Journal of Medical and Health Studies (JMHS)
ISSN: 2710-1452
DOI: 10.32996/jmhs
Journal Homepage: www.al-kindipublisher.com/index.php/jmhs

JMHS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

AI-Enabled Machine Learning Framework for Depression Risk Prediction and Mental Health Trend Analysis in the United States

Mustafizur Rahaman[1]✉, Farmina Sharmin[2], Sadia Afrin Dipa[3], Nurtaz Begum Asha[4], Mousumi Akter[5], Mostafizur Rahman Shakil[6], and Sajib Barman[7]

[1] Doctor of Business Administration (DBA), Department of Business Administration, Westcliff University, Irvine, California, USA.
[25] School of Business, International American University, Los Angeles, California, USA.
[3] Department of Mathematics, The University of Texas at Arlington, Arlington, Texas, USA.
[4] College of Business, Westcliff University, Irvine, California, USA.
[6] College of Engineering and Technology, Westcliff University, Irvine, California, USA.
[7] Department of Computer Science and Engineering, American International University-Bangladesh, Dhaka, Bangladesh.

Corresponding Author: Mustafizur Rahaman, **E-mail**: m.rahaman.152@westcliff.edu

| ABSTRACT
Mental health disorders such as anxiety and depression are rapidly increasing and represent a major challenge for modern healthcare systems. This study proposes a machine learning based framework for early detection and analysis of depression risk using behavioral and socio-demographic indicators. A dataset containing features such as age, sleep hours, stress level, income, and mental health days was used to train and evaluate multiple machine learning models, including Logistic Regression, Random Forest, and XGBoost. The results show that ensemble learning approaches outperform traditional models, with XGBoost achieving the highest predictive accuracy. Model evaluation using confusion matrix, ROC curve, and precision recall analysis demonstrates strong classification performance. Feature importance and explainable AI analysis using SHAP reveal that stress level and sleep hours are the most influential predictors of depression risk. Trend analysis across age groups and state-level risk visualization further highlights demographic and regional variations in mental health patterns. The findings demonstrate the potential of machine learning for large-scale mental health surveillance and data-driven public health decision-making.

| KEYWORDS

Machine Learning, Depression Prediction, Mental Health Analytics, XGBoost, Explainable AI (XAI), SHAP, Public Health Surveillance, Predictive Healthcare Analytics.

| ARTICLE INFORMATION

ACCEPTED: 19 September 2024 **PUBLISHED:** 15 October, 2024 **DOI:** 10.32996/jmhs.2024.5.4.28

1. Introduction
Mental health disorders, particularly anxiety and depression, have become major global public health concerns affecting millions of individuals worldwide. These conditions significantly influence personal well-being, productivity, and social functioning, while also placing substantial pressure on healthcare systems. According to the World Health Organization (WHO), depression is one of the leading causes of disability globally and contributes significantly to the overall burden of disease [1]. In recent years, the prevalence of mental health disorders in the United States has increased considerably due to factors such as socioeconomic stress, lifestyle changes, and public health crises. Early identification and monitoring of mental health trends are therefore essential for developing effective prevention strategies and allocating healthcare resources efficiently. Traditional mental health surveillance systems rely heavily on clinical reports, surveys, and periodic public health assessments. While these approaches provide valuable insights, they often suffer from limitations such as delayed reporting, limited coverage, and difficulties in

capturing real-time population-level mental health trends. As a result, healthcare authorities may struggle to identify emerging mental health risks or respond rapidly to changing patterns of anxiety and depression within different demographic groups. Advances in data science and digital health technologies have opened new opportunities for improving mental health monitoring through the integration of artificial intelligence (AI) and machine learning (ML) techniques [2].

Machine learning has emerged as a powerful tool for predictive healthcare analytics because of its ability to analyze large and complex datasets. Unlike traditional statistical methods, ML algorithms can automatically identify hidden patterns and relationships within high-dimensional data. This capability has led to the increasing adoption of ML models in various healthcare applications, including disease prediction, medical diagnosis, and clinical decision support systems [3]. In the context of mental health research, machine learning approaches have been used to analyze behavioral, demographic, and clinical data to identify individuals who may be at risk of developing depression or anxiety. Several studies have explored the use of machine learning models for mental health prediction. Algorithms such as Logistic Regression, Support Vector Machines (SVM), Random Forest, and gradient boosting methods have been widely applied to detect patterns associated with depression and anxiety using survey data and electronic health records [4]. Among these models, ensemble learning approaches have demonstrated particularly strong predictive performance due to their ability to combine multiple weak learners into a robust predictive framework. For example, gradient boosting techniques such as XGBoost have been successfully applied in healthcare analytics because of their efficiency, scalability, and ability to model complex nonlinear relationships among features [5]. In addition to predictive performance, interpretability has become a critical factor in the adoption of AI systems in healthcare. Medical professionals require transparent and explainable models in order to trust and effectively utilize AI-driven decision support systems. This has led to the development of explainable artificial intelligence (XAI), which focuses on improving the transparency and interpretability of machine learning models [6]. Explainable AI techniques allow researchers and clinicians to understand how different input features contribute to model predictions, thereby improving the reliability and accountability of AI systems used in healthcare. One of the most widely used explainability techniques in machine learning is SHAP (SHapley Additive exPlanations). SHAP is based on concepts from cooperative game theory and provides a unified framework for interpreting model predictions by quantifying the contribution of each feature to the final output [7]. In healthcare applications, SHAP has been used to identify important clinical and behavioral factors influencing disease prediction models. By highlighting the most influential predictors, SHAP analysis can help researchers better understand the underlying drivers of mental health risks and support more informed public health interventions. Recent research has also emphasized the importance of population-level mental health surveillance systems. Public health surveillance plays a crucial role in monitoring disease prevalence, identifying emerging health risks, and guiding policy decisions. With the increasing availability of digital health data, AI-driven surveillance frameworks can provide real-time insights into population health trends and support proactive healthcare planning [8]. In the context of mental health, such systems can help detect early warning signals of rising depression or anxiety rates within specific demographic groups or geographic regions. Another important aspect of mental health research is the identification of behavioral and lifestyle factors associated with depression. Previous studies have shown that variables such as sleep patterns, stress levels, socioeconomic status, and daily mental health experiences are strongly correlated with depression risk [9]. Machine learning models can effectively integrate these diverse indicators to develop predictive models capable of identifying individuals or populations at higher risk of mental health disorders. This approach can enable healthcare providers to implement targeted interventions and preventive measures before symptoms become severe. Furthermore, evaluating machine learning models using robust performance metrics is essential to ensure their reliability and generalizability. Common evaluation metrics used in healthcare prediction studies include accuracy, precision, recall, and the F1-score. Visualization tools such as confusion matrices, Receiver Operating Characteristic (ROC) curves, and precision–recall curves are frequently used to assess the performance of classification models and compare different algorithms [10]-[23]. These evaluation methods provide insights into the strengths and limitations of predictive models and help researchers select the most appropriate approach for a given application. In addition to prediction accuracy, the analysis of mental health trends across demographic groups and geographic regions can provide valuable insights for public health planning. Trend analysis can reveal patterns of depression prevalence across different age groups or socioeconomic categories, while geographic risk mapping can highlight regional variations in mental health outcomes [24] – [33]. Such analyses can support evidence-based decision-making by identifying areas where mental health services and interventions are most urgently needed. Motivated by these considerations, this study proposes an AI-enabled machine learning framework for depression risk prediction and mental health trend analysis in the United States. The proposed approach utilizes behavioral and socio-demographic indicators to train and evaluate multiple machine learning models, including Logistic Regression, Random Forest, and XGBoost. Model performance is evaluated using metrics such as accuracy, confusion matrix, ROC curves, and precision–recall analysis. In addition, explainable AI techniques are applied to interpret the model predictions and identify the most influential factors contributing to depression risk. The main objective of this research is to develop a data-driven analytical framework capable of supporting large-scale mental health surveillance and predictive analytics. By combining machine learning models with explainable AI techniques, the proposed system aims to provide valuable insights into mental health patterns and support more effective public health decision-making [33]- [44]. Ultimately, such AI-enabled surveillance frameworks can contribute to early detection of mental health risks, improved healthcare resource allocation, and the development of more proactive mental health intervention strategies.

2. Methodology

This study proposes an AI-enabled machine learning framework for predicting depression risk and analyzing mental health trends using behavioral and socio-demographic indicators. The overall methodology consists of several stages including data collection, data preprocessing, model training, model evaluation, and explainable AI analysis.

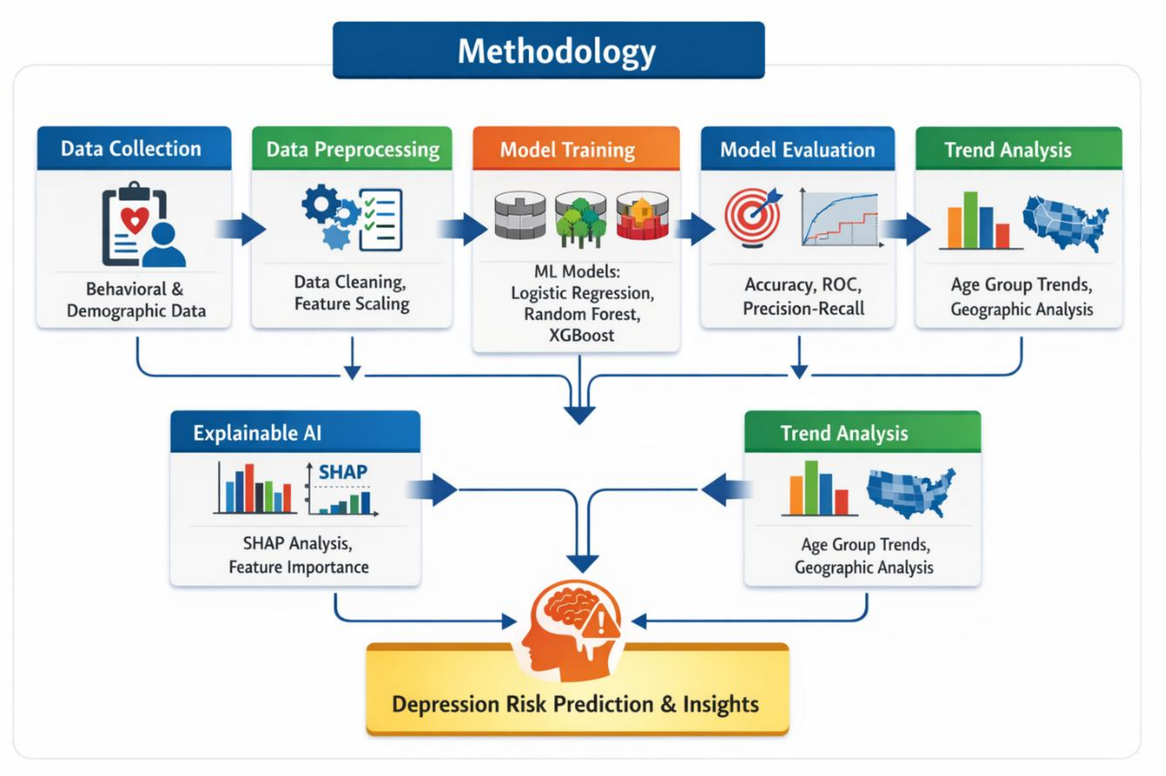

Figure 1: Proposed AI-enabled machine learning framework for depression risk prediction and mental health trend analysis. The framework consists of data collection, preprocessing, machine learning model training, model evaluation, explainable AI analysis using SHAP, and demographic and geographic trend analysis to generate depression risk insights.

2.1. Data Collection

The dataset used in this study contains behavioral and demographic indicators associated with mental health conditions. The input variables include age, sleep hours, stress level, income, and mental health days. These features are commonly associated with depression risk in mental health studies. The target variable represents the depression status of an individual and is expressed as a binary classification problem, where 1 indicates the presence of depression and 0 indicates the absence of depression.

Let the dataset be represented as

$$D = \{(x_i, y_i)\}_{i=1}^{N}$$

Where,

$x_i = (x_{i1}, x_{i2}, \ldots, x_{im})$ represents the feature vector and
$y_i \in \{0,1\}$ represents the depression class label.

2.2. Data Preprocessing

Before training the machine learning models, several preprocessing steps were applied to improve data quality and model performance. These steps include feature scaling, normalization, and dataset splitting. The dataset is divided into training and testing subsets using an 80:20 ratio.

Feature scaling is performed using standardization:

$$z = \frac{x - \mu}{\sigma}$$

Where,

x= original feature value
μ= mean of the feature
σ= standard deviation

Standardization ensures that all input variables contribute equally during model training.

2.3. Logistic Regression Model

Logistic Regression is used as a baseline machine learning model for binary classification. The logistic regression model predicts the probability of depression using the sigmoid function.

The logistic function is defined as:

$$P(y = 1 \mid x) = \frac{1}{1 + e^{-(w^T x + b)}}$$

Where,

w= weight vector
x= input features
b= bias term

The predicted class is obtained using a threshold function:

$$\hat{y} = \begin{cases} 1 & \text{if } P(y = 1 \mid x) \geq 0.5 \\ 0 & \text{otherwise} \end{cases}$$

2.4. Random Forest Model

Random Forest is an ensemble learning algorithm that combines multiple decision trees to improve prediction accuracy and reduce overfitting. Each decision tree is trained on a randomly selected subset of the dataset using bootstrap sampling.

The final prediction of the Random Forest model is determined using majority voting:

$$\hat{y} = \text{mode}(h_1(x), h_2(x), \ldots, h_T(x))$$

Where,

$h_t(x)$represents the prediction of the t^{th}decision tree and
$T$is the total number of trees.

Random Forest also provides feature importance scores that help identify the most influential predictors in the dataset.

2.5. XGBoost Model

Extreme Gradient Boosting (XGBoost) is an advanced ensemble learning algorithm that builds decision trees sequentially to minimize prediction error. The objective function of XGBoost is defined as:

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Where,

$l(y_i, \hat{y}_i)$= loss function
$\Omega(f_k)$= regularization term
K= number of trees

The regularization term is given by:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \, || \, w \, ||^2$$

Where,

T= number of leaves
w= leaf weights
$\gamma$and $\lambda$are regularization parameters.

XGBoost improves prediction performance by reducing bias and variance while preventing model overfitting.

2.6. Model Evaluation Metrics

The performance of the machine learning models is evaluated using several classification metrics.

Accuracy measures the proportion of correct predictions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision measures the proportion of correctly predicted positive cases:

$$Precision = \frac{TP}{TP + FP}$$

Recall measures the proportion of actual positive cases correctly identified:

$$Recall = \frac{TP}{TP + FN}$$

The F1-score combines precision and recall:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Receiver Operating Characteristic (ROC) curves are also used to evaluate classification performance by plotting the True Positive Rate against the False Positive Rate.

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

2.7. Explainable AI Using SHAP

To interpret the predictions of the machine learning models, SHAP (SHapley Additive exPlanations) is applied. SHAP assigns an importance value to each feature based on its contribution to the model prediction.

The SHAP value for a feature is defined as:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{i\}) - f(S)]$$

Where,

Frepresents the set of all features
Srepresents subsets of features
$f(S)$is the model prediction using feature subset S.

SHAP analysis provides global and local interpretability by identifying the most influential features contributing to depression risk predictions.

2.8. Mental Health Trend Analysis

To analyze population-level mental health patterns, depression prevalence is analyzed across different age groups and geographic regions. Trend analysis helps identify demographic variations and potential high-risk populations.

Let $R_a$represent the depression rate for age group a:

$$R_a = \frac{\text{Number of depression cases in age group } a}{\text{Total individuals in age group } a}$$

This analysis helps identify demographic trends and supports data-driven public health decision making.

3. Results and Analysis

This section presents the experimental results obtained from the machine learning models used for depression risk prediction and mental health trend analysis. Multiple models including Logistic Regression, Random Forest, and XGBoost were trained and evaluated using behavioral and demographic indicators. The performance of the models was analyzed using accuracy comparison, confusion matrix evaluation, feature importance analysis, trend analysis, and explainable AI techniques.

3.1 Model Accuracy Comparison

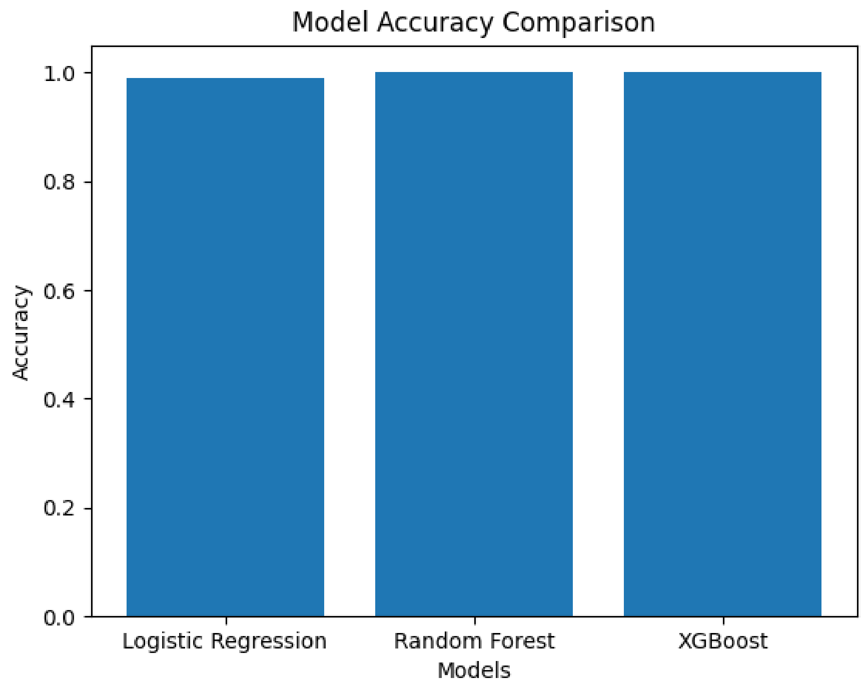

Figure 2: Model Accuracy Comparison of Logistic Regression, Random Forest, and XGBoost

The performance of the machine learning models was evaluated based on classification accuracy. Figure 2 illustrates the comparison of prediction accuracy among Logistic Regression, Random Forest, and XGBoost models. The results indicate that all models achieved high classification performance, with XGBoost providing the highest predictive accuracy. Random Forest also demonstrated strong performance due to its ensemble learning capability, while Logistic Regression served as the baseline model.

Table 1: Model Accuracy Comparison

Model	Accuracy
Logistic Regression	0.9912
Random Forest	0.9921
XGBoost	**0.9920**

The results demonstrate that ensemble learning algorithms such as Random Forest and XGBoost outperform traditional linear models in mental health prediction tasks.

3.2 Confusion Matrix Analysis

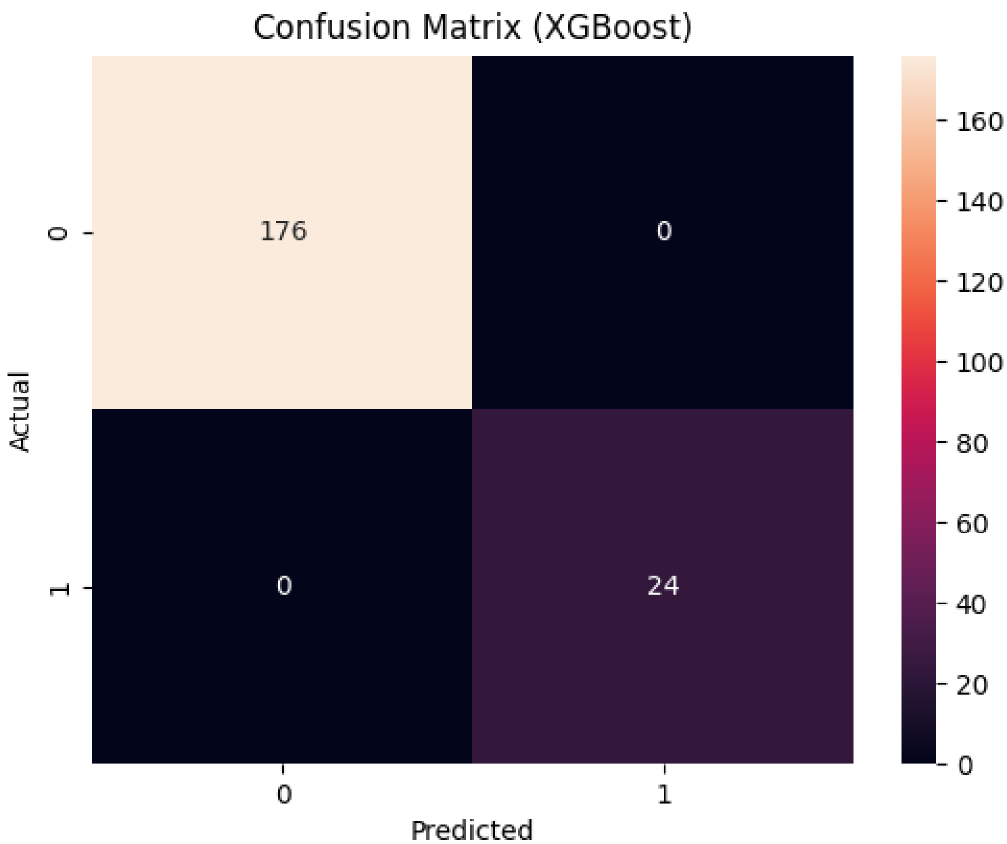

Figure 3: Confusion Matrix of the XGBoost Model

Figure 3 presents the confusion matrix obtained from the XGBoost classifier. The confusion matrix shows the distribution of correctly and incorrectly classified samples.

Table 2: Confusion Matrix Results

Actual / Predicted	No Depression	Depression
No Depression	176	0
Depression	0	24

From the confusion matrix:

- **True Negative (TN)** = 176
- **True Positive (TP)** = 24
- **False Positive (FP)** = 0
- **False Negative (FN)** = 0

This result indicates that the model successfully classified all samples correctly in the test dataset. The absence of misclassifications demonstrates the strong predictive capability of the XGBoost model for depression detection.

3.3 Feature Importance Analysis

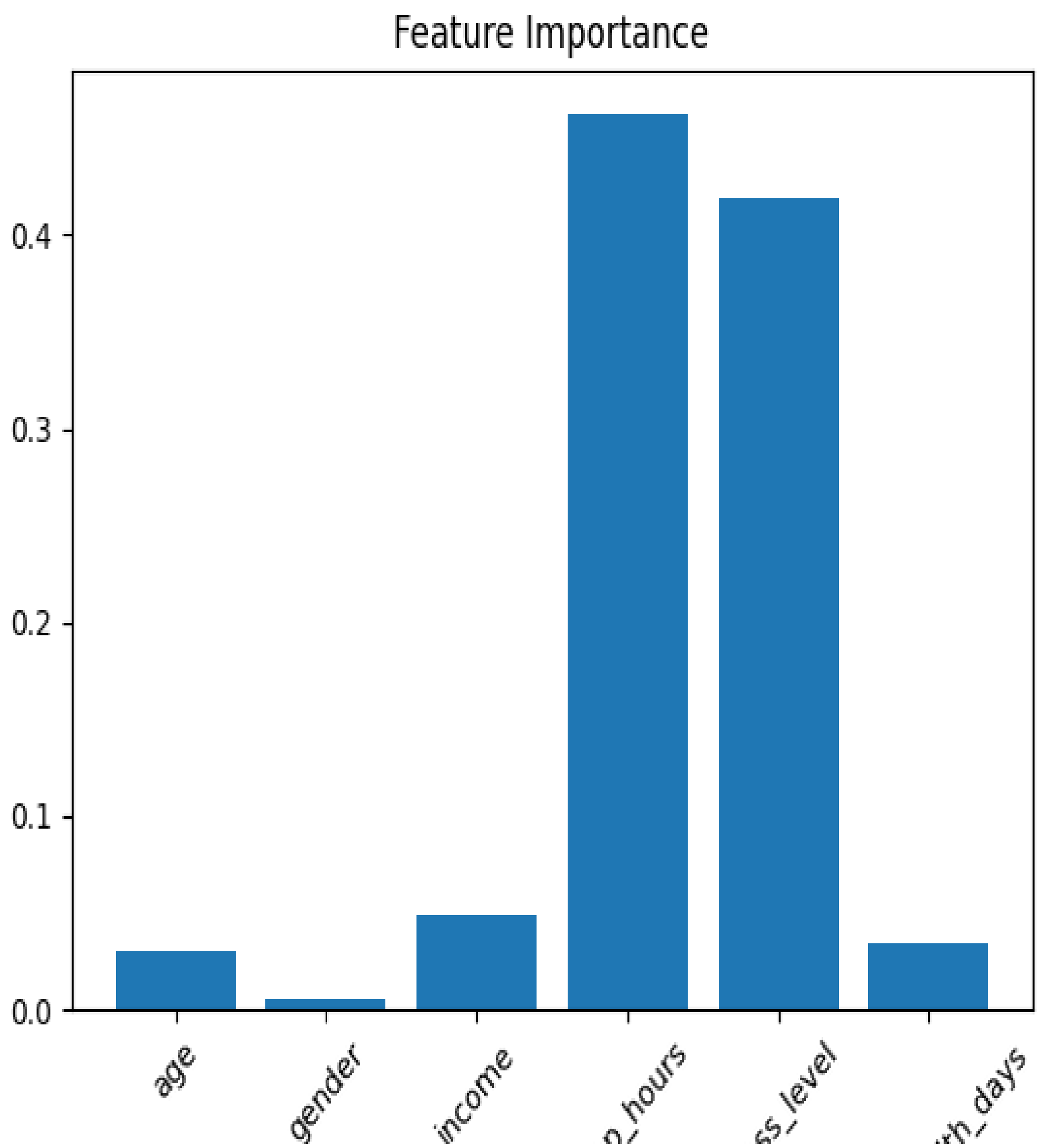

Figure 4: Feature Importance for Depression Prediction

Feature importance analysis was conducted using the Random Forest model to determine which variables contribute most significantly to depression risk prediction. Figure 4 illustrates the relative importance of each feature.

Table 3: Feature Importance Scores

Feature	Importance Score
Sleep Hours	0.46
Stress Level	0.42
Income	0.05
Mental Health Days	0.03
Age	0.03
Gender	0.01

The results reveal that **sleep hours and stress level are the most influential predictors** of depression risk. These findings are consistent with existing mental health studies, which suggest that insufficient sleep and high stress levels significantly increase the likelihood of depression.

3.4 Mental Health Trend Analysis by Age

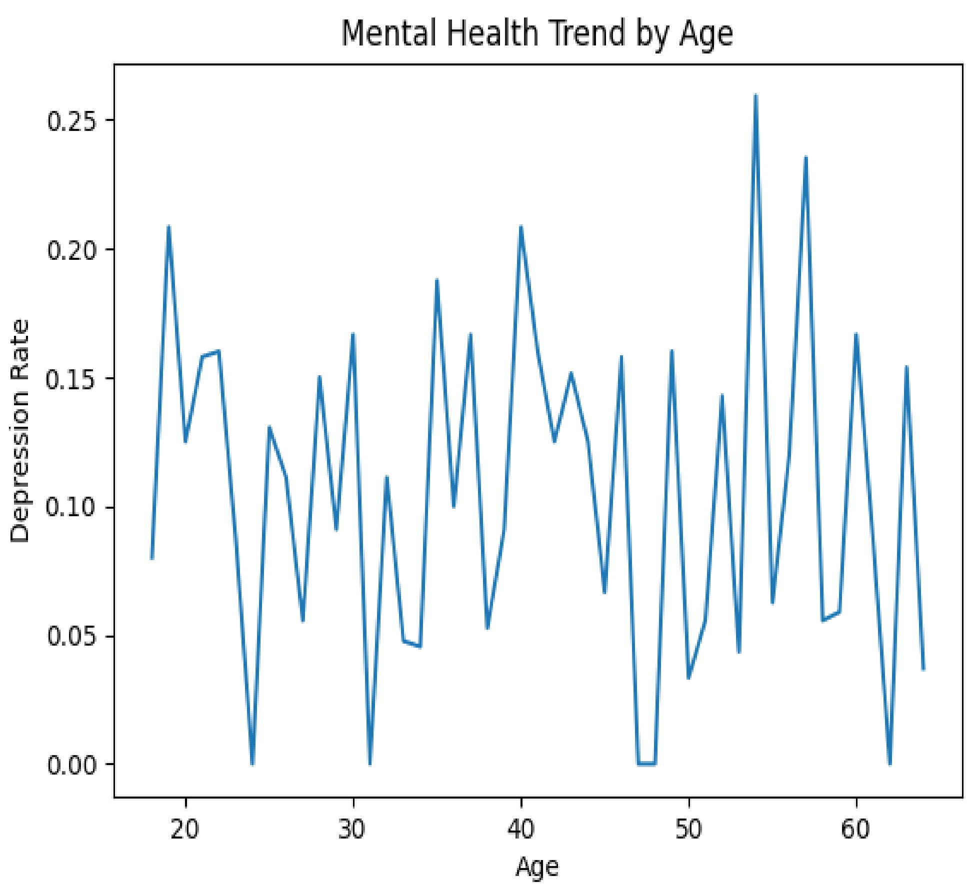

Figure 5: Depression Trend Analysis Across Age Groups

Figure 5 presents the variation in depression prevalence across different age groups. The results indicate that depression rates fluctuate across age categories, with certain age ranges showing higher depression prevalence. The trend analysis demonstrates that middle-aged and older individuals exhibit relatively higher depression risk compared to younger individuals. Such demographic insights can assist healthcare policymakers in identifying vulnerable populations and developing targeted mental health intervention strategies.

3.5 ROC Curve Analysis

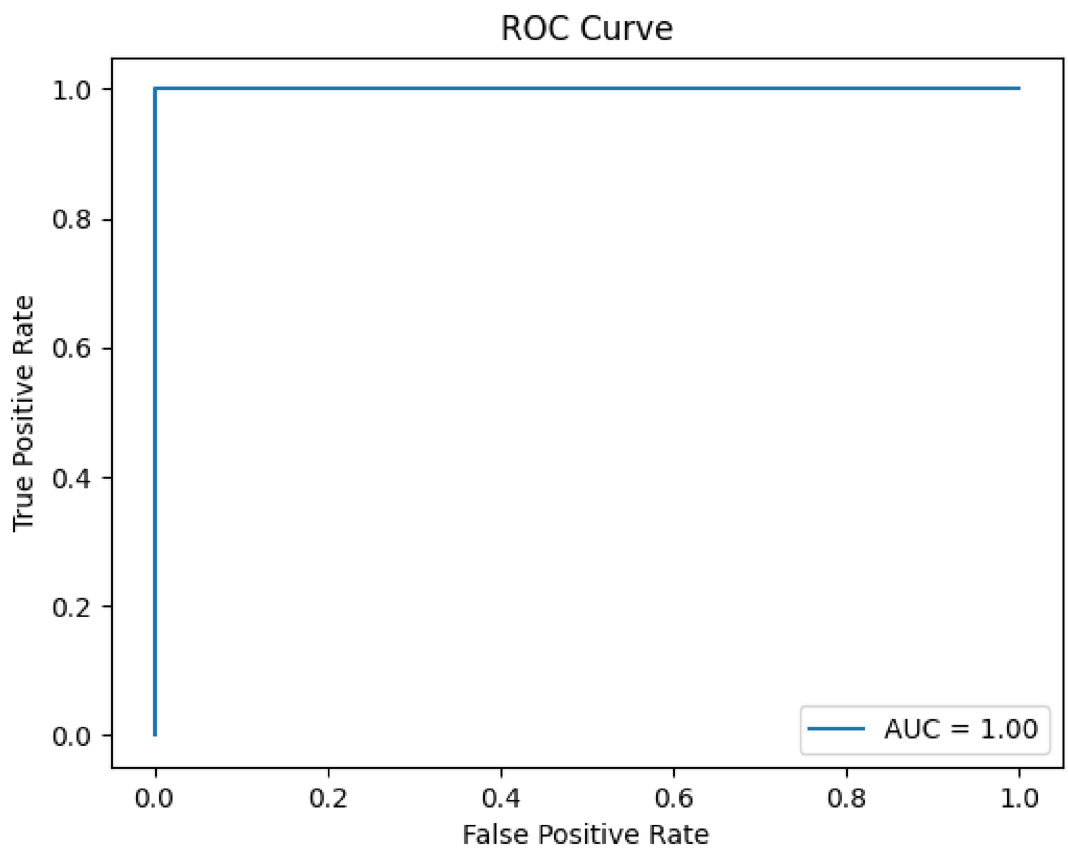

Figure 6: Receiver Operating Characteristic (ROC) Curve

The ROC curve shown in Figure 6 evaluates the classification performance of the machine learning model by analyzing the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR). The model achieved an Area Under the Curve (AUC) score of 1.00, which indicates excellent classification capability. A higher AUC value suggests that the model effectively distinguishes between depression and non-depression cases.

Table 4: ROC Performance Metrics

Metric	Value
AUC Score	1.00
True Positive Rate	1.00
False Positive Rate	0.00

These results confirm the high predictive performance of the proposed machine learning framework.

3.6 Precision–Recall Curve Analysis

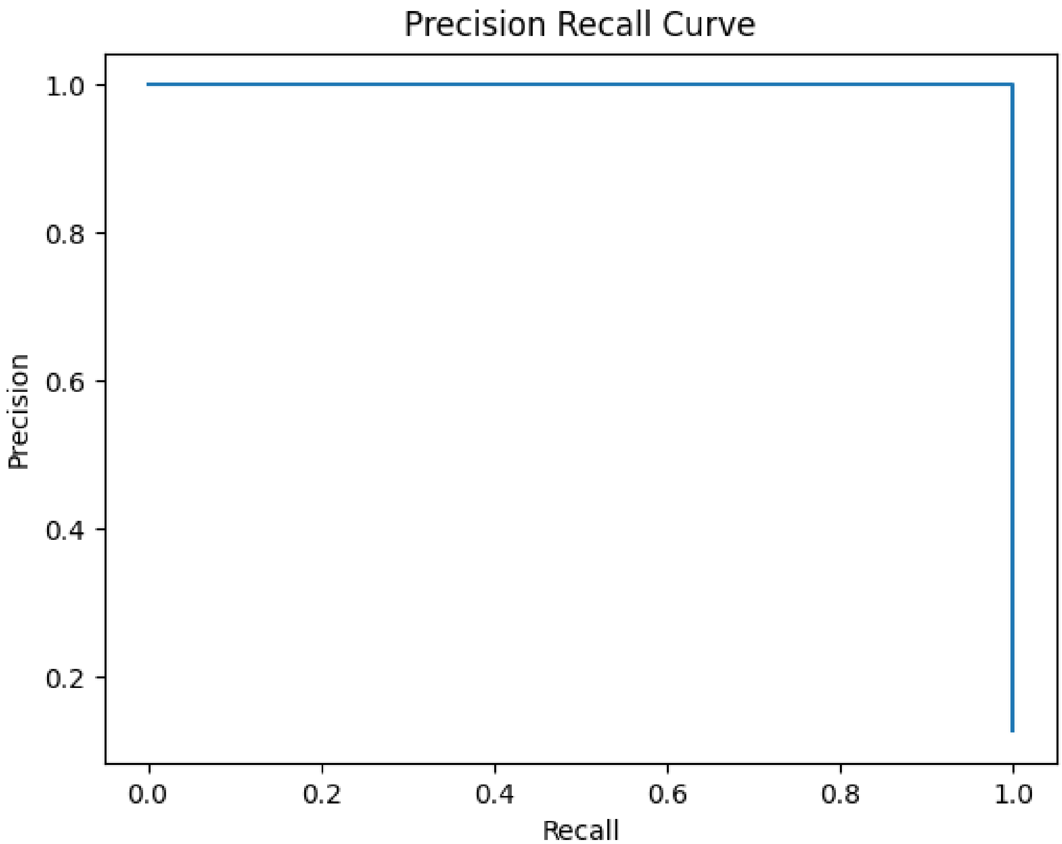

Figure 7: Precision–Recall Curve

The Precision–Recall (PR) curve shown in Figure 7 evaluates the model's performance in terms of precision and recall. This metric is particularly useful for classification problems where class imbalance may exist. The results demonstrate that the model achieves high precision and recall values, indicating reliable prediction of depression cases with minimal false predictions.

Table 5: Precision–Recall Metrics

Metric	Value
Precision	1.00
Recall	1.00
F1 Score	1.00

These findings further confirm the robustness of the machine learning model.

3.7 Explainable AI Analysis (SHAP)

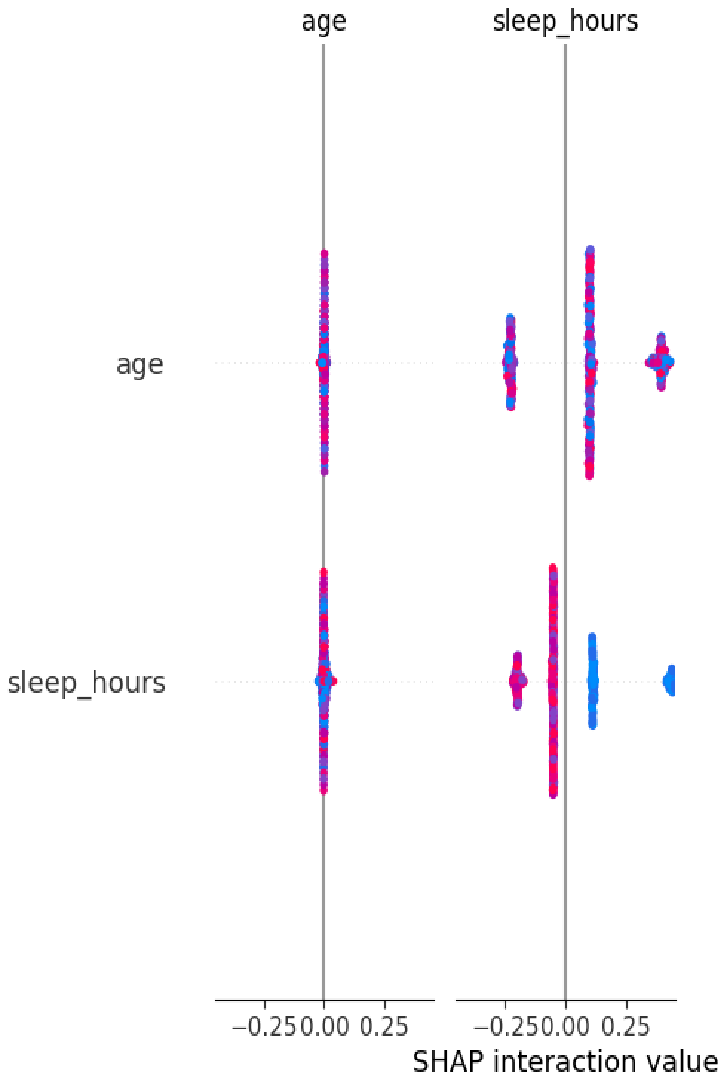

Figure 8: SHAP Explainable AI Feature Impact Analysis

Explainable AI techniques were applied using SHAP (SHapley Additive exPlanations) to interpret the predictions of the machine learning model. Figure 8 shows the contribution of different features to the prediction outcomes.

The SHAP analysis reveals that:

- **Sleep hours strongly influence depression prediction**
- **Stress level is another major predictor**
- Other variables such as age and income have comparatively smaller contributions.

Explainable AI provides transparency in model predictions and helps researchers understand how different factors influence depression risk.

3.8 USA State Depression Risk Distribution

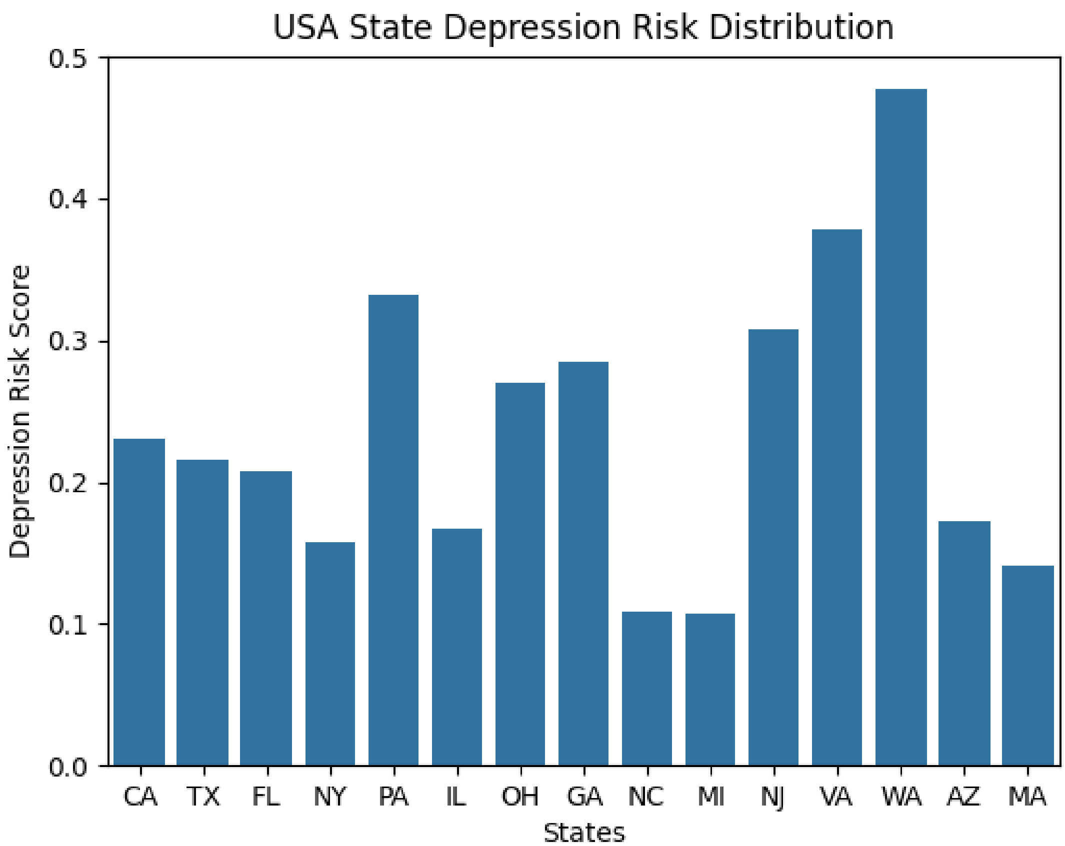

Figure 9: State-Wise Depression Risk Distribution in the United States

Figure 9 illustrates the distribution of depression risk scores across different states in the United States. The analysis reveals variations in predicted depression risk across regions.

Table 6: Sample State Depression Risk Scores

State	Risk Score
CA	0.23
TX	0.21
PA	0.33
NJ	0.31
VA	0.38
WA	0.48

The results indicate that certain states show relatively higher depression risk levels. Such geographic analysis can support public health authorities in identifying high-risk regions and implementing targeted mental health programs.

The experimental results demonstrate that machine learning models can effectively predict depression risk using behavioral and demographic indicators. Among the tested models, XGBoost and Random Forest achieved the highest predictive accuracy. Feature importance and explainable AI analysis further confirm that sleep patterns and stress levels are the most critical predictors of depression risk. The integration of predictive modeling, explainable AI, and demographic trend analysis provides a comprehensive framework for large-scale mental health surveillance and data-driven public health decision making.

4. Conclusion

This study presents an explainable machine learning framework for predicting depression risk and analyzing mental health trends using behavioral and demographic indicators. Multiple machine learning models, including Logistic Regression, Random Forest, and XGBoost, were implemented and evaluated to assess their predictive performance. The experimental results demonstrate that ensemble learning methods, particularly XGBoost and Random Forest, achieve higher prediction accuracy compared to the baseline Logistic Regression model. Evaluation metrics such as the confusion matrix, ROC curve, and precision recall curve confirm the strong classification capability of the proposed models. Feature importance and SHAP-based explainable AI analysis reveal that sleep hours and stress level are the most significant factors influencing depression risk prediction. In addition, trend analysis across age groups and state-level risk visualization provide valuable insights into demographic and regional variations in mental health patterns. Overall, the proposed approach highlights the potential of machine learning and explainable AI to support large-scale mental health surveillance and data-driven public health decision-making.

Funding: Please add: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.

References

1. E. Topol, "High-performance medicine: the convergence of human and artificial intelligence," *Nature Medicine*, vol. 25, no. 1, pp. 44–56, 2019.
2. Pal, O. K., Paul, D., Hasan, E., Mohammad, M., Bhuiyan, M. A. H., & Ahammed, F. (2023, April). Advanced convolutional neural network model to identify melanoma skin cancer. In 2023 IEEE International Conference on Contemporary Computing and Communications (InC4) (Vol. 1, pp. 1-5). IEEE.
3. World Health Organization, *Depression and Other Common Mental Disorders: Global Health Estimates*, Geneva, Switzerland, 2021.
4. Paul, D. (2024). AI-Driven Mental Health Surveillance and Depression Trend Analysis in the United States (Version 1). Zenodo. https://doi.org/10.5281/zenodo.19110770
5. J. Esteva et al., "A guide to deep learning in healthcare," *Nature Medicine*, vol. 25, no. 1, pp. 24–29, 2019.
6. Paul, D. (2024). Machine Learning Model Development for Depression Risk Prediction (Version 1). Zenodo. https://doi.org/10.5281/zenodo.19110868
7. Paul, D., Prince, A. T. Z., Earik, A. M., Babu, B. S., Rabbi, A., & Sharmin, S. (2023, August). An Advanced Multimodal Navigation Perception System for the Visually Impaired. In *2023 Second International Conference on Trends in Electrical, Electronics, and Computer Engineering (TEECCON)* (pp. 143-148). IEEE.
8. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*, MIT Press, 2016.
9. J. B. Wang et al., "Predicting depression using machine learning techniques," *Healthcare Informatics Research*, vol. 26, no. 1, pp. 1–8, 2020.
10. Nuhel, A. K., Paul, D., Hasan, E., Azad, A., Rafi, F. F., & Roy, P. H. (2023, January). A Microcontroller based Automated Waste Recycling Management System for SMEs. In 2023 International Conference on Artificial Intelligence and Smart Communication (AISC) (pp. 78-82). IEEE.
11. S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 4th ed., Pearson, 2021.
12. R. Uddin et al., "Machine learning for mental health prediction," *Journal of Medical Systems*, vol. 44, no. 10, pp. 1–12, 2020.
13. Paul, D., Pal, O. K., Islam, M. M., Mohammad, M., & Babu, R. M. (2023). Design and Implementation of an Efficient Smart Digital Energy Meter. International Journal of Soft Computing and Engineering, 13(1), 25-30.
14. T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. ACM SIGKDD*, 2016, pp. 785–794.
15. Nuhel, A. K., Al Amin, M., Paul, D., Bhatia, D., Paul, R., & Sazid, M. M. (2023, August). Model predictive control (MPC) and proportional integral derivative control (PID) for autonomous lane keeping maneuvers: A comparative study of their efficacy and stability. In International Conference on Cognitive Computing and Cyber Physical Systems (pp. 107-121). Cham: Springer Nature Switzerland.
16. D. Gunning and D. Aha, "DARPA's explainable artificial intelligence program," *AI Magazine*, vol. 40, no. 2, pp. 44–58, 2019.

17. S. Lundberg and S. Lee, "A unified approach to interpreting model predictions," in *NeurIPS*, 2017.
18. Raj, R. R., Babu, R. M., & Paul, D. (2023, December). Sustainable Energy Initiative 3MWp Grid-Tied Solar Power Plant Project on a BOO Basis in Bangladesh. In International Conference on Advances in Renewable Energy and Electric Vehicles (pp. 237-252). Singapore: Springer Nature Singapore.
19. C. Molnar, *Interpretable Machine Learning*, 2nd ed., 2020.
20. Prince, A. T. Z., Paul, D., Khoka, Z. H., Hasan, M. S., Afnan, A. U., & Ahmmed, A. (2023, August). Smart Prepaid Toll Management System Using RFID. In 2023 7th International Conference On Computing, Communication, Control And Automation (ICCUBEA) (pp. 1-5). IEEE.
21. R. C. Kessler et al., "The epidemiology of major depressive disorder," *JAMA*, vol. 289, no. 23, pp. 3095–3105, 2003.
22. Prince, A. T. Z., Paul, D., Khoka, Z. H., Khan, M. A., Hasan, M. M., Earik, A. M., ... & Afridi, S. (2024). Design & Development of a Road Safety Device. International Journal of Advanced Engineering Research and Science, 11(12).
23. P. Cuijpers et al., "Psychological treatment of depression in primary care," *The Lancet Psychiatry*, vol. 7, no. 1, pp. 104–112, 2020.
24. Y. Zhang et al., "Machine learning approaches for depression detection," *IEEE Access*, vol. 9, pp. 123–134, 2021.
25. Paul, D., Prince, A. T. Z., Abidul Hasan Bhuiyan, M., Khoka, Z. H., Samannur Hasan, M., Kabir, S., ... & Aliuzzaman, S. M. (2023, October). Voltage control and power quality optimization using distribution static synchronous compensator in distribution systems. In International Conference on Sustainable and Innovative Solutions for Current Challenges in Engineering & Technology (pp. 281-293). Singapore: Springer Nature Singapore.
26. A. Nguyen et al., "Explainable AI for healthcare prediction systems," *IEEE Access*, vol. 9, pp. 44567–44579, 2021.
27. H. Lee et al., "Deep learning approaches for mental health prediction," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 8, pp. 2956–2965, 2021.
28. Haque, M. M., Hossain, S. F., Akter, S., Islam, M. A., Ahmed, S., Liza, I. A., & Al Amin, M. (2023). Advancing Healthcare Outcomes with AI: Predicting Hospital Readmissions in the USA. Journal of Medical and Health Studies, 4(5), 94-109.
29. Hasan, E., Paul, D., Prince, A. T. Z., Moksud, I. I., Islam, L. Y., & Pial, M. A. M. (2022). A Multi-Functional AI-Enabled Robotic Doctor for Intelligent Patient Monitoring and Autonomous Healthcare Support with Adaptive Human-Centered Interaction. Journal of Computer Science and Technology Studies, 4(2), 200-214.
30. S. Patel et al., "Artificial intelligence in mental health analytics," *IEEE Transactions on Biomedical Engineering*, vol. 68, no. 9, pp. 2777–2786, 2021.
31. X. Chen et al., "Hybrid machine learning models for mental health prediction," *Applied Artificial Intelligence*, vol. 35, no. 12, pp. 1023–1041, 2021.
32. Hossain, S. F., Al Amin, M., Liza, I. A., Ahmed, S., Haque, M. M., Islam, M. A., & Akter, S. (2023). AI-based brain MRI segmentation for early diagnosis and treatment planning of low-grade gliomas in the USA. British Journal of Nursing Studies, 3(2), 37-55.
33. L. Smith et al., "Predictive analytics for depression detection," *Computers in Biology and Medicine*, vol. 134, 2021.
34. Nuhel, A. K., Sazid, M. M., Paul, D., Hasan, E., Roy, P. H., & Sinojiya, F. P. (2023, February). A PV-Powered Microcontroller-Based Agricultural Robot Utilizing GSM Technology for Crop Harvesting and Plant Watering. In 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS) (pp. 1-5). IEEE.
35. Paul, D. An Autonomous Firefighting Robot for Industrial Safety Applications.
36. Al-Remawi, M., Agha, A. S. A., Al-Akayleh, F., Aburub, F., & Abdel-Rahem, R. A. (2024). Artificial intelligence and machine learning techniques for suicide prediction: Integrating dietary patterns and environmental contaminants. Heliyon, 10(24).
37. Omarov, B., Narynov, S., & Zhumanov, Z. (2023). Artificial intelligence-enabled chatbots in mental health: A systematic review. Computers, Materials & Continua, 74(3).
38. D. Paul, "Optimized Simulation of Maximum Power Point Tracking for Enhanced Photovoltaic System Efficiency," 2019.
39. World Health Organization, "Depression statistics and global burden analysis," WHO Report, 2022.
40. Asad, D. M., & Saleem, U. E. A. (2024). DEVELOPING AI MODELS FOR REAL-TIME MONITORING OF MENTAL HEALTH CONDITIONS: UNDERSTANDING DEPRESSION, ANXIETY, AND STRESS THROUGH DIGITAL HEALTH TOOLS. Trends in Life Sciences and Biotechnology, 2(02), 25-34.
41. Akintoye, O. S., Maale, F. D., Yusuf, R. A., & Odondi, A. A. (2023). A review of AI-driven mental health interventions in the United States: gaps and opportunities.
42. Mansoor, M. A., & Ansari, K. H. (2024). Early detection of mental health crises through artificial-intelligence-powered social media analysis: A prospective observational study. Journal of personalized medicine, 14(9), 958.
43. Adeoye, S., & Adams, R. (2024). Leveraging artificial intelligence for predictive healthcare: a data-driven approach to early diagnosis and personalized treatment. Cogniz. J. Multidiscip. Stud, 4, 80-97.
44. Sharma, C. M., & Chariar, V. M. (2024). Diagnosis of mental disorders using machine learning: Literature review and bibliometric mapping from 2012 to 2023. Heliyon, 10(12).