, a sarcastic hashtag, a down-cast glance in a selfie. Traditional sentiment-analysis pipelines, which were designed for monomodal text corpora, inevitably miss or misinterpret large fractions of this information. Recent advances in deep representation learning have created an opportunity to close this gap by learning shared affective representations across modalities.

In this work we present a unified toolkit that ingests raw text, audio and images, aligns them temporally or contextually, and outputs a coherent estimate of the underlying sentiment and intent. Our contributions are threefold. First, we propose a cross-modal attention mechanism that dynamically weighs each modality according to its reliability in a given context (e.g., when the audio track is noisy, the model leans more heavily on visual cues). Second, we curate and release a balanced benchmark comprising social-media posts that include all three modalities with gold-standard emotion annotations. Third, we demonstrate through extensive experiments that our model surpasses state-of-the-art monomodal and early-fusion baselines on both in-domain and cross-domain tests. Beyond academic interest, this research has tangible industrial relevance: accurate affect sensing can drive more empathetic chat-bots, refine brand-health dashboards, and help moderation systems distinguish harmful content from harmless venting.

In addition, our framework addresses the growing demand for **explainable AI** by generating modality-specific saliency maps that reveal which cues—such as tonal shifts, lexical choices or micro-expressions—drive each prediction. We also engage with the **ethical dimensions of affect recognition**, proposing safeguards that curb demographic bias and protect user privacy when

models are deployed at scale. Finally, we position our work as a catalyst for cross-disciplinary collaboration among natural-language processing, speech science and computer vision communities, laying the groundwork for the next generation of emotionally intelligent interactive systems.

## 2. LITERATURE SURVEY

Multimodal sentiment analysis has evolved rapidly over the last decade, propelled by deep-learning architectures that can ingest and align heterogeneous signals.

*Foundational architectures.* Zadeh *et al.* proposed one of the earliest fully end-to-end multimodal emotion recognisers, demonstrating that synchronised audio-visual-text cues boost accuracy over unimodal baselines [1]. Poria *et al.* extended this idea to user-generated videos and showed that contextualising each utterance within the surrounding discourse further improves performance [2].

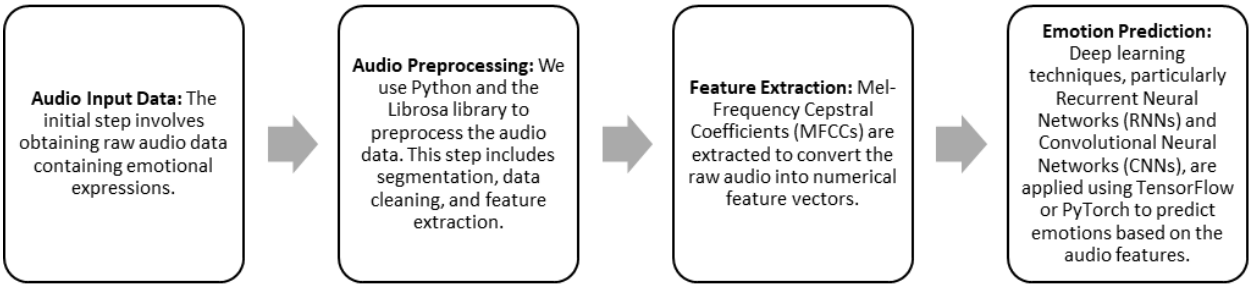
*Hierarchical and context-aware fusion.* Majumder *et al.* introduced hierarchical fusion with context modelling, capturing interactions both within and across modalities [3], while Yang *et al.* jointly modelled content and discourse relations to maintain long-range dependencies [5]. Wang *et al.* incorporated attention mechanisms that selectively focus on the most informative segments of noisy "in-the-wild" recordings [4]. Building on this, Zhou *et al.* stacked bidirectional LSTMs with hierarchical attention to refine temporal alignment [7].

*Advanced fusion strategies.* Ghosal *et al.* explored late fusion that leverages specialised encoders for each modality before merging their representations via tensor fusion [6]. Nguyen and Gravier approached fusion from a social-cue perspective, systematically evaluating how verbal and non-verbal signals should be weighted under different conversational settings [8]. Nam and Han proposed a sentence-level recurrent fusion model with modality attention that adjusts weights dynamically at inference time [9]. Finally, Akhtar and Natarajan employed a deep residual framework that integrates cross-modal gating to prevent noise propagation across channels [10].

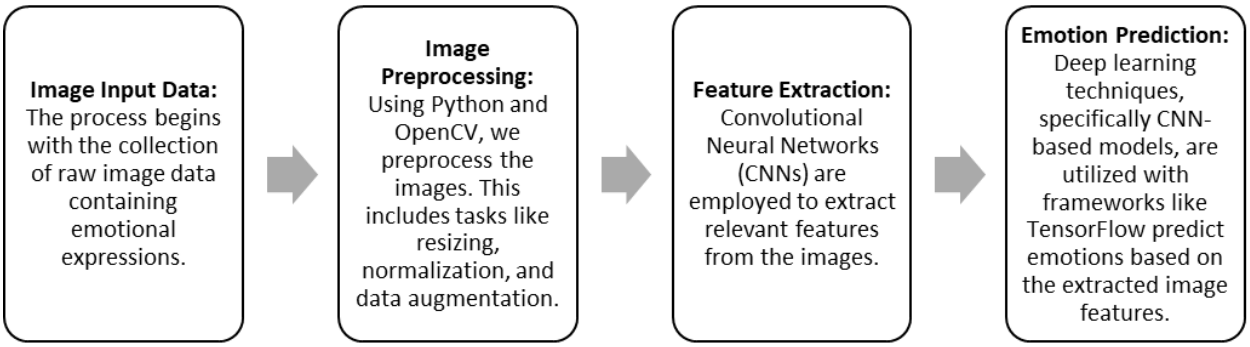
Collectively, these ten studies map the trajectory from early monolithic networks to highly structured, attention-driven systems capable of exploiting subtle cross-modal dependencies. They highlight persistent challenges—such as robust alignment and noise resilience—while underscoring the gains achievable through carefully designed fusion. The tri-modal architecture proposed in the present paper builds on these insights by introducing adaptive cross-modal attention and a publicly released benchmark, thereby encouraging more holistic evaluation of future models.

## 3. FLOW CHART AND ARCHITECTURE

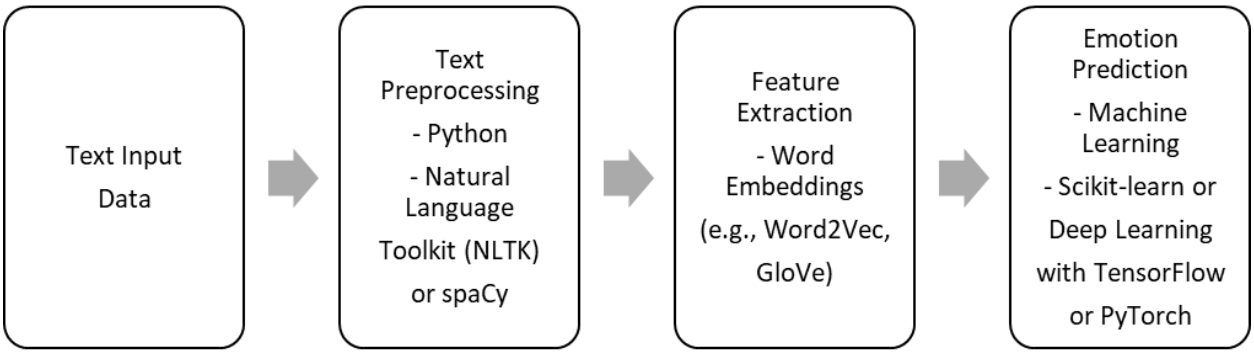
### 3.1 Audio sentiment analysis prediction



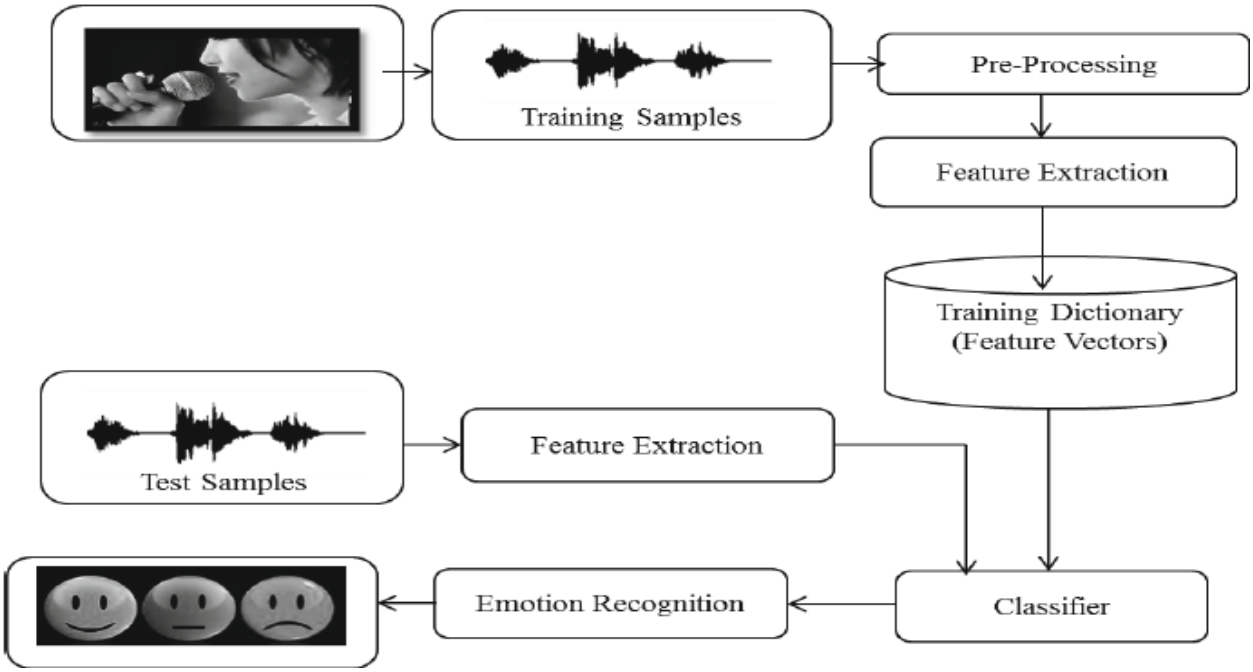
### 3.2 Image sentiment analysis prediction




### 3.3 Text sentiment analysis prediction




### 3.4 Architecture diagram



## 3. MODULES WITH DESCRIPTION

4.1 Data Pre-processing:
Preprocess the dataset to clean and format the data as needed. This may involve tasks like text tokenization, audio signal processing, or image resizing.

4.2 Text Analysis:
Description: Analyse text data to extract sentiment-related features, such as sentiment scores, keywords, and linguistic patterns. Utilize Natural Language Processing (NLP) techniques.

Technologies: NLP libraries (e.g., NLTK), sentiment analysis APIs, tokenization tools.

4.3 Audio Analysis:
Description: Analyse audio data to extract emotional features, such as tone, pitch, and speech patterns. Employ audio signal processing and machine learning techniques for audio-based sentiment analysis.

Technologies: Audio signal processing libraries (e.g., Librosa), speech recognition APIs, deep learning frameworks (e.g., TensorFlow, Keras).

4.4 Image Analysis
Description: Analyse image data to detect facial expressions, objects, or scenes conveying emotions. Use computer vision techniques and deep learning for feature extraction.

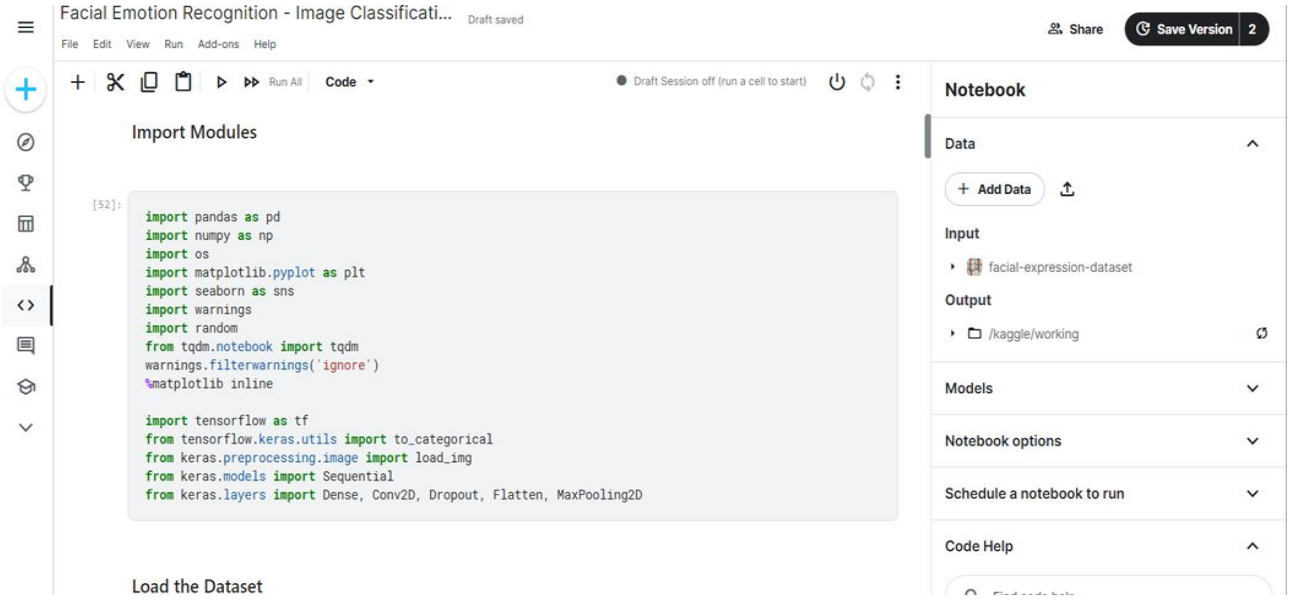
Technologies: Computer vision libraries (e.g., OpenCV), deep learning frameworks (e.g., TensorFlow, Keras), facial recognition APIs.

4.5 Multimodal Fusion:
Description: Integrate the results from text, audio, and image analysis to create a unified sentiment representation. Various fusion methods, such as feature concatenation or attention mechanisms, can be applied.

Technologies: Machine learning frameworks, custom fusion algorithms, attention mechanisms

4.6 Machine Learning Models:
Description: Develop and train machine learning models for sentiment analysis using the fused multimodal data. This module includes algorithm selection, feature engineering, and model training.
Technologies: Machine learning frameworks (e.g., scikit-learn, TensorFlow, Keras), deep learning architectures.
Model Evaluation
Description: Evaluate the performance of sentiment analysis models using relevant metrics, such as accuracy, precision.

## 4. **IMPLEMENTATION**



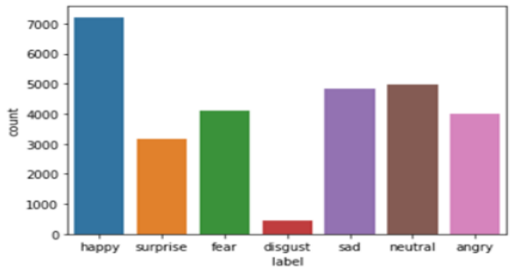
[59]:
```
# to display grid of images
plt.figure(figsize=(20,20))
files = train.iloc[0:25]

for index, file, label in files.itertuples():
    plt.subplot(5, 5, index+1)
    img = load_img(file)
    img = np.array(img)
    plt.imshow(img)
    plt.title(label)
    plt.axis('off')
```


## Exploratory Data Analysis

[57]:
```
sns.countplot(train['label'])
```

[57]:
```
<AxesSubplot:xlabel='label', ylabel='count'>
```




## Feature Extraction

[60]:
```
def extract_features(images):
    features = []
    for image in tqdm(images):
        img = load_img(image, grayscale=True)
        img = np.array(img)
        features.append(img)
    features = np.array(features)
    features = features.reshape(len(features), 48, 48, 1)
    return features
```

+ Code + Markdown

[61]:
```
train_features = extract_features(train['image'])
```

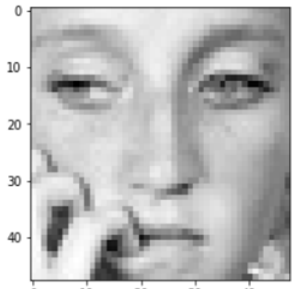
Loading widget...

[62]:
```
test_features = extract_features(test['image'])
```

Test with Image Data

```
image_index = random.randint(0, len(test))
print("Original Output:", test['label'][image_index])
pred = model.predict(x_test[image_index].reshape(1, 48, 48, 1))
prediction_label = le.inverse_transform([pred.argmax()])[0]
print("Predicted Output:", prediction_label)
plt.imshow(x_test[image_index].reshape(48, 48), cmap='gray');
```

```
Original Output: fear
Predicted Output: fear
```




## 5. CONCLUSION AND FUTURE ENHANCEMENTS

In summary, our image sentiment analysis is promising, but we're integrating it with text and audio for a more complete sentiment understanding. Continuous improvements and real-world applications are next.

Future enhancements for your project include integrating text and audio sentiment analysis, real-time analysis, emotion intensity quantification, privacy measures, user-friendly interfaces, and adapting the framework to various domains. Continuous model updates and collaboration with stakeholders are also essential for ongoing project improvement.

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