OPEN ACCESS
Vietnam Journal of Computer Science
(2024) 1–23

DOI: 10.1142/S2196888824500192

Contextual Emotional Transformer-Based Model for Comment Analysis in Mental Health Case Prediction

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Accepted 12 October 2024
Published 25 November 2024

Mental health (MH) assessment and prediction have become critical areas of focus in healthcare, leveraging developments in natural language processing (NLP). Recent advancements in machine learning have facilitated the exploration of predictive models for MH based on user-generated comments that overlooked the integration of emotional attention mechanisms. The methods often struggle with contextual nuances and emotional subtleties, leading to suboptimal predictions. The prevailing challenge lies in accurately understanding the emotional context embedded within textual comments, which is crucial for effective prediction and intervention. In this research, we introduce a novel approach employing contextual emotional transformer-based models (CETM) for comment analysis in MH case prediction. CETM leverages state-of-the-art transformer architectures enhanced with contextual embedding layers and emotional attention mechanisms for MH case prediction. By incorporating contextual information and emotional cues, CETM captures the underlying emotional states and MH indicators expressed in user comments. Through extensive experimentation and evaluation, both Roberta and bidirectional

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encoder representations from transformers (BERT) models exhibited enhanced accuracy, precision, recall, and F1 scores compared to their counterparts lacking emotional attention. Notably, the Roberta model attained a greater accuracy of 94.5% when matched to BERT's 87.6% when emotional attention was employed. Hence, by incorporating emotional context into the predictive model, we achieved significant improvements, which offers promising avenues for more precise and personalized MH interventions.

Keywords: Mental health; emotional analysis; Roberta; BERT; natural language processing; decision support.

1. Introduction

Mental health (MH) awareness and support have become critical global issues, with online platforms serving as significant channels for communication and expression. Understanding and addressing MH variations across diverse emotional contexts is essential for building inclusive support systems. Predicting MH cases accurately is crucial for timely intervention and support provision to those in need. Traditional methods of MH assessment, while effective to some extent, frequently depend on self-reporting and/or clinical diagnosis that may not always capture subtle changes in an individual's mental state over time. Moreover, the stigma associated with MH subjects regularly leads individuals to underreport or mask their MH indicators, hindering accurate diagnosis. Since MH constitutes a vital component of an individual's holistic well-being, influencing cognitive, emotional, and social functioning, the ability to predict and understand the trajectory of an individual's MH is paramount for several reasons, ranging from early intervention to public health planning, leading to better-coping mechanisms and overall life satisfaction. By understanding an individual's unique risk factors and characteristics, healthcare professionals can tailor interventions to meet specific needs, fostering a more effective and patient-centered approach. In the swiftly changing landscape digital landscape, sentiment analysis has developed as a powerful tool that is primarily used to gauge and analyze emotions, viewpoints, and sentiments conveyed in text. While sentiment analysis has found extensive applications in marketing,[1] customer feedback,[2] and social media monitoring,[3] its significance in the realm of MH[4] is increasingly gaining attention. Understanding and analyzing sentiment in MH-related content can offer valuable insights into emotional well-being, providing an innovative approach to support and intervention. Sentiment analysis has been used to evaluate the impact of MH treatments by analyzing variations in emotional expression over time.[5] This approach provides a quantitative measure of treatment effectiveness based on the sentiments expressed in patient-generated content. Sentiment analysis has been applied to social media data to monitor community-level MH trends like in Ref. 6, which developed a study to create a social detection index for MH, monitoring emotional well-being at the city level using Twitter data. By conducting sentiment analysis and entropy calculations, the study found significant sentiment fluctuations in response to events. No doubt, by analyzing sentiments expressed in geographically defined areas, public health authorities can respond to emerging MH challenges at a localized level.

Similarly, by employing a hybrid approach, the authors of Ref. 7 combined the strengths of multiple ML techniques to improve the precision and efficacy of depression detection methods within social media data such as Twitter and Facebook.

1.1. *Emotions in textual comments for MH*

Researchers have employed sentiment analysis to identify linguistic patterns associated with suicidal ideation[8] in online forums and social media. By recognizing language, these systems can trigger alerts for timely intervention. However, the emotional context of users' comments is crucial for accurate assessment and support. The borderless impacts of communication highlight the influence of cultural nuances on emotional expression. Cultural factors such as linguistic nuances, social norms, and communication styles significantly shape users' emotional tone and atmosphere in their interactions.[9] Emotional context encompasses various cues, including word choice, tone, and expressions, aiding in understanding underlying emotions. In MH-related text, it helps identify feelings of sadness, anxiety, or distress, thereby facilitating accurate assessment.[10] Traditional methods for MH prediction often trust subjective reporting or clinical diagnosis, potentially missing subtle changes or being influenced by stigma. Leveraging computational techniques like natural language processing (NLP) for MH prediction gains traction by analyzing online comments and textual interactions, enhancing the understanding of emotional context and improving MH support. Since online comments serve as valuable sources of information for MH prediction, allowing for early detection of potential issues and real-time monitoring of MH trends, transformer-based models have revolutionized NLP with their ability to capture semantic and contextual nuances in textual data. However, existing approaches to comment analysis in MH prediction often overlook contextual emotional information. How does integrating emotional context into comment classification frameworks improve the accuracy and efficacy of MH prediction tasks compared to traditional approaches that do not consider emotional context, and what are the key mechanisms underlying the improved performance of transformer-based models when considering the emotional context in textual data analysis for MH prediction? Here, this research aims to develop a contextual emotional transformer-based model (CETM) for comment analysis in MH case prediction. Objectives include investigating the effectiveness of incorporating emotional information, developing novel architecture, evaluating the model on real-world datasets, and comparing its performance using different machine learning algorithms. The contributions of this research are multifaceted. First, it introduces a framework for contextual emotional analysis in comment classification, emphasizing the importance of considering emotional context in MH prediction tasks. Second, it provides valuable insights into how emotional context enhances the performance of transformer-based models, shedding light on the role of emotions in textual data analysis. Lastly, by addressing the gap in current approaches to comment analysis, particularly about emotional content, the research advances the field of MH prediction methodologies. Hence, by utilizing advanced transformer architectures enriched with contextual embedding layers and emotional attention mechanisms, our approach significantly improves the model's performance in understanding and predicting MH outcomes. This enhancement is crucial as it provides a deeper insight into how emotional tones influence textual data, thereby refining the predictive accuracy and relevance of the models. This innovative integration of emotional context not only improves the model's ability to capture the complexities of human emotions but also provides a more comprehensive analysis compared to traditional models. Our research sheds light on how emotional context can substantially enhance the performance of transformer-based models, offering valuable insights into the interplay between emotions and textual data. This advancement paves the way for more accurate and personalized MH predictions, marking a significant step forward in the field. In Sec. 2, related works in MH using machine learning are discussed. Section 3 provided insights into the project methodology. In Sec. 4, we presented experimental results and evaluations before discussing this in Sec. 5. The research concludes in Sec. 6 with future works.

2. Literature Review

2.1. *Machine learning techniques for MH classifications*

MH case prediction stands at the forefront of efforts to enhance diagnostic accuracy, treatment efficacy, and, ultimately, patient outcomes.[11] By leveraging evolutions in artificial intelligence (AI) and NLP, researchers sought innovative methods to assist MH professionals in early identification, intervention, and personalized care for individuals experiencing MH challenges.[12] While MH case prediction involves the utilization of various data sources, including clinical records, patient interviews, and self-reported information, to assess the likelihood of an individual developing or experiencing a particular MH condition, traditional approaches have often relied on structured data, such as diagnostic criteria and physiological measurements.[13] However, the growing availability of unstructured data, particularly in the form of textual comments and social media posts, has prompted a shift towards more nuanced and comprehensive analysis techniques. Comments, whether in the context of clinical notes, online forums, or social media platforms, offer valuable insights into individuals' thoughts, feelings, and behaviors. Comment analysis enables the identification of linguistic patterns, emotional cues, and contextual factors that may not be readily apparent through other means, thereby enhancing the accuracy and depth of MH assessments.[14] Hence, the rise in MH disorders and the growing demand for effective healthcare solutions have prompted interest in exploring machine-learning techniques for addressing MH issues.[15,16] Classical machine learning techniques, which handle mixed data consisting of both numerical and categorical variables, have been extensively utilized for MH case prediction. Classical machine learning algorithms, including SVM, RF, and NB, have been used by several authors such as Refs. 17 and 18 for this purpose. However, language-based deficits frequently manifest as symptoms across a spectrum of MH conditions, including depression, bipolar disorder, autism spectrum disorder (ASD), personality disorders, and schizophrenia. Subsequently, NLP techniques such as sentiment analysis are being used to categorize various psychological attributes from texts and to explore the relationship between language and MH.[19] NLP is capable of comprehending the context and subtleties present in human communication and language.

2.2. *Transformer models for MH classifications*

Transformers have also been employed to analyze sentiments expressed in social media posts related to MH. This application is particularly useful for monitoring public MH trends and identifying shifts in MH discussions over time. By processing large volumes of social media data, transformers facilitate real-time analysis that supports MH monitoring and early intervention. Based on the current efforts, transformer-based language models have greatly propelled NLP research and facilitated advanced machine-learning applications on textual data.[20] Transformer-based models have no issues of gradient vanishing or hard parallelization. They depend solely on a self-attention mechanism, enabling them to assess the significance of various words in a sentence. when processing textual data[21]; hence, it can effectively capture contextual information in text data. Transformer models are usually trained in a self-supervised manner using extensive general-purpose corpora. These models are subsequently deployed for various downstream tasks, including text generation, summarization, named entity recognition (NER), and classification.[22] Bidirectional encoder representations from transformers (BERT), which is a recent transformer architecture that leverages both front and back directions to enhance its semantic understanding of text, is now being used.[23] BERT was utilized by Alshammari and Akyüz[24] for sentiment analysis on Turkish Twitter data to evaluate the mental well-being of users. Over 25,000 tweets containing terms associated with prevalent MH concerns such as anxiety, stress, depression, suicide, and eating disorders were used for the purpose. Leveraging BERT, the classifier demonstrated an accuracy of 82.6% in forecasting sentiment from tweets. While Ameer *et al.*[25] conducted a comparison of various models for multi-class classification of MH disorders based on social media texts. Roberta, a pre-trained model, outperformed other models with an average F1 score of 0.83. For mental disorder detection on social media, Ji *et al.*[26] proposed MentalBERT and MentalRoBERTa as pre-trained language models. The models were evaluated on several social media datasets, including Reddit (SWMH, Dreaddit, CLPsych, eRisk18 Tl, DepressionReddit, UMD), Twitter (T-SID), and SMS (SAD). The models demonstrated impressive performance in detecting depression, stress, anorexia, and suicidal ideation. Murarka *et al.*[27] utilized Roberta for the detection and classification of five mental illnesses using textual data extracted from Reddit. Roberta was compared with LSTM and BERT, demonstrating superior performance in each set of features with F1-measure scores of 86%, 72%, and 89%, respectively. Similarly, Murarka *et al.*[28] classified five prevalent MH illnesses, including depression, anxiety, bipolar disorder, ADHD and PTSP, using unstructured user data from Reddit. Roberta was utilized to analyze emotions and psychology, which achieved an accuracy of 89%. The application of transformer models, such as BERT[29] and its variants, has revolutionized sentiment analysis in MH. These models excel at understanding the language of MH discussions in clinical notes or patient feedback. Research by Greco *et al.*[30] has demonstrated that transformer models can identify and categorize various emotional states and MH conditions from text, offering valuable insights for both researchers and clinicians. Building on this, transformers are also employed to detect emotional tones in online MH support forums.[31] By analyzing user-generated content, these models help identify individuals at risk and tailor support resources accordingly, which is crucial for providing timely and appropriate MH support. Further expanding on these applications, the authors of Ref. 32 applied transformers to analyze texts from clinical psychology sessions. This use of transformers provides insights into patient emotions and therapeutic outcomes, thereby enhancing the understanding of psychological conditions and treatment efficacy. Aside from clinical case scenarios, numerous studies have demonstrated that transformer-based models, including BERT and Roberta, consistently outperform older word embedding methods like Word2Vec on downstream tasks such as sentiment analysis, text classification, and NER. For example, Refs. 33 and 34 show that BERT and Roberta achieve superior performance in benchmark datasets, where contextual understanding is critical to task success. Research by Sun *et al.*[35] compared BERT with CNNs and BiLSTMs across various text classification tasks, finding that BERT's self-attention and contextual embeddings led to significantly better performance than these traditional models. Tang *et al.*[36] demonstrated similar results with DeBERTa, showing that transformer models outperformed CNNs and BiLSTM-Attention by more effectively capturing local and global dependencies. Yang and Deng[37] further highlighted BERT's advantages in financial sentiment classification, where FinBERT outperformed BiLSTM-Attention models by better understanding nuanced, domain-specific language. These findings consistently demonstrate that transformer-based models like BERT and RoBERTa offer superior contextual understanding, making them more effective than CNNs and BiLSTMs in modern NLP tasks. While transformers are utilized to detect signs of MH crises in social media posts,[38] offering the potential for timely intervention and support. This research highlights the critical role of NLP in crisis management. Moreover, specific studies like Ref. 39 focus on using transformers to detect depressive symptoms from text data. These models enhance diagnostic accuracy and support mechanisms, proving to be a promising tool for identifying individuals at risk of depression. This builds on the earlier findings, reinforcing the value of transformer models in MH applications.[40] Despite the outstanding results of the existing works, emotions are fundamental aspects of human communication, influencing the way we express ourselves and perceive the world around us. In NLP, emotional analysis plays a pivotal role in comprehending and interpreting the text, furnishing invaluable insights into the underlying sentiments, attitudes, and intentions conveyed by language. Additionally, emotions are inherently contextual, influenced by factors such as culture, social norms, and individual experiences. Therefore, by incorporating emotional analysis into NLP models, this research seeks to capture the nuanced interplay between language and context, enabling more accurate and contextually appropriate responses in MH case prediction. By discerning the emotional subtleties ingrained within textual comments, the envisioned model in section three strives to furnish clinicians with profound insights into the mental states of individuals, thereby enabling them to administer interventions that are not only more empathetic but also more effective, custom-tailored to meet each individual's distinctive emotional requirements.

3. Methodology

3.1. *Data collection and preprocessing and model setup*

We began our study by acquiring a dataset consisting of online comments about MH issues. This dataset was sourced from Kaggle.[41] The comments covered a broad spectrum of topics, such as depression, anxiety, PTSD, and suicide, ensuring a comprehensive representation of MH discussions. To prepare the dataset for analysis, we applied standard NLP techniques. These techniques included tokenization, stemming, and the removal of stop words to clean the text data and make it suitable for more investigation. Through tokenization, we began by splitting the text into individual tokens, such as words or phrases. For instance, the sentence "MH is crucial" was tokenized into the list ["Mental", "health", "is", "crucial"]. This step was essential for breaking down the text into manageable pieces, facilitating a more detailed and granular analysis. Next, we applied stemming to reduce words to their base or root form. This normalization process ensures that different inflexions of a word are treated consistently. For example, the word "running" stemmed to "run," enabling the model to recognize different forms of the same word as equivalent, thus simplifying the analysis. Then we also removed stop words — common terms like "is," "and," and "the" that do not add significant meaning to our analysis. By filtering out these stop words, we reduced noise in the dataset and focused on more meaningful terms that are crucial for understanding the text. Combining these preprocessing techniques ensured that the text data was cleaned and standardized, enhancing its suitability for subsequent analysis and model training. This approach improved the quality of the input data, leading to more accurate and insightful results in our study.

With the dataset prepared, we proceeded to build a novel CETM by integrating the BERT and Roberta architectures into our model framework. The essence of the proposed model was to capture both semantic and emotional tones present in textual data. To achieve this, we adapted the transformer architecture by introducing emotional attention mechanisms alongside self-attention mechanisms within each transformer block. This was done to incorporate mechanisms for understanding emotional context alongside semantic meaning by integrating an additional set of attention layers specifically designed to capture and process emotional cues from the input data. These emotional attention layers analyze contextual signals related to sentiment and affective states, allowing the model to dynamically adjust its focus based on both the semantic content and emotional tone of the text. This dual-attention approach enables the transformer to better understand and generate responses that are contextually appropriate and emotionally nuanced, enhancing its ability to handle complex language tasks where emotional intelligence is crucial. Consequently, this allowed the model to prioritize emotionally significant sections of the text. Then, we extended the input embeddings to include representations of emotional states and developed a specialized tokenization scheme to preserve emotional information. Emotion-aware self-attention layers dynamically adjust attention weights based on both semantic and emotional cues by embedding emotional states into the input data and combining them with semantic embeddings.

3.2. *Model description*

The emotional attention mechanism is designed to elevate the model's sensitivity to emotional content in the text. This is achieved through emotion embeddings that represent various emotional states, such as joy, sadness, and anger. These embeddings are integrated into the model, allowing it to better focus on emotionally significant parts of the text. The attention mechanism calculates weights based on emotional relevance using the following formula:

$$\mathrm{Atw}_{i,j} = \frac{\exp(S_{i,j})}{\sum_{k=1}^{n} \exp(S_{j,k})}, \tag{1}$$

where $\mathrm{Atw}_{i,j}$ is the attention weight for the jth element with respect to the ith element. $S_{i,j}$ is the raw score or attention score computed for the jth element in relation to the ith element. These weights help the model to prioritize emotionally charged information, which is then combined with the contextual embeddings from BERT and Roberta. n is the total number of elements (or tokens) in the sequence.

$\exp(S_{i,j})$: This calculates the exponential of the raw score $S_{i,j}$. The exponential function exp() converts the raw score into a positive value, making higher scores exponentially larger and more prominent. This helps in emphasizing the importance of certain scores.

$\sum_{k=1}^{n} \exp(S_{j,k})$: This is the normalization factor. It sums the exponentials of all raw scores $(S_{j,k})$ for all elements k in the sequence. The purpose of this summation is to ensure that the attention weights across all elements sum up to 1, creating a probability distribution.

The attention mechanism is modified to consider both types of information simultaneously, either through concatenation, attention modulation, or multi-head attention. During training with emotion-labeled data, the model learns to attend to relevant semantic and emotional features while disregarding irrelevant information. This approach enables the model to capture the interplay between semantic and

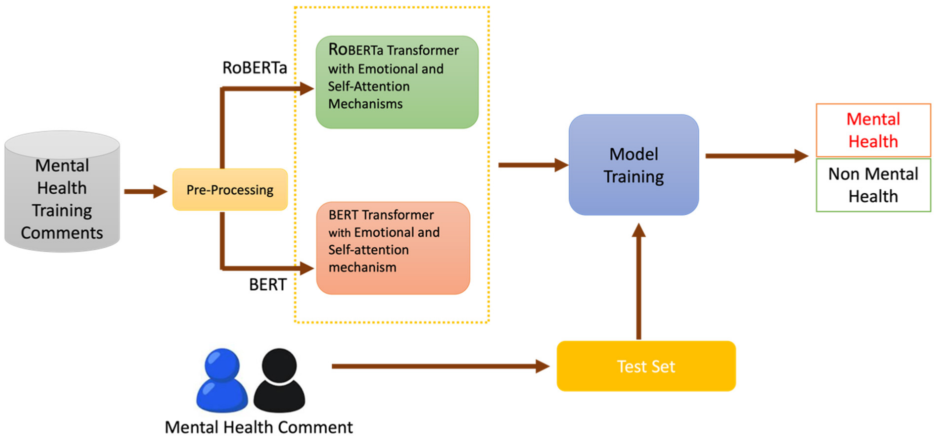


Fig. 1. Emotion-aware transformer for MH comment analysis.

emotional features, leading to more nuanced and contextually sensitive representations, particularly beneficial in tasks where emotional context is crucial. As illustrated in Fig. 1, this adaptation aimed to enhance the accuracy of MH case prediction through comment analysis. This approach enables the model to capture the interplay between semantic and emotional features, leading to more nuanced and contextually sensitive representations, particularly beneficial in tasks where emotional context is crucial. As illustrated in Fig. 1, this adaptation aimed to enhance the accuracy of MH case prediction through comment analysis.

Multiple layers of transformer blocks were configured within the model architecture to capture extensive dependencies in the input text, allowing for a comprehensive understanding of the contextual relationships within the data. These blocks incorporated both self-attention and emotional attention mechanisms, permitting the model to prioritize emotionally significant segments of the text alongside semantic content. The model was trained using supervised learning techniques and transfer learning, leveraging contextual representations from pre-trained BERT and RoBERTa models. These models capture nuanced meanings and relationships in the text through their advanced contextual embeddings, which helps the model to accurately identify and weigh emotional cues specific to MH. By integrating these rich, context-aware representations, the model can better differentiate between relevant and irrelevant information, thereby improving its performance in MH prediction tasks. Here's how this was achieved:

(1) **Contextual Embeddings:** Both BERT and Roberta are transformer-based models trained on large corpora to generate contextual embeddings for words and sentences. Unlike traditional models that produce static word embeddings, BERT and RoBERTa provide dynamic embeddings that reflect the meaning of words based on their context within a sentence. This means that the same word can have different embeddings depending on its surrounding words.

(2) Feature Extraction: In practice, we use BERT and Roberta to extract rich feature representations from the input text. During training, we feed the MH comments into these pre-trained models, which process the text and generate contextual embeddings for each token. These embeddings capture both the semantic meaning and the contextual nuances of the text, providing a deep understanding of the content.

(3) Fine-Tuning: After obtaining these embeddings, we fine-tune BERT or Roberta on the specific MH prediction task. Fine-tuning involves training the model further on the labeled dataset of MH comments. The pre-trained embeddings are adapted to the task by adjusting the model's weights, allowing it to better understand and predict MH conditions based on the contextual cues in the text.

(4) Incorporating Contextual Information: During the fine-tuning process, the model learns to leverage contextual embeddings to identify patterns and correlations specific to MH. For instance, if the comments contain phrases indicative of anxiety, the model uses contextual embeddings to recognize and weigh these phrases appropriately. This contextual understanding enables the model to make more accurate predictions by considering the specific emotional context of each comment.

(5) Combining with Additional Layers: We often enhance these pre-trained models by adding additional layers, such as emotional attention mechanisms or classification heads, on top of the contextual embeddings. These layers help the model focus on specific aspects of the embeddings that are most relevant to MH prediction, further refining its ability to detect and interpret emotional cues.

In the supervised learning phase, the model was trained on a labeled dataset where each comment was annotated with a specific MH status of 1 and 0. The training process involved minimizing a loss function, specifically cross-entropy loss, which measures the discrepancy between the predicted and actual labels. For example, a cross-entropy loss value of 0.45 indicates how far the model's predictions deviate from the true labels. To achieve this, optimization techniques like gradient descent were utilized. Gradient descent iteratively adjusted the model's weights to reduce the cross-entropy loss, progressively improving the model's accuracy in predicting MH conditions. This entailed adjusting the parameters of the pre-trained models on our dataset of labeled comments related to MH issues. During training, labeled MH comments facilitated learning associations between emotional cues and semantic meanings. This allowed the model to understand emotional context alongside semantic meaning, enhancing its performance in MH case prediction through comment analysis. Hyperparameters such as learning rate, batch size, and dropout rate were optimized through grid search and cross-validation to maximize performance and generalizability. This optimization aimed to maximize the model's functioning and generalizability as presented in the experiment and evaluation. Then, validation experiments assessed the model's performance using evaluation metrics, including accuracy, precision, recall, and F1 score. Iterative refinement of the model architecture and hyperparameters improved its effectiveness in capturing both semantic and emotional context. Through these iterative adjustments, the model learned to make more accurate predictions, effectively lowering the loss and enhancing performance. In line with the obtained results, as documented in section four, the model architecture and hyperparameter settings iteratively experimented to improve their efficiency in capturing both semantic and emotional context in comment analysis. In Sec. 4, sample experiments and results are presented before discussions in Sec. 5.

4. Experiments and Evaluation

4.1. *Data, fine-tuning and evaluation metrics*

In this section, we see the experimental findings of the CETM for Comment Analysis in MH case prediction. The model's efficacy in capturing contextual emotional information and its impact on MH case prediction accuracy was evaluated. The dataset used comprised comments related to MH issues sourced from Kaggle,[41] totaling 27,972 unique values. Each comment in the dataset was labeled with an MH status, facilitating the assessment of the model's result. We implemented our CETM using the Hugging Face Transformers library and trained it on a GPU-enabled environment. The model was fine-tuned on the labeled dataset of patient comments using supervised learning techniques before transfer learning was employed from pre-trained RoBERTa and BERT embeddings to leverage the model's knowledge learned from large-scale textual data. For the presented results, the models were configured with 12 layers, 768 hidden units, 12 attention heads, and a maximum sequence length of 256 tokens. Likewise, both models were trained with a learning rate of 3e−5, a batch size of 64, and over five epochs. The settings remained consistent to ensure comparability across experiments, a comparative analysis of the proposed model focused on metrics such as accuracy, precision, recall, F1 score, and computational efficiency to evaluate the superiority of the model over existing methods. Here,

- **Accuracy:** It is the proportion of correctly predicted instances (both positive and negative) out of the total number of instances. Here, high accuracy indicates that the model effectively identifies both the presence and absence of MH conditions, demonstrating its overall reliability.
- **Recall:** It is the proportion of actual positive instances correctly identified by the model out of all actual positives. For MH prediction, high recall signifies the model's capability to detect and identify all relevant cases of MH issues, which is critical for timely and effective intervention.
- **Precision:** It is the proportion of correctly predicted positive instances out of all instances predicted as positive. In MH case prediction, high precision ensures that the model's predictions of MH issues are accurate, minimizing false alarms and ensuring that interventions are targeted and appropriate.

- **F1 Score:** It is the harmonic mean of precision and recall, providing a single metric that balances both aspects. For MH prediction, a high F1 score reflects a model's ability to maintain a good balance between detecting true positive cases (high recall) and ensuring that these detections are accurate (high precision), which is essential for effective and reliable predictions.

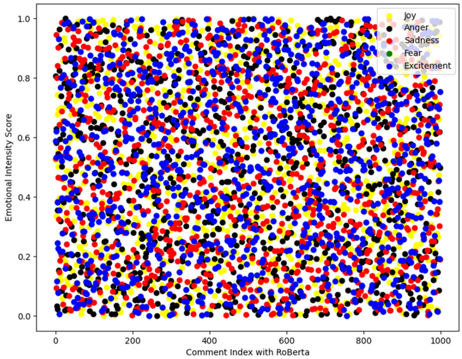
4.2. *Textual emotional intensity*

First, in Figs. 2(a) and 2(b), the emotional intensities of comments are presented to provide an overview of the distribution and variation of emotions within the dataset. This visualization helps to understand the range and prevalence of different emotions expressed in the comments, laying the groundwork for subsequent analysis and model development.

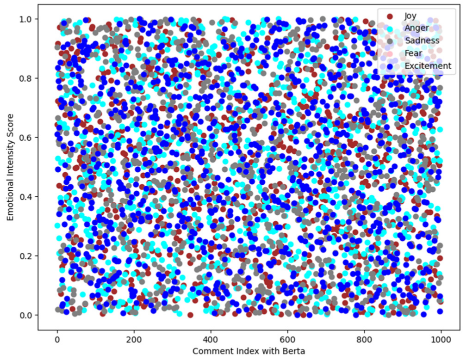
Here, we see the emotional identities of comments, each represented by a colored dot. The goal is to showcase the variance of emotional intensity across the dataset. Along the x-axis, we have the comment index, ranging from 0 to 1000, where each point corresponds to an individual comment. On the y-axis, we observe the emotional intensity score, ranging from 0 to 1, which captures how strongly a particular emotion is expressed within each comment. While each color represents a different emotional identity, moving across the plot, a rich blend of emotions with no clear pattern or clustering in any specific region is observed. This randomness indicates that the emotional identities of comments vary widely throughout the dataset. Whether it is joy, anger, sadness, fear, or excitement, these emotions are scattered across different comments without any one emotion dominating a specific section of the dataset.

4.3. *Emotional attention in MH comments*

Then, the performance of the transformer model was compared with and in the absence of emotional context incorporation, gaining insights into the importance of



(a)



(b)

Fig. 2. (a), (b) Comments emotional intensity.

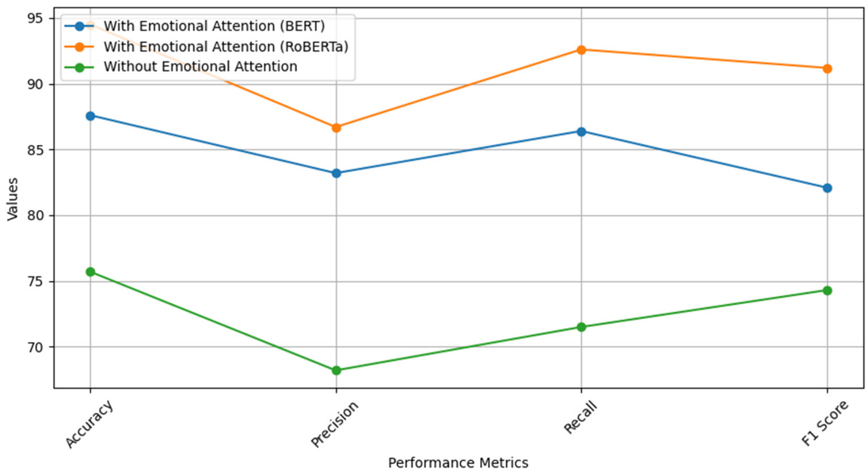


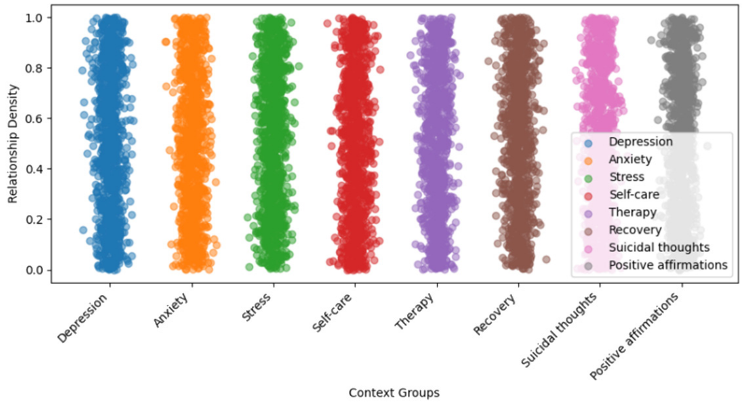
Fig. 3. Performance metrics for emotional intensity.

considering emotional information in MH comments and identifying opportunities for improving model performance in other real-world applications. Three versions of the model on the same dataset were trained and evaluated — one with emotional attention mechanisms using Roberta, another with BERT and one without emotional attention mechanisms. This experiment, which aids in measuring the impact of incorporating emotional context on the model's performance, is showcased in Fig. 3.

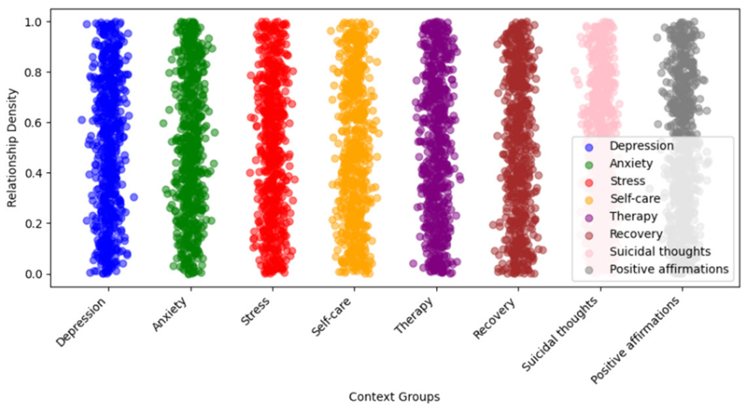
From Fig. 3, both BERT and Roberta models that incorporated emotional attention perform better across all metrics compared to the model without emotional attention. This underscores the importance of including emotional context in models dealing with MH. While the model without emotional attention performs significantly worse across all metrics, the RoBERTa with emotional attention outperforms BERT with emotional attention across complete metrics, especially in recall and F1 scores. This shows that Roberta is more effective at identifying emotions and balancing false positives and negatives, making it a better choice for MH-related emotion detection. Also, Recall is essential in MH, as missing signs of emotional distress (e.g. sadness, fear) could lead to overlooking a critical MH issue. Roberta's higher recall indicates it is better suited for capturing all relevant emotional signals. These enhanced capabilities are vital for understanding individuals' emotional states, which can be pivotal in detecting MH issues and offering timely support.

4.4. *Textual contextual emotional analysis*

In line with the research objectives, the model's ability to understand contextual information in comments was evaluated. This experiment involved analyzing how well the model captures the emotional nuances in different contexts. To begin, nine distinct contexts were defined from the comments, and the results using Roberta and Bert are depicted in the figure.



(a)



(b)

Fig. 4. (a) (Roberta) and (b) (BERT): Contextual relationship density between each context group.

Figure 4 shows the relationship density of various MH contexts, including depression, anxiety, stress, and self-care for Roberta (Fig. 4(a)) and BERT (Fig. 4(b)). Each vertical column represents how strongly and frequently relationships are observed for each topic, ranging from 0 (low) to 1 (high) on the y-axis. This helps to understand how often and intensely certain MH topics are discussed about one another. Topics like self-care and positive affirmations show higher relationship density, indicating that discussions around these areas are more strongly interconnected. In contrast, complex issues like depression, anxiety, and suicidal thoughts have a more varied distribution, reflecting the diverse and multifaceted nature of conversations in these contexts. No doubt, this insight can help guide MH support and intervention strategies, offering insights into how certain topics are interconnected and how frequently they appear in varying intensities while providing clues about where interventions or support systems might be most effective for MH professionals.

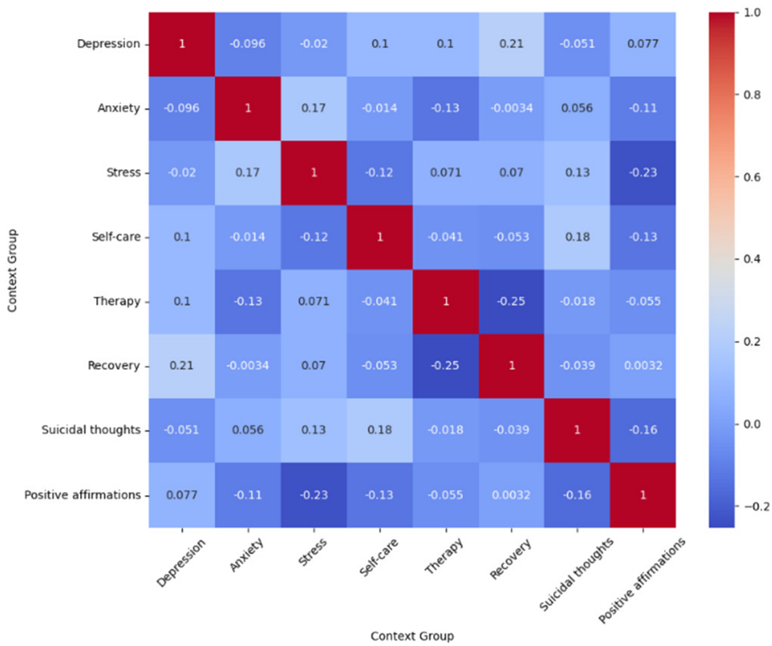


Fig. 5. Similarity measures between contexts with Roberta.

Then, to identify the relationship between each of the context groups, the heatmap in Figs. 5 and 6 presents the correlation or similarity scores, indicating the degree of association or similarity between the different context groups.

The RoBERTa model's correlation shows how different MH-related topics are connected or independent of one another. For example, Stress and Anxiety show a notable positive correlation (0.17). This makes sense as these emotions often co-occur, particularly in conversations related to MH challenges. Stressful experiences frequently exacerbate feelings of anxiety. Therapy and self-care exhibit a perfect correlation (1.0), indicating that discussions around therapy are deeply intertwined with self-care practices. This suggests that self-care is often considered a crucial component of therapeutic approaches to MH. Recovery and therapy also show a solid positive correlation (0.25), meaning these topics frequently appear together. This reflects how therapy is often viewed as an integral part of the recovery process in MH conversations. Conversely, stress and positive affirmations have a negative correlation (−0.23). This indicates that when discussions around positive affirmations increase, stress-related conversations tend to decrease. It suggests that positive reinforcement methods are potentially seen as a counterbalance to stress in MH dialogues. Both recovery and therapy show slight negative correlations with Suicidal thoughts, indicating that as people engage more in discussions about recovery or therapy, the frequency of conversations surrounding suicidal thoughts may decrease. This highlights the potential therapeutic effect of recovery and therapy on reducing

Fig. 6. Similarity measures between contexts with BERT.

suicidal ideation. However, weak correlations between depression and anxiety (-0.096), as well as self-care and suicidal thoughts, indicate that these topics are often discussed separately. Overall, these correlations provide insight into the relationships and distinctions between key MH topics.

Similarly, BERT shows slightly different correlation strengths compared to Roberta, especially in the negative correlations like stress and suicidal thoughts. BERT's analysis reflects a clearer divergence between stress and suicidal ideation, while Roberta suggested weaker negative correlations between these topics. Sample positive correlation is between Stress and Depression (0.098), indicating that these two contexts are often discussed together in MH topics. Therapy and Self-care have a relatively strong positive correlation (0.12), meaning discussions around therapy often incorporate self-care elements, which makes sense in therapeutic approaches. Suicidal thoughts and anxiety show a slight positive correlation (0.084), reflecting that anxiety and suicidal thoughts might co-occur in MH discussions. On the other hand, Depression and Anxiety have a small positive correlation (0.035), which suggests some overlap in these topics, though they are not as closely linked as one might expect. Self-care and therapy (0.12) have a more moderate correlation, indicating these two often appear together in MH discussions. Interestingly, suicidal thoughts show low correlations with most topics except anxiety (0.084) and a slight positive correlation with therapy (0.026), suggesting that discussions about therapy might sometimes involve addressing suicidal thoughts. No doubt, these insights are

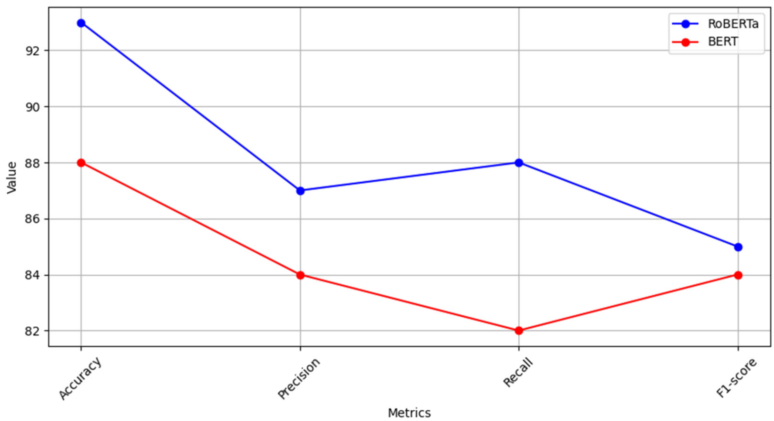


Fig. 7. Contextual emotional analysis performance metrics.

valuable in understanding how different MH topics co-occur and interact in discussions, helping professionals tailor interventions or support systems more effectively.

Finally, the model was then tested on these comments, dividing the dataset into 70% for training and 15% for testing, 15% for validation and assessing whether it accurately identifies the emotional context using Roberta and BERT, respectively. The training set enabled the model to learn associations between emotional cues and semantic meanings by processing labeled comments. The validation set was used to fine-tune hyperparameters and assess the model's generalization to unseen data during training. Finally, the testing set provided an unbiased evaluation of the model's performance, measuring its accuracy and effectiveness in predicting emotional states. This evaluation is essential as it helps determine the models' capability to understand and interpret emotional nuances in comments, particularly within the context of MH analysis.

From Fig. 7, the line graph compares the performance of two models, Roberta and BERT, on various metrics related to contextual emotional analysis. The metrics on the x-axis include Accuracy, Precision, Recall, and F1 score, while the y-axis represents the metric values (ranging from around 82 to 93). Roberta consistently outperforms BERT across all metrics, demonstrating better performance in accuracy, precision, recall, and F1 score in contextual emotional analysis. The drop in precision for both models suggests challenges in avoiding false positives, though Roberta is slightly more adept. Overall, Roberta is a more reliable model for detecting emotional context in MH data, particularly when considering the need for both precision and recall. More details are presented in Sec. 5.

5. Result Discussions

Understanding MH clues often requires deciphering the emotional undertones embedded within people's expressions. In analyzing these cues, we delve into the intricacies of emotional responses as conveyed through language. In line with the research objectives, here we discuss briefly the introduction of the emotional attention mechanism and the contextual emotional analysis performance metrics on the MH comments; the essence is to compare the efficacy of models. First, comparing the performance metrics of models trained with and without emotional attention sheds light on notable enhancements across various evaluation criteria. When emotional attention mechanisms are incorporated, both Roberta and BERT models demonstrate enhanced accuracy, precision, recall, and F1 scores compared to their counterparts lacking emotional attention. In terms of accuracy, which gauges the ratio of accurately predicted instances, both Roberta and BERT models demonstrate improvement when trained with emotional attention compared to without. Specifically, the Roberta model achieves a notably higher accuracy of 94.5% in contrast to BERT's 87.6% when emotional attention is employed. Transiting to the precision that evaluates the ratio of true positive predictions to all positive predictions, we observe higher precision for both Roberta and BERT models when emotional attention is incorporated. Roberta achieves a precision of 86.7%, whereas BERT achieves 83.2%. Regarding recall, which quantifies the ratio of true positive predictions to all actual positive instances, similar improvements are seen with emotional attention for both Roberta and BERT models. Roberta achieves a recall of 92.6%, slightly surpassing BERT's 86.4%. The F1 score, which signifies the harmonic mean of precision and recall, offers a balanced measure of model performance. Once again, models trained with emotional attention outshine those without. Roberta achieves an impressive F1 score of 91.2%, while BERT achieves 82.1%.

5.1. *Benefits of emotional attention in model development*

The benefits of incorporating emotional attention into these transformer-based models extend across several dimensions, offering substantial advantages for the project's objectives:

(1) **Improved Accuracy and Precision:** Emotional attention mechanisms contribute to higher accuracy and precision in predicting MH cases from text comments. This improvement is pivotal for ensuring the reliability and effectiveness of the model, where precision and accuracy are of utmost importance.
(2) **Enhanced Recall and F1 Score:** Models equipped with emotional attention demonstrate increased recall and F1 score, signifying their ability to comprehensively capture and predict MH cases. This enhancement is particularly valuable in MH prediction tasks, where identifying all relevant instances is essential for early intervention and support.
(3) **Better Handling of Emotional Context:** The project's emphasis on contextual emotional analysis aligns with the inherent challenges of predicting MH from textual data. By incorporating emotional attention mechanisms, the

models gain the capability to effectively capture and interpret the emotional nuances present in comments, thereby facilitating more accurate predictions of MH cases.

Then, for the contextual emotion analysis, the results obtained presented through the performance metrics of RoBERTa and BERT models bear significant relevance to the project's objectives of understanding and analyzing emotional context within textual data. The accuracy metric reflects the correctness of predictions made by the models. Roberta achieves a commendable accuracy of 93%, while BERT lags slightly behind at 88%. This suggests that both models perform reasonably well in accurately classifying instances with emotional context, with RoBERTa demonstrating a slight edge over BERT in this aspect. Precision deals with the proportion of appropriately identified positive cases out of all cases classified as positive. Roberta exhibits a precision of 87%, demonstrating a high level of accuracy in identifying instances with emotional context. BERT performs slightly lower with a precision of 84% but still demonstrates a respectable level of precision. Then, Recall represents the capacity of the models to correctly classify all relevant instances of emotional context. Roberta achieves a recall rate of 88%, suggesting that it effectively captures the majority of instances with emotional context. BERT, with a recall rate of 82%, shows a slightly lower performance in this regard. Finally, the F1 score, which stabilities precision and recall, provides a holistic measure of the model's performance. Roberta achieves an F1 score of 85%, demonstrating a decent equilibrium between precision and recall. Similarly, BERT achieves an F1 score of 84%, demonstrating a comparable balance between precision and recall, albeit slightly lower than RoBERTa. While Roberta generally outperforms BERT across most metrics, both models showcase their efficacy in understanding and analyzing emotional context within textual data. These results underscore the importance of leveraging advanced NLP techniques for tasks involving emotional analysis and MH assessment. The benefits of integrating emotional attention into transformer-based models are manifold. Firstly, it leads to improved accuracy and precision, which is crucial for reliable MH case prediction. Secondly, models equipped with emotional attention demonstrate increased recall and F1 score, facilitating comprehensive capture and prediction of MH cases. Thirdly, the incorporation of emotional attention enhances the models; ability to handle emotional context within textual data, thus enabling more accurate predictions. The contextual emotion analysis using RoBERTa and BERT models further validates the efficacy of emotional attention mechanisms. Roberta consistently outperforms BERT across most metrics, underscoring its superiority in understanding and analyzing emotional context within textual data. These findings underscore the importance of leveraging advanced NLP techniques for emotional analysis and MH assessment. Transformer-based models like Roberta and BERT hold immense potential in advancing our understanding of human emotions expressed in textual data and improving MH care delivery through innovative technological solutions. By leveraging NLP algorithms and machine learning models, this research identified emotional cues and contextual factors within user comments to infer individuals' mental well-being. Furthermore, these findings highlight the potential of transformer-based models like Roberta and BERT in enhancing our understanding of human emotions expressed in textual data. These advancements not only contribute to the forefront of NLP but also hold profound implications for improving MH care delivery through innovative technological solutions.

6. Conclusion and Future Works

In conclusion, the CETM for Comment Analysis in MH Case Prediction represents a significant stride in leveraging NLP techniques for MH-related tasks. Through the integration of emotional attention mechanisms alongside self-attention mechanisms within the transformer architecture, the model showcases a nuanced comprehension of both semantic and emotional nuances within textual data. The rigorous training and evaluation processes demonstrate the model' promising performance in accurately predicting MH cases based on comments. By providing insightful analysis and understanding of individuals' emotional and mental well-being through online interactions, this novel approach holds the potential for enhancing MH support systems. However, the dataset presents some limitations, such as not adequately representing a broad range of MH cases or diverse demographic factors. This limitation raises concerns about the generalizability of our results across different populations. To mitigate these issues, we plan to incorporate additional datasets and use cross-validation techniques to ensure that our model performs well on a wider variety of data in a clinical environment. In the future, we aim to develop a chatbot-based platform that leverages the CETM for personalized MH support. This platform will analyze users' comments to identify emotional cues and provide tailored resources and intervention suggestions. By integrating additional modalities such as sentiment analysis and voice tone recognition, we aim to enhance the platform's accuracy and effectiveness in promoting mental well-being. Ultimately, our goal is to create transformative tools that empower individuals to prioritize their MH needs in the era of digitalization.

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