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A Dual Attention AI Model for Emotion Recognition and Therapeutic Communication

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Abstract

In this paper, a Dual Attention framework is proposed to improve textual emotion recognition and AI-assisted therapeutic communication. Unlike traditional single-attention models, the proposed framework uses parallel semantic and affective attention mechanisms to highlight significant linguistic patterns and emotional intensity features. A transformer encoder is used to model contextual dependencies, and bidirectional sequence modeling is used to improve representation learning. The emotion classification result is used to guide an AI-assisted therapeutic response mechanism to produce empathetic and contextually relevant interactions. Experimental results show improved classification robustness and response relevance compared to traditional models. The proposed framework provides a scalable and adaptive solution for intelligent mental health support systems and conversational well-being applications NLP, Deep Learning.

Keywords: Emotion Recognition, Dual Attention, Therapeutic Chatbot.

1. Introduction

Conversational AI has made considerable progress with the help of emotional understanding in applications. Emotion detection from text is very important for therapeutic response generation. Textual emotion detection is a challenging task due to the presence of ambiguity in the context and the subtlety of emotional variations.

The traditional single-attention model is not capable of modeling semantic relevance and emotional intensity simultaneously. To address this problem, this paper proposes a Dual Attention model that models semantic and emotional features separately and then combines them for better emotion detection.

The proposed model combines the benefits of transformer-based contextual representation and bidirectional sequence modeling to improve emotional feature representation and facilitate context-aware therapeutic response generation, which will be helpful in developing reliable mental health support systems using AI.

2. Related Works

i). **Zaidi, S.A.M., Latif, S., Qadir, J.:** "Enhancing Cross-language Multimodal Emotion Recognition with Dual Attention Transformers." IEEE Open Journal of the Computer Society, 2024.

ii). **R. Liu, Y. p. Du, and Z.-P. Liang:** "Information – Theoretic Analysis of Multimodal Image Transition" IEEE Transactions on Medical Imaging, 2024.

iii). **Y. C. Yoon.:** "Can we exploit all datasets? Multimodal emotion recognition using cross – modal translation." IEEE Access, June, 2022.

iv). **M.S. Zitouni, C. Y. Park, U. Lee, and A. Khandoke.:** "LSTM-Modeling of emotion recognition using peripheral physiological signals in naturalistic conversations" IEEE Journal, 2023

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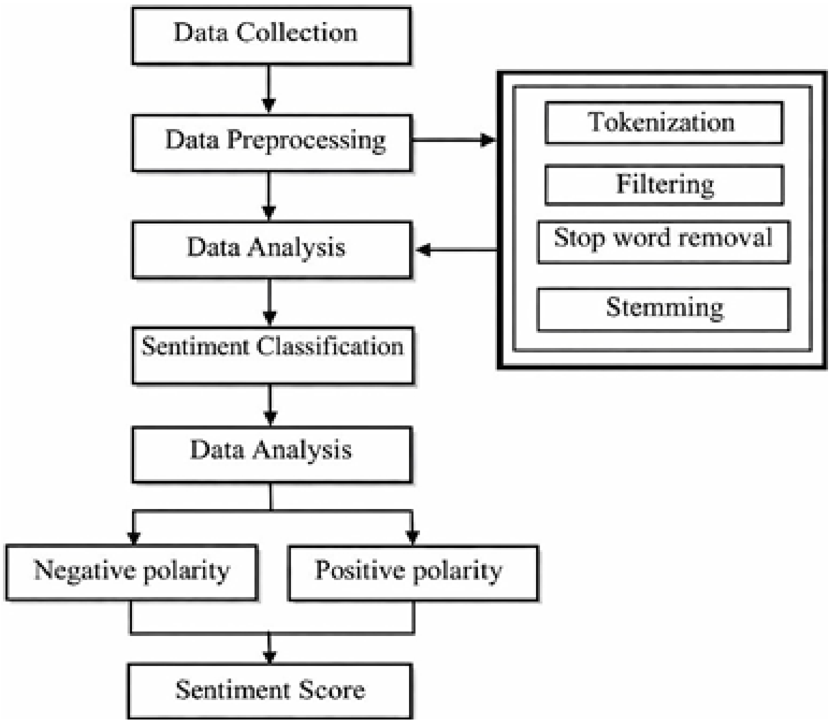
3. Block Diagram



4. The Proposed Construction

The proposed system includes a Dual Attention Model for Emotion Recognition and AI Therapeutic Communication that aims to correctly identify the emotional state from the text input and provide a corresponding empathetic response. The system has a number of interconnected modules as follows:

i). **Data Acquisition and Preprocessing Module:** The system accepts user-submitted textual data input through a chatbot interface. The preprocessing steps include text cleaning, lowercasing, noise removal (URLs, special characters), tokenization, and sequence padding. The text is then represented as dense vectors using embeddings or contextual embedding models to capture semantic relationships.

ii). **Contextual Feature Extraction (Transformer Encoder):** A transformer encoder is used to extract the deep semantic features of the text. The self-attention mechanism allows the model to give context-specific weights to each word in the sentence compared to other words, which helps to better understand complex emotional expressions.

iii). **Bidirectional Sequential Modeling (Bi-LSTM Layer):** The contextual embeddings are fed into a Bidirectional Long Short-Term Memory (Bi-LSTM) network. This layer is responsible for processing the sequence in both forward and backward passes, thus ensuring that the contextual information is well understood.

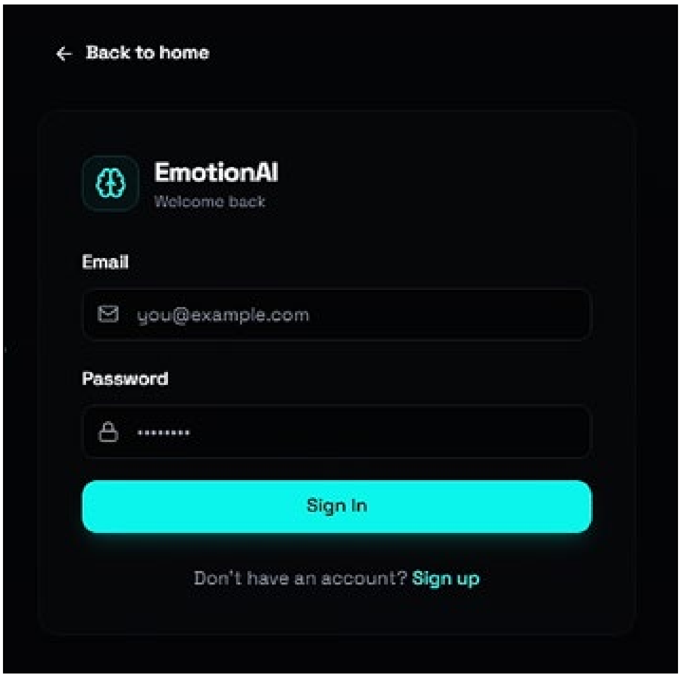
iv). **Emotion Classification Layer:** The combined attention-weighted features are passed to fully connected dense layers, followed by a softmax activation function for multi-class emotion classification. The system classifies the input into predefined classes of emotions like happiness, sadness, anger, fear, surprise, or neutral.

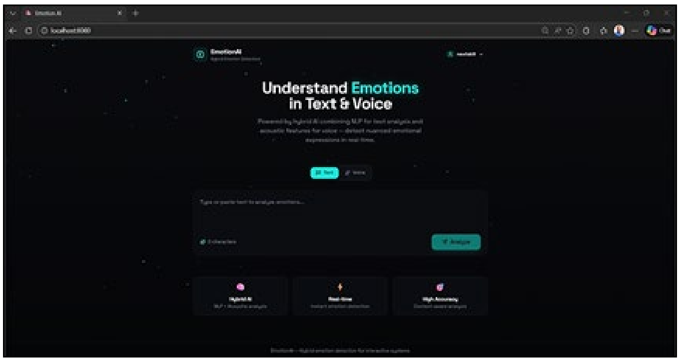
v). **AI Therapeutic Communication Module:** After the emotional state has been determined, the system then activates the response generation module. The response generation module employs controlled natural language generation processes to generate empathetic and supportive responses that are psychologically appropriate. The generated responses are intended to be coherent while following basic principles of therapeutic communication.

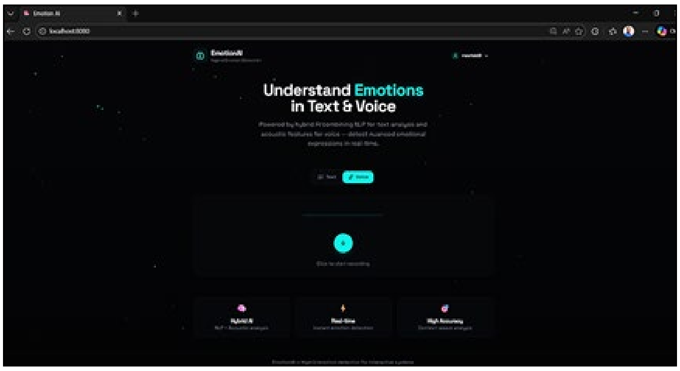
vi). **Training and Optimization:** The model is trained on labeled datasets of emotions. Cross-entropy loss functions are used for multi-class classification problems, and optimization algorithms like Adam are used to optimize the loss. Regularization and dropout layers are used to avoid overfitting.

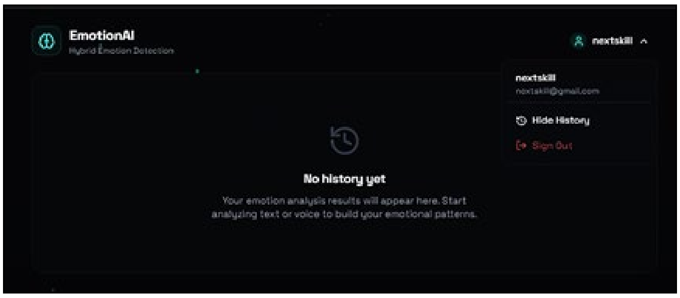
vii). **Evaluation Metrics:** The performance of the system is measured using the standard performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis.

5. Output









6. Conclusion

This research work has proposed a Dual Attention Model for Emotion Recognition and AI Therapeutic Communication to enhance the process of emotion recognition and empathetic response generation. The proposed model has been able to effectively identify the meaning and intensity of emotions from the text by integrating semantic and emotional attention models with deep learning models.

The experimental outcome shows that the proposed model performs better than the traditional single-attention model. The proposed framework is a scalable solution for mental health chatbots and digital well-being applications, which can be further improved by incorporating personalization and multimodal approaches.

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