Non-Verbal Bio-Markers for Automatic Depression Analysis

Abstract—**Automatic depression risk analysis has not received significant focus in prior studies. This paper aims to propose an automatic depression risk analysis approach on non-verbal biomarkers. This approach focused on facial expression and emotion, socially shared thoughts, mobile utilization, and biometrics. Machine learning, Deep learning, and Natural Language Processing (NLP) techniques have been applied in depression analysis. We have observed that Facial and emotional features perform better in identifying depression risk compared to the head pose and emotional features, the study showed that linguistic-based depression risk analysis functioned well for Sinhala with 95% accuracy. Biometrics analysis, mobile utilization analysis outperformed with K – Nearest Neighbors (KNN).**

Keywords— Depression Analysis, Facial Expression, Sentiment Analysis, Biometric Analysis, Phone Usage Aanalysis

I. INTRODUCTION

Mental well-being is essential for the balance and growth of life. However, depression is one of the major psychological disorders involved in declining mental health. Statistics from the World Health Organization (WHO) shows that more than 300 million of the global population suffers from a depressive disorder, and estimated that by 2030, it might be the most common mental health disorder [1]. According to a study conducted in Sri Lanka, the lifetime prevalence of depression is up to 16% [2].

Individuals are considered depressive when they experience negative thoughts and feeling for a prolonged duration, less motivation, aversion to activity, and experiencing suicidal thoughts. In the most critical cases, individuals with depression have a high risk of committing suicide. Hence early identification of the risk of having depression would help in reducing the suicidal rate and providing timely psychiatric and psychological intervention.

However, depression diagnoses are challenging due to access limitations such as expenses and social stigma. In low- and middle-income countries, 76% to 85 % of victims go untreated [3]. Moreover, the current clinical standards for assessing depression severity are subjective to professional psychologists [4] and must depend on clinical experience and professional knowledge. Hence, an objective evaluation must explore to analyze the risk of having depression through clinical interviews and verbal reports. Considering the challenges of assessing depression, an assessment of depression based on non-verbal biomarkers has attracted prominent attention in the computer vision and machine learning community.

In recent years studies have been conducted to identify depression with different aspects. Several deep learning models have been proposed for depression analysis on spatial-temporal facial features [5], Facial expressions [4], face landmarks [6], and head pose [7], [8].

Similarly, information on social networks has been considered in several studies [3], [9-12]. Most of the studies focused on English-based linguistics [9], while few researchers considered Bangla [10], Chinese [3], Thai [11], and Arabic [12] languages. Furthermore, studies have been conducted to identify depression with the mobile utilization of individuals [13-15], determine the correlation with social media usage, internet usage, and depression among younger generations [16], [17].

Moreover, studies have been focused on machine-learning algorithms to screen depression using wearable devices [18 - 20] and identify physical, biometric changes toward depression [21], [22].

However, to the best of our knowledge, none of the studies have focused on machine-learning-based depression screening and severity assessing considering the aspects of visual cues, linguistic, biometrics, and mobile utilization.

In this paper, we focus on how to address the above limitations and come up with non-verbal biomarkers for assessing the risk of depression, which cover areas that have not been researched in parallel. The aspects that cover,

1. Early depression risk analysis on Facial and emotional features (EDRAE).
2. Early depression risk analysis on Head posture and emotional features (EDRAH).

3. Early depression risk analysis on social network content. (EDRASN).
4. Early depression risk analysis on Mobile Phone Usage. (EDRAP).
5. Early depression risk analysis on Heart Rate (EDRAHR).
6. Early depression risk analysis on sleep pattern (EDRASP)

II. METHODOLOGY

The procedures we used to implement the model for predicting early identification of the risk of having depression in individuals are explained in this section. The steps followed in this approach include data labeling, preprocessing, feature extraction, and depression risk classification. Fig 1 illustrates the proposed system.

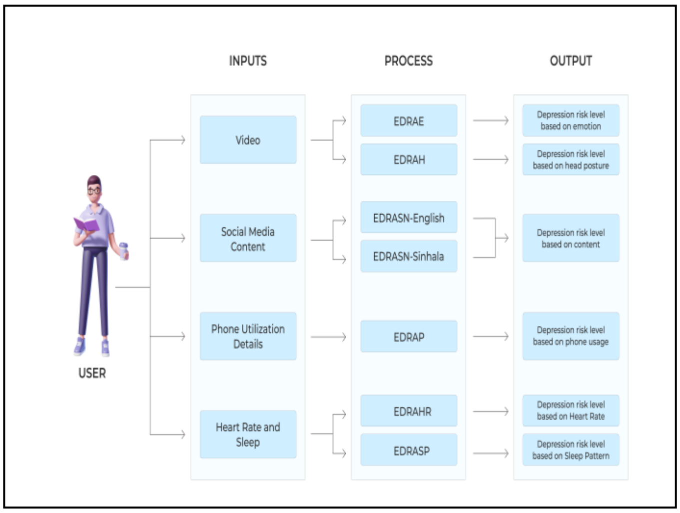

Fig. 1. Overall System Architecture.

A. Data Collection

The required data were collected from mental health specified YouTube channels for the visual cues-based depression risk analysis. Three YouTube channels related to the mental health domain were referred for the videos of Psychiatric Interviews with Depressed individuals. "Make the Connection" YouTube channel was chosen to collect a non-depressed dataset, which included the videos about True Depression Recovery Stories of U.S. Army Officers. Altogether, 18 videos were collected to create both depressed and non-depressed datasets. The video length of all the videos exceeds 1min, and the maximum duration is about 38 mins. The videos were approved and classified into depressive and non-depressive categories by an experienced psychologist. In this research, 1322 frames from depressed individuals and 1747 frames from non-depressed individuals were chosen and analyzed.

Moreover, we collected the required data for the content-based depression risk analysis from Kazakhstan research [23]. It collected Depressive Posts from public accounts of VKontakte's social network in the Commonwealth of Independent States countries. As explained in [23], the dataset consists of 32 018 depressive posts and 32 021 non-depressive posts classified by psychologists. Further, we collected a dataset for conversation content from the DAIC-WOZ database. The database includes recorded interviews conducted by an animated virtual interviewer called Ellie, controlled by a human interviewer in another room [24]. The database consists of 189 sessions of recorded interviews ranging between 7-33min. Each session includes the transcript of the interview.

The heart rate data was collected from the research, Health assessment of French university students, and risk factors associated with mental health disorders [25]. We have obtained 483 depressive individuals' data. Sleep pattern data have been collected from research by Stockholm University, the University of Sao Paulo, and the University of Surrey [26]. The dataset is a combination of data about light exposure and sleep pattern data, therefore, we have to conduct a relevant machine learning procedure to select only sleep parameters. The procedure is explained in section II-B. With the results. We have obtained 71 depressive individuals' sleep data.

Moreover, required data for Early Depression Risk Analysis on Phone Usage (EDRAP) was collected through a questionnaire according to psychological standards with a combination of phone usage habits and PHQ-9 questions[27]. We were able to collect 350 individuals' data within the Age Range of 16 – 30. To label the data we have used PHQ-9 scores and Proposed Treatment Actions. After data labeling, we have observed 100/350 shows risk towards early depression. All the above procedures have been conducted under the guidance of an experienced Clinical Psychologist.

B. Feature Extraction & Preprocessing

A model for the emotion-based depression risk analysis classifier was required to extract facial features and emotions. We used Affectiva JavaScript API to obtain facial features and emotions. Affectiva is one of the leaders in emotion recognition technology [28]. And to model the head pose-based depression analysis, pre-defined model RealHePoNet was used for Head Pose Estimation. It estimates vertical and horizontal angles. The RealHePoNet model itself has the best accuracy [29]. Similarly, as the initial step to model both English content-based and Sinhala content-based classifiers, The Russian dataset was required to translate to English and Sinhala. To translate Russian to English, we have used a pre-defined model, MarianMT Transformers, and Google Translator for Russian to Sinhala.

All the selected datasets were gone through preprocessing stage prior to feature extraction and model training. In this stage, we have conducted the necessary preprocessing steps. Which are add necessary headings, remove rows with missing values, encoding, data labeling, and data categorizing. Moreover, prior to the Early Depression Risk Analysis on Social Network (EDRASN) model training, the pre-trained Glove word vector was employed for word embedding in English [30]. Similarly, the Sinhalese Vector Model was used for word embedding on Sinhala [31].

C. Model Implementation

In the Early Depression Risk Analysis on Emotion (EDRAE) model, we used a sequential model consisted of several dense layers. The first dense layer consisted of an input dimension of 33 neurons since we had 33 embedded features. The initial dense layer output was the dimension of 100 neurons. The input layer was followed by three fully connected dense layers and the output layer. Similarly, the Early Depression Risk Analysis on Head pose (EDRAH) implemented as a sequential model consisted of four dense layers. The first dense layer consisted of an input dimension of 11 neurons and the output dimension of 100 neurons. The layer was followed by two fully connected dense layers and the output layer. Moreover, LeakyReLU activation was employed after every Dense Layer. The last dense layer used sigmoid as the activation function to compute the probability distribution over the defined classes. The models used Adam Optimizer. Note that the input of the model is a video.

The model of EDRASN used the pre-trained model, fastText, for both English and Sinhala-based depression risk analysis. fastText is a Library for word Embeddings and Text Classification [32]. It can achieve high accuracy on the least resources.

The hyperparameters were tuned to ensure compatibility with the Glove word embedding vectors. The EDRASN model consists of three layers: embedding layer, linear layer, and average pooling 2D layer. The embedding layer calculates the word embedding for each word and the liner layer computes the average for all embeddings. The output of the linear layer feed to average pooling 2D layer for classification. The model used sigmoid as the activation function to compute the probability distribution over the classes. The motive of using the sigmoid activation function is that the analysis is a binary classification problem. The models used Adam Optimizer. Note that the input of the model is text.

The biometric data analysis consists of Early Depression Risk Analysis on Heart Rate (EDRAHR) and Early Depression Risk Analysis on Sleep Patterns. (EDRASP), both have been conducted with two supervised learning classification algorithms. EDRAHR models can be explained like this. For the KNN algorithm first, we have identified the best possible K value for the model train, which is marked as 5. Using the best K model has been trained. The Support Vector Machine (SVM) algorithm for EDRAHR conducts with kernel poly, degree 1. Moreover, the EDRASP consists of KNN and SVM models. For the KNN model, we have obtained the finest K and trained the model with it, which is k = 5. The SVM model trained with the poly kernel, degree 1. Note that the inputs of the above models are the heart rate, sleep patterns.

The EDRAP consists of three supervised learning classification algorithms to determine an accurate model. For the KNN model first, we have identified the best k which is 14 after that we have trained the model with KNeighborsClassifier to k = 14. SVM model train for the same dataset has been performed with kernel poly for degree 2. Lastly, we have trained a random forest model with RandomForestClassifier, the number of estimators is 20 and random_state is 0. Note that the inputs of the above models are phone usage parameters.

III. RESULTS AND DISCUSSION

The following section outlines the results and performance of each model in predicting early identification of the risk of having depression in individuals.

A. *Visual Cues based Depression Risk Analysis*

Although we have trained the machine learning algorithms, random forest, and SVM upon highly correlated parameters, we could achieve 70%-75% test accuracy for emotion and head pose analysis. Hence, we considered machine learning algorithms for our baseline model and carried a deep learning approach as explained in section II-C. The sequential model for EDRAE achieved 81% test accuracy with an 81.54 AUC value. Further, EDRAH achieved 77% test accuracy with a 76.79 AUC value using the sequential model. According to the analysis, we can see that the proposed deep learning architectures outperformed the standard machine learning algorithm. Note that the dataset split for all the models was the ratio of 50 training, 20 validation, and 30 test sets. Fig 2 and Fig 3 illustrate the ROC curve of the EDRAE model and Confusion matrix of the EDRAH model, respectively.

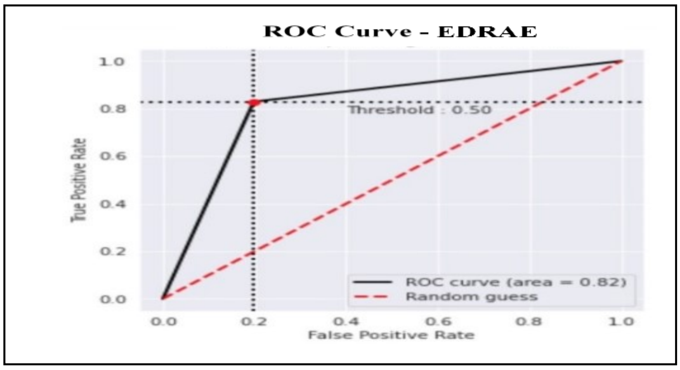

Fig. 2. ROC Curve of the EDRAE.

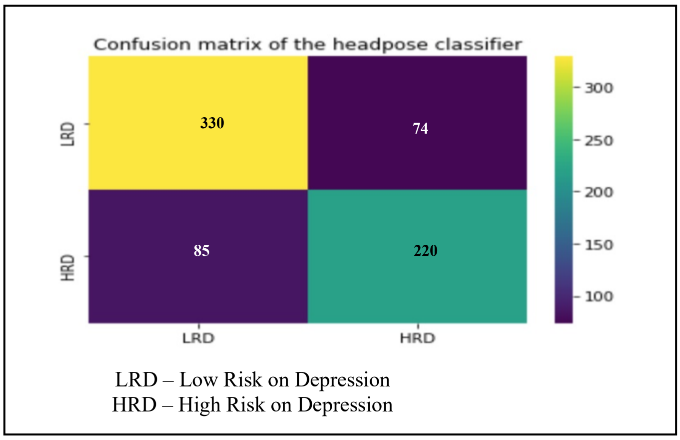

Fig. 3. Confusion Matrix of the EDRAH.

B. *Linguistic based Depression Risk Analysis*

The standard machine learning algorithm SVM could achieve 80%-85% test accuracy for text classification in English and Sinhala. Hence, we considered machine learning algorithms for our baseline model and carried a deep learning approach as explained in section II-C.

The fastText model of EDRASN achieved 95% accuracy for content in Sinhala and 96% accuracy obtained with English content. According to the analysis, we can see that the proposed deep learning architectures outperformed the standard machine learning algorithm. Note that the dataset split for all the models was the ratio of 60 training, 20 validations, and 20 test sets. Fig 4 and Fig 5 indicate the ROC curve of the EDRASN model for Sinhala and English content, respectively.

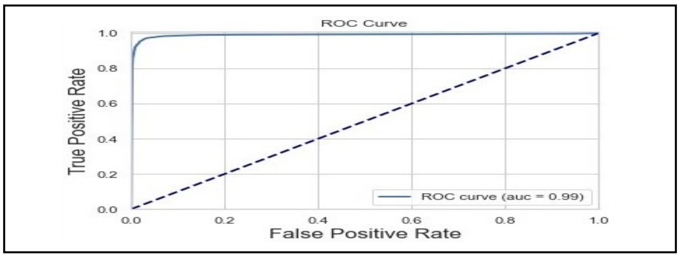

Fig. 4. ROC Curve of the EDRASN (Sinhala).

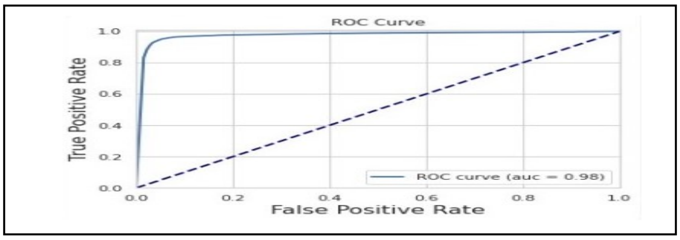

Fig. 5. ROC Curve of the EDRASN (English).

C. *Biometrics based Depression Risk Analysis*

The EDRAHR was conducted with two algorithms as mentioned in Section II-C. The KNN algorithm trainset achieved 89% of maximum accuracy, while minimum k was marked as k = 5 with a misclassification rate of 10%. For the test data model obtain AUC of 84% sensitivity of 5% and Specificity of 94%. Meanwhile, The Support Vector Machine (SVM) algorithm attains 86% of accuracy with kernel poly at degree = 1. According to the Classification report observations, the SVM achieved much more accuracy than the KNN but the sensitivity of the SVM is low. Therefore, the KNN model is recommended model for EDRAHR.

The KNN for the EDRASP AUC is 95%, the model's sensitivity is marked as 60% and Specificity is 99%. KNN obtained 95% of accuracy for the test dataset while train dataset accuracy was marked as 96% at k = 5 with a misclassification rate of 3.7%. when we look at the SVM for the same sleep pattern dataset, the model achieved 95% of test accuracy with a 5% of misclassification rate, AUC of 85% as well as the model sensitivity and Specificity is 65% and 100%. As the observations, both models scale in the same matter but KNN has slightly better performance than the SVM model. Note that the dataset split for all the models was the ratio of 80 training and 20 test sets. The following Fig 6 and Fig 7 exhibit the ROC curves of KNN and SVM models.

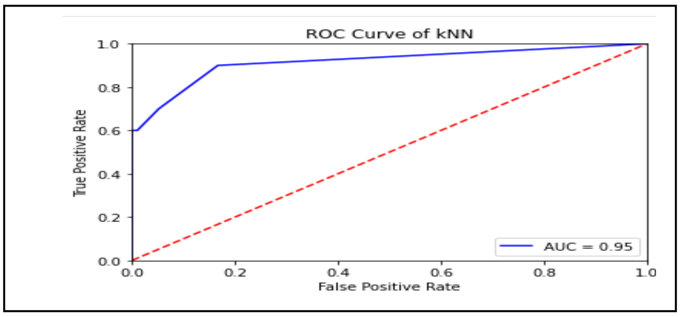

Fig. 6. ROC Curve of the EDRASP (KNN).

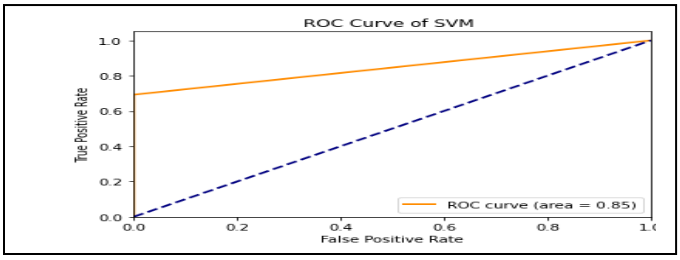

Fig. 7. ROC Curve of the EDRASP (SVM).

D. *Mobile Utilization based Depression Risk Analysis*

KNN algorithm achieved 81% of test accuracy while the train set maximum accuracy is marked as 82% at k = 14. Model's AUC is 81% sensitivity is 31% and Specificity is 87%, as well as the model, showed a 17% of misclassification rate. The random forest model has obtained 62% overall accuracy meanwhile sensitivity and Specificity are marked as 37% and 73% with a misclassification rate of 38%. We have observed even the SVM obtained 72% test accuracy, 63% of AUC, and 27% of misclassification rate but the model has failed to achieve a good sensitivity rate. When we conclude overall results KNN is the best model to use for further prediction works. Note that the dataset split for all the models was the ratio of 80 training and 20 test sets. The following Fig 8 indicates the ROC curve of the KNN model.

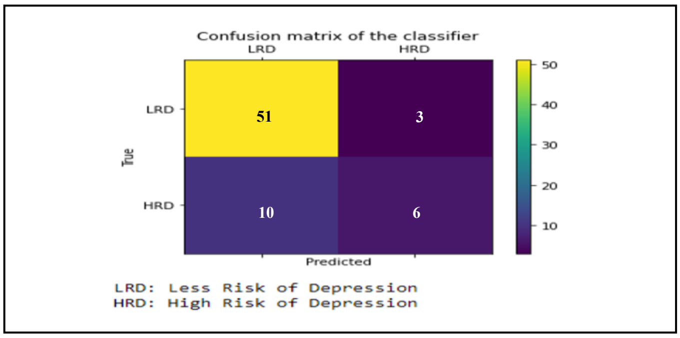

Fig. 8. Confusion Matrix of the EDRAP (KNN).

E. *Performance Evaluation*

Note that the test image for EDRAE model and EDRAH model (Fig 9) is blurred for privacy concerns.

Fig. 9. Test Image for EDRAE and EDRAH models.

EDRAE (Fig 10) predicts the depression risk based on emotion. Further, EDRAH (Fig 11) analyzes the depression risk based on the tilt and pan values [29]. Note that the "risk prob" column indicates the risk level of depression.

	joy	sadness	disgust	contempt	anger	fear	surprise	dep	risk prob (%)
0	99.930618	9.203016e-07	0.000297	0.000107	0.000069	0.000024	0.207015	0	0.008255

Fig. 10. Performance Evaluation of EDRAE.

	tilt	pan	headpose_dep	risk prob (%)
0	-5.359996	-1.864105	0	0.012613

Fig. 11. Performance Evaluation of EDRAH.

According to the performance evaluation of EDRAE (Fig 10), the person (Fig 9) is having no risk of depression (0%). However, the performance evaluation of EDRAH indicate the person is having low risk of depression (1%). It explains that facial and emotional features can learn and identify depression risk compared to the head pose and emotional features.

In this section Table 1 indicates performance evaluation of the models, Table II compares the classification results, and Table III summarizes the model performance.

TABLE I. PERFORMANCE EVALUATION

Model	Input	Score	Output
EDRASN – English	I'm writing this for the first time, and I'll be glad if anyone can help me or at least just talk.	1.0	HRD
	A visiting medical team from CSTO will arrive in the village of Pena Kurchatovsky district on Friday, 12 April.	0.0	LRD
	I don't want to live when this life is over. I'm almost 28 years old, and I don't know why it's happening to me. Why isn't it? Why am I so unhappy	1.0	HRD
EDRASN – Sinhala	මට සියදිවි නසා ගැනීමට අවශ්‍යයි	1.0	HRD
	අගමැතිතුමාගෙ උපදෙස් පරිදි වැඩි වූ තෙල් මිල අඩු කරන ලදී කොටස කවදද පෙන්වන්නෙ?	0.0	LRD
EDRASP	Total Sleep: 9.5 Deep Sleep: 74 REM Sleep: 121 Light Sleep: 287	1	HRD
	Total Sleep: 9.5 Deep Sleep: 75 REM Sleep: 158 Light Sleep: 312	0	LRD
EDRAP	No Social Media Apps: 9 Social Media App usage:6 Gaming App Usage: 7 Night Usage: 12	1	HRD
	No Social Media Apps: 5 Social Media App usage:4 Gaming App Usage: 3 Night Usage: 3	0	LRD

HRD: High-Risk of Depression
LRD: Low-Risk 0f Depression

TABLE II. COMPARISON OF CLASSIFICATION RESULTS

	MODEL	ALGORITHM	ACCURACY
***(A)**Visual cues*	EDRAE	SVM	73%
		Random Forest	70%
		Sequential [33]	**81%**
	EDRAH	SVM	74%
		Random Forest	73%
		Sequential [33]	**77%**
***(B)**Linguistic*	EDRASN – English	SVM	86%
		FastText [32]	**96%**
	EDRASN – Sinhala	SVM	83%
		FastText [32]	**95%**
***(C)**Biometrics*	EDRAHR	**KNN**	**84%**
		SVM	87%
	EDRASP	**KNN**	**95%**
		SVM	94%
***(D)**Mobile utilization*	EDRAP	**KNN**	**81%**
		SVM	72%
		Random Forest	62%

TABLE III. MODEL PERFORMANCE SUMMARY

	PRECISION	RECALL	F1-SCORE
EDRAE	0.82	0.81	0.81
EDRAH	0.77	0.77	0.77
EDRASN - English	0.95	0.95	0.95
EDRASN - Sinhala	1.00	1.00	1.00
EDRAHR - KNN	0.80	0.84	0.82
EDRAHR - SVM	0.76	0.87	0.82
EDRASP - KNN	0.95	0.95	0.95
EDRASP - SVM	0.96	0.96	0.96
EDRAP - KNN	0.72	0.74	0.73
EDRAP - SVM	0.52	0.72	0.61
EDRAP - Random Forest	0.64	0.63	0.63

IV. CONCLUSION

The aim of this paper is to propose an automatic depression risk analysis approach on non-verbal biomarkers. This approach focused on facial and emotional features, head posture, linguistic, mobile utilization, and biometrics in identifying the depression risk. We have shown that Facial and emotional features can learn and identify depression risk compared to the head pose and emotional features. Moreover, the study shows that depression risk analysis based on linguistic performed well with 95% accuracy for Sinhala. Identifying the depression risk based on Biometrics, the sleep pattern analysis obtain 95% accuracy with the KNN Finally, the mobile utilization analysis with the KNN model achieved 81% accuracy towards the Depression Risk analysis. The above Analysis models can be extended to perform as a single model and observe preferable accuracy on early depression risk analysis. Moreover, we can connect the models to mobile applications and provide depression risk analysis according to all aspects. These further steps can be cooperative for better and accurate early depression risk analysis.

REFERENCES

[1] Q. Liu, H. He, J. Yang, X. Feng, F. Zhao and J. Lyu, “Changes in the global burden of depression from 1990 to 2017: Findings from the Global Burden of Disease study,” Journal of Psychiatric Research, vol. 126, pp. 134–140, Jul. 2020, doi: 10.1016/j.jpsychires.2019.08.002

[2] D. R. R. Abeyasinghe, S. Tennakoon and T. N. Rajapakse, “The development and validation of the Peradeniya Depression Scale (PDS)--a culturally relevant tool for screening of depression in Sri Lanka,” Journal of affective disorders, vol. 142, no. 1–3, pp. 143–149, 2012.

[3] Y. Wang, Z. Wang, C. Li, Y. Zhang and H. Wang, "A Multimodal Feature Fusion-Based Method for Individual Depression Detection on Sina Weibo," 2020 IEEE 39th International Performance Computing and Communications Conference (IPCCC), 2020, pp. 1-8, doi: 10.1109/IPCCC50635.2020.9391501.

[4] X. Li, W. Guo and H. Yang, “Depression severity prediction from facial expression based on the DRR_DepressionNet network,” in 2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2020, pp. 2757-2764, doi: 10.1109/BIBM49941.2020.9313597.

[5] M. Al Jazaery and G. Guo, "Video-Based Depression Level Analysis by Encoding Deep Spatiotemporal Features," in IEEE Transactions on Affective Computing, vol. 12, no. 1, pp. 262-268, 1 Jan.-March 2021, doi: 10.1109/TAFFC.2018.2870884.

[6] L. Yang, D. Jiang, W. Han and H. Sahli, "DCNN and DNN based multi-modal depression recognition," 2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII), 2017, pp. 484-489, doi: 10.1109/ACII.2017.8273643.

[7] J. Joshi, "An Automated Framework for Depression Analysis," 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, 2013, pp. 630-635, doi: 10.1109/ACII.2013.110.

[8] S. Alghowinem, R. Goecke, J. F. Cohn, M. Wagner, G. Parker and M. Breakspear, "Cross-cultural detection of depression from nonverbal behaviour," 2015 11th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG), 2015, pp. 1-8, doi: 10.1109/FG.2015.7163113.

[9] K. A. Govindasamy and N. Palanichamy, "Depression Detection Using Machine Learning Techniques on Twitter Data," 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), 2021, pp. 960-966, doi: 10.1109/ICICCS51141.2021.9432203.

[10] A. H. Uddin, D. Bapery and A. S. M. Arif, "Depression Analysis from Social Media Data in Bangla Language using Long Short Term Memory (LSTM) Recurrent Neural Network Technique," 2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2), 2019, pp. 1-4, doi: 10.1109/IC4ME247184.2019.9036528.

[11] K. Katchapakirin, K. Wongpatikaseree, P. Yomaboot and Y. Kaewpitakkun, "Facebook Social Media for Depression Detection in the Thai Community," 2018 15th International Joint Conference on Computer Science and Software Engineering (JCSSE), 2018, pp. 1-6, doi: 10.1109/JCSSE.2018.8457362.

[12] N. S. Alghamdi, H. A. Hosni Mahmoud, A. Abraham, S. A. Alanazi and L. García-Hernández, "Predicting Depression Symptoms in an Arabic Psychological Forum," in IEEE Access, vol. 8, pp. 57317-57334, 2020, doi: 10.1109/ACCESS.2020.2981834.

[13] K. Demirci, M. Akgönül and A. Akpinar, "Relationship of smartphone use severity with sleep quality, depression, and anxiety in university students," *Journal of Behavioral Addictions,* vol. 4, no. 2, pp. 85-92, 2015.

[14] A. Višnjić, V. Veličković, D. Sokolović, M. Stanković, K. Mijatović, M. Stojanović, Z. Milošević and O. Radulović, "Relationship between the Manner of Mobile Phone Use and Depression, Anxiety, and Stress in University Students," *International Journal of Environmental Research and Public Health,* vol. 15, no. 4, p. 697, 2015.

[15] S. Thomée, A. Härenstam and M. Hagberg, "Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults - a prospective cohort study," 2020.

[16] E. Hoare, K. Milton, C. Foster and S. Allender, "Depression, psychological distress and Internet use among community-based Australian adolescents: a cross-sectional study," *BMC Public Health,* vol. 17, no. 1, 2017.

[17] A. Chowdhry , "Research Links Heavy Facebook And Social Media Usage To Depression," 2017.

[18] Y. Tazawa, K.-c. Liang, M. Yoshimura, M. Kitazawa, Y. Kaise and A. Takamiya, "Evaluating depression with multimodal wristband-type wearable device: screening and assessing patient severity utilizing machine-learning," *Heliyon,* vol. 6, no. 2, 2020.

[19] I. Moshe, Y. Terhorst, K. O. Asare, L. B. Sander, D. Ferreira, H. Baumeister, C. M. David and L. Pulkki-Råback , "Predicting Symptoms of Depression," January 2021.

[20] R. Wang, W. Wang, A. daSilva, J. F. Huckins, W. M. Kelley, T. F. Heatherton and A. T. Campbell, "Tracking Depression Dynamics in College Students Using Mobile Phone and Wearable Sensing," Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, vol. 2, no. 1, pp. 1-26, 2018.

[21] M. M. Ohayon, "Epidemiology of insomnia: what we know and what we still need to learn," *Sleep Medicine Reviews,* vol. 6, no. 2, pp. 97-111, 2002.

[22] D. Kuang, "Depression recognition according to heart rate variability using Bayesian Networks," *Journal of Psychiatric Research,* vol. 95, pp. 282-287, 2017.

[23] S. Narynov, D. Mukhtarkhanuly, and B. Omarov, “Dataset of depressive posts in Russian language collected from social media,” Data Brief, vol. 29, no. 105195, p. 105195, 2020.

[24] J. Gratch et al., “The Distress Analysis Interview Corpus of human and computer interviews,” in Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC’14), 2014, pp. 3123–3128.

[25] Tran, Antoine, Laurie, Geghre, Nicolas, Darmon, David, Rampal and Marion, "Health assessment of French university students and risk factors associated with mental health disorders," vol. 12, no. 11, 2018.

[26] M. E. Cristina, V. S. S. D. J., M. C. Roberta, L. and A. , "Natural Light Exposure, Sleep and Depression among Day Workers and Shiftworkers at Arctic and Equatorial Latitudes," vol. 10, no. 4, p. e0122078, 2015.

[27] D. K. Kroenke, "PHQ-9 (Patient Health Questionnaire-9)," Mdcalc, [Online]. Available: https://www.mdcalc.com/phq-9-patient-health-questionnaire-9.

[28] L. Kulke, D. Feyerabend, and A. Schacht, “A comparison of the affectiva iMotions facial expression analysis software with EMG for identifying facial expressions of emotion,” Front. Psychol., vol. 11, p. 329, 2020.

[29] R. Berral-Soler, F. J. Madrid-Cuevas, R. Muñoz-Salinas, and M. J. Marín-Jiménez, “RealHePoNet: a robust single-stage ConvNet for head pose estimation in the wild,” Neural Comput. Appl., vol. 33, no. 13, pp. 7673–7689, 2021.

[30] J. Pennington, R. Socher, and C. Manning, “Glove: Global vectors for word representation,” in Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), 2014.

[31] E. Grave, P. Bojanowski, P. Gupta, A. Joulin, and T. Mikolov, “Learning word vectors for 157 languages,” arXiv [cs.CL], 2018.

[32] A. Joulin, E. Grave, P. Bojanowski, and T. Mikolov, “Bag of tricks for efficient text classification,” in Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, 2017.

[33] Keras Team, “The sequential model,” Keras.io. [Online]. Available: https://keras.io/guides/sequential_model/