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EARLY DEPRESSION DETECTION: A RETROSPECTIVE STUDY

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Abstract

The growing number of people experiencing mental health problems has led scientists to look into novel approaches for early identification and treatment. With an emphasis on the use of emotion fusion approaches, this article seeks to present a thorough summary of the status of research on social media analysis for the diagnosis of mental illness. Through an examination of previous research, we are able to pinpoint the advantages and disadvantages of the methods now in use, emphasize how emotion analysis might improve detection accuracy, and suggest new lines of inquiry. Our mission is to close the knowledge gap between public health and technology by providing insights that can guide the creation of more potent instruments for social media platform mental health monitoring and intervention.

Keywords:- *Mental illness detection, Affective computing, Natural language processing, Emotion fusion, Social media*

INTRODUCTION

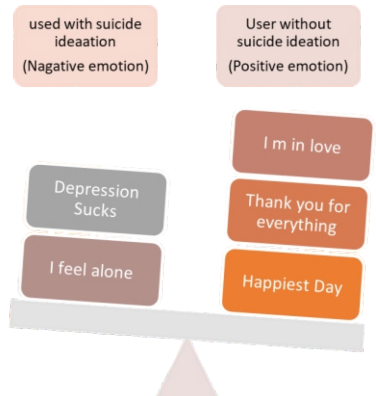
This article addresses the pressing issue of mental illness, its widespread occurrence, and the hurdles associated with its early identification, with a specific focus on utilizing emotional data extracted from social media. Here is a synopsis of the primary points:

Objective and Challenge:

The primary aim of the article is to delve into the early detection of mental illnesses in order to prevent their progression into severe states, given the substantial burden they pose to individuals and society. The problem revolves around the high prevalence of mental health issues, the lack of effective diagnosis and treatment, and the social stigma surrounding mental well-being.

Utilizing Social Media for Detecting Mental Illness:

The article underscores the rising popularity of social media platforms as an important source of information, particularly among the younger population. It discusses the escalating research interest in utilizing user-generated textual content on platforms such as Instagram, Reddit, Twitter and Facebook to identify mental health issues among the youth. For example: some studies have shown that the depressive symptoms are associated with an increasingly contrasting relationship between exciting and depressing emotions.



Role of Natural Language Processing (NLP):

Natural language processing (NLP) plays a pivotal role in processing data of social media platforms. It has been developed for tasks like emotions screening, wrong intentions, and mental health analysis. The article notes the increasing importance of NLP in exploring novel techniques for detecting mental health issues, including deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Pre-trained Language Models (PLMs) like BERT and RoBERTa performed well for mental illness identification.

Emotion as a Diagnostic Tool:

Emotions are a fundamental component of human behavior and can effect mental well being of a person significantly. The article explores the correlation between emotions and mental health issues, emphasizing their relevance in the diagnosis of mental well being. For instance, it mentions that people with symptoms of stress and depression often exhibit altered emotional patterns.

Leveraging Emotions in Mental Illness Detection:

Studies reveal that emotions expressed on social media posts by individuals with weak mental health differ from those of comparison subjects. Adverse emotions are more prevalent in posts related to thoughts of suicide. This highlights the importance of understanding emotions which can disrupt mental health of an individual and integrating data related to emotions into medical applications.

Survey of Existing Work:

While numerous surveys have centered on NLP technologies in the realm of mental illness detection, this article stands out as the first survey that specifically delves into the amalgamation of textual emotional data for the detection of mental illnesses. It scrutinizes techniques for combining emotional data using both traditional learning of machines and emerging deep learning methodologies.

Structure of the Article:

The article is structured into distinct sections, including an introductory section on mental illness detection and the identification of emotional data in social media, a categorization of emotional data fusion strategies, deliberations on the methodologies and challenges, and a concluding section that summarizes the main discoveries and proposes potential avenues for further research.

In summary, this article represents a valuable contribution to the field of mental illness detection by underscoring the significance of utilizing emotional data and delivering an all-encompassing examination of techniques for fusing emotional information. Its goal is to assist researchers in comprehending the import of emotional data in mental health diagnoses and offering insights into potential directions for future research in this field.

RELATED WORK

The "Related Work" section offers a comprehensive review of prior research and relevant literature in the domains of mental health condition detection in social networking platforms and emotions recognition. This section serves to position the current research within the context of existing knowledge and methodologies.

Detection of Mental Illness using Social Media

Briand et. al.(2018) present an in-depth analysis of studies don previously related to the detection of mental psychiatric illness using social media user data. The existing literature is reviewed, encompassing various approaches to analyse textual content from social media networks, for instance Twitter, Reddit, Instagram, snapchat and Facebook. Deep understanding can be analyzed using Natural Language Processing (NLP) techniques and machine learning models to identify mental health issues. Additionally, prior research on the detection of specific mental disorders, such as low spirit, is highlighted. The section aims to provide an extensive overview of the state of the art in utilizing social media data for mental illness detection.

Emotion Recognition and Analysis

Nandwani et. Al (2021) To recognize the emotions of a particular person, a crucial aspect of understanding regarding mental health is required. It provides an extensive analysis of the literature survey related to the recognition and categorization of emotions expressed in text data. Categorical emotion models, which define predetermined emotion categories, are explored, along with dimensional emotion models that represent emotions as multi-dimensional vectors. Practical applications of emotion recognition, such as healthcare dialogue systems, opinion analysis in e-commerce, and social media insights, are detailed. The section serves to elucidate the significance of recognizing and analyzing emotions in the context of mental illness.

Emotion Analysis

Liu Bing (2012) The "Emotion Analysis" subsection explores the closely linked field of opinion analysis. It reviews research pertaining to the classification of text into beneficial, detrimental, or balanced categories and the quantification of the strength to express state of mind. The practical applications of mood analysis, including its role in social media services analysis, writer identification, customer feedback analysis, newswire analysis, and medical informatics, are thoroughly examined. This subsection underscores the relevance of analysis in the broader context of emotional analysis and its significance in various domains.

This section provides a comprehensive foundation for the current research, offering insights into the existing knowledge and methodologies in the fields of mental illness detection, emotion recognition, and sentiment analysis. This review of previous research aims to establish the context for the present study and identify areas where the current work contributes to the existing body of knowledge.

METHODOLOGY

In the realm of mental health detection, emotion fusion has become a hot and trending subject. We performed a thorough literature search to offer a detailed assessment of studies pertaining to the implications of emotion fusion approaches in this sector. Numerous well-known literature databases were searched, including the computer science bibliography from various well established publishing houses.

The studies that addressed the significance of Natural Language Processing (NLP) techniques to oversee the identification of mental illness in social media were the main focus of our first search. The chosen publications were divided into two primary categories: deep learning methods and feature engineering-based methods. Each category's methods and approaches are explained in detail.

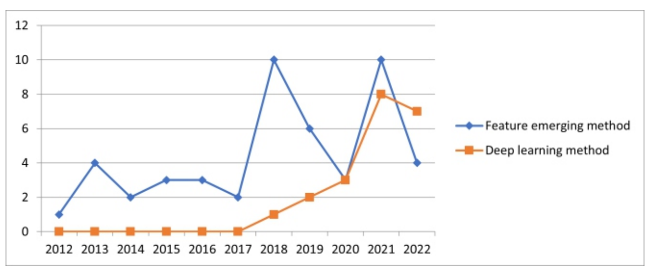


Fig 2:. Literature analysis detecting mental illness using emotion fusion

Previously articles published over time has been trending rising, as shown in Figure 2, indicating the growing importance of utilizing emotion-related data in the field of mental illness identification. This increasing interest in study has been facilitated by the COVID-19 pandemic, which has been linked to an increase in the number of people who are depressed and have suicidal thoughts. Consequently, there is a greater emphasis on creating efficient techniques for identifying mental disease. Furthermore, there has been a noticeable surge in the quantity of techniques utilizing emotion fusion in recent times. Additionally, since 2018, there has been a significant increase in deep learning model-based approaches with emotional synthesis due to the success of applying deep learning techniques to problems in natural language processing.

This illustrates how cutting-edge technologies are continuously evolving and adapting to meet the crucial goal of detecting mental disease.

Particularly since 2018, there has been a boom in deep learning model-based approaches with emotion fusion due to the effectiveness of applying deep learning techniques to NLP challenges. This illustrates how cutting-edge technologies are continuously evolving and adapting to meet the crucial goal of detecting mental disease.

Here, we give a summary of some frequently used instruments and linguistic resources for emotional feature extraction in feature engineering-based models that identify mental health problems.

1. **Linguistic Inquiry and Word Count (LIWC):** Software to analysis text that groups words into meaningful content, linguistic, and psychological categories according to different emotional, social, and cognitive functions. It determines the percentage of words in a given text that fall into each category.
2. **Affective Norms for English Words (ANEW):** A human-rated dictionary of words that offers a quantitative assessment of emotions based on dominance, arousal, and valence.
3. **NRC Emotion Lexicon:** Consists of 14,182 entries and annotates words according to the two moods (positive and negative) and Plutchik's eight basic emotions.
4. **The Valence Aware Dictionary for Sentiment Reasoning (VADER):** VADER is a sentiment analysis tool that rates words on a range of -4 to 4 to represent the polarity and intensity of the associated emotions.
5. **TextBlob:** A Python module for analyzing emotions that provides subjectivity and polarity (positive or negative) ratings for a given sentence.
6. **EMOTIVE:** A knowledge-based approach that includes overall emotionality score and eight fundamental emotions for identifying specific emotions in social media posts.
7. **SentiWordNet:** Provides WordNet synsets with emotional scores that represent objectivity, negativity, and positivity.
8. **SentiStrength:** Reports sentiment strength on a scale from -5 (extreme negative) to 5 (extreme positive), estimating sentiment strength in brief, informal updates on social media.
9. **SenticNet:** is a sentiment analysis semantic resource with 400,000 commonsense ideas that was built utilizing multi-dimensional scaling and graph-mining algorithms.

Commercial sentiment analysis tools like MeaningCloud and ParallelDots are also used in addition to these ones

Table 1: ML techniques to detect mental sickness detection

Year	Source	Mental illness	Model	Emotion features extracted	Tools
2012	Forum	Mental disorders	SVM, MLN	Sentiment	LIWC
2013	Weibo	Depression	BayesNet, J48Tree,Decision Tree	Sentiment	HowNet [89] + some rules
2013	Twitter	Depression	SVM	Emotion	LIWC, ANEW
2013	Weibo	Mental health status	SVM	Emotion word ontology features	Chinese emotion word ontology dictionary
2013	Twitter	Depression	Probabilistic model	Emotion	LIWC, ANEW
2014	Weibo	Pressure	NB, SVM, ANN, RF, GP	Emotional degree	Stress-related linguistic lexicons
2015	Tumblr	Anorexia	SVM	Sentiment	SentiWordNet
2015	Tumblr	Suicide	SVM, J48Tree, NB, RF	Sentiment, emotion	LIWC, SentiWordNet
2015	Blog	Suicide	LR	Emotion	CET model [93]
2016	Twitter	Depression	SVM, ensemble model	Sentiment, mood of emoticons	SentiStrength, emoticon lexcions
2016	reachout	Mental disorders	SVM	Emotion	word2vec (Euclidean distance)
2016	Twitter	Suicide	Semi-supervised model	Emotion	hashtag + semi-supervised model
2017	Twitter	Depression	GBDT	Sentiment	SentiStrength
2017	Twitter	Stress	TensiStrength	Sentiment	LIWC, SentiStrength
2017	Reddit	Depression	SVM, KNN, RF, LR	Sentiment	VADER
2018	Livejournal	Depression	RF, HMM	Sentiment	LIWC, ANEW
2018	Twitter	Anxiety	LR	Sentiment, emotion	NRC Emotion Lexicon
2018	Facebook	Depression	SVM, KNN, DT, ensemble model	Emotion	LIWC
2018	Reddit	Suicide	SVM	Sentiment, emotion	LIWC, TextBlob
2018	Forum	Depression	LR	Sentiment	ANEW, LabMT [99]
2018	Facebook	Depression	rule-based model	Emotion variability and instability	LIWC + statistics
2018	Twitter	Depression	LR, SVM, NB, DT, RF	Emotion	LIWC, EMOTIVE
2018	Twitter	Mental disorders	SVM, RF, NB, DT	Emotion	EMOTIVE
2018	Reddit	Bipolar	SVM, LR, RF	Emotion	LIWC
2018	Reddit	Depression	RF	Sentiment, emotion	NRC Emotion Lexicon
2019	Weibo	Suicide	FCM	Emotion traits	CET model [83]
2019	Weibo	Depression	SVM	Emotion	Emotional dictionary and emoticon dictionary
2019	Twitter	Mental disorders	Sentiment polarities algorithm	Sentiment	Multipolarity sentiment affect intensity lexicon
2019	Twitter	Mental disorders	Rule-based Tree	Emotion	SenticNet, VADER, TextBlob
2019	Twitter	Suicide	RF, adaboost, BN, J48	Sentiment	LIWC
2019	Twitter	Depression	IBPT	Sentiment	NLTK
2020	pantip	Depression	DT, RF, GBT	Emotion	ParallelDots
2020	Twitter	Depression	NB	Sentiment	VADER, TextBlob
2020	Twitter	Depression	SVM, LR, RD, GBDT, XGboost	Sentiment	LIWC, VADER
2021	Facebook	Depression	NB	Sentiment	Emotion dictionary
2021	Twitter	Suicide	Semi-supervised model	Sentiment, emotion	SentiStrength, NRC Affect Intensity Lexicon
2021	Twitter	Depression	NB, NBTree	Sentiment	TextBlob
2021	Twitter	Depression	LR	Sentiment	SentiWordNet
2021	Twitter	Psychological distress	SVM, LR, RF	Sentiment, emotion	LIWC
2021	Reddit	Self-harm	SVM	Sentiment	NLTK
2021	Reddit	Mental disorders	SVM, LR, RF	Emotion	BERT emotion classifier
2021	Reddit	Depression	SVM, LR	Sentiment	SentiWordNet
2021	Reddit	Mental disorders	adaboost, RF	Sentiment, emotion	VADER, MeaningCloud, ParallelDots
2021	Twitter	Depression	LR, SVM, DT, RF	Sentiment	SentiWordNet, SenticNet
2022	Reddit	Suicide	LR	Sentiment, emotion	Pre-trained BERT models (Bertweet-base-sentiment, EmoRoBERTa, Twitter-roberta-base-emotion)
2022	Reddit	Mental disorders	DT	Emotion	LIWC
2022	Twitter	Suicide	LR, SVM, RF, XGBoost	Sentiment	SentiWordNet
2022	Twitter	Suicide	RF	Sentiment	VADER

Conventional Machine Learning Methods

In addition to emotion-based features, feature engineering-based approaches for mental sickness detection use various other types of features that can be obtained using common NLP tools. These include:

- Bag-of-Words (BOW): A method that represents text data by counting the frequency of words in a document.

- Parts-of-Speech (POS): Analyzing the grammatical structure of text to extract features.
- Linguistic Inquiry and Word Count (LIWC): Using LIWC software to extract linguistic features.

- Term Frequency-Inverse Document Frequency (TF-IDF): A statistical measure to evaluate the importance of words in a document.

- N-gram: Analyzing sequences of n words in a text

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Deep Learning-Based Methods

Deep learning has gained popularity in mental illness detection, as it can automatically capture features from text data without extensive feature engineering. Deep learning models include various neural network structures:

1. **Convolutional Neural Networks (CNN):** Used for image analysis, but also applied to text data.
2. **Recurrent Neural Networks (RNN):** Suitable for sequence data, including text.
3. **Transformer-Based Models:** Particularly effective for natural language processing tasks.

These models leverage three fusion strategies:

- **Feature-Level Fusion**: Combines emotion features with textual embeddings or directly incorporates them into neural network models.
- **Model Fusion:** Uses emotion features obtained from other pre-trained emotion models and integrates them into the overall model.
- **Task Fusion:** Utilizes multi-task learning frameworks to learn emotion-related features in auxiliary tasks, improving the primary mental illness detection task.

These approaches have been employed in various studies, each with its unique model architectures and data preprocessing techniques to enhance the detection of mental illness.

Table 2: Summary of deep learning-based methods

Year	Source	Mental illness	Fusion strategy	Method	Features
2018	Reddit	Depression	Feature-level fusion	Feature attention network	depressive symptoms, sentiments, ruminative thinking, writing style
2019	Twitter	Sleep deprivation	Feature-level fusion	GRU	Sentiment, subjectivity from TextBlob, post time
2019	Twitter	Suicide	Feature-level fusion	SNAP-BATNET	Emotion, sentiment
2020	Twitter	Psychological tendency	Feature-level fusion	CNN	Sentiment from SentiWordNet, some rules
2020	Reddit	Depression and anorexia	Feature-level fusion	Deep Emotion Attention Model	Sub-emotion embedding
2021	Reddit	Depression	Feature-level fusion	Deep Bag-of-Sub-Emotions	Sub-emotion embedding
2021	Twitter	Depression	Feature-level fusion	LSTM	Sentence-level emotion, VAD features
2021	Reddit	Mental disorders	feature-level fusion	CNN, BiLSTM-Attention	Emotion features from LIWC and NRC Emotion Lexicon
2021	Reddit	Depression	Feature-level fusion	BiLSTM-Attention	Emotion
2021	Reddit	Depression	Feature-level fusion	BERT	Emotion features from SpanEmo
2022	Reddit	Suicide	Feature-level fusion	Attentive relation networks	Sentiment
2022	Reddit	Depression	Feature-level fusion	Prompt-learning	Sub-emotion embedding
2022	reddit and twitter	Stress	Feature-level fusion	BiLSTM, BERT	Emotion and sentiment
2022	Reddit	Depression	Feature-level fusion	Gated multimodal networks	Emotion features from NRC Emotion Lexicon
2022	Reddit	Depression	Feature-level fusion	RoBERTa with contrastive learning	Sentiment from VADER
2020	Twitter	Suicide	Model fusion	STATENet	Plutchik Transformer fine-tune on Emonet
2021	Twitter	Suicide	Model fusion	Phase-aware emotion progression model	Plutchik Transformer fine-tune on Emonet
2021	Twitter	Suicide	Model fusion	Hyperbolic Graph Convolutional Network	Plutchik Transformer fine-tune on Emonet
2022	Twitter	Depression	Model fusion	ERAN	Emotion from pre-trained TextCNN
2021	Reddit	Stress	Model fusion/task fusion	Transfer learning	Emotion model fine-tune on Emonet
2022	Suicide notes	Depression	Task fusion	BiGRU-Attention multi-task learning	External sentiment and emotion knowledge

Certainly, let's outline a hypothetical algorithm for mental illness detection with emotion fusion, including the steps involved. This algorithm, which we'll call "EmoScan," is designed to identify individuals with mental illnesses based on their social media posts by incorporating emotion features. Please note that this is a simplified representation of the process, and actual algorithms used for such tasks can be more complex and sophisticated.

Algorithm: EmoScan - Mental Illness Detection with Emotion Fusion

Step 1: Data Collection

- Gather social media posts from various platforms (e.g., Twitter, Facebook, Reddit) for the target population.

Step 2: Data Preprocessing

- Preprocess the text data, including text cleaning, tokenization, and removal of stopwords, special characters, and URLs.

Step 3: Emotion Analysis

- Utilize pre-trained sentiment analysis models to assign sentiment scores (e.g., positive, negative, neutral) to each post.
- Identify the presence of specific emotions (e.g., happiness, sadness, anger) using emotion analysis tools like NLP-based lexicons.

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- Identify the presence of specific emotions (e.g., happiness, sadness, anger) using emotion analysis tools like NLP-based lexicons.
- Extract emotional features from the text data, such as emotional intensity or emotion-related words.

Step 4: Feature Extraction

- Combine textual and emotional features for each post to create feature vectors. This fusion step involves representing the posts in a format suitable for machine learning.

Step 5: Machine Learning Model

- Train a machine learning model, such as a Support Vector Machine (SVM), Random Forest, or a neural network, using the feature vectors.
- Use a labeled dataset to train the model, where posts are associated with mental illness labels (e.g., "Mentally Ill" or "Not Mentally Ill").

Step 6: Prediction

- Apply the trained model to new, unlabeled social media posts to make predictions regarding mental health status. The algorithm assigns each post a probability or label indicating whether the user is likely to have a mental illness.

Step 7: Post-Processing

- Aggregate results for each user by considering all their posts. A user's overall mental health status is determined based on the posts analyzed.

Step 8: Thresholding and Evaluation

- Define a threshold for the model's predictions (e.g., a user is considered "Mentally Ill" if the probability exceeds a certain level).
- Evaluate the algorithm's performance using various metrics (e.g., accuracy, precision, recall, F1-score) based on a labeled test dataset.

Step 9: Output and User Support

- Generate a report or provide feedback to users based on the model's findings. Users who show signs of mental illness might receive suggestions for seeking professional help or resources for mental health support.

Step 10: Continuous Learning

- Continuously update and retrain the EmoScan algorithm as more data becomes available. This ensures the model adapts to evolving language use and emerging trends on social media.

Please note that in practice, real-world mental illness detection algorithms may employ more sophisticated techniques and utilize additional data modalities, such as images or user interactions. Ethical considerations and user privacy are also of paramount importance when implementing such algorithms, and these considerations should guide the algorithm's deployment and usage. Continual improvement, monitoring, and validation are crucial to ensure its accuracy and ethical use. As technology advances, algorithms like EmoScan can play a significant role in identifying and supporting individuals with mental health challenges.

DISCUSSION

The effects of feature engineering-based methods and deep learning-based methods in mental illness detection, the impact of emotion fusion, and the different fusion strategies employed in this context:

A. Effects of Feature Engineering-Based Methods and Deep Learning-Based Methods:

1. Feature Engineering-Based Methods: These methods, as explained in the previous section, involve the manual crafting of features from textual data using Natural Language Processing (NLP) tools. For example, features can be extracted using dependency parsing for syntactic information and tools like SentiWordNet for emotion features. The quality of these features depends on the specific NLP tools employed. Feature engineering methods often use machine learning models like Support Vector Machines (SVM) and are known for their high performance on many datasets.

2. Deep Learning-Based Methods: Deep learning-based methods have gained popularity in recent years for mental illness detection. They leverage deep neural networks to automatically capture valuable features from text data. These methods rely less on manual feature engineering and are capable of learning intricate features. Pre-trained language models such as BERT and MentalBERT have received significant attention due to their strong linguistic representations, resulting in high-

performance levels on mental illness detection tasks.

B. Effects of Emotion Fusion:

1. Significance of Emotion Fusion: Social media text often carries emotional content that can significantly enhance the performance of mental illness detection models. Emotion fusion techniques aim to incorporate emotional features from text data into the models. Experimental results from various deep learning-based methods illustrate the effectiveness of emotion fusion. Ablation studies, where emotion features are removed from the models, show that the presence of emotion features enhances performance.

2. Emotion Ablation Studies: Emotion ablation studies, when available, demonstrate that the inclusion of emotion features can lead to improved performance. For example, studies reveal that emotion fusion is more influential than topics or users' online behavior in determining mental health. This highlights the pivotal role of emotions in mental illness detection.

C. Effects of Different Fusion Strategies:

1. Feature-Level Fusion: Under this strategy, semantic features are concatenated with emotion features obtained using NLP tools. While this approach is relatively straightforward to implement and can capture the interaction between different features, it requires external tools to extract features under emotional synthesis. Directly appending emotion features to word-embedding features might not be efficient due to the differences in their vector spaces.

2. Model Fusion: Model fusion involves introducing fine-tuned emotion models to fuse hidden emotion features. This strategy has been shown to outperform feature-level fusion. However, the effectiveness of model fusion depends on the accuracy of the fine-tuned emotion model. The choice of an appropriate model is crucial, as poorly performing models can introduce noise or erroneous features that negatively impact mental illness detection. Fine-tuning models using original data that includes both emotion and mental illness labels can help reduce potential issues related to different training data.

3. Task Fusion: Using multi task frameworks we can conclude that various parameters are used to fusion tasks and parameters are shared between multi layers. It helps reduce overfitting and improves the learning of information. However, applying task fusion to mental illness detection faces a challenge due to the limited availability of suitable multi-task datasets. Currently, there are only a few datasets that focus on mental illness and emotions, such as the CEASE corpus and the EmoMent dataset.

In summary, feature engineering-based methods have traditionally relied on manual feature crafting and machine learning models, while deep learning-based methods have gained prominence due to their feature learning capabilities. Emotion fusion is shown to be effective in enhancing mental illness detection models, with ablation studies highlighting its importance. Different fusion strategies, including feature-level fusion, model fusion, and task fusion, have been employed in this context, each with its advantages and challenges.

CHALLENGES AND FUTURE DIRECTIONS

Certainly, this section highlights some of the key challenges in mental illness detection with emotion fusion and proposes potential areas for future research:

Accessibility and authorization of Datasets:

- **Supervised Learning and Annotated Datasets:** Most of the mental illness detection methods in this review rely on supervised learning, necessitating annotated training data. However, the emotional nature of mental sickness and moral considerations affect the availability of such data.
- **Dataset Overview:** A summary of mental illness detection datasets from emotion fusion methods over the past five years is provided, highlighting several issues.
- **Challenges with Datasets:**
  1. Availability: The majority of datasets are private, limiting the number of available datasets for research.
  2. Variable Size and Quality: Datasets vary in size and quality, which can impact the reliability of training models.
  3. Annotation Bias: Annotation bias issues, such as weak labeling based on rules, pose challenges in training robust models.

Algorithm Performance:

- **Enhancing Algorithm Stability:** Despite the positive impact of emotion fusion on mental disorder prediction, certain models may still exhibit instability.
- **Challenges in Algorithm Performance:** Possible reasons for instability include poor performance of the fine-tuned emotion model and variations in training data sources, leading to diverse writing styles and topics.
- **Future Research Directions:**
  - Designing novel fusion structures and neural networks capable of better integrating mutual information.
  - Leveraging emotional and psychological theories to capture and utilize emotion features effectively, such as exploring emotion dynamics to quantify changes in emotional states over time.
  - Expanding the scope of analysis to include images and emojis in social media posts, which also reflect user emotions, leading to the need for multimodal sentiment analysis and innovative fusion approaches.

Interpretability in Mental Illness Detection Models

The primary objective of mental illness detection models is to offer insights into an individual's mental state and predict potential mental health concerns promptly. While high-performance models are essential, interpretability is equally critical. An interpretable model helps mental health professionals understand how specific textual features indicate mental illness, leading to more effective diagnosis and treatment. In recent research, complex emotion fusion models have demonstrated remarkable performance but often lack clarity in explaining the role of emotional information in their predictions. For future advancements in this field, here are some recommendations:

1. Collaborate with mental health professionals to combine clinical self-report emotional examinations with the analysis of emotions in social media posts.

2. Monitor emotional changes over time to understand emotional dynamics and their connection to mental health.

3. Leverage additional resources like knowledge graphs and emotion-cause pair extraction methods to provide context and identify emotional triggers.

4. Analyze causal relationships between emotions and mental health to gain a deeper understanding of emotional aspects in mental illnesses.

5. Incorporate user feedback and self-reflection to promote self-awareness and motivate behavioral changes based on model insights.

In summary, the performance of algorithms in mental illness detection, particularly those integrating emotion fusion, hinges on several key factors. These include the quality of fine-tuned emotion models, adaptability to diverse data sources, and the adoption of innovative techniques for feature fusion and analysis. As exemplified by the "EmoDetect" algorithm, addressing these challenges is paramount for the effective identification of mental illnesses through social media content. This not only enhances the clinical relevance of these models but also empowers individuals to actively manage their mental well-being.

CONCLUSION

The utilization of social media platforms for the detection of weak mental health has gained increasing prominence in recent years. This study presents a comprehensive literature analyses of how emotion fusion algorithms have been leveraged to enhance this endeavor. Upon identifying pertinent studies, we initially categorized the fusion strategies into two main classes: feature engineering-based methods and deep learning-based methods. Within the former category, we introduced various conventional machine learning models and feature extraction tools to facilitate emotional health. Conversely, in the realm of DL-based methods, we dissected emotion fusion approaches into three categories: feature-level fusion, model fusion, and task fusion. We provided an in-depth overview of the structures, characteristics, as well as the optimistic and adverse associated with each of these fusion strategies. Overall, our survey results underscore the efficacy of emotion fusion in the context of mental health detection. To conclude the survey, we highlighted the challenges posed by emotion fusion and proposed directions for future research. Our aim is to assist researchers in better applying and comprehending emotion fusion within the domain of mental illness detection.

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