



**Faculty of Cognitive Sciences & Human Development**

**Leveraging sMRI, Self-Attention Mechanisms, and Evolving Spiking  
Neural Networks for Enhanced Suicide Ideation Detection in Depressed  
Young Adults**

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Leveraging sMRI, Self-Attention Mechanisms, and Evolving Spiking Neural  
Networks for Enhanced Suicide Ideation Detection in Depressed Young  
Adults

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## DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



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## ABSTRACT

Accurate assessment of suicide ideation (SI) risk in depressed young adults remains a critical challenge, with existing methods exhibiting limited effectiveness. This study proposes a novel machine learning approach leveraging Evolving Spiking Neural Networks (ESNN) to enhance SI risk detection utilizing structural magnetic resonance imaging (sMRI) data. ESNNs, inspired by the brain's information processing mechanisms, excel at capturing temporal and spatial patterns in data, making them well-suited for modeling the complex dynamics of SI risk factors. Unlike traditional neural networks, ESNNs employ spiking neurons and adaptive learning mechanisms that continuously update internal representations, enhancing their robustness to changing risk factors and individual SI trajectories. However, their application in SI detection has been largely underexplored, creating a gap in leveraging their unique capabilities for this critical task.

To address this gap, the self-AM-ESNN model is introduced, which integrates self-attention mechanisms (self-AM) with ESNN to enable effective feature extraction and learning from sMRI data. By integrating self-AM with ESNN's dynamic learning capabilities, the model can capture complex neuroanatomical patterns associated with SI risk while adapting to individual variations. Evaluated on a dataset of 20 depressed individuals and 60 healthy controls, the self-AM-ESNN model demonstrated exceptional performance in classifying depression, achieving 94% test accuracy, 100% sensitivity, 92% specificity, and an area under the curve of 0.96.

These promising results highlight the potential of ESNN-based approaches to augment clinical decision-making and mental health interventions for SI risk assessment. Furthermore, the study incorporates a user-centric evaluation framework that enables mental

health professionals and service users to assess the model's detections and rationale, facilitating informed decision-making processes. By providing interpretable insights into the underlying factors contributing to SI risk, this approach empowers stakeholders to make more informed choices and tailor interventions accordingly.

**Keywords:** Suicide ideation; evolving spiking neural networks; structural MRI; depression; clinical decision-making

***Memanfaatkan sMRI, Mekanisme Perhatian Kendiri, dan Rangkaian Neural Berduri Berubah untuk Meningkatkan Pengesanan Ideasi Bunuh Diri dalam Kalangan Dewasa Muda yang Mengalami Kemurungan***

**ABSTRAK**

*Penilaian yang tepat terhadap risiko ideasi bunuh diri (SI) dalam kalangan dewasa muda yang mengalami kemurungan masih menjadi cabaran kritikal, dengan kaedah sedia ada menunjukkan keberkesanan yang terhad. Kajian ini mencadangkan pendekatan pembelajaran mesin baharu yang memanfaatkan Rangkaian Neural Berduri Berubah (ESNN) untuk meningkatkan pengesanan risiko SI menggunakan data pengimejan resonans magnetik struktur (sMRI). ESNN, yang diilhamkan oleh mekanisme pemprosesan maklumat otak, cemerlang dalam menangkap corak temporal dan spatial dalam data, menjadikannya sesuai untuk memodelkan dinamik kompleks faktor risiko SI. Tidak seperti rangkaian neural tradisional, ESNN menggunakan neuron berduri dan mekanisme pembelajaran adaptif yang sentiasa mengemas kini representasi dalaman, meningkatkan ketahanannya terhadap faktor risiko yang berubah-ubah dan trajektori SI individu. Walau bagaimanapun, penggunaannya dalam pengesanan SI sebahagian besarnya belum diterokai, mewujudkan jurang dalam memanfaatkan kemampuan unik mereka untuk tugas kritikal ini.*

*Untuk mengatasi jurang ini, model self-AM-ESNN diperkenalkan, yang mengintegrasikan mekanisme perhatian kendiri (self-AM) dengan ESNN untuk membolehkan pengekstrakan ciri dan pembelajaran yang berkesan daripada data sMRI. Dengan mengintegrasikan self-AM dengan keupayaan pembelajaran dinamik ESNN, model ini dapat menangkap corak neuroanatomi kompleks yang berkaitan dengan risiko SI sambil menyesuaikan diri dengan variasi individu. Dinilai berdasarkan dataset yang terdiri daripada 20 individu yang mengalami kemurungan dan 60 kawalan yang sihat, model self-AM-ESNN menunjukkan*

*prestasi yang luar biasa dalam mengklasifikasikan kemurungan, mencapai ketepatan ujian sebanyak 94%, sensitiviti 100%, kekhususan 92%, dan kawasan di bawah lengkung sebanyak 0.96.*

*Hasil yang menjanjikan ini menonjolkan potensi pendekatan berasaskan ESNN untuk meningkatkan proses membuat keputusan klinikal dan intervensi kesihatan mental untuk penilaian risiko SI. Selain itu, kajian ini menggabungkan rangka kerja penilaian berpusatkan pengguna yang membolehkan profesional kesihatan mental dan pengguna perkhidmatan menilai pengesanan dan rasional model, memudahkan proses membuat keputusan yang lebih berinformasi. Dengan menyediakan wawasan yang boleh ditafsirkan mengenai faktor-faktor asas yang menyumbang kepada risiko SI, pendekatan ini memperkasakan pihak berkepentingan untuk membuat pilihan yang lebih berinformasi dan menyesuaikan intervensi dengan sewajarnya.*

**Kata kunci:** *Ideasi bunuh diri; Rangkaian neural berduri berubah; MRI struktur; kemurungan; Membuat keputusan klinikal*



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## LIST OF ABBREVIATIONS

|          |                                                                         |
|----------|-------------------------------------------------------------------------|
| 2D       | Two-dimensional                                                         |
| 3D       | Three-dimensional                                                       |
| ACC      | Accuracy                                                                |
| AM       | Attention Mechanism                                                     |
| AUC      | Area Under the Curve                                                    |
| CNN      | Convolutional Neural Network                                            |
| COVID-19 | Coronavirus Disease 2019                                                |
| CSF      | Cerebrospinal Fluid                                                     |
| DARTEL   | Diffeomorphic Anatomical Registration Through Exponentiated Lie Algebra |
| DASS-21  | Depression Anxiety & Stress Scale Questionnaire – 21 Questions          |
| DenseNet | Densely Connected Convolutional Networks                                |
| DL       | Deep Learning                                                           |
| ECOS     | Evolutionary Computation of Structures                                  |
| EDA      | Exploratory Data Analysis                                               |
| EEG      | Electroencephalography                                                  |
| ESNN     | Evolving Spiking Neural Network                                         |
| FC       | Frontal Cortex                                                          |
| FCNN     | Fully Connected Neural Network                                          |
| FN       | False Negative                                                          |
| FP       | False Positive                                                          |
| GA       | Genetic Algorithm                                                       |
| GM       | Gray Matter                                                             |

|              |                                                                                               |
|--------------|-----------------------------------------------------------------------------------------------|
| GMV          | Gray Matter Volume                                                                            |
| HC           | Healthy Controls                                                                              |
| HP           | Hyperparameter                                                                                |
| INDI         | International Neuroimaging Data-Sharing Initiative                                            |
| KNN          | K-Nearest Neighbors                                                                           |
| LR           | Logistic Regression                                                                           |
| MDD          | Major Depressive Disorder                                                                     |
| ML           | Machine Learning                                                                              |
| MNI          | Montreal Neurological Institute                                                               |
| MRI          | Magnetic Resonance Imaging                                                                    |
| NIfTI        | Neuroimaging Informatics Technology Initiative Neuroimaging Informatics Technology Initiative |
| NLP          | Natural Language Processing                                                                   |
| PCA          | Principal Component Analysis                                                                  |
| PFC          | Prefrontal Cortex                                                                             |
| PNG          | Portable Network Graphics                                                                     |
| RBF          | Radial Basis Functions                                                                        |
| RF           | Random Forest                                                                                 |
| ROC          | Receiver Operating Characteristics                                                            |
| ROC-AUC      | Receiver Operating Characteristics-Area Under the Curve                                       |
| ROI          | Regions of Interest                                                                           |
| SA           | Suicide Attempters                                                                            |
| Self-AM      | Self-Attention Mechanism                                                                      |
| Self-AM-ESNN | Self-Attention Mechanism and Evolving Spiking Neural Network                                  |
| SEN          | Sensitivity                                                                                   |

|         |                                                        |
|---------|--------------------------------------------------------|
| SI      | Suicide Ideation                                       |
| SIB     | Suicide Ideation and Behaviors                         |
| SLIM    | Southwest University Longitudinal Imaging Multimodal   |
| sMRI    | Structural Magnetic Resonance Imaging                  |
| SMOTE   | Synthetic Minority Over-sampling Technique             |
| SNN     | Spiking Neural Network                                 |
| SPEC    | Specificity                                            |
| SPM12   | Statistical Parametric Mapping 12                      |
| SVM     | Support Vector Machine                                 |
| SVM-RFE | Support Vector Machine - Recursive Feature Elimination |
| T1w     | T1 weighted                                            |
| TN      | True Negative                                          |
| TP      | True Positive                                          |
| UNIMAS  | Universiti Malaysia Sarawak                            |
| VBM     | Voxel-Based Morphometry                                |
| WM      | White Matter                                           |
| XGB     | Extreme Gradient Boosting                              |

# CHAPTER 1

## INTRODUCTION

### 1.1 Overview

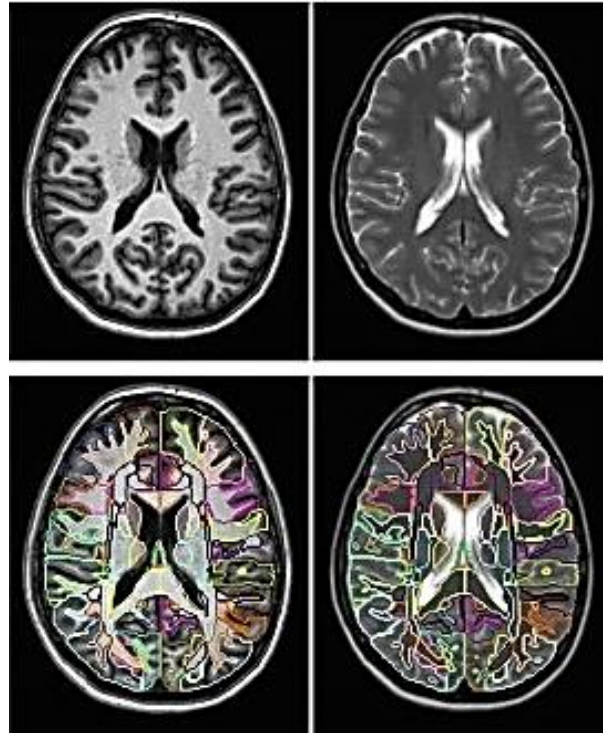
This study aims to improve suicide ideation (SI) assessment accuracy in depressed young adults by integrating machine learning (ML) methods such as Attention Mechanism (AM) and Spiking Neural Network (SNN) on structural magnetic resonance imaging (sMRI) data. The model involves the integration of self-AM and evolving SNN (ESNN), filling a critical gap in mental health assessment and offering insights for better intervention and support.

### 1.2 Study Background

The coronavirus disease (COVID-19) pandemic has intensified mental health issues, contributing to increased suicidal tendencies (Sher, 2020a; Sher, 2020b). Suicide ideation (SI), characterized by distressing death-related thoughts, predicts suicide attempts across various age groups (Harmer et al., 2020; Cheung et al., 2021). Additionally, Moller et al. (2023) found a correlation between SI and depression, highlighting the interconnectedness of these mental health issues. Since the onset of the pandemic, the prevalence of depression has remarkably increased, affecting over 8% of the US population, with nearly 17% affected in the 18 – 25 age group (Wang et al., 2024). Existing SI assessment tools lack accuracy, necessitating a novel method focusing on the SI-depression association (Deming et al., 2021).

ML has become foundational in suicide detection, offering faster and more accurate detection of SI (Yang et al., 2024). Models such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Neural Networks show promise in classifying mental illnesses such as depression (Barua et al., 2024). KNN, in particular, demonstrated exceptional accuracy of 91.45% in predicting SI among university students (Sara et al., 2024). Moreover, ML's ability to integrate diverse data sources enhances detection accuracy, emphasizing its importance in future research (Pigoni et al., 2024). Thus, integrating ML with diverse data sources is crucial for refining SI detection models and guiding future investigations in this critical area.

Understanding the neural underpinnings of psychiatric disorders is important in mental health research (Hauser et al., 2022). sMRI data, as depicted in Figure 1.1, provides insights into depression's biomarkers (Schmaal et al., 2020; Guy-Evans, 2023). However, existing studies utilizing sMRI and ML for SI detection have limitations (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023). These studies lack crucial performance metrics such as sensitivity, specificity, and area under the curve (AUC) (Suragala et al., 2021; Carrington et al., 2022). Thus, further research and methodological advancements are needed to improve SI detection accuracy in depressed individuals.



**Figure 1.1:** sMRI visualization - potential biomarkers for depression (Wu & Mori, 2023)

This study employed an integrated ML model called self-AM-ESNN to perform SI assessment based on the sMRI data of depressed young adults. The self-AM component emphasized crucial features within the input images (Choi & Yang, 2024), aiding ESNN in classification. Inspired by the brain's adaptability, ESNN continuously evolves to capture meaningful patterns (Kasabov, 2019). Integrating self-AM enhances feature focus, improving prediction accuracy.

The self-AM-ESNN model was trained on datasets from publicly available repositories of OpenNeuro<sup>1</sup> and the International Neuroimaging Data-Sharing Initiative (INDI)<sup>2</sup>. It primarily integrates selected data from studies focusing on depression within OpenNeuro (Bezmaternykh, 2021a; Bezmaternykh, 2021b; Manelis et al., 2021). The data

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<sup>1</sup> <https://openneuro.org/>

<sup>2</sup> [https://fcon\\_1000.projects.nitrc.org/](https://fcon_1000.projects.nitrc.org/)

for healthy controls (HC) were sourced from the Southwest University Longitudinal Imaging Multimodal (SLIM) dataset within INDI, as detailed in Liu et al. (2017). To address imbalances in the datasets, various techniques are employed, including stratified train-test split, Synthetic Minority Over-sampling Technique (SMOTE), stratified 5-fold cross-validation, and data augmentation (Brownlee, 2020c; Singh, 2020; Muralidhar, 2021; Mathews & Seetha, 2022).

Moreover, hyperparameter tuning utilizing the Genetic Algorithm (GA) was employed to optimize the configuration of the self-AM-ESNN model (Nikbakht et al., 2021). GAs, inspired by natural selection (Mehdary et al., 2024), excel in exploring vast solution spaces (Díaz-Álvarez et al., 2022). Performance evaluation employs metrics such as accuracy (ACC), sensitivity (SEN), specificity (SPEC), and AUC. Furthermore, comparative analyses include established ML classifiers such as ESNN, KNN, Logistic Regression (LR), and SVM (Kharel, 2020; Das, 2024; GeeksforGeeks, 2024), along with key studies (Weng et al., 2020; Chen et al., 2021a; Hong et al., 2021; Bajaj et al., 2023; Hu et al., 2023).

In essence, this study aims to improve SI detection accuracy among depressed young adults by utilizing ML models and their sMRI data. By leveraging advanced ML models, such as self-AM and ESNN, and employing techniques for handling imbalanced data, the research seeks to develop a more precise method for detecting SI. Comprehensive evaluations, including comparisons with traditional classifiers, key studies, and a thorough literature review, will advance intervention strategies at the intersection of mental health and technology.