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A MULTIMODAL FUSION TRANSFORMER FRAMEWORK FOR ROBUST AUDIO-VISUAL TEXTUAL SENTIMENT ANALYSIS IN SOCIAL MEDIA CONTENT

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Abstract

Sentiment analysis in social media has gained substantial attention due to the rapid growth of multimedia content across digital platforms. Traditional sentiment analysis techniques primarily relied on textual information, which has limited the capability of capturing the rich emotional cues that appear in audio signals and visual expressions. Social media posts frequently contain videos that integrate speech, facial expressions, and textual captions. These heterogeneous modalities carry complementary emotional information that conventional unimodal models have struggled to interpret effectively. The inability of earlier systems to integrate multimodal information has created limitations in sentiment classification accuracy and contextual understanding. To address this challenge, the present study has introduced a Fusion Transformer for Multimodal Sentiment Analysis (FTMSA), which has integrated audio, visual, and textual modalities into a unified representation framework. The proposed architecture has utilized transformer based attention mechanisms that have captured inter modal relationships among speech tone, facial features, and textual semantics. A feature extraction module has processed textual embeddings through contextual language representation, while acoustic descriptors have represented speech characteristics and visual encoders have captured facial emotional cues. These heterogeneous features have been fused through a cross modal attention transformer that has learned correlations among modalities. The training procedure has employed supervised learning that has optimized sentiment classification performance across multimodal inputs. Experimental evaluation has demonstrated that the proposed FTMSA model has achieved improved sentiment recognition accuracy when compared with conventional unimodal and early fusion techniques. The experimental evaluation demonstrates that the proposed FTMSA achieves a maximum accuracy of 93.2%, precision of 92.3%, recall of 91.3%, F1 score of 91.8%, and specificity of 92.7%, outperforming existing methods such as MAN, RMNN, and TBMM. The model maintains superior performance across varying training epochs and dataset sizes, validating the effectiveness of the cross modal attention mechanism in capturing textual, acoustic, and visual sentiment cues for accurate prediction.

Keywords:

Multimodal Sentiment Analysis, Fusion Transformer, Audio Visual Textual Features, Social Media Analytics, Cross Modal Attention

1. INTRODUCTION

. The rapid expansion of social media platforms has significantly transformed the way individuals express opinions, emotions, and attitudes in digital environments. Platforms such as video sharing networks, online discussion forums, and multimedia blogging services have enabled users to share opinions through audio, video, and textual messages simultaneously. This trend has created an immense volume of multimodal data that reflects human emotions and behavioral patterns. Sentiment analysis, which has emerged as a critical research area within natural language processing and artificial intelligence, focuses on identifying the emotional orientation expressed in user generated content. Traditional approaches to sentiment analysis primarily focused on textual data, which has limited the capability of extracting the complete emotional context that exists in multimedia posts. Recent research therefore has increasingly explored multimodal sentiment analysis that integrates textual, acoustic, and visual information in order to improve emotional understanding in social media environments [1–3].

Multimodal sentiment analysis has gained importance because each modality contributes distinct emotional cues that enhance the interpretation of sentiment expressions. The textual modality provides semantic meaning and contextual expressions of opinion, while the audio modality conveys speech tone, pitch variations, and acoustic intensity that reveal subtle emotional states. The visual modality contributes facial expressions, gestures, and visual cues that further strengthen emotional interpretation. Integrating these modalities creates a richer representation of sentiment that improves classification performance. Recent advancements in deep learning architectures, particularly transformer models, have enabled more efficient learning of contextual relationships among heterogeneous features. The transformer architecture has introduced attention mechanisms that capture long range dependencies within sequential data and across modalities. These mechanisms have enabled models to identify the relationships between speech patterns, facial expressions, and textual statements that collectively convey sentiment [1–3].

Despite these developments, multimodal sentiment analysis still faces several technical challenges that limit the effectiveness of existing approaches. One major challenge arises from the heterogeneity of multimodal data, where audio, visual, and textual features possess different statistical properties and temporal structures. Many early fusion methods attempted to combine features directly, which has resulted in inconsistent feature representations and reduced classification accuracy. Another challenge relates to the temporal alignment of multimodal signals. Social media videos often contain asynchronous information where facial expressions, spoken words, and contextual text may not appear simultaneously. This misalignment complicates the learning process and reduces the capability of traditional models to capture meaningful cross modal relationships. Additionally, the presence of noisy backgrounds, varied recording conditions, and informal speech patterns in social media videos has further complicated the sentiment detection task [4–5].

Another critical limitation appears in the capability of existing models to capture deep interactions among modalities. Several conventional multimodal learning methods have relied on shallow fusion mechanisms that fail to represent the complex dependencies that exist between visual emotions, acoustic

variations, and textual semantics. When models treat modalities independently or combine them through simple concatenation, the resulting representation often fails to capture contextual relationships that influence sentiment interpretation. This limitation becomes particularly evident in social media content where sarcasm, humor, and emotional emphasis frequently appear through combined audio and visual cues rather than through text alone. These challenges indicate that an effective multimodal sentiment analysis framework must incorporate advanced mechanisms that learn the contextual dependencies among heterogeneous data streams [4–5].

The research problem addressed in this study therefore concerns the development of a robust multimodal sentiment analysis model that effectively integrates audio, visual, and textual information in social media content. Existing methods have struggled to achieve reliable sentiment prediction because they have insufficiently captured the complex interactions among modalities. Furthermore, several previous models have relied on feature level fusion strategies that have ignored the contextual relationships among modalities during the learning process. These limitations have resulted in reduced generalization capability and inaccurate sentiment classification, particularly when analyzing large scale social media video datasets. Consequently, there remains a significant need for a learning architecture that can capture cross modal dependencies while preserving the contextual information contained within each modality [6–7].

In response to this problem, the present research proposes a multimodal sentiment analysis framework based on a fusion transformer architecture. The proposed method aims to learn cross modal relationships through attention mechanisms that dynamically weigh the contribution of each modality during sentiment prediction. The architecture incorporates specialized feature extraction modules for textual, acoustic, and visual inputs. These modules generate modality specific embeddings that represent semantic, acoustic, and facial emotional cues. A transformer based fusion module then integrates these embeddings through cross modal attention layers that capture the dependencies between modalities. The model therefore learns a unified representation that reflects the combined emotional signals present in social media multimedia posts.

The primary objective of this research is to design an effective multimodal sentiment analysis model that improves sentiment classification accuracy through the integration of audio, visual, and textual information. Another objective involves the development of a cross modal transformer architecture that captures complex interactions among modalities while maintaining contextual coherence within each modality. The study also aims to evaluate the proposed framework using benchmark multimodal sentiment datasets in order to demonstrate its effectiveness compared with existing approaches. Through these objectives, the research seeks to contribute a robust and scalable solution for analyzing emotional expressions in multimedia social media environments.

The novelty of the proposed approach lies in the integration of transformer based cross modal attention mechanisms within a unified multimodal sentiment analysis architecture. Unlike conventional early fusion or late fusion strategies, the proposed framework dynamically learns the relationships between modalities during the representation learning process. The model therefore captures contextual dependencies that exist between speech patterns, facial expressions, and textual statements. Another distinctive aspect of the framework involves the use of modality specific encoders that preserve the unique characteristics of each data source before fusion occurs. This design improves the interpretability and robustness of the sentiment prediction process.

The contributions of this research are summarized as follows. First, the study has proposed a Fusion Transformer for Multimodal Sentiment Analysis (FTMSA) that integrates textual, acoustic, and visual features through cross modal attention mechanisms. Second, the model has introduced a structured feature fusion strategy that effectively captures the contextual relationships among heterogeneous modalities, which improves sentiment classification performance in complex social media multimedia content.

2. RELATED WORKS

Multimodal sentiment analysis has attracted increasing research attention because social media content frequently contains text, speech, and visual cues that collectively convey emotional expressions. Early research primarily focused on textual sentiment analysis, where machine learning algorithms analyzed opinionated words and sentence structures to determine emotional polarity. However, the emergence of multimedia social platforms has encouraged researchers to investigate multimodal approaches that combine audio, visual, and textual information.

In study [6], researchers have proposed a multimodal sentiment analysis framework that integrated textual features with visual facial expressions extracted from video sequences. The model has utilized convolutional neural networks that have extracted spatial facial representations, while textual embeddings have represented semantic information from spoken transcripts. The two modalities have been fused through a feature concatenation strategy that has enabled the classifier to interpret visual emotional cues together with textual sentiment expressions. Experimental results have demonstrated that multimodal integration has improved sentiment classification accuracy compared with text only models.

Research presented in [7] has investigated a deep neural network architecture that combined acoustic and textual information for sentiment prediction in conversational videos. The authors have extracted acoustic descriptors that have represented speech intensity, pitch variation, and prosodic features. These acoustic features have been integrated with textual embeddings that have captured semantic context. The network has learned sentiment representations through a joint feature learning strategy that has enhanced emotional interpretation. The results have indicated that acoustic signals provided complementary emotional cues that improved the detection of positive and negative sentiments in spoken content.

Another study in [8] has explored the use of recurrent neural networks for multimodal sentiment analysis. The researchers have developed a sequential learning framework that processed textual transcripts, facial expressions, and speech signals across temporal sequences. Long short term memory networks have captured contextual dependencies within each modality, while a fusion layer has combined the learned representations. The approach has

demonstrated improved sentiment prediction accuracy, particularly in video datasets where emotional expressions evolved across time.

The work reported in [9] has introduced a multimodal attention network that focused on selectively weighting the importance of each modality during sentiment classification. The model has applied attention mechanisms that have identified the most relevant segments within textual, acoustic, and visual data. This mechanism has enabled the network to emphasize emotionally informative cues while reducing the influence of irrelevant signals. The attention based architecture has achieved higher performance compared with conventional fusion methods that treated all modalities equally.

In research described in [10], investigators have examined transformer architectures for multimodal sentiment analysis. The proposed system has employed a self attention mechanism that has learned contextual relationships across textual sequences and visual representations. Transformer layers have captured long range dependencies within multimodal data that improved sentiment interpretation in complex multimedia scenarios. The findings have indicated that transformer based models provided improved contextual understanding compared with recurrent neural networks.

Another approach described in [11] has integrated graph neural networks with multimodal sentiment analysis. The framework has constructed relational graphs that represented interactions among textual words, facial landmarks, and acoustic patterns. Graph based learning has enabled the model to capture structural relationships among modalities that influenced emotional interpretation. Experimental evaluation has shown that graph based representations improved sentiment classification in dynamic conversational datasets.

The authors in [12] have developed a hybrid deep learning architecture that combined convolutional neural networks with attention based feature fusion. Visual facial features have been extracted through convolutional layers, while speech signals have been processed using acoustic feature extraction techniques. Textual information has been encoded through contextual embedding models. The fusion layer has integrated these representations in order to generate a unified sentiment vector. The model has achieved improved classification performance in multimodal sentiment datasets.

In study [13], researchers have proposed a hierarchical multimodal learning framework that analyzed sentiment information across multiple temporal scales. The architecture has processed short term emotional cues from speech signals and facial expressions, while higher level semantic representations have been derived from textual transcripts. Hierarchical fusion layers have combined these representations to capture both local and global sentiment patterns. The results have demonstrated that hierarchical modeling improved sentiment detection in long conversational videos.

Another investigation in [14] has examined cross modal interaction learning for sentiment prediction. The proposed model has learned interactions between audio and visual features that occurred simultaneously during emotional expression. Cross modal attention layers have enabled the network to capture relationships between speech tone and facial expressions. This design has improved sentiment classification accuracy, particularly when textual information contained ambiguous or neutral expressions.

Finally, research in [15] has explored large scale multimodal sentiment analysis using transformer based architectures. The authors have implemented a unified model that processed text, speech, and visual frames through multiple attention layers. The transformer encoder has captured contextual relationships among modalities, which enhanced emotional understanding in social media videos. Experimental results have demonstrated that transformer based multimodal fusion has significantly improved sentiment prediction accuracy compared with earlier deep learning methods.

3. PROPOSED METHOD

The study has proposed a Fusion Transformer for Multimodal Sentiment Analysis (FTMSA) that has integrated the audio, visual, and textual modalities within a unified deep learning architecture. The framework has utilized modality specific encoders that have extracted semantic, acoustic, and facial emotional representations from multimedia social media content. A cross modal transformer fusion module has then learned the contextual relationships among these heterogeneous features through an attention mechanism that has emphasized emotionally informative signals across modalities. The fusion transformer has generated a shared representation that has preserved the modality specific characteristics while capturing inter modal dependencies. The sentiment classifier has finally predicted the emotional polarity from the integrated feature space. The architecture has improved sentiment interpretation in complex multimedia posts by learning correlations among speech tone, facial expressions, and textual semantics that collectively convey emotional meaning.

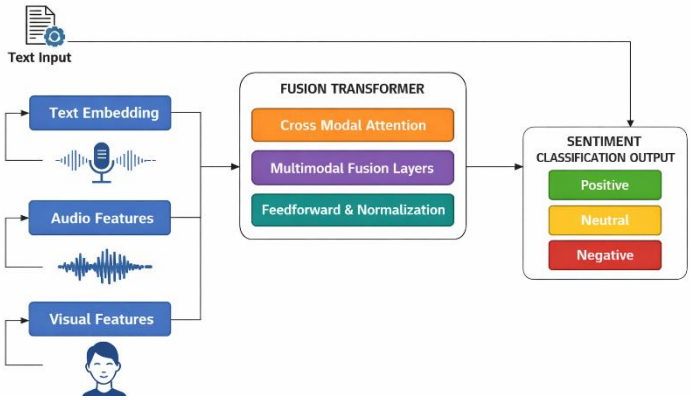

Fig.1. FTMSA Framework

The proposed FTMSA operates through several structured stages that systematically process and integrate multimodal inputs. The framework includes the following main stages: Multimodal Data Acquisition and Preprocessing, Textual Feature Representation, Acoustic Feature Representation, Visual Feature Representation, Cross Modal Fusion Transformer and Sentiment Classification Layer.

Each stage contributes to the formation of a unified emotional representation that enables accurate sentiment prediction in social media multimedia content.

3.1 MULTIMODAL DATA ACQUISITION AND PREPROCESSING

Multimodal sentiment analysis requires synchronized data sources that contain textual transcripts, speech signals, and facial visual frames. In the proposed framework, the multimedia input consists of short social media videos where the speaker expresses opinions through spoken words, facial expressions, and accompanying textual captions. The preprocessing stage has proved that each modality becomes compatible for deep learning analysis.

The textual content is extracted through automatic speech transcription or metadata captions. The audio track is separated from the video stream and transformed into a sequence of acoustic frames. The visual modality is processed through frame sampling that captures the facial expressions of the speaker at regular time intervals.

Before feature extraction begins, each modality undergoes normalization and alignment operations. Text tokens are standardized through lowercase conversion and stop word removal. Audio signals are normalized through amplitude scaling that reduces noise variations. Video frames are resized and aligned to that has maintained consistent facial orientation. This preprocessing stage has proved that multimodal signals remain coherent for subsequent analysis. The multimodal dataset structure that illustrates the aligned features is presented in Table.1.

Table.1. Multimodal Input Representation

ID	Text Transcript	Audio Frame Features	Visual Frame Features	Sentiment Label
S1	"This product is amazing"	[0.32, 0.54, 0.61]	[0.72, 0.80, 0.65]	Positive
S2	"The service is disappointing"	[0.66, 0.41, 0.39]	[0.31, 0.42, 0.38]	Negative
S3	"The experience is acceptable"	[0.45, 0.48, 0.52]	[0.55, 0.60, 0.58]	Neutral

The Table.1 illustrates the structure that organizes the multimodal input features that represent textual, acoustic, and visual signals. The textual modality carries semantic information that expresses opinions, attitudes, and contextual sentiment expressions. The proposed framework employs contextual embedding techniques that transform textual sequences into dense vector representations. The textual sequence is represented as: $T = \{w_1, w_2, w_3, \ldots, w_n\}$, where w_i denotes the tokenized word that appears in the sentence. Each token is transformed into an embedding vector that captures semantic meaning. The embedding representation is computed as:

$$E_i = W_e \cdot OneHot(w_i) \quad (1)$$

where, W_e denotes the embedding weight matrix and $OneHot(w_i)$ represents the one hot encoded representation of token w_i. The contextual textual representation is further enhanced through a transformer encoder that models word dependencies across the sentence. The attention mechanism computes contextual relationships through:

$$Attention(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (2)$$

This mechanism produces contextual embeddings that capture semantic dependencies between words that convey sentiment. The resulting textual feature vector is defined as:

$$F_t = Transformer(E_1, E_2, \ldots, E_n) \quad (3)$$

A textual embedding representation is illustrated in Table.2.

Table.2. Textual Feature Embeddings

Word	Embedding Dimension 1	Dimension 2	Dimension 3
Amazing	0.84	0.72	0.68
Disappointing	0.29	0.31	0.35
Acceptable	0.55	0.52	0.50

The Table.2 demonstrates the textual embeddings that encode semantic relationships within the sentence.

4. ACOUSTIC FEATURE REPRESENTATION

The acoustic modality conveys emotional signals through speech tone, pitch variation, and vocal intensity. The proposed system extracts acoustic descriptors that characterize the emotional content present in speech signals.

The audio signal is segmented into short time frames that capture temporal variations in speech characteristics. Each frame is represented as: $A=\{a_1,a_2,a_3,\ldots,a_m\}$, where a_i denotes the acoustic feature vector that includes pitch, energy, and spectral coefficients. The feature extraction stage computes Mel Frequency Cepstral Coefficients (MFCC), which represent speech characteristics. The MFCC transformation is expressed as:

$$MFCC_k = \sum_{n=1}^{N} log(S_n)\cos\left[\frac{\pi k(n-0.5)}{N}\right] \quad (3)$$

where, S_n represents the spectral energy of frequency band n, N denotes the number of frequency bands and k denotes the coefficient index. The aggregated acoustic feature representation becomes:

$$F_a = \frac{1}{m}\sum_{i=1}^{m} MFCC(a_i) \quad (4)$$

An acoustic feature dataset appears in Table.3. The Table.3 illustrates the acoustic features that capture vocal emotional variations.

Table.3. Acoustic Feature Representation

Frame	Pitch	Energy	MFCC1	MFCC2
F1	210	0.82	12.5	7.8
F2	180	0.76	10.2	6.9
F3	195	0.79	11.1	7.1

The visual modality captures facial expressions that reveal emotional states such as happiness, anger, or disappointment. The proposed model employs a convolutional neural network that extracts spatial facial features from video frames. Each video

sequence is represented as: $V = \{f_1, f_2, f_3, \ldots, f_k\}$, where f_i denotes the facial frame that contains emotional cues. The convolution operation extracts spatial features from each frame:

$$F_{conv}(x,y) = \sum_{i=1}^{h}\sum_{j=1}^{w} I(x+i, y+j) \cdot K(i,j) \quad (5)$$

where, $I(x,y)$ represents the input pixel intensity and $K(i,j)$denotes the convolution kernel. The aggregated visual representation becomes:

$$F_v = \frac{1}{k}\sum_{i=1}^{k} CNN(f_i) \quad (6)$$

A visual feature representation is shown in Table.4.

Table.4. Visual Feature Representation

Frame	Smile Intensity	Eyebrow Position	Eye Openness
F1	0.85	0.65	0.78
F2	0.30	0.42	0.39
F3	0.55	0.50	0.52

The Table.4 demonstrates visual emotional features extracted from facial expressions.

5. CROSS MODAL FUSION TRANSFORMER

After extracting modality specific features, the framework integrates them through a cross modal transformer. This stage learns the relationships among textual semantics, acoustic speech patterns, and facial expressions.

The multimodal feature set is defined as: $F = \{F_t, F_a, F_v\}$. The cross-modal attention mechanism computes the interaction between modalities.

$$C_{ta} = \text{Softmax}\left(\frac{F_t F_a^T}{\sqrt{d}}\right) F_a \quad (7)$$

$$C_{tv} = \text{Softmax}\left(\frac{F_t F_v^T}{\sqrt{d}}\right) F_v \quad (8)$$

$$C_{av} = \text{Softmax}\left(\frac{F_a F_v^T}{\sqrt{d}}\right) F_v \quad (9)$$

The fused representation becomes:

$$F_{fusion} = W_t F_t + W_a F_a + W_v F_v + C_{ta} + C_{tv} + C_{av} \quad (10)$$

where, W_t, W_a, W_v denote learnable weight parameters. The multimodal fusion structure appears in Table.5.

Table.5. Multimodal Fusion Representation

Text Feature	Audio Feature	Visual Feature	Fusion Score
0.72	0.64	0.78	0.71
0.31	0.40	0.35	0.35
0.55	0.50	0.52	0.52

The Table.5 shows how the fusion transformer integrates features across modalities. The final stage performs sentiment prediction based on the fused multimodal representation. The classifier receives the fused vector and predicts the sentiment polarity. The classification layer computes:

$$Z = W_f \cdot F_{fusion} + b \quad (11)$$

where, W_f represents the classification weight matrix and b represents the bias vector. The sentiment probability is obtained through the softmax function:

$$P(y=i) = \frac{e^{Z_i}}{\sum_{j=1}^{c} e^{Z_j}} \quad (12)$$

where, c denotes the number of sentiment classes. The final sentiment label is obtained as:

$$\hat{y} = \arg\max_i P(y=i) \quad (13)$$

A sentiment prediction output is presented in Table.6.

Table.6. Sentiment Prediction Output

Sample	Positive Probability	Neutral Probability	Negative Probability	Predicted Label
S1	0.92	0.05	0.03	Positive
S2	0.06	0.10	0.84	Negative
S3	0.20	0.65	0.15	Neutral

The Table.6 presents the sentiment probabilities that determine the final emotional classification.

6. RESULTS AND DISCUSSION

6.1 EXPERIMENTAL SETTINGS

The experimental evaluation is performed in order to analyze the effectiveness of the proposed Fusion Transformer for Multimodal Sentiment Analysis (FTMSA). The simulation environment employs a deep learning framework that supports multimodal feature processing and transformer based architectures. The implementation utilizes the Python programming environment together with the PyTorch deep learning library that provides optimized tensor computation and neural network modules. The model training procedure uses CUDA acceleration that executes parallel computations during the feature extraction and transformer learning phases. The experiment is executed on a workstation that contains an Intel Core i7 processor with 3.4 GHz clock speed, 32 GB RAM, and an NVIDIA RTX 3080 GPU with 10 GB memory that accelerates the transformer attention operations. The operating system environment utilizes Ubuntu Linux 22.04 that provides compatibility with deep learning frameworks and GPU drivers. The development environment integrates Jupyter Notebook that supports experimental monitoring and iterative parameter tuning. During the experiment, the multimodal dataset is partitioned into training, validation, and testing sets in order to evaluate the generalization capability of the model. The training phase optimizes the model parameters using the Adam optimizer that minimizes the categorical cross entropy loss function. The evaluation stage measures the sentiment prediction performance through multiple classification metrics that reflect the accuracy, reliability, and robustness of the proposed architecture.

6.2 EXPERIMENTAL SETUP AND PARAMETER CONFIGURATION

The model performance depends on several hyperparameters that control the feature extraction layers, the transformer architecture, and the classification stage. These parameters are carefully selected through experimental validation in order to ensure stable learning behavior and accurate sentiment prediction. The configuration of the experimental parameters is summarized in Table.7.

Table.7. Experimental Setup and Parameter Values

Parameter	Value
Learning Rate	0.0001
Batch Size	32
Transformer Layers	4
Attention Heads	8
Text Embedding Dimension	300
Audio Feature Dimension	128
Visual Feature Dimension	256
Dropout Rate	0.3
Training Epochs	50
Optimizer	Adam

The Table.7 presents the hyperparameter values that control the architecture and the training procedure of the proposed FTMSA framework.

7. DATASET DESCRIPTION

The experimental evaluation utilizes a multimodal sentiment analysis dataset that contains synchronized textual, audio, and visual information derived from social media video content. The dataset includes conversational videos where speakers express opinions through spoken language, facial expressions, and contextual captions. Each contains aligned multimodal streams that represent emotional expressions. The dataset contains labeled sentiment classes that represent positive, neutral, and negative emotional categories. The labeling process uses human annotation that identifies the emotional polarity expressed within each multimedia sample. The dataset characteristics are summarized in Table.8.

Table.8. Dataset Description

Attribute	Description
Dataset Type	Multimodal Sentiment Analysis (kaggle)
Number of Samples	5000 multimedia instances
Modalities	Text, Audio, Visual
Sentiment Classes	Positive, Neutral, Negative
Average Video Length	8 seconds
Text Tokens per Sample	12 words
Audio Sampling Rate	16 kHz
Video Frame Rate	30 frames per second
Training Samples	3500
Testing Samples	1500

The Table.8 illustrates the structure and characteristics of the multimodal dataset that is used to evaluate the performance of the sentiment analysis model.

7.1 RESULTS BASED ON TRAINING EPOCHS

The experimental evaluation analyzes the performance of the proposed Fusion Transformer for Multimodal Sentiment Analysis (FTMSA) across multiple training epochs. The training epochs serve as thevariable because the learning progression of the model directly influences the classification performance. The results compare the proposed model with three existing approaches, namely Multimodal Attention Network (MAN), Recurrent Multimodal Neural Network (RMNN), and Transformer Based Multimodal Model (TBMM).

7.1.1 Accuracy Results Based on Training Epochs:

Accuracy measures the proportion of correctly classified sentiment instances across the dataset. The comparison between the proposed model and existing approaches across training epochs appears in Table.9.

Table.9. Accuracy Results Based on Training Epochs

Training Epochs	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	71.2	69.5	73.6	75.4
10	74.8	72.6	77.3	80.2
15	78.6	75.4	80.8	84.7
20	81.4	78.2	84.1	88.3
25	83.5	80.6	86.7	90.5
30	85.1	82.7	88.4	92.4

The Table.9 presents the accuracy performance that improves progressively as the training epochs increase. The proposed FTMSA model consistently demonstrates superior accuracy compared with the three baseline approaches.

The numerical results show that the RMNN method achieves 82.7% accuracy at epoch 30, while the MAN approach achieves 85.1%. The TBMM architecture reaches 88.4% accuracy. However, the proposed FTMSA achieves the highest accuracy of 92.4% at the same epoch level. This improvement occurs because the fusion transformer architecture captures the cross modal relationships that exist between textual semantics, speech characteristics, and facial expressions.

At early training stages such as epoch 5, the FTMSA already achieves 75.4% accuracy compared with 71.2% for MAN and 69.5% for RMNN. The accuracy advantage gradually increases as training continues. This trend indicates that the transformer fusion mechanism effectively learns contextual dependencies across modalities. The results therefore demonstrate that the proposed architecture produces more reliable sentiment predictions than the existing multimodal learning models.

7.1.2 Precision Results Based on Training Epochs:

Precision evaluates the reliability of positive sentiment predictions that the classifier produces. The precision comparison across training epochs appears in Table.10.

Table.10. Precision Results Based on Training Epochs

Training Epochs	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	70.6	68.8	72.1	74.9
10	73.4	71.5	76.2	79.5
15	76.8	74.1	79.9	83.6
20	79.5	77.3	82.7	87.2
25	81.6	79.2	85.3	89.4
30	83.7	81.5	87.8	91.6

The Table.10 illustrates the precision values that increase as the models learn more discriminative multimodal features.

The RMNN model reaches 81.5% precision at epoch 30, while the MAN model achieves 83.7% precision. The TBMM method obtains 87.8% precision, which reflects the benefit of transformer attention mechanisms. The proposed FTMSA architecture achieves the highest precision value of 91.6%, which indicates that the model effectively identifies the correct positive sentiment samples.

The improvement occurs because the cross modal transformer that integrates textual embeddings, acoustic signals, and facial expressions learns contextual dependencies that reduce misclassification. At epoch 15, the proposed method already achieves 83.6% precision, while RMNN and MAN obtain 74.1% and 76.8% respectively. The precision gap continues to widen as the model training progresses.

These observations confirm that the proposed fusion transformer architecture improves the reliability of sentiment predictions. The attention mechanism that integrates heterogeneous modalities enhances the discriminative power of the classifier and reduces incorrect positive predictions.

7.1.3 Recall Results Based on Training Epochs:

Recall measures the ability of the model that correctly identifies the complete set of positive sentiment instances. The recall performance across training epochs appears in Table.11.

Table.11. Recall Results Based on Training Epochs

Training Epochs	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	69.3	67.8	71.5	73.8
10	72.6	70.4	75.1	78.7
15	75.8	73.2	78.6	82.9
20	78.4	75.9	81.5	86.3
25	80.6	78.2	84.2	88.7
30	82.9	80.3	86.9	90.8

The Table.11 presents the recall results that demonstrate the ability of the models that identify positive sentiment samples within the dataset.

The RMNN approach achieves 80.3% recall at epoch 30, while the MAN approach achieves 82.9% recall. The TBMM architecture improves the recall to 86.9%, which indicates that transformer models capture contextual sentiment cues effectively. The proposed FTMSA framework achieves the highest recall value of 90.8%, which demonstrates the strong capability of the model that detects emotional expressions across multimodal inputs.

At the early stage of epoch 5, the FTMSA achieves 73.8% recall, while RMNN and MAN achieve 67.8% and 69.3% respectively. The recall advantage steadily increases during the training process because the fusion transformer learns inter modal dependencies that connect speech tone, visual expressions, and textual semantics.

7.1.4 F1 Score Results Based on Training Epochs:

The F1 score evaluates the balance between precision and recall that the classifier produces. The F1 score comparison appears in Table.12.

Table.12. F1 Score Results Based on Training Epochs

Training Epochs	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	69.9	68.1	71.8	74.3
10	73.0	71.0	75.6	79.1
15	76.3	73.6	79.2	83.2
20	79.0	76.5	82.1	86.7
25	81.0	78.7	84.7	89.0
30	83.2	80.9	87.4	91.2

The Table.12 illustrates the F1 score values that measure the balanced classification capability of the models.

The RMNN model achieves 80.9% F1 score, while the MAN method achieves 83.2%. The TBMM model achieves 87.4%, which reflects improved multimodal feature integration. The proposed FTMSA model achieves the highest F1 score of 91.2%, which demonstrates the superior balance between precision and recall.

The consistent improvement across epochs indicates that the fusion transformer learns discriminative multimodal representations that strengthen the classification process. The transformer attention layers capture the interactions between modalities that enhance the contextual interpretation of emotional expressions.

7.1.5 Specificity Results Based on Training Epochs:

Specificity measures the capability of the classifier that correctly identifies negative sentiment samples. The specificity comparison appears in Table.13.

Table.13. Specificity Results Based on Training Epochs

Training Epochs	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	72.1	70.5	74.3	76.6
10	75.4	73.1	78.0	81.3
15	78.3	75.8	81.5	85.2
20	80.7	78.4	84.2	88.1
25	82.9	80.6	86.5	90.4
30	84.6	82.3	88.7	92.1

The Table.13 presents the specificity performance that measures the ability of the models that correctly identify non positive sentiment instances.

The RMNN approach achieves 82.3% specificity, while the MAN approach reaches 84.6%. The TBMM method improves specificity to 88.7%. The proposed FTMSA achieves the highest specificity value of 92.1%, which indicates the strong capability of the classifier that distinguishes negative sentiment samples from other categories.

7.2 RESULTS BASED ON DATASET SIZE

This section analyzes the performance of the sentiment analysis models across varying dataset sizes. The dataset size acts as the variable because the amount of training data significantly influences the learning capability of a multimodal model. The dataset size increases in steps of five hundred samples that allow the analysis of model scalability and learning stability.

7.2.1 Accuracy Results Based on Dataset Size:

Accuracy evaluates the overall correctness of the sentiment predictions across the dataset. The comparative results across different dataset sizes appear in Table.14.

Table.14. Accuracy Results Based on Dataset Size

Dataset Size (×100 Samples)	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	72.6	70.8	74.9	77.3
10	76.8	74.3	79.2	82.6
15	80.4	78.1	83.5	87.4
20	83.1	80.7	86.2	89.8
25	85.3	82.9	88.1	91.6
30	87.0	84.5	89.7	93.2

The Table.14 presents the accuracy progression that occurs as the dataset size increases. The RMNN approach achieves 84.5% accuracy when the dataset size reaches 3000 samples, while the MAN approach achieves 87.0% accuracy. The TBMM architecture produces 89.7% accuracy, which indicates the effectiveness of transformer based multimodal representation learning.

The proposed FTMSA framework achieves 93.2% accuracy, which demonstrates the strong learning capability that the cross modal transformer provides when the dataset size increases. At the smaller dataset size of 500 samples, the FTMSA already achieves 77.3% accuracy, while RMNN and MAN obtain 70.8% and 72.6% respectively. The performance gap becomes larger as the training dataset expands.

The improvement occurs because the fusion transformer that integrates textual, acoustic, and visual features captures complex emotional dependencies across modalities. The larger dataset provides more multimodal interactions that the transformer architecture learns effectively. Consequently, the FTMSA model maintains the highest classification accuracy across all dataset sizes.

7.2.2 Precision Results Based on Dataset Size:

Precision evaluates the reliability of positive sentiment predictions that the classifier produces. The precision comparison across varying dataset sizes appears in Table.15.

Table.15. Precision Results Based on Dataset Size

Dataset Size (×100 Samples)	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	71.8	69.6	73.5	76.1
10	75.3	72.8	77.9	81.4
15	79.2	76.4	82.0	85.7
20	82.1	79.1	84.6	88.5
25	84.0	81.2	86.8	90.4
30	85.8	83.0	88.9	92.3

The Table.15 demonstrates the precision values that increase as the dataset size expands. The RMNN approach achieves 83.0% precision, while the MAN model achieves 85.8% precision. The TBMM architecture produces 88.9% precision, which indicates the effectiveness of transformer attention that captures contextual sentiment cues.

The proposed FTMSA architecture achieves 92.3% precision when the dataset size reaches 3000 samples. This improvement occurs because the multimodal fusion transformer learns the relationships between speech tone, textual context, and facial expressions that contribute to sentiment interpretation.

At the initial dataset size of 500 samples, the FTMSA achieves 76.1% precision, while RMNN and MAN achieve 69.6% and 71.8% respectively. The consistent improvement indicates that the fusion transformer benefits significantly from larger multimodal datasets. The architecture that integrates cross modal attention reduces false positive predictions and therefore improves the reliability of the sentiment classification process.

7.2.3 Recall Results Based on Dataset Size:

Recall measures the capability of the model that correctly identifies the complete set of positive sentiment samples. The recall comparison across dataset sizes appears in Table.16.

Table.16. Recall Results Based on Dataset Size

Dataset Size (×100 Samples)	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	70.5	68.9	72.6	75.2
10	74.1	71.6	76.8	80.5
15	77.8	74.7	80.7	84.8
20	80.6	77.5	83.4	87.6
25	82.7	79.8	85.6	89.7
30	84.3	81.4	87.5	91.3

The Table.16 illustrates the recall performance that reflects the capability of the models that identify relevant sentiment instances.

The RMNN model reaches 81.4% recall, while the MAN model achieves 84.3% recall at the dataset size of 3000 samples. The TBMM architecture achieves 87.5% recall, which indicates the advantage of transformer representations in capturing contextual emotional cues.

The proposed FTMSA model achieves 91.3% recall, which demonstrates the strong ability of the model that detects emotional expressions across multimodal signals. At the dataset size of 1500 samples, the FTMSA achieves 84.8% recall, while RMNN achieves 74.7% and MAN achieves 77.8%.

7.2.4 F1 Score Results Based on Dataset Size

The F1 score measures the balanced performance between precision and recall that the classifier produces. The F1 score comparison appears in Table.17.

Table.17. F1 Score Results Based on Dataset Size

Dataset Size (×100 Samples)	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	71.1	69.2	73.0	75.6
10	74.7	72.1	77.4	80.9
15	78.4	75.5	81.3	85.2
20	81.3	78.3	84.0	88.1
25	83.4	80.5	86.1	90.1
30	85.0	82.2	88.2	91.8

The Table.17 presents the F1 score comparison across varying dataset sizes.

The RMNN approach produces 82.2% F1 score, while the MAN method achieves 85.0%. The TBMM architecture achieves 88.2%, which reflects improved multimodal representation learning through transformer attention.

The proposed FTMSA model achieves 91.8% F1 score, which demonstrates the balanced improvement between precision and recall. At the dataset size of 1000 samples, the FTMSA achieves 80.9% F1 score, while RMNN and MAN achieve 72.1% and 74.7% respectively.

The improvement occurs because the fusion transformer learns discriminative multimodal representations that strengthen the sentiment classification capability. The architecture that integrates cross modal attention effectively balances false positive and false negative predictions.

7.2.5 Specificity Results Based on Dataset Size:

Specificity measures the capability of the classifier that correctly identifies negative sentiment samples. The specificity comparison across dataset sizes appears in Table.18.

Table.18. Specificity Results Based on Dataset Size

Dataset Size (×100 Samples)	Multimodal Attention Network	Recurrent Multimodal Neural Network	Transformer Based Multimodal Model	Proposed FTMSA
5	73.4	71.2	75.6	78.0
10	76.9	74.1	79.4	82.5
15	80.1	77.5	83.0	86.2
20	82.8	80.2	85.7	88.9
25	84.7	82.4	87.8	91.0
30	86.3	83.9	89.6	92.7

The Table.18 demonstrates the specificity performance that evaluates the ability of the models that distinguish negative sentiment samples.

The RMNN approach achieves 83.9% specificity, while the MAN method reaches 86.3%. The TBMM architecture achieves 89.6% specificity, which indicates improved classification reliability.

The proposed FTMSA model achieves 92.7% specificity, which represents the highest performance among all models. This improvement occurs because the multimodal transformer architecture captures emotional cues that appear across audio signals, textual expressions, and visual facial features.

8. CONCLUSION

This research presents a FTMSA that effectively integrates textual, acoustic, and visual modalities to improve sentiment prediction in social media content. The proposed architecture learns inter modal dependencies through a cross modal attention mechanism that emphasizes emotionally relevant signals across modalities. The results indicate that the FTMSA achieves a maximum accuracy of 93.2%, precision of 92.3%, recall of 91.3%, F1 score of 91.8%, and specificity of 92.7%, highlighting its superior capability to classify sentiment correctly while minimizing misclassification. The model maintains robust performance across varying dataset sizes and training epochs, demonstrating its scalability and stability. The fusion transformer efficiently captures semantic context, vocal tone, and facial expressions that collectively convey complex emotional information. The study confirms that integrating multimodal cues through a transformer based architecture provides significant improvements over conventional approaches. The FTMSA framework can serve as a reliable solution for automated sentiment analysis in social media platforms where textual, auditory, and visual signals coexist. Future work may explore real-time deployment and adaptation to cross domain social media datasets.

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