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EXPLORING DEPRESSION THROUGH SOCIAL MEDIA DATA: AN IN-DEPTH ANALYSIS

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Abstract: Depression is classified as one of the most debilitating mental health conditions, often linked to suicidal tendencies. Given the seriousness of the matter, it is crucial to methodically examine the facts about the identification of depression indicators on social media using data supplied by users. Extensive study on detecting signs of depression within the domain of social media has identified Twitter as the main area of interest. Word embedding is the most commonly used technique for extracting linguistic features. This highlights the importance of utilizing sophisticated methods and platforms, including social media, to improve the comprehension and detection of signs of depression. This research emphasizes the crucial need of discovering and synthesizing evidence pertaining to the detection of signs of depression on social media, specifically focusing on Twitter as an extensively researched medium. Depression, a profound psychiatric disorder frequently linked to suicidal inclinations, requires early identification for prompt management. Word embedding is the primary method used in research for extracting linguistic features. The utilization of social media data, in conjunction with computational tools and categorization methods, is becoming increasingly valuable in public healthcare projects. Integrating user-provided data from platforms such as Twitter that improves the ability to identify initial indications of depression, in line with current initiatives to better mental health monitoring and intervention methods. This research adds to the developing field of employing technology for promoting mental health awareness and providing assistance. The research article focuses on the review of different research on depression analysis with the assistance of social media information

Keywords: Sentiment, Social Media Data, Depression Analysis, Machine Learning, Accuracy, and deep Learning.

Introduction

Depression is one of the most common mental disorders that affects 121 million people worldwide [1]. It is estimated by the World Health Organization that depression will be the second major disability causing disease in the world by 2020. Reviewed the studies related to the problem and looking at how depression is reflected in communication behavior [2]. Among the wide range of communication activities, this study focuses on the activities that take place within social networking sites. The aim of this research is to conduct a comprehensive survey and analysis of these issues and to help understand the study of emotional analysis in social media contexts [3].

Each social media, such as Twitter, Instagram, and Facebook, has different characteristics and functions. Although the specific operation methods are different in each of these social media sites, it can be seen that they provide a common experience in a wide range. The possible actions in social network services can be generalized into three categories. The first is to broadcast a message so that an unspecified number of people can see it. The second is to communicate with individuals directly connected by following or making friends. Direct communication can be divided into receiving messages or communication actions from others and giving them to others. The third action involves only reading messages posted on the networking service (passive consumption). Among the above three types of behavior, passive message consumption is not identified as a practical interpersonal communication behavior. This study aims to focus on communication behavior in which the exchange of behavior is visible, thus excluding the behavior of passive message consumption [4]. Existing studies also focus on communication behavior other than message consumption.

Stress can threaten the well-being of an individual by exceeding his/her abilities or resources. Suicidal behavior is the result of failure to adequately cope with the needs and expectations of an individual and this can be attributed to stress [5]. Even when experiencing the same intensity of stress, the degree of influence on suicidal behavior is different for each individual. Several studies have been conducted to investigate the mediating factors of stress and suicidal behavior. Previous studies report cognitive traits such as self-esteem, family and social support, and lifestyle habits such as smoking, alcohol, exercise, and nutrition as mediating factors. Among lifestyle-related factors, problematic drinking behaviour in particular has been reported to lead to abuse other addictive substances and to induce suicidal thoughts in situations where self-control is difficult [6].

On the contrary, the driving factor among the lifestyle behaviors to maintain and promote health is not only disease prevention, but also rapid recovery from disease, and the maintenance and promotion of the current state of health, ultimately improving the quality of life. In the case of divorce or bereavement of a spouse, the suicide rate is higher than that in normal families, and it is observed that the elderly and unemployed elderly who suffer from economic difficulties become a factor of suicide in situations where they lack the ability to adapt to a new life [6]. As a result of attempting analysis using social variables such as divorce rate, birth rate, women's participation rate in economic activity, population movement, income, and education level, it is found that the level of urbanization is strongly related to suicide [7].

Emotional Analysis in Social Media

Nowadays social life is the key stage for the examination to dissect and anticipate the ecological circumstances and furthermore think about the individual musings and assessments [8]. The use of social life is expanded in this 21st century by various network of individuals everywhere throughout the world. Online networking stage is utilized to impart the insight and conduct the person, by which gigantic corpus can be gathered related with the individual contemplations which they think in their mind on their present circumstances [9]. The post which broadcasted by the client is divided by their assortment of burdensome and nervousness contemplations about film, game, individual, governmental issues, about items, restorative and so forth.

Henceforth, the information which the online life as can be utilized by the scientists in various expectation system and their significant research application. The utilization of social life for look into work. Our commitment is to foresee the downturn level of the individual by utilizing their conduct post and their common supposition. In this way, the two control we work under is arithmetic with building and wellbeing sciences.Social media provides a valuable reservoir of opinion data, offering the chance to investigate and extract user viewpoints on particular topics. Researchers are increasingly focusing on analyzing emotions and opinions via social media. A multitude of scholars are currently involved in analyzing user remarks on social platforms to extract and forecast practical outcomes, such as product reviews, stock market performance, political election results, and other related areas [10].

At the core of these studies lies the scrutiny of emotions (opinions) expressed by users on social media, usually referred to as emotional analysis. The field of research in question is constantly evolving, fueled by the need to improve the precision of automatically detecting emotional expressions. The copious volume of relevant data produced on social platforms, as individuals disseminate their perspectives and encounter facts, makes a huge contribution to study [24].

Although numerous researchers have been diligently working to advance state-of-the-art emotional analysis technology and its applications, there is yet to be a thorough investigation or integration of these study findings. Hence, it is imperative to methodically arrange pertinent material, explore the study findings and difficulties linked to emotion analysis in the present social media environment, and provide direction for future research undertakings.

Industrial Engineering Journal
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Emotion Classification and Analysis

Emotional classification, also known as emotional polarity classification, is the most common task in emotional analysis. It is based on the assumption that the opinion in the target text is about an aspect or attribute of an entity or the entity itself, and that the opinion can simply be divided into two opposite emotional polarities, or that it is positioned to be measured on a continuous variable between the two emotional polarities. Therefore, emotions are divided into three main categories: positive, negative, or neutral. In order to express the intensity of emotion, different measures are used. For example, the commonly used measurement range is between -1 and 1, where -1 represents the maximum negative emotion, 1 represents the maximum positive emotion, and 0 represents neutral attitude. Other studies have divided emotional ratings into 5, with 0 as maximum negative and 4 as maximum positive. However, Thelwall and others believe that both positive and negative emotions can coexist, and proposed an algorithm to measure both the emotional polarities at the same time, indicating that there are both positive and negative values in the emotional classification to express the emotional intensity.

The study of emotional psychology holds that although positive and negative are important emotional dimensions, there are still many other measures of emotional type and intensity, and positive and negative polarity do not meet the needs of emotional classification. This sort of classification task of subdividing emotional types is also called emotional analysis. Bollen and others analyzed public sentiment using six dimensions: nervousness, depression, anger, energy, fatigue, and confusion, based on the Profile of Mood States, a psychological measure of mood. Another study is based on Platschke's theory of emotional development psychology. The eight emotions namely, anger, fear, sadness, disgust, surprise, anticipation, trust, and happiness were mapped into four emotional polar pairs to identify changes in the moods of Twitter users at major events.

The notion of time is a fundamental factor in delineating emotional analysis. Over time, people may adopt, alter, or create new concepts. Therefore, the ability to predict future thoughts or events is an essential aspect of emotional analysis. The goal is to determine the emotional classification expressed in the text, analyze the changing pattern of emotions over time, closely matching emotional forecasting.

A time series analysis was conducted to examine Twitter topics and classify them into peak, early, late peak, and other time periods. The investigation confirmed a correlation between the popularity of Twitter subjects and the strength of pleasant and negative emotions. This emphasizes the importance of taking into account the time dynamics while comprehending the variations in emotions on social media sites [28, 29].

Comprehensive Analysis of Depression using Machine Learning and Deep Learning Technique

The detailed analysis of machine learning techniques in Table 1 for depression sign detection reveals nuanced performances across diverse datasets and classifiers. On Twitter, Support Vector Machines (SVM) and Naive Bayes (NB) exhibit comparable accuracies of 74.18% and 74.2%, respectively, while refined SVM configurations achieve an elevated 81.2%. Random Forests (RF), Tree Augmented Naive Bayes (TAN), and Boosted Forest Tree Augmented Naive Bayes (BF TAN) showcase accuracies of 72.5%, 72.1%, and 76.4%, respectively. Multinomial NB achieves 78%, and SVM on Twitter competes closely with an accuracy of 79.7%. Notably, Ensemble methods on Twitter, including Vote Classifier and Gradient Boosting, yield varying accuracies, with Vote Classifier reaching the highest at 85.09%. Facebook's SVM achieves 68.57%, whereas Random Forest outperforms with 84.6%. Across various sources, SVM impressively attains 90% accuracy. Additionally, on Twitter, Multinomial NB excels at 92.2%, while SVM and Logistic Regression achieve 93.1% and 93.2%, respectively. In contrast, SentiWordNet on Twitter registers a lower accuracy of 21.05%. The comprehensive examination highlights the nuanced effectiveness of different classifiers and platforms in the challenging task of depression sign detection from social media data.

Industrial Engineering Journal
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The deep learning techniques applied to depression sign detection exhibit diverse performances across different architectures and datasets. On Twitter, Long Short-Term Memory (LSTM) achieves an accuracy of 74.18%, while Convolutional Neural Network (CNN) and CNN-LSTM yield accuracies of 75.97% and 74.7%, respectively [24]. Another Twitter dataset demonstrates improved results, with LSTM achieving 80.83%, BiLSTM reaching an impressive 87.17%, and Gated Recurrent Unit (GRU) achieving 64.92% [25]. A multi-source approach, incorporating word embeddings and various neural architectures, displays promising outcomes. Notably, DECR—BiLSTM—CNN achieves a high accuracy of 87.92%, and GloVe—BiGRU—CNN and GloVe—BiLSTM—CNN demonstrate accuracies of 84.9% and 84.09%, respectively [26].

Facebook's LSTM exhibits a commendable accuracy of 85% [27]. On Reddit, a character-level CNN without embeddings achieves 92.5% accuracy, while a version without embeddings registers 77.7% accuracy [28]. Different architectures on Twitter, such as 1-layer LSTM, 1-layer CNN, and LSTM + CNN, showcase accuracies of 85.07%, 83.09%, and 92.06%, respectively [29]. In a KBRS dataset, CNN—BiLSTM—RNN attains 89% accuracy, while CNN—LSTM—RNN achieves 87% accuracy [30]. Various models applied to book reviews dataset exhibit compelling results, with CNN, CNN+Attention, BiGRU, and BiGRU+Attention achieving accuracies of 90.09%, 91.4%, 92.6%, and 93.1%, respectively [31].

On Twitter, different embeddings and CNN architectures demonstrate varying accuracies, with CNN + BiLSTM+ FastText Embedding + Word Embedding achieving 82.14% [32]. In SentiDrugs dataset, LSTM, BiGRU, and TD-LSTM attain accuracies of 71.15%, 71.35%, and 72.83%, respectively [34]. Overall, the comprehensive analysis underscores the versatility of deep learning techniques in capturing nuanced patterns for depression sign detection across diverse datasets and architectures.

Table 1. Analysis of ML and DL Technique

Technique	Dataset	Classifier	Accuracy	Reference
Machine Learning Technique	Twitter	SVM	74.18	[11]
	Twitter	NB	74.2	[12]
		SVM	81.2	
		RF	72.5	
		TAN	72.1	
		BF TAN	76.4	
	Twitter	Multinominal NB	78	[13]
		SVM	79.7	
	Facebook	SVM	68.57	[14]
		RF	84.6	
	Twitter	Multinominal NB	77.89	[15]
		RF	81.04	
		Ensemble Vote Classifier	85.09	
		Gradient Boosting	79.12	
	Reddit	Logistic Regression	84.8	[16]
		SVM	85	
	Twitter	KNN	72	[17]
		RF	82	
		NB	71	
		SVM	79	
	Twitter	SVM	82	[18]
		NB	64	
		KNN	73	

Industrial Engineering Journal
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	Various Sources	SVM	90	[19]
	Twitter	Multinominal NB	92.2	[20]
		SVM	93.1	
		LOG	93.2	
	Twitter	Multinominal NB	83	[21]
		SVM	79	
	Facebook	NB	76.6	[22]
	Twitter	SentiWordNet	21.05	[23]
		NB	69.92	
		HMM	64.06	
		Ensemble Approach	71.46	
Deep Learning Technique	Twitter	LSTM	74.18	[11]
		CNN	75.97	
		CNN-LSTM	74.7	
	Twitter	LSTM	80.83	[25]
		BiLSTM	87.17	
		GRU	64.92	
	Multi-source	word2vec—BiLSTM—CNN	82.73	[26]
		word2vec—BiGRU—CNN	81.17	
		GloVe—BiLSTM—CNN	84.09	
		GloVe—BiGRU—CNN	84.9	
		FastText—SW—BiLSTM—CNN	83.75	
		FastText—SW—BiGRU—CNN	83.97	
		Random—SW—BiLSTM—CNN	80.11	
		Random—SW—BiGRU—CNN	79.57	
		DECR—BiLSTM—CNN	87.92	
		DECR—BiGRU—CNN	86.79	
	Facebook	LSTM	85	[27]
	Reddit	char—CNN (no emb)	92.5	[16]
		char—CNN (w/o embed)	77.7	
	Twitter	1—layer LSTM	85.07	[17]
		1—layer CNN	83.09	
		LSTM + CNN	92.06	
	KBRS	CNN—BiLSTM—RNN	89	[30]

Industrial Engineering Journal

ISSN: 0970-2555

Volume : 54, Issue 12, No.1, December : 2025

		CNN—LSTM—RNN	87	
	Book Reviews	CNN	90.09	[31]
		CNN+Attention	91.4	
		BiGRU	92.6	
		BiGRU+Attention	93.1	
	Twitter	CNN + FastText	68.48	[32]
		CNN + Character Embedding	69.25	
		CNN + Word Embedding	67.14	
		CNN + FastText Embedding	65.35	
		CNN + BiLSTM+ FastText Embedding + Word Embedding	82.14	
	Twitter, Kaggle	DNN	64.5	[33]
		LSTM + FastText	66	
		LSTM + GloVe	67.7	
		LSTM +GloVe Twitter	69.9	
		LSTM + w/o pretrained embed	66	
	SentiDrugs	LSTM	71.15	[34]
		BiGRU	71.35	
		TD-LSTM	72.83	

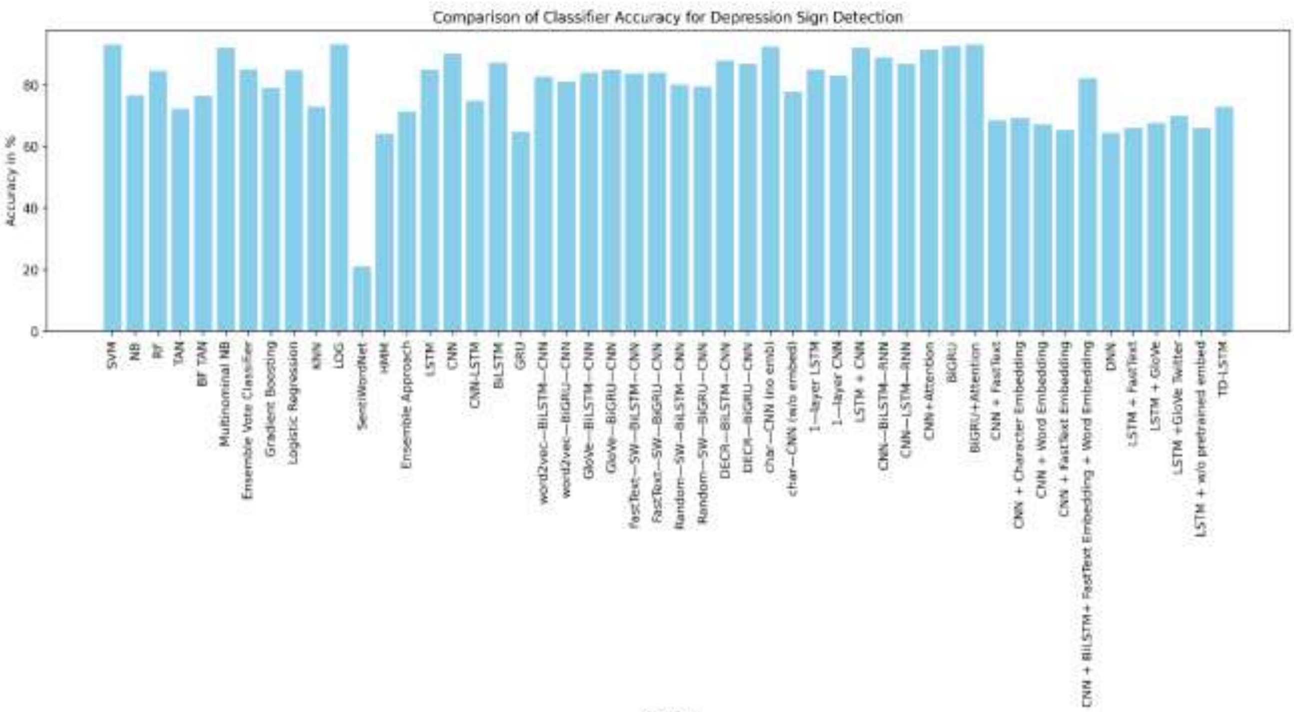

Figure 1. Comparison of Classifier Accuracy for Depression Sign Detection

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An examination of different classifiers for detecting signs of depression using both classic machine learning (ML) and deep learning (DL) techniques uncovers valuable trends. The Support Vector Machine (SVM) consistently and reliably achieves accuracies ranging from 68.57% to 93.1%, showcasing its adaptability and robust performance. Naive Bayes (NB) demonstrates strong performance, achieving accuracies ranging from 64% to 92.2%, highlighting its appropriateness for the task. The Random Forest (RF) algorithm demonstrates consistent performance, with accuracy ranging from 72.5% to 84.6%. Ensemble approaches, such as the Ensemble Vote Classifier, and gradient boosting enhance accuracy by stressing the efficacy of model combination. Within the realm of deep learning classifiers, the Bidirectional LSTM (BiLSTM) and Convolutional Neural Network (CNN) architectures are notable for their high accuracies, which range from 87.17% to 93.1% and 65.35% to 92.5%, respectively. The study highlights the superior ability of some deep learning models to capture subtle patterns when compared to typical machine learning models. The disparities in precision among datasets and classifiers underscore the importance of meticulously evaluating dataset attributes when choosing a model. In summary, the research offers vital insights into the effectiveness of several classifiers in detecting depression on social media platforms. This paves the way for future enhancements and advancements in this important field.
The research provided offers a thorough examination of machine learning and deep learning methods for detecting signs of depression on social media platforms. However, there are significant gaps in the research that require more investigation. Initially, it is imperative to establish consistent benchmark datasets in order to enable equitable comparisons among various models and methodologies. The heterogeneity of datasets utilized in various studies poses a challenge in determining the applicability of the presented methodologies. Moreover, the predominant portion of the examined studies concentrates on widely-used social media platforms such as Twitter and Facebook, so creating a study void in comprehending the suitability and efficacy of these methods on new or specialized platforms. In addition, there has been insufficient focus on temporal factors, such as the progression of language and mood on social media over time, which could offer useful insights into the changing characteristics of depression indicators. Furthermore, there is a lack of research that specifically investigates the ethical implications and possible biases linked to the utilization of social media data for mental health analysis. This highlights the need for a more comprehensive exploration of these crucial factors. Addressing these research gaps would enhance the precision and progress of approaches for detecting signs of depression on social media.

Conclusion

This analysis explores the complex field of detecting depression via social media, focusing on both machine learning and deep learning methods. The study highlights the gravity of depression, which is frequently associated with suicidal inclinations, emphasizing the importance of promptly identifying and synthesizing facts pertaining to the detection of signs of depression. Twitter plays a significant role in this research, with word embedding being highlighted as a prominent way for extracting linguistic features. The utilization of machine learning techniques, as seen in Table 1, demonstrates intricate performances across different classifiers and datasets. Twitter, Facebook, and many sources exemplify the adaptability of classifiers such as Support Vector Machines (SVM), Naive Bayes (NB), Random Forest (RF), and ensemble approaches. Deep learning approaches, which are extensively explored, provide varied performances on different architectures, highlighting the flexibility of models like LSTM, CNN, and BiLSTM. Nevertheless, there are still notable deficiencies in study, such as the requirement for uniform datasets, investigation beyond widely used social media platforms, and a more profound comprehension of temporal dynamics. The exploration of ethical problems and potential biases in the utilization of social media data for mental health analysis is still limited. It is essential to bridge these gaps in order to progress accurate and ethical methods for detecting depression. This aligns with the broader objective of utilizing technology to improve awareness and intervention for mental health.

Reference

[1]. Babu, N. V., & Kanaga, E. G. M. (2022). Sentiment analysis in social media data for depression detection using artificial intelligence: a review. *SN Computer Science*, *3*, 1-20.

[2]. Salas-Zárate, R., Alor-Hernández, G., Salas-Zárate, M. D. P., Paredes-Valverde, M. A., Bustos-López, M., & Sánchez-Cervantes, J. L. (2022, February). Detecting depression signs on social media: a systematic literature review. In *Healthcare* (Vol. 10, No. 2, p. 291). MDPI.

[3]. Liu, M., Kamper-DeMarco, K. E., Zhang, J., Xiao, J., Dong, D., & Xue, P. (2022). Time Spent on Social Media and Risk of Depression in Adolescents: A Dose–Response Meta-Analysis. *International journal of environmental research and public health*, *19*(9), 5164.

[4]. Liu, D., Feng, X. L., Ahmed, F., Shahid, M., & Guo, J. (2022). Detecting and measuring depression on social media using a machine learning approach: systematic review. *JMIR Mental Health*, *9*(3), e27244.

[5]. Lopes, L. S., Valentini, J. P., Monteiro, T. H., Costacurta, M. C. D. F., Soares, L. O. N., Telfar-Barnard, L., & Nunes, P. V. (2022). Problematic social media use and its relationship with depression or anxiety: a systematic review. *Cyberpsychology, Behavior, and Social Networking*, *25*(11), 691-702.

[6]. Garg, M. (2023). Mental health analysis in social media posts: a survey. *Archives of Computational Methods in Engineering*, *30*(3), 1819-1842.

[7]. Angskun, J., Tipprasert, S., &Angskun, T. (2022). Big data analytics on social networks for real-time depression detection. *Journal of Big Data*, *9*(1), 69.

[8]. Shin, M., Juventin, M., Chu, J. T. W., Manor, Y., & Kemps, E. (2022). Online media consumption and depression in young people: A systematic review and meta-analysis. *Computers in Human Behavior*, *128*, 107129.

[9]. Shannon, H., Bush, K., Villeneuve, P. J., Hellemans, K. G., & Guimond, S. (2022). Problematic social media use in adolescents and young adults: systematic review and meta-analysis. *JMIR mental health*, *9*(4), e33450.

[10]. Tandoc Jr, E. C., & Goh, Z. H. (2023). Is Facebooking really depressing? Revisiting the relationships among social media use, envy, and depression. *Information, Communication & Society*, *26*(3), 551-567.

[11]. Chen B, Cheng L, Chen R, Huang Q, Phoebe Chen Y-P. Deep neural networks for multiclass sentiment classifcation. In: IEEE 20th International Conference on high performance computing and communications, IEEE 16th International Conference on Smart City, IEEE 4th International Conference on Data Science and Systems 2018; pp. 854–59.

[12]. Ruz GA, Henriquez PA, Mascareno A. Sentiment analysis of Twitter data during critical events through Bayesian networks classifers. Future Gener Comput Syst. 2020;106:92–104.

[13]. Arora P, Arora P. Mining Twitter data for depression detection. In: IEEE International Conference on signal processing and communication (ICSC), 2019; pp. 186–89, https://doi.org/10.1109/ ICSC45622.2019.8938353.

[14]. Katchapakirin K, Wongpatikaseree K, Yomaboot P, Kaewpitakkun Y. Facebook social media for depression detection in the Thai community. In: 15th International Joint Conference on computer science and software engineering (JCSSE), 2018; pp. 1–6, https://doi.org/10.1109/JCSSE.2018.8457362.

[15]. Kumar A, Sharma A, Arora A. Anxious depression prediction in real-time social data. In: International Conference on advanced engineering, science, management and technology—2019 (ICAESMT19).

[16]. Cornn K. Identifying depression on social media. 2019. https:// web.stanford.edu/.

[17]. . Ahmad S, Asghar MZ, Alotaibi FM, Awan I. Detection and classifcation of social media-based extremist affiliations using sentiment analysis techniques. Human Centric Comput Inf Sci. 2019;24:1–23.

[18]. Gaikwad G, Joshi DeJ. Multiclass mood classifcation on twitter using lexicon dictionary and machine learning algorithms. In: International Conference on inventive computation technologies (ICICT) 2016; pp. 1–6, https://doi.org/10.1109/INVENTIVE. 2016.7823247

[19]. . Jayakrishnan R, Gopal GN, Santhikrishna MS. Multi-class emotion detection and annotation in Malayalam novels. In: 2018 International Conference on computer communication and informatics (ICCCI -2018), Jan. 04–06, 2018, Coimbatore 2018; pp. 1–5, https://doi.org/10.1109/ICCCI.2018.8441492.

[20]. . Solakidis GS, Vavliakis KN, Mitkas PA. Multilingual sentiment analysis using emoticons and keywords. In: IEEE/WIC/ACM International Joint Conferences on web intelligence (WI) and intelligent agent technologies (IAT) 2014; pp. 102–9, https://doi. org/10.1109/WI-IAT.2014.86.

[21]. Deshpande M, Rao V. Depression detection using emotion artifcial intelligence. In: International Conference on intelligent sustainable systems (ICISS 2017) 2017; pp. 858–62, https://doi. org/10.1109/ISS1.2017.8389299.

[22]. Chatterjee R, Gupta RK, Gupta B. Depression detection from social media posts using multinomial Naive theorem. IOP Conf Ser Mater Sci Eng. 2021;1022:012095.

[23]. . Jose R, Chooralil VS. Prediction of election result by enhanced sentiment analysis on Twitter data using classifer ensemble approach. In: International Conference on data mining and advanced computing (SAPIENCE) 2016; pp. 64–7, https://doi. org/10.1109/SAPIENCE.2016.7684133.

[24]. Lambert, J., Barnstable, G., Minter, E., Cooper, J., & McEwan, D. (2022). Taking a one-week break from social media improves well-being, depression, and anxiety: a randomized controlled trial. *Cyberpsychology, Behavior, and Social Networking*, *25*(5), 287-293.

[25]. Arora P, Arora P. Mining Twitter data for depression detection. In: IEEE International Conference on signal processing and communication (ICSC), 2019; pp. 186–89, https://doi.org/10.1109/ ICSC45622.2019.8938353.

[26]. Katchapakirin K, Wongpatikaseree K, Yomaboot P, Kaewpitakkun Y. Facebook social media for depression detection in the Thai community. In: 15th International Joint Conference on computer science and software engineering (JCSSE), 2018; pp. 1–6, https://doi.org/10.1109/JCSSE.2018.8457362.

[27]. Kumar A, Sharma A, Arora A. Anxious depression prediction in real-time social data. In: International Conference on advanced engineering, science, management and technology—2019 (ICAESMT19).

[28]. Valkenburg, P. M. (2022). Social media use and well-being: What we know and what we need to know. *Current Opinion in Psychology*, *45*, 101294.

[29]. Ulvi, O., Karamehic-Muratovic, A., Baghbanzadeh, M., Bashir, A., Smith, J., & Haque, U. (2022). Social media use and mental health: A global analysis. *Epidemiologia*, *3*(1), 11-25.

[30]. Rosa RL, Schwartz GM, Ruggiero WV, Rodrıguez DZ. A knowledge-based recommendation system that includes sentiment analysis and deep learning. IEEE Trans Ind Inf. 2019;15(4):2124–35. https://doi.org/10.1109/TII.2018.2867174.

[31]. Yang L, Li Y, Wang J, Sherrarat RS. Sentiment analysis for E-commerce product reviews in chinese based on sentiment lexicon and deep learning. IEEE Access. 2020;8:23522–30. https:// doi.org/10.1109/ACCESS.2020.2969854.

[32]. Salur MU, Aydin I. A novel hybrid deep learning model for sentiment classifcation. IEEE Access. 2020;8:58080–93. https://doi. org/10.1109/ACCESS.2020.2982538.

[33]. Imran AS, Daudpota SM, Kastrati Z, Bharat R. Cross-cultural polarity and emotion detection using sentiment analysis and deep learning on COVID-19 related tweets. IEEE Access. 2020;8:181074–90

[34]. Han Y, Liu M, Jing W. Aspect-level drug reviews sentiment analysis based on double BiGRU and knowledge transfer. IEEE Access. 2020;8:21314–25. https://doi.org/10.1109/ACCESS. 2020.2969473.