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Smartphone Based Real-Time Detection of Postural and Leg Abnormalities using Deep Learning Techniques

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Abstract

This research presents an innovative real-time method for detecting leg postural abnormalities using deep learning techniques and smartphone sensors. The objectives are to: (1) develop a smartphone-based system for real-time classification of leg postures using accelerometer and gyroscope data, (2) evaluate the effectiveness of three deep learning models DNN, CNN, and CNN-LSTM in identifying spatial and temporal features, and (3) offer a low-cost, objective alternative to traditional assessment methods by addressing issues such as observer inconsistency and computational complexity. Accelerometer and gyroscope data from smartphones were used to develop a system that classified four leg postures: Pronation, Supination, Normal, and Postural Sway. Participants from various age groups carried a smartphone in their left pocket while standing and walking for 10, 20, and 30 seconds. This process produced a dataset of 29,823 records, which were verified and labeled by medical professionals based on observed postural characteristics. The CNN-LSTM model achieved the highest accuracy (96.4%) with strong class differentiation, demonstrating its effectiveness in capturing temporal dependencies. All three models were employed for unknown instances, and a majority voting approach was used for final classification. This proposed smartphone-based assessment system addresses limitations of traditional methods, such as inconsistencies due to subjective visual evaluations. This approach supports applications where leg posture is critical, such as in military, sports assessments, and disability certification, by offering an objective and accessible solution. Unlike video-based methods, it leverages widely available mobile technology, offering a low-computation, tamper-proof, and nonintrusive real-time surveillance system. Designed for automated and transparent evaluation, it has the potential to enhance the integrity of physical disability certifications.

Keywords: *deep learning; accelerometer; gyroscope; sensor; classification; CNN; LSTM*

1. Introduction

Postural and leg abnormalities are critical considerations in physical assessments across various sectors, including healthcare, military, sports, and security. Postural balance and leg stability are essential indicators of physical fitness and functional ability in these fields (Rakpongsiri et al., 2023). In recent years, fraudulent disability certifications have become more prevalent, often exacerbated by inconsistencies in subjective medical assessments.

Since mobility impairments can influence eligibility for specific roles or financial support, there is an increasing demand for accessible, objective assessment methods. This research proposes a real-time, tamper-proof, and accurate solution using widely available smartphone sensors and deep learning models. This study detects and classifies leg postures using smartphone accelerometer and gyroscope data. It focuses on four posture categories: Postural Sway, Pronation, Supination, and Normal Posture. The proposed system offers an objective method for evaluating postural abnormalities, enhancing fairness and transparency in assessments with potentially significant outcomes for individuals or institutions. To ensure accurate and reliable classification, the study employs deep learning models including Dense Neural Networks (DNN), Convolutional Neural Networks (CNN), and a hybrid CNN-LSTM model. By replacing subjective visual assessments with precise sensor data and algorithmic analysis, this approach offers a transformative advancement in posture evaluation (Barrett et al., 2020). Undetected postural abnormalities can lead to long-term musculoskeletal problems, impairing an individual's ability to perform in physically demanding roles or daily activities (Calcaterra et al., 2022). In sectors like the military and sports, even minor impairments can hinder performance and increase safety risks. Furthermore, many governments offer financial aid and benefits to individuals with disabilities, which has unfortunately led to cases of fraud involving illegitimate disability certifications. In such scenarios, reliance solely on subjective assessments introduces risks of inconsistency and bias, potentially leading to false positives or negatives in diagnosis and certification. In a typical leg examination, doctors observe individuals while standing, walking, or performing simple movements and then make a subjective judgment about their posture. While this method can be effective when performed by trained professionals, it is still prone to bias and human error due to its reliance on visual cues alone. Additionally, individuals may deliberately alter their behavior to influence the assessment, making it difficult to detect subtle abnormalities. This highlights the urgent need for objective, scalable, and accurate methods to evaluate leg posture free from human bias.

1.1 Prior work

Existing approaches to posture and gait analysis typically rely on video-based systems (Stenum et al., 2024) or wearable sensors (Prasanth et al., 2021). While video-based methods can be effective, they come with high computational costs and raise privacy concerns due to continuous video monitoring (Rezaee et al., 2024). These methods often require high-resolution cameras and controlled environments, which limit their scalability. For example, conducting such assessments in hospitals may be feasible, but they become impractical in remote locations or for large-scale evaluations. Another method for capturing postural data involves wearable sensors, such as accelerometers and gyroscopes, placed on various parts of the body (Anikwe et al., 2022). However, these systems can be intrusive, requiring users to wear multiple devices that may be uncomfortable or impractical for long-term use. Additionally, the setup and maintenance costs of specialized sensors can be prohibitive, especially in low-resource settings or scenarios requiring rapid, high-volume assessments. While wearable technology has significantly advanced postural analysis, its complexity and cost underscore the need for a simpler, more affordable alternative (Banyam, & Rakpongsiri, 2023). In contrast, smartphones are ubiquitous and come equipped with powerful built-in sensors. Most modern smartphones include accelerometers and gyroscopes capable of measuring movement across multiple dimensions, providing rich data on body motion and balance (Sarmadi et al., 2023). Despite this potential, relatively few studies have explored the use of smartphone sensors for real-time postural abnormality detection using deep learning techniques. Advances in smartphone technology and deep learning algorithms offer a unique opportunity to develop a real-time, portable, and cost-effective system for detecting leg abnormalities (Kristanto et al., 2023). Modern smartphones possess powerful sensors and processors capable of performing complex computations, making them ideal for on-device data collection and analysis. Furthermore, the widespread use of smartphones means that many individuals already carry devices capable of recording accelerometer and gyroscope data (Grouios et al., 2022). The large volume of multidimensional data generated by smartphone sensors is well-suited for analysis using deep learning models, which excel at identifying complex patterns in large datasets (Xiao et al., 2024). In this study, we utilize deep learning architectures DNN, CNN, and CNN-LSTM to detect postural abnormalities. DNNs effectively model structured data relationships, while CNNs are adept at capturing spatial hierarchies. The hybrid CNN-LSTM model, which combines convolutional layers with long short-term memory units, is particularly well-suited for detecting subtle, time-dependent changes in posture from time-series data (Sulistianingsih & Martono, 2024). In recent years, medical professionals have relied on visual assessments or video-based analysis to detect gait and posture abnormalities. While practitioners can observe individuals walking, standing, or performing specific movements to identify symptoms such as sway, pronation, or supination (Ward, 2024), video-based methods offer frame-by-frame analysis for greater detail (Ahmedt-Aristizabal et al., 2024). Systems like Vicon and OptoGait provide precise data on joint angles, foot placement, and body symmetry (Trautmann et al., 2021). However, these techniques are computationally intensive, require controlled environments, and raise significant privacy concerns, making them unsuitable for real-time or large-scale assessments (Badidi et al., 2023). Wearable sensors have offered an alternative for postural and gait analysis. Strategically placed accelerometers and gyroscopes can capture detailed movement data, enabling the detection of subtle gait irregularities or balance disorders (Guo et al., 2022; Siaw, & Han, 2024). While effective, these devices often require multiple sensors, making them uncomfortable for prolonged use and logistically complex for deployment in real-world applications (Chen et al., 2016; Booth et al., 2019).

Smartphones provide a promising solution by combining accessibility, cost-effectiveness, and convenience. Built-in accelerometers and gyroscopes in modern smartphones can capture three-dimensional movement and rotation data, enabling accurate tracking of balance and leg posture (Salchow-Hömmen et al., 2022). Prior studies have demonstrated the feasibility of using smartphone sensors for assessing postural balance and detecting gait abnormalities, especially in elderly populations (Ren, & Peng, 2019; Amjad et al., 2024). However, while these efforts confirm the value of smartphone-based sensing, few have integrated deep learning techniques for real-time classification of postural abnormalities. Deep learning models excel at pattern recognition and have demonstrated strong performance in human activity recognition using sensor data (Sharma et al., 2024). Traditional machine learning models such as decision trees, k-nearest neighbors (k-NN), and support vector machines (SVM) have been applied with moderate success in classifying postural data (Di Biase et al., 2024; Casilari-Pérez et al., 2019; Tasjid, & Marouf, 2022; Tambe et al, 2025). However, these models often fall short when handling complex, non-linear temporal patterns in time-series data.

This gap has fueled interest in deep learning architectures like convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), which can capture spatial and temporal dependencies respectively. CNNs have been successfully adapted for analyzing inertial measurement unit (IMU) data, extracting spatial features related to balance and movement (Renani, 2023). Yet, postural abnormalities often evolve over time, necessitating models capable of temporal learning. LSTMs, a type of recurrent neural network, are well-suited for this task, as they can identify temporal progressions in sequential sensor data (Minango et al., 2023; Zhang et al., 2022). Hybrid CNN-LSTM models combine the strengths of both architectures, making them particularly effective for analyzing smartphone sensor data. These models have shown superior performance in activity classification tasks, including those involving complex human movements (Sabah et al., 2024; Lalwani, & Ganeshan, 2024). While simpler models like XGBoost have been explored for structured data (Liu et al., 2021) they lack the ability to model the intricate temporal and spatial dynamics found in sensor-based posture assessments.

While smartphones have proven effective in collecting sensor data, their integration with deep learning for real-time leg postural abnormality detection remains underexplored. Existing solutions, such as video-based systems, often require high computational resources and raise privacy concerns. Wearable sensor-based methods, though accurate, tend to be costly and intrusive, limiting their usability in real-world, large-scale scenarios. This study addresses a clear research gap by integrating smartphone-based sensor data with deep learning models specifically CNN, LSTM, and CNN-LSTM, for real-time classification of leg postural abnormalities. The proposed system offers an objective, cost-effective, and non-invasive approach that eliminates human bias and supports consistent, real-time assessments across diverse environments.

2. Objectives

This research aims to develop a smartphone-based system for real-time detection of leg posture abnormalities using accelerometer and gyroscope data.

The system is intended to:

1. Improve diagnostic accuracy compared to traditional, subjective assessment methods.
2. provide a scalable and accessible solution applicable to healthcare, military, and sports domains.
3. Achieve robust and accurate classification of leg postures including unseen instances using deep

learning models, namely CNN, LSTM, and CNN-LSTM.

3. Materials and Methods

3.1 System Overview

The system architecture for real-time detection of postural and leg abnormalities is illustrated in Figure 1. It incorporates three deep learning models: Dense Neural Network (DNN), Convolutional Neural Network (CNN), and a hybrid CNN-LSTM model. These models analyze sensor data collected from smartphones to classify leg postures.

3.1 Data Collection (Smartphone Sensors)

A custom smartphone application was developed to capture sensor data from the built-in accelerometer and gyroscope at a sampling rate of 50 Hz. Participants placed their smartphone in their left pocket while standing or walking for intervals of 10, 20, and 30 seconds. The collected dataset includes:

- Accelerometer data: Acc_X, Acc_Y, Acc_Z (linear acceleration across axes)
- Gyroscope data: Gyr_X, Gyr_Y, Gyr_Z (rotational movement)
- Metadata: Postural class (Normal, Postural Sway, Pronation, Supination), gender, age, activity type, and recording duration

Medical professionals reviewed the recordings and labeled each instance based on observed postural characteristics. The final dataset contained 29,823 labeled records.

3.2 Data Processing and Model Training

A low-pass filter was applied to reduce high-frequency noise from sensor readings caused by vibrations or external disturbances. The data were normalized to account for variability in sensor placement, standardizing input features across participants. These preprocessing steps ensured that the data were consistent, clean, and well-suited for training deep learning models.

Dense Neural Networks (DNNs) are fully connected to neural architectures that process each input feature independently (Pradeepa & Jeyakumar, 2022). In the context of detecting leg posture abnormalities, the DNN operates as follows:

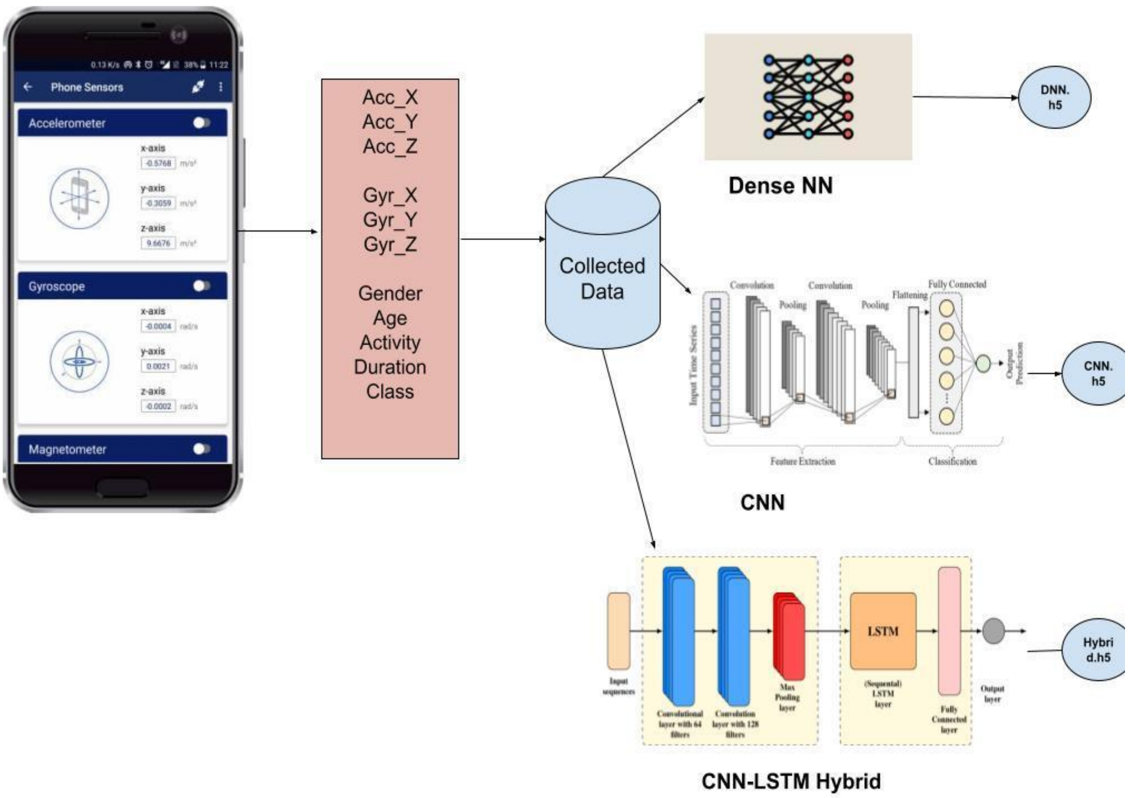

Figure 1 System architecture

Input Layer: Sensor features collected from the smartphone including accelerometer (Acc_X, Acc_Y, Acc_Z), gyroscope (Gyr_X, Gyr_Y, Gyr_Z), and user-specific data like gender, age, activity type, and recording duration are fed into the DNN. These inputs contain essential information about leg movement and posture.

Hidden Layers: The hidden layers consist of multiple neurons that apply weights and biases to the inputs, enabling the model to learn complex patterns. These layers help identify motion patterns associated with various leg posture abnormalities.

Output Layer: The output layer predicts the class Normal posture, Postural sway, Pronation, or Supination by computing probabilities for each and selecting the highest.

Through this architecture, the DNN processes sensor data and, via backpropagation and optimization, learns to recognize patterns that correspond to specific postural conditions. Convolutional Neural Networks (CNNs) process time-series sensor data by applying filters to capture localized spatial patterns across the X, Y, and Z axes of acceleration and rotation. Convolutional Neural Networks (CNNs) are well-suited for analyzing data with spatial or sequential structures, such as time-series signals from motion sensors. In the context of detecting leg posture abnormalities, CNNs process smartphone sensor data as follows: Input Layer: The model receives input features including accelerometer (Acc_X, Acc_Y, Acc_Z) and gyroscope (Gyr_X, Gyr_Y, Gyr_Z) readings, along with contextual information such as gender, age, activity type, and recording duration. These features capture movement, orientation, and individual-specific factors relevant to posture analysis.

Convolutional Layers: Convolutional filters scan the data to detect local patterns. For example, specific sequences in accelerometer values might indicate postural sway. These layers extract spatial and temporal features that may not be visible in raw data.

Pooling Layers: Pooling layers reduce dimensionality by summarizing key information, helping to simplify computation and improve generalization by retaining the most important features.

Fully Connected Layer (Dense Layer): The output from the final pooling layer is flattened and passed to a dense layer, where extracted features are combined for high-level interpretation and classification.

Output Layer: The model predicts one of four posture classes: Normal Posture, Postural Sway, Pronation, or Supination, based on the learned patterns. The CNN-LSTM hybrid model combines the spatial pattern recognition of CNNs with the temporal sequence modeling of LSTMs. This approach is particularly well-suited for analyzing time-series sensor data, such as accelerometer and gyroscope readings from smartphones, to detect leg posture abnormalities.

3.3 Model Output

After training the three models (DNN, CNN, and CNN-LSTM) respectively, each model produces a .h5 produced file, named DNN.h5, CNN.h5 and Hybrid.h5 respectively). These trained models can be used for real-time classification or batch processing.

When dealing with sensor data from accelerometers and gyroscopes with dependent x, y and z axes, performance greatly depends on the choice of model, DNNs, CNNs, or CNN-LSTM since each handle dependencies and sequential data differently.
A comparative evaluation of these models is provided below, emphasizing their respective strengths and limitations in handling tri-axial sensor data.

3.3.1 Dense Neural Networks (DNNs)

In DNNs, every neuron in a layer is connected to every neuron in the next layer, which defines a fully connected architecture. DNNs treat each feature (Acc_X, Acc_Y, Acc_Z, Gyro_X, Gyro_Y, Gyro_Z) independently and lack mechanisms to recognize inter-feature relationships. Moreover, DNNs cannot learn sequential information or temporal dependencies. They perform well on static data but fail to capture patterns over time or interdependencies among features. As a result, DNNs are generally less effective for accelerometer and gyroscope data, as they cannot exploit inherent spatial and temporal dependencies.

3.3.2. Convolutional Neural Networks (CNNs)

CNNs use filters to extract spatial patterns and dependencies across neighboring features. CNNs can treat the x, y, and z axes as components of a spatial structure, enabling recognition of patterns across axes (e.g., coordinated 3D movement). This is particularly effective when data are structured in fixed windows (e.g., 1-second segments). However, CNNs alone do not inherently capture temporal sequences or long-term dependencies across windows. They can detect local patterns within each window but don’t capture changes over time. CNNs are effective for detecting short, localized patterns in accelerometer and gyroscope data. For example, detecting specific movements within a single step can work well, but CNNs are limited for tasks requiring an understanding of longer-term sequences.

3.3.3. CNN-LSTM Hybrid

CNN-LSTM hybrids combine CNNs' spatial feature extraction with LSTMs' ability to handle temporal sequences. CNN layers extract spatial features within each window, while LSTM layers model temporal dependencies across these sequences. The CNN layers learn spatial patterns across the x, y, and z axes, and the LSTM layers capture their temporal evolution, providing a comprehensive understanding of spatial and temporal dynamics. This hybrid model detects inter-axis relationships (via CNNs) and tracks their temporal changes (via LSTMs), making it ideal for accelerometer and gyroscope data. CNN-LSTM models are powerful for complex tasks involving both spatial dependencies (e.g., 3D movement) and temporal sequences (e.g., progression of movement over time). For activities such as fall detection, walking analysis, or sport-specific actions, CNN-LSTM models are often the most effective choice.

4. Results and Discussion

A Swift-based smartphone application was developed to record raw sensor data from participants, who placed the device in their left pocket while standing and walking for intervals of 10, 20, and 30 seconds. Participants represented diverse age groups and genders. Medical experts labeled each posture instance, resulting in a dataset of 29,823 samples. The data was used to train three deep learning models DNN, CNN, and CNN-LSTM using an 80:20 train-test split with 10-fold cross-validation. Model performance was evaluated using accuracy, precision, recall, and F1-score and summarized in Table 1.

The model achieved an overall classification accuracy of 94.1% across all posture classes.

- F1 Score: 0.941, a weighted average across all classes, reflecting the balance between precision and recall.
- Precision: 0.941, indicates that 94.1% of the model's predictions were correct.
- Recall: 0.941, shows that 94.1% of actual instances were correctly identified.
- Training Accuracy: 0.946, the model performed slightly better on training data (94.6%), which is typical due to overfitting tendencies.

The corresponding confusion matrix is shown in Figure 2.

A comparative analysis of model performance was undertaken. Table 2 presents the CNN model's metrics, highlighting its strengths and limitations.

- Precision: Reflects the proportion of correct positive predictions for each class. A precision of 1.00 for *Normal Posture* and *Postural Sway* indicates perfect prediction accuracy for these classes. *Pronation* and *Supination* show slightly lower precision values (0.89 and 0.88), suggesting minor misclassifications.
- Recall: Measures the proportion of actual positive cases correctly identified. Recall is also 1.00 for *Normal Posture* and *Postural Sway*, while *Pronation* and *Supination* have recall values of 0.88 and 0.90, respectively.
- F1 Score: As the harmonic mean of precision and recall, the F1 score offers a balanced view of performance. Both *Normal Posture* and *Postural Sway* achieved an F1 score of 1.00, whereas *Pronation* and *Supination* scored 0.89, indicating slightly lower but still strong performance.
- Overall Accuracy: The CNN model achieved a test accuracy of 94.3%, reflecting the proportion of correctly classified samples across all classes.
- Training Accuracy: With a training accuracy of 95.1%, the model demonstrates good generalization, as the performance on training and test data is closely aligned, suggesting minimal overfitting.

The confusion matrix corresponding to these results is shown in Figure 3.

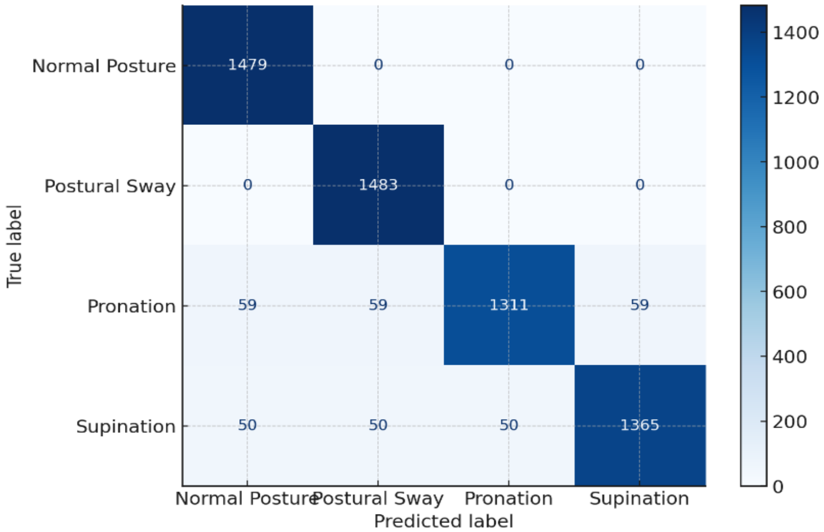

Figure 2 Confusion Matrix of DNN Model

Table 1 Performance Metrics of Dense Neural Network (DNN) for Postural Classification

Class	Precision	Recall	F1 Score	Support
Normal Posture	1	1	1	1479
Postural Sway	1	1	1	1483
Pronation	0.9	0.86	0.88	1488
Supination	0.87	0.91	0.89	1515
Accuracy	0.941			
F1 Score	0.941			
Precision	0.941			
Recall	0.941			
Training Accuracy	0.946			

Table 2 Performance Metrics of Convolutional Neural Network (CNN) for Postural Classification

Class	Precision	Recall	F1 Score	Support
Normal Posture	1	1	1	1479
Postural Sway	1	1	1	1483
Pronation	0.89	0.88	0.89	1487
Supination	0.88	0.9	0.89	1516
Accuracy	0.943			
F1 Score	0.945			
Precision	0.943			
Recall	0.945			
Training Accuracy	0.951			

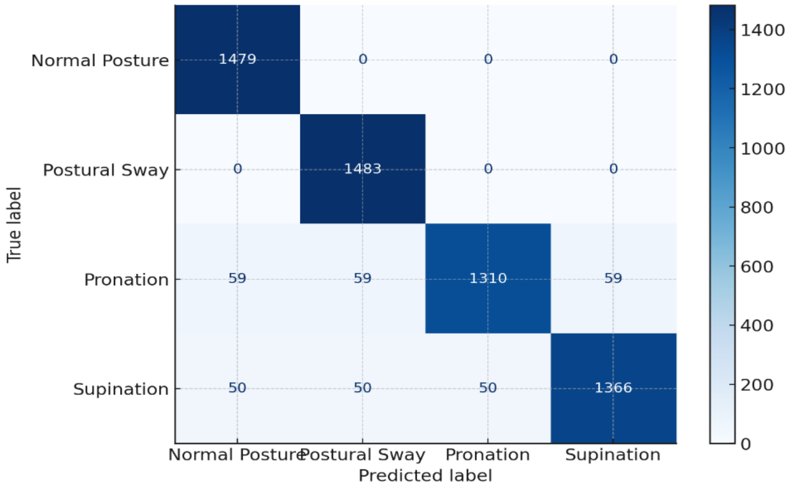

Figure 3 Confusion Matrix of CNN Model

Table 3 Performance Metrics of CNN-LSTM Hybrid Model for Postural Classification

Class	Precision	Recall	F1 Score	Support
Normal Posture	1	1	1	1479
Postural Sway	1	1	1	1483
Pronation	0.95	0.93	0.93	1489
Supination	0.92	0.92	0.89	1514
Accuracy	0.964			
F1 Score	0.955			
Precision	0.967			
Recall	0.962			
Training Accuracy	0.949			

CNN-LSTM Model Performance Analysis:

Table 3 provides a comprehensive analysis of the CNN-LSTM model's classification performance across different postural categories.

- Precision: The model achieved perfect precision (1.00) for *Normal Posture* and *Postural Sway*, indicating all predictions for these classes were correct. Precision for *Pronation* and *Supination* was slightly lower at 0.95 and 0.92, respectively, suggesting minor misclassifications.
- Recall: Recall was also 1.00 for *Normal Posture* and *Postural Sway*, meaning the model correctly identified all actual instances. For *Pronation* and *Supination*, recall values were 0.93 and 0.92, reflecting high but slightly reduced sensitivity.
- F1 Score: The F1 score, which balances precision and recall, was 1.00 for *Normal Posture* and *Postural Sway*. *Pronation* and *Supination* scored 0.93 and 0.89, respectively, indicating strong but not perfect classification.
- Overall Accuracy: The model achieved an accuracy of 96.4%, demonstrating highly reliable performance across all classes.
- Training Accuracy: A training accuracy of 94.9% indicates strong generalization with no signs of overfitting.

The corresponding confusion matrix is presented in Figure 4.

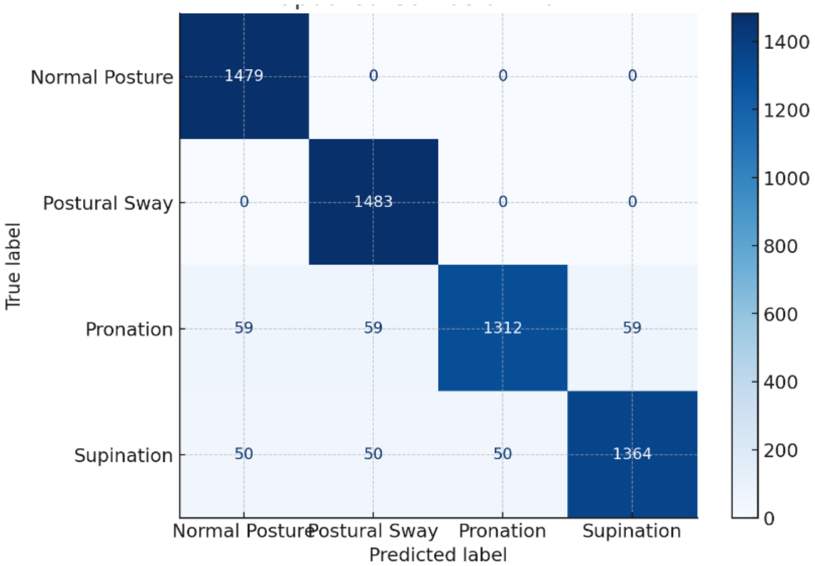

Figure 4 Confusion Matrix of CNN-LSTM Model

Table 4 Comparative Analysis of DNN, CNN, and CNN-LSTM Models

	DNN	CNN	CNN-LSTM
Accuracy	0.941	0.941	0.964
F1 Score	0.941	0.941	0.955
Precision	0.941	0.941	0.967
Recall	0.941	0.941	0.962
Training Accuracy	0.946	0.946	0.949

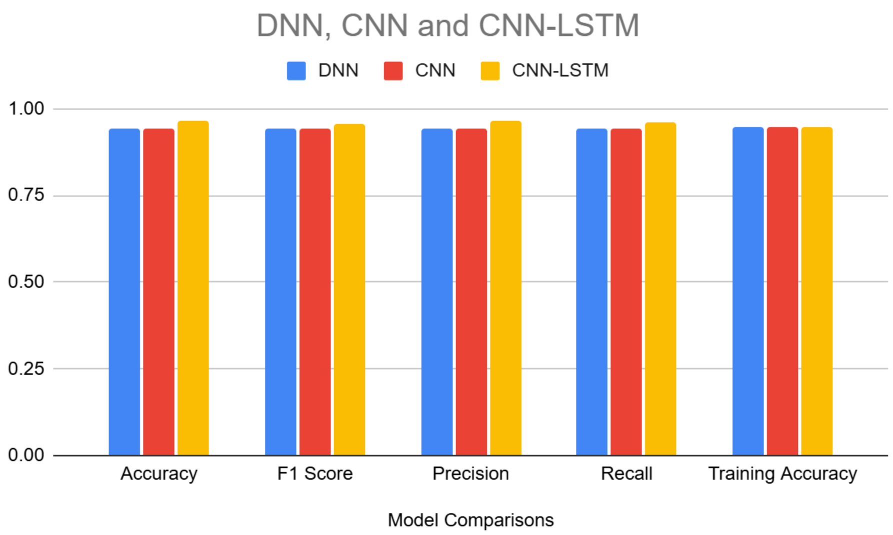

Figure 5 Model Performance Comparison

A comparison of all model performance metrics is presented in Table 4, with a visual representation provided in Figure 5.

The CNN-LSTM model achieved the highest overall accuracy at 96.4%, outperforming both DNN and CNN, which each recorded 94.1%. Its F1 score of 95.5% also exceeds that of DNN and CNN (both at 94.1%), indicating a superior balance between precision and recall.

In terms of precision, CNN-LSTM reached 96.7%, compared to 94.1% for DNN and CNN, suggesting fewer false positives. Similarly, its recall of 96.2% surpasses the 94.1% achieved by the other models, demonstrating better performance in identifying true positives across all classes.

While all models performed well during training, CNN-LSTM again led with a training accuracy of 94.9%, slightly ahead of DNN and CNN at 94.6%.

This superior performance highlights the effectiveness of the hybrid CNN-LSTM architecture, which combines the spatial pattern recognition capabilities of CNNs with the temporal sequence modeling strengths of LSTMs. The CNN component captures localized postural shifts, while the LSTM component models movement sequences over time making this architecture particularly suitable for real-time leg posture abnormality detection.

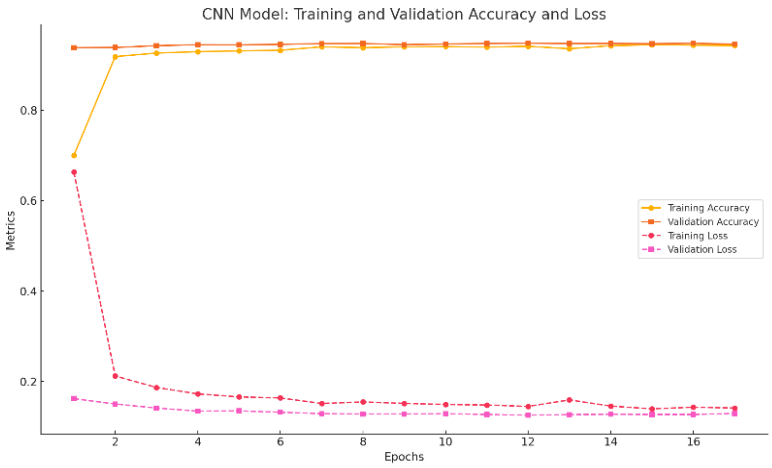

Figure 6 Training and Validation Accuracy and Loss of CNN

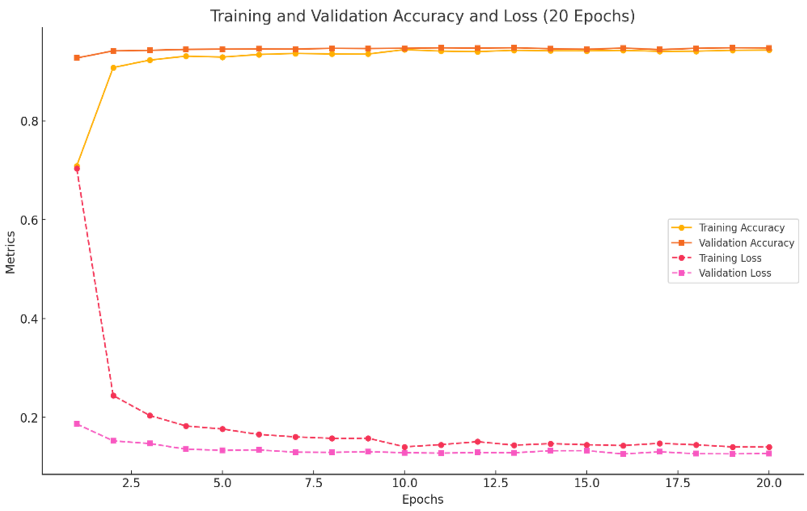

Figure 7 Training and Validation Accuracy and Loss of DNN

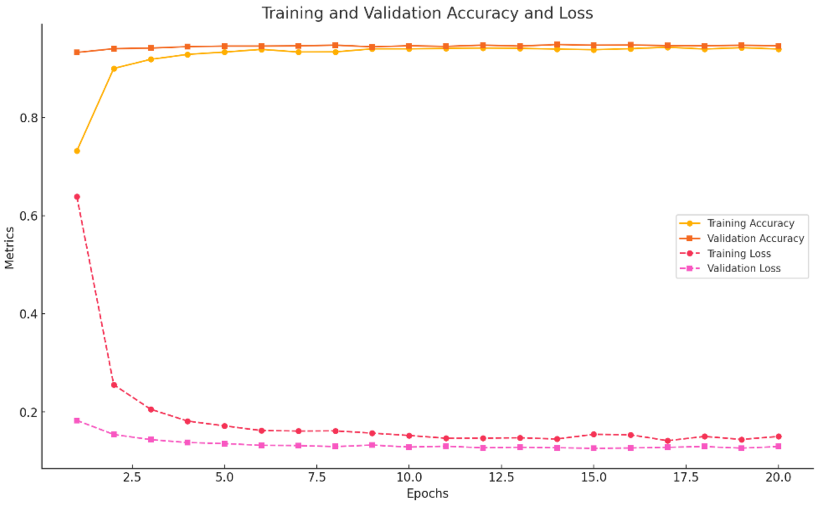

Figure 8 Training and Validation Accuracy and Loss of CNN-LSTM

Figures 6, 7, and 8 illustrate the training and validation accuracy curves for the DNN, CNN, and CNN-LSTM models, respectively.

Figure 6 shows that by Epoch 7, the training accuracy reaches 93.98%, while the loss decreases to 0.1512, indicating rapid learning during the early training phase. After Epoch 12, accuracy stabilizes between 94% and 94.5%, and the training loss further reduces to approximately 0.1447, suggesting that the model is converging effectively.

Figure 7 illustrates that training accuracy starts at 70.91% and steadily increases, reaching 94.34% by epoch 20. Validation accuracy begins at 92.73% and stabilizes around 94.7%–94.8%, indicating strong generalization. Training loss decreases significantly from 0.7036 to 0.1403, demonstrating effective learning. Similarly, validation loss steadily drops from 0.1868 and stabilizes near 0.1262–0.1272, closely aligning with the training loss.

Figure 8 shows a consistent upward trend in both training and validation accuracies. Training accuracy starts at 73.18% and increases to around 94% by epoch 20, while validation accuracy begins at 93.25% and stabilizes near 94.7%. The close alignment between training and validation accuracies indicates strong generalization to unseen data. Similarly, both losses steadily decline: training loss decreases from 0.6389 to approximately 0.1439, and validation loss drops from 0.1827 to around 0.1293 by the end of training.

5. Conclusion

This study presents a real-time system for detecting leg postural abnormalities using smartphone-based accelerometer and gyroscope data. By classifying four posture types Pronation, Supination, Postural Sway, and Normal the system provides a low-cost, non-invasive alternative to traditional posture assessments. Deep learning models, including DNN, CNN, and CNN-LSTM, were evaluated, with the CNN-LSTM model achieving the highest accuracy of 96.4%. This confirms its superior ability to capture both spatial and temporal patterns in time-series sensor data. The proposed system addresses key limitations of existing video-based and wearable sensor methods by offering an accessible, scalable, and tamper-proof solution. It has significant potential in healthcare, sports, and disability certification, where objective and consistent postural assessment is critical.

Future work will focus on enhancing model generalizability by incorporating larger, more diverse datasets and integrating contextual and biometric data such as surface type, footwear, heart rate, or temperature to improve classification accuracy. These enhancements will help create a robust, real-world solution for automated leg posture evaluation across varied environments and populations.

6. Funding

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7. Conflict of Interest

There is no conflict of interest between the authors.

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