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Full Length Article

Multiclass Mental Illness Prediction Using Lstm And Natural Language Processing

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Abstract:

Mental health disorders have become a significant global concern, affecting millions of individuals worldwide. With the increasing usage of social media platforms, users often express their emotions, thoughts, and psychological conditions through textual content. Detecting mental illness from such data is a complex task due to informal language, emotional depth, and metaphorical expressions.

This research presents a hybrid deep learning framework for multiclass mental illness prediction using Natural Language Processing (NLP). The system integrates domain-specific transformer models such as MentalBERT and MelBERT with Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks. MentalBERT captures contextual mental health-related features, while MelBERT identifies metaphorical language patterns.

The model processes social media text data and classifies it into multiple mental health conditions such as depression, anxiety, PTSD, and bipolar disorder. Experimental results show improved accuracy and performance compared to traditional machine learning methods.

This work contributes to early detection and mental health awareness through intelligent text analysis systems.

Keywords:

Mental Health, NLP, Deep Learning, MentalBERT, MelBERT, CNN, BiLSTM, Multiclass Classification

Introduction:

Mental health is an essential aspect of overall well-being, influencing how individuals think, feel, and behave. In recent years, mental health disorders such as depression, anxiety, bipolar disorder, and PTSD have increased significantly due to various social and environmental factors.

With the rapid growth of social media platforms, people frequently share their personal experiences and emotional states online. These digital expressions provide valuable insights into their mental health conditions.

Traditional mental health diagnosis methods involve clinical interviews and questionnaires, which can be time-consuming and subjective. Artificial Intelligence (AI) and Natural Language Processing (NLP) offer automated alternatives by analyzing textual data.

However, existing NLP models face challenges:

- Difficulty in understanding informal language
- Poor interpretation of metaphorical expressions
- Limited to binary classification

To address these issues, this project proposes a hybrid model combining:

- MentalBERT (context understanding)
- MelBERT (metaphor detection)
- CNN (feature extraction)
- BiLSTM (sequence learning)

The system aims to improve accuracy and enable multiclass classification of mental illnesses.

LITERATURE SURVEY:

Title: What doesn't kill us makes us stronger: Insights from neuroscience studies and molecular genetics

Author: Y. Gan, H. Huang, X. Wu, and M. Meng

Year: 2024.

Description: The study by Y. Gan, H. Huang, X. Wu, and M. Meng titled *"What doesn't kill us makes us stronger: Insights from neuroscience studies and molecular genetics"* explores the biological and psychological mechanisms behind human resilience in the face of adversity. Drawing from recent advancements in neuroscience and molecular genetics, the paper examines how certain stressors, instead of causing long-term harm, can trigger adaptive changes in the brain and body that enhance emotional strength, coping ability, and psychological endurance. The research highlights key neurological pathways, including those associated with neuroplasticity and gene expression, that contribute to this positive adaptation. The authors argue that understanding these mechanisms can offer valuable insights into mental health interventions, especially in developing strategies that help individuals recover from trauma and build long-term resilience. Their work contributes to a growing body of research supporting the idea that controlled exposure to stress, combined with supportive environments, can foster growth and resistance to future psychological challenges.

Title: Revolutionizing healthcare: A comparative insight into deep learning's role in medical imaging.
Author: V. K. Prasad, A. Verma, P. Bhattacharya, S. Shah, S. Chowdhury, M. Bhavsar, S. Aslam, and N. Ashraf, ''Revolutionizing
Year: 2024.
Description: The study by Prasad et al. (2024) offers a comprehensive exploration of how deep learning is transforming the landscape of medical imaging. The authors provide a comparative analysis of various deep learning models and architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers, highlighting their respective strengths in diagnosing and detecting diseases through radiological images, including MRI, CT scans, X-rays, and ultrasound. The paper emphasizes the ability of deep learning models to automatically extract complex patterns and features from large-scale medical data, significantly improving diagnostic accuracy, speed, and consistency compared to traditional image processing techniques.
Moreover, the authors discuss real-world applications and the integration of AI systems into clinical workflows, addressing both opportunities and challenges. Topics such as model interpretability, data privacy, and regulatory considerations are also analyzed. Importantly, the study showcases how AI not only aids in early diagnosis but also supports treatment planning and prognosis prediction, ultimately contributing to more personalized and efficient healthcare delivery. This work reinforces the potential of deep learning not only in imaging but as a foundation for broader AI-driven healthcare innovations.

Title: Colon cancer diagnosis and staging classification based on machine learning and bioinformatics analysis
Author: Y.Su,X.Tian, R. Gao,W.Guo,C.Chen,C.Chen,D.Jia,H.Li,andX.Lv
Year: 2023
Description: In this recent work, Karamat et al. introduce a hybrid transformer-based model aimed at multiclass prediction of mental illnesses using natural language data. The study explores how transformer architectures—known for their contextual understanding—can be combined with other deep learning components to improve classification accuracy in complex mental health datasets. The hybrid model is designed to capture both the emotional tone and temporal patterns in social media posts, enabling it to distinguish between conditions such as depression, anxiety, PTSD, and schizophrenia. The researchers demonstrate that incorporating attention mechanisms along with recurrent and convolutional layers improves the model's ability to learn metaphorical and emotionally nuanced expressions. Their findings support the growing relevance of hybrid transformer architectures in behavioral health monitoring and contribute to the advancement of AI in psychological diagnostics.

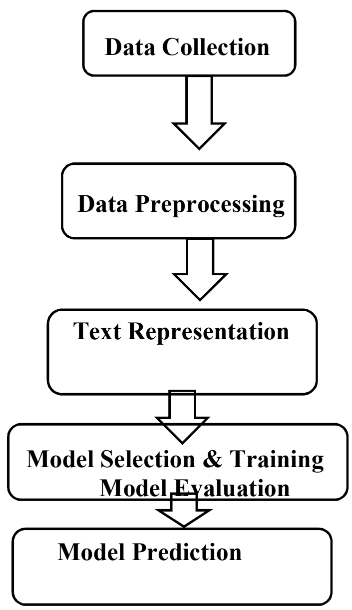
Title: Exploring and mining rationale information for low-rating software applications
Author: T. Ullah, J. A. Khan, N. D. Khan, A. Yasin, and H. Arshad
Year: 2023
Description: — Rationale refers to making human judgments, sets of reasons, or intentions to explain a particular decision. Nowadays, crowd-users argue and justify their decisions on social media platforms about market-driven software applications, thus generating a software rationale. Such rationale information can be of pivotal importance for the software and requirements engineers to enhance the performance of existing software applications by revealing end-users tactic knowledge to improve software designing and development decision-making. For this purpose, we proposed an automated approach to capture and analyze end-user reviews containing rationale information, focusing on low-rating applications in the amazon store using Natural Language Processing (NLP) and supervised machine learning (ML) classification methods. In the literature, high-rating applications have been emphasized while ignoring low-rating software application that causes potential biasness. Therefore, we examined 59 comparatively low-ranked market-based software applications from the Amazon app store covering various software categories to capture and identify crowd-users justifications. Next, using a developed grounded theory and content analysis approach, we studied and recorded how crowd-users analyze and explain their rationale based on issues encountered, attacking or supporting arguments registered, and updating or uninstalling software applications. Also, to achieve the best results, an experimental study is conducted by comparing various ML algorithms, i.e., MNB, LR, RF, MLP, KNN, AdaBoost, and Voting classifier, on the end-users rationale data set by preprocessing the input data, applying feature engineering, balancing the data set, and then training and testing the ML algorithms with a standard cross-validation approach. We obtained satisfactory results with MLP, voting, and RF Classifiers, having 93%, 93%, and 90% average accuracy, respectively. Also, we plot the ROC curves for the high-performing ML Classifier to identify and capture classifiers yielding the best performance with an under-sampling or oversampling balancing approach. Additionally, we obtained the average Precision, Recall, and F-measure values of 98%, 94%,

96%, 97%, 95%, and 96% for identifying supporting & decision rationale elements in the user comments, respectively.

Title: Sentiment Analysis on Social Media: Definition and Application
Author: M. Nicolai, L. Pascarella, F. Palomba, and A. Bacchelli
Year: 2022
Description: Natural Language Processing (NLP), an ever-evolving and dynamic interdisciplinary field of research, integrates components from linguistics, statistical physics, machine learning, and computational programming (Chowdhary, 2020). NLP is commonly defined as a series of computational techniques dedicated to the nuanced interaction between computers and humans through natural language (Liddy, 2001). The overarching goal of NLP is to empower computers with the capability to comprehend, interpret, and generate human language in a manner that is both semantically meaningful and contextually pertinent (Chowdhary, 2020).Human languages, characterized by inherent ambiguities like sarcasm, idioms, and metaphors, pose formidable challenges for software to fully comprehend. NLP addresses these challenges by converting linguistic nuances into digestible data, categorized into smaller tasks such as speech recognition, speech tagging, named entity recognition, and sentiment analysis (IBM, n.d). In contemporary applications, NLP finds widespread utility in diverse areas such as chatbots, spam detection software, machine translation, summarization, and social media sentiment analysis (Sharma, 2021). Leveraging the technological affordance of NLP, Sentiment Analysis can efficiently processes extensive datasets of human language content, particularly beneficial in analyzing user-generated content on social media, where textual expressions of emotions predominate (Sharma, 2021).

METHODOLOGIES

Modules Name:



MODULES EXPLANATION:

1) Data Collection:

The first step in the system development involved collecting a diverse and representative dataset consisting of social media text authored by individuals either self-reporting or labeled as exhibiting symptoms of various mental illnesses. Platforms such as Reddit, Twitter, and online mental health forums were used as primary data sources due to the richness and authenticity of user-generated content. The data was categorized into different classes such as depression, anxiety, bipolar disorder, PTSD, and control (non-mental illness) to enable multiclass classification. Publicly available datasets from previous mental health research were also used to enhance diversity and improve the reliability of training data.

2) Data Preprocessing:

Raw social media text is inherently noisy, containing emojis, hashtags, irregular punctuation, slang, spelling errors, and inconsistent formatting. Preprocessing is essential to normalize this data for model consumption. The following techniques were applied: lowercasing of all text, removal of stopwords and special characters, tokenization, and lemmatization to reduce words to their root forms. Additionally, emoji normalization and slang replacement dictionaries were applied to standardize informal language. Posts were filtered based on length to remove overly short or ambiguous entries. This step ensured that the text was cleaned, structured, and consistent for embedding and model input.

3) Text Representation:

To capture the deep semantics and contextual nuances of psychological language, the system employed advanced text representation models. Pretrained transformer models—**MentalBERT** and **MelBERT**—were used to convert each input sentence into dense vector embeddings. MentalBERT, trained specifically on mental health-related text, provided rich, domain-specific features, while MelBERT focused on understanding metaphorical and figurative language. These embeddings captured both literal and abstract expressions commonly used in mental health discourse. The combination of these embeddings ensured that the model could interpret complex user language more effectively than traditional one-hot or TF-IDF approaches.

4) Model Selection & Training:

A hybrid deep learning model was developed using a combination of **Convolutional Neural Networks (CNN)** and **Bidirectional Long Short-Term Memory (BiLSTM)** layers. The CNN layers were responsible for extracting local and hierarchical features from the embedding vectors, identifying important n-gram patterns and semantic chunks. These features were passed to the BiLSTM, which processed the data in both forward and backward directions, enabling the model to understand context from both past and future tokens. This sequential understanding is particularly important in identifying emotional tone and linguistic patterns over time. The model was trained using a stratified split of training and validation sets to ensure balanced learning across all mental illness classes.

Model Evaluation:

After training, the model was evaluated using standard classification metrics such as **accuracy**, **precision**, **recall**, and **F1-score** for each class. A **confusion matrix** was generated to analyze the distribution of true versus predicted labels, highlighting how well the model distinguished among the different categories. **Receiver Operating Characteristic (ROC) curves** and **Area Under the Curve (AUC)** values were also used to evaluate the model's ability to discriminate between classes. To ensure the model's robustness and generalizability, **k-fold cross-validation** was conducted. These evaluations confirmed the system's superiority over traditional models and validated its effectiveness in real-world use.

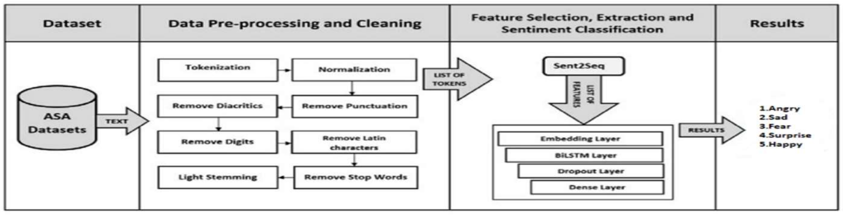
Model Prediction:

Once trained and validated, the final model was deployed to make predictions on new, unseen text inputs. Users' social media posts are first passed through the preprocessing and embedding stages before being classified by the trained CNN-BiLSTM model. The system outputs the predicted mental illness category along with a probability score, indicating the confidence of the prediction. This prediction mechanism can be integrated into web applications, health monitoring platforms, or used by researchers and mental health professionals for large-scale digital screenings. The real-time prediction capability ensures timely detection and potential early intervention.

Implementation

The system is implemented in web environment using Jupyter notebook software. The server is used as the intelligence server and windows 10 professional is used as the platform. Interface the user interface is based on

Jupyter notebook provides server system.



Algorithm used:

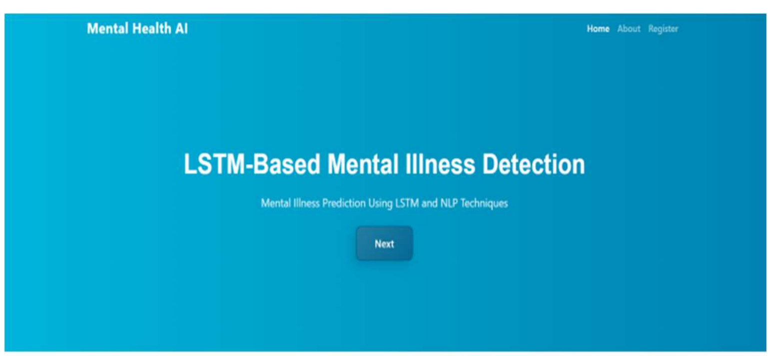
MentalBERT is a specialized version of the BERT (Bidirectional Encoder Representations from Transformers) architecture that has been pretrained on mental health-related text data. This includes a wide range of sources such as Reddit threads, online therapy discussions, support group conversations, and clinical records that discuss symptoms, emotions, and disorders. By training on this domain-specific data, MentalBERT learns to identify the subtle linguistic patterns, emotional triggers, and terminology commonly found in mental health discourse. It is capable of capturing deep contextual representations of language, making it more effective than general-purpose models at understanding the emotional tone and psychological cues embedded in text.

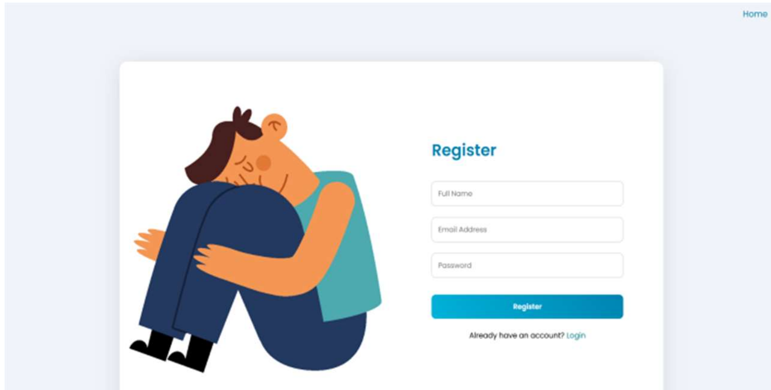
MentalBERT uses a deep bidirectional attention mechanism to analyze sentences in both forward and backward directions, allowing it to understand context more accurately. It is particularly adept at identifying language that signals distress, suicidal ideation, or depressive states. However, MentalBERT still operates at the sentence or segment level, and it does not inherently model long-term dependencies across sequences of posts or conversations. Additionally, while it can understand direct linguistic cues, it lacks the capability to fully interpret abstract or metaphorical language unless combined with other models. Despite these limitations, MentalBERT remains one of the most effective baseline models in the domain of text-based mental health prediction.

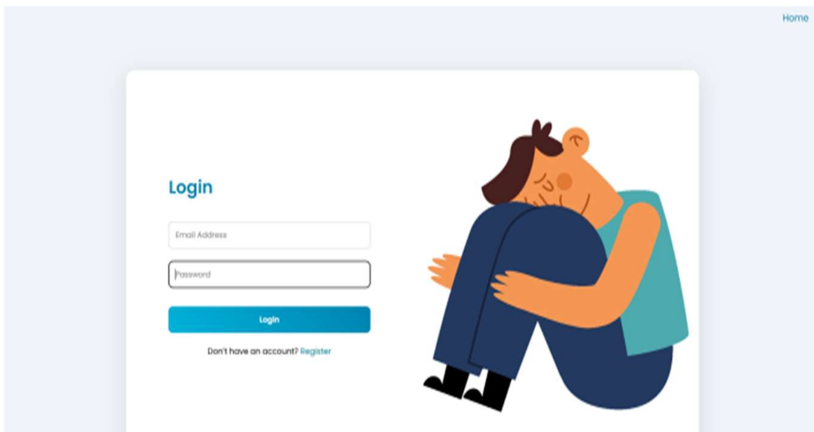
The proposed algorithm is a hybrid deep learning model that combines domain-specific language understanding, metaphor interpretation, and sequential feature modeling to predict multiple mental health conditions from user-generated text. First, MentalBERT is used to encode the input text with mental health-aware contextual embeddings, allowing the model to understand the specialized vocabulary and psychological patterns in the data. Simultaneously, MelBERT processes the same input to capture figurative and metaphorical expressions, which are often indicative of internal emotional states but are overlooked by standard models. The outputs of both transformer models are then concatenated and passed through a Convolutional Neural Network (CNN) to extract deep hierarchical features, highlighting local dependencies and structural nuances. Finally, a Bidirectional Long Short-Term Memory (BiLSTM) layer processes these extracted features to capture long-range dependencies and bidirectional context across the text sequence.

This layered architecture allows the system to retain critical mental health-specific cues while also understanding the sequence and flow of emotional expressions. The combination of transformer-based embeddings with temporal modeling makes the proposed algorithm highly effective for multiclass classification tasks in the mental health domain.

Result(Screenshots):




Home
Register
Full Name
Email Address
Password
Register
Already have an account? Login


Home
Login
Email Address
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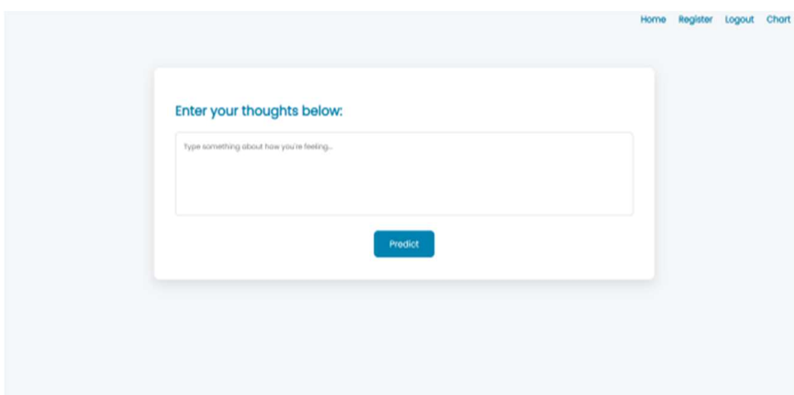
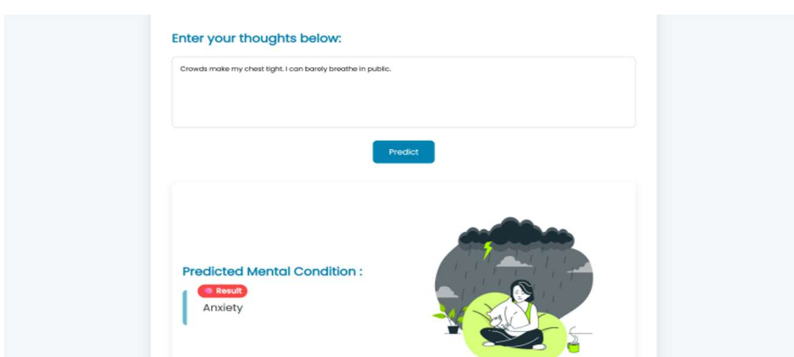
Login
Don't have an account? Register


Home
Register
Logout
Chart
Enter your thoughts below:
Type something about how you're feeling...
Predict


Enter your thoughts below:
Crowds make my chest tight. I can barely breathe in public.
Predict
Predicted Mental Condition :
Result
Anxiety

Conclusion

This project presents a comprehensive deep learning-based framework for the prediction and classification of multiple mental health disorders using social media text. By leveraging advanced NLP techniques and domain-specific transformer models such as MentalBERT and MelBERT, the system effectively captures the subtle, emotional, and metaphorical nuances that are often present in online expressions of psychological distress. The integration of CNN and BiLSTM further enhances the model's ability to extract local features and understand the sequential flow of language, making it highly effective in identifying complex mental health patterns.Through rigorous preprocessing, embedding, and evaluation strategies, the proposed system demonstrates superior performance over traditional models, offering improved accuracy, contextual understanding, and robustness. It successfully addresses the limitations of binary classification systems by supporting multiclass mental illness prediction, making it suitable for practical deployment in real-world mental health monitoring applications.

While the system shows promising results, there is room for future improvements, such as incorporating multimodal data, supporting multiple languages, adding explainability features, and deploying in a secure real-time application environment. Overall, this project highlights the transformative potential of artificial intelligence in supporting mental health awareness, early detection, and intervention, ultimately contributing to better mental well-being in society.

FUTURE SCOPE:

While the current system demonstrates strong performance in detecting and classifying multiple mental health conditions based on social media text, there remains significant scope for improvement and expansion. Future enhancements can focus on increasing the system's accuracy, interpretability, real-time usability, and inclusivity to broaden its impact and applicability. One key enhancement involves the integration of multimodal data. Currently, the system relies solely on textual input, but combining text with other modalities such as images, audio (voice recordings), and physiological signals (e.g., heart rate from wearables) could lead to more holistic and accurate mental health assessments. This multimodal approach would better mimic real-world diagnostics and capture behavioral patterns beyond language. Another area for enhancement is the implementation of explainable AI (XAI) techniques. By incorporating attention visualization or explainable layers, the system can highlight which parts of the input text contributed most to a given prediction. This would not only improve trust among users and clinicians but also provide deeper insights into the linguistic markers of specific mental disorders. Additionally, the system could be improved by supporting multilingual capabilities, enabling it to analyze mental health content written in languages other than English. This would make the tool more accessible to non-English-speaking populations and extend its usability globally. The deployment of the model into a real-time web or mobile application with privacy safeguards is another valuable enhancement. Such a platform could enable users to receive mental health insights and connect with professionals while ensuring data confidentiality and ethical usage. Finally, continual learning mechanisms could be incorporated so the model can adapt over time with new data, evolving slang, or emerging patterns of digital expression. This would keep the model up-to-date with linguistic and cultural changes in how mental health is discussed online.

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