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Abstract. *The article develops an engineering method for adjusting (or readjusting during operation) the controllers of electric drives of manipulator mobility units, which takes into account the presence of significant nonlinearities. This method prevents the occurrence of "primary self-oscillations" in the automatic control system of electric drives of manipulator mobility units, which stimulate the occurrence of resonant elastic vibrations and self-oscillations (self-oscillation effect). The proposed method allows not only to eliminate the cause of the autoelasticity effect, but also to do so at the engineering level of mastery of mathematical apparatus, computer mathematics systems, and programming skills. The manifestation of the autoelasticity effect is associated with the presence of factors such as: the dynamic properties of the drive of the mobility nodes; the elastic flexibility of manipulators; significant nonlinearities of a structural and technological nature or those that arise during operation in mechanical and electrical devices. The engineering simplicity and convenience of the method is expressed in the fact that the adjustment of the electric drive controllers of the mobility nodes during the manufacture of the manipulator or their readjustment during operation does not require specialized scientific research, but can be performed by a specialist with an engineering level of mathematical training in interactive mode in a short time.*

Keywords: *automatic control system, PID controller, significant nonlinearity, numerical optimization methods, computer mathematical model, directional antenna, manipulato*

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METHODOLOGY FOR IDENTIFYING POST-TRAUMATIC STRESS DISORDER INDICATORS IN TEXT DATA

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Abstract. *This study introduces the methodology for detecting indicators of post-traumatic stress disorder (PTSD) within textual data produced by users. Unlike traditional approaches, the proposed solution emphasizes two critical aspects: the refinement of contextual dependencies that are characteristic of PTSD, and the ability to more clearly distinguish PTSD-related signals from those of other mental* *health conditions. By concentrating on PTSD-specific linguistic patterns, the method provides a more accurate and contextually grounded analysis.The evaluation of the approach demonstrated robust performance, yielding Accuracy of 0.934, Precision of 0.948, F_1-score of 0.841, and AUC of 0.872. When compared against existing analogues, the proposed method showed consistent improvements across key metrics: Accuracy increased by 0.130%, the F_1-score improved by 0.031, and AUC rose by 0.132. A key technical innovation lies in the use of relative rather than absolute positional embeddings within the neural architecture. This enables the model to capture the nuanced relationships between words depending on their contextual displacement, thereby enhancing its sensitivity to subtle textual cues that often signal PTSD manifestations. In parallel, improved differentiation from other mental disorders was ensured by expanding the dataset to include samples reflecting manifestations of alternative psychological conditions, which were placed in an orthogonal reference category. This design decision helped the model to learn sharper boundaries between PTSD-specific content and symptoms indicative of other mental illnesses.*

Keywords. *Post-traumatic stress disorder, NLP, neural network, text data*

Problem Statement

Post-traumatic stress disorder (PTSD) represents a severe and often long-lasting psychological condition that affects a significant portion of the global population, with prevalence rates reaching approximately 10% [1, 2]. The growing influence of digital technologies and the rapid expansion of social media platforms have created new avenues for studying PTSD manifestations through the lens of user-generated textual content [3]. This research direction gains particular urgency in the context of armed conflicts, large-scale natural disasters, and other traumatic events, all of which leave profound and lasting marks on human mental health [4, 5].

The analysis of user-generated materials, such as social media posts, blog entries, online forum discussions, and comment sections, offers unique opportunities to gain insight into the psychological state and emotional well-being of individuals affected by traumatic experiences [6, 7]. By applying advanced machine learning techniques and natural language processing (NLP) methods, it becomes possible to automatically detect subtle indicators of PTSD within text data [8, 9]. Such technological applications are not limited to identifying isolated cases of PTSD but also hold the potential to support large-scale monitoring, the design of preventive strategies, and the development of targeted assistance programs for populations at risk [10].

In contemporary society, which is increasingly exposed to wars, global pandemics, and socio-political crises, the timely identification of PTSD manifestations from textual data is of critical importance [11]. This type of research contributes not only to scientific understanding but also provides practical tools for psychologists, social workers, and healthcare professionals who are directly engaged in supporting vulnerable groups [12, 13]. The integration of automated

PTSD detection methods into professional practice thus offers a pathway toward more responsive and adaptive forms of psychological care [14].

The central objective of this paper is to present a methodology for identifying indicators of PTSD in user-generated text content. The proposed approach differentiates itself from existing solutions by placing special emphasis on context dependencies unique to PTSD, thereby reducing misclassification with other mental health disorders [15]. This is achieved by constructing a custom training dataset enriched with examples of alternative psychological conditions, which are placed in an orthogonal category to guide the model toward sharper diagnostic boundaries [16, 17]. Additionally, the methodology employs specialized positional embeddings designed to more accurately account for the location of words in a sequence, which significantly improves the accuracy and sensitivity of the neural network model [18].

The key contributions of this study can be outlined as follows. First, a novel method for identifying PTSD manifestations in text data has been developed, advancing the computational tools available for mental health analysis. Second, a specialized dataset was constructed to emphasize PTSD-related linguistic patterns while simultaneously reducing confusion with textual signals of other mental disorders by incorporating them into a separate category. Finally, the effectiveness of the methodology has been empirically validated, demonstrating not only its ability to detect PTSD with high accuracy but also to provide a visual interpretation of results, making the system more transparent and practically useful compared to existing analogues.

Analysis of Previous Studies

Over the years, the scientific community has made considerable efforts to design monitoring strategies aimed at detecting a wide spectrum of mental health conditions and high-risk behaviors [19]. Among these, depression, eating disorders, gambling addiction, and suicidal ideation have been of particular interest, as their timely identification enables the activation of preventive or mitigating interventions, and in severe cases, the initiation of clinical treatment [20]. In recent years, the prevalence of post-traumatic stress disorder has risen sharply, especially in the wake of the COVID-19 pandemic [21]. The global health crisis not only generated new traumatic experiences but also severely restricted access to traditional psychological support due to isolation measures and the limited availability of therapeutic interventions. These challenges have emphasized the urgent need for supplementary screening tools capable of enhancing PTSD identification and diagnosis within virtual or remote environments.

Recent advancements in artificial intelligence, and particularly in large language models (LLMs), have opened promising new opportunities for PTSD detection. Preliminary studies have suggested that ChatGPT possesses a degree of feasibility for mental health assessment, although its ability to provide accurate and reliable diagnoses remains under investigation [22]. One notable study compared the performance of ChatGPT with the text-embedding-ada-002 (ADA) model in the detection of childbirth-related PTSD (CB-PTSD), a condition that affects millions of new mothers worldwide and frequently goes undiagnosed due to the lack of standardized screening procedures. The research, conducted on a cohort of 1,295 women within six months postpartum and recruited from hospitals, social media platforms, and professional organizations, evaluated the effectiveness of these models in classifying maternal birth narratives. Ground truth was established using the PTSD Checklist for DSM-5, ensuring methodological rigor. The ADA model, leveraging numerical vector representations for narrative classification, demonstrated superior performance (F_1 score = 0.81) compared to ChatGPT and six previously published text embedding models trained on mental health or clinical data. This finding suggests that ADA-based approaches may serve as a reliable framework for identifying CB-PTSD and could potentially be extended to the detection of other psychiatric conditions.

Further research has also investigated the role of language itself as a diagnostic biomarker for PTSD. One study [23] analyzed a dataset of 148 individuals who survived the Paris terrorist attacks of November 13, 2015. The participants, all of similar socioeconomic background and exposed to the same traumatic event, underwent interviews 5–11 months after the incident, which were later transcribed and subjected to analysis. An interdisciplinary methodology was employed, bringing together psychiatry, linguistics, and NLP to examine the connection between linguistic patterns and PTSD symptoms. The methodology comprised three stages. First, a clinical psychiatrist attempted to diagnose PTSD using only the transcribed interviews, achieving an area under the curve (AUC) of 0.72, which was comparable to the gold standard questionnaire (AUC ≈ 0.80). In the second stage, statistical and machine learning methods were applied to extract psycholinguistic features and evaluate their predictive power, achieving an AUC of 0.69. Finally, deep learning methods were tested in a hypothesis-free setting, with performance reaching an AUC of 0.64. The results confirmed that language carries clinically relevant information, while also demonstrating the limitations of current automated approaches. Importantly, the study controlled for potential confounding factors, established clear links between language and DSM-5 subsymptoms, and demonstrated how automated approaches can be complemented by qualitative analysis. Similar research conducted with military personnel deployed in Afghanistan reported a model AUC of 0.74 [24], further highlighting the potential of language-based methods for PTSD detection.

Unresolved Issues

The review of existing work in this domain indicates a persistent problem: relatively low detection accuracy. In most cases, the performance of current PTSD detection systems has not exceeded 81% accuracy, which is insufficient for reliable deployment in real-world psychological or clinical practice. This limitation underscores the need for more advanced artificial intelligence models that combine several essential properties. Such models should demonstrate a high capacity for generalization, enabling them to handle diverse expressions of trauma in text, as individuals often describe their experiences in highly variable linguistic forms.

Furthermore, they should be explicitly context-oriented, allowing the identification of subtle linguistic markers that signal the presence of PTSD while avoiding confusion with other mental health conditions. Finally, the models must support visual interpretability of their results, ensuring that the decision-making process can be explained and validated by human experts. Together, these requirements form the foundation for the methodology proposed in this paper, aimed at enhancing the accuracy, reliability, and transparency of PTSD detection from user-generated text data.

Objective of the Article

The object of research is the process of for identifying post-traumatic stress disorder indicators in text data. The subject of research is methods, algorithms, information technologies, models, and tools for identifying post-traumatic stress disorder indicators in text data.

Methodology for identifying post-traumatic stress disorder indicators

The methodology proposed for detecting manifestations of post-traumatic stress disorder in user-generated textual content is schematically illustrated in Figure 1. The general workflow demonstrates the transformation of input data, represented by raw text content, into structured analytical output through the use of a trained, context-oriented neural network of transformer architecture combined with a tokenizer. The outcome of this process is expressed as a probabilistic percentage indicating the likelihood of PTSD-related signals within user content.

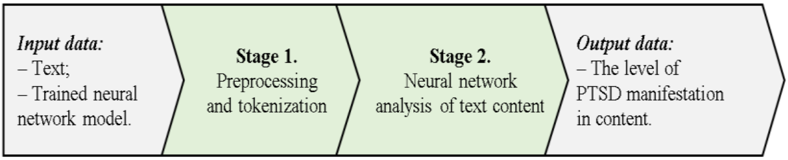

Figure 1. Approach to identifying post-traumatic stress disorder indicators

At the initial stage, preprocessing and tokenization of text data are performed. Each text entry is examined to ensure that it is non-empty and of sufficient length for analysis. Unlike conventional preprocessing pipelines, punctuation marks, emoticons, and other subtle textual features are deliberately retained, since they may contain valuable contextual information associated with PTSD indicators. Tokenization is then carried out using the same tokenizer that was employed during neural network training, ensuring compatibility and consistency between training and inference stages.

The second stage involves neural network–based analysis of PTSD indicators in the processed user content. For this purpose, a context-oriented model of transformer architecture is applied, specifically the DeBERTa model. The structure of this model, depicted in Figure 2, is organized into five primary component groups: *Embedding*, *Encoder*, *Pooler*, *Classifier*, and *Dropout*. The *Embedding* layer incorporates word embeddings along with normalization operations. The *Encoder* section contains six stacked DeBERTaV3Layer blocks, each including attention, intermediate, and output modules. These layers form the core of text processing, capturing hierarchical representations of words and contexts. Unlike traditional transformer mechanisms, DeBERTa employs a disentangled attention mechanism, where semantic content and positional information are processed separately. This modification enhances the model's ability to capture nuanced interactions between words and contextual dependencies. Furthermore, instead of absolute positional encoding, DeBERTa applies relative positional displacement, enabling more robust modeling of long-range dependencies through variance estimation. The *Pooler* component aggregates contextual embeddings to produce compact summary representations, while the *Classifier* layer performs the final decision-making task. The *Dropout* layer ensures model regularization, reducing the risk of overfitting during training.

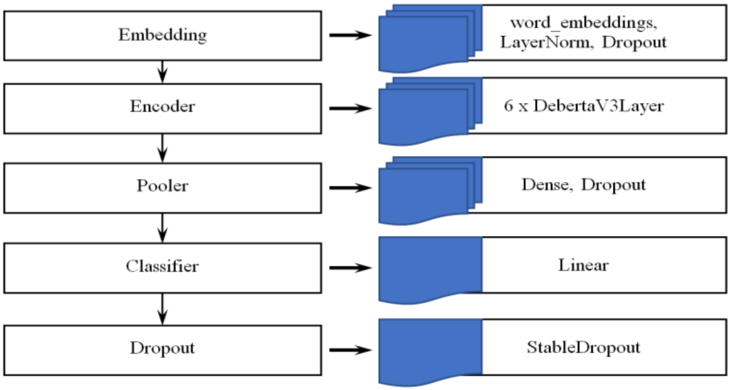

Figure 2. Architecture of DeBERTa model

The complete methodological scheme is shown in Figure 3. According to this workflow, the process begins with the preparation of training data. For effective PTSD detection, a composite dataset is constructed from multiple sources and subjected to balancing and preprocessing procedures. This ensures sufficient representation of positive and negative cases, thereby improving training stability and reducing bias. The dataset is then vectorized and divided into training and validation subsets in 80:20 ratio. At this stage, training hyperparameters such as batch size and number of epochs are also defined.

Subsequently, the transformer-based model undergoes retraining on the prepared dataset. Upon completion of the training process, the performance of the model is rigorously evaluated using a set of standard classification metrics, including Accuracy, Precision, F_1-score, and AUC. Only models achieving satisfactory results – defined as performance above 80% across all metrics – are preserved. The trained model and tokenizer are then stored for integration into downstream applications.

The final step of the methodology addresses the interpretability of the model's decisions. To this end, explainability frameworks designed for transformer-based architectures are employed. These allow for the visualization and explanation of how specific words, phrases, or contextual structures contributed to the classification decision.

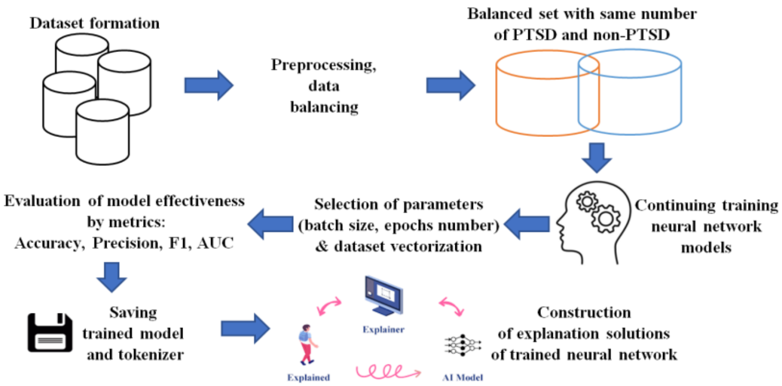

Figure 3. Steps for identifying of PTSD stress disorder indicators in text data

The methodological contributions are multifold. By implementing relative positional shifts instead of absolute encodings, the model achieves enhanced sensitivity to PTSD-specific contextual dependencies. Dispersion estimation techniques further improve the capacity to analyze relationships at varying textual distances. Additionally, the disentangled treatment of semantic and positional attention components enables the model to capture complex, layered dependencies that are characteristic of PTSD-related linguistic patterns. Finally, the inclusion of textual examples of other mental health conditions in the dataset strengthens the separation between PTSD and non-PTSD categories, reducing misclassification and improving overall robustness of detection.

Experiment

The scheme for constructing the dataset is presented in Figure 4. Since publicly available datasets with a sufficient number of records for training a neural network are lacking, a composite dataset was created by combining data from the "Human Stress Prediction" and "Aya PTSD" datasets.

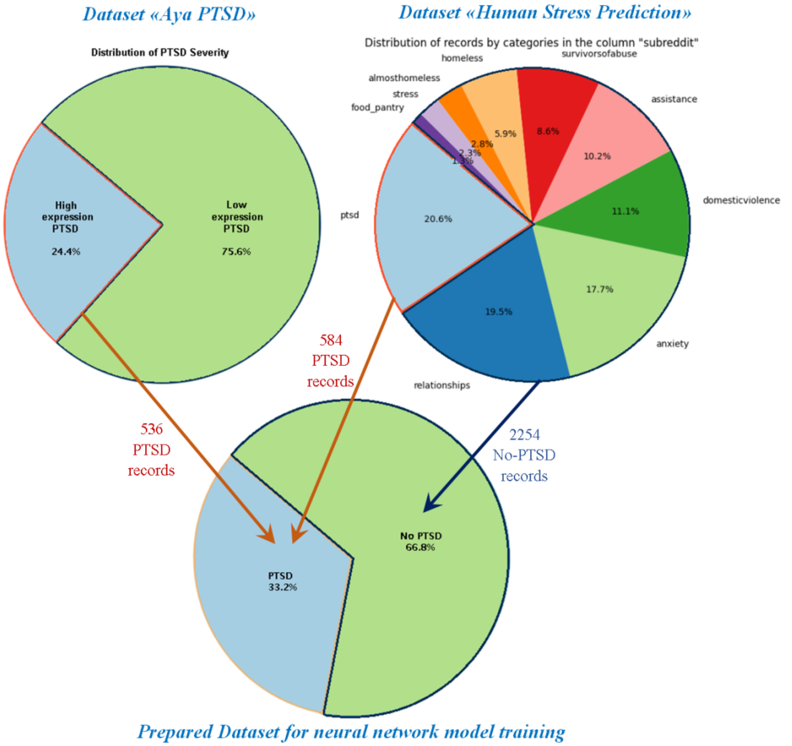

Figure 4. Dataset formation scheme for neural network training

The "Human Stress Prediction" dataset [25] contains user posts collected from subreddits focused on mental health discussions. It encompasses a wide range of issues people share regarding their personal experiences. The dataset includes fields such as "subreddit," "post_id," "sentence_range," "text," "label," "confidence," and "social_timestamp," which form the structure of the "Stress.csv" file. For this study, only the entries labeled "PTSD" in the "subreddit" column were selected, which correspond to posts explicitly associated with post-traumatic stress disorder. All other entries, not marked with PTSD, were used as the negative class. Within this dataset, there are 584 posts labeled as "PTSD" and 2,254 posts without such indications.

Although the negative class includes not only records from healthy individuals but also posts linked to various other psychological disorders, this diversity is beneficial for learning contextual dependencies unique to PTSD. At the same time, it may lead to a slight reduction in training accuracy due to overlap between mental conditions.

The dataset derived from this source appeared to be imbalanced, with the PTSD class being nearly four times smaller than its counterpart. To address this, additional data were integrated from the "Aya PTSD" dataset [26], available via Kaggle. This dataset specifically targets PTSD and provides a richer description, including attributes such as clinical assessments, socio-demographic information, and related textual data ("ID," "PTSD Severity," "label," "text," "file_path," and "response"). For the purposes of this research, only entries with "PTSD Severity" values exceeding 50% were selected. Incorporating these records expanded the PTSD class to 1,120 entries. As a result, a balanced dataset of 3,374 samples was formed, with 1,120 labeled as "PTSD" and 2,254 labeled as "No PTSD." For training purposes, 2,200 records were utilized – 1,100 belonging to each category.

To evaluate the proposed method for analyzing PTSD manifestations in textual content, dedicated software was developed and implemented as a Notebook in the Google Colab cloud environment. As the pretrained backbone, the "microsoft/deberta-v3-small" transformer model from the HuggingFace library was adopted. The DeBERTaV3 model builds on the original DeBERTa architecture, replacing the masked language modeling (MLM) task with replaced token detection (RTD), which provides more efficient pretraining. The model was fine-tuned on the constructed dataset for 3 epochs. Performance assessment was carried out on a validation set. The trained model achieved Accuracy of 0.934, Precision of 0.948, F_1-score of 0.841, and AUC of 0.872. The ROC curve, presented in Figure 5, illustrates the classification quality. The Precision value of 0.948 indicates that among all samples classified as positive (PTSD), 94.8% were indeed correct, which is particularly significant for PTSD detection since minimizing false positives prevents unnecessary interventions. The F_1-score of 0.841 demonstrates a balanced trade-off between Precision and Recall, confirming the model's reliability in identifying true PTSD cases. The ROC curve further validates the effectiveness of the classifier by comparing the true positive rate and false positive rate at various thresholds, with an AUC of 0.872 highlighting the model's ability to correctly distinguish PTSD cases with a low incidence of false alarms.

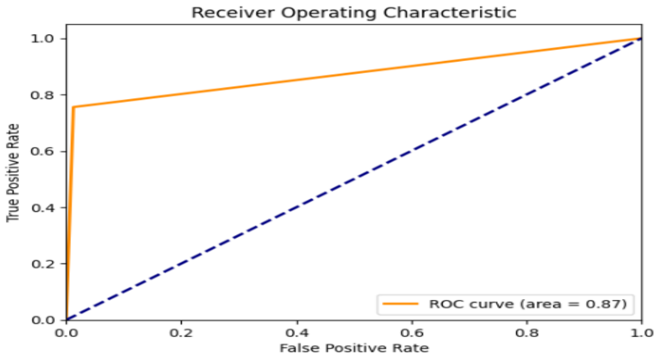

Figure 5. ROC curve for neural network performance evaluation

Additionally, the interpretability of the classification process was examined by employing the Transformers Interpret tool, designed for the transformers library. This approach allowed for visualization and explanation of the neural network's decision-making, providing a more transparent understanding of how PTSD-related textual cues are captured and analyzed.

Results and discussion

The F_1-score, which was previously reported at 0.81 in [22], increased to 0.841 in this study. The diagnostic AUC of the machine learning model described in [23] was 0.69, and the developed approach in [24] reached 0.74. In contrast, the current method achieved an AUC of 0.872, marking a substantial improvement over existing solutions. Overall, compared with established analogues, the efficiency of PTSD detection increased noticeably: Accuracy improved by 13 percentage points (from 80.4% to 93.4%), the F_1-score rose by 0.031 (from 0.810 to 0.841), and AUC improved by 0.132 (from 0.740 to 0.872). These enhancements demonstrate the robustness of the developed method, which effectively reduces confusion with other mental health conditions. This robustness stems from the fact that the negative class in the dataset was not limited to psychologically healthy individuals, but also included cases of other psychological disorders, thereby strengthening the model's ability to distinguish PTSD-specific patterns.Despite these promising outcomes, further optimization remains possible. The metrics suggest that additional epochs could improve the results, as the training loss continued to decline, indicating potential for better generalization. However, due to computational resource constraints and the 12-hour session limit in Google Colab, the training process was restricted to 10 hours. The confusion matrix obtained for the validation set is shown in Figure 6. According to these results, only 10 out of 220 PTSD-labeled entries were incorrectly classified as "No PTSD." Conversely, 24 out of 220 non-PTSD records were mistakenly identified as PTSD. Although false positives were observed, these values remain competitive when compared to prior studies, confirming the effectiveness of the developed model.

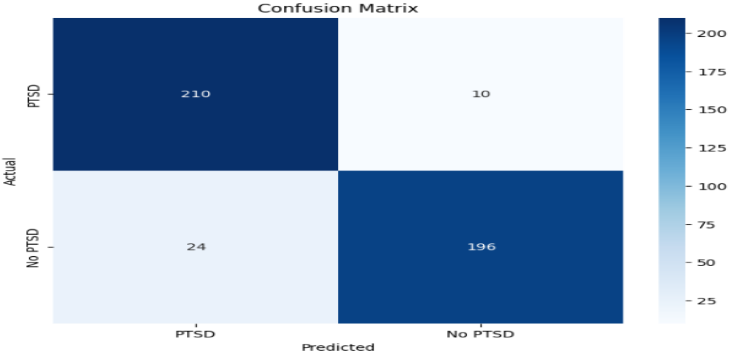

Figure 6. Confusion matrix in neural network detection of PTSD manifestations

Beyond classification, the method also provides interpretability of decisions, enabling a deeper understanding of model reasoning. An example is illustrated in Figure 7, where the input text was: *"He said he had not felt that way before, suggested I go rest and so I decide to look up feelings of doom in hopes of maybe getting sucked into some rabbit hole of ludicrous conspiracy, a stupid are you psychic test or new age b.s., something I could even laugh at down the road. No, I ended up reading that this sense of doom can be indicative of various health ailments; one of which I am prone to.. So on top of my doom to my gloom..I am now f'n worried about my heart. I do happen to have a physical in 48 hours."* This text was classified as PTSD-related, as it contains strong indicators such as "sense of doom" and the phrase "doom to my gloom," reflecting heightened anxiety and stress. Figure 8 highlights that tokens such as *"doom"* and *"gloom"* had the greatest influence on the model's decision, while additional words like *"conspiracy," "psychic,"* and *"rabbit"* also contributed significantly.

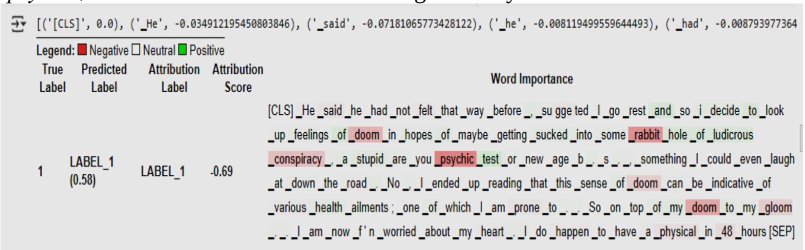

Figure 7. Interpretation of transformer model solution

In parallel, the study explored how the model distributes attention across different tokens to capture contextual dependencies. The visualization tool BertViz was applied to illustrate attention weights across all layers and heads of the transformer. Figure 8 shows an example where brighter colors represent stronger attention contributions to the final decision. Each attention head forms a distinct representation of token-to-token dependencies, visualized through arrows whose thickness and color denote the intensity and direction of attention.

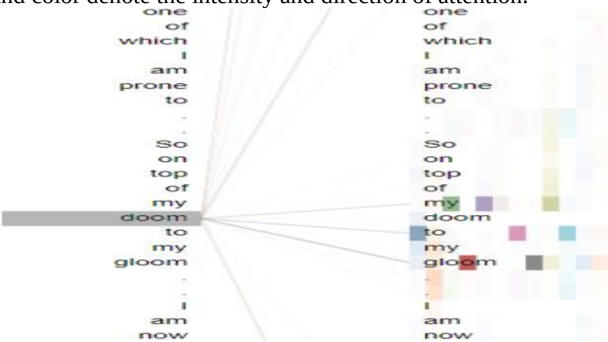

Figure 8. Visualization of attention weights using the "BertViz" model interpreter

Thus, the combined use of *Transformers Interpret* and *BertViz* not only enabled accurate PTSD detection in user-generated content but also allowed detailed interpretation of the neural network's internal decision-making process. This interpretability adds significant value, as it makes the model's predictions more transparent and reliable for practical applications in mental health diagnostics.

Conclusions and Prospects

The conducted research has resulted in the development of a methodology for detecting indicators of post-traumatic stress disorder in user-generated text data. Unlike traditional approaches, the proposed method emphasizes deeper consideration of PTSD-specific contextual dependencies and enhances the ability to separate these patterns from manifestations of other mental health conditions.

The improved focus on contextual dependencies was achieved through several architectural and algorithmic solutions. In particular, instead of the conventional single attention mechanism used in transformer networks, the proposed approach employs separate attention components for words and positional embeddings. This modification increases the granularity of interaction captured between lexical units and their context, which is critical for identifying subtle linguistic markers of PTSD. Additionally, the model implements relative positional displacement rather than absolute, which allows it to capture long-range semantic dependencies more effectively by estimating variance across different distances. These adjustments collectively improved the accuracy and robustness of PTSD-specific feature recognition.

To further reduce false associations with other psychological conditions, the training dataset was deliberately structured so that the non-PTSD category contained not only samples from psychologically healthy individuals but also examples representing other mental illnesses. This strategy created a more orthogonal dataset structure, improving the model's ability to distinguish PTSD-specific linguistic cues. As a result, a custom training dataset consisting of 3,374 records was formed, which provided a solid foundation for model learning.

The developed solution transforms raw text input into structured output, presenting the probability of PTSD manifestation in percentage terms. Importantly, the methodology supports interpretability of the neural network's decisions, enabling researchers and practitioners to trace which textual elements contributed most to classification outcomes. This transparency significantly strengthens the potential application of the method in clinical and preventive scenarios.

Experimental evaluation demonstrated that the trained transformer-based neural network achieved Accuracy of 0.934, Precision of 0.948, F_1-score of 0.841, and AUC of 0.872. Compared with existing studies, this represents a marked improvement: Accuracy increased by 13.0% (from 80.4% to 93.4%), the F_1-score rose by 0.031 (from 0.810 to 0.841), and AUC improved by 0.132 (from 0.740 to 0.872). These results confirm the effectiveness of the proposed methodology in reliably identifying PTSD manifestations in text.

Future research directions include expanding the dataset with additional labeled examples to enrich the spectrum of PTSD-related linguistic markers and further improve classification reliability. Another promising direction involves increasing the number of training epochs, since the observed decrease in loss during experiments indicates that the model has not yet reached its full generalization capacity. Continued work in these areas is expected to yield even higher performance metrics and enhance the interpretability of the model's decisions, thereby contributing to more accurate and transparent detection of PTSD manifestations in textual content.

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МЕТОДОЛОГІЯ ВИЯВЛЕННЯ ОЗНАК ПОСТТРАВМАТИЧНОГО СТРЕСОВОГО РОЗЛАДУ В ТЕКСТОВИХ ДАНИХ

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Анотація. *Дослідження присвячене розробці методології виявлення ознак посттравматичного стресового розладу (ПТСР) у текстових даних, що створюються користувачами. На відміну від традиційних підходів, запропоноване рішення підкреслює два критичні аспекти: уточнення контекстних залежностей, характерних для ПТСР, та здатність чіткіше розрізняти сигнали, пов'язані з ПТСР, від сигналів інших психічних розладів. Зосереджуючись на специфічних для ПТСР лінгвістичних шаблонах, метод забезпечує більш точний та контекстуально обґрунтований аналіз.*

Оцінка підходу продемонструвала надійну продуктивність, забезпечивши точність 0,934, повноту 0,948, F_1 0,841 та AUC 0,872. У порівнянні з існуючими аналогами, запропонований метод показав послідовні покращення за ключовими показниками: точність збільшилася на 0,130%, F_1-оцінка покращилася на 0,031, а AUC зросла на 0,132.

Ключова технічна інновація полягає у використанні відносних, а не абсолютних позиційних вбудовувань у нейронну архітектуру. Це дозволяє моделі фіксувати нюансовані зв'язки між словами залежно від їх контекстного зміщення, тим самим підвищуючи її чутливість до тонких текстових сигналів, які часто сигналізують про прояви ПТСР. Також, покращена диференціація від інших психічних розладів була забезпечена шляхом розширення набору даних, щоб включити зразки, що відображають прояви альтернативних психологічних станів, які були розміщені в ортогональній референтній категорії. Це рішення допомогло моделі вивчити чіткіші межі між специфічним для ПТСР контентом та симптомами, що вказують на інші психічні захворювання.

Ключові слова. *Посттравматичний стресовий розлад, NLP, нейромережа, текстові дані*

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НОРМОВАНА ВІДОКРЕМЛЕНІСТЬ МАКСИМАЛЬНОГО СИНГУЛЯРНОГО ЧИСЛА БЛОКУ ЦИФРОВОГО ЗОБРАЖЕННЯ ЯК ПОКАЗНИК ДОЦІЛЬНОСТІ ЙОГО СТЕГАНОПЕРЕТВОРЕННЯ

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Анотація. *Одним із найбільш перспективних та ефективних напрямів захисту інформації сьогодні є стеганографія. Серед низки вимог до стеганосистеми одною з основних є забезпечення надійності сприйняття стеганоповідомлення. Однак багато існуючих стеганометодів, зокрема стійких до атак проти вбудованого повідомлення, не в змозі систематично забезпечувати ацю вимогу та не розраховані на роботу з випадковим контейнером, який на практиці є найчастіше застосовуваним. Метою роботи є підвищення ефективності стеганосистеми при використанні довільного стеганометоду і випадкового контейнеру шляхом розробки методу вибору блоків контейнера, в якості якого використовується цифрове*