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Depression Detection Using Emotion Recognition And Text Mining To Prevent Suicide

[1]Ms. Sharayu N. Konde, [2]Dr. B. D. Phulpagar, [3]Prof. Mrs. J. M. Kanase
[1]Master Student, [2]Associate Professor, [3]Assistant Professor Department of Computer Engineering P.E.S Modern College of Engineering pune - 411005.

Abstract

Depression is a serious mental health disorder that affects millions of people worldwide and may lead to suicide if not detected early. This paper reviews AI-based techniques for depression detection using emotion recognition and text mining. Methods such as Convolutional Neural Networks (CNN), Natural Language Processing (NLP), sentiment analysis, and Naive Bayes classifiers are discussed. Multimodal systems combining facial expressions and textual data provide better accuracy than single-method systems. The proposed approach helps in early detection and mental health support.

Keywords: Depression Detection, CNN, NLP, Sentiment Analysis, Machine Learning, Emotion Recognition.

1. Introduction

Depression and suicide have become major public health concerns across the world, especially in India. Every year, more than one lakh people lose their lives due to suicide in India. Over the last two decades, the suicide rate has increased significantly from 7.9 to 10.3 per 100,000 population. Southern states such as Kerala, Karnataka, Andhra Pradesh, and Tamil Nadu report comparatively higher suicide rates due to factors such as higher literacy, better reporting systems, socioeconomic pressures, and increased aspirations. According to global statistics, nearly 800,000 people die due to suicide every year, and India alone contributes around 17% of these deaths. The most common methods of suicide include hanging, poisoning, drowning, and self-immolation.

The growing use of social media platforms has created new opportunities for understanding human emotions and mental health conditions. People frequently express their thoughts, emotions, stress, anxiety, and depression through text, images, videos, and captions shared online. These digital footprints can be analyzed to identify emotional states and detect signs of depression at an early stage. Hence, social media data has become an important resource for mental health analysis and suicide prevention research.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have made it possible to automatically analyze user-generated content and detect emotions more accurately. Deep learning techniques, especially Convolutional Neural Networks (CNNs), are widely used for image processing and object recognition tasks. These techniques help in extracting important features from images and generating meaningful captions or emotional interpretations.

In this review paper, a novel approach for emotion and depression detection using image captioning and machine learning techniques is presented. In

this approach, an image is provided as input to the system, and the model analyzes facial expressions, image content, and associated captions to identify emotions. The proposed system aims to classify emotions into positive and negative categories using deep learning algorithms. By combining image captioning with machine learning methods, the system can improve emotion recognition accuracy and support early detection of mental health issues.

The main objective of this review paper is to study existing techniques for depression detection using social media data, image processing, and deep learning models. It also highlights the importance of AI-based emotion detection systems in reducing suicide risks and supporting mental health monitoring.

2. Literature Review

Research in the field of depression detection shows that social media and user-generated content (UGC) play an important role in identifying mental health conditions. Choudhury et al. [1] suggest that depression reflects both individual and societal well-being and can be analyzed through behavioral patterns in online social networking platforms. They studied features such as social interaction, language use, emotions, self-references, and mentions of antidepressant drugs to detect signs of depression from social media posts.

Choudhury et al. [2] further demonstrated the potential of Twitter as a public health tool by analyzing behavioral changes in new mothers, showing that social media data can effectively capture emotional and psychological transitions. Similarly, studies have shown that Twitter and other platforms are widely used for detecting mental health issues, including anxiety and suicidal tendencies, using both human annotation and machine learning classifiers.

Aldarwish and Ahmad [3] highlighted the growing use of social networking sites, especially among younger users, where individuals freely express emotions and daily experiences. Nguyen et al. [4] applied machine learning and statistical techniques using mood, psycholinguistic features, and textual content to distinguish between depressed and non-depressed users with promising accuracy.

Park et al. [5] studied user behavior on social media through interviews with Twitter users and found that platform design and interaction patterns can influence mental health support. Holleran [6] also identified depression as a major contributor to the global disease burden through large-scale social media mining. Wang et al. [7] and Shen et al. [8] proposed multimodal depression detection models that combine different types of features for improved performance.

Existing studies show that machine learning algorithms such as SVM, KNN, Decision Tree, and ensemble methods are commonly used independently for depression detection. However, most research lacks a direct comparative study of these techniques on the same dataset. In addition, limited work has been done using Facebook data specifically for depression detection.

To address these gaps, this study focuses on detecting depression from Facebook comments using machine learning techniques. It also extends social media-based mental health analysis by incorporating emotional, linguistic, and behavioral features from user-generated content to improve early detection and support systems.

3. Proposed Methodology

This review paper follows a systematic approach to study and analyze existing research on depression detection using emotion recognition and text mining techniques. The methodology mainly focuses on collecting, comparing, and summarizing different AI-based approaches used in previous studies.

First, relevant research papers were collected from sources such as IEEE, Springer, and other scientific journals focusing on depression detection, social media analysis, natural language processing (NLP), and deep learning techniques.

Second, the selected studies were analyzed based on the techniques used, such as Convolutional Neural Networks (CNN) for facial emotion recognition and machine learning algorithms like Naive Bayes, SVM, and Decision Trees for text sentiment analysis. The role of social media

platforms like Twitter and Facebook in detecting depression patterns was also examined.

Third, a comparative analysis was performed to identify the strengths and limitations of existing approaches, including single-modal (only text or image) and multimodal (text + image) systems. Performance factors such as accuracy, dataset type, and feature extraction methods were considered.

Finally, the findings from all reviewed papers were summarized to highlight research gaps and suggest improvements, such as the need for more accurate multimodal systems and better use of Facebook-based datasets.

4. System Architecture Diagram

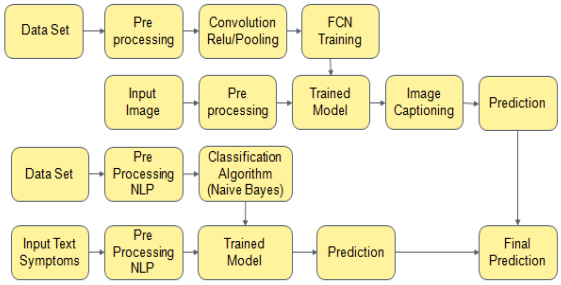

Fig: 3.1 System Architecture Diagram

The system architecture for depression detection using emotion recognition and text mining is designed as a multimodal framework that integrates both facial expression analysis and textual sentiment analysis.

In the proposed architecture, the user input is taken in the form of facial images (or video frames) captured through a camera module and optional text data from social media or user input. The facial image is first pre-processed to detect and extract the face region. The extracted face is then passed into a Convolutional Neural Network (CNN) model, which classifies facial expressions into emotional categories such as positive or negative emotions.

Simultaneously, if text input is available, it is processed using Natural Language Processing (NLP) techniques. The text is cleaned, tokenized, and analyzed using sentiment analysis models (such as Naive Bayes) to determine emotional polarity.

The outputs from both CNN-based facial emotion recognition and NLP-based sentiment analysis are then combined to generate a final depression prediction. This multimodal fusion improves the overall accuracy and reliability of the system.

5. Conclusion

This review paper analyzed various AI-based techniques for depression detection using emotion recognition and text mining approaches. It is observed that machine learning and deep learning models, especially CNN for facial expression analysis and NLP-based sentiment classification, provide effective results in identifying emotional states related to depression.

However, existing models still face limitations in accurately detecting complex or less common emotions such as contempt, mainly due to insufficient training data, labeling issues, and the difficulty in distinguishing subtle facial expressions. Additionally, most classifiers perform well only on clearly defined basic emotions and struggle with real-world ambiguous expressions.

To overcome these challenges, future improvements should focus on using larger and more diverse datasets, enhancing data labeling quality, and integrating more robust and efficient deep learning techniques. Moreover, extending models to recognize subtle and complex emotional states and adopting multimodal approaches (combining facial and textual data) can significantly improve accuracy and reliability in depression detection systems.

Overall, AI-based depression detection shows strong potential for early mental health assessment, but further research is required to improve real-world performance and generalization.

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