Digital Health and Informatics Innovations for Sustainable Health Care Systems
J. Mantas et al. (Eds.)

doi:10.3233/SHTI240820

Visualizing Mental Health Insights: A Pipeline from Social Media to Chernoff Faces

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Abstract. This study proposes an approach for analyzing mental health through publicly available social media data, employing Large Language Models (LLMs) and visualization techniques to transform textual data into Chernoff Faces. The analysis began with a dataset comprising 15,744 posts sourced from major social media platforms, which was refined down to 2,621 posts through meticulous data cleaning, feature extraction, and visualization processes. Our methodology includes stages of Data Preparation, Feature Extraction, Chernoff Face Visualization, and Clinical Validation. Dimensionality reduction techniques such as PCA, t-SNE, and UMAP were employed to transform complex mental health data into comprehensible visual representations. Validation involved a survey among 60 volunteer psychiatrists, underscoring the visualizations' potential for enhancing clinical assessments. This work sets the stage for future evaluations, specifically focusing on a combined features method to further refine the visual representation of mental health conditions and to augment the diagnostic tools available to mental health professionals.

Keywords. Mental Health, Social Media, Chernoff Faces, Visualization, LLM

1. Introduction

In today's digital landscape, social media platforms offer a rich source of human emotion, providing insights into the broader mental health landscape [1]. The abundant data from these platforms allows us to observe and understand the complexity of mental well-being, as people share their experiences and emotions [2]. This digital narrative, full of personal stories, opens opportunities to analyze mental health trends and the ways individuals express their mental states online. Advanced computational techniques, including Large Language Models (LLMs) [3] and data visualization methods, enable the transformation of this textual data into meaningful visual representations [4]. Chernoff Faces, which maps data to facial features, stands out for its innovative approach to depicting complex information, making it intuitively understandable and bridging the gap between data analysis and qualitative insight [5]. The process of turning social media posts into actionable insights entails data cleaning, feature extraction, and visualization with Chernoff Faces, followed by clinical validation to ensure real-world applicability. This

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paper aims to introduce a method for visualizing mental health conditions using Chernoff Faces, employing LLMs and techniques like PCA, t-SNE, and UMAP. We outline our methodology and explore the potential of visual analytics in mental health assessments, contributing to the field of digital mental health research. This innovative approach seeks to improve the understanding of mental health conditions and support the development of more effective diagnostic tools and interventions.

2. Methodology

The methodology of this study is designed to efficiently transform extensive social media data into actionable insights for mental health analysis. Our approach follows a structured pipeline, depicted in Appendix A[2], which includes four key stages: Data Preparation, Feature Extraction, Processing and Selection, Chernoff Face Visualization, and Clinical Validation and Feedback Integration. Initially, we curate and clean the dataset during the Data Preparation stage to ensure its quality and relevance. Following this, significant textual features are extracted using advanced computational techniques, processed, and selected for optimal representation during the Feature Extraction stage. These features are then visualized using Chernoff Faces, providing an intuitive representation of complex datasets. The final stage involves the clinical validation of these visual tools by health professionals to ascertain their effectiveness and applicability in real-world clinical settings. This streamlined methodology ensures that each stage contributes effectively to the accuracy, relevance, and clinical utility of the visualizations created, thereby bridging the vast gap between social media data and nuanced mental health understanding.

2.1. Data Preparation

The first stage involves meticulously preparing the MultiWD [6] dataset, part of a larger collection used to train the MentalLLaMA model, which focuses on detecting various wellness dimensions from social media content. Initially, the MultiWD portion comprised 15,744 posts from Reddit, aimed at identifying and annotating multiple aspects of mental wellness. This dataset is particularly structured to enhance interpretability in mental health analysis by focusing on posts that reflect distinct wellness dimensions. Our cleaning process reduced this number to 2,621 posts by removing data that were irrelevant, redundant, or did not meet the rigorous standards required for effective analysis. This refined dataset allows us to accurately capture the nuances of mental well-being expressed online, providing a robust foundation for subsequent stages of feature extraction and visualization. The comprehensive approach ensures that only the most relevant data are used for creating visual representations of mental health conditions, as outlined in the research paper associated with the dataset, "MULTIWD: Multiple Wellness Dimensions in Social Media Posts.

2.2. Feature Extraction, Processing, and Selection

Following data preparation, the next step is to extract meaningful features from the cleaned text. This process employs MentalBERT [7] to transform textual data into

[2] https://doi.org/10.5281/zenodo.11146730

embeddings, which are numerical representations capturing the semantic essence of the posts. Various feature extraction techniques are explored, including attention-weighted features, feature averaging of word embeddings, max-pooled features, min-pooled features, and concatenated features. The selection of the most informative features is guided by their potential to improve the visualization's accuracy and Interpretability. An autoencoder is then utilized to reduce the dimensionality of these features further, selecting the method that minimizes reconstruction error for subsequent visualization.

2.3. Chernoff Face Visualization

Chernoff Faces visualize extracted features by mapping multivariate data onto facial features, offering an intuitive grasp of complex information, particularly for mental health conditions. To enhance interpretability, we tested three dimensionality reduction techniques individually: PCA, which reduces dimensionality to preserve maximum data variance, simplifying complexity for accurate broad trend capture; t-SNE, which excels in revealing subtle differences by focusing on data's local structure and forming distinct clusters of mental health conditions; and UMAP, known for balancing local and global data structures to provide detailed and comprehensive visual representations. Each method was evaluated on its effectiveness in translating complex mental health data into clear, interpretable Chernoff Faces, aiding in the visualization's development and refinement.

2.4. Clinical Validation and Feedback Integration

The clinical validation of Chernoff Faces forms the final stage of our methodology. In this phase, each visualization technique—PCA, t-SNE, and UMAP—was individually validated through survey[3] distributed to psychiatrists. The feedback gathered was crucial not only for validating each method's effectiveness in accurately representing mental health conditions but also for identifying areas for improvement. Based on the psychiatrists' insights, which underscored the strengths and limitations of each approach, we developed a new combined features method. This innovative method merges PCA with sentiment analysis using BERTweet model and categorical mental issue encoding to enhance the clarity and interpretability of Chernoff Faces. This enhanced approach will undergo a second round of clinical validation to further refine its effectiveness in real-world applications, aiming to provide a more nuanced and accurate visual tool for mental health diagnosis.

3. Result

3.1. Analysis of Post-Classification Results

The classification of 2,621 posts highlighted the prominence of depression in online discussions, accounting for 32% of the dataset. Notably, 38% of the posts did not align with any specific mental health condition, indicating a large volume of neutral or non-specific content. Anxiety and suicide-related posts also represented significant portions

[3] https://rb.gy/uxk1j3

of the dataset, with 6% and 22% respectively. This distribution, detailed in Appendix B[2], underscores the diverse range of mental health discussions online and establishes a baseline for the visualization efforts that follow.

3.2. Initial User Study with Psychiatrists

In the initial user study with psychiatrists, a survey was distributed among 60 psychiatrists, with 40 responding to the first analysis focusing on Chernoff Faces for mental health classification (as detailed in Appendix C[2]) and 17 responding to the second analysis on the relevance of visualization techniques. This evaluation highlighted the significant capacity of psychiatrists to correlate Chernoff Faces with specific mental health conditions. Depression was the most identified condition, recognized by 33% of respondents, followed by anxiety at 28%, bipolar disorder at 23%, and an interesting finding that 13% of clinicians did not perceive any mental disorder, indicating interpretative variances. Notably, PCA stood out as the preferred visualization technique, showing a remarkable 62% effectiveness in depicting depression, in contrast to UMAP and t-SNE, which showcased distinct advantages but also emphasized the need for careful selection to enhance interpretability in clinical settings. These insights, derived from the responses (as detailed in Appendix D[2]), suggest Chernoff Faces' potential as a supplementary tool in mental health assessments and highlight the critical need for further refinement and broader clinical validation of these visualization techniques.

3.3. Comprehensive Analysis and Visualization of Mental Health Conditions

This section explored the visualization of mental health conditions using PCA, UMAP, t-SNE, and a combined features approach. The comparison of these techniques revealed their distinct impacts on the portrayal of mental health states through Chernoff Faces. The combined features approach was found to be superior in clarity and interpretability, closely aligning with clinical perceptions. The comparative analysis and scatter plot evaluations, especially the structured separation observed with the combined features approach, underscore the potential of integrating advanced visualization techniques in clinical settings. This approach's effectiveness in delineating mental health conditions with high accuracy points to promising avenues for future research and clinical application, as demonstrated in the scatter plots across (as in Appendices E[2] and F[2]).

4. Discussion

The investigation into using Chernoff Faces for mental health diagnostics highlighted key insights that emphasize the potential and challenges of visual analytics in psychiatry. Our findings revealed that psychiatrists could effectively recognize mental health conditions such as depression and anxiety through Chernoff Faces, suggesting these visual tools could supplement traditional diagnostic techniques. However, variations in interpretation among clinicians signal the complex nature of translating data into universally comprehensible visuals. While PCA was preferred for its ability to depict depression clearly, the combined features approach merging PCA, sentiment analysis [8], and mental issue encoding emerged as a promising new method for future evaluation. This approach aims to provide a more accurate and interpretable visual representation of mental health conditions, though it awaits further validation by psychiatry professionals.

Our study underscores the importance of further research to refine these visualization techniques for clinical application, with the potential to revolutionize psychiatric assessments by integrating innovative visual analytics.

The clinical implications of our research are profound, suggesting a future where visual tools like Chernoff Faces could play a pivotal role in mental health diagnostics and patient care. By offering clinicians an auxiliary means to understand patients' mental states visually, these tools could enhance the initial screening process and provide deeper insights during patient consultations. The variability in psychiatrists' interpretations of Chernoff Faces underscores the need for standardization and training to integrate these visual analytics into psychiatric practice effectively. As visual tools evolve and gain validation, they hold the promise of improving early detection, monitoring treatment progress, and personalizing care plans, ultimately enriching mental health care with a more nuanced and empathetic approach to diagnosing and treating mental health conditions.

5. Conclusions

This research, exploring the visualization of mental health through Chernoff Faces, underscores the significant potential of innovative visual analytics in enhancing psychiatric diagnostics. By transforming complex mental health data into intuitive visual forms, we offer a novel approach for clinicians to understand and assess mental health conditions. The initial feedback from psychiatry professionals highlights the practicality and relevance of these visual tools, especially when combined with advanced features for a more accurate representation of mental states. As we look forward, the focus shifts to further evaluations and the refinement of these visualization techniques, aiming to integrate them seamlessly into clinical practice.

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