TERT-Ensemble: A Two-Stage Fusion Approach for Tri-modal Emotion Recognition

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Abstract—Automated emotion recognition is essential for advancing human-computer interaction and affective computing. While unimodal systems using image, text, or audio offer valuable insights, they often struggle with the inherent ambiguity and complexity of human emotional expression. Multi- modal approaches promise enhanced robustness by integrating complementary information from diverse sources. This paper introduces 'TERT-Ensemble', a technique employing a two-stage fusion process for tri-modal emotion recognition. Initially, we establish strong unimodal predictors by systematically evaluating diverse deep learning architectures (CNNs, ViT, Transformers, LSTM) for each modality (image, text, audio) on combined benchmark datasets (CK+, FER-2013, RAF-DB; Twitter datasets; CREMA-D, RAVDESS, SAVEE). Optimal performance within each modality was achieved through intra-modal ensembles, yielding weighted F1-scores of 77.98% (Image), 73.69% (Text), and 66.43% (Audio) on their respective test sets. Subsequently, a tri-modal late fusion model was implemented, combining the outputs of these intra-modal ensembles via weighted probability averaging. Evaluated on a simulated tri-modal test set designed to ensure congruent emotional labels across modalities, this final fusion model achieved high performance, with an accuracy of 95.56% and a weighted F1-score of 0.96. We detail the data preprocessing, model architectures, training protocols, and the two-stage fusion strategy implemented within Kaggle notebooks. An interactive demonstration interface showcasing the unimodal components is also presented. While acknowledging the limitations inherent in using simulated data for the final fusion evaluation, these results validate the effectiveness of the intra- modal ensembles and highlight the significant potential of the proposed staged fusion approach for robust tri-modal emotion recognition.

Index Terms—Emotion Recognition, Multimodal Learning, Late Fusion, Ensemble Learning, Deep Learning, Affective Computing, Image Recognition, Text Classification, Speech Emotion Recognition, Convolutional Neural Networks (CNN), Vision Transformer (ViT), BERT, DeBERTa, LSTM, EfficientNet, Gradio.

I. INTRODUCTION

The automatic recognition of human emotions is a corner- stone for progress in diverse fields, including mental health diagnostics, driver safety systems, personalized content delivery, and the creation of more natural and empathetic human- computer interaction (HCI) systems [1]. Human emotions are inherently multimodal phenomena, conveyed concurrently through facial expressions, vocal prosody, linguistic content, and other physiological cues [2]. Traditional computational systems often focus on analyzing these cues in isolation, leading to specialized domains like Facial Expression Recognition (FER) [3], text-based sentiment/emotion analysis [4], and Speech Emotion Recognition (SER) [5].

However, these unimodal approaches inherently struggle to capture the complete emotional state due to potential ambiguity, contextual dependencies, or modality-specific noise [6]. For instance, facial expressions can be deliberately masked, text lacks paralinguistic information, and vocal tone can be misleading without semantic context, especially in real-world conditions involving noise or sarcasm. Integrating information from multiple modalities offers a promising path towards more comprehensive, robust, and accurate emotion recognition, mirroring human perceptual processes [6].

Motivated by the need for improved emotion recognition systems, this paper introduces the 'TERT-Ensemble' technique, focusing on tri-modal analysis using image, text, and audio data. Our methodology emphasizes a structured, two- stage approach. First, we focus on building highly reliable unimodal predictors. This involves systematically evaluating a diverse set of contemporary deep learning architectures—including Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), language Transformers (BERT, DeBERTa,

RoBERTa), and sequence models like Long Short-Term Memory networks (LSTMs) [7]–[10]—on carefully aggregated benchmark datasets (CK+, FER-2013, RAF-DB; Twitter Emotions; CREMA-D, RAVDESS, SAVEE). To further enhance unimodal performance, we implement intra- modal ensembles, combining the predictions from the base models within each modality using weighted averaging based on their validation performance. This initial stage yielded robust unimodal ensemble predictors with weighted F1-scores of 77.98% (Image), 73.69% (Text), and 66.43% (Audio) on their respective test sets.

The second stage involves "tri-modal late fusion". We com- bine the probabilistic outputs generated by the three optimized intra-modal ensembles using a weighted averaging strategy, where weights reflect the empirically determined reliability of each modality's ensemble predictor. This final fusion model was evaluated on a simulated tri-modal test set, constructed by pairing congruent emotional samples from the individual test sets due to the lack of a naturally aligned corpus matching our training data. On this simulated set, the tri-modal fusion achieved a high accuracy of 95.56% and a weighted F1-score of 0.96. An interactive demonstration interface using the best single unimodal models was also developed.

This work contributes through: (1) A systematic evaluation of architectures for unimodal emotion recognition. (2) Demonstration of intra-modal ensembling benefits. (3) Implementation and evaluation of a two-stage (intra-modal then tri-modal) late fusion model, showing high potential on simulated data. (4) Establishment of strong unimodal and fused performance baselines. This research supports UN SDGs 3 (Health), 9 (Innovation), and 4 (Education) [11]–[13]. The paper proceeds as follows: Section II reviews literature, Section III discusses key parameters, Section IV details the methodology, Section V describes datasets, Section VI covers the experimental setup, Section VII presents results, and Section VIII concludes.

II. LITERATURE SURVEY AND LIMITATIONS

Emotion recognition research has progressed significantly within individual modalities, although persistent challenges motivate multimodal approaches. In FER, deep learning mod- els like CNNs and ViTs dominate over earlier handcrafted features [14], with ensembles enhancing robustness [15]. For Text ER, Transformers like BERT [9], RoBERTa [17], and DeBERTa [18] excel over RNNs/LSTMs [16], and ensembling them can offer further gains [19]. In SER, features like MFCCs [20] are classified using CNNs, LSTMs [21], or hybrid models [22], with ensembling often improving accuracy [23]. While Multimodal ER generally outperforms unimodal systems [6], [24], fusion is complex, ranging from early/late [25] to attention/transformer-based methods [26]. Late fusion remains a viable strategy when leveraging strong unimodal predictors [24]. Key limitations motivating our work include: Data Constraints (spontaneous data scarcity, acted data generalization limits) [22]–[24], [26], Fusion Complexity [24], [26], Computational Cost [15], [19], [23], [26], Inherent Ambiguity (sarcasm, speaker variability, masked expressions) [15], [19], [23], and Inter-Class Similarity [15], [22].

III. PARAMETERS AFFECTING PERFORMANCE

Model performance is contingent upon numerous factors:

1. Data Quality/Characteristics: Dataset diversity, volume, class balance, annotation quality.

2. Preprocessing/Augmentation: Image normalization/augmentation, text cleaning/tokenization, audio feature extraction/augmentation choices.

3. Model Architecture/Configuration: Base model selection, pre-training, fine-tuning strategy, classifier head de- sign.

4. Training Hyperparameters: LR schedule, batch size, optimizer, epochs, early stopping, loss function, weighting strategies, regularization.

5. Ensemble/Fusion Configuration: Both intra-modal (base model diversity, validation F1 weighting) and tri-modal (intra-modal ensemble test F1 weighting) strategies impact final results.

IV. METHODOLOGY: TERT-ENSEMBLE UNIMODAL ANALYSIS AND FUSION

Our methodology adopted a two-stage fusion process, be- ginning with optimizing unimodal performance via intra- modal ensembling, followed by tri-modal

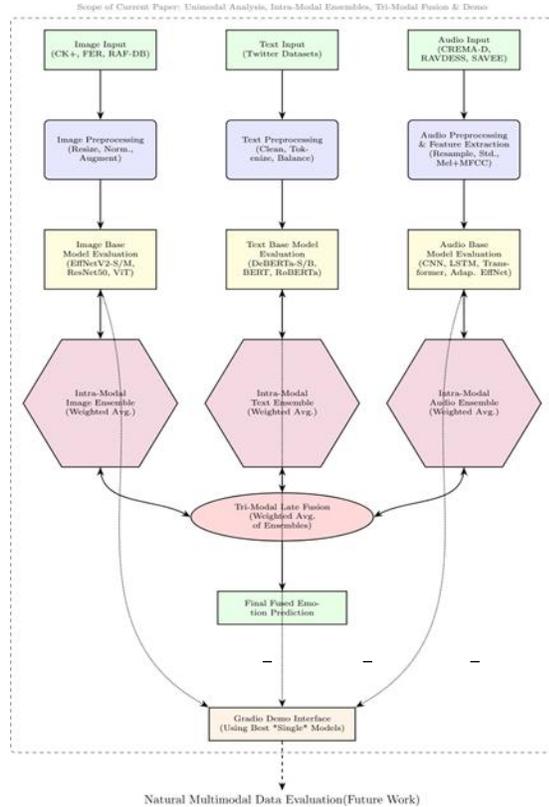late fusion. The workflow is illustrated in Fig. 1.

Fig. 1. Methodology flowchart showing parallel unimodal evaluation leading to intra-modal ensembles, followed by tri-modal fusion and demo integration.

A. Unimodal Base Model Training

Multiple diverse architectures were independently trained for each modality using combined datasets and standardized procedures (detailed in Sec. VI). Model weights corresponding to the best validation weighted F1-score were saved for each architecture.

- Image Models Trained: EfficientNetV2-S/M [27], ResNet50 [28], ViT-B/16 [8].
- Text Models Trained: DeBERTa-v3-small/base [18], BERT-base [9], RoBERTa-base [17].
- Audio Models Trained: Custom 2D CNN, CNN-LSTM w/ Attention [30], CNN-Transformer, Adapted EfficientNetV2-S [27].

B. Intra-Modal Ensemble Fusion

For each modality, a fused prediction was generated by combining the outputs of its constituent trained models.

Technique: Late Fusion via Weighted Averaging of Prob- abilities.

- Process: For a given input, softmax probabilities were obtained from all relevant trained models (e.g., all 4 image models for an image input).
- Weighting: Probabilities were averaged using weights (W_{intra}) derived from each base model's performance on the *validation* set (using weighted F1, normalized to sum to 1, see Sec VII-B logs for values).
- Output: A single probability vector ($P_{img\ ens}$, $P_{txt\ ens}$, $P_{aud\ ens}$) per modality.

These intra-modal ensembles were evaluated on their respective test sets (Results in Sec. VII-B).

C. Tri-Modal Late Fusion

The final fusion stage combined the outputs of the three optimized intra-modal ensembles.

- Technique: Late Fusion via Weighted Averaging of Intra- Modal Ensemble Probabilities.
- Process: For a tri-modal input (image, text, audio), the probability vectors $P_{img\ ens}$, $P_{txt\ ens}$, $P_{aud\ ens}$ were ob- tained from the respective intra-modal ensembles.
- Weighting: These vectors were combined using $P_{fused} = w_{img\ tri}P_{img\ ens} + w_{txt\ tri}P_{txt\ ens} + w_{aud\ tri}P_{aud\ ens}$. Tri-modal weights ($w_{tri}$) reflected the overall reliability of each intra-modal ensemble, based on their respective *test set* weighted F1-scores (ImageEns: 0.7798, TextEns: 0.7369, AudioEns: 0.6643), normalized ($w_{img\ tri} \approx 0.358$, $w_{txt\ tri} \approx 0.338$, $w_{aud\ tri} \approx 0.305$).
- Prediction: Final emotion based on $\arg\max(P_{fused})$.

D. Simulated Test Set for Tri-Modal Evaluation

Lacking an aligned natural tri-modal corpus, a simulated test set (1195 samples) was created by pairing same-label samples from the individual modality test sets, limited by the minimum count per class across modalities. This facilitates fusion evaluation but is a limitation.

E. Demonstration Interface

An interactive Gradio [51] interface was built using the best *single* unimodal models identified during the initial base model evaluation stage (EffNetV2-M, DeBERTa-v3-small, adapted EfficientNet).

V. DATASETS USED

Publicly available datasets were combined per modality for 7 emotion classes.

A. Image Datasets

CK+ [31], FER-2013 [32], and RAF-DB [33] combined (5~2k total samples). 'Contempt' mapped to 'disgust'. Sample diversity shown in Fig. 2.

B. Text Datasets

Emotion Detection from Text [34] and Emotions Dataset [35] combined. Labels mapped; class balancing and dummy data used (7~3k samples).
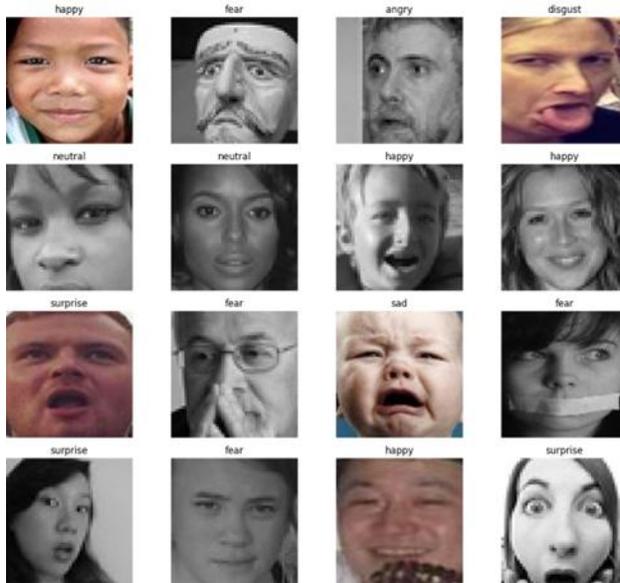

Fig. 2. Sample images from combined datasets.

C. Audio Datasets

CREMA-D [36], RAVDESS [37] (speech only, 'calm' to 'neutral'), and SAVEE [38] combined (9,362 files), mostly acted speech.

VI. EXPERIMENTAL SETUP

A. Implementation Environment

Kaggle Notebooks, NVIDIA GPUs. Libraries: PyTorch [39], Transformers [40], torchaudio [41], librosa [42], pandas [43], NumPy [44], scikit-learn [45], Matplotlib [46], Seaborn [47], Albumentations [50], Gradio [51].

B. Training Procedures

- Data Split: Approx. 70/15/15 Train/Val/Test. Test Sizes: Image=7831, Text=10971, Audio=1405. Stratified.
- Optimization: AdamW [48] (WD: 1e-4 img/aud, 0.01 txt).
- LR Scheduling: OneCycleLR [49] (Max LR: Img 8e-4, Txt 5e-5, Aud 1e-3).
- Loss Function: Cross-Entropy. Class weights (img/aud); Label smoothing (0.1 img/txt).
- Batching/Epochs: Batch Sizes (Img 32, Txt 16, Aud 32). Grad Accum (Img 2, Txt 4, Aud 2). Max Epochs (Img 30, Txt 6, Aud 30).
- Regularization: Weight decay, Dropout, Gradient clip- ping (norm=1.0 txt/aud).
- Mixed Precision: 'torch.cuda.amp' used.
- Early Stopping: Based on validation weighted F1 (Pa- tience: Img 10, Txt 3, Aud 10). Best model saved.

VII. RESULTS, METRICS, AND DISCUSSION

A. Evaluation Metrics

Standard metrics were used: Accuracy, Precision, Recall, Weighted F1-score (primary), Macro F1-score, Confusion Ma- trices.

B. Intra-Modal Ensemble Performance

Ensembles combining multiple architectures within each modality were evaluated on their respective test sets.

1) *Image Ensemble Results:* The weighted average ensemble slightly outperformed the best single image model (EfficientNetV2-M), achieving a weighted F1 of 77.98% (Ta- ble I). The confusion matrix is shown in Fig. 3.

TABLE I IMAGE MODALITY: BEST SINGLE VS. ENSEMBLE

Model	Test Acc.	Test F1 (Wgt)
Best Single (EffNetV2-M)	0.7621	0.7635
Intra-Modal Ensemble	0.7794	0.7798

Fig. 3. Confusion Matrix (Intra-Modal Image Ensemble)

Discussion (Image Ensemble): The ensemble provided a notable improvement (+1.63% F1 absolute) over the best single model, indicating value in combining

diverse vision architectures (CNNs and ViT) for FER.

2) *Text Ensemble Results:* The text ensemble also showed a modest improvement over the best single model (DeBERTa- v3-small), reaching 73.69% weighted F1 (Table II). Confusion matrix in Fig. 4.

TABLE II TEXT MODALITY: BEST SINGLE VS. ENSEMBLE

Model	Test Acc.	Test F1 (Wgt)
Best Single (DeBERTa-S)	0.7249	0.7292
Intra-Modal Ensemble	**0.7302**	**0.7369**

Discussion (Text Ensemble): The gain (+0.77% F1 absolute) was smaller than for images, possibly due to the relative similarity of the base Transformer models.
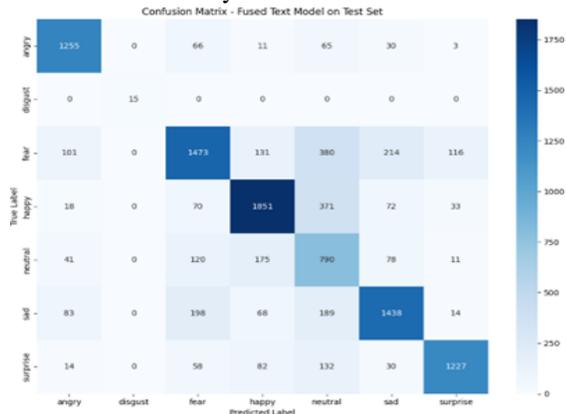
Fig. 4. Confusion Matrix (Intra-Modal Text Ensemble)

3) *Audio Ensemble Results:* The audio ensemble pro- vided only marginal improvement over the best single model (LSTM), achieving 66.43% weighted F1 (Table III). Confusion matrix in Fig. 5.

TABLE III AUDIO MODALITY: BEST SINGLE VS. ENSEMBLE

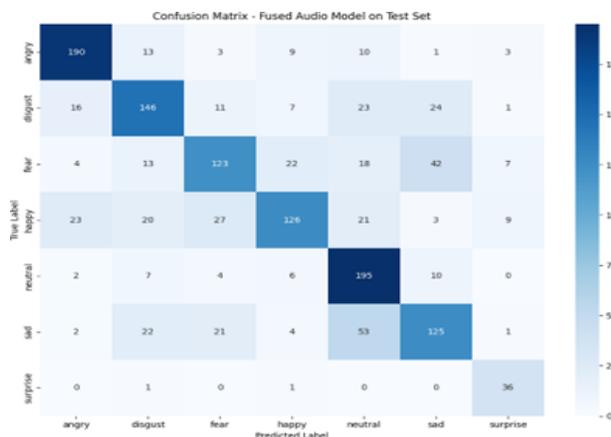| Model	Test Acc.	Test F1 (Wgt)
Best Single (LSTM)	0.6676	0.6634
Intra-Modal Ensemble	**0.6698**	**0.6643**

Fig. 5. Confusion Matrix (Intra-Modal Audio Ensemble)

Discussion (Audio Ensemble): The minimal improvement suggests the inclusion of the poorly performing Transformer likely limited the ensemble's effectiveness.

C. Tri-Modal Fusion Performance

The final fusion model combined the outputs of the three intra-modal ensembles using weights derived from their test F1 scores. Performance on the simulated test set is in Table IV.

TABLE IV- TRI-MODAL FUSION MODEL PERFORMANCE (SIMULATED TEST SET)

Metric	Value
Accuracy	95.56%
Weighted F1-Score	0.96
Macro F1-Score	0.96

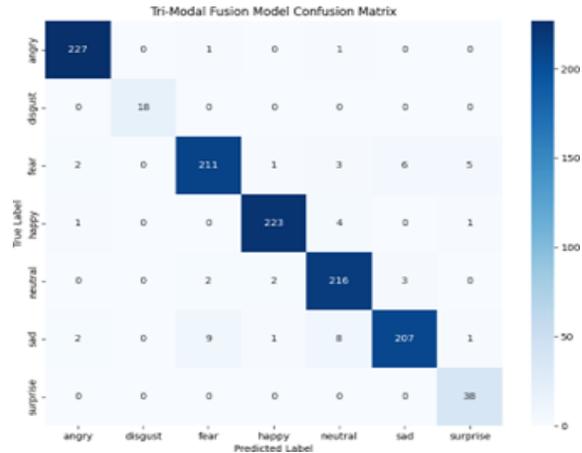Figs. 6 and 7 show the confusion matrix and ROC curves.

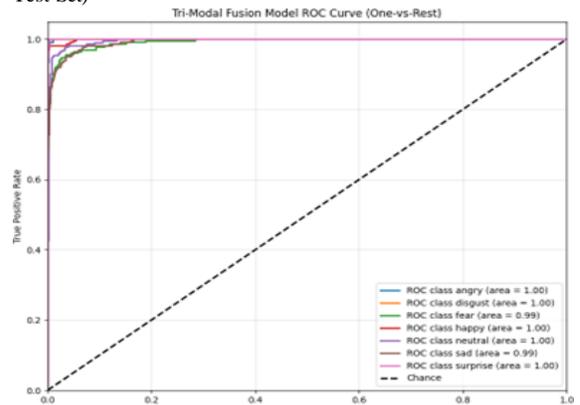Fig. 6. Confusion Matrix (Tri-Modal Fusion Model - Simulated Test Set)

Fig. 7. ROC Curves (Tri-Modal Fusion Model - Simulated Test Set)

Discussion (Tri-Modal Fusion): Exceptionally high performance (95.56% Acc, 0.96 F1) was achieved. This strongly validates the fusion approach's potential

but must be interpreted cautiously due to the simulated test set containing congruent emotional cues across modalities, likely simplifying the task compared to real-world data.

D. Sample Predictions Visualization

Qualitative results comparing intra-modal ensemble predictions and the final tri-modal fusion output on sample data are illustrated in Figs. 8-10.
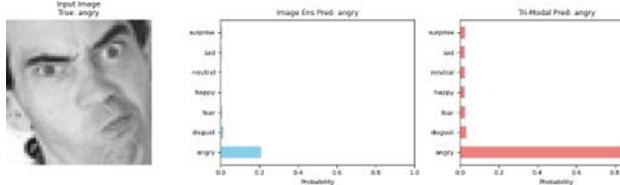

Fig. 8. Sample Image Predictions (Intra-Modal Ensemble vs. Tri-Modal Fused).
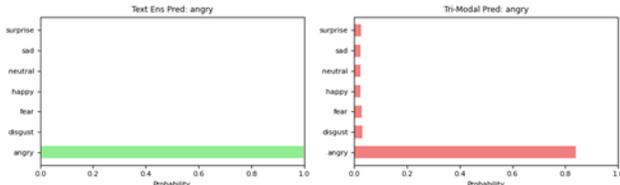

Fig. 9. Sample Text Predictions (Intra-Modal Ensemble vs. Tri-Modal Fused).

E. Demonstration Interface

An interactive Gradio interface [51] (Figs. 11-13) using the best *single* unimodal models provides a practical demonstration of individual component capabilities.

F. Overall Discussion

This study successfully developed robust unimodal predictors via intra-modal ensembling (Image F1: 77.98%, Text F1: 73.69%, Audio F1: 66.43%), generally improving over the best single models. A subsequent tri-modal late fusion model combining these ensembles achieved high accuracy (95.56%) and F1 (0.96) on simulated congruent data, confirming the potential of the TERT-Ensemble fusion approach. However, the reliance on simulated data requires cautious interpretation and
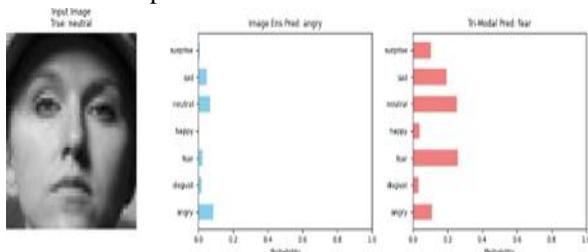

Fig. 10. Sample Audio Predictions (Intra-Modal Ensemble vs. Tri-Modal Fused).
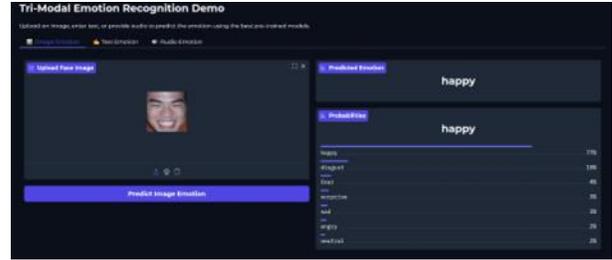

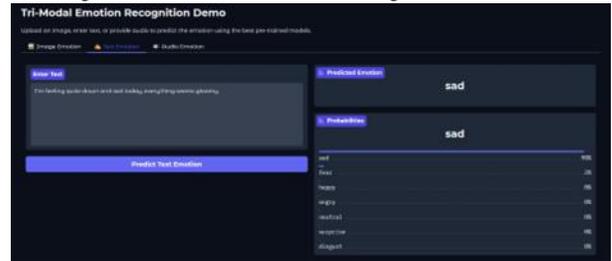Fig. 11. Gradio Demo Interface: Image Emotion Tab.

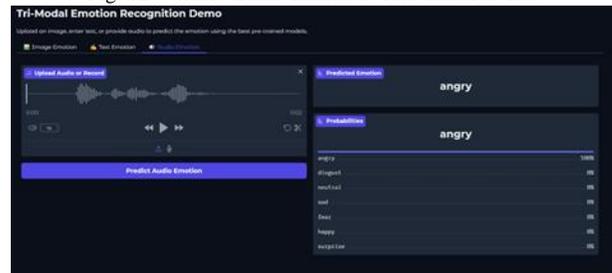Fig. 12. Gradio Demo Interface: Text Emotion Tab.

Fig. 13. Gradio Demo Interface: Audio Emotion Tab.

necessitates future validation on natural multimodal datasets. The Gradio demo provides a functional showcase.

VIII. CONCLUSION AND FUTURE WORK

This paper presented the TERT-Ensemble approach, de- tailing the development of optimized unimodal emotion predictors through intra-modal ensembling and their subsequent combination via tri-modal late fusion. We established strong unimodal ensemble baselines (Image F1: 77.98%, Text F1: 73.69%, Audio F1: 66.43%) and demonstrated the high potential of the final fusion stage (95.56% accuracy, 0.96 F1) on simulated data. An interactive demo illustrates component functionality. This work provides a validated methodology and robust benchmarks. Future research will focus on evaluating the tri-modal fusion model on naturalistic multimodal datasets and exploring advanced fusion techniques to better handle potential cross-modal conflicts and dependencies.

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