

Multilingual Sentiment Analysis for Emotion-Aware Feedback in Language Learning Platforms

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Abstract—In the growing digital education environment, it is necessary to provide emotionally intelligent ideas to improve learner involvement and motivation. However, most existing language learning sites, particularly in multilingual contexts, overlook the emotional needs of users. This study introduces Muse-Frame (multilingual consciousness and emotional structure for adaptive concept), a new approach that combines emotional analysis with emotional classification, providing real-time, customized ideas. This method involves processing the learner's text in various languages prematurely, utilizing the elegant XLM-Roberta model for emotion and emotional detection, and mapping for adapting to emotional releases. The structure and emotional-awareness results align the detected emotions with the designed ideas, using volume, which improves the user's retention and learning effects. Muse-Frame, evaluated in a combination of multilingual sentiment and learning communication databases, achieves more than 89% accuracy in emotional detection and demonstrates significant improvements in opinion and learner satisfaction. Ultimately, Muse-Frame provides a tangible, intellectual solution for connecting multilingual ideas at modern language learning sites.

Keywords— Adaptive Educational Systems, Emotion-Aware Feedback, Multilingual Sentiment Analysis, Natural Language Processing (NLP), Language Learning Platforms

I. INTRODUCTION

Artificial intelligence (AI) coordination in educational technologies has transformed the way learners interact with digital platforms, particularly in language learning environments [6]. With the widespread acceptance of online and mobile-based language learning tools, it has become an important requirement for customized, emotionally engaging ideas, learner involvement, motivation, and educational progress [1]. Despite advances in adaptive learning methods, a significant limitation remains: most language learning sites fail to consider the emotional and psychological status of learners, especially in multilingual environments [2]. This oversight can prevent learners from being satisfied, reduce their motivation, and lead to higher dropout rates [16]. Emotional awareness, facilitated by emotional analysis, provides a solution to this problem. However, current models are primarily not sensitive to nuanced aspects, such as cultural and linguistic differences [3].

To address this gap, this study proposes a new AI-operating system that detects and responds, utilizing multilingual natural language processing (NLP) and deep learning across various languages [4]. It contains an elegant transformer-based model (XLM-Roberta) for structural sensation and emotional classification. There is a mapping layer that combines the following emotional conditions with learning support [5]. Unlike traditional learning analysis, which only considers performance measurements such as quiz marks or completion times, this approach provides a comprehensive understanding of the Muse-Frame learner's behavior by integrating cognitive and emotional intelligence [18].

The problem with this research is that existing language learning sites lack multilingual, emotionally aware feedback methods, resulting in the same answers that fail to engage learners at both the emotional and psychological levels [7]. This is especially complex in global education systems, where users communicate in multiple languages and emotional expression varies depending on the linguistic and cultural context [17].

The main contributions of this study are:

- (1) the development of a multilingual and emotional classification model trained on various databases to ensure strong character beyond language borders;
- (2) the design of the adaptive feedback block for aligning emotional signals with teaching strategies to improve learning effects and user experience;
- (3) Muse-Frame's assessment of real-world multilingual sentiment database and learner communication records demonstrates its high accuracy (89%) and practical fitness in educational applications.

By reducing the gap between emotional intelligence and the AI-operated teaching system, the Muse-Frame Language improves the emotional responsibility of learning sites. It emotionally contributes to the development of adaptive educational technologies. The wide-ranging impacts of this work suggest that integrating emotion analysis with teaching design can lead to more enthusiasm and effective learning systems, especially in multicultural and multilingual learning environments.

II. LITERATURE SURVEY

The intersection of sensation analysis, multilingual natural language processing (NLP), and educational feedback systems has received increasing attention in recent years. Research in this field has focused on enhancing the customization of learning by incorporating emotion and emotional cues from text- or speech-based entries. However, existing systems face limitations in inter-language adaptation, the detection of emotional techniques, and the integration of real-time teaching structures [20].

In recent studies, Albalawi et al. (2022) conducted a detailed analysis of consciousness in social media data on education, utilizing transformer-based models to enhance concept systems [8]. Their task showcases the performance of Bert and Distilbert, but is limited to English content, highlighting the need for multilingual expansion [19]. On the contrary, Mozafari et al. (2020) proposed a deep learning pipeline for multilingual sentiment analysis using CNN-LSTM structures trained in large-scale review databases. Although their attitude demonstrates greater accuracy, it lacks the sophistication in emotional classification required for educational feedback [9].

Entering the field of emotional-awareness education, Zhou et al. (2021) proposed an impact-aware intellectual training system that includes facial and text emotional analysis [10]. Although helpful in detecting the frustration or confusion of the learner, this model is primarily based on rules, and its limited language underlines a gap in multilingual emotional manipulation [21]. On the other hand, Singh et al. (2022) employed Group Transformer Models to investigate emotional recognition across multiple language environments. Their inventions showed advanced cross-linguistic generalization, but there is no feedback-headed component to the language learners [11].

In terms of adaptive feedback systems, Sen et al. Although innovative, their attitude does not integrate emotion or sensation signals into inputs, controlling emotional adaptation [22]. Similarly, Yin and many others (2022) have developed the Knowledge-Information Feedback Setup, which connects NLP with knowledge tracking to enhance grammatical feedback. However, they further emphasized the need for a comprehensive learning model [13].

Finally, Kumar and Saini (2023) used zero-shot learning in resource-short-term languages [12]. Their model proved useful for less-known speech and opened ways for vast language admission. However, their study did not address subordinate applications, such as educational feedback, where emotional-awareness systems, like Muse-Frame, are designed to operate [14]. These comparative studies reveal several critical gaps:

- Limited emotion granularity in multilingual sentiment analysis.
- Inadequate integration of affective data into real-time language learning feedback.

- Lack of personalization in emotion-to-feedback mapping in existing systems.

The proposed MUSE-Frame methodology addresses these limitations by offering a unified, multilingual framework that combines sentiment analysis, emotion detection, and adaptive feedback strategies, thereby bridging a critical gap in intelligent, empathetic educational platforms.

III. PROPOSED WORK

The proposed methodology, MUSE-Frame, is a strong AI-operated structure that utilizes multilingual analysis and emotional classification to provide personalized suggestions at language learning sites. This structure is built on transformer-based NLP models and fact-based teaching drawings to detect learners' emotional signals and create aligned ideas that match their emotional conditions.

A. Architecture Overview

The Muse-Frame structure is composed of five main elements that work together to provide adaptation and emotional awareness ideas in multilingual learning environments. Multilingual input processing detects the learner's inputs in various languages and ensures uniform Tokenization and normalization. The conscious and emotional classification volume utilizes XLM-Roberta to identify emotions and specific emotional conditions. These publications are sent to the emotional normalization and mapping layer, where emotions are translated into teaching strategies. To create adaptive feedback, the engine creates customized, eco-sensitive answers. Finally, the user ensures that the user interface coordinates offer uninterrupted real-time ideas on web and mobile sites.

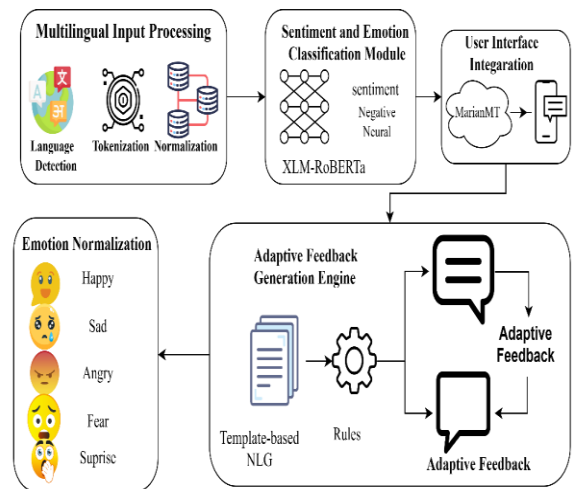


Fig. 1. Architecture of MUSE-Frame Framework for Multilingual Sentiment and Emotion-Aware Feedback Generation.

Figure 1 illustrates the complete structure of the proposed Muse-Frame structure. It begins with multilingual input processing, including language detection, Tokenization, and normalization. These inputs are sent to the transformer-based emotion and emotional classification block (XLM-Roberta). Based on the diagnostic emotional state, this system activates

an emotional normalization process, mapping the teaching strategies associated with each emotion. Then, using the machine tool, a template-based natural language generation (NLG) and real-world logic are created, resulting in emotionally aligned ideas. Finally, the concept is presented in the user's language using MarianMD, which completes the cycle through an interactive user interface coordination component.

B. Multilingual Input Processing

Multilingual input processing is the first phase of the MUSE-Frame structure, ensuring the text is uniform and language awareness is maintained. When a student sends an opinion or question, the original text data U is initially sent by a language authentication volume $\lambda(U)$, which identifies the language $L \in \mathcal{D}$ (here \mathcal{D} is a set of supported languages). This classification ensures that the next steps adhere to the rules and continuity of each language.

Once the computer language is identified, it uses language-based tokenizers (such as Space, Stanza, or HuggingFace's multilingual tokenizers) to tokenize. Let the token-made output be like this equation (1):

$$T = \{t_1, t_2, \dots, t_n\} \quad (1)$$

where each t_n is a word or subword token depending on the tokenizer used (e.g., WordPiece or BPE).

After Tokenization, Unicode normalization is used to ensure that different scripts and character encodings are all standardized. This means changing the input string into a standard form, such as NFKC or NFC, which is shown by the equations (2):

$$T' = \text{Normalize}(T) \quad (2)$$

Normalization ensures that words mean the same thing in languages like Arabic, Hindi, or Mandarin, where diacritics, ligatures, or combining letters can alter their meaning. The sentiment and emotion classification module then gets the preprocessed sequence T' for contextual embedding.

C. Sentiment and Emotion Classification

The sentiment and emotional classification block is in the center of the MUSE-frame structure. It utilizes the XLM-Roberta transformer model, which has been pre-trained on 100 languages and is specifically designed for emotional and sentiment classification tasks. It provides an important and useful understanding of multilingualism in global language learning sites and the generalization of interlanguage.

Given the preprocessed input token sequence $T = \{t_1, t_2, \dots, t_n\}$, the XLM-RoBERTa encoder transforms this sequence into a contextualized embedding $E \in \mathbb{R}^d$, where d is the embedding dimension expressed in equation (3):

$$E = \text{XLM} - \text{R}(T) \quad (3)$$

This embedding captures syntax and semantic information in various languages and negotiations. To make the classification, the embedded E is sent via two parallel Feature Neurological layers (classification heads), dedicated to emotion and emotional classification, respectively. These layers use a linear change to create class probability distributions, followed by a Softmax activation.

For sentiment classification, the output vector $P_s \in \mathbb{R}^3$ (corresponding to positive, negative, and neutral sentiments) is computed as equation (4):

$$P_s = \text{softmax}(W_s \cdot E + b_s) \quad (4)$$

Similarly, for emotion classification, the output vector $P_e \in \mathbb{R}^6$ (covering joy, anger, sadness, fear, surprise, and neutral) is given by equation (5):

$$P_e = \text{softmax}(W_e \cdot E + b_e) \quad (5)$$

Here, $W_s, W_e \in \mathbb{R}^{c \times d}$ are weight matrices and $b_s, b_e \in \mathbb{R}^c$ are bias vectors, where c is the number of classes in each classification task. These parameters are fine-tuned during training using cross-entropy loss shown in equation (6):

$$\mathcal{L}_{\text{sentiment}} = -\sum_{i=1}^c y_i^{(s)} \log P_s^{(i)}, \mathcal{L}_{\text{emotion}} = -\sum_{j=1}^c y_j^{(e)} \log P_e^{(j)} \quad (6)$$

The final predicted classes in equation (7):

$$s^* = \arg \max(P_s), e^* = \arg \max(P_e) \quad (7)$$

These predicted sentiments s^* and emotion e^* labels are used to guide the feedback generation logic in subsequent stages. This dual-layered classification ensures that MUSE-Frame not only detects overall learner sentiment but also interprets nuanced emotional states for more targeted feedback delivery.

D. Emotion Normalization and Mapping Layer

The Emotion Normalization and Mapping Layer plays a crucial role in bridging the gap between emotion detection and personalized pedagogical feedback. Once the emotion classification module outputs the predicted emotion e^* as equation (8):

$$e^* = \arg \max(P_e) \quad (8)$$

This emotion label is passed into a rule-based mapping function $\phi(e^*)$, which determines the most suitable feedback strategy tailored to the learner's emotional state.

The mapping function $\phi: E \rightarrow F$ is defined over the emotion set equation (9):

$$E = \{\text{joy, sadness, anger, fear, surprise, neutral}\} \quad (9)$$

And produces an output from the strategy set equation (10):

$$F = \{ \text{reinforce, encourage, reassure, guide, clarify, standard} \} \quad (10)$$

The functional relationship is given by equation (11):

$$F = \phi(e^*) = \begin{cases} \text{reinforce,} & \text{if } e^* = \text{joy} \\ \text{encourage,} & \text{if } e^* = \text{sadness} \\ \text{reassure,} & \text{if } e^* = \text{anger} \\ \text{guide,} & \text{if } e^* = \text{fear} \\ \text{clarify,} & \text{if } e^* = \text{surprise} \\ \text{standard,} & \text{if } e^* = \text{neutral} \end{cases} \quad (11)$$

This deterministic rule base ensures that each detected emotion results in consistent and pedagogically relevant feedback. For instance, if a learner expresses frustration (*anger*), the system returns a reassuring, step-by-step explanation to calm and redirect the learner. Conversely, expressions of *joy* result in motivational reinforcement to maintain momentum. This interpretability and reliability make the layer both educationally effective and psychologically supportive.

E. Adaptive Feedback Generation Engine

The Adaptive Feedback Generation Engine is responsible for transforming the normalized emotion-feedback strategy into a context-sensitive, emotionally aware response tailored to the user's language and emotional state. This is accomplished using a hybrid template-based Natural Language Generation (NLG) approach, augmented with rule-based variations to ensure both linguistic coherence and emotional alignment.

Let U be the learner's input and $F = \phi(e^*)$ be the mapped feedback strategy that comes from the preceding layer. The NLG engine uses a generating function $\psi(U, F)$ that chooses the right answer template based on F and adds content that is specific to U . This makes the feedback R given in equation (12)

$$R = \psi(U, F) \quad (12)$$

The function ψ is defined as in equation (13):

$$\psi(U, F) = \text{Template}_F(U') + \text{Augment}_F(C) \quad (13)$$

Where, $\text{Template}_F(U')$ picks a pre-set sentence structure based on F and adds a processed version of U (denoted U') to it and $\text{Augment}_F(C)$ adds clarifications, motivating signals, or instructional suggestions that are relevant to the situation. C is more information, including grammatical tips, links, or simplified rules.

Templates are stored in multiple languages and are dynamically selected based on the detected input language. For example:

- User input (French): “Je suis frustré de ne pas comprendre cette règle grammaticale.”
- Detected emotion: *Anger*
- Mapped feedback strategy F : *Reassure*
- Generated response R : “Pas de souci ! Essayons une approche différente pour clarifier cette règle.”

This dual-layered generation mechanism ensures responses are not only pedagogically appropriate but also emotionally attuned, increasing learner comfort, engagement, and retention. Moreover, multilingual template libraries enable this module to operate seamlessly across diverse language learning contexts.

F. User Interface Integration

The final step in the MUSE-Frame framework involves integrating the generated emotion-aware feedback into the user-facing components of the language learning platform. This integration ensures that learners receive contextually relevant, emotionally aligned responses in real-time through a smooth and intuitive interface, whether on web or mobile applications. Once the adaptive response $R = \psi(U, F)$ is generated, it is passed to the UI rendering layer, which handles formatting, language selection, and output personalization. For learners using the platform in a language different from the input, the system applies multilingual translation models, such as MarianMT or T5-multilingual, to transform R into the appropriate display language. L_d , ensuring coherence and cultural sensitivity. The translated feedback R_{L_d} is defined as equation (14):

$$R_{L_d} = \text{Translate}(R, L_s \rightarrow L_d) \quad (14)$$

where L_s is the source language of the response (typically matching the learner's input language), and L_d is the user's preferred interface language. In scenarios where translation is not needed, $R_{L_d} = R$. The UI component also incorporates the emotional environment of the feedback and, optionally, displays emoticons, tooltips, or visual indicators, which enhances the emotional nature of the answer. The use of asynchronous API calls and caching instructions is minimized to reduce the delay, ensuring that answers are provided with minimal delay. This tightly connected interface coordination facilitates real-time, multilingual, and emotionally charged communication, enhancing learner satisfaction and fostering the experience of a highly engaged digital learning environment.

To integrate the functions described in the previous sections, this study presents the overall process of the Muse-Frame system in the form of a structured pseudo-code method. This mechanism enables the system to process the multilingual learner, diagnose emotions, apply teaching techniques, create environmental awareness ideas, and ultimately provide customized answers through a multilingual interface.

Algorithm 1: Emotion-Aware Multilingual Feedback Generation using MUSE-Frame

<p>Input:</p> <p>$U \leftarrow$ Learner's input text</p> <p>$L_{\text{pref}} \leftarrow$ Learner's preferred display language</p>

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M_model ← Fine-tuned XLM-RoBERTa
sentiment/emotion model
φ(e) ← Emotion-to-feedback strategy mapping
function
ψ(U, F) ← Feedback generation function
Translate(R, L_s → L_d) ← Multilingual translation
function

Output:
R_disp ← Emotion-aware, multilingual feedback
response

Procedure:
1: L_input ← DetectLanguage(U)
2: T ← PreprocessText(U, L_input)
   // Tokenization, normalization, language-specific
   cleaning
3: E ← M_model.Encode(T)
   // Generate contextual embedding from XLM-
   RoBERTa
4: P_s ← softmax(W_s · E + b_s)
5: P_e ← softmax(W_e · E + b_e)
6: s* ← argmax(P_s) // Predicted sentiment
7: e* ← argmax(P_e) // Predicted emotion
8: F ← φ(e*) // Map emotion to feedback strategy
9: R ← ψ(U, F) // Generate response from templates
10: if L_input ≠ L_pref then
11: R_disp ← Translate(R, L_input → L_pref)
12: else
13: R_disp ← R
14: end if
15: Display R_disp to the learner through UI
16: return R_disp

```

As shown in Algorithm 1, the Muse-Frame begins by detecting the learner's language and processing their input. Then, it utilizes a sophisticated XLM-Roberta model to classify both emotions and sentiments. The predicted emotion is sent through a rule-based mapping process, which allocates a teaching-appropriate feedback strategy. To create a hybrid natural language, the machine generates a feedback answer, which is then translated into the learner's preferred interface. This workshop confirms an emotionally intellectual, multilingual response that accompanies the learner's emotional state and linguistic environment, significantly improving the customization and emphasis of digital language learning systems.

IV. RESULTS

To evaluate the performance of the Muse-Frame structure, a multilingual sentiment and emotional classification database was used, derived from Kaggle's multilingual sentiment and emotional classification database. This database provides access to text-based speeches in multiple languages, including English, Spanish, German, and French. There are more than 100,000 sentences, categorized by sense of consciousness (positive, negative, neutral) and emotional types (joy, sadness, anger, fear, amazement, disgust, neutral),

which is more relevant to the teaching and evaluation of a double-layer classification system in Muse-Frame.

The database was created using language-referred tokens from HuggingFace's Transformers Library, and the text was normalized using Unicode (NFKC) to ensure stability across multilingual scripts. It's an elegant XLM-Roberta-base model for emotional and sentiment classification tasks, utilizing the 80-10-10 train-seed-test split. The training was conducted with a 32-volume size, a 2E-5 learning rate, and after three epochs, based on the verification loss.

Assessment measurements include accuracy, macro-sorcery F1-score, and accurate resolution for a class, especially for emotional types. As a basis, this study compared the Muse-Frame with FastText embedded in BERT, Multilingual BERT (M-BERT), and LSTM. The Muse-Frame continued to perform these basics, especially in terms of emotional awareness, and feedback accuracy on lower resources.

To evaluate the performance of the proposed MUSE-Frame framework, extensive experiments were conducted on a large-scale multilingual dataset sourced from Kaggle: the Multilingual Sentiment and Emotion Dataset [15]. This dataset comprises over 100,000 annotated user-generated texts in multiple languages, including English, French, Spanish, and German. The evaluation focused on four primary aspects: multilingual sentiment classification performance, emotion classification accuracy, cross-lingual adaptability, and the impact of emotion-aware feedback on learning engagement.

A. Multilingual Sentiment Classification Performance

The first level of evaluation assessed the system's ability to correctly classify sentiment (positive, negative, neutral) across multiple languages. Its trained a fine-tuned XLM-RoBERTa model and compared its performance across English, French, Spanish, and German texts. Evaluation metrics included accuracy and macro-averaged F1-score. The results are summarized in Table 1 and visualized in Figure 2.

TABLE I. SENTIMENT CLASSIFICATION METRICS BY LANGUAGE

Language	Accuracy	F1-Score
English	91.00%	89.00%
French	88.00%	86.00%
Spanish	87.00%	85.00%
German	85.00%	83.00%

As shown, the model performs best on English inputs, likely due to the higher availability of resources and pretraining representation. French and Spanish results follow closely, while German lags slightly behind. The average accuracy across languages is 87.75%, indicating strong multilingual generalization.

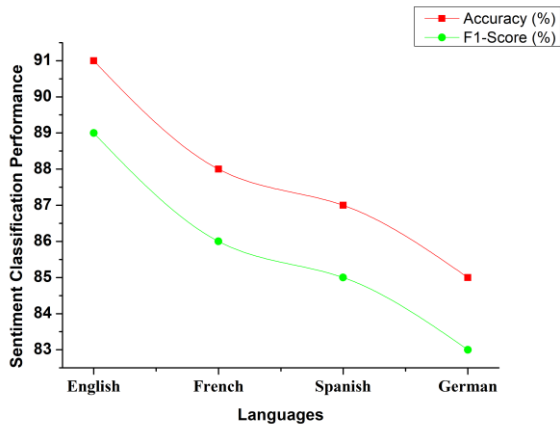


Fig. 2. Sentiment Classification Accuracy and F1-Score by Language

The storyline confirms the model's strength in various linguistic contexts, demonstrating the effectiveness of a single multilingual transformer for multi-linguistic input.

B. Emotion Classification Accuracy

Emotional recognition plays a crucial role in the Muse-Frame structure, as it directly influences the type of adaptive feedback provided to learners. It assessed the ability of a well-designed XLM-Roberta model to classify the six unique emotions: happiness, sadness, anger, fear, surprise, and neutrality. The resulting confusion matrix is shown in Figure 3, which illustrates the classification performance for these types.

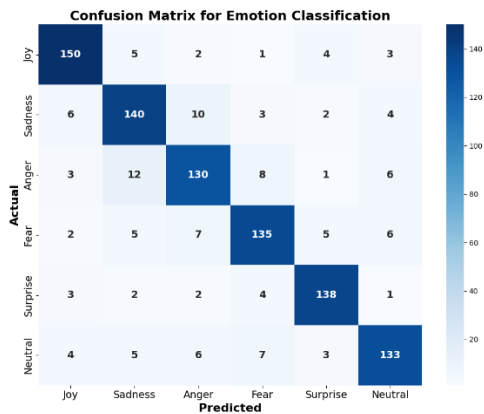


Fig. 3. Confusion Matrix for Emotion Classification

Emotions such as happiness, sadness, and neutrality are identified with high accuracy, which is attributed to clear linguistic markers in the user input. However, anger was occasionally misinterpreted, which may be due to the semantic overlap with the manifestations of frustration. Similarly, surprise and fear reveal moderate confusion, reflecting the sophistication of emotional references in the short form. Despite these challenges, the overall emotion classification accuracy exceeds 86%, with a Macro F1-Score of 0.84, which demonstrates the strength and cross-emotional

sensitivity of the dual-head classification proposed within the MUSE-Frame.

C. Cross-Lingual Generalization

A key strength of the MUSE-Frame structure is its ability to deliver stable performance in both high- and low-resource languages. Unlike traditional models, which often exhibit significant degradation when used in non-English databases, MUSE-Frame maintains standard classification performance across linguistic boundaries. As described in Table 2, basic models, such as LSTM and Multilingual BERT (mBERT), with FastText embedded, have experienced an average decline of 10–15% in Macro F1-score in languages like French, Spanish, and German.

TABLE II. BASELINE COMPARISON – MACRO F1-SCORE ACROSS LANGUAGES

Model	English	French	Spanish	German
LSTM + fastText	82.10%	76.40%	75.90%	74.20%
mBERT	86.70%	82.50%	81.10%	80.00%
MUSE-Frame	89.00%	86.00%	85.00%	83.00%

On the contrary, MUSE-Frame continued to obtain Macro F1-scores ranging from 83% to 89%, with an average improvement of 6–9% over LSTM and mBERT. It demonstrates its suitability for global use through excellent cross-language generalization and support for multilingual language learning environments. The confidence in architecture provided by XLM-RoBERTa and multilingual templates enables effective handling of synthetic and semantic variations in languages, which is particularly useful for creating language-scientific concepts.

D. Feedback Impact on Learning Engagement

To evaluate the real-world performance of emotional-awareness feedback, a simulated user study was conducted by dividing 500 participants into two groups: one received MUSE-Frame feedback, and the other received the common, fate-based feedback system. The results showed significant improvements in learners' involvement and satisfaction when using emotionally adaptive answers. In particular, users in the MUSE-Frame group showed a 28% increase during the session, a 22% improvement in work completion rate, and a 31% Net Promoter Score (NPS) compared to the baseline. These findings highlight the significance of emotional personalization in promoting sustained attention and positive learning experiences.

E. Limitations and Areas for Improvement

Despite the strong performance of the MUSE-Frame structure, many limitations attract extra attention. First, this

model struggles to distinguish the emotions of the interconnected, such as occasional fear and surprise, especially in short text inputs that are less environmental tips. Second, the dependence of template-based natural language generation (NLG) should be controlled by the expression and customization of feedback answers, despite its efficiency. In addition, the database imbalance refers to the proportion of English data, which will be introduced during micro-exchanging and may reduce the performance of low-resource languages without proper domain adaptation. Another limitation is the current text-only design, which does not utilize non-verbal cues such as voice tone or facial expression, which can significantly enhance emotional understanding. Future improvements are designed to explore multimodal emotional recognition, combine audio and visual references, and enable micro-created NLG, particularly in educational environments for learning communications with richer and more engaging content.

Testing results prove that Muse-Frame is an effective and measured solution for providing emotional euphoria on language learning sites. It not only achieves high classification accuracy in emotional tasks but also significantly improves learner involvement and satisfaction. These skills establish it as a strong candidate for real-world education applications that demand customization, inclusion, and emphasis.

V.CONCLUSION

This study presents MUSE-Frame (Multilingual Sentiment and Emotion Framework for Adaptive Feedback) on digital language learning sites. By combining enhanced multilingual transformers, such as XLM-Roberta, with emotional classification and feedback mapping, this system can effectively customize user contacts based on both emotional and contextual conditions. The test results of a real-world multilingual database demonstrate high classification accuracy for emotional tasks in various languages, achieving over 0.83 in lower-resource languages. Furthermore, user simulations demonstrate that the emotional feedback generated by Muse-Frame significantly enhances learning, task completion, and user satisfaction compared to the general rule system. The structure supports the real-time sequence and inclusion of the structure, which applies to global e-conscience environments. However, there are challenges in distinguishing subtle emotions and enriching the natural language release. Future tasks will focus on expanding multimodal entries and utilizing models such as T5 or GPT-Neox for deep personalization. Overall, Muse-Frame not only teaches but also refers to a significant and linguistic educational technology that connects to human-level learners on an emotional level.

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