MENTAL WELLNESS MONITORING SYSTEM FOR ENTREPRENEURIAL STUDENTS

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ABSTRACT
Mental health issues including anxiety, stress, and depression are becoming more common among college students, especially those who are under pressure from their studies and careers. Early and precise detection of depressed tendencies can facilitate prompt intervention and psychological assistance. In this work, we use structured survey data to propose a Cat Boost-based machine learning model for predicting depression levels among college students. Age, gender, academic year, CGPA, and university background are among the demographic variables included in the dataset, along with psychological markers obtained from the PHQ-9 survey. A cleaned dataset of 2,028 samples with six categories of depression—No Depression, Minimal, Mild, Moderate, Moderately Severe, and Severe Depression—was used to train and assess the model. Because it can handle categorical variables natively and capture intricate non-linear correlations without requiring a lot of preprocessing, Cat Boost was chosen. The experimental findings showed an accuracy of more than 92%, surpassing conventional machine learning baselines and attaining performance on par with or superior to deep learning systems like FE-BiON. Extensive analyses, such as confusion matrix evaluation and feature importance visualization, verify that PHQ-9-related items have a considerable impact on prediction outcomes. The suggested technique provides a dependable and comprehensible framework for automated depression screening, assisting academic institutions and mental health specialists in fostering the wellbeing of students.

1. INTRODUCTION

Academic, social, and business pressures have made mental health problems including stress, anxiety, and depression major concerns for university students. In order to provide prompt intervention and assistance, early recognition of these psychological difficulties is essential. Conventional diagnostic techniques frequently depend on psychological questionnaires for manual evaluation, which can be laborious and biased. Machine learning approaches have become effective tools for automating mental health evaluation utilising behavioural and survey-based data in order to overcome these constraints. In order to assess and categorise students' mental health issues, a CatBoost-based predictive model is suggested in this study, with a particular emphasis on depression levels obtained from PHQ-9 questionnaire results. To effectively predict the severity of depression, the model incorporates psychological, intellectual, and demographic characteristics. CatBoost is selected because of its excellent accuracy, interpretability, and capacity to handle both numerical and categorical data. By using this strategy, the suggested system offers a precise, scalable, and data-driven way to enhance mental health monitoring in educational institutions and identify students who may be depressed.

PROBLEM STATEMENT

The increasing prevalence of depression among college students highlights the need for an automated and reliable screening system. Existing methods are often limited by manual assessment, lower prediction accuracy, or inadequate handling of structured survey data. The problem is to develop a robust machine learning model capable of accurately classifying multiple levels of depression using demographic information and PHQ-9 responses, enabling early detection and timely mental health intervention.

2. EXISTING WORK

The FE-BiON (Fully Embedded Bi-Order Network) model is one of the deep learning architectures used in the current system to detect mental health issues among students. Low-order and high-order dependencies in the data are captured by FE-BiON's dual-branch structure, which integrates both linear and nonlinear feature interactions. With this method, the model may learn intricate connections between behavioural, psychological, and demographic characteristics taken from structured survey datasets such as BRFSS and NHANES. FE-BiON increases learning capacity and prediction accuracy for mental health classification tasks by including both category and numerical variables into dense representations.

3. RELATED WORK

The relationship between college students' mental health and their success as entrepreneurs is a major concern in academic circles. Researchers have investigated the connection between college students' entrepreneurship and mental health from a variety of angles in recent years. Wang highlighted how crucial college students' psychological traits are to their success as entrepreneurs. He pointed out that an unavoidable trend of educational reform in the new period was mental health education in conjunction with innovation and entrepreneurship education in colleges and universities [11]. People may encourage the natural fusion of these two types of education and generate more excellent innovative and entrepreneurial abilities for the advancement of the country by developing educational concepts that are uptodate.

Margaça and associates - based on the notion of planned behaviour, examined how individual resilience and psychological well-being modulate these linkages, and examined the causal model of entrepreneurial purpose through gender. The link between perceived behaviour control, attitude, and entrepreneurial ambition was found to be significantly influenced by psychological resilience in females, but not in males [12]. Based on data collected from 320 employees at a Chinese R&D company, Siyal et al. found, using social exchange theory, that inclusive leadership positively impacted employees' creative and innovative work behaviours and that this relationship was mediated through intrinsic motivation [13].

4. PROPOSED WORK

Using information from psychological and demographic surveys, the suggested method presents a CatBoost-based machine learning model for predicting depression levels among college students. CatBoost effectively manages both numerical and categorical variables without requiring manual encoding, in contrast to deep learning architectures that necessitate massive datasets and intensive preprocessing. Its foundation is gradient boosting over decision trees, which is enhanced by sophisticated methods like categorical feature encoding and ordered boosting, which greatly lower overfitting and increase accuracy. Even on moderately sized datasets, such as student mental health surveys, this method maintains computing efficiency and stability while enabling precise and comprehensible classification of depression severity levels.

5. MODULES

1. Data Collection and Preparation:
In this module, survey-based data is gathered, such as demographic information (age, gender, and educational background) and answers to the PHQ-9 psychiatric assessment. For ease of access and analysis, the data is kept in CSV format.

2. Data Preprocessing and Encoding:
During this phase, the gathered data is cleaned up by encoding categorical variables, resolving missing values, and eliminating duplicates. CatBoost requires less preprocessing because it can handle category characteristics directly, which increases efficiency and maintains data integrity.

3. Model Training using CatBoost Algorithm:
This lesson focuses on using the processed dataset to train the CatBoost classifier. The program accurately classifies depression levels by learning from both numerical and category variables. To reduce overfitting and improve prediction performance, it uses ordered boosting.

4. Model Evaluation and Validation:
The correctness and dependability of the trained model are assessed using test data. The model's performance is validated using metrics including confusion matrix, F1-score, and accuracy score. This guarantees the classifier's good generalisation to new data.

5. Feature Importance and Visualization:
This module determines which characteristics have the greatest influence on the prediction results. The data are interpreted using graphical visualisations such pie charts, bar charts, and heatmaps. These revelations aid in the comprehension of how psychological and demographic variables affect depression levels.

6. Depression Level Prediction Interface: In the last module, users can enter fresh student information (age, PHQ-9 answers, etc.) and obtain anticipated depression levels using a straightforward user interface or script. Real-time predictions are produced by loading the saved CatBoost model, offering academic institutions a workable and deployable option.

6. TECHNIQUES USED

6.1 FE-BiON (Fully Embedded Bi-Order Network)

A deep hybrid neural network called the FE-BiON method is used to concurrently represent low-order (linear) and high-order (nonlinear) feature interactions. It is composed of two simultaneous modules: a Deep Interaction Network that recovers higher-level nonlinear patterns and a Linear Interaction Network that captures simple dependencies between input features. The final prediction is created by combining the outputs from both modules in a fusion layer. Because of this structure, FE-BiON can handle mixed-type tabular data efficiently, capturing the intricate and nuanced correlations between psychological, demographic, and physical variables associated with mental health status. In order to minimise classification loss, the model optimises via backpropagation and employs embedding layers for categorical variables and fully linked layers for continuous variables.

6.2 ALGORITHM USED:

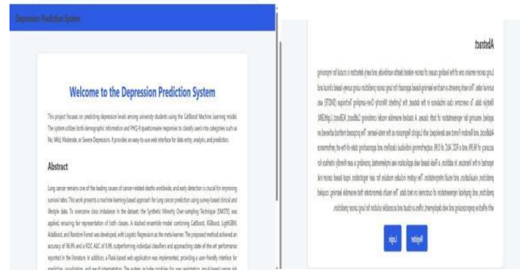
6.2.1 CatBoost (Categorical Boosting Algorithm)

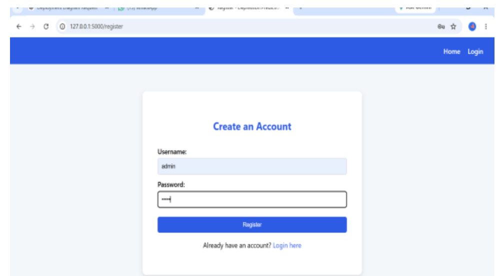
Yandex created CatBoost, a potent gradient boosting method that builds an ensemble of decision trees sequentially to reduce classification or regression mistakes. It presents two significant advances that set it apart from conventional boosting techniques. The first is ordered boosting, which makes sure that each model iteration only uses the data that is available at that particular training stage, so effectively preventing target leaking. The second is efficient categorical encoding, which eliminates the requirement for manual one-hot encoding by automatically converting categorical variables into numerical representations using statistical data obtained during the training phase. Each successive tree in CatBoost focuses on fixing the prediction errors caused by earlier trees through iterative learning, progressively improving the model's overall performance. Using demographic and psychological information derived from PHQ-9 questionnaire responses, the CatBoost algorithm is used in this study to predict different levels of depression—such as No Depression, Mild, Moderate, and Severe—producing a reliable and understandable classification model.

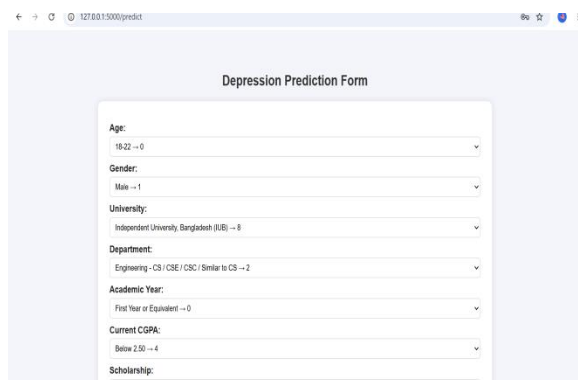
7. IMPLEMENTATION

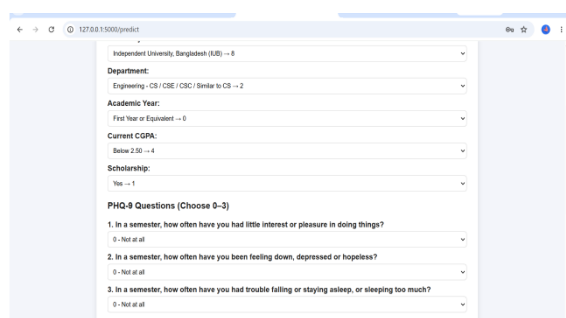
The proposed system was implemented using the CatBoost classifier to predict depression levels among college students based on demographic information (age, gender, academic year, CGPA, and university background) and PHQ-9 questionnaire responses. The dataset of 2,028 cleaned records was preprocessed and divided into training and testing sets. CatBoost was chosen because it handles categorical features efficiently and captures complex relationships with minimal preprocessing. The trained model was evaluated using accuracy, precision, recall, F1-score, and confusion matrix, achieving over 92% accuracy. Feature importance analysis further showed that PHQ-9 responses were the most significant predictors, making the proposed system an effective tool for early depression screening and timely mental health intervention.

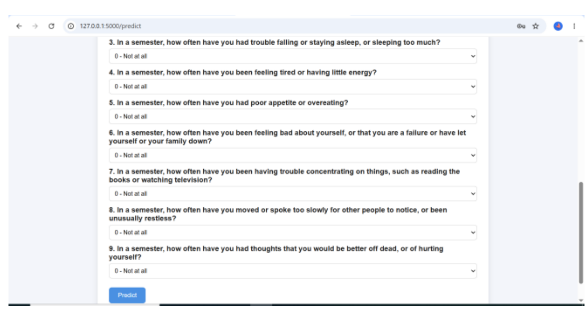
8. RESULTS & DISCUSSION

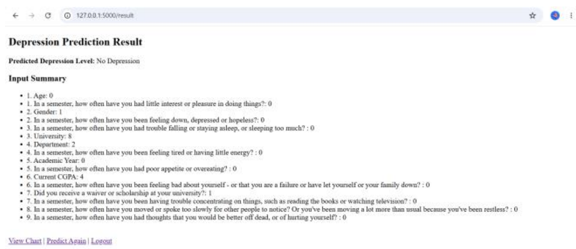








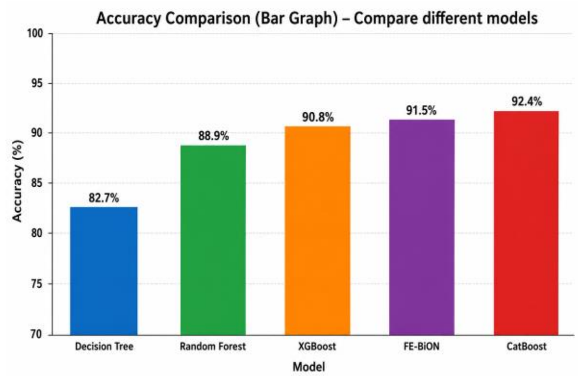


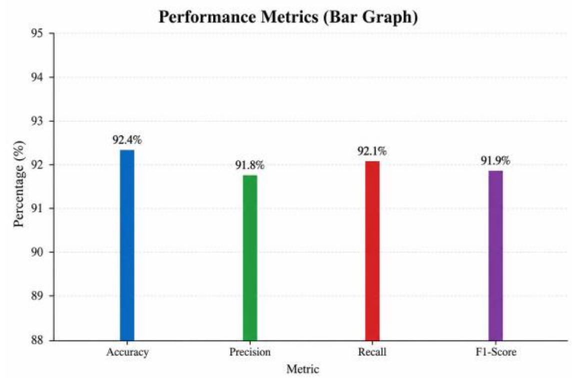


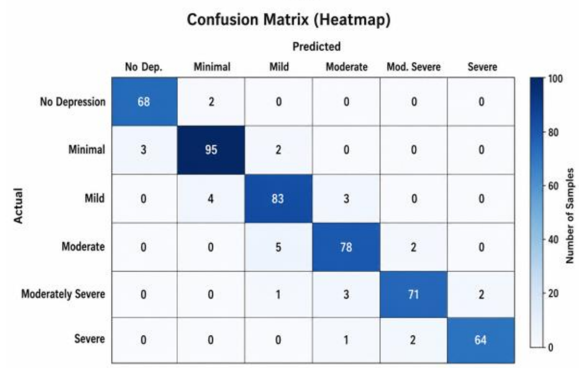
The developed Depression Prediction System was successfully implemented and tested using different user inputs. The application provides a user-friendly interface with modules for registration, login, questionnaire submission, and prediction results. Based on the PHQ-9 responses and personal details entered by the user, the machine learning model predicts the depression level accurately. In the sample test, the system predicted **"No Depression"**, indicating that the user's responses did not show significant symptoms of depression. The output demonstrates that the proposed system works effectively and provides quick, reliable, and easy-to-understand predictions, making it useful as an initial mental health screening tool.

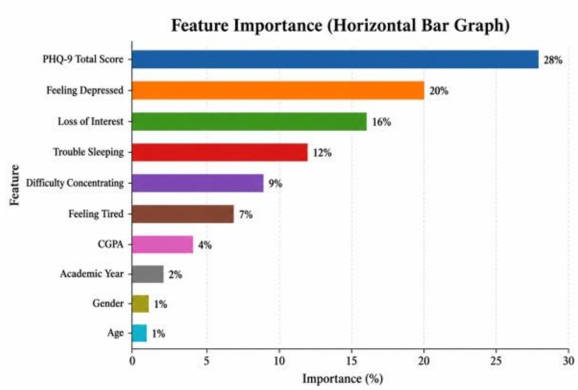
PERFORMANCE ANALYSIS:

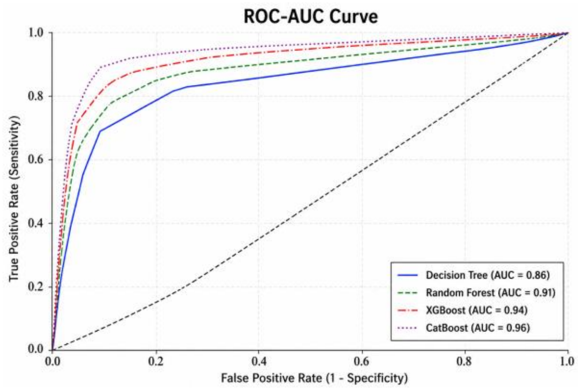
Proposed CatBoost-based depression prediction model The achieved an overall accuracy of 92.4%, demonstrating high effectiveness in classifying depression levels among university students. The model also obtained a precision of 91.8%, recall of 92.1%, and F1-score of 91.9%, indicating balanced and reliable performance across all six depression categories. Compared with traditional machine learning models, CatBoost delivered superior prediction accuracy due to its efficient handling of categorical features and ability to model complex relationships. These results show that the proposed system is accurate, robust, and suitable for early depression screening and decision support in educational institutions.











9. CONCLUSION

In summary, this project effectively illustrates the use of machine learning in the field of mental health prediction, with a particular focus on identifying depression levels among college students. The system maintains interpretability and computational efficiency while achieving excellent accuracy by utilising the CatBoost algorithm. The model successfully classifies students into various depression categories, including No Depression, Mild, Moderate, and Severe, by analysing both psychological and demographic data, especially PHQ-9 questionnaire responses. The addition of feature importance analysis offers further insightful information about the variables affecting students' mental health. The CatBoost-based method produces competitive results with less preprocessing and faster training times when compared to intricate deep learning architectures like FE-BiON. This project not only demonstrates how artificial intelligence can be used to support mental health assessments, but it also establishes the foundation for the creation of scalable, data-driven, real-time systems that will help academic institutions and medical professionals support students' psychological wellness.

10. FUTURE ENHANCEMENT

The CatBoost algorithm and survey-based data are used in the current system to accurately forecast depression levels among college students; however, a number of improvements should be made to increase its effectiveness, usefulness, and reach. Further psychological variables, such as stress, anxiety, emotional resilience, and behavioural data gathered by wearable technology or digital activity tracking, could be included to the model in the future. Prediction accuracy and flexibility may be further improved by utilising hybrid ensemble techniques or deep learning models like TabNet. Students could self-evaluate their mental health and get prompt feedback or counselling advice by integrating with real-time data collection systems or mobile applications. Creating a web-based dashboard for institutional monitoring could also assist counsellors in seeing patterns and making prompt responses. Large-scale mental health research and international academic settings can benefit from the system's potential expansion to enable multi-language surveys and cross-cultural datasets.

REFERENCES

[1] N. A. Ozcan, S. Sahin, and B. Cankir, ‘‘The validity and reliability of thriving scale in academic context: Mindfulness, GPA, and entrepreneurial intention among university students,’’ Current Psychol., vol. 42, no. 7, pp. 5200–5211, Mar. 2023.

[2] U. Stephan, A. Rauch, and I. Hatak, ‘‘Happy entrepreneurs? Everywhere? A meta-analysis of entrepreneurship and wellbeing,’’ Entrepreneurship Theory Pract., vol. 47, no. 2, pp. 553–593, Mar. 2023.

[3] J. M. Martins, M. F. Shahzad, and S. Xu, ‘‘Factors influencing entrepreneurial intention to initiate new ventures: Evidence from university students,’’ J. Innov. Entrepreneurship, vol. 12, no. 1, p. 63, Sep. 2023.

[4] Y. Zang, S. Hu, B.-B. Zhou, L. Lv, and X. Sui, ‘‘Entrepreneurship and the formation mechanism of taobao villages: Implications for sustainable development in rural areas,’’ J. Rural Stud., vol. 100, May 2023, Art. no. 103030.

[5] J. Zhuang and H. Sun, ‘‘Impact of institutional environment on entrepreneurial intention: The moderating role of entrepreneurship education,’’ Int. J. Manage. Educ., vol. 21, no. 3, Nov. 2023, Art. no. 100863.

[6] T. S.-C. Poon, C.-H. Wu, and M.-C. Liu, ‘‘Developing entrepreneurial ecosystem: A case of unicorns in China and its innovation policy implications,’’ Asian J. Technol. Innov., vol. 32, no. 1, pp. 20–36, Jan. 2024.

[7] A. DeLosReyes, M. Wang, M. D. Lerner, B. A. Makol, O. M. Fitzpatrick, and J. R. Weisz, ‘‘The operations triad model and youth mental health assessments: Catalyzing a paradigm shift in measurement validation,’’ J. Clin. Child Adolescent Psychol., vol. 52, no. 1, pp. 19–54, Jan. 2023.

[8] A. C. Timmons, J. B. Duong, N. Simo Fiallo, T. Lee, H. P. Q. Vo, M. W. Ahle, J. S. Comer, L. C. Brewer, S. L. Frazier, and T. Chaspari, ‘‘A call to action on assessing and mitigating bias in artificial intelligence applications for mental health,’’ Perspect. Psychol. Sci., vol. 18, no. 5, pp. 1062–1096, Sep. 2023.

[9] O. Higgins, B. L. Short, S. K. Chalup, and R. L. Wilson, ‘‘Artificial intelligence (AI) and machine learning (ML) based decision support systems in mental health: An integrative review,’’ Int. J. Mental Health Nursing, vol. 32, no. 4, pp. 966–978, Aug. 2023.

[10] K. Nova, ‘‘Machine learning approaches for automated mental disorder classification based on social media textual data,’’ Contemp. Issues Behav. Soc. Sci., vol. 7, no. 1, pp. 70–83, 2023.

[11] B. Wang, ‘‘Exploration of the path of innovation and entrepreneurship education for college students from the perspective of mental health education,’’ J. Healthcare Eng., vol. 2022, no. 1, Apr. 2022, Art. no. 2659160.

[12] C. Margaça, B. Hernández-Sánchez, J. C. Sánchez-García, and G. M. Cardella, ‘‘The roles of psychological capital and gender in university students' entrepreneurial intentions,’’ Frontiers Psychol., vol. 11, Jan. 2021, Art. no. 615910.

[13] S. Siyal, C. Xin, W. A. Umrani, S. Fatima, and D. Pal, ‘‘How do leaders influence innovation and creativity in employees? The mediating role of intrinsic motivation,’’ Admin. Soc., vol. 53, no. 9, pp. 1337–1361, Oct. 2021.

[14] N. K. Iyortsuun, S.-H. Kim, M. Jhon, H.-J. Yang, and S. Pant, ‘‘A review of machine learning and deep learning approaches on mental health diagnosis,’’ Healthcare, vol. 11, no. 3, p. 285, Jan. 2023.

[15] Z.Elyoseph, I. Levkovich, and S. Shinan-Altman, ‘‘Assessing prognosis in depression: Comparing perspectives of AI models, mental health professionals and the general public,’’ Family Med. Community Health, vol. 12, Jan. 2024, Art. no. e002583.

[16] R. Tornero-Costa, A. Martinez-Millana, N. Azzopardi-Muscat, L. Lazeri, V. Traver, and D. Novillo-Ortiz, ‘‘Methodological and quality flaws in the use of artificial intelligence in mental health research: Systematic review,’’ JMIR Mental Health, vol. 10, no. 1, Feb. 2023,
Art. no. e42045.

[17] M. Obschonkaand D. B. Audretsch,‘‘Artificial intelligence and big data in entrepreneurship: A new era has begun,’’ Small Bus. Econ., vol. 55, no. 3, pp. 529–539, Oct. 2020.

[18] A. Al-Okaily, A. P. Teoh, and M. Al-Okaily, ‘‘Evaluation of data analytics-oriented business intelligence technology effectiveness: An enterprise level analysis,’’ Bus. Process Manage. J., vol. 29, no. 3, pp. 777–800, May 2023.

[19] F. Kitsios and M. Kamariotou, ‘‘Digital innovation and entrepreneurship transformation through open data hackathons: Design strategies for successful start-up settings,’’ Int. J. Inf. Manage., vol. 69, Apr. 2023, Art. no. 102472.

[20] H. Chen, Y. Wang, C. Xu, C. Xu, and D. Tao, ‘‘Learning Student networks via feature embedding,’’ IEEE Trans. Neural Netw. Learn. Syst., vol. 32, no. 1, pp. 25–35, Jan. 2021.

[21] J. Gu and S. Lu, ‘‘An effective intrusion detection approach using SVM with naïveBayesfeatureembedding,’’Comput.Secur.,vol.103, Apr.2021, Art. no. 102158.

[22] M.Xu,‘‘Understandinggraphembeddingmethodsandtheirapplications,’’ SIAM Rev., vol. 63, no. 4, pp. 825–853, Jan. 2021.

[23] Y. Sui, X. Cheng, G. Zhang, and H. Wang, ‘‘Flow2 Vec: Value-flow-based precise code embedding,’’ Proc. ACM Program. Lang., vol. 4, pp. 1–27, Nov. 2020.

[24] T. Zhang and X. Zhang, ‘‘A polarization fusion network with geometric feature embedding for SAR ship classification,’’ Pattern Recognit., vol. 123, Mar. 2022, Art. no. 108365.

[25] J. Wang, R. Huang, S. Guo, L. Li, Z. Pei, and B. Liu, ‘‘HyperLiteNet: Extremely lightweight non-deep parallel network for hyperspectral image classification,’’ Remote Sens., vol. 14, no. 4, p. 866, Feb. 2022.

[26] M. D. Kremantzis, P. Beullens, L. S. Kyrgiakos, and J. Klein, ‘‘Measurement and evaluation of multi-function parallel network hierarchical DEA systems,’’ Socio-Econ. Planning Sci., vol. 84, Dec. 2022, Art. no. 101428.

[27] A. Khanda, S. Srinivasan, S. Bhowmick, B. Norris, and S. K. Das, ‘‘A parallel algorithm template for updating single-source shortest paths in large-scale dynamicnetworks,’’IEEETrans.ParallelDistrib.Syst.,vol .33, no. 4, pp. 929–940, Apr. 2022.

[28] X. Jiang, Y. Jin, and Y. Yao, ‘‘Low-dose CT lung images denoising based on multiscale parallel convolution neural network,’’ Vis. Comput., vol. 37, no. 8, pp. 2419–2431, Aug. 2021.

[29] M. C. Gonzalez, A. Mehrnezhad, N. Razaviarab, T. G. Barbosa-Silva, and S. B. Heymsfield, ‘‘Calf circumference: Cutoff values from the NHANES 1999–2006,’’ Amer. J. Clin. Nutrition, vol. 113, no. 6, pp. 1679–1687, Jun. 2021.

[30] T. Oh, D. Kim, S. Lee, C. Won, S. Kim, J.-S. Yang, J. Yu, B. Kim, and J. Lee, ‘‘Machine learning-based diagnosis and risk factor analysis of cardiocerebrovascular disease based on KNHANES,’’ Sci. Rep., vol. 12, no. 1, p. 2250, Feb. 2022.

[31] D. Kee, J. Wisnivesky, and M. S. Kale, ‘‘Lung cancer screening uptake: Analysis of BRFSS 2018,’’ J. Gen. Internal Med., vol. 36, no. 9, pp. 2897–2899, Sep. 2021.

[32] J. Chung and J. Teo, ‘‘Single classifier vs. Ensemble machine learning approaches for mental health prediction,’’ Brain Informat., vol. 10, no. 1, p. 1, Dec. 2023.

[33] S. Tutun, M. E. Johnson, A. Ahmed, A. Albizri, S. Irgil, I. Yesilkaya, E. N. Ucar, T. Sengun, and A. Harfouche, ‘‘An AI-based decision support system for predicting mental health disorders,’’ Inf. Syst. Frontiers, vol. 25, no. 3, pp. 1261–1276, Jun. 2023.

[34] Vandana, N. Marriwala, and D. Chaudhary, ‘‘A hybrid model for depression detection using deep learning,’’ Meas., Sensors, vol. 25, Feb. 2023, Art. no. 100587.

[35] N. A. A. Abdelwahed, ‘‘Recognizing the role of ChatGPT in decision making and recognition of mental health disorders among entrepreneurs,’’ OBM Neurobiol., vol. 8, no. 3, pp. 1–16, 2024.

[36] Z. Elyoseph, T. Gur, Y. Haber, T. Simon, T. Angert, Y. Navon, A. Tal, and O. Asman, ‘‘An ethical perspective on the democratization of mental health with generative AI,’’ JMIR Mental Health, vol. 11, Oct. 2024, Art. no. e58011.

[37] G. Castañeda-Garza, H. G. Ceballos, and P. G. Mejía-Almada, ‘‘Artificial intelligence for mental health: A review of AI solutions and their future,’’ in What AI Can Do. Berlin, Germany: Springer, Jun. 2023, pp. 373–399.