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New method for assessing suicide ideation based on an attention mechanism and spiking neural network

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ABSTRACT

The COVID-19 pandemic has had a substantial effect on global mental health, leading to increased depression and suicide ideation (SI), particularly among young adults. This study introduces a novel method for enhancing SI assessment in young adults with depression, utilizing machine learning (ML) techniques applied to structural magnetic resonance imaging (SMRI) data. SMRI data from 20 individuals with depression and 60 healthy controls were analyzed. A hybrid ML algorithm, integrating self-attention mechanism and evolving spiking neural networks, successfully classified depression with 94% accuracy, 100% sensitivity, 92% specificity, and an area under the curve of 0.96. These results offer potential for enhancing mental health intervention and support in the context of the ongoing and post-pandemic period influenced by COVID-19.

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1. INTRODUCTION

The COVID-19 pandemic has significantly impacted young adults' mental health, leading to increased depression and suicidal tendencies, including suicide ideation (SI) [1]. This has resulted in a troubling rise in self-harm cases among individuals aged 18 to 24, with suicide becoming the second leading cause of death in this demographic [2]. Understanding the complex relationship between depression and SI is crucial for strengthening suicide prevention efforts [3]. Traditional methods for assessing suicide risk, such as the PHQ-9 self-report measure and face-to-face interviews, have limitations in accurately predicting suicidal behavior and potentially misidentifying people's risk level [4], [5]. These limitations underscore the urgent need for innovative approaches that focus on the association between SI and depression.

Machine learning (ML) offers promising possibilities for improving predictions across various medical domains [6]. In the field of suicide science, ML has emerged as a valuable tool for identifying complex patterns and analyzing diverse datasets [7]. Integrating ML with neuroimaging techniques presents new opportunities to identify biomarkers and understand the neural correlates of suicidal behaviors [8].

Structural magnetic resonance imaging (SMRI) plays a critical role in visualizing brain abnormalities, especially in depressed individuals [9]. Studies have revealed cortical thinning and volume reductions in specific brain regions associated with emotion regulation, executive function, and reward processing [10]. Utilizing ML and neuroimaging data aims to identify brain patterns linked to suicide risk, ultimately aiding in enhancing diagnostic accuracy for assessing an individual's likelihood of suicide.

This study introduces innovative ML models of self-attention mechanism (self-AM) and evolving spiking neural networks (ESNN), to enhance SI assessment among depressed young adults utilizing SMRI data [11], [12]. Self-AM organizes image features and measures their correlation to improve classification tasks, while ESNN excels in rapid learning and dynamic interaction. By combining these techniques, the model aims to enhance feature extraction and overall performance in SI assessment.

By combining self-AM with ESNN, the model enhances feature extraction and overall performance in neuroimaging analysis [13], [14]. This hybrid approach offers a powerful tool for assessing SI using SMRI data from depressed young adults, addressing a critical gap in existing literature that primarily relies on traditional ML classifiers [15]–[19]. The study aims to provide a unique and innovative approach to SI assessment, deepening our understanding of depression/SI links and offering precise tools to address vulnerabilities in this population.

In summary, this study addresses the urgent need to strengthen suicide prevention strategies among young adults. By leveraging innovative ML approaches and neuroimaging techniques, the study objectives were to enhance SI assessment and deepen the understanding of the complex link between depression and SI. The proposed research offers novel understandings and methodologies that hold promise for advancing the field of suicide science and improving mental health outcomes among young adults.

2. METHODS

This section presents the research methodology covering data acquisition, pre-processing, research design, and procedures. Data acquisition involved selecting public sMRI datasets of depressed young adults, chosen for their quality and comprehensiveness. Pre-processing steps included cleaning, normalization, and alignment of the sMRI data to a common reference framework to reduce errors and ensure data consistency. Each step was carefully planned and executed to ensure accuracy and reliability in the study's outcomes.

2.1. Data acquisition: dataset

The study utilized SMRI data from 20 depressed individuals (aged 19-24, mean age 21.95) and 60 healthy controls (aged 19-22, mean age 19.78. These datasets were obtained from reputable sources, including the OpenNeuro and SLIM dataset repositories [20]–[23]. The selection of these datasets was based on their availability, quality, and relevance to the study's objectives.

2.2. Data pre-processing

The sequential data preprocessing steps in this study are based on [24], [25]. It utilized subjects' baseline rest images and employed MATLAB R2021a software to initiate voxel-based morphometry (VBM) [26] analysis within statistical parametric mapping (SPM12) [27] for magnetic resonance imaging data pre-processing.

- Step 1. Registration: Images were oriented with Montreal Neurological Institute's T1-weighted templates [25].
- Step 2. Segmentation: Brain tissue was categorized into gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) [28]. The resulting GM and WM structural images were utilized as the input dataset for next stage of the process.
- Step 3. DARTEL: The image fitting accuracy was enhanced by developing regional templates for GM and WM [29], [30].
- Step 4. Normalization and smoothing: Aligned structural pictures with MNI brain template and reduced noise [31].
- Step 5. Image format conversion: Converted data to PNG format [32], [33], selecting the 61st image for each subject, resized to 50×50 pixels and cropped Figure 1.

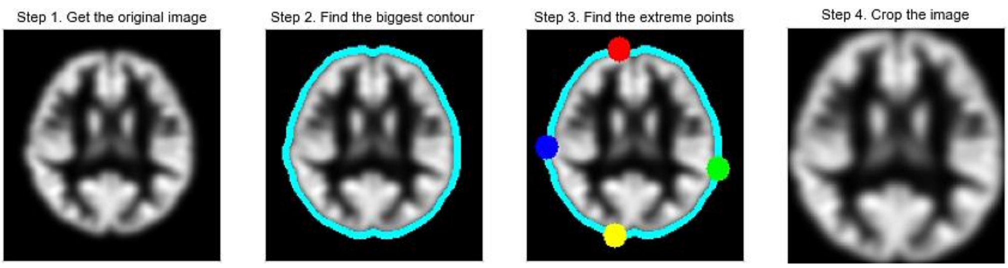

Figure 1. Image background cropping process

2.3. Research design

This study introduced a hybrid ML approach integrating self-AM and ESNN:
- Feature selection enhancement: Self-AM module prioritizes relevant features [34].
- Dynamic neuronal evolution: ESNN autonomously evolves and clusters neurons [35].
- Classification optimization: Final decisions determined by fastest responding neuron [36].
- Encoder functionality: Radial basis function serves as encoder [37], with self-AM layer preceding encoding stage.
- Training dynamics: Neurons continually update based on input data and labels.

The entire classification process is visually represented in Figure 2.

Input: Dataset $D = \{(X_i, Y_i)\}_{i=1}^{N}$, where '$X_i$' is the i-th input image and 'Y_i' is the corresponding binary label (0 or 1).

1. Data Preprocessing:
   for each image X_i in D:

   Normalize X_i #Apply normalization if needed
2. Feature Extraction:
   for each image X_i in D:

   $A_i = SelfAttention(X_i)$ #Apply self-attention layer
3. ESNN Encoding:
   for each feature representation A_i in D:

   $S_i = Encoder(A_i)$ #Encode into spike train
4. Initialize ESNN Model Parameters:
   Initialize neuron weights w and biases b
5. Model Training:
   for each (S_i, Y_i) in D:

   #Compute neuron activation

   $A_i = sum(S_i * w) + b$

   #Update neuron parameters

   $merge_{count} = sum(Y_i)$

   $$w_{new} = \frac{(merge_{count} \cdot w_{old} + w_i)}{(merge_{count} + 1)}$$

   $$b_{new} = \frac{(merge_{count} \cdot b_{old} + b_i)}{(merge_{count} + 1)}$$
6. Model Detection:
   for each new input image X_{test}:

   $A_{test} = SelfAttention(X_{test})$

   $S_{test} = Encoder(A_{test})$

   $Y_{pred} = Activate(S_{test}, w, b)$ #Propagate through adapted neurons

   return Y_{pred}
7. Evaluation:
   $Evaluate(Y_{pred}, Y_{true})$ #Compute classification metrics

Figure 2. The proposed model design for image classification

2.4. Research procedures

To address the challenge of imbalanced datasets in ML, strategic techniques were employed during both data preparation and model evaluation phases.
- Data normalization: Pixel values were normalized to the range [0, 1] [38].
- Stratified train-test split: Maintained balance of class frequencies [39].
- Synthetic minority oversampling technique (SMOTE): Generated synthetic instances of minority class [40].

– Stratified K (5)-fold cross-validation: Ensured consistent class distribution [41].
– Data augmentation: Applied random transformations to enrich training data [42].
– Hyperparameter tuning: Employed genetic algorithm for optimization [43].

Figure 3 illustrates the classification task design.

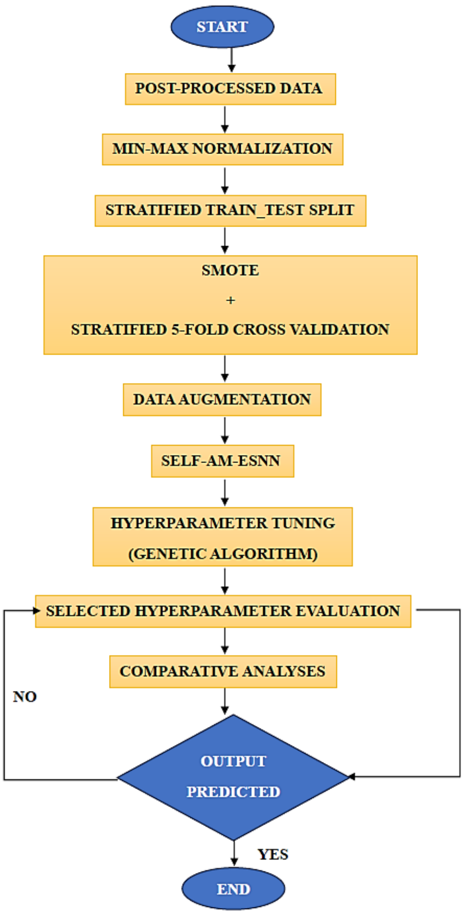

Figure 3. Design of the classification task for SI assessment

3. RESULTS AND DISCUSSION

This research introduces an innovative approach to SI assessment by combining advanced ML models with neuroimaging data. Unlike previous studies that relied on traditional ML classifiers [15]–[19], this method provides a more comprehensive analysis of brain patterns linked to SI. By leveraging modern techniques, the approach addresses significant gaps in earlier research, offering enhanced predictive capabilities.

3.1. Result interpretation and evaluation

Depressed and healthy control subjects were labeled as '1' and '0' respectively. The genetic algorithm explored hyperparameters, producing ten unique configurations evaluated through ten trials on accuracy, sensitivity, specificity, and area under the curve (AUC). The best configuration became the proposed model's main hyperparameter. The model was compared to traditional ML classifiers (K-nearest neighbor (KNN), logistic regression (LR), and support vector machine (SVM)) and relevant prior work.

3.2. Proposed model performance evaluation

The optimal hyperparameter configuration included 20 attention units, and ESNN parameter values of 0.17 Mod, 0.13 C, and 0.55 Sim. Across ten trials, the proposed model achieved the highest performance of accuracy 94%, sensitivity: 100%, specificity: 92%, and AUC: 0.96. These results highlight the model's potential in enhancing SI assessment utilizing SMRI data from depressed young adults. Figure 4 illustrates the model's performance across ten trials, showing consistent high performance in most trials with some variability.

Figure 5 presents self-attention visualizations, revealing focal points in the network and highlighting brain regions attracting heightened attention.

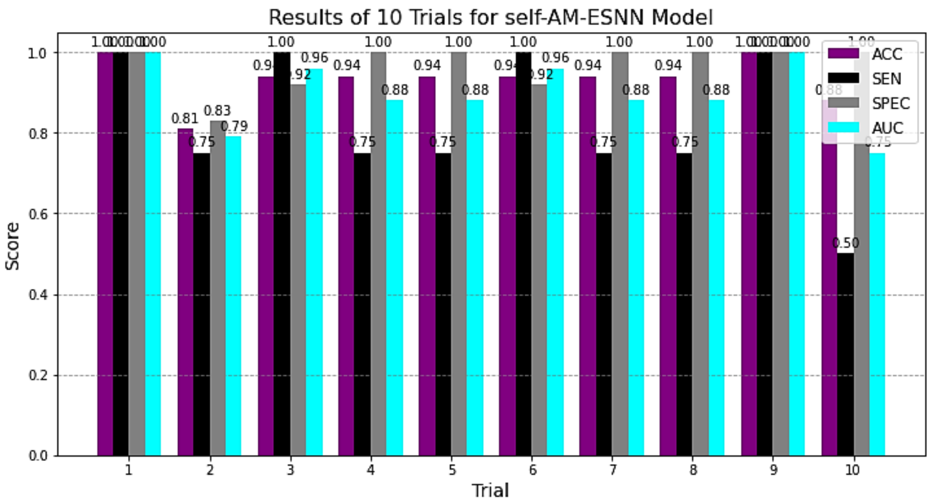

Figure 4. The results of ten trials of the proposed self-AM-ESNN model

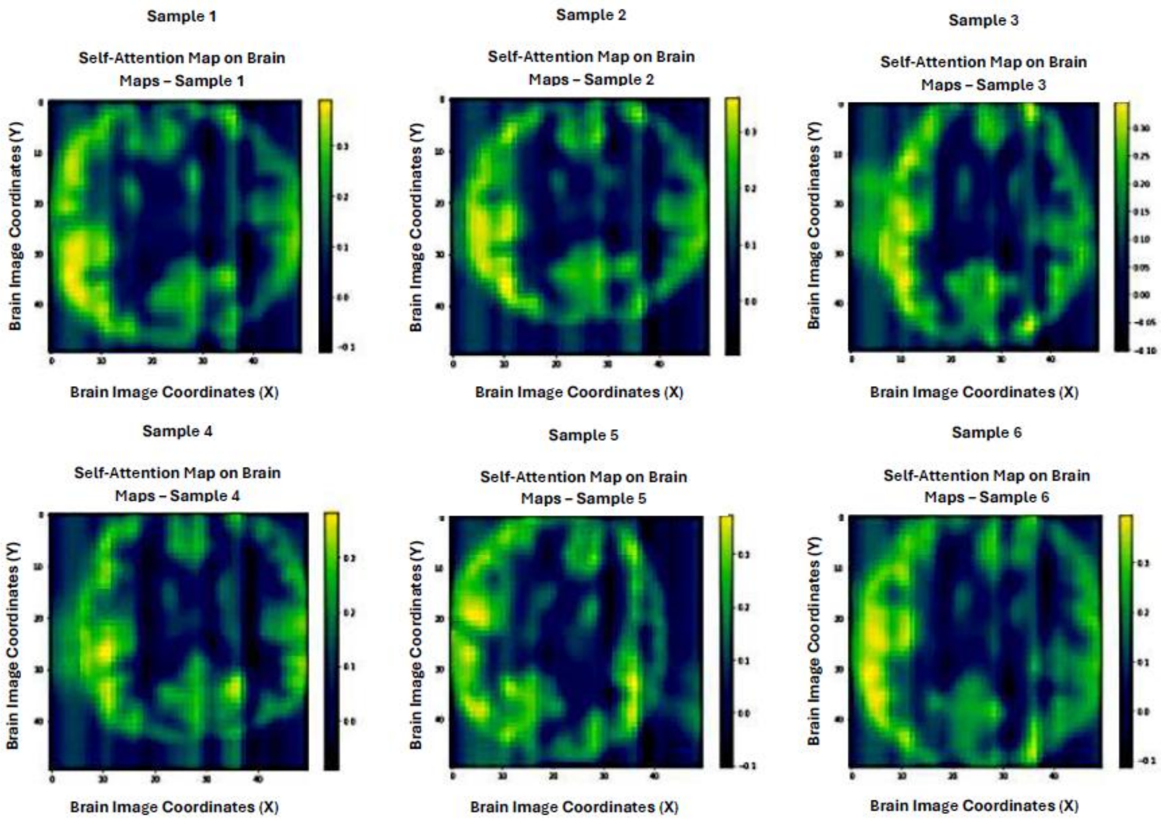

Figure 5. Self-AM maps for brain images

3.3. Comparative analysis

3.3.1. Traditional machine learning classifiers analysis

This study evaluated four classifiers–KNN (K=2), LR, SVM, and the proposed model–for brain image classification. Table 1 shows the average scores derived from ten trial results of each model. The proposed model outperformed traditional classifiers (KNN, LR, SVM) in average accuracy, specificity, and AUC. While KNN showed perfect sensitivity, it had lower accuracy and specificity. LR exhibited strong performance but did not surpass the proposed model's capabilities.

Table 1. Performance comparison of traditional ML classifiers (KNN, LR, SVM) with proposed model (average results)

Model	Average accuracy (%)	Average sensitivity (%)	Average specificity (%)	Average Auc
KNN	69	100	58	0.79
LR	91	85	93	0.89
SVM	83	50	94	0.72
Self-AM-ESNN	93	83	97	0.90

3.3.2. Past studies analysis

To demonstrate the advancements of the proposed model, it was compared to state-of-the-art SI assessment methods. Table 2 presents the highest results obtained from prior studies alongside those achieved by the proposed model. The proposed model outperformed existing studies, achieving the highest accuracy (94%) and perfect sensitivity (100%). It also showed competitive specificity and AUC values, surpassing or matching previous research outcomes.

Table 2. Performance comparison of the proposed model with existing studies (highest results)

Author	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
[15]	SVM, and ensemble	74.79	75.90	74.07	0.87
[16]	CNN, SVM, and XGB	85	75	100	
[17]	CNN	58.90	-	-	-
[18]	SVM	78.59	73.10	84	-
[19]	FCNN	70.12	75.61	63.08	-
Proposed model	Self-AM-ESNN	94	100	92	0.96

3.4. Discussion

This study addresses challenges exacerbated by COVID-19, particularly regarding the relationship between depression and SI in young adults. The proposed model's exceptional performance highlights its potential for enhancing SI assessment and advancing mental health research and practice. The integration of neuroimaging and ML techniques offers promising avenues for identifying new risk markers and developing patient-specific treatments [44], [45]. However, limitations such as the relatively small sample size and potential biases in data selection should be acknowledged. Future research should focus on larger sample sizes, more rigorous data collection procedures, and enhanced analytical methods. The application of this model in longitudinal studies, real-time SI assessment, and clinical settings warrants further investigation.

4. CONCLUSION

This study presents compelling evidence supporting the effectiveness of the hybrid self-AM-ESNN model for SI assessment. By outperforming traditional ML classifiers and surpassing the performance of previous research, our findings establish new benchmarks for SI brain image classification and assessment. The integration of advanced ML techniques with neuroimaging data holds significant promise for enhancing suicide prevention efforts. Moving forward, future research should focus on further validating and refining this approach, exploring its application in longitudinal studies, real-time SI assessment, and clinical settings. Collaborative efforts between researchers, clinicians, and policymakers are crucial for translating these findings into actionable interventions aimed at identifying and supporting individuals at risk of SI.

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