Libyan Journal of Science & Technology 15:2 (2025) 254-258

Faculty of Science - University of Benghazi

Libyan Journal of Science & Technology

journal home page: https://journals.uob.edu.ly/LJST

A Multi-Modal Approach to Emotion-Aware Automatic Speech Recognition Using Dynamic Emotion Trajectories and Global Style Tokens.

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Highlights

- **A novel emotion-aware ASR framework is proposed that models dynamic emotion trajectories by jointly leveraging acoustic features, physiological signals, and Global Style Tokens (GSTs).**
- **The integration of multimodal fusion and temporal emotion modelling significantly improves emotion recognition performance, achieving up to 88.1% accuracy, F1-scores of 0.87, and AUC of 0.90 on benchmark datasets (IEMOCAP and RAVDESS).**
- **Experimental results demonstrate that GST-based dynamic emotion modelling outperforms state-of-the-art static and joint ASR–AER approaches, enabling more accurate detection of nuanced and evolving emotional states in speech.**

ARTICLE INFO

Article history:

Received 05 November 2024
Revised 08 December 2025
Accepted 23 December 2025

Keywords:

Emotion-aware ASR, Global Style Tokens, Speech Emotion Recognition, Emotion Trajectory, Multimodal Fusion.

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ABSTRACT

This paper presents a novel approach to emotion-aware Automatic Speech Recognition (ASR) by integrating emotion detection and dynamic emotion trajectory modelling. Our system combines acoustic features and physiological signals to achieve more accurate and contextually aware emotion recognition. The use of Global Style Tokens (GSTs) enhances the system's ability to detect nuanced emotional transitions in speech, outperforming existing state-of-the-art models. We evaluate the system using the IEMOCAP and RAVDESS datasets, achieving emotion classification accuracies of 88.1% and 85.6%, respectively. The system also achieves an F1-score of 0.87 on IEMOCAP and 0.85 on RAVDESS, with Area Under the Curve (AUC) scores of 0.90 and 0.88, and Root Mean Squared Error (RMSE) values of 0.13 and 0.14. Additionally, we propose future enhancements, including expanding multimodal inputs, improving real-time scalability, handling mixed emotions, and adapting the model for cross-lingual and low-power environments. Our findings contribute to the development of emotionally intelligent ASR systems capable of improving human-computer interactions in various applications.

1. Introduction

Automatic Speech Recognition (ASR) has progressed significantly in recent years, enabling reliable transcription of spoken language in applications such as virtual assistants, customer services, and healthcare systems. Despite these improvements, conventional ASR systems remain largely insensitive to the emotional cues embedded in human speech. Elements such as tone, rhythm, and vocal intensity carry essential information that contributes to meaning and user intention (Cowen & Keltner, 2021). When these cues are ignored, ASR outputs may lose contextual relevance and may misinterpret the speaker's communicative state, especially in interactive or affect-sensitive scenarios.

Emotion-aware ASR has therefore become an important research direction, aiming to integrate speech recognition with reliable emotional understanding. Traditional emotion recognition methods often rely on static acoustic features or treat emotions as discrete labels (Sahu *et al.*, 2019). However, emotions naturally evolve over time and may fluctuate within a dialogue, creating temporal patterns that static models fail to capture. Moreover, emotional expression is influenced by noise conditions, speaker variability, and complex internal states, all of which require more robust modelling strategies (Anagnostopoulos *et al.*, 2015).

To address these limitations, multimodal and sequential approaches have emerged as promising solutions. Combining speech with complementary sensory or behavioural signals provides richer information about emotional states (Zhang *et al.*, 2020a), while dynamic modelling techniques can track the evolving nature of emotions across an interaction (Tripathi *et al.*, 2022). These approaches enable ASR systems to become not only more accurate in transcription but also more sensitive to the emotional context in which speech occurs.

In this work, we propose a multimodal, dynamic emotion-aware ASR framework that integrates acoustic features, physiological signals, and emotion-trajectory modelling. Our main contributions are as follow:

- **A dynamic emotion trajectory model** that captures the temporal evolution of emotions rather than assigning static labels.
- **A multimodal fusion strategy** combining acoustic and physiological cues to improve robustness in noisy and naturalistic conditions.
- **The integration of Global Style Tokens (GSTs)** to better encode prosodic and expressive variations relevant to emotional changes (Kyung et al., 2023).
- **Extensive evaluation on benchmark datasets**, demonstrating improvements in accuracy, F1-score, AUC, and RMSE when compared with state-of-the-art techniques on emotional speech

 ISSN: Online 2663-1407, Print 2663-1393; National Library of Libya, Legal number: 390/2018

corpora such as IEMOCAP (Busso et al., 2008) and RAVDESS (Livingstone & Russo, 2018).

The remaining sections of this work are organized as follows. Section 2 reviews the related work and summarizes the main advances in emotion-aware speech recognition. Section 3 presents the methodology and the materials used in the proposed approach. The experimental results and their discussion are provided in Section 4. Finally, Section 5 concludes the paper and outlines future research directions.

2. Related Work

Research on emotion-aware ASR has expanded considerably, with several approaches exploring how emotional cues can be integrated into speech recognition systems. One major line of work focuses on joint modelling of ASR and Automatic Emotion Recognition (AER). For example, Wu et al. (2023a) proposed a unified multi-task framework in which ASR, emotion recognition, and speaker-related tasks share a common encoder. Their system benefits from shared acoustic representations, improving emotional awareness during transcription. Although effective, joint learning models can suffer from error propagation, as inaccuracies in one task may negatively influence the others.

Another significant direction involves the use of Global Style Tokens (GSTs) to capture expressive and prosodic variations in speech. Kyung *et al*. (2023) integrated GSTs into the ASR pipeline to better represent emotion-dependent stylistic patterns such as pitch dynamics, intensity, and rhythm. Their method resulted in improved recognition of emotional content, demonstrating that prosodic patterns are useful cues for emotion-aware decoding. However, GST-based models tend to require increased computational resources and may exhibit reduced generalisation across different languages and speaking styles.

Classical feature-engineering approaches remain relevant as well. Martin *et al*. (2021) explored the use of Mel-Frequency Cepstral Coefficients (MFCCs), modulation spectral features, and traditional machine-learning classifiers including Support Vector Machines and Recurrent Neural Networks. These methods offer strong performance in controlled laboratory settings but often degrade under noisy conditions or when emotional states overlap, revealing the limitations of using static, handcrafted acoustic features for dynamic emotional speech.

Recent research has also incorporated visual information to complement audio signals. Ivanko *et al.* (2023) demonstrated that combining lip-reading features with speech improves the identification of emotional states, especially in low-quality audio scenarios. Visual cues such as lip movements, facial micro-expressions, and articulation patterns provide additional context that is not captured by audio alone. However, multimodal audio–visual systems require high-quality video input and are therefore less suitable for real-time or resource-constrained environments.

Another important challenge in emotional speech processing is the scarcity of labelled training data. To address this issue, Qu et al. (2022) proposed a GAN-based style-transfer framework that generates synthetic emotional variations, helping to balance classes and improve model generalisation. Although GAN-based augmentation enriches datasets, it may produce samples with limited emotional authenticity, highlighting the need for careful quality control.

In summary, existing work spans joint learning architectures, prosodic tokenisation, engineered acoustic features, multimodal audio–visual fusion, and data augmentation using generative models. While these approaches offer valuable insights, most continue to treat emotions as discrete categories rather than evolving states. In contrast, the present study emphasises the modelling of dynamic emotional trajectories and explores multimodal fusion that incorporates both acoustic and physiological cues, aiming to provide a more temporally coherent and context-sensitive understanding of emotional speech.

3. Methodology and Materials

3.1 Methodology

Our contribution to emotion-aware Automatic Speech Recognition (ASR) involves the development of a multi-modal, dynamic emotion recognition model. This section outlines the steps involved in building and evaluating the system, which integrates both acoustic features and physiological data to capture the full spectrum of emotional nuances in speech.

3.1.1 Data Collection

The first step in our methodology involves gathering multimodal datasets that include both speech and physiological signals. We use publicly available emotion-labelled speech datasets, such as IEMOCAP and RAVDESS, for the acoustic data, while physiological data such as heart rate and galvanic skin response (GSR) are collected from subjects participating in emotionally charged conversations. This dataset allows for the synchronization of speech signals and physiological responses, providing rich emotional contexts. Preprocessing is conducted to normalize and clean the data, filtering out noise and irrelevant signals.

3.1.2 Feature Extraction

For the speech data, we extract acoustic features including Mel-Frequency Cepstral Coefficients (MFCCs), pitch, tone, intensity, and speech rate. These features are essential for identifying emotion from speech, as they represent the fundamental properties of human vocal expression. In addition, we extract temporal features that capture shifts in emotional intensity and variation over time, which are crucial for the dynamic nature of our model. For the physiological data, we process signals such as heart rate variability (HRV) and skin conductance to detect physiological responses to emotional stimuli. These signals are known to vary in response to different emotional states (e.g., increased heart rate in anxiety or anger). Feature extraction involves filtering and segmenting the physiological signals to match corresponding speech segments.

3.1.3 Emotion Trajectory Modelling

A central part of our contribution is the creation of an emotion trajectory model. This model tracks emotional shifts throughout a conversation rather than assigning a static emotion to each speech segment. Using both speech and physiological features, the model identifies emotional transitions (e.g., from neutral to angry, or from happy to frustrated) by applying a Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) units. The LSTM architecture is well-suited for handling the sequential nature of conversations, allowing the model to remember and update emotional states as the dialogue progresses. The emotion trajectory is represented as a time-series graph of emotional intensity levels, where key emotional changes (peaks and troughs) are marked. This dynamic model captures not only the current emotional state but also the emotional evolution over time.

3.1.4 Multimodal Fusion

To enhance the emotion detection accuracy, we integrate both acoustic and physiological features through multi-modal fusion. We use a hybrid neural network that combines a Convolutional Neural Network (CNN) for extracting high-level features from the physiological data and the LSTM model for sequential speech features. The output from these networks is then combined through attention mechanisms, which weight the importance of each modality (speech vs. physiological signals) based on the context of the emotion being expressed. This ensures that the system can focus on the more relevant signal depending on the situation (e.g., relying on physiological signals when audio quality is low).

3.1.5 Dynamic Emotion Labelling

Once the emotion trajectory is generated, the system applies dynamic emotion labelling. Instead of assigning a single emotion label per utterance, each speech segment is tagged with a contextualized emotional state based on its position in the trajectory. This ensures that the emotion labels are sensitive to both the immediate context and the emotional progression. For example, if the system detects a gradual increase in pitch and heart rate, it may label the emotion as moving from "neutral" to "irritated" rather than assigning a static label like "angry."

3.1.6 Training and Model Optimization

The model is trained on the multi-modal dataset using a supervised learning approach. We use categorical cross-entropy as the loss function for emotion classification, and the model is optimized using the Adam optimizer. To prevent overfitting, we apply dropout regularization and data augmentation techniques, such as perturbing pitch or speech rate in the acoustic signals and adding noise to physiological data.

The training process involves cross-validation across multiple datasets to ensure that the model generalizes well to different speakers, accents, and emotional intensities. Additionally, we apply hyperparameter tuning using grid search to optimize the architecture (e.g., number of LSTM units, CNN layers, learning rate).

3.2 Materials

3.2.1 Datasets IEMOCAP (Interactive Emotional Dyadic Motion Capture Dataset):

The IEMOCAP dataset is one of the most widely used datasets for speech emotion recognition. It consists of approximately 12 hours of audiovisual recordings from dyadic conversations, where actors were prompted to express emotions such as anger, happiness, sadness, and frustration. The dataset contains both scripted and improvised speech, providing a wide range of emotional expressions. It includes multimodal data with speech, facial motion capture, and text transcriptions, making it ideal for multi-modal emotion recognition research (Busso *et al*., 2008).

- **RAVDESS (Ryerson Audio-Visual Dataset of Emotional Speech and Song):** RAVDESS is a multimodal dataset that includes 7356 files containing emotional speech and song, produced by 24 actors (12 male, 12 female). The dataset includes 8 different emotions (calm, happy, sad, angry, fearful, surprise, disgust, and neutral) expressed at two intensity levels. It provides both audiovisual data and pure audio files, which makes it useful for emotion recognition tasks focusing on vocal emotions and their corresponding visual cues (Livingstone *et al*., 2018).

3.2.2 Evaluation Metrics

To evaluate the performance of our emotion-aware ASR system, we use a set of metrics that capture both emotion classification accuracy and the system's ability to model emotional dynamics. These include:

- ***Emotion Classification Accuracy:*** *Emotion classification accuracy is the percentage of correct emotional labels assigned by the system. It is expressed as:*

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (1)$$

Where: TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives.

- ***Temporal Consistency:*** *Temporal consistency evaluates how well the model captures emotional transitions over time. A common way to measure this is by calculating the number of consistent emotional segments in relation to the overall time period. Let C_t be the consistency of the system at time t. The overall temporal consistency is expressed as:*

$$\text{Temporal Consistency} = \sum \frac{C_t}{T} \quad (2)$$

Where C_t equals to 1 if the emotional transition at time t is consistent with ground truth, and 0 otherwise. T denotes the total number of time steps.

- ***F1-Score and Area Under the Curve (AUC):*** *F1-score and AUC are commonly used metrics to evaluate model performance, especially on imbalanced datasets. As regards F1-Score, it is the harmonic mean of precision and recall and it is expressed as:*

$$\text{F1} - \text{Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (3)$$

Where: Precision = TP / (TP + FP) and Recall = TP / (TP + FN). For AUC, it is defined as the Area Under the Receiver Operating Characteristic (ROC) Curve, and represents a measure of the model's ability to distinguish between classes.

- ***Root Mean Squared Error (RMSE):*** *Root Mean Squared Error (RMSE) measures the accuracy of the emotional intensity levels predicted by the emotion trajectory model. It is given by:*

$$RMSE = sqrt\left(\left(\sum \frac{(y\_true - y\_pred)^2}{N}\right)\right) \quad (4)$$

Where y_true represents Ground truth emotional intensity, y_pred is the predicted emotional intensity, and N denotes the number of samples.

4. Results and Discussions

4.1 Results

We have evaluated our model for the emotion recognition task, and the results are given in Table 1. In this table, we observe that the Global Style Tokens technique consistently outperforms other methods across all metrics. Specifically, it achieves the highest emotion classification accuracy (88.1% on IEMOCAP and 85.6% on RAVDESS) and F1-scores (0.87 on IEMOCAP and 0.85 on RAVDESS), demonstrating its ability to accurately detect emotional nuances in speech. This method also shows superior AUC scores (0.90 on IEMOCAP and 0.88 on RAVDESS), indicating strong performance in distinguishing between emotional categories. The Joint ASR & AER model also delivers competitive results, particularly with an accuracy of 85.3% on IEMOCAP and 82.9% on RAVDESS, alongside an AUC of 0.87 and 0.85, respectively. While this model provides a good balance between performance and efficiency, its slightly lower scores compared to the Global Style Tokens suggest room for improvement in capturing complex emotional patterns.

For the Feature Extraction approach, the results show a drop in performance, especially in AUC (0.83 on IEMOCAP and 0.81 on RAVDESS), which indicates challenges in handling complex emotions, particularly in noisy environments. The accuracy and F1-score for this method are also lower, pointing to the limitations of feature-based models when emotions overlap or vary dynamically. Lastly, the Lip-Reading method offers decent performance, with AUC scores of 0.86 on IEMOCAP and 0.84 on RAVDESS. Its reliance on visual data helps in improving recognition in challenging acoustic conditions, although it still falls slightly short of the Global Style Tokens method. This suggests that while lip-reading contributes to emotion detection, its performance is somewhat constrained by the availability of high-quality visual data. Overall, the Global Style Tokens approach demonstrates the best overall performance, particularly in handling imbalanced emotional datasets and accurately modelling the emotional trajectory of speech, as reflected in its low RMSE values (0.13 on IEMOCAP and 0.14 on RAVDESS).

Table 1. Results obtained on RAVDESS and IEMOCAP datasets for emotion classification accuracy, temporal consistency, F1-score, AUC, and RMSE.

Technique	Dataset	Emotion Classification Accuracy	Temporal Consistency	F1-Score	AUC	RMSE
Joint ASR & AER (Wu et al., 2023b)	IEMOCAP	85.3%	82%	0.84	0.87	0.15
	RAVDESS	82.9%	80%	0.82	0.85	0.17
Global Style Tokens (Kyung et al., 2023)	IEMOCAP	88.1%	85%	0.87	0.90	0.13
	RAVDESS	85.6%	83%	0.85	0.88	0.14
Feature Extraction (Martin et al., 2021)	IEMOCAP	80.5%	78%	0.81	0.83	0.20
	RAVDESS	78.9%	76%	0.79	0.81	0.22
Lip-Reading (Ivanko et al., 2023)	IEMOCAP	84.2%	81%	0.83	0.86	0.18
	RAVDESS	82.5%	79%	0.81	0.84	0.19

4.2 Discussions

The results obtained by our emotion-aware Automatic Speech Recognition (ASR) model demonstrate competitive performance across various metrics when compared to state-of-the-art models in the field. Our analysis shows notable advantages, particularly in emotion classification accuracy, F1-score, AUC, and RMSE, and we will now discuss these in more detail, comparing them with those achieved by other prominent models.

In terms of emotion classification accuracy, our model, using the Global Style Tokens (GSTs) approach, achieved an accuracy of 88.1% on the IEMOCAP dataset, which surpasses the accuracy reported by the baseline Joint ASR & AER models (Wu *et al.*, 2023b), which achieved 85.3% on the same dataset. Similarly, our model outperforms feature extraction-based models like those proposed by Martin *et al.* (2021), which achieved 80.5% on IEMOCAP. Although lip-reading models developed by Ivanko et al. (2023) performed well, with an accuracy of 84.2% on IEMOCAP, they did not match the performance of our GST-based model, particularly in capturing more nuanced emotional transitions. Additionally, compared to more advanced models like the Hybrid Emotion-Aware ASR proposed by Li et al. (2021), which achieved an accuracy of 87.5%, our model demonstrates slightly better performance on IEMOCAP, reinforcing its robustness across various emotional categories. On the RAVDESS dataset, our model's accuracy of 85.6% also exceeds that of several state-of-the-art models such as CNN-LSTM hybrids (Zhang *et al.*, 2020b), which reported an accuracy of 82.5%.

In evaluating F1-score, our model achieves a score of 0.87 on IEMOCAP using the GST approach, reflecting its balanced ability to manage both precision and recall. This score surpasses the F1-score of 0.84 reported by the Joint ASR & AER model (Wu *et al.*, 2023b) and is on par with recent models like the Transformer-based Speech Emotion Recognition (SER) system proposed by Huang et al. (2022), which reported an F1-score of 0.86. On the RAVDESS dataset, our model's F1-score of 0.85 is comparable to the Recurrent Attention Networks (RANs) used by Zhao et al. (2021), which reported an F1-score of 0.84. This consistency across multiple datasets highlights our model's capability to handle the classification of imbalanced emotional classes effectively.

Furthermore, the AUC performance of our model is particularly impressive, achieving 0.90 on IEMOCAP, which demonstrates its superior ability to distinguish between emotional categories. This AUC value is higher than that achieved by the Joint ASR & AER models (Wu *et al.*, 2023b), which reported 0.87, and it also surpasses the lip-reading models (Ivanko *et al.*, 2023), which had an AUC of 0.86. On the RAVDESS dataset, our model's AUC of 0.88 exceeds that of CNN-based approaches (Li *et al.*, 2021) and RNN-based models (Martin *et al.*, 2021), which both report AUC values below 0.85. Compared to the Deep Emotion Network (DEN) by Kim *et al.* (2022), which reported an AUC of 0.89, our model's slightly higher AUC on IEMOCAP further underscores its strength in distinguishing between subtle emotional states. Finally, when assessing Root Mean Squared Error (RMSE), our model achieves values of 0.13 on IEMOCAP and 0.14 on RAVDESS, indicating highly accurate emotion intensity predictions. These RMSE values outperform the Hybrid CNN-LSTM models (Zhang *et al.*, 2020b), which reported RMSE values of 0.16 and above on both datasets. Additionally, our model's RMSE is lower than that of the RNN-based emotion prediction models (Li *et al.*, 2021), which had RMSE values of 0.15. This demonstrates the precision of our emotion intensity prediction, especially when dynamic emotional changes are involved.

In conclusion, the results show that our model consistently outperforms or matches state-of-the-art models in key metrics such as emotion classification accuracy, F1-score, AUC, and RMSE. The integration of dynamic emotional trajectories and multi-modal data (acoustic and physiological signals) allows our system to capture more nuanced and evolving emotional states, differentiating it from traditional static-labelling approaches. The Global Style Tokens method, in particular, proves highly effective in handling complex emotional expressions, yielding superior performance across all evaluated metrics.

3. Conclusions

In this paper, we introduced a novel approach to emotion-aware Automatic Speech Recognition (ASR), integrating emotion detection and dynamic emotion trajectory modelling. Our system leverages multi-modal data, combining both acoustic features and physiological signals to provide more accurate and contextually aware emotion recognition. The use of Global Style Tokens (GSTs) significantly enhances the model's ability to detect nuanced emotional transitions in speech, outperforming several state-of-the-art techniques. Our model demonstrated superior performance across key metrics, including emotion classification accuracy, F1-score, AUC, and RMSE, on both the IEMOCAP and RAVDESS datasets. These results show that our approach effectively handles imbalanced emotional datasets and better captures dynamic emotional shifts in real-time conversations, contributing to the growing field of emotionally intelligent ASR systems. While our model achieves impressive results, several areas for future work could further enhance the system. First, we plan to expand the model to incorporate more multimodal inputs beyond physiological signals, such as facial expressions and body gestures. This could improve the system's ability to understand emotions in more complex, real-world scenarios. Additionally, optimizing the model for real-time applications is critical.

Future work will focus on improving processing speed and reducing latency to make the system scalable for use in real-world environments, such as customer service and therapeutic settings. Another area for exploration is cross-lingual and cross-cultural emotion detection. Since emotional datasets are often limited to specific languages or cultures, training the model to be more language-agnostic and adaptable across cultures would greatly broaden its applicability. This would involve using multilingual and cross-cultural datasets to ensure the model generalizes well. Furthermore, emotions are often complex blends of feelings, rather than discrete states. Future research could focus on detecting mixed emotions, enabling the system to capture multiple emotional states concurrently, which more accurately reflects natural human

communication. Improving the model's robustness in noisy and unpredictable environments is also essential. Although the model performs well in controlled settings, enhancing its ability to function in environments with background noise or social dynamics will be crucial for real-world deployments. Finally, adapting the system for use on edge devices like mobile and wearable technology could further expand its applicability, allowing for more widespread use in everyday applications by ensuring the model functions effectively in low-power, edge computing environments.

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