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Research Article

Anxiety-Focused Classification Using Smartphone-Based Gait Analysis and Deep Learning Models

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Abstract: Mood disorders, such as anxiety, significantly impact individual well-being and present challenges to healthcare systems globally. Traditional screening methods, including self-administered symptom questionnaires, provide valuable insights into symptoms but may miss dynamic fluctuations. This study explores the potential of smartphone inertial sensors and deep learning models for anxiety risk classification. Using gait data from 36 participants, collected via smartphone accelerometers and gyroscopes, we evaluated three models: Attention-CNN, Attention-LSTM, and a hybrid CNN-Attention-LSTM. The hybrid model achieved the highest accuracy of 87.5% in classifying at-risk for anxiety versus no-risk groups, outperforming individual models by effectively capturing spatial and temporal gait features. While the findings highlight the feasibility of smartphone-based gait analysis for anxiety risk classification, the study's limitations include a small sample size and controlled data collection settings. Future research should focus on larger, diverse datasets and real-world scenarios, with an expanded scope to other mood disorders. This approach offers scalable, non-invasive mental health monitoring and early classification.

Keywords: Mood Disorders, Anxiety, Smartphone Inertial Sensors, Deep Learning

Introduction

Mood disorders, including anxiety (National Institute of Mental Health, 2024a), affect millions of individuals worldwide, posing significant challenges to public health systems. According to the Global Burden of Disease 2019 estimates, approximately 301 million people worldwide were affected by anxiety disorders in 2019, representing about 4.05% of the global population (Javaid et al., 2023). The World Health Organization also identifies anxiety disorders as among the most prevalent mental health conditions worldwide (World Health Organization, 2024). Traditional methods of screening and monitoring often rely on self-reported symptoms and limited clinical evaluations (Kampmann et al., 2018), which can be subjective and may not capture the dynamic nature of mood fluctuations.

In recent years, technology has emerged as a promising tool in mental healthcare, offering new avenues for objective and continuous monitoring. Smartphones, ubiquitous in modern society, are equipped with inertial sensors such as accelerometers (OMEGA Engineering, 2024), gyroscopes (Epson, 2026), and rotation vectors (Arvo, 1992) that passively collect data on user movements and activities. These sensors can provide valuable insights into behavioral patterns associated with mood disorders (Lim et al., 2024). Deep learning, a subset of Artificial Intelligence (AI), has demonstrated remarkable success in recognizing complex patterns within large datasets. When applied to data from smartphone inertial sensors, deep learning algorithms have the potential to detect subtle changes in movement and activity levels that may correlate with mood states.

Despite the potential, there is a gap in research regarding the integration of deep learning with smartphone sensors for mood disorder recognition. This study aims to explore the effectiveness of deep learning models in classifying anxiety risks based on

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data collected from smartphones' inertial sensors. By developing and evaluating a deep learning-based framework, we seek to contribute to the early classification and continuous monitoring of anxiety and to provide timely mental health support, ultimately improving patient care and reducing the burden of mood disorders on individuals and society.

Background

Mood disorders, including anxiety, are among the most prevalent mental health conditions worldwide, with significant impacts on an individual's quality of life. The disorders often manifest in physical ways, with affected individuals exhibiting subtle changes in movement patterns (Katerndahl et al., 2007), posture (Veenstra et al., 2017), and gait (Michalak et al., 2009). Gait analysis has emerged as a promising non-invasive biomarker for mood disorders, as it can capture these physical manifestations objectively. Studies indicate that individuals with mood disorders may walk with slower speeds (Corneliusson et al., 2025), reduced variability (Thompson et al., 2017), and shorter stride lengths (Nuoffer et al., 2022), among other gait alterations. This makes gait analysis a valuable tool for detecting and monitoring mood disorders in real-world settings.

Over the years, numerous studies have been conducted for classifying risks of anxiety using gait data (National Institute of Mental Health, 2024b; Adolph et al., 2021; Deligianni et al., 2019). Hence, researchers have leveraged numerous means, such as laboratory-based assessments, which include 3D motion capture systems, electronic walkways, photogrammetry, and real-world assessments, which include wearable devices like accelerometers and Microsoft Kinect cameras (Altinok et al., 2024; Zhang et al., 2024; Trombeta et al., 2022; Helgadóttir et al., 2015; Zhao et al., 2019).

In this case study, we utilized smartphone inertial sensors to explore the relationship between mood disorders broadly, with a specific focus on anxiety symptoms. Smartphone-based inertial sensors, such as accelerometers, gyroscopes, and rotation vectors, offer accessible, cost-effective, and scalable solutions for mood disorder monitoring. Their ease of use and ubiquity make them well-suited for gait analysis, as each individual possesses a unique gait pattern. The widespread availability of smart devices enhances the practicality of using Inertial Measurement Units (IMUs) in gait analysis, providing continuous and unobtrusive data collection. This approach not only allows for real-world gait monitoring but also facilitates longitudinal analysis, capturing subtle, mood-related gait changes as they evolve. Unlike episodic lab assessments, smartphones support ongoing tracking, enabling early risk classification and timely intervention. Furthermore, mood disorder recognition through gait analysis using smartphone inertial sensor data remains an underexplored area, presenting significant opportunities for advancement in this field.

Methods

Dataset

In this study, we utilized a mobile health walking balance (mHealth-WB) app on smartphones to collect gait data. In a descriptive study approved by the institutional review board at the University of Nevada, Las Vegas (UNLV) (IRB# UNLV-2021-198), voluntary adult participants were recruited (Park et al., 2024). Gait data were collected from a total of 36 participants via the mHealth-WB app on smartphones (Lee et al., 2021). Prior to the gait data collection, participants completed the Generalized Anxiety Disorder-7 (GAD-7) questionnaire (Spitzer et al., 2006) through an online Google Forms survey in a research office. The online survey captured self-reported symptoms of anxiety, as well as demographic and other characteristics (Park et al., 2024).

For the gait data collection, participants wore smartphones at three different body locations: One at the middle of the front waist, one at the middle of the back waist, and one placed in a right-side bottom pocket pouch. The participants were instructed to walk a total of 440 feet, including a turning point, while maintaining a straight trajectory along an imaginary line and walking at their normal pace. The walk concluded at the starting position. Each walking session lasted approximately 4-5 minutes and was conducted in an indoor hallway to ensure consistency in environmental conditions.

During the walking sessions, smartphones recorded gait data using their built-in sensors, including accelerometer, gyroscope, and rotation vector sensors, with a sampling rate of 100 Hz. Based on the survey results, participants were categorized into two groups: Those with anxiety symptoms (n=19) and those without (n = 17) (Park et al., 2024).

Data Preprocessing and Segmentation

In this study, we leveraged the use of data collected from the accelerometer and the gyroscope. As the signal data are easily prone to external noise, signal denoising was applied to the data using a zero-phase Finite Impulse Response (FIR) filter as shown in Figure 1 (Li et al., 2022). A zero-phase filter ensures that the signal's phase remains intact during filtering, which is crucial for preserving the temporal structure of the gait cycles. A zero-phase filter is a special case of a linear-phase filter where the phase slope is zero, meaning the filter introduces no phase shift in the signal. The impulse response h(n) of a zero-phase filter is even, meaning it satisfies the condition.

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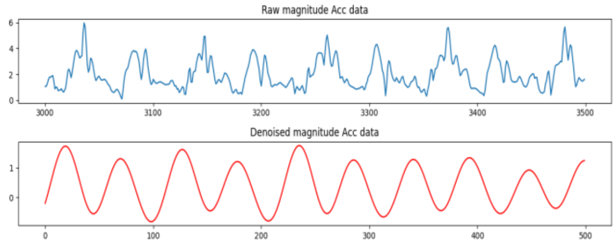

Fig. 1: Raw and denoised acceleration signal

This property ensures that the filter is symmetric around time zero, so the filtering process affects all parts of the signal equally without shifting or distorting the timing of different frequency components. Although zero-phase filters cannot be causal, meaning they cannot be applied in real-time scenarios, this limitation does not apply in our study, which involves offline analysis or pre-recorded gait data. For offline filtering, zero-phase filters are preferred due to their ability to preserve the structure. The frequency response of a zero-phase filter is a real, even function, which can be derived from the Discrete-Time Fourier Transform (DTFT) of the impulse response h(n). (Wang, 1984) the zero-phase filter was applied to attenuate the high-frequency noise in the data while maintaining the integrity of the original gait signal. By ensuring that the filter's passband, which refers to the range of frequencies that the filter allows to pass through, remains undistorted, we were able to remove noise without affecting key gait features.

Table 1 shows the different parameters used when applying denoising to the data. Since the average walking speed is 1.4 m/s, we used a bandpass filter with a passband from 0.75 Hz to 2.25 Hz. The sampling rate was set to 100 Hz, which allowed us to capture the necessary resolution for accurate gait analysis, while the zero-phase filter provided clean, denoised data for further processing using deep learning models.

After the participant-level train-test split described in Section 3.4, MinMaxScaler normalization (Scikit-Learn, 2024) was fitted only on the training set and then applied to the held-out test set. The normalized data were then segmented using a window length of 150 points with a 50 percent overlap.

The 150-point window length was selected to capture a short but meaningful segment of gait dynamics while preserving sufficient temporal resolution for deep learning-based sequence modeling. Because the sensor data were sampled at 100 Hz, each window corresponded to approximately 1.5 seconds of walking data, which is close to the duration of a complete gait cycle in adults. A 50 percent overlap was applied to increase the number of training samples while maintaining continuity between adjacent windows. This setting was intended to balance temporal context, sample size, and computational efficiency for the pilot-scale dataset.

Table 1: List of FIR parameters

Name	Value
Numtaps	101
Lowcut	0.75 Hz
Highcut	2.25 Hz
Sampling rate	100 Hz

Deep Learning Models

Attention Mechanism

The attention mechanism is adopted as a core component of deep learning models. Attention (Bahdanau et al., 2016) was first introduced for sequence-to-sequence machine translation, where it enabled a model to refer back to the most relevant parts of the input sequence instead of relying on a single fixed-length representation. The same principle was later generalized in the transformer architecture (Vaswani et al., 2017) and now underlies many large-scale generative models (OpenAI, 2023).

The central idea is that not all parts of an input sequence are equally informative for a given prediction. Rather than treating every time step or feature equally, the attention mechanism learns a set of weights that indicate how much each part of the sequence should contribute to the output. This lets the model concentrate on the segments that are most relevant to the target, which is especially useful for long sequences in which the discriminative information is concentrated in only a few time steps. In the context of gait analysis, this allows the model to emphasize the portions of the sensor signal that are most informative for distinguishing between classes.

Formally, let H = {h1, h2, ..., hT} denote the sequence of hidden states produced by the LSTM, or equivalently, the feature maps produced by the CNN. For each time step t, a scalar energy score is obtained through a learned linear transformation, et = Wa * ht + ba, where Wa and ba are a trainable weight matrix and bias vector. These scores are normalized with a softmax function so that the resulting attention weights sum to one, at = exp(et) / sum_j(exp(ej)). The context vector is then formed as the weighted sum of the hidden states, c = sum_t(at * ht), and is passed to the fully connected output layer for the final classification. For the CNN-based variant, the attention weights are instead produced by a 1D convolutional layer with a kernel size of 1 followed by a softmax activation, and are applied element-wise to the feature maps.

Gait Analysis With 1D CNN and Attention

The 1D CNN (Moya et al., 2018) processes raw gait data as a temporal feature, learning spatial patterns within each segment. With an attention layer added after the convolutional layers, the model assigns importance to specific segments, the most relevant features. This selective focus enhances robustness to noise and improves interpretability by clarifying which features influence predictions.

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This study employed a 1D attention-based CNN model, and the architecture is presented in Figure 2. The architecture design includes four convolutional layers, two dropout layers, two max-pooling layers, an attention mechanism, and two fully connected layers.

Gait Analysis With LSTM and Attention

LSTM models capture temporal dependencies in sequence data but may struggle with long sequences. (Hochreiter and Schmidhuber, 1997) by adding attention, the LSTM can focus on relevant time steps within the gait sequences. The attention layer weighs each hidden state, emphasizing critical time steps like a change in cadence or stride length, which improves long-range dependency handling and model interpretability.

The LSTM model architecture used is illustrated in Figure 3. The design includes one LSTM layer, a dropout layer, an attention mechanism, and two fully connected layers.

Gait Analysis With 1D CNN and Attention-LSTM

The 1D CNN and Attention-LSTM model combines the CNN's local pattern extraction with the LSTM's sequential learning, allowing for comprehensive analysis of gait data. Attention in the LSTM assigns importance to the most relevant temporal features extracted by CNN, enhancing the model's ability to capture subtle gait abnormalities and improving classification.

The combination of the 1D CNN model and attention-based LSTM architecture results in a combination of the two previous models. This model architecture combines the CNN model without attention and the LSTM model with attention as presented in Figure 4.

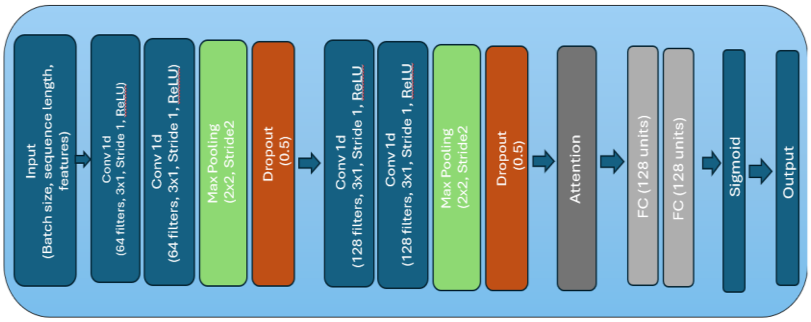

Fig. 2: Attention-based CNN architecture

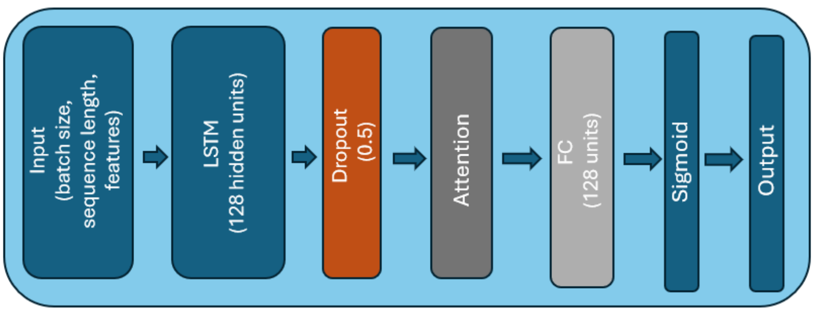

Fig. 3: Attention-based LSTM architecture

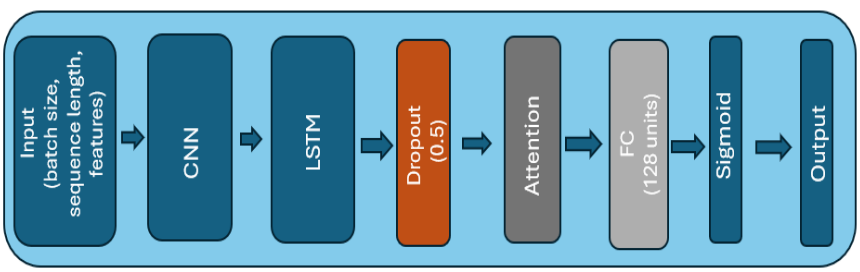

Fig. 4: CNN-attention-based LSTM architecture

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Table 2 compares the structural characteristics of the three attention-based architectures described above. The comparison focuses on the arrangement of layers, the position at which the attention mechanism is applied, and the activation and regularization strategies.

Training Process

The dataset used in this study is composed of data collected from two groups of participants: At-risk for anxiety (n = 19) and no-risk (n = 17) groups. To prevent data leakage, the train-test split was performed at the participant level prior to any data preprocessing: 80 percent of participants (n = 28) were allocated to the training set and the remaining 20 percent (n = 8) to the held-out test set. This design ensured that all windows generated from the same participant were assigned exclusively to either the training set or the held-out test set, preventing overlap of participant-specific gait patterns between training and testing. The MinMaxScaler normalization was fitted exclusively on the training set and subsequently applied to the test set, ensuring that no information from the test set influenced model training. After applying segmentation to the signal data, the windowed samples were used for model training and evaluation. Identification values were assigned to each group: "0" for the no-risk group and "1" for the anxiety-risk group. All models were implemented in PyTorch (Paszke et al., 2019) with a fixed random seed (seed = 42) for reproducibility. Each model was trained using the Binary Cross Entropy Loss function (Paszke et al., 2019), suitable for binary classification, and optimized with the Adam optimizer (Kingma and Ba, 2017) at a learning rate of 0.001. A 10-Fold cross-validation was applied within the training set to assess generalization, with each fold's normalization computed independently to maintain data integrity.

Table 3 summarizes the model-specific hyperparameter configurations used in this study. For the Attention-CNN model, four convolutional layers with filter sizes of 64, 64, 128, and 128 were used with a kernel size of 3 for each layer; MaxPool1D (kernel = 2) was applied after the 2nd and 4th layers; dropout of 0.5 was applied after each pooling layer. The attention in the CNN was implemented as a 1D convolution (kernel = 1, out = 1) followed by softmax. For the CNN-Attention-LSTM model, the CNN sub-network used the same architecture as the Attention-CNN (without its own attention), and the LSTM sub-network used 256 hidden units with 1 layer; an attention mechanism based on a linear scoring layer followed by softmax was applied after the LSTM output. All models shared the same optimizer (Adam, lr = 0.001), loss function (BCELoss), batch size (32), epoch limit (100), and early stopping patience (20 epochs).

Table 2: Model Architecture Comparison

Item	Attention-CNN	Attention-LSTM	CNN-Attention-LSTM
Layer flow (data flow)	4 Conv layers (2 MaxPool, 2 Dropout) -Attention - 2 FC layers - Output	LSTM - Dropout - Attention - FC - Output	CNN - LSTM - Dropout - Attention - FC - Output
Feature extraction approach	Local pattern extraction	Temporal dependency modeling	Local patterns combined with sequential dependencies
Position of attention	Weighting over convolutional feature maps	Weighting over LSTM hidden states	Weighting over the LSTM output
Hidden / FC activation	ReLU	ReLU	ReLU
Output activation	Sigmoid	Sigmoid	Sigmoid
Regularization	4 Conv layers (2 MaxPool, 2 Dropout) - Attention - 2 FC layers - Output	LSTM - Dropout - Attention - FC - Output	CNN - LSTM - Dropout - Attention - FC - Output

Table 3: Hyperparameter Configuration for All Models

Parameter	Att-LSTM	Att-CNN	CNN-Att-LSTM
Input features	6	6	6
Window length	150	150	150
Batch size	32	32	32
LSTM hidden units	128	—	256
CNN filters	—	64→64→128→128	64→64→128→128
CNN kernel size	—	3, 3, 3, 3	3, 3, 3, 3
Dropout rate	0.5	0.5	0.5
Learning rate	0.001	0.001	0.001
Optimizer	Adam	Adam	Adam
Epochs	100	100	100
K-Fold (k)	10	10	10
Random seed	42	42	42

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Experiments and Results

Figure 5 illustrates the validation performance of each model. For the Attention-LSTM model, the loss gradually decreased, and the accuracy increased after approximately the 50th epoch in both the training and validation sets. This suggests that the model began to capture meaningful differences between the no-risk and anxiety-risk groups after the early training stage.

A similar trend was observed for the Attention-CNN model, although the improvement appeared later, around the later training stage, the loss progressively decreased, and the accuracy increased, indicating that the model gradually learned discriminative gait patterns from the input data.

In contrast, the CNN-Attention-LSTM model showed a faster decrease in loss and a faster increase in accuracy compared with the other two models. This result suggests that combining CNN-based local feature extraction with attention-based LSTM temporal modeling was more effective in capturing differences in gait patterns between the no-risk and anxiety-risk groups.

The held-out test set consisted of 8 participants, including 4 no-risk and 4 anxiety-risk participants. After applying 150-point windows with 50 percent overlap, model performance was evaluated at the window level on this participant-independent test set.

Therefore, the reported accuracy, precision, recall/sensitivity, specificity, F1-score, and ROC-AUC represent window-level performance, while participant-level separation was maintained during the train-test split to prevent data leakage. For concise reporting in the table, the evaluation metrics are abbreviated as follows: Acc. for Accuracy, Prec. for Precision, Rec. for Recall/Sensitivity, Spec. for Specificity, F1 for F1-Score, and AUC for ROC-AUC. Table 4 presents the accuracy results, while Table 5 presents the full suite of evaluation metrics for each model. The CNN-Attention-LSTM achieved the highest accuracy (87.5%), precision (0.800), specificity (0.750), F1-score (0.889), and ROC-AUC (0.875), outperforming both the Attention-LSTM (Accuracy = 83.0%, Precision = 0.746, Recall = 1.000, Specificity = 0.659, F1 = 0.854, ROC-AUC = 0.867) and the Attention-CNN (Accuracy = 82.2%, Precision = 0.740, Recall = 0.992, Specificity = 0.652, F1 = 0.848, ROC-AUC = 0.869). All three models achieved high recall (≥0.992), demonstrating strong sensitivity to the at-risk group. The CNN-Attention-LSTM's superior specificity (0.750 vs. 0.659 and 0.652) suggests it better discriminates true negatives (no-risk participants), a critical property for screening applications. The CNN layers extract spatial features from the input sequences, while the LSTM layers, coupled with the attention mechanism, capture temporal dependencies, leading to superior overall performance.

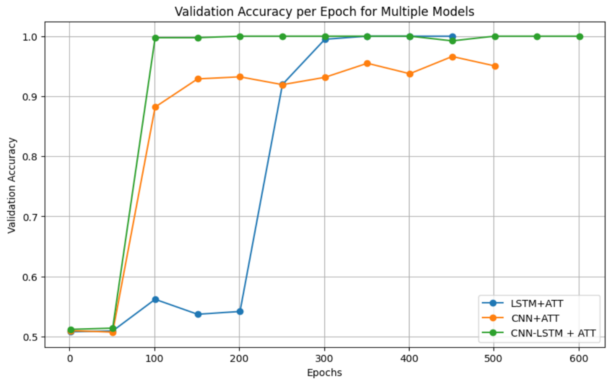

Fig. 5: Validation accuracy for each model

Table 4: Accuracy Results for Each Model

Model	Att-LSTM	Att-CNN	CNN-Att-LSTM
Accuracy	83	82.2	87.5

Table 5: Evaluation Metrics for Each Model

Model	Acc	Prec.	Rec.	Spec.	F1	AUC
Attention -LSTM	83.0	74.6	100.0	65.9	85.4	86.7
Attention -CNN	82.2	74.0	99.2	65.2	84.8	86.9
CNN-Attention -LSTM	87.5	80.0	100.0	75.0	88.9	87.5

Importance Analysis

Figure 6 presents the feature-level attribution comparison across the three models. Feature-level attribution was calculated by aggregating gradient-based contributions of the model output with respect to the six input channels: accX, accY, accZ, gyroX, gyroY, and gyroZ. Overall, the gyroscope-derived difference features showed relatively high contributions to anxiety-risk classification. In particular, the Y- and Z-axis gyroscope difference features showed consistently high importance across the models, suggesting that rotational movement patterns contributed to the classification process. The Attention-LSTM model assigned the highest importance to the vertical acceleration difference feature, while the gyroscope Y- and Z-axis difference features also remained highly ranked. In contrast, the Attention-CNN and CNN-Attention-LSTM models placed greater importance on gyroscope-derived features, especially the Z-axis gyroscope difference feature. These results suggest that different model architectures may emphasize different aspects of gait signals, but gyroscope-based rotational dynamics were consistently important across the models. Compared with the other features, the X-axis acceleration difference feature showed relatively low importance across all models.

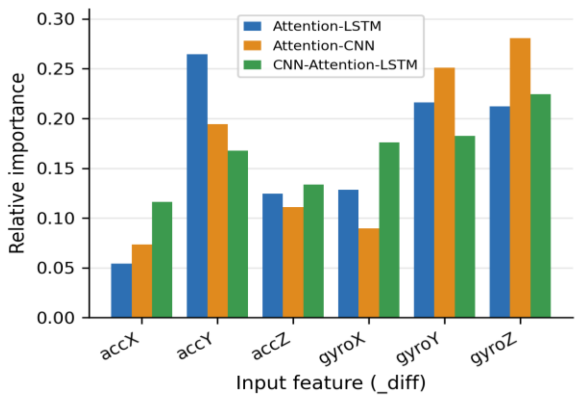

Fig. 6: Feature-level importance across models

This indicates that mediolateral acceleration changes contributed less to the model outputs than vertical acceleration and gyroscope-based rotational features. Overall, the explainability results suggest that anxiety-risk classification was influenced not only by acceleration-based changes but also by rotational gait dynamics. However, these attribution results should be interpreted as model-specific importance patterns rather than direct causal relationships.

Discussion

This study explored anxiety risk classification using gait data collected through the m Health-WB app, which accessed smartphone inertial sensors. While many studies have addressed anxiety and other mood disorder recognition using gait analysis, the use of gait data collected from smartphone inertial sensors for this purpose remains underexplored. Compared with prior Kinect-based gait analysis that reported up to 84% accuracy (Zhao et al., 2019), our smartphone-based approach achieved comparable or superior performance. We employed deep learning models and attention mechanisms and were able to achieve an accuracy of 87.5%. The feature-level explainability analysis further showed that gyroscope-derived rotational features, particularly the Y- and Z-axis difference features, contributed substantially to the model outputs. This suggests that the model outputs were associated not only with acceleration-based changes, but also with rotational gait dynamics that may reflect subtle differences in balance, body sway, or movement stability. However, these attribution patterns should be interpreted as model-specific indicators rather than direct causal evidence. The results indicate the potential to identify meaningful patterns between individuals at risk for anxiety and those not at risk. However, because this study was conducted with a relatively small sample size, the findings should be interpreted as a pilot investigation rather than as definitive clinical evidence. First, the small sample size limits the model's ability to generalize, highlighting the need for larger and more balanced datasets with diverse demographics to improve model robustness and generalizability across different populations. Second, participants were not randomized prior to the train-test split, and the use of GAD-7 self-report labels rather than clinician-validated diagnoses may introduce labeling bias. Third, we obtained promising results with the models achieving good accuracy on the data collected in an indoor and controlled environment, but their applicability to other contexts, such as outdoor settings or varying levels of physical activity, is uncertain. Lastly, this study focused solely on anxiety, potentially overlooking other mood disorders that might also influence gait patterns, such as depression and bipolar disorder. Future research should include individuals with various mood disorders to allow comparative analysis of gait patterns, enhancing the model's specificity and utility for broader mood disorder recognition. In future work, sensitivity analyses using different window lengths and overlap ratios should also be conducted to evaluate the robustness of the proposed framework. In addition, more specialized architectural components, such as gating mechanisms designed for gait-specific temporal dynamics, may further improve model interpretability and classification performance.

Conclusion

This study demonstrates the potential of smartphone inertial sensors and deep learning for anxiety risk classification. Among the three models tested, the hybrid CNN-Attention-LSTM achieved the highest accuracy of 87.5%, effectively capturing spatial and temporal gait features. The feature-level explainability analysis further suggested that gyroscope-derived rotational features contributed meaningfully to anxiety-risk classification. These results support the feasibility of smartphone-based gait analysis for mental health monitoring. However, limitations such as a small sample size and controlled indoor settings restrict generalizability. Future studies should address these issues by collecting larger, more diverse datasets and exploring real-world applications. Extending the analysis to other mood disorders could further enhance this technology's utility for mental health care.

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Author's Contributions

Minchan Kang: Designed the study, developed the methodology, implemented the software, analyzed the data, and wrote the manuscript.

Gou-Sung Degbey: Contributed to data analysis and methodology and reviewed the manuscript.

Hyunhwa Lee: Contributed to data collection and reviewed the manuscript.

Jonghyuk Kim: Contributed to conceptualization and data analytics.

Sungchul Lee: Supervised the project and served as the corresponding author.

Hoon Ko: Supervised the research and reviewed the manuscript.

Jinyoung Park: Contributed to data collection.

Ethics

This study received ethical approval from the Institutional Review Board of the University of Nevada, Las Vegas (IRB No. UNLV-2021-198). Data collection and all related research procedures were carried out under the approved protocol and in accordance with the ethical principles for human-subject research. Before participating in the study, all participants were informed of the study's purpose and procedures, and written consent was obtained. The authors report no conflicts of interest related to this work.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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