A Social Cognitive-Inspired Social Media Sentiment Classification Model

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ABSTRACT

Social cognition, encompassing the perception, interpretation, and response to social stimuli, plays a vital role in understanding human interactions. Nowadays, with the surge of social media platforms, analyzing social cognition through digital text has become an imperative task. Traditional cognitive architectures like ACT-R and SOAR face challenges in processing large-scale, unstructured data, such as those produced from social media platforms. This study addresses this problem by proposing a fine-tuned BERT-based model for understanding social cognition and emotions. The objective was to enhance social cognitive emotion classification accuracy and contextual understanding of social interactions. The methodology involved fine-tuning BERT with adaptations inspired by cognitive models, enabling the classification of emotions (neutral, positive, and negative) and the analysis of social interaction patterns. The model was evaluated on a Twitter dataset, achieving an accuracy of 83.1%, outperforming existing models such as RoBERTa (80.54%) and standard BERT (79.25%). The results underscore the effectiveness of task-specific fine-tuning in capturing social and emotional cognition. This work's novelty lies in integrating transformer-based models with cognitive principles, providing a robust, scalable framework for analyzing social cognition.

Keywords-social cognition; transformer models; BERT; emotion classification; cognitive modeling; social media analysis

I. INTRODUCTION

Social cognition is a vital aspect of human functioning, encompassing the ability to perceive, interpret, and respond to social stimuli. Albert Bandura's social cognition theory [1-3] formed the foundation for modern understanding of how individuals acquire behaviors and attitudes through a triadic interplay of personal cognitive factors, behaviors, and environmental influences, a concept he termed reciprocal determinism. Unlike traditional behavioral models, Bandura's approach includes internal mental processes, placing importance on self-efficacy, observational learning, and the processing of social experiences [4-7]. For example, high self-efficacy can encourage proactive behavior, which then positively influences environmental feedback, further strengthening personal beliefs. Expanding upon Bandura's theory, recent studies have emphasized the critical role of emotions in social cognition. Emotions such as happiness, sadness, anger, or neutrality significantly shape how individuals interpret social cues [8]. Adolphs introduced a neurocognitive framework, that links emotional processing with social reasoning capabilities [9, 10]. On the left side of Adolphs' model, basic sensory processing forms the initial stage, where facial expressions, tone, and body language are interpreted. This information then undergoes social reward evaluation and motivational analysis, affecting how individuals choose to engage socially [11]. Empathetic processing follows, enabling deeper emotional resonance and allowing people to understand and share others' feelings. On the right side of the model, complex sensory interpretation, action perception, Theory of Mind, and social reasoning stages contribute to the understanding and execution of socially appropriate responses [12]. However, disruptions in social cognition, often seen in individuals with brain injuries or developmental disorders, can severely affect social functioning. Such impairments may manifest as impulsivity, poor emotional regulation, or lack of empathy [13, 14]. These difficulties hinder the formation of meaningful relationships and participation in social and occupational settings [15-17]. For instance, individuals with deficits in Theory of Mind may misinterpret intentions, leading to socially awkward or even inappropriate responses. Thus, personalized interventions that target emotional, cognitive, and behavioral elements are essential for rehabilitation. This has led researchers to explore various cognitive models and AI-based tools to understand and improve social cognition.

Cognitive architectures such as ACT-R, SOAR, EM-ONE, and SMCA have been traditionally employed to simulate social cognition. ACT-R (Adaptive Control of Thought-Rational) decomposes human cognition into modules—each representing memory, perception, or motor actions—to simulate thought processes [18-21]. SOAR uses production rules and a goal-oriented structure to model social decision-making [22, 23]. EM-ONE adds a layer of emotional intelligence by incorporating emotional perception in decision-making [24, [25. The Socially-Motivated Cognitive Architecture (SMCA) integrates internal motivations like the need for social approval, highlighting how intrinsic drives shape social behaviors [26, 27]. Other architectures like CLARION [28] and LIDA [29] offer hybrid symbolic and sub-symbolic models, simulating explicit social learning and unconscious cue processing.

Despite their contribution, traditional cognitive models struggle with processing unstructured, large-scale data like those encountered in social media platforms. Their rule-based nature limits scalability and real-time adaptability. To address these limitations, transformer-based architectures like BERT (Bidirectional Encoder Representations from Transformers) have emerged as powerful tools for understanding social cognition in digital environments. Recent studies have demonstrated the efficacy of using BERT and other Natural Language Processing (NLP) methods to assess social emotions and sentiments. Authors in [30] developed SEANCE, a sentiment-analysis engine for modeling social sentiments using various linguistic agents. Authors in [31] adopted an NLP approach with Support Vector Machines (SVM) to model sentiment cognition using Amazon datasets, achieving high accuracy and reduced experimental costs. Authors in [32] employed BERT to classify Twitter data into positive, negative, and neutral sentiments, focusing on social cognition in a geographic area in Singapore. Their methodology included zero-shot learning and topic analysis to understand user attitudes and behavior patterns. Similarly, authors in [33] explored cognitive-inspired deep learning frameworks to enhance sentiment evaluation, emphasizing how cognitive models can be integrated with modern AI techniques. Authors in [34] collected Twitter data spanning eight years from the Borsa Istanbul (BIST). They aimed to correlate user sentiment with stock market behavior. Their analysis showed that GRU (Gated Recurrent Unit)-based models achieved 98% accuracy, while BERT attained 91% accuracy for classifying social cognitive emotions. These results underscore the capability of BERT in extracting emotional cues and understanding social behavior on digital platforms. However, BERT models are not without challenges. They are computationally intensive, difficult to interpret, and lack explicit reasoning capabilities like the Theory of Mind. Nonetheless, their generalization capabilities and adaptability through fine-tuning on task-specific data make them invaluable in contemporary research on social cognition. To build upon this foundation, the current work contributes in three major ways:

- It investigates the impact of emotions on social cognition, deepening the understanding of how emotional states affect interpersonal behavior and reasoning.
- It provides a comprehensive understanding of cognitive models, highlighting their mechanisms, strengths, and limitations.
- It introduces a fine-tuned BERT model specifically developed to analyze social-emotional cognition in virtual environments. This model effectively captures the sentiments of users, providing insights that are critical for applications in education, mental health, social media analysis, and beyond.

II. METHODOLOGY

The transformer architecture, as shown in Figure 1, forms the foundation of many modern NLP models due to its ability to capture contextual relationships across sequences through a self-attention mechanism. A transformer comprises two main components: an encoder and a decoder. The encoder processes input text, generating contextual embeddings, while the decoder predicts outputs sequentially, typically for tasks like text generation. The encoder's key functionality lies in multi-head self-attention, where attention weights between tokens Q (queries), K (keys), and V (values) are calculated. The scaled dot-product attention for a single head is defined as:

$$\text{Attention}(Q,K,V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (1)$$

where d_k is the dimensionality of the keys, ensuring proper scaling for stable gradients. Moreover, the attention heads enable the model to focus on different parts of the input simultaneously. The output is passed through a feedforward network for further transformation. The encoder-decoder attention in the decoder leverages the encoder's output, providing context for tasks like text generation.

The Positional Encodings (PE) in transformers, added to token embeddings, allow transformers to capture sequential information:

$$PE_{(pos,2i)} = \cos\left(\frac{pos}{10000^{\frac{2i}{d_{model}}}}\right) \qquad (2)$$

where pos is the token position and i is the dimension index.

This architecture has been adapted in BERT to enable contextualized understanding of text, as shown in Figure 2. BERT's primary innovation is bidirectional training, allowing it to consider both left and right context during pretraining, which is critical for capturing important social and emotional cues in text. BERT processes input as a concatenated sequence of tokens, sentences A and B, separated by a special token $[SEP]$. A classification token $[CLS]$ is added at the start to aggregate information for sequence-level predictions.

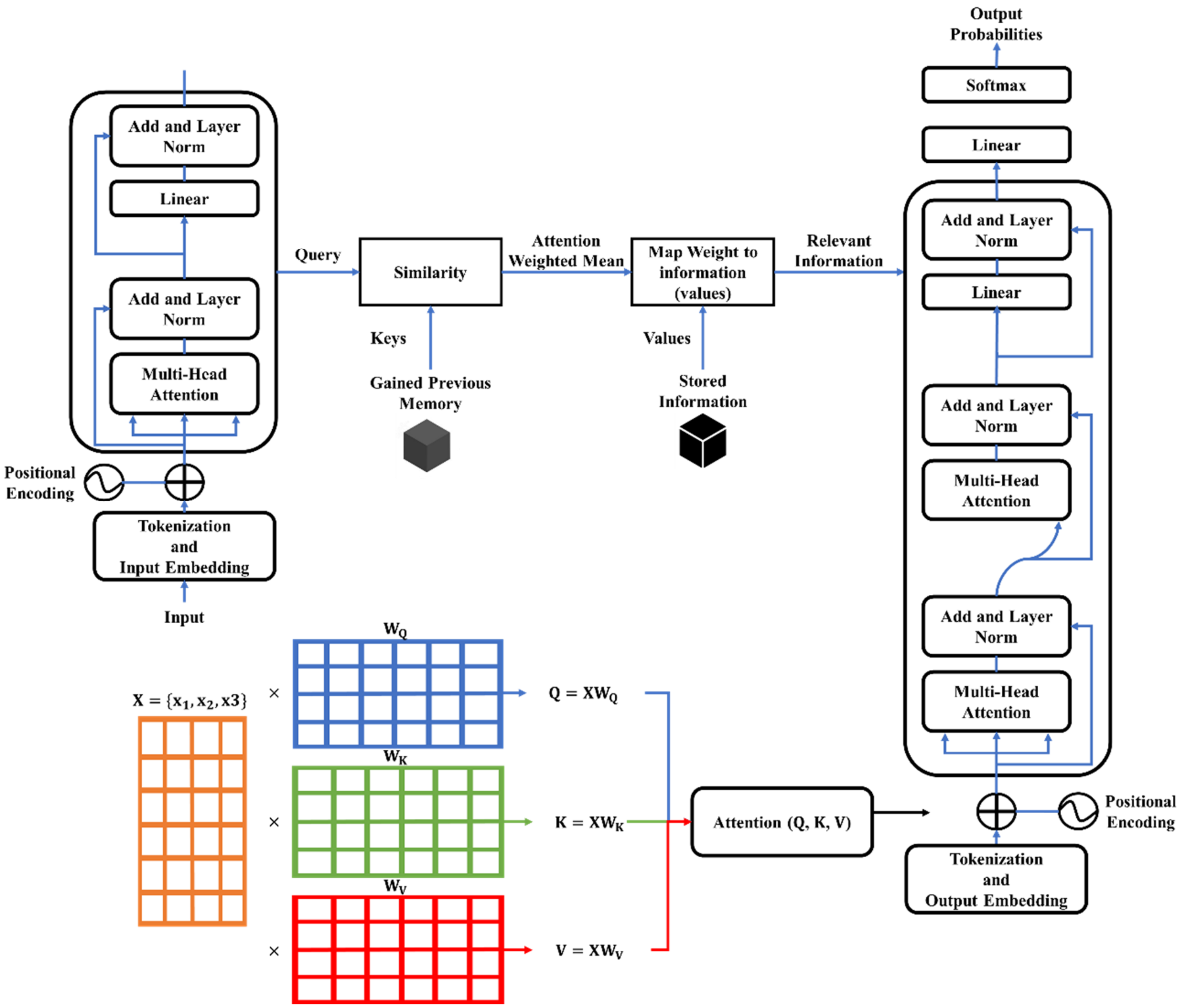

Fig. 1. The proposed transformer model.

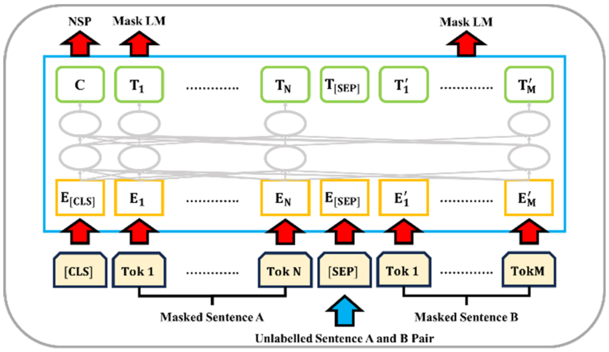

Fig. 2. BERT architecture.

Each token is represented as a sum of its token embedding E_{Token}, segment embedding $E_{Segment}$ (indicating whether a token belongs to sentence A or B), and positional embedding $E_{Position}$ as presented in (3):

$$E_i = E_{Token_i} + E_{Segment_i} + E_{Position_i} \quad (3)$$

The combined embedding sequence X is passed through L transformer layers to produce the contextualized embeddings H^L. The BERT's training involves two objectives, first is the Masked-Language-Modeling (MLM) and Next Sentence Prediction (NSP).

In MLM, BERT randomly masks 15% of tokens in the input and predicts them using their contextual embeddings. For a token T_i masked at position i, the probability distribution over the vocabulary is evaluated by:

$$P(T_i|X_{masked}) = \text{Softmax}(W_o H_i^L) \quad (4)$$

where W_o is projection matrix.

In NSP, this task models relationships between paired sentences. Given the sentence embeddings C from the $[CLS]$ token, the NSP head predicts whether the second sentence is the actual continuation of the first using (5):

$$P(NSP|C) = Softmax(W_{NSP} C) \quad (5)$$

To model the social cognition and emotional understanding using data from social media platforms (e.g., Twitter, Facebook) in this work, BERT has been fine-tuned to classify emotions (neutral, negative, positive). A cognitive model inspired by ACT-R and SMCA was designed using BERT as the processing core in this work. Consider an input sequence X, the output embedding C of the $[CLS]$ token is mapped to emotion probabilities for multi-label classification to predict multiple emotions simultaneously using (6):

$$P(e_i|X) = \text{Softmax}(W_e C) \tag{6}$$

where W_e maps the contextual representation to emotion classes.

NSP tasks are adapted to capture interaction context (e.g., reply chains in tweets). For the fine-tuning of sentence pairs (A, B) for modeling social interaction, (7) is used:

$$P(Interaction|C) = \text{Softmax}(W_{interaction} C) \tag{7}$$

For predicting actions like likes, shares, or replies based on conversational tone and context, the final transformer layer's outputs $H(L)$ generates probabilities for user actions:

$$P(Action_i|X) = \text{Softmax}(W_a H^L) \tag{8}$$

For modelling group dynamics, BERT embeddings were aggregated across messages to compute sentiment trajectories. Hence, the overall sentiment S at time t is evaluated by:

$$S_t = \frac{1}{N_t} \sum_{i=1}^{N_t} H_i^L \tag{9}$$

where N_t is the number of reviews at time t.

BERT's attention mechanisms can highlight critical words or phrases contributing to predictions, offering insights into social cognition. The fine-tuned BERT identifies influential cues in review using the visualizing attention scores α_{ij} between tokens:

$$\alpha_{ij} = \text{Softmax}\left(\frac{Q_i K_j^T}{\sqrt{d_k}}\right) \tag{10}$$

This approach, combining BERT's capabilities with a cognitive modeling approach, provides a scalable and interpretable tool for analyzing emotions and social cognition on social media. When evaluated on Twitter reviews, the BERT model analyzed public sentiment around trending topics, identifying polarizing conversations by modeling contextual inconsistencies.

III. RESULTS AND DISCUSSION

The dataset offered in [32] was utilized for the evaluation. It encompasses geotagged tweets collected from Singapore between 2008 and 2023. The total dataset contains 96686894 tweets from 2008 to 2023. For this study, similar to [32], this work considered tweets from 2020 to 2021, which contained 49939017 tweets, which were pre-processed, and a total of 40659542 tweets were considered for evaluation. Moreover, for evaluation of Fine-Tuned BERT and other BERT approaches [32, 34], the training and testing split ratio was 80:20, where 80% of data was used for training and 20% of data was used for testing, i.e., 32527634 tweets were considered for training and 8131908 tweets were considered for testing

The data are organized into three JSON files: tweets.json (96M+ tweets), place.json (10,000+ place records), and subzones.json (332 subzone details). Analytical approaches include sentiment analysis using a zero-shot pretrained model and bursty topic detection with the Biterm Topic Model. The system used to assess the performance of existing BERT models [32, 34] and the proposed fine-tuned BERT featured an AMD Ryzen 5 processor with 4 cores and 8 logical processors, complemented by 16 GB of RAM to ensure efficient operation. Python served as the primary programming language, with the Anaconda distribution employed to manage the development environment. Additionally, an NVIDIA GeForce GTX 1650 GPU was utilized to expedite the execution of NLP tasks. The models were evaluated using standard performance metrics:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{11}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{12}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{13}$$

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \tag{14}$$

where TP, TN, FP, and FN represent the number of True Positives, True Negatives, False Positives, and False Negatives, respectively. The results obtained from the experiments demonstrate the effectiveness of transformer-based models, i.e., BERT, for understanding social cognition and emotion. Figures 3-5 show the confusion matrices and Figures 6-9 the performance results of RoBERTa [32], BERT [34], and the proposed Fine-Tuned BERT model.

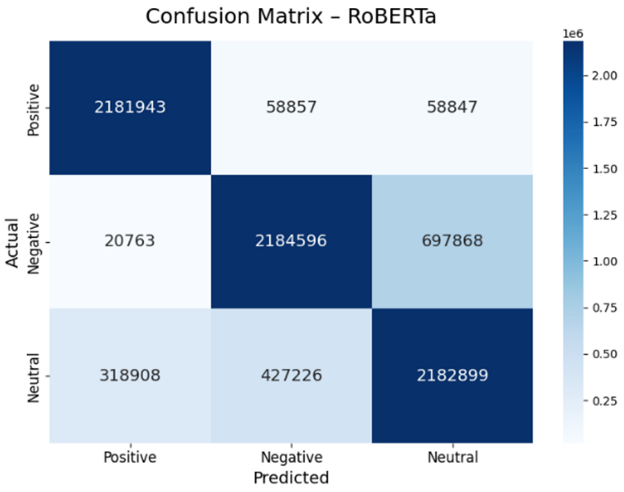

Fig. 3. RoBERTa Confusion Matrix.

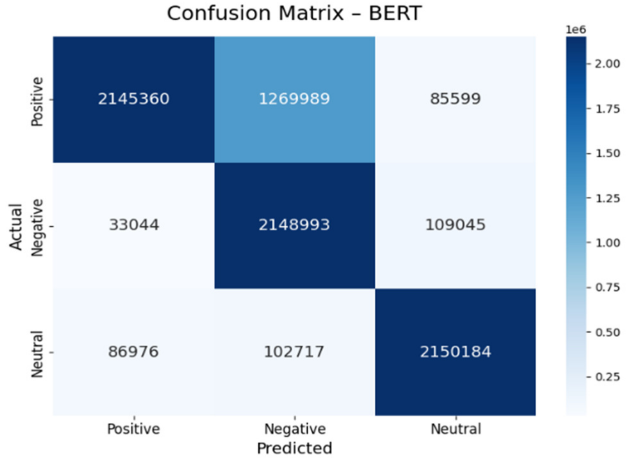

Fig. 4. BERT Confusion Matrix.

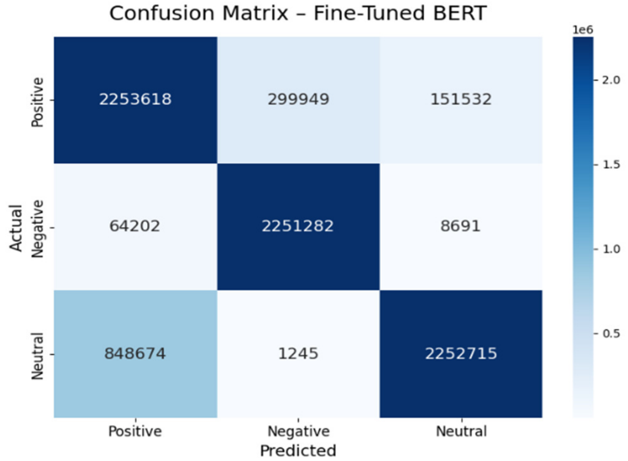

Fig. 5. Fine-Tuned BERT Confusion Matrix.

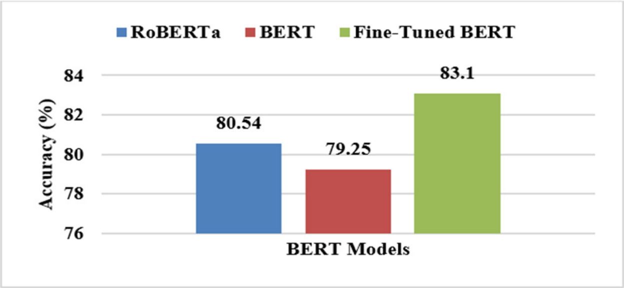

Fig. 6. Accuracy.

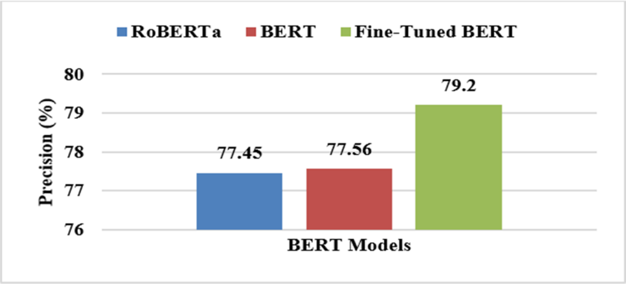

Fig. 7. Precision.

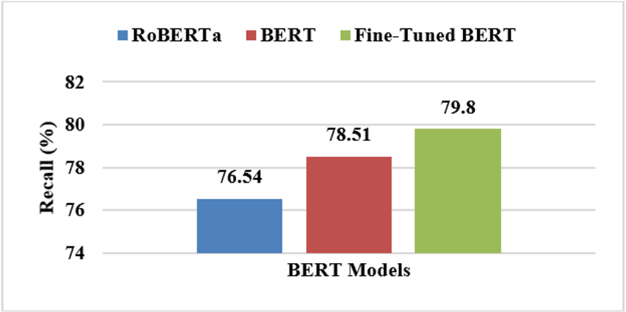

Fig. 8. Recall.

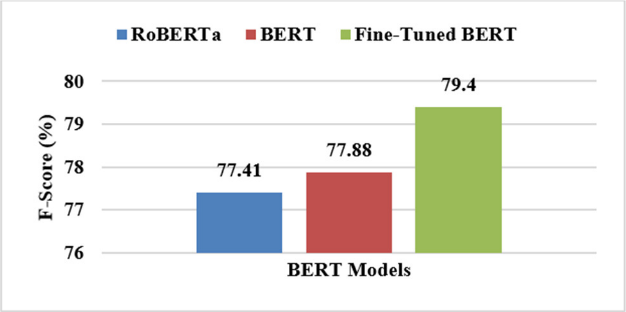

Fig. 9. F1-Score.

RoBERTa [32] achieved 80.54% accuracy, 77.45% precision, 76.54% recall, and 77.41 F1-score. The high accuracy and F1-score indicate that RoBERTa effectively captures social cognition cues, due to its robust pretraining on a large corpus and its ability to contextualize input data effectively. However, its performance slightly lags in recall compared to precision, denoting that it accurately identifies positive and negative social sentiments, but misses some relevant instances, which limits its ability to generalize. BERT [34] attained 79.25% accuracy, with precision, recall, and F1-score values of 77.56%, 78.51%, and 77.88, respectively. While BERT's performance is slightly lower than RoBERTa's in terms of accuracy, its recall is slightly higher, indicating a more balanced ability to identify relevant instances of positive, negative, and neutral sentiments. This shows that BERT's bidirectional training effectively captures social interactions, although it does not fully leverage all linguistic subtleties compared to RoBERTa. The fine-tuned BERT model outperforms both RoBERTa and standard BERT, achieving 83.1% accuracy, 79.2% precision, 79.8% recall, and 79.4% F1-score. The improvement in all metrics highlights the effectiveness of task-specific fine-tuning, which has been done in the pretrained BERT model. Fine-tuning allowed the model to adapt to domain-specific linguistic patterns and social sentiment cues, resulting in better classification performance. Notably, the fine-tuned BERT achieves a balance between precision and recall, demonstrating its ability to both accurately classify sentiments and generalize across diverse input samples.

These results underscore the importance of fine-tuning transformer models for specialized tasks. While generic pretrained models like RoBERTa and BERT perform well on standard benchmarks, fine-tuning enhances their ability to address domain-specific challenges. This is particularly critical in social cognition tasks where contextual understanding and sentiment classification play a pivotal role. The fine-tuned BERT model's superior performance makes it most suitable for applications such as analyzing social behaviors on platforms like social media, where precision and recall are equally vital for understanding the underlying cognitive and emotional states of users.

IV. CONCLUSION

This study explored the development of a social cognitive transformer-based BERT model for understanding social cognition and emotional states on social media platforms. The introduction of this work underscored the significance of analyzing social behaviors and emotions in the digital age, where large-scale user interactions shape public sentiment and collective decision-making. Through the literature survey, it was evident that transformer models like BERT and RoBERTa have revolutionized Natural Language Processing (NLP), yet their application to specialized domains like social cognition remains underdeveloped. The proposed methodology leveraged the transformer architecture, fine-tuning BERT to model emotional cues and social interactions with domain-specific adaptations, such as capturing sentiment information and contextualizing interaction sequences. The results demonstrated the superiority of the fine-tuned BERT model, which outperformed baseline models like RoBERTa and standard BERT in accuracy, precision, recall, and F1-score. This highlights the efficacy of task-specific fine-tuning in enabling transformers to understand specific and important social and emotional contexts. By integrating BERT's attention mechanisms with cognitive modeling principles, the model not only achieved higher classification accuracy but also offered interpretability in identifying key linguistic cues influencing sentiment. Future work can expand upon this foundation by incorporating synthetic agents to enhance the cognitive model. These agents could simulate complex social behaviors and generate synthetic data to address domain-specific challenges, such as data sparsity in underrepresented scenarios.

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