JOURNAL OF DATA SCIENCE | Vol.2024:37
eISSN:2805-5160

An Enhanced Affective Computing Technology for Fostering an Emotionally Healthy Workplace

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Abstract

The mental health of workers is of paramount importance in today's fast-paced and demanding workplaces. This research establishes a strong connection between affective decision-making and mental health, presenting a novel method to improve affective computing technologies for developing emotionally healthy workplaces. We use Multinomial Naive Bayes Integrated Gated Recurrent Units (MNB-GRU) for classification and prediction to reach our goals. This dataset includes many measures of mental health, working climate, and individual variables. Data Exploration is performed to learn more about the properties of the dataset, and Preprocessing Grouping is used to get the data ready for analysis. Relationships between emotional decision-making and mental health markers are shown using data visualization approaches to give intuitive insights. To evaluate the reliability of the connection, a correlation analysis is used in Model Assessment. Understanding how people are feeling emotionally at work can be gained via this assessment, which examines the degree of association between affective decision-making and mental health. As a result of using categorization methods to divide the workforce into several categories based on their emotional well-being, we can better assist businesses in meeting the varying demands of their staff members. This method guarantees that efforts to improve mental health are focused and productive. By creating a solid connection between effective decision-making and mental health, businesses can take preventative measures to aid their workers' emotional well-being and create a more upbeat and productive workplace.

Keywords

Affective Computing, Multinomial Naïve Bayes integrated gated recurrent units, Grouping, Correlation Coefficient, Model Evaluation, Mental health

Introduction

Individuals with mental illnesses or disorders often experience significant shifts in emotional state, cognitive processes, or outward behavior, which disrupt their daily lives and lead to emotional distress. Mental health disorders encompass a broad range, including anxiety, depression, eating disorders, personality disorders, post-traumatic stress disorder (PTSD), and psychosis (Collins et al., 2021). Modern mental health screening approaches emphasize both well-being and distress,

Submission: 24 July 2024; **Acceptance:** 28 October 2024

fitting within a dual-continuum model that considers both positive and negative mental health indicators (Banerjee et al., 2021).

Recent research strongly supports a mental health model that addresses both psychological wellness and mental illness, aligning with positive psychology's emphasis on promoting resilience and well-being. Over the past two decades, positive psychology has particularly focused on young people's attitudes of optimism and gratitude, which are associated with higher levels of happiness and academic success (Cheung et al., 2020). Mental illness can lead to severe outcomes, including self-harm, criminal activity, or harm to others, emphasizing the importance of mental health services and the critical need to take mental health issues seriously (Jiang & Koo, 2020; Drake et al., 2022). Unfortunately, mental health concerns are often dismissed or ridiculed, which can worsen the affected individual's distress and lead to tragic outcomes (Ren et al., 2019).

Mental health challenges are prevalent among college students, with many experiencing psychological difficulties during their studies (Negriff, 2020). Affective computing, which aims to develop systems that can recognize and respond to human emotions, holds promise for enhancing emotional well-being in the workplace (Lirio & Plusquellec, 2023).

In the work environment, employees' mental health and job satisfaction are closely linked to emotional well-being. Employers can leverage advanced technologies like machine learning and emotion detection to assess employee sentiment, offering valuable insights that can shape programs and policies supporting mental health in the workplace (Lee, 2021; Rezvani & Khosravi, 2019). Through these tools, businesses can foster an inclusive and supportive work culture that promotes employee well-being and productivity (Boyd & Andalibi, 2023; Shen et al., 2023).

Key Contributions

- Dataset Preprocessing and Exploration: The initial preprocessing and grouping of datasets facilitated a comprehensive data exploration phase, enhancing data quality and reliability for subsequent analysis (Bruns et al., 2019; Tinetti et al., 2019).
- Data Visualization Techniques: A variety of data visualization methods were utilized to uncover significant relationships between emotional decision-making and psychological well-being. This approach provided clear insights into emotional factors that impact mental health (Steinert & Friedrich, 2020; Fernández-Theoduloz et al., 2019).
- Use of MNB-GRU Model: The MNB-GRU model was applied to predict and classify mental health outcomes, specifically in the context of workplace emotional well-being, demonstrating the utility of advanced machine learning techniques in mental health prediction (Sahlan et al., 2021; Chicco et al., 2021).
- Affective Decision-Making Assessment: This assessment focused on the correlation between affective decision-making and mental health, offering valuable insights into workers' emotional well-being. It highlights the critical role of affective factors in understanding workplace mental health (Kirk, 2019; Attridge, 2019).

These contributions underscore the importance of data-driven approaches and advanced models in enhancing mental health insights, particularly in the workplace and educational contexts.

Through this approach, the study sheds light on the significant role of affective computing and machine learning in promoting mental health and supporting emotional well-being in diverse environments, from education to the workplace (Suhaimi et al., 2020; Aggarwal et al., 2022; Cui, 2021).

Methodology

To use practical computing skills in order to promote an emotionally healthy workplace and evaluation among effective decision-making as well as mental health usually follows a set approach that includes steps for gathering and analyzing data. Figure 1 displays the suggested methods.

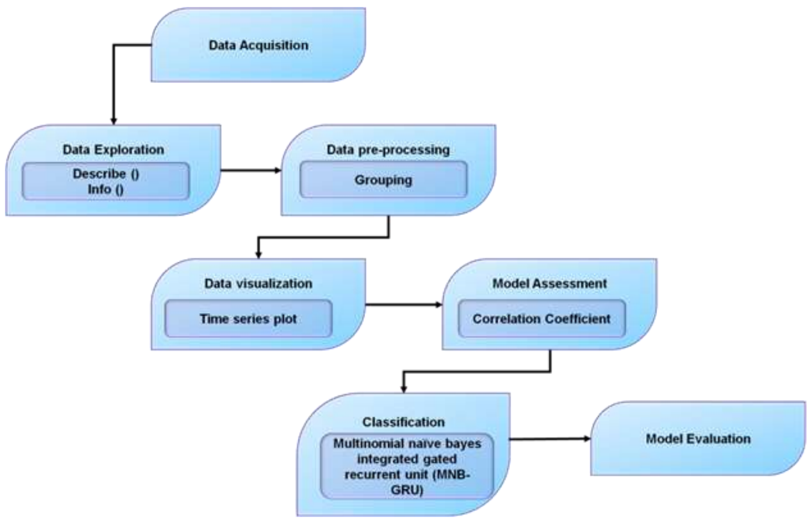

Figure 1. Overview of suggested method

a. Dataset

A patient's dataset is used to facilitate research on medical disorders and treatment results to aid in clinical decision-making. Because of the invaluable information they contain on patient demographics, illness trends, treatment effectiveness, and healthcare system performance, these databases are indispensable to healthcare professionals, researchers, and data scientists. This dataset comprises various types of data, including demographics, health records, laboratory results, and psychological or social data https://www.kaggle.com/datasets/mikethetech/sample-patient-health-data. The dataset contains 8760 rows and 11 columns, which are depicted in Table 1.

Table 1. Example of the caption for the table

	ID	Date	Gender	Heart Rate	Blood Pressure (systolic)	Blood Pressure (diastolic)	Steps	Maas (kg)	Sleep Duration (hours)	Calories Burned	Water Intake (L)
0	1	01-01-2022	Female	62	122	81	10385	79.6	85	2304	1.3
1	2	01-01-2022	Female	61	119	79	9621	79.6	83	2752	1.3

2	3	01-01-2020	Female	59	121	82	10445	80.1	5.6	2545	1.4
3	4	01-01-2022	Female	62	120	82	9850	80.1	5.0	2764	1.6
4	5	01-01-2022	Female	58	119	80	10200	80.1	7.2	2296	1.2
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8758	23	31-12-2022	Female	75	131	88	5852	88.6	6.0	1415	1.6
8759	24	31-12-2022	Female	75	127	88	5709	89.2	5.3	1706	2.7

i. Data exploration

To describe () and info () methods in Python's Pandas library are used in data exploration for gaining first insights into a dataset. These features provide summaries of the data and critical insights into its organization.

ii. Data preprocessing using Grouping

Data preprocessing comprises cleaning, converting, and improving raw data to prepare it for analysis or modeling. This stage ensures that the data is correct, consistent, and in the proper format.

- **Data cleaning:** Processing data by erasing or correcting for issues, including missing numbers, outliers, and mistakes. We need to impute missing values or exclude an outlying data point that has high error rates.
- **Data Transformation:** Transforming information into a usable form. Some examples of this include encoding a set of categories, scaling a set of numbers, or applying a logarithmic transformation.

iii. Data visualization using Time series plot

Time series plots are helpful in many industries, including finance, economics, climate science, and many more, because of their ability to reveal trends, patterns, and anomalies in time-dependent data. They are helpful for researchers and analysts because they allow them to make predictions based on previous data. Collect information about workers' mental health using polls and text analyses of office discussions, such as the frequency with which stress-related occurrences are recorded and the frequency with which mental health-related absences are excused. Figure 2 displays the outcomes of the Time series plot.

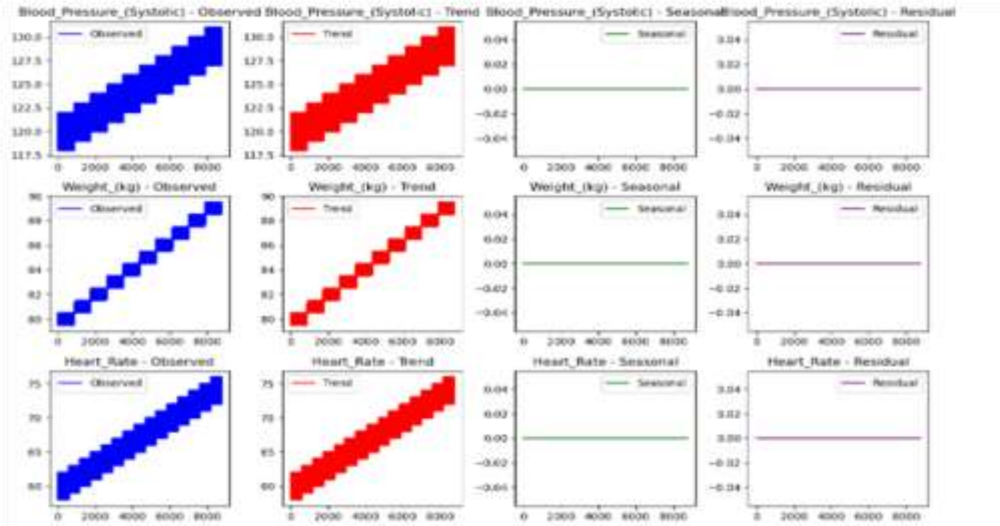

Figure 2. Seasonal decomposition plot for anxiety levels

iv. Model Assessment using correlation coefficient

As a statistical measure, the correlation coefficient indicates what proportion of the dependency factors' overall variation is capable of accounted for by the framework's distinct variables. If this metric has a value of zero, the model fails to describe any interpretation, but if it has a value of one, variation is explained.

b. Classification using Multinomial naïve bayes Gated Recurrent Units (MNB-GRU)

The MNB-GRU model integrates the best features of Multinomial Naive Bayes and Generalized Relational Units, making it suitable for text-based classification problems in the mental health sector. This method is used to automatically diagnose or classify mental health issues based on textual input, allowing for earlier intervention and more targeted treatment for those in need.

- **Multinomial Naive Bayes (MNB)**

The Multinomial Naive Bayes classification method is utilized in the field of text mining for sentiment analysis. In principle, this approach excels at keeping data consistent and producing organized numerical outcomes. Numerous classification methods rely on NB in various iterations, such as Unigram MNB, Multinomial MNB, and Maximum Entropy Classification. The principal value of the Naive Bayes classification is that it can provide a credible hypothesis for every situation. MNB probability distributions are calculated using Bayesian equation (1).

$$P(X|Y) = \frac{P(y|x)p(x)}{P(x)} \quad (1)$$

Text mining is a powerful technique for mining useful information from massive databases. Extraction of Twitter views using an MNB model. It is possible to crawl data by specifying keywords over a certain period. After finishing up data collecting, sentiment analysis moves on to the labeling stage.

The distribution of PP probabilities and the percentage of documents in each class are combined in equation (2).

$$\Pr(d) =\propto \pi_d \prod_{x=1}^{|U|} \Pr(x|d)^{e_x} \tag{2}$$

Underflow is prevented by adding the algorithm in equation (3) and (4).

$$\Pr(d) \propto \log(\pi_d \prod_{x=1}^{|U|} Pr(x|d)^{e_x}) \tag{3}$$

$$\Pr(d) = \log \pi_d + \prod_{x=1}^{|U|} e_x \log\big(Pr(x|d)\big) \tag{4}$$

One difficulty is that the odds of a word's recurrence increase each time it occurs. To smooth this out, we use the log of the frequency (Equation 5).

$$\Pr(d) = \log \pi_d + \prod_{x=1}^{|U|} \log(1 + e_x) \log(Pr\ (x|d)) \tag{5}$$

- **Gated Recurrent Unit (GRU)**

Flattening the spatial information along the temporal dimension, we use GRU to analyze the resulting data. In this paper, we introduce GRU, an enhanced version of long short-term memory (LSTM) that incorporates many of the same features found in LSTM. When compared to the GRU's two inputs, LSTM's three are more than enough. With fewer parameters, GRU can train earlier and improve the network's performance. Figure 3 depicts the structure of GRU neurons. Consider the GRU's input and the resulting ct as its output. The expression of GRU is somewhat different from that of LSTM, as can be shown in Figure 3 using the following Equations (6) to (9).

$$y_s = \sigma\big(X_y.[g_{s-1}, w_s]\big) \tag{6}$$

$$q_s = \sigma\big(X_q.[g_{s-1}, w_s]\big) \tag{7}$$

$$\overline{g_s} = \tan g\ (X.[q_s * g_{s-1}, w_s]) \tag{8}$$

$$g_s = (1 - y_s) * g_{s-1} + y_s * \tilde{g}_s \tag{9}$$

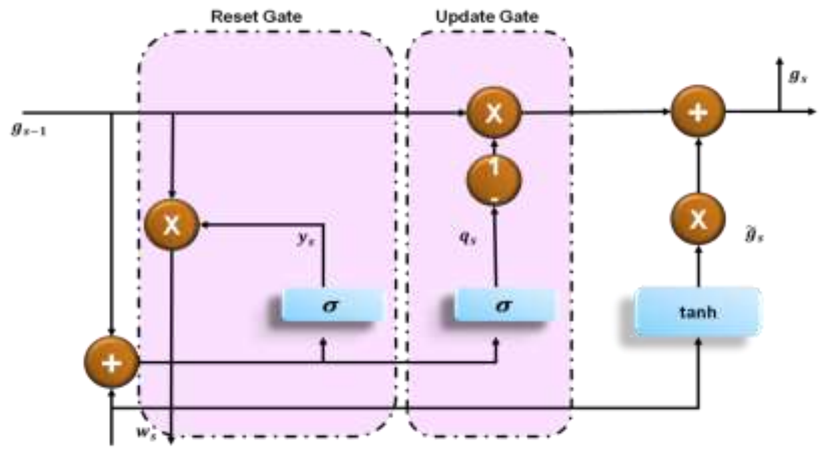

Figure 3. Gated recurrent units neuron architecture

Both the reset gate q_s and the concealed unit $\overline{g_s}$ are indicated. g_s is the output at this very instant. Weights are represented by X_q,X_q, and X. A function of activation is denoted by the symbol *tanh*—both the GRU and the LSTM function in a similar manner. Instead of having separate gates for forgetting and input, the GRU unit employs a hidden state to merge both into a single update gate. It regulates both the amount of data erased from the instant before and the amount of data added to the moment's buried layer of memory. The reset gate, a fresh "gate" in the GRU, determines whether the state g_{s-1} from the preceding mum is used in the calculation of q_s. Since GRU is more straightforward to teach, it has the potential to improve the effectiveness of education.

Results and Discussion

We evaluate the suggested approach in comparison to state-of-the-art authentication methods. Use accuracy, precision, recalls, and F1-score to examine how people feel about having a mentally and emotionally healthy workplace. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R-squared (R2), and computational cost are used to evaluate the performance of the presented models in predicting maintainability.

- **Outcomes of RMSE and MSE**

RMSE is an abbreviation for the error that is determined as the root mean square of the data. The average dissimilarity between a model's forecasts and actual outcomes is a frequently used metric in regression assignments. With Equation 10, RMSE used to evaluate the performance of models making predictions for continuous numeric data.

$$RMSE = \sqrt{\frac{1}{n} * sum(predicted_i - actual_i)^2} \tag{10}$$

The results of a comparison between the RMSE of the new approach and the RMSE of the existing methodology are shown in Table 2 and Figure 4. The new method (MNB-GRU 0.248%) improves upon the existing one [22], with DT performance increasing to 0.546%, RF to 0.361% and LR to 0.498%. Our method saves money compared to the existing options out there. This indicates the inefficacy of the MNB-GRU when compared to other approaches for mistake assessment, fault identification, and adaptive correction.

Mean squared error (MSE) is the average squared difference between two images. Comparison between the original and the processed or compressed version is the most familiar approach for evaluating the success of picture compression or restoration. Figure 4 and Table 2 show the results of a comparison between the suggested techniques. The DT, RF, LR [22], and MNB-GRU MSE values are 0.311%, 0.133%, 0.260%, and 0.061%. The MSE value of the suggested MNB-GRU algorithms is less than that of the traditional approaches. This demonstrates that the proposed technique requires less effort for mistake detection, fault isolation, and corrective action.

Table 2. Numerical outcomes of RMSE and MSE

Methods	**Values (%)**	
	MAP	**RMSE**
RF [22]	0.133	0.361
LR [22]	0.26	0.498
DT [22]	0.311	0.546
MNB-GRU [Proposed]	0.061	0.248

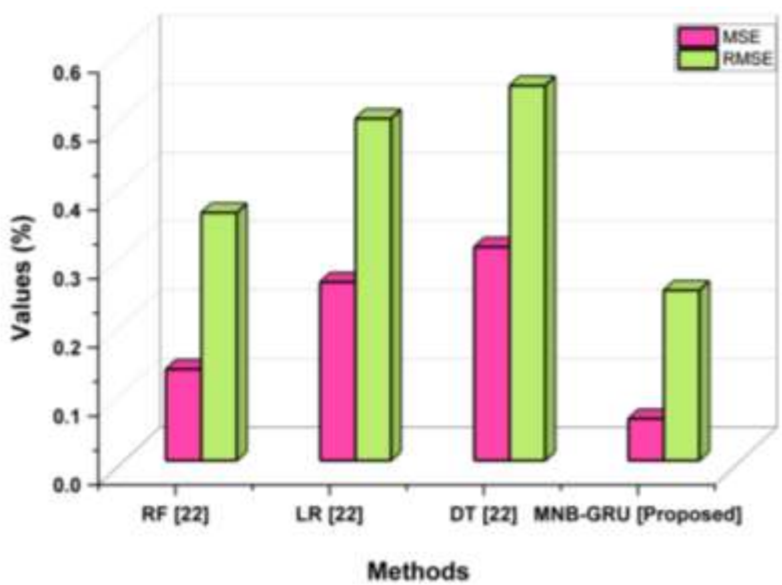

Figure 4. Comparison of RMSE and MSE

- Outcomes of R2

The R2 statistic measures the extent to which a regression model's independent (predictor) variables explain the variance in the dependent (outcome) variable. The R2 value of a regression model is a measure of the model's accuracy in predicting observed values. The R2 values obtained using the suggested and the standard methods are compared and contrasted in Figure 5 and Table 3, respectively. However, the R2 values for Support Vector Regression (SVR), KNN, DT [24], and MNB-GRU applications are 0.44%, 0.50%, 0.44% and 0.74%, respectively. The proposed MNB-GRU algorithm has a lower R2 value than the conventional methods. This proves that the proposed method needs to be revised for error assessment, fault identification, and adaptive correction.

Table 3. Numerical outcomes of R^2

Methods	R2 (%)
SVR [24]	0.44
KNN [24]	0.5
DT [24]	0.44
MNB-GRU [Proposed]	0.74

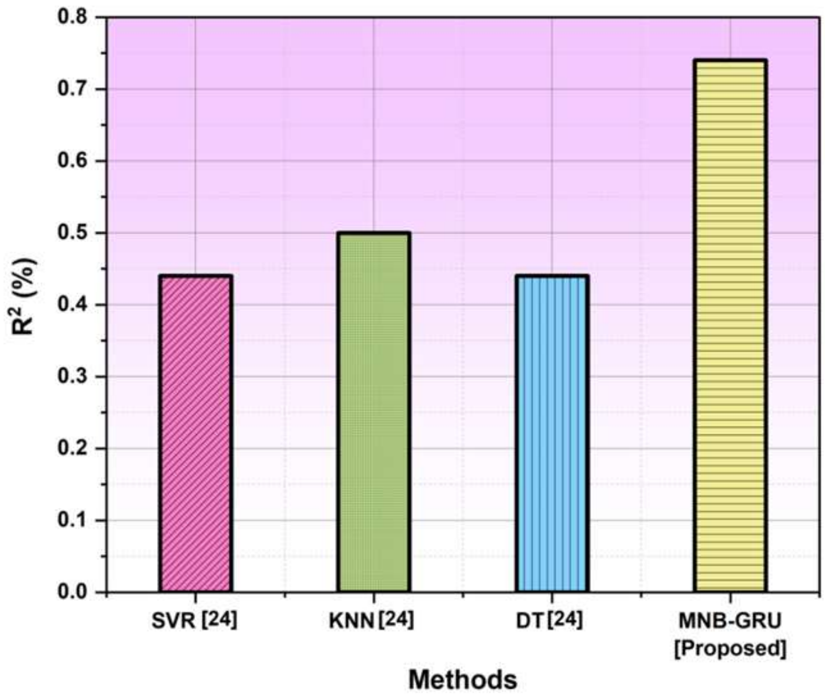

Figure 5. Comparison of R^2

- **Outcomes of Accuracy and Precision**

One standard metric for evaluating the success of machine learning systems is their ability to classify data. The accuracy of a model is measured by the number of reliable forecasts it can make. In order to determine how a model performs, it compares the actual labels with the predicted labels from the training data. If a prediction is a good match for the actual brand, it is accurate. To get the percentage of accurate forecasts, we divide the total number of estimates by the number of correct predictions.

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} \quad (11)$$

The results of a comparison between the suggested method and the existing method in terms of accuracy are shown in Figure 6. The MNB-GRU (98%) achieves superior accuracy compared to the DT (64%), KNN (59%), and SVM (44%). Table 4 displays the enhanced performance of the MNB-GRU proposal compared to the baseline methods of data classification. An accuracy comparison shows that our suggested method outperforms the current gold standard.

In the field of classification, precision is used as a metric of success. Models create a set of genuine optimistic forecasts and, from that set, determine what percentage of those predictions is correct. We calculate accuracy by dividing the number of accurate predictions by the total number of predictions.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)+False Positives (FP)}} \tag{12}$$

Figure 6 shows a comparison between the suggested method and the industry standard. When compared to other state-of-the-art processes, such as DT (61%), KNN (45%), and SVM (31%), the proposed technique uses MNB-GRU and achieves 97% accuracy. Table 4 displays the results of using the MNB-GRU recommendation compared to other state-of-the-art data classification techniques. Our proposed method outperforms current best practices in terms of accuracy.

Table 4. Numerical Outcomes of Accuracy and Precision

Matrix	**Values (%)**			
	DT [23]	**SVM [23]**	**KNN [23]**	**MNB-GRU [Proposed]**
Accuracy	0.64	0.59	0.44	0.98
Precision	0.61	0.45	0.31	0.97

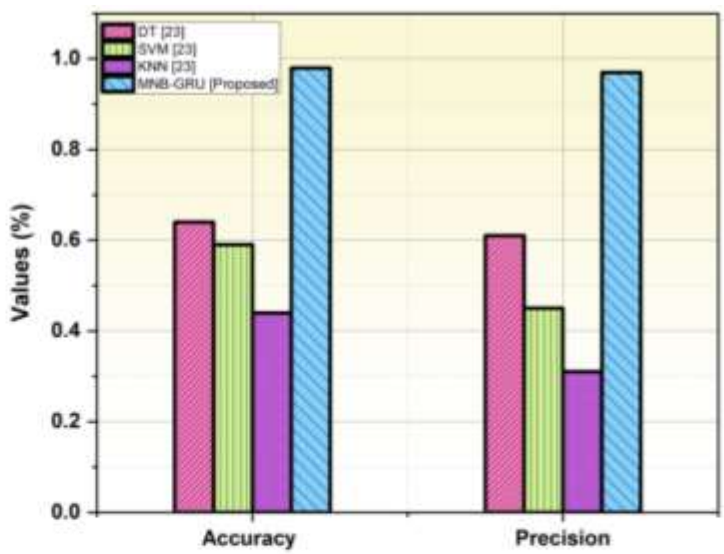

Figure 6. Comparison of Accuracy and precision

- **Outcomes of Recall and F1- score**

One of the most critical measures of success in deep learning, particularly for classification problems, is recall (also known as sensitivity or real positive rate). To determine memory, we divide the sum of all correct forecasts by two categories: those that are optimistic and those that are incorrect. It is the fraction of occurrences in the data set that has been appropriately categorized.

$$\text{Recall} = \frac{\text{FN}}{\text{FN+TP}} \tag{13}$$

We compare the current technique to the suggested method in terms of recall, and the results are shown in Figure 7. Compared to DT (62%), KNN (56%), and SVM (25%), the recall performance of the proposed method employing MNB-GRU is 98%. Several well-liked data recall classification methods are included in Table 5, along with how they stack up against the MNB-GRU suggestion. The contrast in recall shows that our suggested strategy is better than other methods.

F1 scores are employed as a performance metric, especially for classification jobs. Harmonic mean is a method that provides a single result that suggests a middle ground between accuracy and recall, taking into consideration their mutually beneficial connection. Possessing a high F1 score indicates that the model is able to find a medium between accuracy and recall. Although the range for the F1 score is 0–1, flawless recall and accuracy would indicate a score of 1.

$$\mathrm{F1-score} = \frac{(\mathrm{precision})\times(\mathrm{recall})\times 2}{\mathrm{precision}+\mathrm{recall}} \qquad (14)$$

Figure 7 and Table 5 provide a comparison of the F1 scores for the proposed strategy. The 98% F1-score achieved by MNB-GRU (98%) is greater than that of the widely used DT (61%), KNN (49%), and SVM (26%). The comparison of F1 scores demonstrates that our proposed strategy is superior to the conventional approaches.

Table 5. Numerical outcomes of Recall and F1-score

Matrix	**Values (%)**			
	DT [23]	**SVM [23]**	**KNN [23]**	**MNB-GRU [Proposed]**
Recall	0.62	0.56	0.25	0.98
F1-Score	0.61	0.49	0.26	0.98

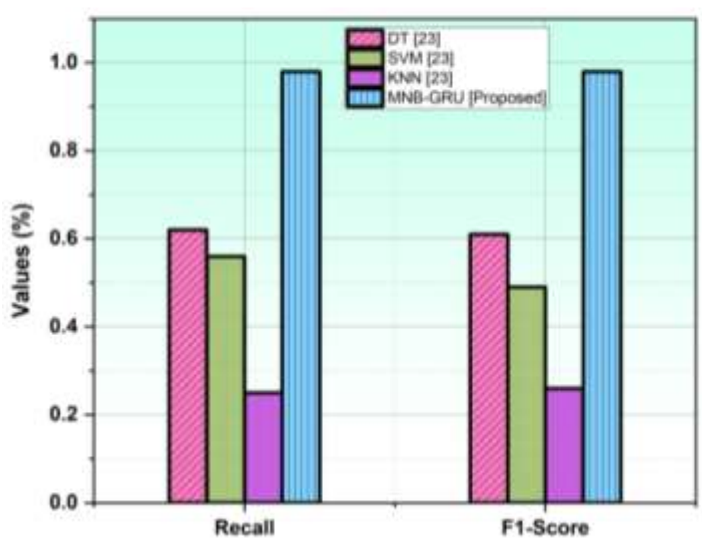

Figure 7. Comparison of Recall and F1- score

- **Study outcomes of Depression, Anxiety and mental health**

The matrix assessing a classification model for mental health is shown in the table along with its performance criteria. The model displays excellent efficacy in properly recognizing and classifying individuals' mental health conditions, demonstrating a robust and dependable prediction capability. It does this by showing high accuracy, precision, recall, and F1-score values across depression, anxiety, and overall mental health levels. Table 6 and Figure 8 depicts outcome of three levels.

Table 6. Findings of three levels

Parameters	**Depression**	**Anxiety**	**mental health**
Accuracy	97	99	96
Precision	97	98	96
Recall	97	99	96
F1 score	97	98	96

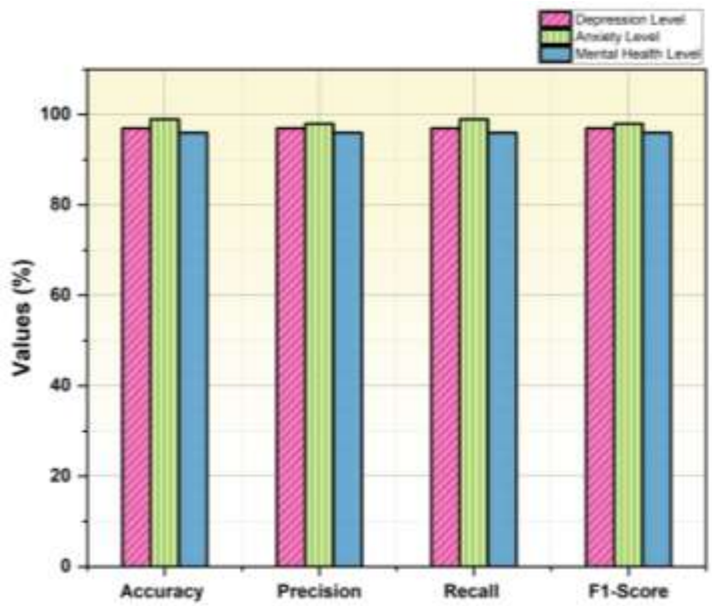

Figure 8. Comparison of Recall and F1- score

References

Aggarwal, S., Aggarwal, M., & Gupta, V. (2022). Gen Z entering the workforce: Restructuring HR policies and practices for fostering task performance and organizational commitment. *Journal of Public Affairs, 22*(3), e2535. https://doi.org/10.1002/pa.2535

Attridge, M. (2019). A global perspective on promoting workplace mental health and the role of employee assistance programs. *American Journal of Health Promotion, 33*(4), 622-629. https://doi.org/10.1177/0890117119838101c

Banerjee, D., Kosagisharaf, J. R., & Rao, T. S. (2021). The dual pandemic of suicide and COVID-19: A biopsychosocial narrative of risks and prevention. *Psychiatry Research, 295*, 113577. https://doi.org/10.1016/j.psychres.2020.113577

Boyd, K. L., & Andalibi, N. (2023). Automated emotion recognition in the workplace: How proposed technologies reveal potential futures of work. *Proceedings of the ACM on Human-Computer Interaction*, *7*(CSCW1), 1-37. https://doi.org/10.1145/3579528

Bruns, E. J., Kerns, S. E. U., Pullmann, M. D., Hensley, S., Lutterman, T., Hoagwood, K. E., & Jensen, P. S. (2019). The role of the outer setting in implementation: Associations between state demographic, fiscal, and policy factors and use of evidence-based treatments in mental healthcare. *Implementation Science, 14*, 1-13. https://doi.org/10.1186/s13012-019-0944-9

Cheung, T., Wong, S. Y. S., Wong, K. Y., Law, T., Ng, K., Tong, M. T., Wong, K. H., & Yip, P. S. F. (2020). Depression, anxiety, and stress in different subgroups of first-year university students from 4-year cohort data. *Journal of Affective Disorders, 274*, 305-314. https://doi.org/10.1016/j.jad.2020.05.041

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE, and RMSE in regression analysis evaluation. *PeerJ Computer Science, 7*, e623. https://doi.org/10.7717/peerj-cs.623

Collins, S. C., Tamati, T. L., London, J., & Engdahl, S. M. (2021). No safe space: School climate experiences of Black boys with and without emotional and behavioral disorders. *School Psychology Review*, 1-14. https://doi.org/10.1080/2372966X.2021.2021783

Cui, Y. (2021). The role of emotional intelligence in workplace transparency and open communication. *Aggression and Violent Behavior*, 101602. https://doi.org/10.1016/j.avb.2021.101602

Drake, R. E., Deegan, P. E., & Rapp, C. A. (2022). Shared decision making in mental health: Prospects for personalized medicine. *Dialogues in Clinical Neuroscience*. https://doi.org/10.31887/DCNS.2009.11.4/redrake

Fernández-Theoduloz, G., Ríos-Lago, M., Gómez-Pérez, E., & Ibáñez, A. (2019). Social avoidance in depression: A study using a social decision-making task. *Journal of Abnormal Psychology*, *128*(3), 234. https://doi.org/10.1037/abn0000415

Jiang, M., & Koo, K. (2020). Emotional presence in building an online learning community among non-traditional graduate students. *Online Learning*, *24*(4), 93-111. https://doi.org/10.24059/olj.v24i4.2307

Kirk, H. (2019). Prediction versus management models relevant to risk assessment: The importance of legal decision-making context. *Clinical Forensic Psychology and Law*, 347-359. https://doi.org/10.4324/9781351161565-3

Lee, H. (2021). Changes in workplace practices during the COVID-19 pandemic: The roles of emotion, psychological safety, and organizational support. *Journal of Organizational Effectiveness: People and Performance*, *8*(1), 97-128. https://doi.org/10.1108/JOEPP-06-2020-0104

Lirio, P., & Plusquellec, P. (2023). Affective computing technology for fostering an emotionally healthy workplace. *Strategic HR Review*. https://doi.org/10.1108/SHR-04-2023-0024

Negriff, S. (2020). ACEs are not equal: Examining the relative impact of household dysfunction versus childhood maltreatment on mental health in adolescence. *Social Science & Medicine*, *245*, 112696. https://doi.org/10.1016/j.socscimed.2019.112696

Ren, G., & Koo, K. (2019). HealthSit: Designing posture-based interaction to promote exercise during fitness breaks. *International Journal of Human–Computer Interaction*, *35*(10), 870-885. https://doi.org/10.1080/10447318.2018.1506641

Rezvani, A., & Khosravi, P. (2019). Emotional intelligence: The key to mitigating stress and fostering trust among software developers working on information system projects. *International Journal of Information Management*, *48*, 139-150. https://doi.org/10.1016/j.ijinfomgt.2019.02.007

Sahlan, M., Murtaza, G., Hassan, A., Shah, H., & Asghar, Z. (2021). Prediction of mental health among university students. *International Journal on Perceptive and Cognitive Computing*, *7*(1), 85-91. https://journals.iium.edu.my/kict/index.php/IJPCC/article/view/225

Shen, X., Yin, F., & Jiao, C. (2023). Predictive models of life satisfaction in older people: A machine learning approach. *International Journal of Environmental Research and Public Health*, *20*(3), 2445. https://doi.org/10.3390/ijerph20032445

Steinert, S., & Friedrich, O. (2020). Wired emotions: Ethical issues of affective brain–computer interfaces. *Science and Engineering Ethics*, *26*, 351-367. https://doi.org/10.1007/s11948-019-00087-2

Suhaimi, N. S., Rashid, R. A., Nor, H. M., & Mohamad, A. R. (2020). EEG-based emotion recognition: A state-of-the-art review of current trends and opportunities. *Computational Intelligence and Neuroscience, 2020*. https://doi.org/10.1155/2020/8875426

Tinetti, M. E., Naik, A. D., Dindo, L., Costello, D. M., Esterson, J., & Aguirre, A. C. (2019). Association of patient priorities–aligned decision-making with patient outcomes and ambulatory health care burden among older adults with multiple chronic conditions: A nonrandomized clinical trial. *JAMA Internal Medicine, 179*(12), 1688-1697. https://doi.org/10.1001/jamainternmed.2019.4235