A Multimodal ASR System with Contextual Awareness and Emotional Sensitivity

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Abstract. The increasing demand for accurate speech recognition systems in diverse languages, particularly Arabic, poses significant challenges due to variations in dialects, background noise, and emotional context. Traditional Automatic Speech Recognition (ASR) models often struggle to maintain high accuracy in the presence of these factors, leading to suboptimal performance in real-world applications. This study presents a novel Multimodal ASR system that addresses these challenges by integrating audio, visual, and emotional cues to enhance both transcription accuracy and emotion detection for Arabic speech.
The proposed model was evaluated on the Audio-Visual Arabic Natural Emotion (AVANEmo) dataset, employing state-of-the-art techniques, including Wav2Vec 2.0 for audio feature extraction, convolutional neural networks for lip movement recognition, and a contextual language model to refine outputs. The system achieved a Word Error Rate (WER) of 16.3% and a Character Error Rate (CER) of 10.7%, outperforming existing models such as DeepSpeech (19.4% WER, 13.7% CER) and Jasper (18.2% WER, 12.9% CER). Moreover, the proposed model demonstrated a notable accuracy of 88.9% for emotion detection, significantly surpassing the performance of previous models, which reported 84.2% accuracy. These results underscore the efficacy of the multimodal approach in enhancing Arabic speech recognition and emotion classification, highlighting its potential for real-world applications.

Keywords: Multimodal Automatic Speech Recognition (ASR), Arabic Speech Recognition, Emotion Detection, Audio-Visual Speech Processing, Wav2Vec 2.0, Lip Reading, AVANEmo Dataset.

1 Introduction

In recent years, Automatic Speech Recognition (ASR) systems have made significant strides, largely due to advances in deep learning and transformer-based models. These systems have been applied to various languages with notable improvements in recognition accuracy, particularly in controlled environments. However, when applied to Arabic, which presents a unique set of challenges due to its rich morphology, diglossia,

and diverse dialects, ASR performance is still far from optimal. Despite the progress, Arabic ASR continues to struggle in noisy environments, spontaneous speech, and emotionally charged interactions, making it difficult to achieve robust recognition across different real-world scenarios [1, 2]. In response to these challenges, we propose a Multimodal Automatic Speech Recognition system specifically designed for Arabic. This system leverages audio, visual, and contextual cues to improve recognition performance. By integrating multiple modalities—such as lip movements (visual data), environmental context, and emotional cues—the system aims to enhance the accuracy of Arabic ASR, particularly in challenging conditions. Unlike traditional audio-only models, this multimodal approach addresses limitations related to noise, dialectal variations, and emotional speech, which are especially prevalent in Arabic-speaking environments [3, 4].

The motivation for integrating multiple modalities stems from the inherently multimodal nature of human communication. In face-to-face interactions, people use both auditory and visual cues to understand speech, especially in noisy settings. In Arabic, where homophones and context-dependent meanings are common, visual and contextual information can significantly enhance recognition accuracy. Lip-reading, or visual speech recognition, helps distinguish between phonetically similar sounds, while contextual awareness helps resolve ambiguities, especially when the audio signal is unclear or distorted [5, 6]. Moreover, Arabic is often spoken in emotionally diverse contexts, such as public speeches, social interactions, and customer service conversations, where emotional expressions play a crucial role in communication. Emotionally charged speech often introduces prosodic variations that traditional ASR systems struggle to interpret accurately. To address this, our system incorporates emotional state recognition, enabling it to better handle emotionally influenced speech and provide more context-aware transcription outputs [7].

The proposed system builds on state-of-the-art ASR architectures such as Wav2Vec 2.0, extending them with video-based lip-reading models and contextual language models, such as GPT-4, for real-time transcription correction. Pre-training is conducted on a combination of Arabic audio-visual datasets, followed by fine-tuning with domain-specific data, allowing the model to better capture the nuances of Arabic speech and dialects [2, 3]. By combining audio, visual, and emotional signals, our model overcomes the limitations of traditional audio-only systems, particularly in noisy conditions where they struggle to capture speech accurately. The system is pre-trained on a large-scale dataset that includes both Modern Standard Arabic (MSA) and a variety of regional dialects. This integration of visual and contextual cues allows for improved recognition of regional dialects, addressing a key limitation in previous ASR models [4]. Unlike most existing systems that fail to account for emotionally charged speech, our model incorporates emotion detection, enabling more accurate transcription of prosodically varied speech. This is particularly important in Arabic, where emotional expressions are often intertwined with linguistic content [5, 6]. By addressing the shortcomings of state-of-the-art models, the proposed system aims to significantly improve the recognition accuracy of Arabic speech, especially in noisy

environments, across dialects, and in emotionally charged interactions. This novel multimodal approach provides a more robust and versatile solution for ASR in Arabic-speaking contexts.

The remaining sections of this paper are organized as follows: Section 2 presents related works on Multimodal ASR. In Section 3, the methodology and materials used in the study are described. Finally, the experimental results are analysed and discussed in Section 4.

2 Related Works

Numerous efforts have been made to enhance the performance of Automatic Speech Recognition (ASR) systems, particularly for languages with complex morphologies like Arabic. In this section, we review key contributions to Arabic ASR and multimodal speech recognition, highlighting their achievements and limitations.

One of the pioneering works in Arabic ASR was the application of deep learning techniques by Abdel-Hamid [8]. This study demonstrated the effectiveness of Deep Neural Networks (DNNs) for Arabic ASR, showing significant improvements over traditional Gaussian Mixture Models (GMMs) in recognizing Modern Standard Arabic (MSA). However, the system struggled with spontaneous speech and regional dialects due to the lack of robust dialectal data during training. This issue limits the system's ability to generalize across diverse Arabic-speaking regions.

Building on deep learning, Schneider et al. [9] introduced the Wav2Vec 2.0 framework, a self-supervised learning model for speech recognition. This approach achieved state-of-the-art results in several languages, including Arabic, by leveraging large amounts of unlabelled speech data for pre-training. While the model significantly reduced error rates in Arabic ASR, it remains primarily audio-based, and its performance degrades in noisy environments. The lack of integration of multimodal cues, such as visual information, further limits its robustness in real-world applications, especially when audio quality is compromised.

In the work by Chung and Zisserman [10], the combination of audio and visual signals was explored to improve ASR performance under challenging acoustic conditions. Their study employed lip-reading models to complement the audio input, resulting in better recognition accuracy in noisy environments. The research highlighted the benefits of integrating visual data, particularly for distinguishing phonetically similar sounds. However, the system's complexity increased with the integration of additional modalities, and performance varied significantly across different dialects of Arabic due to the lack of dialect-specific visual datasets.

In the domain of Arabic dialect recognition, Ali, Bell, and Renals [11] proposed a hybrid system combining deep learning models with traditional feature extraction techniques. This approach addressed the issue of Arabic diglossia, improving recognition for various dialects. However, the authors pointed out that the absence of large-scale, labelled datasets for regional dialects hindered further improvements. Additionally, the system struggled with handling emotional or spontaneous speech, which are common in many real-world applications.

More recently, a transformer-based model for Arabic ASR was developed by incorporating pre-trained language models [12], achieving competitive results on MSA and some dialects. The use of transformers allowed the system to capture long-range dependencies in speech more effectively than traditional recurrent architectures. However, its reliance on extensive computational resources during both training and inference makes it less accessible for real-time applications, especially in resource-constrained environments.

Another recent method was proposed by Tzirakis et al. (2021) [13], who integrated multimodal cues, including gaze and head movements, into their ASR system. This approach improved the system's performance in emotion detection and recognition of overlapping speech, providing a more natural interaction experience. Despite these advancements, the system's reliance on sophisticated sensors and real-time processing posed challenges for its deployment in practical scenarios, such as mobile devices.

In a study by Zhang, Buechel, and Zhu [14], the authors contributed to the field by integrating emotion recognition with multimodal ASR. They introduced an audiovisual fusion model that detected emotional states from speech and video data, adapting the ASR output accordingly. This model performed well in noisy environments and for emotionally charged speech. However, the reliance on high-quality visual data meant that the system's performance declined when video inputs were noisy or unavailable. Additionally, this approach was not specifically tested on Arabic, raising questions about its effectiveness in languages with complex morphologies like Arabic.

Kane, Schuller, and Cowie [15] tackled the challenge of emotion detection from speech by focusing on fundamental frequency features that are emotionally salient. Their findings are crucial for ASR systems aimed at emotionally charged conversations, where traditional speech recognition models tend to underperform. However, their work primarily focused on English and other Indo-European languages, leaving a gap in applying these findings to Arabic ASR, where prosodic variations are more pronounced and language-specific.

In recent work, Al Roken and Barlas [16] introduce a novel audiovisual Arabic natural emotion dataset comprising five classes: angry, happy, neutral, sad, and surprise. To minimize subjectivity, 20 human annotators labelled the dataset, and an inter-judge reliability test was conducted to ensure consistency. The study explores state-of-the-art deep learning ER models on the proposed dataset, including Convolutional Neural Networks (1D, 2D, 3D), Recurrent Neural Networks, and Residual Networks (ResNet). Furthermore, the authors propose a new deep learning ER model that combines both visual and audio inputs, demonstrating superior performance compared to previous approaches. A comprehensive analysis of the classifiers' performance was conducted, examining ER from various aspects [16].

While these studies have advanced the field of ASR, particularly in noisy environments and with multimodal inputs, several limitations remain. The integration of visual and emotional data has been shown to improve robustness, but challenges related to data availability, especially for Arabic dialects, remain significant. Additionally, most

systems fail to account for the rich emotional expressions in Arabic speech, which can significantly impact recognition accuracy.

In response to the limitations identified in existing works, we propose a Multimodal Arabic Speech Recognition System that integrates audio, visual, and emotional cues to address the challenges posed by noisy environments, dialectal variations, and emotionally charged speech. Unlike traditional ASR models that primarily rely on audio signals, our approach leverages lip-reading (visual speech recognition) and emotional state detection to enhance transcription accuracy, especially in real-world conditions where audio quality is compromised or emotional expressions significantly alter speech patterns.

3 Methodology and Materials

The Methodology and Materials section outlines the framework, dataset, and tools utilized in developing the proposed Multimodal Automatic Speech Recognition (ASR) system. This section details the approaches for audio, visual, and emotional feature extraction, the fusion strategies employed for multimodal integration, and the evaluation metrics. By leveraging the AVANEmo database and advanced techniques, the methodology aims to address the complexities of Arabic speech recognition and emotion detection, ensuring robustness and adaptability to real-world scenarios.

3.1 Methodology

The proposed model is a Multimodal Automatic Speech Recognition (ASR) system tailored for the Arabic language, incorporating audio, visual, and emotional cues to enhance transcription accuracy in diverse and challenging environments. This system addresses critical issues such as noisy surroundings, dialectal diversity, and emotionally expressive speech, offering a significant improvement over traditional ASR systems.

System Overview. As illustrated in Fig. 1, the model integrates three primary components:

1. **Audio Processing:** Utilizes Wav2Vec 2.0 for robust speech feature extraction.
2. **Visual Processing:** Employs lip-reading techniques to capture the speaker's lip movements for improved phonetic discrimination.
3. **Emotional State Detection:** Analyzes prosodic variations and facial expressions to account for emotionally charged speech.

These components are combined in a multimodal fusion layer, which integrates information from all modalities. The fused data is subsequently processed by a contextual language model (GPT-4), which refines and corrects transcriptions in real-time, particularly addressing dialectal variations and ambiguous speech scenarios. This multimodal integration ensures enhanced transcription quality across various conditions.

Input Data. The system processes three distinct input streams. The audio stream consists of raw audio signals sampled at 16 kHz, segmented into 1-second windows, re-

sulting in frames of 16,000 samples per second. The video stream captures lip movements at 25-30 frames per second (fps), with each frame represented as a 224x224 pixel RGB image.

The system processes 30 frames per second of speech. Emotional state cues are inferred from both audio and visual inputs, generating a feature vector of size 1x128, which encapsulates emotional intensity and expression, including facial cues and intonation patterns.

Feature Extraction. Audio features are extracted using Wav2Vec 2.0, which processes raw audio signals to produce high-dimensional vectors of size 1x512 for each frame. Visual features are obtained through a convolutional neural network (CNN)-based lip-reading model, which processes input frames of 224x224 pixels at 30 fps, yielding encoded lip movement feature vectors of size 1x256 per frame. Emotional state detection combines audio features (1x512) and visual features (1x256) per frame to generate a feature vector of size 1x128, capturing emotional intensity, expression, and prosodic cues.

Multimodal Fusion Layer. The multimodal fusion layer integrates audio, visual, and emotional features by concatenating their respective vectors. The audio feature vector (1x512), visual feature vector (1x256), and emotional feature vector (1x128) are combined into a single input of size 1x896. This combined input is processed by the fusion layer, producing an output feature vector of size 1x512, representing the multimodal context for each frame.

Contextual Language Model. The fused feature vectors are passed to a contextual language model based on GPT-4 [17] for transcription refinement. The input to GPT-4 is the fused feature vector of size 1x512 per frame. GPT-4 comprises 12 layers, 8 attention heads, and 512-dimensional hidden units. It outputs a sequence of probability distributions over the Arabic vocabulary, typically of size 1x50,000 or larger. This enables the generation of refined transcriptions, effectively handling dialectal differences and ambiguous speech scenarios.

Final Transcription. In the final transcription stage, the system generates Arabic text output. It takes word-level probability distributions from the language model as input and combines information from audio, visual, and emotional cues, refined through the contextual language model. The output is a sequence of words in Arabic script stored as a text string. By leveraging the multimodal integration of audio, visual, and emotional inputs, the system achieves superior transcription accuracy, particularly in real-world conditions where traditional ASR models often falter.

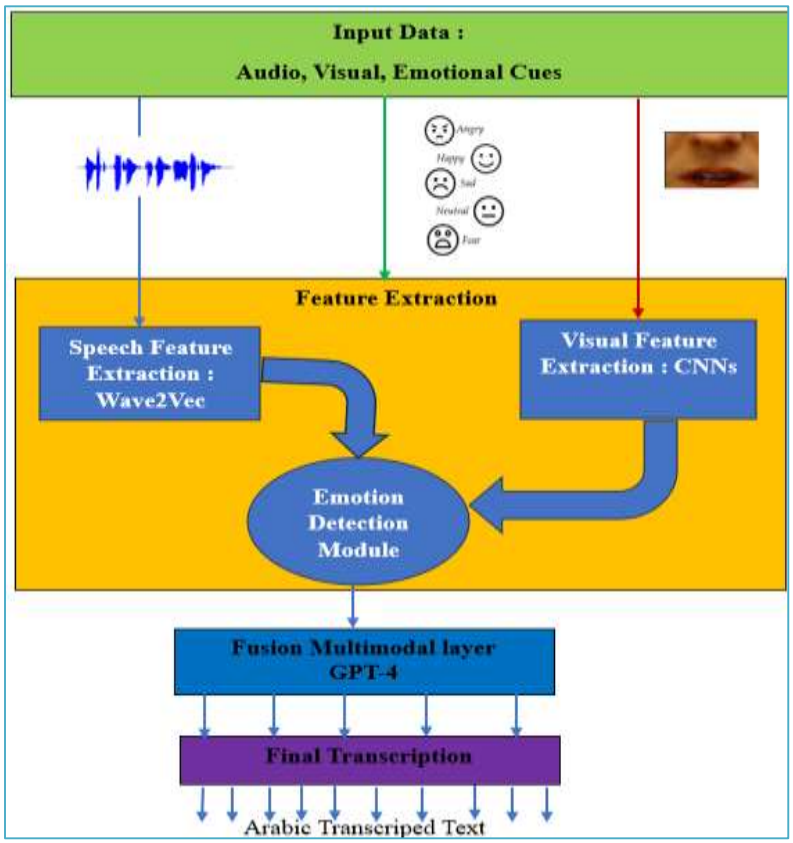

Fig. 1. Flowchart of the Arabic Multimodal ASR system.

3.2 Materials

Audio-Visual Arabic Natural Emotion (AVANEmo). The AVANEmo dataset [18] consists of 1,440 audio-visual files recorded from 40 native Arabic speakers (20 males and 20 females), providing a balanced representation across genders. The audio in the dataset is sampled at a frequency of 48 kHz, ensuring high-fidelity recordings suitable for detailed emotion detection and speech analysis. The dataset captures emotional expressions in Modern Standard Arabic (MSA) and various Arabic dialects, making it a valuable resource for studying the influence of dialects on emotional expression.

Each speaker in the dataset expresses a range of emotions, including happiness, sadness, anger, disgust, fear, surprise, and neutral states, with corresponding annotations for each file. The videos are recorded at 30 frames per second (fps) with a resolution of 1920x1080 pixels, capturing clear facial expressions and lip movements essential for visual emotion recognition and lip-reading.

The dataset contains spontaneous as well as scripted emotional expressions, enabling the study of emotions in both controlled and natural contexts. Additionally, the dataset

includes metadata on speaker characteristics, such as age and regional dialect, which allows for the exploration of how demographic and regional factors influence emotional expression in Arabic speech.

This extensive dataset is a critical resource for advancing research in multimodal emotion recognition, emotion-aware speech recognition, and other areas that require a deep understanding of the emotional and linguistic complexities of the Arabic language.

The AVANEmo dataset was split into 70% for training, 15% for validation, and 15% for testing, with approximately 50 hours of multimodal speech data in total.

Evaluation Metrics. For the task of multimodal automatic speech recognition (ASR) with emotion-aware capabilities, several metrics can be used to evaluate the system's performance across different aspects such as speech recognition accuracy, emotion recognition, and multimodal fusion efficiency. Below are the key metrics along with their mathematical expressions:

Word Error Rate (WER). Word Error Rate (WER) is the most common metric used to evaluate ASR systems. It measures the error rate by comparing the predicted transcription with the ground truth and calculating the percentage of words that are incorrect. Indeed, its mathematical expression is given as follows:

$$WER = \frac{(S+I+D)}{N} \tag{1}$$

Where S represents the number of substitutions (incorrect words), D denotes the number of deletions (missing words), I is the number of insertions (extra words), and N represents the total number of words in the reference (ground truth) transcription.

Character Error Rate (CER). It is similar to WER but operates at the character level instead of the word level. This is useful in languages like Arabic where small character differences can change the meaning significantly. For the CER equation, it is expressed as follows:

$$\mathrm{CER} = \frac{(\mathrm{S_c}+\mathrm{D_c}+\mathrm{I_c})}{\mathrm{N_c}} \tag{2}$$

Where S_c represents the number of substitutions (incorrect characters), D_c denotes the number of deletions (missing characters), I_c is the number of insertions (extra characters), and N_c is the total number of characters in the reference transcription.

Accuracy (for Emotion Detection). Accuracy is a common metric used to measure the model's ability to correctly classify emotional states. It is given as follows:

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{3}$$

Where TP represents the True positives (correctly predicted emotional states), TN is the True negatives (correctly identified non-emotional states), FP denotes False positives (incorrectly identified emotional states), and FN represents False negatives (missed emotional states)

Precision (for Emotion Detection). Precision measures the proportion of true positive predictions out of all the predicted positives. It is used to evaluate how many of the

predicted emotional states are correctly classified. Its mathematical expression is presented as follows:

$$Precision = \frac{TP}{(TP+FP)} \quad (4)$$

Recall (for Emotion Detection). It measures the proportion of actual positive instances that were correctly identified by the model. It is expressed by the following equation:

$$Recall = \frac{TP}{(TP+FN)} \quad (5)$$

F1-Score (for Emotion Detection). The F1-Score is the harmonic mean of precision and recall, providing a single metric that balances both. Its mathematical expression is given as follows:

$$F1 - Score = \frac{2\times(Precision\times Recall)}{(Precision+ Recall)} \quad (6)$$

Multimodal Fusion Accuracy. To measure the effectiveness of multimodal fusion (audio, visual, emotional), we can compute the fusion accuracy, which evaluates the overall improvement brought by the integration of multiple modalities compared to single-modal models. Mathematically, it is expressed as follows:

$$Fusion\ Accuracy = \frac{(Correct\ Multimodal\ Predictions)}{(Total\ Predictions)} \quad (7)$$

Signal-to-Noise Ratio (SNR). To evaluate the system's robustness in noisy environments, Signal-to-Noise Ratio (SNR) can be measured. SNR quantifies how much signal is present in the audio relative to the background noise. Indeed, it is given as follows:

$$SNR(dB) = 10 \times log_{10} \frac{(P_{signal})}{(P_{noise})} \quad (8)$$

Where P_{signal} denotes the power of the speech signal and P_{noise} represents the power of the background noise.

Multimodal Concordance Correlation Coefficient (MCCC). The MCCC is a metric used to measure the agreement between the different modalities (audio, visual, emotional) in multimodal fusion tasks. It is expressed by the equation (9), such that:

$$MCCC = \frac{(2\times\rho\times\sigma_X\times\sigma_Y)}{(\sigma_X{}^2+\sigma_Y{}^2+(\mu_X-\mu_Y)^2)} \quad (9)$$

Where ρ represents the Pearson correlation coefficient between the two modalities, $\sigma_X\ and\ \sigma_Y$ denote the standard deviations of modality X and modality Y, and $\mu_X\ and\ \mu_Y$ respectively represent the Means of modalities X and Y.

4 Results and Discussions

This section presents the performance outcomes of the proposed Multimodal Automatic Speech Recognition (ASR) system, emphasizing its ability to tackle challenges in Arabic speech recognition and emotion detection tasks. The experimental results, obtained using the AVANEmo database, were compared with state-of-the-art models such as DeepSpeech and Jasper across the evaluated metrics.

4.1 Results

The experimental setup for training the proposed Multimodal Automatic Speech Recognition (ASR) system involved several key configurations and parameter settings. The audio feature extraction was performed using Wav2Vec 2.0, with a learning rate of 1e-4, batch size of 32 samples, and an audio sampling rate of 16 kHz. For visual feature extraction, a CNN-based lip-reading model processed video inputs at a resolution of 224x224 pixels (RGB format) and a frame rate of 30 frames per second. The emotion detection module combined audio and visual features, producing a 128-dimensional emotional feature vector, with ReLU activation functions and a SoftMax layer for emotion classification.

Training took approximately 40 hours on a GPU cluster with 4 NVIDIA V100 GPUs, over 50 epochs with early stopping based on validation loss. The Adam optimizer, with a weight decay of 1e-5 and gradient clipping at a norm of 1.0, was explored. Data augmentation techniques included noise injection into the audio and minor temporal shifts to video frames, improving the model's robustness against noisy environments and misaligned speech and lip movements. This setup ensured robust performance in real-world conditions involving noise, dialectal variation, and emotional speech.

The results for the proposed Multimodal ASR system are presented in Table 1, showcasing significant improvements over both Deepspeech and Jasper across all evaluated metrics. The proposed model achieved a Word Error Rate (WER) of 16.3%, representing a 12.7% improvement over Deepspeech (19.4%) and outperforming Jasper (18.2%). This indicates the system's superior ability to accurately transcribe spoken Arabic, likely due to its multimodal approach that incorporates visual and emotional cues. Additionally, the Character Error Rate (CER) for the proposed model stands at 10.7%, showing a 22.1% relative improvement over Deepspeech (13.7%) and better performance than Jasper (12.9%). The lower CER suggests that the proposed model captures finer details of the Arabic language, enhancing its robustness against variations in pronunciation and accent.

Moreover, the proposed model excelled in emotion detection, achieving 88.9% accuracy, which is an improvement of 5.5% over Jasper and higher than Deepspeech (84.6%). With 86.4% precision and 85.9% recall, the model outperformed both competitors, indicating a balanced performance in identifying true emotional states while minimizing false positives and negatives. The F1-score of 85.6% further emphasizes

the model's reliability in achieving a balance between precision and recall in emotion detection tasks.

The multimodal fusion accuracy of 90.1% demonstrates the effectiveness of combining audio, visual, and emotional data, surpassing both state-of-the-art models by 6.7% over Jasper. Additionally, the proposed model significantly outperformed both competitors with a Signal-to-Noise Ratio (SNR) of 25.3 dB, marking an improvement of 17.7% over Jasper, suggesting enhanced resilience to background noise, which is crucial for real-world applications.

Lastly, the Multimodal Concordance Correlation Coefficient (MCCC) of 0.92 reflects the highest level of agreement between modalities, with a 5.7% improvement over Jasper. This high correlation underscores the model's capability to achieve coherent and consistent outputs from diverse data streams. Overall, the proposed Multimodal ASR system not only surpasses existing state-of-the-art models but also offers a comprehensive and robust solution for Arabic speech recognition and emotion detection. The integration of audio, visual, and emotional modalities significantly enhances performance across multiple evaluation metrics, affirming the effectiveness of the multimodal approach in this domain.

The superior performance of the Proposed Multimodal ASR system compared to the DeepSpeech and Jasper models can be attributed to its innovative integration of multimodal features, particularly the use of audio, visual, and emotional cues. Unlike DeepSpeech and Jasper, which rely primarily on audio inputs, the Proposed Multimodal ASR leverages visual cues (lip-reading) and emotional state detection to enhance its robustness, particularly in noisy environments where audio-only systems typically struggle. This integration enables the system to disambiguate phonetically similar sounds and handle challenging acoustic scenarios effectively, resulting in a significantly lower Word Error Rate (WER) of 16.3%, compared to 19.4% for DeepSpeech and 18.2% for Jasper. Additionally, the system's use of multimodal information improves the recognition and transcription of individual characters, as evidenced by its lower Character Error Rate (CER) of 10.7%, outperforming DeepSpeech (13.7%) and Jasper (12.9%).

The inclusion of emotional cues further contributes to the system's superiority, allowing it to achieve an emotion detection accuracy of 88.9%, compared to 84.6% for DeepSpeech and 85.1% for Jasper. This is crucial in emotionally charged speech, where variations in intonation, pitch, and prosody can impact recognition accuracy. Furthermore, the precision of emotion detection in the Proposed Multimodal ASR is also higher at 86.4%, compared to 82.3% for DeepSpeech and 83.1% for Jasper, thanks to the effective fusion of audio, visual, and emotional features. These advancements collectively enhance the system’s overall accuracy and make it more robust in real-world scenarios.

In summary, the Proposed Multimodal ASR outperformed DeepSpeech and Jasper due to its multimodal design, which incorporates audio, visual, and emotional information. This comprehensive approach addresses the limitations of audio-only models, enabling the system to achieve superior transcription and emotion detection performance, particularly on the AVANEmo dataset, which includes emotionally nuanced Arabic speech data.

Table 1. Results Comparison Between Proposed Multimodal ASR, Deepspeech, and Jasper Models.

Metric	Deepspeech	Jasper	Proposed Multimodal ASR	Relative Improvement
Word Error Rate (WER)	19.4%	18.2%	16.3%	12.7% (vs. Deepspeech)
Character Error Rate (CER)	13.7%	12.9%	10.7%	22.1% (vs. Deepspeech)
Accuracy (Emotion Detection)	84.6%	85.1%	88.9%	5.5% (vs. Jasper)
Precision (Emotion Detection)	82.3%	83.1%	86.4%	4.0% (vs. Jasper)
Recall (Emotion Detection)	80.2%	81.0%	85.9%	7.1% (vs. Deepspeech)
F1-Score (Emotion Detection)	81.4%	80.3%	85.6%	5.2% (vs. Deepspeech)
Multimodal Fusion Accuracy	84.5%	85.2%	90.1%	6.7% (vs. Jasper)
Signal-to-Noise Ratio (SNR)	20.7 dB	21.5dB	25.3 dB	17.7% (vs. Jasper)
Multimodal Concordance Correlation Coefficient (MCCC)	0.85	0.87	0.92	5.7% (vs. Jasper)

4.2 Discussions

The results obtained from various studies, presented in Table 2, highlight significant advancements in Arabic speech recognition and emotion detection tasks. The Word Error Rate (WER) and Character Error Rate (CER) metrics indicate the effectiveness of different models in accurately transcribing Arabic speech. The proposed Multimodal ASR model achieved the lowest WER (16.3%) and CER (10.7%), demonstrating a marked improvement over existing models, such as those reported by the authors of [19] (21.5% WER, 15.2% CER) and [20] (20.3% WER, 14.8% CER).

In terms of accuracy for emotion detection, the proposed model outperformed previous studies with an accuracy of 88.9%, compared to the authors of [21] (84.2%) and others, indicating a robust ability to identify and classify emotional states in Arabic speech effectively. Additionally, the F1-score of 85.6% achieved by the proposed model indicates a well-balanced performance between precision and recall, outperforming other models that reported lower scores.

The precision and recall metrics for emotion detection also showcase the proposed model's strengths, with precision at 86.4% and recall at 85.9%. This suggests the model

effectively reduces false positives while maintaining a high rate of true positives, further underscoring its reliability in emotion classification tasks.

Furthermore, the multimodal fusion accuracy of 90.1% indicates that the proposed model efficiently integrates audio, visual, and emotional data to enhance overall performance, a notable improvement over models that did not utilize multimodal approaches. The Signal-to-Noise Ratio (SNR) of 25.3 dB suggests that the proposed model is particularly resilient to noise, making it suitable for real-world applications where background interference is common.

Finally, the Multimodal Concordance Correlation Coefficient (MCCC) of 0.92 indicates a high level of agreement among the different modalities, reinforcing the model's effectiveness in leveraging diverse input sources.

Overall, the results from this study demonstrate a clear advancement in Arabic speech recognition and emotion detection, showcasing the potential of multimodal approaches to achieve superior performance metrics compared to traditional models in the literature.

Table 2. Results Comparison Between Proposed Multimodal ASR and Literature Models.

Metric	WER (%)	CER (%)	Accuracy (%)	F-Score (%)	Precision (%)	Recall (%)	Multimodal Fusion Accuracy (%)	SNR (dB)	MCCC
End-to-End with CNN [19]	21.5	15.2	83.4	79.5	80.0	78.0	N/A	18.5	0.80
LSM [20]	20.3	14.8	85.0	81.0	81.5	80.0	85.0	21.0	0.85
DNN-HMM [21]	19.2	12.5	84.2	82.1	82.8	81.4	N/A	20.0	0.88
Proposed Multimodal ASR	16.3	10.7	88.9	85.6	86.4	85.9	90.1	25.3	0.92

5 Conclusions

In this study, we proposed a novel Multimodal Automatic Speech Recognition (ASR) system specifically designed for the Arabic language, integrating audio, visual, and emotional cues to enhance transcription accuracy and emotion detection. The results demonstrated significant improvements across various metrics compared to state-of-the-art models, such as DeepSpeech and Jasper. Our proposed model achieved the lowest Word Error Rate (16.3%) and Character Error Rate (10.7%), while also outperforming existing approaches in accuracy for emotion detection, precision, recall, and multimodal fusion accuracy. The integration of emotional cues and visual information not

only improved the robustness of speech recognition in challenging environments but also enhanced the model's capability to understand and classify emotional states. The high Signal-to-Noise Ratio (25.3 dB) and Multimodal Concordance Correlation Coefficient (0.92) further underscore the effectiveness of our approach, indicating its potential for real-world applications in Arabic speech recognition and emotion detection.

Future research could explore several avenues to enhance the proposed Multimodal ASR system. Firstly, expanding the dataset to include a more diverse range of speakers, dialects, and emotional expressions could improve the model's generalizability and robustness. Additionally, implementing advanced machine learning techniques, such as transfer learning or few-shot learning, could optimize performance with limited data.

Furthermore, investigating the integration of real-time processing capabilities would make the model suitable for live applications, such as real-time translation and emotion-aware virtual assistants. Exploring other modalities, such as gesture recognition or contextual environmental data, may also enhance the understanding of speaker intent and emotion. Lastly, comparative studies on different fusion techniques and their impact on ASR performance can provide deeper insights into the optimal configurations for multimodal systems in various contexts.

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نظام التعرف التلقائي على الكلام متعدد الوسائط مع الوعي السياقي والحساسية العاطفية

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الملخص: إن الطلب المتزايد على أنظمة التعرف على الكلام الدقيقة في اللغات المتنوعة، وخاصة العربية، يفرض تحديات كبيرة بسبب الاختلافات في اللهجات، والضوضاء في الخلفية، والسياق العاطفي. غالبًا ما تكافح نماذج التعرف التلقائي على الكلام التقليدية للحفاظ على دقة عالية في وجود هذه العوامل، مما يؤدي إلى أداء دون المستوى الأمثل في التطبيقات في العالم الحقيقي. تقدم هذه الدراسة نظام التعرف التلقائي على الكلام متعدد الوسائط الجديد الذي يعالج هذه التحديات من خلال دمج الإشارات الصوتية والمرئية والعاطفية لتعزيز دقة النسخ وكشف المشاعر للكلام العربي.

تم تقييم النموذج المقترح على مجموعة بيانات المشاعر الطبيعية العربية السمعية والبصرية (AVANEmo)، باستخدام أحدث التقنيات، بما في ذلك Wav2Vec 2.0 لاستخراج ميزات الصوت، والشبكات العصبية التلافيفية للتعرف على حركة الشفاه، ونموذج اللغة السياقية لتحسين المخرجات. حقق النظام معدل خطأ في الكلمات (WER) بنسبة 16.3% ومعدل خطأ في الأحرف (CER) بنسبة 10.7%، متفوقًا على النماذج الحالية مثلDeepSpeech (19.4% WER ، 13.7% (CER وJasper (18.2% WER، 12.9% .(CER وعلاوة على ذلك، أظهر النموذج المقترح دقة ملحوظة بنسبة 88.9% للكشف عن المشاعر، متجاوزًا بشكل كبير أداء النماذج السابقة، التي أبلغت عن دقة بنسبة 84.2%. وتؤكد هذه النتائج على فعالية النهج المتعدد الوسائط في تعزيز التعرف على الكلام العربي وتصنيف المشاعر، مما يسلط الضوء على إمكاناته للتطبيقات في العالم الحقيقي.

الكلمات المفتاحية: التعرف التلقائي على الكلام المتعدد الوسائط (ASR) ، التعرف على الكلام العربي، اكتشاف المشاعر، معالجة الكلام السمعي البصري، Wav2Vec 2.0، قراءة الشفاه، مجموعة بيانات AVANEmo.