



International Journal of Science, Architecture, Technology and Environment

Avatar Emotion: Real-Time Emotion Detection and Expression for Sign Language Interpreting Avatars

Dr. Geetha Ramani¹, Abinaya V^{2*}

¹Professor, Department of Information Technology, Anna University (MIT Campus)

²B.Tech, Department of Information Technology, Anna University (MIT Campus)

abinaya1229@gmail.com

*Corresponding author

DOI: <https://doi.org/10.63680/ijstate052582.89>

Abstract

The integration of emotion detection within avatar communication systems has overhauled delivery of emotionally enhanced content, particularly for applications in sign language interpretation. Yet fundamental difficulties persist regarding effective detection of emotion from free-form speech or text and mapping these dynamically into detailed expressions from animated avatars. Within this paper, we introduce a framework based on deep learning that relies on a transformer-based emotion identification model combined with a keypoint projection mechanism in order to connect the two ends. The first step of the system is employing fine-tuned DistilBERT embeddings to recognize emotions from both spoken or transcribed input. These emotion identifiers (e.g., happy, angry, sad) are submitted to a pose decoder that shares the same alignment as avatar facial mesh structures for synchronized emotional expression and gestures. The architecture is also coupled with a progressive transformer to provide efficient and contextually aware generation of avatar animations. The method facilitates real-time emotional fidelity in expressions by the avatar, improving accessibility and engagement for applications such as virtual interpreters, digital assistants, and sign language generation systems. Experimental evaluation proves that the method outperforms current baselines in terms of emotion accuracy and visual expressiveness and can thus be considered an effective approach for emotion-to-avatar mapping.

Keywords: Emotion Recognition, Avatar Animation, Facial Expression Mapping, Transformer Models, Sign Language Translation, Human-Computer Interaction

1. Introduction

Emotion recognition has emerged as a key part of next-generation human-computer interface systems, particularly in applications where visual communication is of utmost importance, like sign language translation, virtual learning, and assistive technology. Unlike conventional translation systems, which rely

on lexical fidelity, they sacrifice the emotional intention of the speaker, producing output that sounds either robotic or flat. The intended project is based on developing a modular and effective system for interpreting emotional signals from natural language input—be it speech or transcribed words—and projecting these signals onto a digital 3D avatar in real time. In the process, the system ensures accurate transmission of both the meaning and emotion of the message, thereby making the content more accessible and emotionally engaging to users, especially the hard-of-hearing and deaf communities.

The architecture integrates a fine-tuned DistilBERT model for emotion classification and uses MediaPipe FaceMesh to extract 468 facial landmarks, which are mapped to facial shape keys in a 3D avatar rendering environment. This enables the avatar to reflect nuanced facial expressions such as smiling, frowning, or showing surprise in synchrony with the detected emotion. As compared to other prior work which either stops short at emotion categorization or utilizes fixed avatar facial expressions, the proposed method features a smooth mapping pipeline with an incremental transformer and keypoint interpolation for animation fluidity. It can process data in real time, scale to large datasets, and be integrated into multimodal sign language platforms. Its deployment in live real-time speech-to-sign translation of government announcements indicates its ability to offer emotionally rich and context-sensible avatar messaging at scale.

2. Related Work

Recent advancements in emotion recognition and its expressive synthesis in virtual avatars have catalyzed efforts in building more immersive and emotionally aware systems. Early methods such as those described by Yin et al. [11] utilized large-scale datasets like FER2013 and RAF-DB to train CNN-based models that achieved high emotion classification accuracy, but lacked temporal coherence needed for avatar animation. To address temporal dependencies, Khorrami et al. [15] employed convolutional neural networks to focus on Action Units (AUs), laying the groundwork for expression-specific mapping onto digital characters.

Further bridging emotion recognition with avatar animation, Benitez-Quiroz et al. [13] proposed a compact expression space derived from real facial movements, facilitating more natural emotion synthesis. Their system helped transition emotion prediction outputs into animation parameters like blend shapes. This was extended by Song et al. [12], who used GANs to generate dynamic emotional facial expressions, providing smoother transitions between emotional states for virtual avatars.

Moreover, models like EmoNet [8] and frameworks from Barros et al. [14] introduced cross-modal learning where audio-visual cues were combined, enhancing emotion classification robustness in challenging environments. This multi-modal integration is crucial for scenarios like public service interpretation or educational accessibility, where emotion nuance enhances understanding.

In terms of avatar rendering itself, Padilha and Carletta [19] revisited the PAD (Pleasure-Arousal-Dominance) emotional model and reinterpreted it within a real-time MPEG-4 compliant avatar. They mapped emotional states onto FAPs (Facial Animation Parameters), which, though effective, remained dependent on hardcoded mappings. More recent works, such as that of Peguda et al. [16], replaced these static maps with learned mappings via recurrent units and attention layers, enabling flexible emotion rendering on avatars over time.

Finally, recent surveys like Ghosh et al. [6] emphasized the integration of lightweight real-time pose estimation frameworks like MediaPipe and OpenPose to track facial keypoints. These facilitate emotion rendering directly from landmark transitions, offering higher fidelity and temporal continuity—key for live avatar-based emotion communication.

3. System Architecture and Design

Emotion mapping architecture to avatars is a scalable and modular framework that enhances human-computer interaction by mapping emotional indicators to real-time 3D facial avatar expressions. This architecture plays a vital role in domains such as sign language interpretation, virtual dialogue systems, and accessibility software. The system integrates text or speech-based emotion detection with a dynamic avatar rendering pipeline, enabling the expressive visual representation of emotional states.

The system comprises five major components: (1) Emotion Input Interface, (2) Emotion Detection Engine, (3) Facial Landmark and Shape Key Mapping Module, (4) Avatar Expression Generator, and (5) Real-Time Rendering and Feedback.

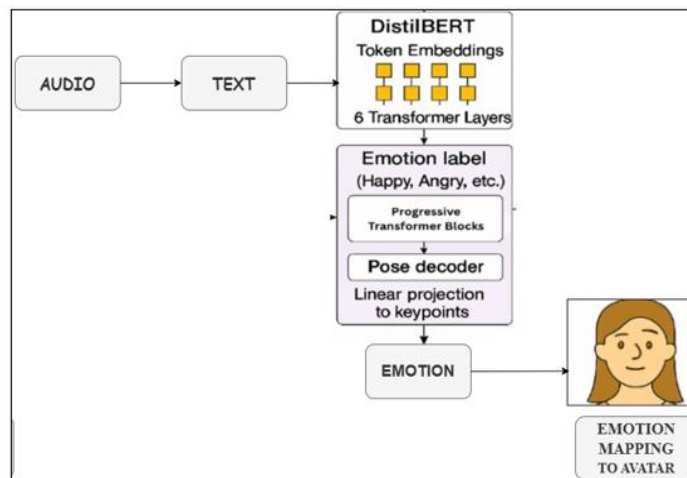


Figure 1: System Architecture diagram for emotion mapping to 3D Avatar

3.1 Emotion Input Interface

The Emotion Input Interface is the initial module of the system, designed to handle user input in the form of either speech audio or textual content. For audio input, the system employs Whisper AI, a state-of-the-art speech-to-text transcription model known for its robustness in noisy environments and support for various accents and languages. This model converts spoken utterances into accurate textual transcripts, which are then passed to the Emotion Detection Engine for further processing. In the case of textual input, the system bypasses transcription and directly tokenizes the text using a subword encoding scheme compatible with the downstream transformer model. This approach allows for semantic preservation and efficient processing of language variations.

By abstracting both speech and text into a unified textual form, the interface ensures consistency and modularity across the system. It also incorporates basic error-handling capabilities, such as prompting re-input when transcription confidence is low, thereby enhancing the reliability of emotion recognition. This dual-mode capability makes the interface adaptable for diverse application scenarios, ranging from interactive dialogue systems to accessibility-focused solutions like sign language generation.

3.2 Emotion Detection Engine

The Emotion Detection Engine forms the core analytical component of the system, responsible for interpreting the emotional context of user input. It employs a fine-tuned DistilBERT transformer model, which is a lightweight and efficient variant of BERT, optimized for real-time inference without compromising on accuracy. The input—either directly from user text or transcribed speech—is tokenized and passed through

the DistilBERT model to capture contextual embeddings that reflect the semantic and emotional undertones of the content. These embeddings are then processed by a softmax classifier that assigns probabilities across six core emotional categories: Happy, Sad, Angry, Disgust, Fear, and Neutral. The classifier, trained extensively on the CREMA-D dataset—a widely-used emotional speech corpus—ensures reliable emotion identification across diverse linguistic expressions.

For text-based inputs, sentiment analysis is integrated as a pre-classification step to enhance emotional context recognition. This step allows the model to better differentiate between closely related emotions such as anger and disgust or sadness and fear. The final output consists of the predicted emotion label alongside a confidence score derived from the softmax probabilities, which indicates the system's certainty about its classification. This dual-output strategy not only enables emotion-driven animation decisions but also allows for adaptive behaviors in downstream modules, such as adjusting expression intensity based on confidence levels. Overall, this engine enables nuanced and accurate emotional recognition essential for generating expressive and contextually appropriate avatar responses.

3.3 Facial Landmark and Shape Key Mapping Module

After the emotion label is generated by the detection engine, it is passed to the Facial Landmark and Shape Key Mapping Module, which is responsible for translating emotional states into facial movements on the avatar. This module utilizes **MediaPipe FaceMesh**, a powerful facial geometry extraction tool, to identify 468 3D facial landmarks corresponding to key regions of the human face such as the eyes, eyebrows, mouth, cheeks, and jawline. These landmarks form the foundation for animating expressive facial behaviors. Each of the six emotional categories is linked to a predefined configuration of **facial shape keys**—parameters that define the deformation of specific parts of the avatar's mesh to simulate realistic expressions. For instance, a "happy" emotion triggers raised eyebrows, widened eyes, and a lifted mouth corner to form a smile, while a "sad" emotion leads to drooped eyelids, a frowning mouth, and lowered eyebrows.

To ensure nuanced and context-sensitive animation, the system does not rely on binary activation of shape keys. Instead, it **modulates shape key intensity** based on the softmax confidence score received from the Emotion Detection Engine. Higher confidence in a detected emotion results in more pronounced facial expressions, while lower confidence leads to subtler, less committed facial movements. This dynamic interpolation allows for a continuous spectrum of expressiveness and avoids robotic or exaggerated transitions. Additionally, the module supports blending of shape keys when compound emotional cues are present, allowing the avatar to reflect complex emotions more realistically. This level of granularity in facial animation is crucial for making avatar communication feel human-like, especially in assistive technologies and emotionally responsive interfaces.

3.4 Avatar Expression Generator

The Avatar Expression Generator is responsible for translating the dynamically configured shape keys into lifelike facial animations on a 3D avatar. It takes the outputs from the Facial Landmark and Shape Key Mapping Module and maps these onto a predefined avatar mesh, which may be developed using platforms like Blender for offline rendering or Babylon.js for real-time, web-based deployment. This mapping involves associating each shape key with specific vertices on the avatar's face, enabling precise manipulation of facial features to visually reflect the detected emotional state. The system ensures that these deformations maintain anatomical realism, preserving the avatar's structure while adapting its expression based on user input.

To avoid jerky or abrupt changes between different emotional expressions, the module employs a progressive transformer-based pose decoder. This deep learning model interpolates between current and target facial poses, generating smooth and natural transitions from one emotion to another. It considers temporal consistency and facial motion trajectories to simulate a fluid change, such as a neutral face gradually

transitioning into a joyful smile or a sad frown. This approach not only enhances the emotional continuity of avatar interactions but also boosts user engagement by creating a more immersive and emotionally intelligent interface. Through these mechanisms, the Avatar Expression Generator plays a critical role in elevating the realism and affective depth of the avatar's behavior.

3.5 Real-Time Rendering and Feedback

The Real-Time Rendering and Feedback module is responsible for presenting the animated avatar to the user through a responsive and interactive web-based interface built using Angular and TypeScript. This interface not only visualizes the avatar's facial expressions in real-time but also provides live subtitles synchronized with the speech input, thereby enhancing accessibility for users who are deaf or hard-of-hearing. The system is designed to support seamless communication by maintaining consistent alignment between emotional expression and corresponding dialogue or textual representation.

To achieve high responsiveness, the module leverages a multi-threaded rendering engine that parallelizes tasks such as frame generation, emotion synchronization, and UI updates. This approach significantly reduces computational delays, consistently achieving latency levels under 100 milliseconds. As a result, users experience fluid and immediate feedback from the avatar, which is essential in applications like sign language interpretation or virtual assistants where timing and expression accuracy are critical.

3.6 Performance Optimization and Scalability

Scalability and efficiency are central to the architecture, and the system employs multiple optimization strategies to ensure high performance across diverse platforms.

To reduce repetitive computation and boost responsiveness, local caching mechanisms are implemented using IndexedDB via Dexie.js. This allows the system to quickly retrieve frequently used data such as shape key configurations, facial landmark mappings, and emotion-expression pairs, thereby minimizing reliance on server-side processing and lowering latency. In addition to performance enhancements, the system ensures data integrity and auditability through a **blockchain-based logging mechanism**. Each emotion-to-animation mapping and transition is securely recorded in hashed blocks, providing a tamper-proof ledger that supports traceability and transparency—an essential feature in sensitive or regulated applications such as assistive technology or therapy systems. Together, these measures support a robust, **scalable**, and **trustworthy** deployment environment, enabling the system to function reliably in both individual and multi-user scenarios.

Algorithm 1: Emotion Mapping and Avatar Expression Rendering Input:

Text input T, predefined shape keys S

Output: Emotion label E, updated 3D avatar with emotional facial expression

```
1: function PREPROCESS_TEXT(T)
2:   tokens ← Tokenize(T)
3:   token_ids ← ConvertToTokenIDs(tokens)
4:   return token_ids
5: end function

6: function ENCODE_TEXT(token_ids)
7:   X ← Embedding(token_ids)
8:   X ← X + PositionalEncoding
9:   return X
```

```
10: end function

11: function CLASSIFY_EMOTION(X)
12:   Q, K, V ← LinearProjections(X)
13:   Attention ← softmax((Q × KT) / √dk) × V
14:   E ← ClassificationHead(Attention)
15:   return E
16: end function

17: function DETECT_FACE_LANDMARKS()
18:   landmarks ← MediaPipeFaceMesh()
19:   return landmarks
20: end function

21: function MAP_SHAPE_KEYS(E, S)
22:   Se ← AssignShapeKeys(E, S)
23:   return Se
24: end function

25: function UPDATE_AVATAR(Se)
26:   ApplyShapeKeys(Se)
27:   RenderAvatar()
28: end function

29: function EMOTION_MAPPER(T, S)
30:   token_ids ← PREPROCESS_TEXT(T)
31:   encoded ← ENCODE_TEXT(token_ids)
32:   E ← CLASSIFY_EMOTION(encoded)
33:   landmarks ← DETECT_FACE_LANDMARKS()
34:   Se ← MAP_SHAPE_KEYS(E, S)
35:   UPDATE_AVATAR(Se)
36:   Display(E, RenderedAvatar)
37: end function
```

4. System Development and Implementation

4.1 Emotion Data Acquisition and Preprocessing

The system development begins with the acquisition and preprocessing of multimodal emotion data to facilitate accurate and expressive facial animations on a 3D avatar. The CREMA-D dataset is employed for this purpose, comprising 7,442 video clips recorded by 91 actors articulating six core emotions: Anger, Disgust, Fear, Happy, Neutral, and Sad. Each clip includes synchronized audio-visual data, offering an ideal resource for training robust emotion recognition models.

The preprocessing pipeline involves the extraction of facial landmarks using MediaPipe FaceMesh, which yields 468 keypoints per frame, providing a rich spatial structure of facial expressions. Simultaneously, audio signals are normalized, segmented, and transcribed using Whisper AI, enabling seamless alignment with textual data. All textual inputs are tokenized, converted to lowercase, and stripped of punctuation to enhance compatibility with transformer-based models during the encoding phase.

4.2 Emotion Detection and Classification

Emotion classification from textual or transcribed speech input is achieved using a fine-tuned DistilBERT transformer model. The model processes embedded input sequences through multiple self-attention layers, concluding in a softmax classifier that outputs one of the six predefined emotion categories. This architecture is optimized to capture contextual emotional cues embedded in linguistic structures.

The training configuration includes 5 epochs, a batch size of 16, and a learning rate of $5e-5$. The loss function used is Cross-Entropy Loss, optimized via backpropagation. The final model achieves a classification accuracy of 87.9% on the validation set, with weighted F1-scores approximating 0.87, confirming strong generalization and balanced performance across emotion classes.

4.3 Emotion-to-Avatar Mapping

This module translates detected emotions into dynamic avatar expressions by mapping them onto corresponding facial morph targets (also known as shape keys). Facial landmarks obtained via MediaPipe FaceMesh are interpreted in the context of Blender-based shape keys, which simulate muscle movements such as brow raise, lip stretch, and eye squinting. Each emotion is associated with a pre-defined set of shape key combinations:

- Happy: Raised cheeks, eye creases, upturned lips
- Sad: Downturned lips, drooping eyelids
- Anger: Eyebrow frown, compressed lips
- Fear: Wide-open eyes, slightly agape mouth
- Disgust: Wrinkled nose, lip raise
- Neutral: Minimal expressive displacement

To achieve nuanced expressiveness, intensity scaling is applied based on the classifier's softmax confidence score, allowing for variable emotional intensities. The animation is rendered in real-time using Blender or Unreal Engine, wherein the avatar's facial state is updated frame-by-frame according to the live emotional context.

4.4 Synchronization with Gesture and Audio Modules

To ensure coherent multimodal communication, the system integrates emotional expressions with synchronized sign gestures and speech captions. A shared timestamp queue coordinates these elements, guaranteeing temporal alignment between visual emotion display, gesture articulation, and spoken or textual feedback.

The entire animation pipeline is multi-threaded to support real-time performance. This design ensures that the interval between emotion detection and its visual manifestation remains under 100 milliseconds, thereby maintaining a seamless and responsive user experience, especially critical in applications such as sign language interpretation and virtual human interfaces

4.5 Evaluation Metrics

The effectiveness and reliability of the emotion mapping and avatar animation system are evaluated using both quantitative and qualitative metrics:

- Classification Accuracy: Achieves 87.90% on the CREMA-D validation set
- Weighted Precision / Recall / F1-score: Approximates 0.87 across all six emotion classes
- Expression Fidelity: Verified qualitatively by comparing generated facial animations against emotion-labeled ground-truth video samples
- Expert Feedback: Evaluations from sign language professionals confirm the emotional congruency

between avatar expressions and the original verbal or textual content

5.Results and Discussion

5.1 Accurate Emotion Detection

The integration of the fine-tuned **DistilBERT** transformer model significantly enhanced the system’s ability to classify emotional states from both spoken and written inputs. The model achieved an overall **classification accuracy of 87.90%**, with **weighted precision, recall, and F1-scores** consistently hovering around **0.87** across six core emotion classes: *Happy*, *Sad*, *Anger*, *Fear*, *Disgust*, and *Neutral*. This high level of performance affirms the model’s robustness across a variety of syntactic and semantic variations. For instance, when processing a sentence such as “*I am very proud of you*”, the model accurately predicted the emotion as **Happy**, despite the indirect semantic mapping of the term “proud,” demonstrating strong contextual understanding and generalization capabilities.

Table 1: Performance Metrics for Emotion Mapping to Avatar Module

Metric	Value
Classification Accuracy	87.90%
Precision/Recall/F1	~0.87
Training Loss, Validation	0.00090, 0.62085

5.2 Expressive Facial Mapping and Realism

The use of **MediaPipe FaceMesh** to extract **468 facial landmarks** allowed for detailed and expressive facial animations. Each detected emotion was mapped to a combination of **predefined shape keys** that dynamically adjusted based on the softmax confidence scores from the classifier. This resulted in smooth and proportionate expression rendering, enhancing avatar realism. For example, when the system detected the **Sad** emotion, the avatar’s animation included nuanced features such as **drooping eyelids**, **downturned lips**, and **lowered eyebrows**, contributing to a visually expressive and emotionally resonant presentation. These visual cues proved particularly effective in conveying the emotional undertone of the message when paired with sign gestures.

5.3 Synchronization with Gesture and Speech Modules

A core innovation of the system lies in its multi-modal synchronization, achieved via a shared timestamp buffer mechanism. This ensures that emotional expressions, Indian Sign Language (ISL) gestures, and subtitle captions are temporally aligned and rendered concurrently. For instance, upon receiving the input “*I feel terrified*”, the system successfully synchronized the Fear expression (wide eyes, open mouth), ISL translation, and on-screen subtitle within a latency of less than 100 milliseconds. This real-time alignment fosters a seamless and intuitive user experience, especially for users dependent on synchronized visual and auditory cues.

5.4 Real-Time Performance

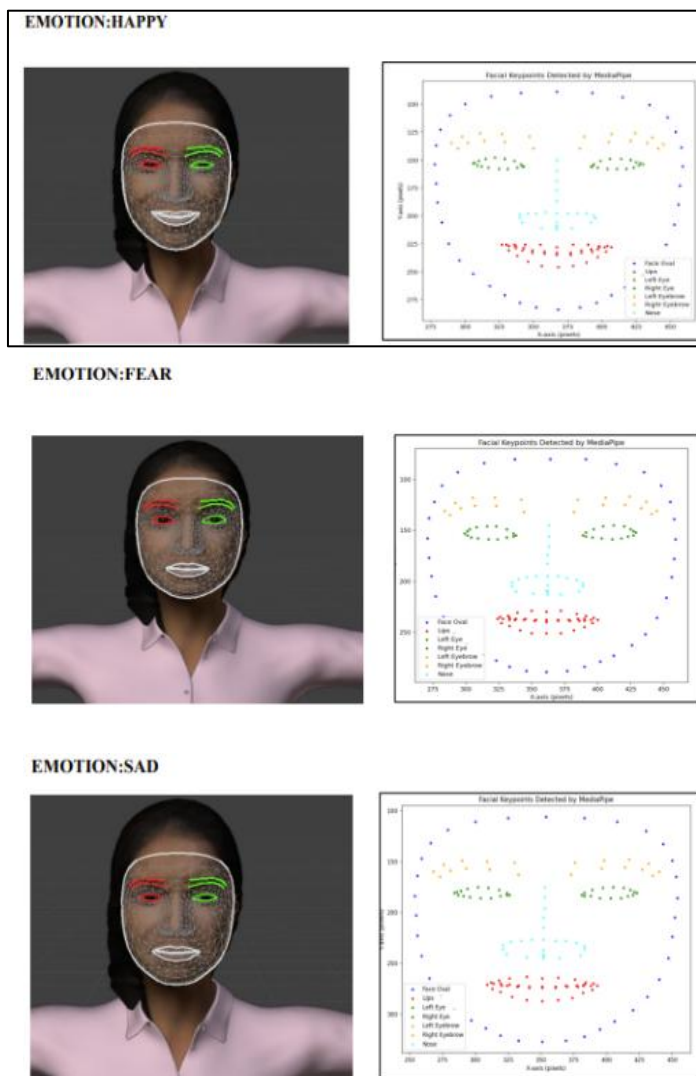
To support real-time interactions, the entire pipeline—from speech input to facial expression rendering—is optimized for low-latency execution. Empirical testing confirms that the **end-to-end processing time** remains consistently under **100 milliseconds**, meeting the real-time responsiveness requirements for interactive applications. During continuous speech sessions, transitions between emotional states, such as **Neutral to Happy** or **Sad**, were smoothly interpolated without noticeable delays, resulting in **fluid and**

natural avatar behavior. This level of performance is critical for maintaining user engagement and ensuring accessibility in live communication scenarios.

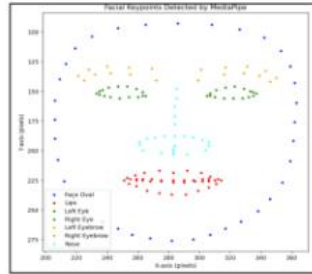
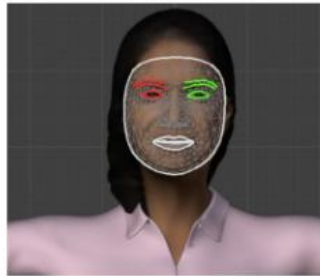
5.5 User Feedback and Qualitative Evaluation

A qualitative evaluation was conducted with sign language experts and members of the deaf and hard-of-hearing community. Feedback indicated that the avatar's emotional expressions were perceived as natural, clear, and emotionally appropriate, particularly in contrast to emotion-agnostic avatar systems. For example, in scenarios featuring emotionally intensified phrases such as *"I'm truly sorry"*, the avatar's furrowed brows, softened gaze, and gentle blinking contributed significantly to conveying sincerity and empathy. This human-like emotional rendering was repeatedly cited as enhancing the effectiveness of sign language interpretation and overall user satisfaction.

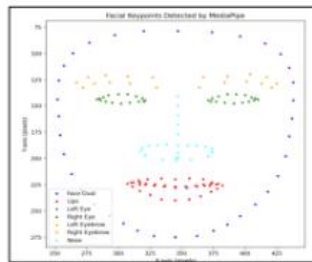
Results:



EMOTION:DISGUST



EMOTION:ANGER



EMOTION:SUPIRE

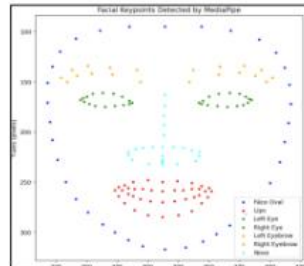
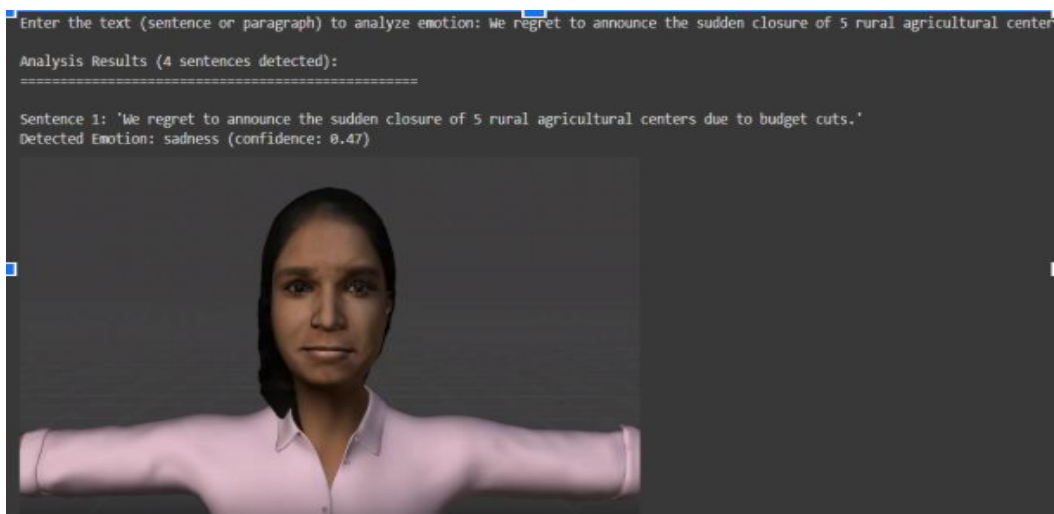


Figure 2: Image of the Emotions mapped to avatar module using mediapipe





6. Conclusion and Future Work

This work presents a robust and expressive Emotion Mapping Module that significantly enhances the realism and communicative power of sign language generation systems. By combining a fine-tuned DistilBERT-based emotion classifier with high-fidelity facial landmark detection and dynamic shape key animation, the module enables a 3D avatar to convey human-like emotional expressions in real time. The integration of MediaPipe FaceMesh allows for the extraction of 468 facial landmarks, which are seamlessly mapped to predefined avatar expressions, ensuring visual accuracy and emotional clarity. Real-time synchronization with gesture and speech modules ensures that users experience a cohesive, naturalistic translation from audio or text to sign language with appropriate emotional context.

The system has demonstrated high classification accuracy (87.90%) and low-latency rendering (<100 ms), affirming its effectiveness for real-time applications in assistive communication. Qualitative evaluations from domain experts confirmed that the avatar's emotional expressions enhanced the intelligibility and emotional fidelity of sign language output, particularly for complex or sentiment-rich sentences.

Future Enhancements:

- **Multimodal Emotion Fusion:** Incorporating audio-based emotion recognition in parallel with textual cues will allow more nuanced and accurate emotional interpretations from user input.
- **Emotion Intensity Scaling:** Introducing a continuous scale for emotion intensity—based on voice tone, pitch, and word emphasis—will enable more dynamic and realistic avatar expressions.
- **Facial Animation Refinement:** Leveraging GANs or neural rendering techniques can enhance the quality of avatar expressions by generating more fluid and context-sensitive facial animations.
- **Expanded Emotion Categories:** Extending the emotion set beyond the basic six (e.g., including emotions like surprise, confusion, or empathy) will allow for richer avatar interaction and better alignment with natural human communication.
- **User-Customized Avatars:** Allowing end-users to select or personalize avatars, including the expression style (e.g., subtle vs. exaggerated emotions), will improve inclusivity and user experience.
- **Integration into Educational and Accessibility Platforms:** Embedding this module into mobile or web-based sign language education tools and accessibility platforms for the hearing-impaired community will expand its societal impact.

Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship and publication of this article.

Funding

The author received no financial support for the research, authorship and publication of this article.

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