**Detecting and Suggesting Solutions for Suicide Risk using Distributed CNN-BiLSTM**

**1. Introduction:**

In this modern era, suicide is regarded as the most severe public health issue. Around 0,7 million individuals lose their lives every year, and many more, particularly the young and middle-aged, attempt suicide [9]. Only a tiny proportion of individuals who made a self-harm attempt present themself to the hospitals, meaning that this behavior is primarily hidden (at least from clinical service) at the community level [10]. Being someone who doesn’t know what to do with their problems is frustrating, and the easiest way to escape is self-harm and suicide. Their suicidal ideation can be cured with the help of healthcare experts and drugs, but most avoid medical treatment due to societal stigma [9] [3]. People of all ages may suffer from suicidal ideation for various reasons, including shock, anger, guilt, depression, and anxiety. Longterm depression may lead to suicide if adequate therapy is not sought, despite the fact that the vast majority of individuals who experience suicidal thoughts do not actually attempt to end their own life [11]. Suicidal ideation can be managed with the assistance of healthcare professionals and medications. However, most people with suicidal ideation avoid medical treatments due to the stigma associated with them. Instead, many people choose to communicate their intent to commit suicide on social media. Because mental illness may be diagnosed and treated, the early identification of warning signs or risk factors may be the most effective way of preventing suicide [8].

Theories of suicide prevention have struggled in their efforts to understand what factors may facilitate suicide risk [12]. A large body of research has shown suicide risk to be influenced by an interaction of biological, psychological, cultural, environmental, and social factors [6]. Suicide has several risk factors that are closely related with social and mental problems [12]. Detection of suicidality, which covers suicidal ideation, suicide plans, and suicide attempts, plays a significant role in suicide prevention [13][14]. Studies reported that people show warning signs before attempting suicide and those warning signs can be detected from their behavioral patterns [15] and words they use [16][17][18]. Therefore, suicidality can be detected from explicit and implicit warning signs. Detecting suicidality in the real-life is hard though, because people rarely talk about their suicidal ideation, plans, and attempts with others and rather try to hide them [19]. However, on social media, people behave much differently. On social media, people share about their daily lives (Paul, 2014), exchange political opinions [20], and even talk about their suicidality [21] [1].

Research indicates that examining social media posts can aid in the detection of depression and other mental health concerns. These online actions prompted them to develop new forms of prospective health care solutions and early suicide detection systems. This is accomplished by detecting suicidal ideas in user postings using machine learning techniques and Natural Language Processing (NLP) methodology. A number of researchers extracted numerous single set feature groups, such as N-grams [22][23], Bag-ofWords [24]][25], Linguistic Inquiry Word Count (LIWC) [26][27], or Latent Dirichlet Allocation (LDA), for diagnosing depression in user messages. Other studies compared the performance of these individual features using other machine learning techniques [28][29]. Some current research work has focused on improving the accuracy of detection by combining some of these features. The authors in [30] combined N-Gram+LIWC to improve the accuracy of detection over single set features. Similarly, in [31], the authors used advanced text preprocessing and used a combination of Bag of Words, LDA, TF-IDF, and Convolutional Neural Networks (CNN) to increase the performance. According to a study by [32], the use of combined features can result in higher performance. They compared the performance of single feature such as bi-gram with Support Vector Machine (SVM) classifier to reach 80 percent accuracy. Over the last few years, there has been a growing body of literature that deals with the early detection of mental illness by utilizing social media information [32][33][34]. Although a substantial amount of progress is being made in this field, there are still some challenges to overcome. The aim of the authors of this research is to explore suicide ideation detection using online user generated material in order to comprehend and detect suicidal ideas from user-generated content [5].

**2. Literature Review**

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| **S. No** | **Author** | **Methods** | **Dataset** | **Advantages** | **Disadvantages** | **Achievements** |
| 1. | Woojin Jung et al. [1] | Random forest (RF) and gradient boosting machine (GBM) with metadata and text features. | Suicide related tweets from Korean Suicide Prevention Center (KSPC). | The model can assist in realworld setting to detect suicidality social meadia posts. | The model requires annotated data and its performance is highly depends on volume and quality of data. | Recall=0.842, Precision=0.827, F1-score=0.834, and roc-auc=0.903. |
| 2. | C.L. van Vuuren et al. [2] | RF and the Lasso Regression | Data from questionnaire of school students in Amsterdam | High response rate even in large sample size. | There are some missing data and the loss of cases after merging the data. | AUC for RF=0.79 and AUC for LASSO=0.76 |
| 3. | Mario Sebastian Santoso et al. [3] | Decision tree (DT) and support vector machine (SVM) | Posts from Reddit | Improved quality of data and efficient classification. | Small dataset may cause generalization issues. | Accuracy for DT=81.57, and for SVM=90.80 |
| 4. | Sayani Ghosal and Amita Jain et al. [4] | XGBoost classifier | Reddit dataset | Fast text contextual analysis improved the accuracy of classification , even though the posts are lengthy. | Not accountable for time complexity and variability of depression. | AUC=0.78 and F1 score=0.71. |
| 5. | Moumita Chatterjee et al. [5] | Multi modal model-XGBoost, SVM AND logistic regression (LR). | Twitter and Reddit data | Efficient feature extraction with high accuracy. | The research lies on self-reported diagnoses of suicide ideation which may not be accurate or consistent. | Accuracy=87%. |
| 6. | Meytal Grimland et al. [6] | Suicide Risk-Bert model | Sahar dataset | The model shows efficient results in large dataset and improves its generalization ability. | The lexicon is limited in its ability to fully encompass all theoretical concepts related to suicide risk. | Recall=78.3%, precision=68.9%, and ROC-AUC=92.1% |
| 7. | Hugo J. Bello et al. [7] | CNN | Data are taken from web scraping | Time series analysis and topological data analysis to reveal the temporal and thematic patterns of suicide-related news in Spanish media. | Relies on web scraping techniques to collect data, which introduce s bias or error in the data quality and quantity | Loss=0.0233 |
| 8. | Theyazn H. H. Aldhyani et al. [8] | CNN-BiLSTM | Reddit dataset | Statistical analysis provides some insights into the linguistic patterns of suicidal ideation. | Focuses only on English posts from Reddit, which may limit the generalizability of the results | Accuracy 95%. |
| 9. | Shini Renjith et al. [42] | LSTM-Attention-CNN | Reddit dataset | Efficiently detects the ideation of suicide from emotion from posts. | Small dataset is used, use of large dataset may limits the performance. | Accuracy=90.3% and F1-score=92.6% |
| 10. | Michael Mesfin Tadesse et al. [43] | LSTM-CNN combined model | Reddit social media dataset | Efficient detection performance in detecting suicide ideation | Data deficiency and annotation bias | Recall=94.1 , Precision=93.2, F1-score=93.4, and accuracy=93.8. |
| 11. | Akshma Chadha and  · Baijnath Kaushik [44] | Attention convolution long short-term memory (ACL) model | Reddit Social media dataset | Use of random embedding increases the detection performance. | Dataset used is very small | Accuracy = 88.48%, Precision=87.36%, F1 score= 90.82% and specificity=79.23% |
| 12. | Kipkebut Andrew et al. [45] | BERT | Data from different sources in kenya | Reduces the computation time. | Superficial and unclear words limits the performance. | Recall=0.87 , Precision=0.91, and F1-score=0.90. |
| 13. | R. Punithavathi et al. [46] | CNN | FER dataset | The system can analyze the mood of patients either in real time or in the form of video files from CCTV cameras. | The study did not cover the interpretation of neutral facial expressions and problems arising due to psychological or social risk factors. | Accuracy=82% |
| 14. | Jun-Cheng Weng et al. [47] | CNN-based autoencoder model, m extreme gradient boosting (XGB)and LR. | Generalized q-sampling imaging (GQI) dataset | Efficiently classify suicidal ideates from non-ideation depressed patients and healthy controls. | The imbalance remained strong after tuning | Accuracy= 85%, specificity= 100% and sensitivity =75% |
| 15. | Shaoxiong Ji et al. [48] | BiLSTM | UMD Reddit Suicidality Dataset. | Encodes the text efficiently with increasedperformance in detection. | Error may be occurs. | Accuracy = 0.8385, Precision=0.8381, F1 score=0.8377, and Recall=0.8385 |

**3. Research Gaps**

* Suicidal thoughts and suicide attempts are low base-rate behaviors which often result in an imbalanced dataset, i.e. one of the classes is much more or much less prevalent than the other classes. This strong imbalanced data proposes a challenge to ML because there are few examples of suicidal behavior to learn from [2].
* Levi-Belz et al. [35] found that the interaction of hopelessness and interpersonal difficulties, such as thwarted belongingness, was highly significant in predicting more severe suicide attempts. However, whereas these studies used self-report measures of only few factors in retrospective studies [6].
* In recent years and based on technological advancement, researchers have begun studying the predictive ability of machine learning (ML) regarding suicide risk. One should bear in mind, however, that applying machine learning methods to enhance predictions do not always result in significantly improved outcomes compared to simpler models [36][6].
* Linguistic characteristics that are established in the field of psychiatry, such as the LIWC [37], emotion features [38], and suicide notes [39], were used. However, this method employs language-specific strategies that can evaluate only individual posts in isolation and cannot perform well with vast amounts of diverse data [8].

**4. Significance of the Research**

Suicide remains a global health crisis, particularly affecting young individuals. Traditional assessment tools have limitations, often failing to predict suicidal thoughts and behaviors accurately. However, deep learning models offer several advantages; they can process complex patterns, learn from large datasets, and analyze textual data using natural language processing techniques. By using benchmark datasets, incorporating suicide theories, and distinguishing risk factors for ideation versus attempts, this research aim to save lives through accurate suicide risk detection systems.

**5. Objectives:**

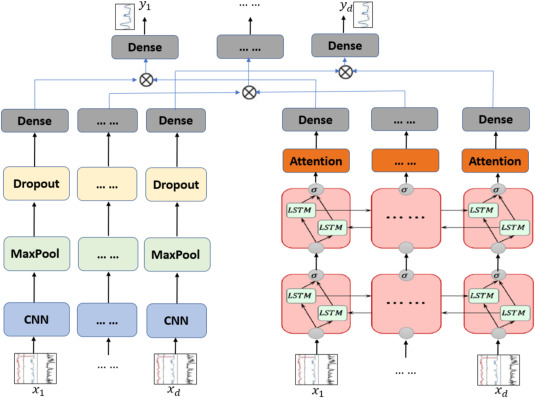
* Design and develop a deep learning model to detect suicide and give suggestions
* Implement various preprocessing steps and extract various features to improve the quality of the data and for efficient processing.
* Develop a hybrid attention module which tunes the classifier to improve the performance of the model.
* Compare and evaluate the effectiveness of the developed model with other existing methods based on metrics such as Accuracy, Sensitivity and Specificity.

**6. Proposed Methodology:**

Suicide is the act of intentionally causing one's own [death](https://en.wikipedia.org/wiki/Death) and that defies detection and prevention efforts worldwide. A suicide result is a complex permutation of health factors, personal, social and therefore suicide prevention is a challenge. The main purpose of the research will be to design and development of suicide detection and suggestion techniques. EAS Instagram text dataset [40], RAVEDESS Audio Dataset [41] and Questionary User Query based answering Dataset have emerged as a means of investigating large datasets for suicide detection. From these datasets the preprocessing steps of Audio and Text takes place. To initiate the process, the Text data will be exposed to preprocessing such as punctuation removal, stop word removal, Lemmatization and Emoji to text conversation and then in the audio preprocessing, the noise will be removed. The features such as TF-IDF, Post tagging, Bags of h-grams and Latent Dirichlet Allocations will be extracted from the preprocessed Text and from the audio signal MFCC, Statistical Audio Texture and Pretrained VGG features will be extracted. The extracted features from both text and audio are concatenated and then the concatenated feature will be fed to the Distributed CNN-BiLSTM model. Here, the Distributed CNN-BiLSTM will be tuned by the hybrid attention model, which is formed by hybridizing the attention free transformer and spatial attention module. The trained model will evaluated using the test data. If the output of the model is suicide and it’s classified into low, medium and high risks, then the Distributed CNN-BiLSTM will train again using user query and the model will give suggestion. The proposed suicide detection and suggestion will be implemented in PYTHON. The performance of the proposed method will be demonstrated be comparing the performance metrics such as Accuracy, Sensitivity and Specificity. Figure 1 illustrates the systematic representation of the proposed model.

Hybrid attention module

Feature Concatenation

Distributed CNN-BiLSTM

Model

Test data

Suicide/Non-suicide

If suicide

Suggestions/helps

**Input**

EAS Instagram dataset

RAVEDESS audio dataset

Questionary user query based Answering dataset

**Preprocessing**

Noise Removal

Punctuation removal

Stop word removal

Lemmatization

Emoji to text conversion

**Feature Extraction**

TF-IDF

POS tagging

Bags of h-grams

Latent Dirichlet Allocations

MFCC

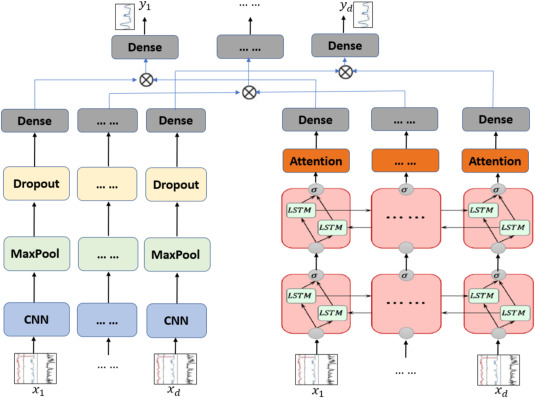
Statistical audio features

Pretrained VGG

Low risk

Medium risk

High risk

Distributed CNN-BiLSTM

Query

**Figure 1:** Systematic representation of the proposed model

**7. Sampling**

Since the proposed model consists of a deep learning approach, it solves the issues regarding oversampling and under sampling. Therefore, there is no need of any sampling techniques.

**8. Data Types and Data Collection Methods**

The experiment is carried out using diverse datasets with text and audio data. In this research, the RAVEDESS Audio Dataset [41] is an audio dataset containing 1440 files: 60 trials per actor x 24 actors = 1440. The RAVDESS contains 24 professional actors (12 female, 12 male), vocalizing two lexically matched statements in a neutral North American accent. EAS Instagram text dataset [40] has over 370,000 preprocessed comments from 40 Instagram channels, which have been collected with the help of data crawlers. A Questionary User Query based answering Dataset is also used which will be created by recording the responses of the public for suicide based questions.

**9. Data Analysis Plan**

In this research, the data analysis is carried out by analyzing the data with extracting features such as TF-IDF, POS tagging, Bags of h-grams, Latent Dirichlet Allocations, MFCC, Pretrained VGG, and Statistical audio features. At first, the model is analyzed with these features separately and then the all the features will be concatenated and analyzed. The experiment is implemented in Python for this analysis.

**10. Chapter Scheme:**

* Section 1 presents the introduction to suicide risk detection
* An overview of existing methods for suicide risk detection and discusses their shortcomings is presented in Section 2.
* Section 3 presents the proposed strategy for suicide risk detection using deep learning.
* Section 4 analyzes and presents the results of the system.
* Finally, in section 5, the paper concludes with a discussion on future scope and potential improvements.

**References:**

[1] Jung, Woojin, Donghun Kim, Seojin Nam, and Yongjun Zhu. "Suicidality detection on social media using metadata and text feature extraction and machine learning." Archives of suicide research 27, no. 1 (2023): 13-28.

[2]Van Vuuren, C. L., Kasper van Mens, Derek de Beurs, Joran Lokkerbol, M. F. van der Wal, Pim Cuijpers, and M. J. M. Chinapaw. "Comparing machine learning to a rule-based approach for predicting suicidal behavior among adolescents: Results from a longitudinal population-based survey." Journal of affective disorders 295 (2021): 1415-1420.

[3]Santoso, Mario Sebastian, Jovan Jonathan Suryadi, Kevin Marchellino, and Ghinaa Zain Nabiilah. "A Comparative Analysis of Decision Tree and Support Vector Machine on Suicide Ideation Detection." Procedia Computer Science 227 (2023): 518-523.

[4]Ghosal, Sayani, and Amita Jain. "Depression and suicide risk detection on social media using fastText embedding and XGBoost classifier." Procedia Computer Science 218 (2023): 1631-1639.

[5]Chatterjee, Moumita, Piyush Kumar, Poulomi Samanta, and Dhrubasish Sarkar. "Suicide ideation detection from online social media: A multi-modal feature based technique." International Journal of Information Management Data Insights 2, no. 2 (2022): 100103.

[6]Grimland, M., Benatov, J., Yeshayahu, H., Izmaylov, D., Segal, A., Gal, K., & Levi-Belz, Y. (2024). Predicting suicide risk in real-time crisis hotline chats integrating machine learning with psychological factors: Exploring the black box. Suicide and Life-Threatening Behavior, 00, 1–9. https://doi.org/10.1111/sltb.13056

[7]Bello, Hugo J., Nora Palomar-Ciria, Enrique Baca-García, and Celia Lozano. "Suicide classification for news media using convolutional neural networks." Health communication 38, no. 10 (2023): 2178-2187.

[8]Aldhyani, Theyazn HH, Saleh Nagi Alsubari, Ali Saleh Alshebami, Hasan Alkahtani, and Zeyad AT Ahmed. "Detecting and analyzing suicidal ideation on social media using deep learning and machine learning models." International journal of environmental research and public health 19, no. 19 (2022): 12635.

[9] Haque R, Islam N, Islam M, Ahsan MM. A Comparative Analysis on Suicidal Ideation Detection Using NLP, Machine, and Deep Learning. Technologies (Basel). 2022 Jun 1;10(3).

[10] Rozova V, Witt K, Robinson J, Li Y, Verspoor K. Detection of self-harm and suicidal ideation in emergency department triage notes. Journal of the American Medical Informatics Association. 2022 Mar 1;29(3):472–80.

[11] Gliatto, M.F.; Rai, A.K. Evaluation and Treatment of Patients with Suicidal Ideation. Am. Fam. Physician 1999, 59, 1500–1506.

[12] Turecki, G., & Brent, D. A. (2016). Suicide and suicidal behaviour. The Lancet, 387(10024), 1227–1239. https://doi.org/10.1016/S0140-6736(15)00234-2

[13] Goldsmith, S. K., Pellmar, T. C., Kleinman, A. M., & Bunney, W. E. (2002). Reducing suicide: A national imperative. Washington, DC: The National Academies Press.

[14] Whitlock, J., & Knox, K. L. (2007). The relationship between self-injurious behavior and suicide in a young adult population. Archives of Pediatrics and Adolescent Medicine, 161(7), 634–640. doi:10.1001/archpedi.161.7.634

[15] Bailey, R. K., Patel, T. C., Avenido, J., Patel, M., Jaleel, M., Barker, N. C., … Jabeen, S. (2011). Suicide: Current trends. Journal of the National Medical Association, 103(7), 614–617. doi:10.1016/S0027-9684(15)30388-6

[16] Baddeley, J., Daniel, G., & Pennebaker, J. (2011). How Henry Hellyer’s use of language foretold his suicide. Crisis, 32(5), 288–292. doi:10.1027/0227-5910/a000092

[17]Fernandez-Cabana, M., Caballero, A. G., Perez, M. T., Garcıa-Garcıa, M., & Mateos, R. (2013). Suicidal traits in Marilyn Monroe’s fragments an LIWC analysis. Crisis, 34(2), 124–127. doi:10.1027/0227-5910/a000183

[18]Fernandez-Cabana, M., Jimenez-Feliz, J., Perez, M. T., Mateos, R., Gomez-Reino, I., & Caballero, A. G. (2015). Linguistic analysis of suicide notes in Spain. The European Journal of Psychiatry, 29(2), 145–155. doi:10.4321/S0213-61632015000200006

[19] Parekh, A., & Phillips, M. (2014). Preventing suicide: A global imperative. Geneva: WHO.

[20] Zuniga, H., de Molyneux, L. G., & Zheng, P. (2014). Social media, political expression, and political participation: Panel analysis of lagged and concurrent relationships. Journal ofCommunication, 64(4), 612–634. doi:10.1111/jcom.12103

[21]Jashinsky, J., Burton, S., Hanson, C., West, J., Giraud-Carrier, C., Barnes, M., & Argyle, T. (2014). Tracking suicide risk factors through Twitter in the US. Crisis, 35(1), 51–59. doi:10. 1027/0227-5910/a000234

[22] Wongkoblap, M. A. Vadillo, & Curcin, V. (2017). Researching mental health disorders in the era of social media: systematic review. Journal of medical Internet research, 19(6), e228. 10.2196/jmir.7215.

[23] Benton, M. Mitchell, & Hovy, D. (2017). Multi-task learning for mental health using social media text. arXiv. 10.48550/arxiv.1712.03538.

[24]Nadeem, M. (2016). Identifying depression on twitter. arXiv. 10.48550/arxiv.1607.07384.

[25]Paul, S., Jandhyala, S. K., & Basu, T. (2018). Early detection of signs of anorexia and depression over social media using effective machine learning frameworks. In Proc. CLEF (pp. 1–9).

[26]Coppersmith, G., Dredze, M., Harman, C., & Hollingshead, K. (2015). From ADHD to SAD: Analyzing the language of mental health on twitter through self-reported diagnoses. In Proc. 2nd Workshop Comput. Linguistics Clin. Psychol. Linguistic Signal Clin. Reality (pp. 1–10). 10.3115/v1/W15-1201.

[27]Maupomés, D., & Meurs, M. (Sep. 2018). Using topic extraction on social media content for the early detection of depression. In Proc. CLEF (Working Notes), v2125 [Online]. Available https://CEUR-WS.org .

[28]Resnik, P., Armstrong, W., Claudino, L., Nguyen, T., Nguyen, V.-A., Boyd-Graber, J., & Beyond, LDA (2015). Exploring supervised topic modeling for depression-related language in twitter. In Proc. 2nd Workshop Com- put. Linguistics Clin. Psychol. Linguistic Signal Clin. Reality (pp. 99–107). 10.3115/v1/W15-1212.

[29] Schwartz, H. A., et al., (2014). Towards assessing changes in degree of depression through facebook. In Proc. Workshop Comput. Linguistics Clin. Psychol. Linguistic Signal Clin. Reality (pp. 118–125). 10.3115/v1/W14-3214.

[30] Tsugawa, S., Kikuchi, Y., Kishino, F., Nakajima, K., Itoh, Y., & Ohsaki, H. (Apr. 2015). Recognizing depression from twitter activity. In Proc. 33rd Annu. ACM Conf. Hum. Factors Comput. Syst. (pp. 3187–3196). 10.1145/2702123.2702280

[31] Wolohan, J., Hiraga, M., Mukherjee, A., Sayyed, Z. A., & Millard, M. (2018). Detecting linguistic traces of depression in topic-restricted text: Attending to self-stigmatized depression with nlp. In Proc. 1st Int. Workshop Lang. Cognition Comput. Models (pp. 11–21). https://aclanthology.org/W18-4102

[32] Tadesse, M. M., Lin, H., Xu, B., & Yang, L. (2019). Detection of depression-related posts in reddit social media forum. IEEE Access, v7, 44883–44893. 10.1109/ACCESS.2019.2909180.

[33] Song, H., You, J., & Park, Jin-Woo Chung Jong C. (2018). Feature attention network: Interpretable depression detection from social media. 32nd Pacific Asia conference on language, information and computation Hong Kong, 1-3 December 2018. Association for Computational Linguistics https://aclanthology.org/Y18-1070

[34] Cacheda, F., Fernandez, D., Novoa, F. J, & Carneiro, V. (2019). Early detection of depression: social network analysis and random forest techniques. Journal of Medical Internet Research, v21(6), e12554. 10.2196/12554.

[35] Levi-Belz, Y., Gvion, Y., Horesh, N., Fischel, T., Treves, I., Or, E., SteinReisner, O., Weiser, M., David, H. S., & Apter, A. (2014). Mental pain, communication difficulties, and medically serious suicide attempts: A case-control study. Archives of Suicide Research, 18(1), 74–87. <https://doi.org/10.1080/13811118.2013.809041>

[36] Salganik, M. J., Lundberg, I., Kindel, A. T., Ahearn, C. E., Al-Ghoneim, K., Almaatouq, A., Altschul, D. M., Brand, J. E., Carnegie, N. B., Compton, R. J., Datta, D., Davidson, T., Filippova, A., Gilroy, C., Goode, B. J., Jahani, E., Kashyap, R., Kirchner, A., McKay, S., … McLanahan, S. (2020). Measuring the predictability of life outcomes with a scientific mass collaboration. Proceedings of the National Academy of Sciences, 117(15), 8398–8403.

[37] Lumontod, R.Z., III. Seeing the invisible: Extracting signs of depression and suicidal ideation from college students’ writing using LIWC a computerized text analysis. Int. J. Res. Stud. Educ. 2020, 9, 31–44

[38] Masuda, N.; Kurahashi, I.; Onari, H. Suicide Ideation of Individuals in Online Social Networks. PLoS ONE 2013, 8, e62262.

[39] Pestian, J.; Nasrallah, H.; Matykiewicz, P.; Bennett, A.; Leenaars, A. Suicide Note Classification Using Natural LanguageProcessing: A Content Analysis. Biomed. Inform. Insights 2010, 3, BII.S4706.

[40] Instagram dataset , “ <https://github.com/sfdk74/EAS> “, accessed on February 2024.

[41] Ravdess Audio dataset, <https://www.kaggle.com/datasets/uwrfkaggler/ravdess-emotional-speech-audio>, accessed on February 2024.

[42] Renjith, Shini, Annie Abraham, Surya B. Jyothi, Lekshmi Chandran, and Jincy Thomson. "An ensemble deep learning technique for detecting suicidal ideation from posts in social media platforms." Journal of King Saud University-Computer and Information Sciences 34, no. 10 (2022): 9564-9575.

[43] Tadesse MM, Lin H, Xu B, Yang L. Detection of Suicide Ideation in Social Media Forums Using Deep Learning. Algorithms. 2020; 13(1):7. <https://doi.org/10.3390/a13010007>

[44] Chadha, Akshma, and Baijnath Kaushik. "A hybrid deep learning model using grid search and cross-validation for effective classification and prediction of suicidal ideation from social network data." New Generation Computing 40, no. 4 (2022): 889-914.

[45] Kipkebut, Andrew. (2023). DEEP LEARNING SUICIDE IDEATION DETECTION MODEL. Proceedings of the IRE.

[46] Punithavathi, R., S. Thenmozhi, R. Jothilakshmi, V. Ellappan, and Islam Md Tahzib Ul. "Suicide Ideation Detection of Covid Patients Using Machine Learning Algorithm." Computer Systems Science & Engineering 45, no. 1 (2023).

[47] Weng, Jun-Cheng, Tung-Yeh Lin, Yuan-Hsiung Tsai, Man Teng Cheok, Yi-Peng Eve Chang, and Vincent Chin-Hung Chen. "An autoencoder and machine learning model to predict suicidal ideation with brain structural imaging." Journal of clinical medicine 9, no. 3 (2020): 658.

[48] Ji, Shaoxiong, Xue Li, Zi Huang, and Erik Cambria. "Suicidal ideation and mental disorder detection with attentive relation networks." Neural Computing and Applications 34, no. 13 (2022): 10309-10319.