INTISARI

Major Depressive Disorder (MDD) merupakan gangguan psikologis yang memengaruhi fungsi emosional dan kognitif seseorang. Salah satu pendekatan menjanjikan dalam memahami gangguan kognitif pada penderita MDD adalah melalui analisis gerakan mata dengan memanfaatkan teknologi *eye tracking*. Namun, keterbatasan jumlah data gerakan mata bernotasi menjadi kendala utama dalam pelatihan model klasifikasi berbasis *deep learning*.

Untuk mengatasi tantangan tersebut, penelitian ini mengusulkan pendekatan augmentasi data menggunakan *Time Series Variational Autoencoder* (*TimeVAE*) untuk menghasilkan data gerakan mata sintetis. Data sintetis tersebut digunakan untuk melatih model klasifikasi *deep learning* berbasis arsitektur 1D-CNN dan BiLSTM.

Hasil menunjukkan bahwa augmentasi data menggunakan *TimeVAE* mampu meningkatkan performa klasifikasi secara signifikan, khususnya pada skor F1 makro. Peningkatan skor F1 untuk tiap kelas (F1: *fixation*=0.8231, *saccade*=0.8434, *smooth pursuit*=0.5868, *noise*=0.8346). Kualitas data sintetis divalidasi secara kualitatif melalui adanya *overlap* pada visualisasi t-SNE dan secara kuantitatif dengan *predictive score* yang berupa nilai MAE mendekati 0, serta *discriminative score* mendekati 0 untuk fitur *x, y* dan mendekati 0,5 untuk fitur hasil ekstraksi yang menandakan bahwa data sintetis tetap menjaga struktur temporal meskipun berbeda secara distribusi.

Konfigurasi optimal augmentasi diperoleh dengan *temporal window*=50, *stride*=10, dan *latent dimension*=8 pada arsitektur *Base TimeVAE*. Temuan ini membuktikan efektivitas *TimeVAE* sebagai solusi augmentasi data sintetis berkualitas yang mampu meningkatkan performa klasifikasi gerakan mata, sekaligus mendorong pengembangan alat diagnosis MDD berbasis gerakan mata yang efektif dan non-invasif.

Kata kunci : *Eye Movement Classification, Deep learning, Time Series Variational Autoencoder, Bidirectional Long Short-Term Memory, K-Fold Cross Validation*

ABSTRACT

Major Depressive Disorder (MDD) is a severe psychological condition characterized by emotional and cognitive dysfunctions that significantly impact an individual's quality of life. A promising approach to understanding cognitive impairments in MDD patients involves the analysis of eye movements using eye-tracking technology. However, the development of deep learning-based classification models for this purpose is often hampered by the limited availability of annotated eye movement data.

Addressing this data scarcity, this study conducts an data augmentation approach utilizing a Time Series Variational Autoencoder (TimeVAE) to generate synthetic eye movement data. This synthetic data is then employed to train and enhance the performance of a deep learning classification model based on a 1D-Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) architecture.

Results show that data augmentation using TimeVAE can significantly improve classification performance, especially in macro F1-score. F1-score improvement for each class (F1: fixation=0.8231, saccade=0.8434, smooth pursuit=0.5868, noise=0.8346). The quality of synthetic data is qualitatively validated through the presence of overlap in t-SNE visualization and quantitatively with a predictive score in the form of an MAE value close to 0, as well as a discriminative score close to 0 for x, y features and close to 0.5 for extracted features, indicating that synthetic data still maintains temporal structure despite differing in distribution.

The optimal augmentation configuration was obtained with a temporal window=50, stride=10, and latent dimension=8 in the Base TimeVAE architecture. These findings prove the effectiveness of TimeVAE as a quality synthetic data augmentation solution capable of improving eye movement classification performance, while also encouraging the development of effective and non-invasive eye movement-based MDD diagnostic tools.

Keywords :*Eye Movement Classification, Deep learning, Time Series Variational Autoencoder, Bidirectional Long Short-Term Memory, K-Fold Cross Validation*