Performance Evaluation of Attention Mechanism and Spiking Neural Networks on sMRI Data for Suicide Ideation Assessment

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Abstract— **The coronavirus disease 2019 (COVID-19) pandemic has had a substantial detrimental impact on mental health, especially depression, and this has led to a high incidence of suicidal ideation (SI) around the globe, with the pandemic's post-peak period seeing the highest incidence in young adults. This study aims to propose an effective non-intrusive method for early detection of SI in young adults utilizing depression as a biomarker in structural magnetic resonance imaging. This paper introduces a hybrid machine learning approach utilizing attention mechanisms and spiking neural networks to differentiate between depression patients without SI and healthy controls. The hybrid method successfully completed the classification task after stratified 5-fold cross-validation, achieving test accuracy, sensitivity, specificity, and area under curve of 94%, 100%, 92%, and 0.96, respectively. The proposed algorithms offer an objective tool for identifying early SI risk in depressed patients without suicidal thoughts, alongside clinical assessment.**

Keywords— attention mechanism, depression, machine learning, spiking neural network, suicide ideation

I. Introduction

The psychological aftermath of the coronavirus disease 2019 (COVID-19) pandemic has been demonstrated by depression and suicidal tendencies [1] with the prevalence of depression, particularly among young adults aged 18 to 29, as well as suicidal tendencies, remaining high throughout the pandemic until after post-pandemic [2]. The Spanish Psychiatry Association highlights that the probability of committing suicide is linked to depression, where the risk is magnified by 21 times [3]. Poor measurement of suicidal outcomes, such as suicidal ideation (SI), is a significant factor in understanding and reducing suicide [4], as depression has been identified as a significant risk factor [5]. The rise in suicide incidents has sparked mounting apprehension as SI has become more prevalent amidst the COVID-19 outbreak among young adults in the age of 18 to 24 [6]. SI denotes the initial phase of the suicidal process, and it can serve as a possible point of intervention for forthcoming suicide prevention measures [7]. Studies on SI detection often utilize traditional methods such as self-reports and medical evaluations, but these methods require active participation, leading to substantial costs [8]. Patients' willingness to disclose information also limits accuracy and predictive value, resulting in potential bias and limited application [9]. Another method involves clinical approaches, that rely on the interaction between professionals and the individuals at risk [10]. According to Samuel Knapp, writer of Suicide Prevention: An Ethically and Scientifically Informed Approach, psychologist believe that the most effective approach to dealing with a patient with SI is to refer them to the emergency department and initiate their prescription of antidepressants without delay [11]. However, some patients may be hesitant to acknowledge SI due to fear of involuntary hospital admission [12]. Traditional procedures frequently fail to recognize suicide in its early stages, and depression scales, SI measures, and risk assessment tools lack a reliable score for predicting a small group of SI patients [13]. This highlights the need for improved procedures and new SI evaluation techniques to improve suicide risk diagnosis and care. Machine learning (ML) techniques are being utilizes to predict and classify mental diseases [14], with the main premise being that computers can learn from data by identifying patterns and understanding it with less human interaction [15]. As new data is exposed, ML's detection patterns can be modified and enhanced, resulting in improved efficacy, complexity, and adaptability [16]. The study by [17] highlights the potential of ML applications in enhancing clinical and research practices in psychology and mental health by analyzing existing literature on the utilization of ML and big data in mental health research. The ML algorithm for forecasting suicidal tendencies yields more precise results than traditional clinical methods [18]. Thus, ML offers new opportunities for enhancing suicide prevention systems and computer-based learning of sophisticated classifiers, which can improve prediction accuracy through large datasets [19]. The utilization of ML in suicide research has rapidly increased in recent years, often highlighting its potential to enhance the anticipation and deterrent of suicidal behavior (SB) [20]. A systematic review of ML studies on SB found that ML approaches can accurately predict SB, with an area under the curve (AUC) of over 90% [9]. Depression is a severe mental disorder that significantly affects daily functioning and quality of life by disrupting concentration, motivation, and mental abilities, leading to limitations in daily activities and potential suicidal tendencies [21]. Therefore, it is crucial for researchers and medical professionals to comprehend its pathophysiology. ML is increasingly being utilizes in neuroimaging research to process complex brain imaging data, which is often utilized to view, measure, and evaluate the anatomical properties of brain structures with structural neuroimaging methods such as MRI and CT [22]. Neuroimaging aids in understanding disease mechanisms and identifying biomarkers [23]. Indeed, previous research indicates that changes in specific brain regions and circuits may play a role in SI and SB, despite limited sample sizes and varied neuroimaging techniques [24]. Researchers are increasingly utilizing supervised ML algorithms and multivariate pattern classification approaches to understand the complexity of psychiatric illnesses, particularly in the investigation of suicide with neuroimaging [25]. This approach can help identify new areas of focus and establish the foundation for accurate management of suicidal individuals [26]. Hence, this study proposes a hybrid technique combining attention mechanism (AM) and spiking neural networks (SNN) models to enhance SI detection in depressive individuals without SI (DNS) and healthy controls (HC) utilizing structural MRI (sMRI) scans of young adults for depression categorization. This study is inspired by previous studies [27], [28], [29], [30] that employed sMRI for SI detection based on a depression biomarker.

II. Related works

Studies suggest that early detection of SI can save lives [31]. Recent interest in SI research has increased, focusing on social media data and text analysis to understand people's suicidal intentions [32]. Social media posts are crucial for diagnosing suicidal individuals due to their ability to reveal rapid behavioral changes [33]. The integration of AM into a neural network framework to understand the textual content in social media data is discussed extensively in the literature on the detection of SI and depression [34]. The main goal of AM is to emphasize the important parts of the data while lessening the attention on the unimportant ones [35]. An average accuracy of 90.15% was attained in [34] when AM and fusion deep learning model were utilized to identify the explicit and implicit context of depression. Furthermore, AM was utilized in [36] to filter significant data on depression diagnosis in social media posts, resulting in a 1.08% increase in the model's accuracy. The study in [37] utilized AM layers to detect SI utilizing individual knowledge graphs and dynamically altering risk factor weights, achieving an accuracy rate of 93.74% on Weibo's dataset and 65.92% on Reddit's. Moreover, [38] integrates SI with topical clues about current events and emotional cues, utilizing AM to prioritize significant relational features, however, it is ineffective in forecasting low-risk SI. The utilization of social media data has limitations in understanding SI, as it does not directly address depression severity or risk factors by incorporating suicide psychology, which is essential for effective suicide prevention [10], [34]. Alternatively, AM makes a significant improvement in the analysis of medical data [39]. Attention-based medical image analysis has shown success in extracting contextual data from MRI scans, leading to a better outcome [40]. By prioritizing key clinical feature regions, AM algorithms can increase resilience [41]. However, despite its effectiveness, most research on suicide that utilized AM has focused on social media data analysis. AM's potential in neuroimaging analysis for SI and depression is worth investigating, as it yields excellent results when applied to medical image data. Spiking neural networks (SNN), the third generation of artificial neural networks, aims to create more accurate neuronal models by closely imitating human brain operations [42]. The model differs from traditional neural networks in the ML community due to its utilization of spikes (electrical impulses), unlike the continuous value utilized in traditional ML [43]. The temporal dynamics making SNN useful for real-time functioning and data-based updates [44]. SNN algorithms are widely utilize in healthcare for medical data classification due to their natural power-efficiency, biological plausibility, and outstanding image recognition ability [45]. In [46], the utilization of SNN led to a classification accuracy rate of 96.97% for breast cancers. Moreover, SNN also has been utilized in neuroimaging for disease detection, with [47] introduces a superior MRI segmentation technique for tumor diagnosis, achieving 98.21% accuracy and MRI classification for Alzheimer's disease achieving accuracy ranging from 70% to 90% [48]. Overall, most SNN-based experiments for medical data demonstrated improved performance with accuracy levels over 70%. However, to our understanding, there is no suicide research studies that have utilized SNN model. This study introduces a hybrid approach that incorporates AM and SNN (AM-SNN) models, utilizing neuroimaging data from DNS and HC subjects to enhance predictive frameworks for SI. Neurons in the brain only fire when they are triggered by external input in which the surroundings or other neurons may provide this input, thus overfitting and high energy consumptions may be avoided [48]. Because SNN can benefit from the sparsity of neuronal activity, they have the potential to be more effective than conventional ML. Moreover, SNN has a dynamic nature, as a result, it performs exceptionally well when utilized with dynamic processes such as speech and visual recognition [44]. AM on the other hand, shows great result in the ML community as it aided to prioritizes crucial data for a ML model to utilize. Therefore, the notion of ESNN and AM are worthy to be explore.

III. Methodology

A. Dataset

The study analyzed sMRI data from publicly available datasets [49], [50], [51], and [52] to show the effectiveness of the proposed model. Participants aged 19 – 24 were selected with a total of 80 sMRI images were collected, in which 20 being DNS and 60 being HC. The dataset details are presented in Table I.

TABLE I. Elaborate data of the experimental dataset

Dataset	OpenNeuro	SLIM
Research subject	DNS	HC
Number of samples	20	60
Average age	21.95 (19 – 24)	19.78 (19 – 22)
Gender (Male/ Female)	5/ 15	20/ 40

B. Data pre-processing

The study utilized a baseline data image of all subjects at rest, and Matlab R2021a software to launch the voxel-based morphometry (VBM) analysis within the Statistical Parametric Mapping (SPM12) for data pre-processing. The data pre-processing steps are as follows:

1. ***Re-orientation***: To ensure that the brain's anatomy is positioned correctly and centered, orientation is necessary as once the data are trained with the ML models, the calibration remains consistent throughout. The sMRI data was oriented based on the Montreal Neurological Institute's (MNI) TW1 templates.

2. ***Segmentation***: The segmentation procedure classifies brain tissue types utilizing the orientated images, with SPM12 automatically distinguishing between gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). The GM structural

graphics were utilized as the input dataset for the AM-SNN model.

3. ***DARTEL***: The Diffeomorphic Anatomical Registration Through Exponential Lie Algebra (DARTEL) was utilized to enhance image fitting accuracy by creating a regional template for GM and WM through repeated iterations of the tissue class images. The process of each cycle enhances the alignment of individual photos, resulting in the creation of clearer templates.

4. ***Normalization + Smoothing***: The normalizing process involves standardization, where the structural pictures are adjusted to fit an MNI brain template, with smoothing being a crucial part of this process.

5. ***Image Format Conversion***: The final format of the data was furnished in raw Neuroimaging Informatics Technology Initiative (NIfTI) format as a 3D images. JPEG, PNG, and TIFF are widely utilize image formats for ML models. Therefore, the NIfTI format are conversed to the PNG format. Converting images to PNG ensures the preservation of original image data while maintaining the authenticity of the original graphics. The Matlab instructions for image conversion can be found at https://alexlaurence.github.io/NIfTI-Image-Converter/. The converted images are rescaled into a fixed 50 x 50 pixels format to ensure the proposed model can efficiently extract features.

The process of pre-processing sMRI data is depicted in Fig. 1.

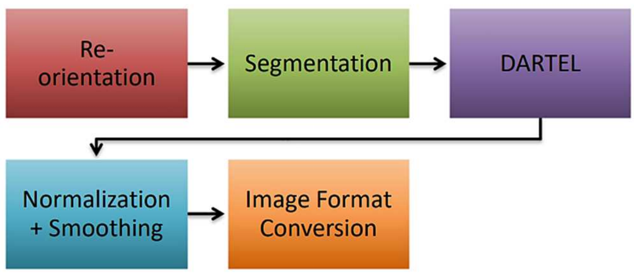

Fig. 1. The workflow for the sMRI data pre-processing

C. Image Augmentation and Cross-Validation

The dataset utilized in this study is an unbalanced one, which often leads to subpar results due to ML techniques ignoring minority classes. To address this issue, the Synthetic Minority Oversampling Technique (SMOTE) and Stratified K-Fold cross-validation were employed to expedite the training and testing processes, as they are the most effective methods for dealing with such data.

D. AM-SNN

This study aims to create integrated neural network structures and implement them to enhance the classification of sMRI images from both DNS and HC participants. The image categorization process involves combining self-AM and ESNN models, with the attention layer integrated into the ESNN architecture. Self-AM is a module in AM that enables inputs to communicate with one another ("self") and determine which ones require more focus [53]. The self-AM layer aids the ESNN model by focusing on the relevant input dataset and passing filtered data for processing, thereby enhancing its performance. Evolving SNN (ESNN) is an enhance version of SNN. Neurogenesis, the process through which new neurons are developed in the brain, is the source of inspiration for ESNN in which the general concept behind ESNN is to determine how many neurons the network will need to complete a task throughout the training phase [54]. In this study, the leaky integrate-and-fire (LIF) neuron model was utilized with the rank order population encoding (ROPE) implementation that was based on the rank order (RO) learning rule. The LIF model is built on a simple resistor-capacitor circuit with extra rules, allowing model neurons to fire when the membrane potential exceeds a threshold, simulating the spiking behavior of neurons [55]. The membrane voltage will then revert to a value below the threshold after each spike in order to continue integrating the input. RO learning posits that the most crucial input pattern information is stored in the previously arrived spikes [56]. The ROPE is an extension of the RO rule, and it assigns data samples to spikes for categorizing actual data. Population encoding involves grouping neurons with similar weight vectors, specified by Euclidean distance. The sum of responses from multiple neurons can estimate input value, allowing ML models to label and structure neurons based on their affiliation with a category during categorization tasks [56]. The proposed AM-SNN model algorithm is presented in Fig. 2.

1. Initialize output neuron repository, $R_l = \{\}$
2. Set ESNN parameters: $mod_l = [0,1], C_l = [0,1], sim_l = [0,1]$
3. ***For all*** $\forall$ input pattern $X^{(i)}$ that belongs to the same class l **do**
4. Encode input pattern into firing time of multiple pre-synaptic neurons j
5. Embedded the self-AM into the ESNN framework.
6. Create a new output neuron i for this class and calculate the connection weight as $w_{ji} = mod^{order(j)}$
7. Calculate $PSP_{max(i)} = sum_j w_{ji} \times mod^{order(j)}$
8. Calculate PSP threshold value $Y_i = PSP_{max(i)} \times C$
9. ***if*** the new neuron weight vector $\leq$ sim of trained output neuron weight vector in R, ***then***
10. ***update*** the weight vector and threshold of the most similar neuron in the same output class group
11. $W = \frac{w_{new} + w.N}{N+1}$
12. $\gamma = \frac{\gamma_{new} + \gamma N}{N+1}$ where N is the number of previous merges of the most similar neuron
13. ***else***
14. Add the weight vector and threshold of the new neuron to the neuron repository R
15. ***end if***
16. ***end for***
17. Repeat above for all input patterns of other output classes

Fig. 2. The proposed AM-SNN model algorithm

IV. RESULT AND DISCUSSIONS

Here, we evaluate the hybrid AM-SNN model's performance, and the findings from numerous trials are explained in more detail.

A. Result Interpretation and Evaluation

In this study, the DNS and HC subjects were divided into "1" and "0" categories, and we utilized the confusion matrix to evaluate the performance of ML model with the metrics of accuracy (ACC), sensitivity (SEN), specificity (SPEC), and area under the curve (AUC). Additionally, the ESNN framework's neuron counts was also utilized to estimate the number of neurons generated during the classification task. Then, the proposed model was compared to traditional ML classifiers by training two classic ML classifiers; support vector machine (SVM) and k-nearest neighbor (KNN).

Additionally, the proposed model also was compared to the past investigations.

B. Results and Discussion

The AM-SNN model achieved a 94% ACC, 100% SEN, and 92% SPEC in classifying DNS and HC utilizing stratified 5-fold cross-validation. Fig. 3 shows the ROC curve of the model with an AUC of 0.96. The ROC curve is a crucial evaluation standard for classification models, with a higher AUC value indicating superior performance, as demonstrated by the AM-SNN model. The result implies that the utilization of ML techniques may be utilized to enhance the SI assessment in order to identify early SI phase based on sMRI of depressed young adults. SNN employs time pulses for spatiotemporal instances to precisely replicate the functioning of the biological brain.

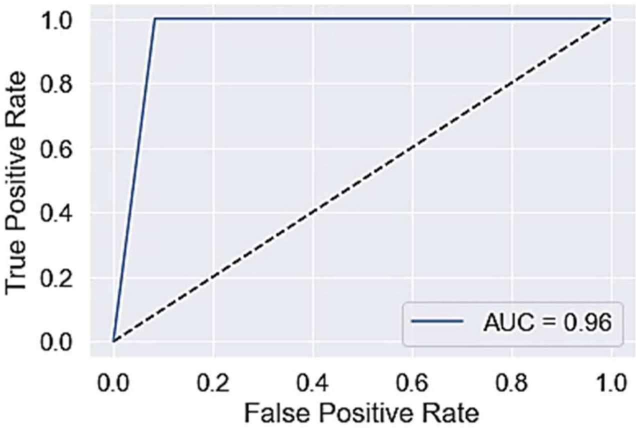

Fig. 3. ROC-AUC graph of the model.

The rate of time pulses between neurons is crucial for accurate classification, allowing for the use of target data for configuration definition. AM plays a crucial role in reinforcing the performance of the SNN framework. AM often resembles human cognitive attention, and in the context of ML, attention aims to emphasize the crucial portions of the image data by giving them more weight while ignoring the less crucial ones. During the training phase, each image's pixels are converted into spike trains, each encoding the intensity of a single pixel. The spike trains are received as input by the spiking neurons connected to the embedded AM. The AM prioritized important spikes, ignoring unimportant ones, and allowed them to spike next. Following that, the SNN learning rule was utilized to calculate and combine the membrane potential of each neuron based on the spiking input. The testing procedure's classification task is generated using the spike output. The experimental results for both the SNN model and the suggested model are presented, with Table II showcasing the SNN model's performance without and with attention module.

TABLE II. THE COMPARISON BETWEEN SNN MODEL WITHOUT AND WITH ATTENTION MODULE

MODEL	ACC	SEN	SPEC	AUC	NEURON COUNTS
SNN	88%	100%	83%	0.92	88
AM-SNN	94%	100%	92%	0.96	90

Table II reveals that incorporating the AM into the SNN model leads to an enhancement in all performance indicators. The SNN model incorporates AM, enabling it to gather knowledge from all image levels, including the lowest layer. Computer vision AM operated by varying the weights or scores given to input components such as pixels, regions, or features. These weights help the model focus on the most relevant areas of the image, ignoring distractions (background), to achieve better image classification tasks. Moreover, the proposed model, when combined with the AM model, resulted in the generation of more new neurons for optimal performance. The AM-SNN model efficiently generates new data without retraining, simplifying the SI assessment process, saving time and money in practice. Table III compares the experimental results of the proposed model with the traditional ML classifiers, SVM and KNN.

TABLE III. COMPARISON WITH TRADITIONAL MACHINE LEARNING CLASSIFIERS, THE BEST PERFORMANCES ARE INDICATED IN BOLD.

MODEL	ACC	SEN	SPEC	AUC
SVM	81%	100%	75%	0.88
KNN (*K*=2)	81%	75%	83%	0.79
AM-SNN	**94%**	**100%**	**92%**	**0.96**

The proposed model outperformed traditional ML classifiers in terms of ACC and AUC value, as shown in Table 3. SVM and KNN achieved 81% ACC but are biased towards the majority class output due to imbalanced data. SVM, a widely recognized supervised learning system, excels in classification and regression problems but may struggle when the number of characteristics exceeds the training data [57]. Our dataset contains 80 samples with each sample consisting of 2,500 features, thus as seen in Table III, despite the model's ability to identify the "1" class accurately, the maximum accuracy the model able to yield is 81% with 0.88 AUC value. The KNN, a "lazy learning" algorithm utilizing instance-based learning, faces a significant challenge in determining the optimal number of neighbors *K* to utilize [58]. The study found that *K*=2 achieved the best outcome with an accuracy of 81% in a comparative experiment. However, the model's classifier performance was mediocre due to a lower AUC value of 0.79, and the SVM outperformed the KNN but failed to beat the AM-SNN model. Lastly, the proposed model is compared with previous studies on SI detection utilizing depression sMRI data, as illustrated in Table IV.

TABLE IV. PAST STUDIES COMPARISON WITH PROPOSED MODEL, THE BEST PERFORMANCES ARE INDICATED IN BOLD.

AUTHOR	MODEL	ACC	SEN	SPEC
Weng et al. [27]	CNN, XGB and LR	85%	75%	100%
Chen et al. [28]	CNN	58.9%	-	-
Hong et al. [29]	SVM	78.59%	73.1%	84%
Hu et al. [30]	FCNN	70.12%	75.61%	63.08%
PROPOSED MODEL	**AM-SNN**	**94%**	**100%**	**92%**

Recent years have seen limited investigations of SI using sMRI and depression biomarkers, as shown in Table IV. Convolutional neural networks (CNN) utilize convolution to analyze images fast by applying filters to extract features for classification, which speeds up data processing and makes it possible for them to process information more effectively than other methods [59]. CNN, through meticulous data analysis, can effectively identify intricate patterns in images with high accuracy rates. However, the dataset utilized in [27], [28], and [30] was relatively small, with the highest number of 288 data in [30]. The utilization of CNN in [27], [28], and [30] has several layers and parameters and the model requires a lot of computing power and memory to operate. Because of this, the CNN was unable to attain high accuracy rates. In [27], it was discovered that extreme gradient boosting (XGB) beat logistic regression (LR) with 85% ACC after feature extraction with CNN. The SVM model utilized in [29] was outperformed as well by the XGB. One advantage of XGB is that it utilizes several trees in an ensemble technique, which allows it more flexibility over time. However, if the parameters are too deep, XGB tend to overfit particularly with noisy data such as MRI. SVM’s strength lies in its ability to project data into a high-dimensional space, enabling linear separation for almost any data, but it also requires a kernel, which may not be perfect for every dataset. Hence, the proposed model demonstrated superior performance compared to the traditional ML classifiers.

V. CONCLUSION

The study utilized the AM-SNN framework to analyze sMRI data for the classification task of DNS and HC individuals. The results offer strong support for technology advancements and approaches that could have a substantial influence on early SI detection and suicidal risk reduction by utilizing depression biomarkers in neuroimaging data. The study compared traditional ML techniques and past SI assessment research, revealing that the AM-SNN framework significantly enhanced sample classification accuracy and demonstrated neuroimaging's potential in SI assessment. This study presents the initial ML frameworks for evaluating SI using neuroimaging depression biomarkers with AM and SNN. Our model will be particularly beneficial in identifying individuals who may need care before they reach a crisis point.

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