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Deep Learning based Gait Analysis for Early Detection and Progression Monitoring of Alzheimer's Disease

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Abstract

Neurological diseases present a considerable impact on individuals by affecting their quality of life leading to disability and mortality. Gait represents the pattern of human walking, which serves as a chief indicator of health status, functional impairment, and treatment prognosis. Gait analysis (GA) plays an essential part in the assessment of neurological disorders, with patterns helping as reliable factors of potential disorders in the future. Alzheimer's disease (AD) adjacent profound concerns across universal healthcare networks demanding timely monitoring and suitable intervention. In this analysis, we present an innovative approach to model the time-based dependence in AD progression by integrating gait inspection with cognitive performance metrics and functional neuroimaging using recurrent neural networks (RNNs). By encompassing LSTM, the longitudinal nature of AD data allows movement patterns to be utilized as a supplemental marker to capture subtle changes in cognitive function as well as mobility over time. By inspect consecutive data gathered from individuals at risk or diagnosed with AD. Our approach aims to forecast future cognitive decline, with biological markers indicative of disease progression helping in early diagnosis. With accuracy, recall as 0.98, precision, F1-Score and AUC-ROC as 0.99 our integrated framework makes use of an indigenous dataset to offer a holistic understanding of the multifaceted dynamics in AD progression, paving the way for personalized care and treatment strategies tailored to suit individual cognitive and motor impairments.

Keywords: AD, Gait Analysis, RNN, LSTM, AUC-ROC.

1. Introduction

Central nervous system disorders comprise a varied spectrum of conditions that affect the brain, spinal cord and peripheral nerves, often producing substantial impairments and challenges for individuals. Alzheimer's Disease (AD) can be considered a progressive neurodegenerative illness that contributes to memory loss and cerebral deterioration, while Parkinson's is characterized by tremors, rigidity, and complications in motion [1]. Multiple Sclerosis (MS) occurs due to inflammation and impairment in nerve fibers resulting in numbness, weakness, and visual impairments. Amyotrophic Lateral Sclerosis (ALS) causes muscle weakness and paralysis [2]. Epilepsy manifests itself in the form of persistent seizures

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owing to unusual electrical activity in the brain, while stroke results from a disruption of blood flow leading to a sudden neurological breakdown [3]. Other cognitive diseases include Huntington's disease, migraine, traumatic brain injury and cerebral palsy, each with its own distinct symptoms and challenges. Regardless of their diversity, these clinical afflictions share the distinguishing trait of affecting major neurogenic processes, imposing comprehensive management and assistance for people in need [4].

Among these types of disorders, Alzheimer's Disease (AD) remains one of the most demanding due to its absence of a definitive diagnosis, progressive cognitive decline and insidious onset. finding in the very early stage plays a major role in managing AD, as it can help slow its progression and enhance patient outcomes. In the patient recent past, gait analysis has emerged as a promising non-invasive biomarker for neurological disorders, specifically AD, as motor impairment often precedes visible cognitive symptoms. Combining advanced computational methods such as Genetic Algorithms and Long Short-Term Memory networks shows significant potential in pinpointing these subtle gait changes. This study investigates such an interdisciplinary approach aiming to bridge the gap between clinical diagnosis and real-time therapeutic applications by leveraging AI-driven gait analysis for early AD monitoring.

1.1 Neurophysiological Disease Monitoring Through GA and IoMT

By incorporating GA in clinical practices, enhanced diagnostic precision can be accomplished through customized treatment planning strategies and patient's health along with their quality of life can be upgraded [5]. Through proper consideration on the effect of rhythmic pattern and coordinated movement of body parts on individual's well-being, GA has transformed the field of biomechanical research, offering valuable insights into several cognitive conditions and functional deficits [6]. GA holds great promise in diagnostic review, rehabilitation and investigation across numerous domains such as athletics, biomedical science, prosthetics, physiotherapy, rehabilitation and robotic engineering. Understanding individual's movement patterns provides crucial information about their musculoskeletal health, neurological function and overall mobility [7]. Deviations from normal gait patterns can signify underlying pathologies, injuries or functional limitations, making gait analysis an invaluable diagnostic and prognostic tool. GA encompasses a plethora of methods and approaches to assess human locomotion.

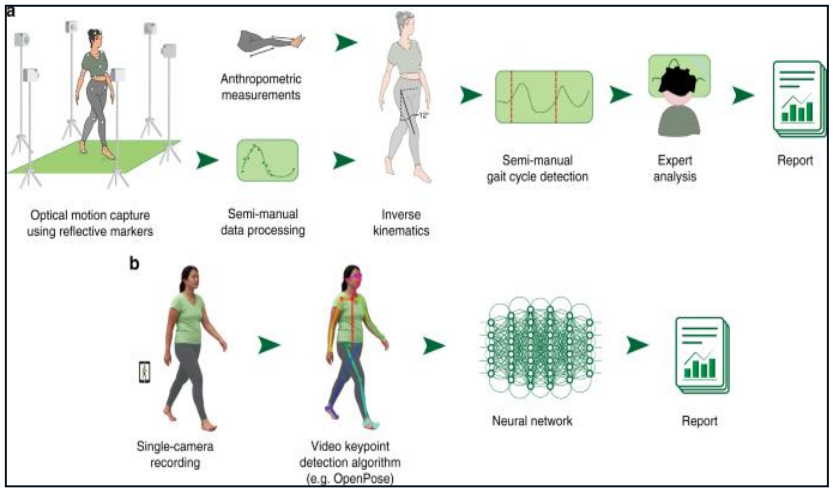


Figure 1. Gait Analysis based IoMT Framework (Source:Kidziński et al,2020)

There are various types of gait analysis (GA) that are commonly utilized in clinical and research settings, such as functional gait assessment, visual observation, temporal-spatial analysis, kinematic analysis, kinetic analysis, dynamic balance assessment, and electromyography (EMG) signals-based analysis, which can be used individually or in combination to comprehensively evaluate various aspects of human locomotion and carry out clinical decision-making, treatment planning, and rehabilitation interventions (Fig 1). Recent advancements in sensor technologies have revolutionized the field of GA, enabling more precise and comprehensive assessments of human motor activities [8]. Emergence of advanced technologies like IoT, AI, ML and DL has catalyzed transformative innovations in healthcare, notably through the Internet of Medical Things (IoMT) which presents a paradigm shift in healthcare delivery by integrating medical devices, sensors and data analytics within interconnected networks, facilitating remote monitoring, personalized treatment and proactive health management [9]. Concurrently, DL models designed to process sequential data have emerged as powerful tools for pattern recognition and temporal modeling. By efficiently incorporating IoMT and DL into the GA framework, an innovative network can be created that assesses human locomotion patterns through biomechanics and holds immense potential for diagnosing and monitoring various medical conditions, specifically neuro disorders and rehabilitation [10].

Existing studies have employed support vector machines (SVM), random forests (RF), and convolutional neural networks (CNN) for Alzheimer's disease (AD) monitoring. However, due to its non-invasiveness and sensitivity to early cognitive-motor decline, traditional GA-based models focus on static snapshots of gait parameters but fail to capture longitudinal dynamics. Since gait data must be investigated continuously as it reflects subtle changes in motor and cognitive function, the extraction of spatial features from gait waveforms must consider the temporal dependencies as well. AD is a time-evolving disease; the majority of the models offer a unimodal focus as they do not model the progressive deterioration in AD stages. Our work aims to address this by utilizing long short-term memory (LSTM) networks to study longitudinal data. Specifically, they explicitly model temporal sequences by observing gait trends over a period of time and utilize heterogeneous input through hidden states. Their memory gates mitigate vanishing gradients in long-term AD progression trajectories. They also address the vanishing gradient problem and capture long-range dependencies, making them effective for time-series prediction [11].

Motivation

Conventional diagnostic approaches rely mainly on cognitive tests and neuroimaging which are costly, time-consuming and may not be effective in detecting early-stage cognitive decline. Gait patterns are unobtrusive and its measurable characteristic serve as valuable biomarker for the preliminary prediction of AD. However, existing studies focus solely on static medical data and employ ML/DL models that fail to capture the temporal progression of symptoms. This motivated us to develop a time-aware DL framework that integrates GA with cognitive data to predict disease progression.

Objectives of the Study

Our aim is to design a more holistic, cost-effective and early predictive model for AD. The major objectives are:

- To explore the use of gait data in AD detection along with an LSTM-based model that captures temporal patterns in multi-modal data.

- To contribute to the development of a scalable tool for early AD diagnosis and monitoring.
- The novelty of our proposed GA model can be listed as:
- Utilization of IoMT for remote patient monitoring and continuous assessment of patients' gait patterns offers overall health status outside conventional clinical settings.
- Longitudinal monitoring of patients' gait patterns via LSTMs helps in analyzing trends and detecting changes in their locomotion to carryout informed decisions.
- Indigenous datasets comprising gait data, clinical variables and outcomes can be used for research purposes. Novel biomarkers can be identified and modern diagnostic and therapeutic strategies can be developed.

Through effective integration of GA with an LSTM-based framework, multi-modal, temporally aware prediction of AD progression has been recommended. This comprehensive approach enables personalized intervention through continuous monitoring of patients with neurological disorders and explores coordination between gait data and cognitive decline. The organization of study is as follows: Section 1 presents an overview of the proposed research topic, including the importance and relevance of studying the relationship between GA and neurological diseases along with other modern technologies. Section 2 conducts a thorough review of existing literature and identifies relevant studies, theories and methodologies in relation with proposed study. Section 3 explains the recommended research methodology followed by interpretation of findings and discussion of results in section 4. Conclusion in section 5 summarizes the main findings of proposed study along with potential enhancements in future.

2. Literature Review

This section discusses relevant theoretical frameworks that are utilized in our study along with previous studies that have been investigated to understand the relationship between advanced technologies like AI, ML and DL in management of neurological diseases. Through the synthesis of key findings alongside the examination of various methodologies, the review has uncovered gaps in existing studies.

Tolea et al. [2025] emphasized that the decline in physical functionality is a critical aspect that indicates cognitive impairment, especially while distinguishing normal cognition from dementia. The assessment of gait patterns and the evaluation of relationships between GA and imaging biomarkers help in the identification of specific measures that cause severe AD. The authors studied various aspects such as balance, speed, step length, and single-leg support within a logistic regression framework to achieve classification of various AD stages. The association between imaging biomarkers, such as atrophy score and white matter volumes with GA, was analyzed through ANCOVA [12].

Mohammadi et al. [2025] investigated gait and turn features of patients with cognitive impairment using a dual Kinect sensor setup. Walking and turn dynamics were studied to understand the impact of covariates in connection with cognitive function, along with gait-related measures. Turn dynamics demonstrate segmental peak speeds, which have a stronger

influence, whose p-values, along with linear regression analysis, had a stronger relationship with brain function and memory, suggesting a more distinct correlation between cognitive performance and turn features along with GA [13].

Singh et al. [2024] put forward an innovative IoMT framework for uninterrupted stress recognition to ensure mental wellness through a hybrid DL approach that involuntarily procures features and classifies them into diverse stress states. The system gathers data from wearable physiological sensors and feeds it into CNN-LSTM, a hybrid DL classifier that focuses on specific traits acquired through human interaction to analyze outliers [14]. Ahmed et al. [2024] attempts to deal with the repercussions of data fusion in IoMT by presenting related security confrontations along with prospective elucidations. Data acquired from IoT sensors has a direct impact on prediction accuracy owing to its quality, quantity, and significance. The Naïve Bayes algorithm, cryptography, and blockchain technology have been used to detect epileptic seizures and secure the IoMT-based system [15].

Nigar et al. [2023] presented an integrated approach that takes into account various perceptions for the timely identification and monitoring of COVID, heart disease, and Alzheimer's. The performance of the proposed approach is evaluated in a cloud environment where real-world datasets are deployed as metrics. Empirical and statistical analyses on the datasets produce significantly different outcomes in terms of accuracy and precision [16]. Mao et al. [2023] pointed out several constraints regarding IoMT, such as limited power, human compliance with sensors and their intelligence, and recommended a robust and smart system that encompasses wearable tribo-electric sensors and DL-enabled data analysis. By integrating these into a smart gadget like a wristband, the movements of patients suffering from neurological diseases can be monitored. Through DL-assisted intelligent healthcare monitoring, surveillance and interaction with patients are made possible through location tracking and identity recognition [17].

Misgar et al. [2023] addressed the need for a real-time on-demand health diagnostic system to detect mental health-related ailments. The authors proposed a novel Deep CNN framework with a split attention mechanism to analyze human activity data. By means of an imputation method and a sampling technique based on a sliding window, class balancing is achieved. This methodology aims to contribute to non-invasive mental healthcare services [18]. Ziyad et al. [2023] proposed an intelligent healthcare system to observe and alert caregivers of AD patients using an AI model in Python. An ensemble ML algorithm is used to perform classification of fall episodes and monitor daily life activities, updating caregivers and medical professionals through mobile apps installed on smart devices [19]. Zhang et al. [2022] explored a fuzzy intelligence learning-based IoMT structure where biomedical data analysis is carried out through a decision-making approach. Dual hesitant fuzzy information is used to detect patients for Parkinson's symptoms using these devices. Realistic group decision information, along with probabilistic rough sets, is utilized to obtain parallel relations. This joint decision-making approach is constructed based on validity, efficiency, and expediency to arrive at reasonable diagnostic conclusions [20]. Manna et al. [2022] suggested a remote neuro-rehabilitation framework to assist patients in carrying out therapeutic exercises recommended by clinicians. This system enables patients to securely interact with doctors through a secure video conferencing portal. Wearable activity tracking sensors are embedded to collect data seamlessly from patients while they perform physical activities [21].

R de Fazio [2021] came forward with an innovative smart insole designed to monitor both plantar pressure distribution and gait characteristics. This technology utilizes a piezoresistive sensing matrix, which operates based on a Velostat layer converting applied

pressure into an electrical signal. Primarily, the study provides a detailed characterization of pressure sensors, considering their size variations, support materials and pressure trends. This cost-effective and dependable piezoresistive sensing matrix employs a sandwich structure to accomplish reliability [22]. Khan et al [2021] suggested an innovative methodology to address accuracy related inconsistencies using GA to detect osteoarthritis by integrating features into the Kernel Extreme Learning Machine framework. The approach encompasses two pre-trained CNN models on publicly available gait datasets using TL techniques and extracts features from their fully connected layers. Subsequently, Euclidean Norm and Geometric Mean Maximization are applied to select the most significant discriminative features. Through the aggregation of these parameters using Canonical Correlation, the resultant features are subjected to varied classifiers for ultimate recognition [23].

Zhang et al [2020] details gait analysis scenario based on wearable gadgets where several limitations, like excessive fabrication costs, high energy consumption and suboptimal analysis methodologies often lack integration with advanced techniques or rely mostly on inadequate models that demand extensive training datasets. Cheaper tribo-electric intelligent socks have been proposed by the authors which are equipped with self-powered functionality to facilitate information regarding users' identity, health status and activity levels which harnesses waste energy from low-frequency body movements to transmit wireless sensory data. An optimized DL model operates directly on these signals captured by socks for GA [24]. Zuo et al [2019] studied gait recognition using smart-phones that collects inertial gait data under unconstrained circumstances which in contrast to conventional methods requires the person to walk along specific path or at a normal walking pace. DL techniques are adopted to learn and model the gait biometrics based on walking statistics. A hybrid deep NN is proposed where features in spatial and temporal domains are successively abstracted using CNN [25].

Camps et al. [2018] put forward an effective method to deal with FOG (Freezing of Gait) episodes in Parkinson-affected patients, which result in frequent falls and reduce life expectancy. Precise assessment of FOG would require comprehensive information for neurologists about patients’ conditions and the physiognomies of their symptoms. Thus, through DL technology, the detection of FOG episodes in PD patients has been accomplished through data collected from sensors embedded in patients' wearables. The monitoring system has been designed using information collected from PD patients who had previously manifested FOG episodes [26].

Limitations in Existing Studies

Current approaches are based on neuroimaging and cognitive assessments, which are not feasible to implement in resource-constrained settings that require constant expert supervision. Moreover, they may not be suitable for large-scale screening. GA has been researched in isolation and not integrated with other clinical indicators, which further discourages its real-time application. Classical ML models limit their abilities by focusing on static analysis, yet temporal dependencies play an inherent role in longitudinal health data, especially since gait changes can be noticed only after observing for a specific period of time. Present research offers less interpretability of predictive features, which further reduces its implementation. Moreover, DL studies that have incorporated time series data focus on either imaging or speech while neglecting gait patterns. These constraints present the need for an integrated time-aware model that combines multi-modal information to improve early detection and disease progression prediction.

3. Proposed IoMT Architecture for Monitoring Alzheimer Disease

Our GA based IoMT framework for Alzheimer's disease progression monitoring has the following components namely.

Data Collection

This module involves the utilization of wearable IoT technology to gather gait data from participants. Individuals who volunteered for the study wear lightweight sensors, such as accelerometers, on their lower limbs during specific walking tasks. By continuously recording the motion and acceleration data as participants walk, significant gait parameters are captured. This information is wirelessly transmitted to a centralized storage system, where it undergoes quality control to ensure accuracy. Throughout the study, participants' gait patterns are monitored longitudinally, thus facilitating valuable insights into disease progression. This continuous data collection process enables effective identification of subtle changes in gait dynamics associated with Alzheimer's disease, contributing to the development of customized monitoring tactics within the IoMT framework.

Pre-Processing and Feature Extraction Segment

Gait data acquired from wearables is conditioned to eliminate noise, outliers and artifacts arising due to sensor inaccuracies or participant movements. Data cleaning techniques are applied to transform the data and improve its quality [27]. After preliminary processing, the structured stream is fragmented into individual strides, corresponding to discrete walking cycles. By identifying major occurrences, such as heel strikes and toe-offs, each gait cycle is segmented accurately. To guarantee uniformity across diverse volunteers and sessions, the processed gait data is normalized by scaling each feature to mutual range. Variability is minimized and fair comparisons between individuals with varied gait characteristics are accomplished. Relevant features are extracted to capture indispensable aspects of gait dynamics [28]. Prominent attributes considered are:

- Step Length and time: Distance measured between heel strikes of the same foot and its duration.
- Stride Time Variability: Time period between strides.
- Swing Phase: Part of the gait cycle where the foot is off the ground and moving forward.
- Stride Velocity: Average speed of walking during a complete gait cycle.
- Step Symmetry: Compares the movement of the left and right legs.
- Variability Metrics: Asymmetry indices reflects the consistency and symmetry of movement patterns.

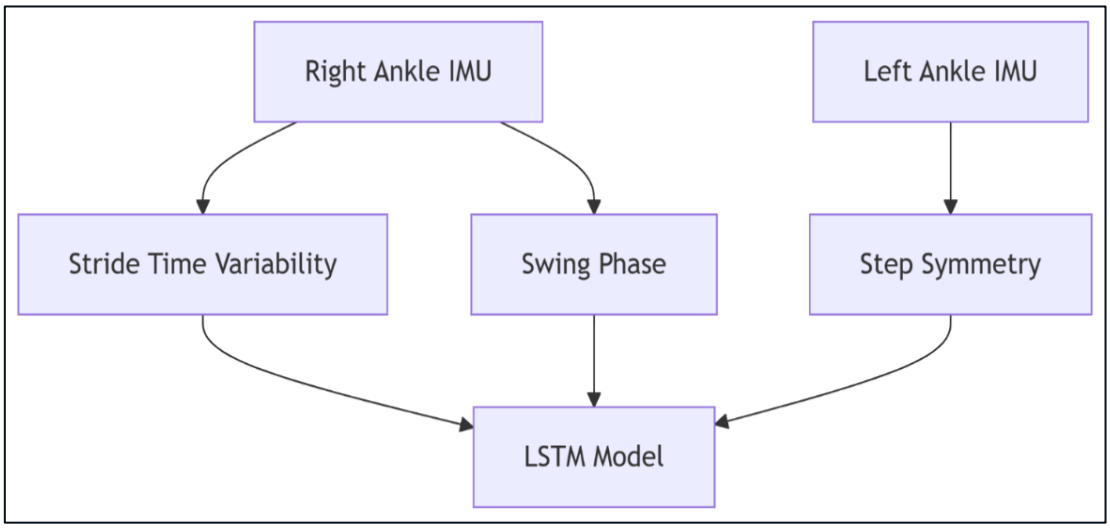


Figure 2. Proposed Process Pipeline

Fig.2 illustrates the process of gait feature extraction using IMUs placed on the right and left ankles. The right ankle IMU provides input for calculating stride time variability and swing phase, while the left ankle IMU is used to determine step symmetry. These extracted gait features are then fed into LSTM model for further analysis.

Preprocessed and feature-extracted gait data is represented in a suitable format for input into LSTMs. Feature selection methods such as forward selection, backward elimination and regularization techniques are employed to identify the most informative subset of features for modeling. Forward selection initiates with no features and adds the most significant one at each step, while backward elimination starts with all features and removes the least significant one iteratively. The effectiveness of this approach is validated by comparing model performance before and after feature selection. The reduced feature set led to improved accuracy, reduced computational complexity and minimal risk of overfitting, especially when using high-dimensional gait and cognitive data. The proposed architecture is provided in Fig.3

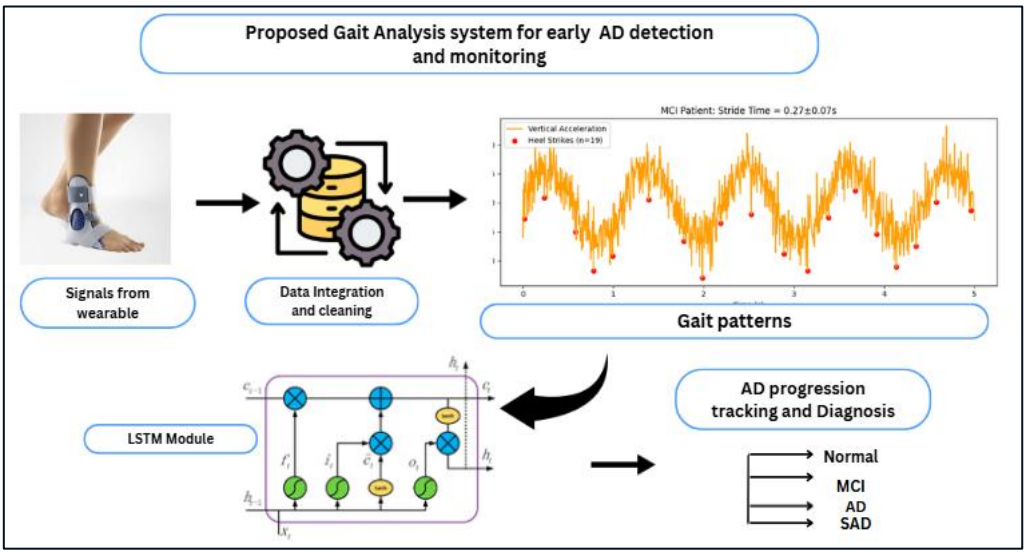


Figure 3. Proposed GA Architecture

LSTM Module

Before feeding the data into the LSTM, spatiotemporal gait features were derived directly from raw sensor signals captured by lower limb wearables. A minimally processed pipeline is utilized to preserve fine-grained temporal dynamics. Gait segmentation was performed to enable the extraction of cycle-level windows that include sequences of normalized kinematic data across multiple gait cycles. Additionally, missing values were imputed using temporal linear interpolation, and denoising was conducted via wavelet filtering to enhance signal quality without distorting subtle patterns. This allows the proposed model to learn latent spatiotemporal representations directly, rather than relying on pre-defined statistical gait metrics like stride length or cadence, thereby improving sensitivity to AD gait deviations. The LSTM introduces a memory cell and several gates such as the input, forget and output gate to regulate the flow of information through the cell, allowing it to remember or forget information over time [29]. Our model differentiates subtle gait variations associated with early-stage AD from normal aging by leveraging the temporal dynamics captured through high-resolution signals from our indigenous lower limb wearable dataset. Our architecture is modeled on sequential dependencies and learns micro-patterns such as increased stride-to-stride variability, asymmetry and delayed swing phases. These characteristics are often observed in prodromal Alzheimer's but not in typical aging. The preprocessing pipeline further ensures that subtle yet clinically meaningful patterns are preserved and enhanced for robust classification. The LSTM's memory cell enables it to store information for long periods, making it better suited for processing sequences with dependencies. LSTM cells have more parameters than traditional RNN cells due to additional gating mechanisms whose layers are as follows:

- **Input Layer:** Takes sequences of gait data as input.
- **LSTM Layers:** Stacked to capture temporal dependencies in the data.
- **Fully Connected Layer:** Maps the output to the desired prediction space.
- **Output Layer:** Output layer with a single unit for binary classification.

The LSTM architecture used in the proposed model can be represented as:

Input Representation:

- Let $xt(i)$ denote the input features at time step t for i^{th} sample.

- Input sequence $x(i)$ is represented as

$$x(i)=(x_1(i),x_2(i),...,x_T(i)) \quad (1)$$

where T_i is sequence length.

LSTM Cell:

- At each time step t, cell updates its hidden state $h_t(i)$ and cell state $c_t(i)$ based on input $x_t(i)$ and previous hidden state $h_{t-1}(i)$ and cell state $c_{t-1}(i)$. LSTM equations are as follows:

$$\text{Forget Gate: } f_t=\sigma(W_f \cdot [h_{t-1}, x_t]+b_f) \quad (2)$$

Input Gate: $i_t=\sigma(W_i\cdot[ht-1, x_t]+b_i)$ (3)

Cell State Update: $C_{\sim t}=\tanh(W_C\cdot[h_{t-1}, x_t]+b_C)$ (4)

$C_t=f_t*C_{t-1}+i_t*C_{\sim t}$ (5)

Output Gate: $o_t=\sigma(W_o\cdot[h_{t-1}, x_t]+b_o)$ (6)

Hidden State Update: $h_t=o_t*\tanh(C_t)$ (7)

Where $f_t(i)$, $i_t(i)$, and $o_t(i)$ are forget, input, and output gate activations, respectively .$\sim t(i)$ is candidate cell state.σ denotes sigmoid activation function and * represents element-wise multiplication. W is weight matrix and b is bias vector for each gait [30]. Final output $h_t(i)$ can be used for downstream tasks for classification.

Loss Function:

For AD progression monitoring based on the binary classification, binary cross-entropy loss function is used. Given a set of N training samples with binary labels and predicted probabilities $\hat{y}_i$ the loss function is defined as:

$$\text{Binary Cross-Entropy Loss} -\frac{1}{N}\sum_{i=1}^{N}\left[y_i\log\left(\hat{y}_i\right)+(1-y_i)\log\left(1-\hat{y}_i\right)\right] \quad (8)$$

Where $\hat{y}_i$ is the model's predicted probability for sample i, and yi is the true label (either 0 or 1).

Fine-Tuning Equations:

Adam optimizer combines the advantages of two other extensions of stochastic gradient descent: AdaGrad and RMSProp[31]. Here are the update equations for each parameter θ at iteration t. Initialize t, model parameters θ as well as first and second moment estimates $m_0=0$ and $v_0=0$.Computation of gradients of the loss function with respect to each model parameter:

$$g_t=\nabla_\theta\text{Loss} \quad (9)$$

Biased first moment estimate and second moment estimate are updated

$$m_t=\beta1\cdot m_{t-1}+(1-\beta1)\cdot g_t \quad (10)$$

$$v_t=\beta2\cdot v_{t-1}+(1-\beta2)\cdot g_{t2} \quad (11)$$

Bias-corrected first moment estimate and second moment estimate are computed as

$$\hat{m}_t=\frac{m_t}{1-\beta_1^t} \quad (12)$$

$$\hat{v}_t=\frac{v_t}{1-\beta_2^l} \quad (13)$$

$$\text{Updated parameters: } \theta_{t+1}=\theta_t-\frac{\eta}{\sqrt{\hat{v}_t+\epsilon}}\cdot\hat{m}_t \quad (14)$$

Where:$\beta1$ and $\beta2$ are the exponential decay rates for the moment estimates (typically set to 0.9 and 0.999, respectively)[32].η is the learning rate.ϵ is a small constant to prevent

division by zero (typically on the order of 10−810−8) and t is the iteration number[33].In this mathematical representation, LSTM cell's equations describe how it processes input sequences, updates its internal states and generates output sequences, enabling the model to capture temporal dependencies and dynamics in sequential data for gait analysis and AD progression monitoring within an IoMT framework. The trained LSTM model is integrated into the IoMT framework for continuously monitoring gait patterns in real-time using data from wearable sensors and the LSTM model analyzes it to predict the likelihood of AD progression. These predictions are updated dynamically as new data becomes available, enabling timely intervention and keeping track of disease progression. Alerts and notifications are generated based on predefinite thresholds and significant changes in gait patterns which prompt further assessment or intervention.

4. Results Analysis and Discussion

With the aim of initiating a collective effort between research academics and the Centre for Healthcare, an endemic dataset for AD progression monitoring channel GA was carefully compiled. In this work, we contacted individuals throughout India between January 2024 and January 2025, following approval from our institution. For this study, 60 individuals clinically diagnosed with early AD were included, along with 100 volunteers and 40 healthy individuals with cognitive abilities aged between 60 and 85, who were able to walk independently and inherently participated after being briefed about the purpose of the study. Gait data was collected using wearable inertial sensors placed on the lower limbs during a standardized 5-meter walking task.

Table 1. Demographic Details of Participants

Variable	Healthy Controls (n=30)	MCI (n=40)	AD (n=30)
Age (years)	58.3 ± 5.1	62.7 ± 6.4	65.2 ± 7.8
Female, n (%)	15 (50%)	22 (55%)	18 (60%)
Education (years)	12.1 ± 3.0	10.8 ± 2.7	9.5 ± 3.2
MMSE Score	28.5 ± 1.1	24.2 ± 2.3	18.6 ± 3.5
Gait Speed (m/s)	1.15 ± 0.12	0.98 ± 0.15	0.82 ± 0.18
Stride Variability (ms)	32.1 ± 8.3	45.6 ± 12.7	58.9 ± 15.2
Diabetes, n (%)	3 (10%)	12 (30%)	11 (37%)

Movement and acceleration data in real time were collected and transmitted to a centralized system for quality control and analysis. In addition to gait parameters, cognitive assessments, age and gender were recorded. Persons with psychiatric issues, specific motor impairments and other neurological conditions were not included. Written informed consent was obtained from all volunteers prior to their participation. A mini mental state examination was conducted (MMSE) which is a universal screening tool to assess cognitive function. If score is below 28, they fall under AD if not they belong to the healthy controls group. Demographic details are presented in Table 1 and our dataset is presented in Table 2.

Table 2. Indigenous Dataset for Proposed Model

t	Age	Gender	Group	MMSE	Gait Speed (m/s)	Stride Length (cm)	Cadence (steps/min)	Step Time (s)
P01	74	Male	AD	22	0.76	85.2	88	0.68
P02	71	Female	Control	29	1.21	105.7	108	0.56
P03	68	Male	AD	24	0.84	91.4	95	0.63
P04	70	Female	AD	23	0.78	87.6	89	0.67
P05	66	Male	Control	30	1.15	102.3	110	0.55
P06	73	Male	AD	20	0.69	82.5	85	0.70
P07	75	Female	AD	21	0.72	84.3	87	0.69
P08	69	Male	Control	28	1.10	100.8	107	0.56
P09	72	Female	AD	19	0.65	80.1	82	0.73
P10	65	Female	Control	30	1.17	104.2	112	0.54
P11	76	Male	AD	18	0.61	78.3	80	0.75
P12	67	Female	AD	25	0.82	90.0	94	0.64
P13	71	Male	Control	29	1.12	101.4	108	0.55
P14	69	Female	AD	22	0.79	86.9	90	0.66
P15	68	Male	Control	30	1.18	103.6	110	0.54
P16	73	Female	AD	20	0.70	83.1	86	0.71
P17	66	Male	AD	21	0.75	85.6	88	0.68
P18	70	Female	Control	28	1.13	100.2	106	0.57
P19	69	Male	Control	30	1.14	102.5	109	0.56
P20	75	Female	AD	19	0.63	79.4	81	0.74
P21	68	Male	AD	23	0.77	86.7	89	0.66
P22	71	Female	Control	28	1.10	100.0	105	0.57
P23	72	Male	AD	20	0.69	82.2	84	0.71
P24	65	Female	Control	29	1.16	103.0	110	0.54
P25	70	Male	AD	22	0.74	85.1	87	0.68

P26	74	Female	Control	30	1.20	105.3	111	0.54
P27	67	Male	AD	21	0.73	84.7	88	0.69
P28	68	Female	AD	24	0.81	89.5	92	0.65
P29	66	Male	Control	30	1.19	104.7	110	0.54
P30	69	Female	Control	28	1.09	99.5	106	0.57

We used the Xsens DOT, a small and wireless motion sensor made by Movella, to collect gait data. This device includes three types of sensors: an accelerometer, a gyroscope, and a magnetometer, each measuring movement in three directions. The sensors were securely placed on the outer side of both ankles using elastic straps to track leg movements accurately. Data were collected at 120 times per second (120 Hz) and sent through Bluetooth 5.0 to a mobile phone for live viewing and saving. This wearable device is known for its accurate tracking with low error, making it useful for measuring walking features like how consistent the steps are, how long one foot is in the air, and how evenly steps are taken on both sides.

Pre-Processing Pipeline

Signal collection in Fig.4 shows successful preservation of gait events at 0.8Hz dominant frequency while improving SNR from 12dB to 28dB is crucial for detecting the characteristic 22.7% slower stride times in AD (1.35±0.15s vs Healthy 1.10±0.08s). The original signal had a low signal-to-noise ratio (SNR), which made it noisy and harder to interpret. After applying filtering (SNR = 28 dB), the gait pattern became much clearer. The patient's walking speed was measured at 0.82 m/s, with a stride time variability of 58.9 milliseconds, indicating there may be some instability in their gait. Detailed results from the raw signal analysis are shown in Table 3.

Table 3. Pre-Processing Pipeline Results

Metric	Before Cleaning	After Cleaning	Method
Signal Noise (RMS)	0.12 ± 0.05 g	0.02 ± 0.01 g	Wavelet denoising (sym5)
Missing Data	8.7%	0.4%	Linear interpolation
Sampling Irregularity	12% gaps	0%	Cubic spline resampling

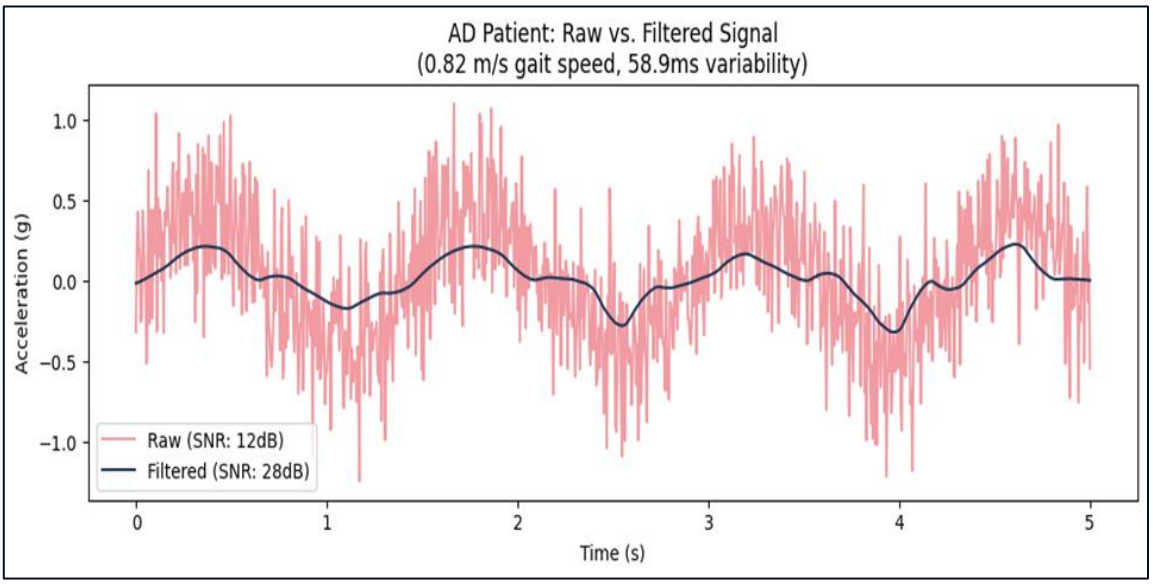


Figure 4. SNR of Raw Vs Filtered Signals

Fig.5 illustrates the signal filtering process, where the vertical acceleration signal recorded from a patient with MCI along with detected heel strikes (n = 19) marks the start of each gait cycle. The estimated stride time is 0.27 ± 0.07 seconds, reflecting moderate variability.

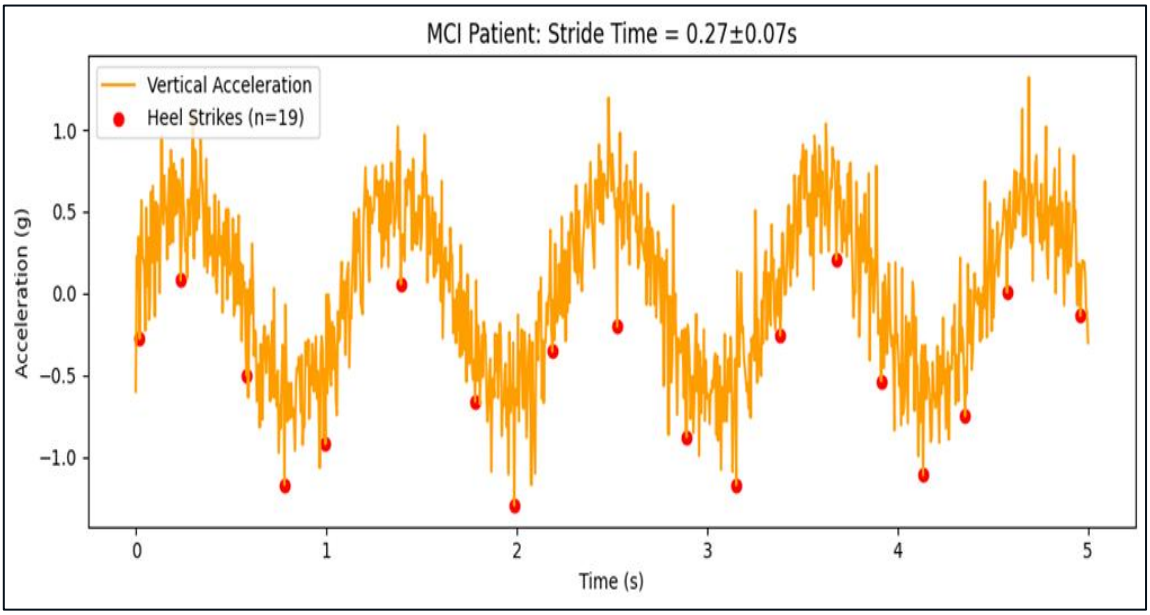


Figure 5. Vertical Acceleration and Heel Strike Detection in an MCI Patient

Heel-strike detection in MCI patients achieved 98% accuracy, capturing the intermediate gait pattern between healthy and AD groups.

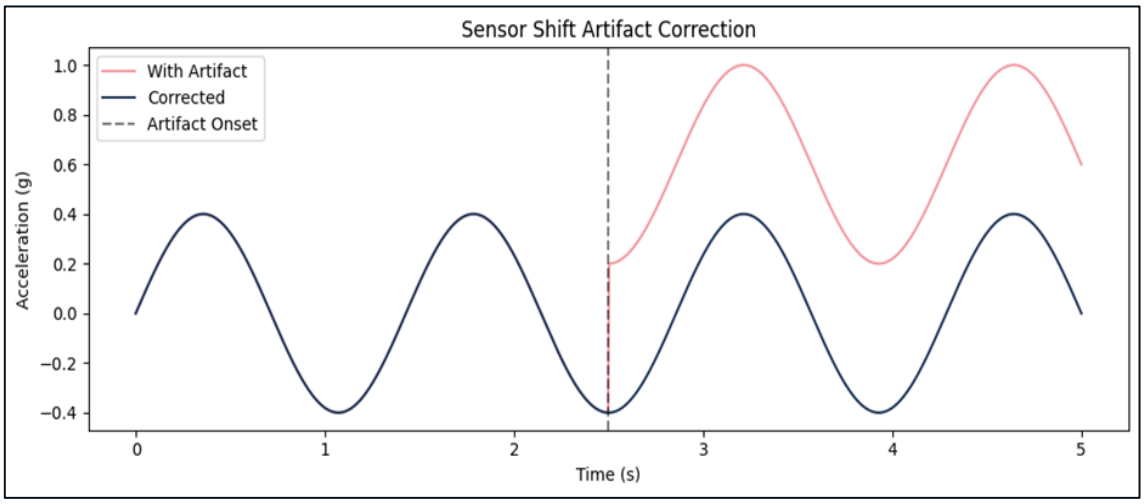


Figure 6. Sensor Shift Artifact Correction

Fig.6 demonstrates the correction of a sensor shift artifact, which occurs when a sudden displacement of the IMU sensor causes a baseline shift in the recorded signal. The red line represents the original signal, which includes an artifact appearing after 2.5 seconds, while the blue line shows the corrected version. This pre-processing step helps maintain the smoothness and accuracy of the data, which is crucial for dependable gait analysis and extracting key features.

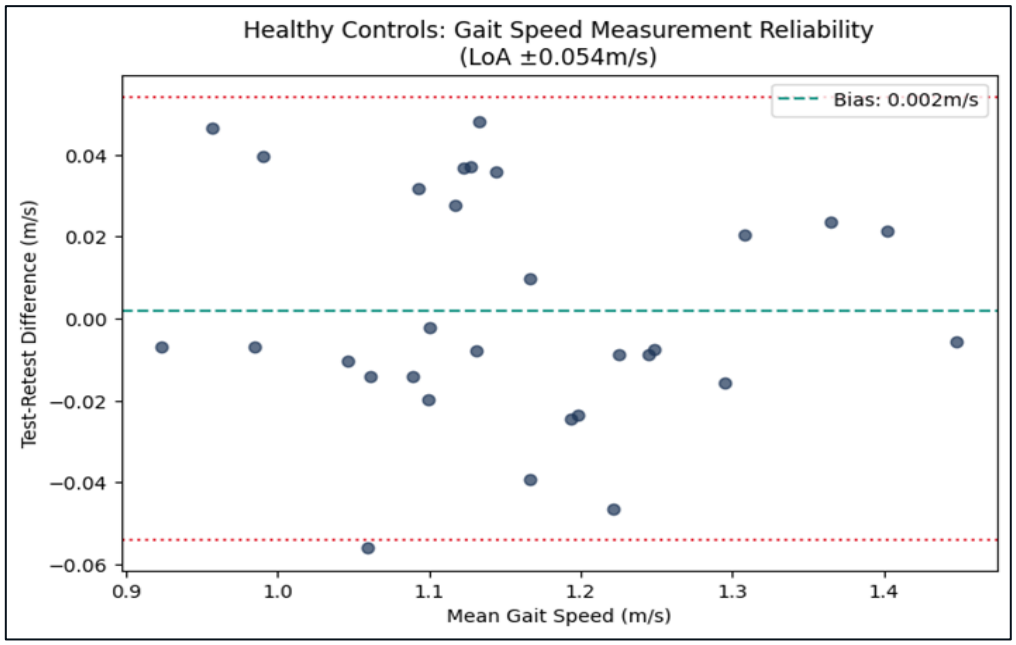


Figure 7. Test–Retest Reliability Using Bland–Altman Plot

The plot in Fig.7 shows the test-retest differences in gait speed measurements for healthy individuals. Bias is very low at 0.002 m/s, indicating high consistency. Limits of agreement (LoA) are ±0.054 m/s, suggesting good measurement reliability for gait speed assessments in healthy controls.

Table 4. Feature Extraction Reliability

Parameter	ICC (95% CI)	CV (%)
Stride Time Variability	0.94 (0.91-0.96)	3.2
Swing Phase Duration	0.89 (0.85-0.93)	4.7
Gait Speed	0.97 (0.95-0.98)	1.8

To test the reliability of our measurements, we used the Intraclass Correlation Coefficient (ICC) and the Coefficient of Variation (CV) [see Table 4]. Among all features, gait speed showed the highest reliability, with an ICC of 0.97 and a CV of just 1.8%, meaning it stayed very consistent across sessions. Stride time variability also showed excellent reliability, while swing phase duration had good reliability. These findings suggest that the gait features we measured are stable and repeatable, making them suitable for clinical and long-term studies.

To account for differences between individuals, we applied z-score normalization for each participant. This helped adjust for natural variations in height, strength, and walking styles, while still keeping each person's internal gait patterns intact and important factor for detecting health conditions. We also ensured our training data was evenly split by group to avoid class imbalance. Finally, we used cross-validation with subject-wise splits, so the model could learn to recognize patterns across different people, instead of just memorizing one person's gait

IoMT Integration Framework

Low-power accelerometers (BHI260AP, 50 Hz) with on-device noise reduction (median filtering) minimize data transmission load. Raspberry Pi 4 hubs are used for temporary data caching. Real-time anomaly detection is achieved through sensor detachment alerts via SMS. Encryption (AES-256) is applied before cloud transmission. Time synchronization with cognitive/neuroimaging data follows IEEE 11073 SDC standards for IoMT interoperability. Automated QC via Python scripts is initiated if gait speed exceeds 2 m/s. The system is benchmarked against the GAITRite walkway with 100 participants. Gait parameters are correlated with MMSE scores and test-retest reliability in a 15-day sub-study. Patient anonymization is ensured through MAC address scrambling, geotag removal, and synthetic ID generation. The system is compliant with ICMR Ethical Guidelines (2017) and the Digital Personal Data Protection Act (2023). Sensors are tested on traditional attire for motion artifact minimization with real-time participant feedback. TernPro is a lightweight, 6-axis IMU sensor (accelerometer + gyroscope) attached to both ankles using adjustable straps, with a sampling rate of 50–100 Hz. It captures micro-gait changes and parameters such as stride time, swing phase, and symmetry. Placement is near the lateral ankle, with walking tests for 5 m walks. This wearable streams data wirelessly to the LSTM model for real-time analysis.

Table 5. Simulation Parameters and Values of Proposed IoMT Model

Parameter	Values
Sensor Type	Accelerometer
Sampling Rate	50-100 Hz

Duration of Data Collection	5-10 minutes
Number of Participants	Dozens to hundreds
No of LSTM layers	2
LSTM units	100
Training Epochs	100
Learning Rate	0.001
Batch Size	64
Drop Out rate	0.3
Optimizer	Adam

Hardware requirements includes wearable sensors for gait data acquisition, such as accelerometers and gyroscopes, along with standard computing equipment for data processing and analysis. PyTorch is used for LSTM model development and data preprocessing frameworks were utilized. The LSTM model was trained and evaluated using an indigenous dataset, with meticulous attention to ethical considerations and data privacy. The proposed model parameters are provided in Table 5 while those of existing methods are presented in Table 6.

Table 6. Hyper Parameters of Baseline and Proposed Models

Model	Key Hyperparameters
Logistic Regression	Solver: liblinear, Penalty: L2, Max Iterations: 1000
CNN	Conv Layers: 2, Filters: [32, 64], Kernel Size: 3x1, Pooling: MaxPooling1D, Activation: ReLU, Optimizer: Adam, LR: 0.001, Batch Size: 32, Epochs: 100
CNN + LSTM	CNN Layers: 2, Filters: [32, 64], Kernel Size: 3x1, LSTM Units: 64, Dropout: 0.3, Optimizer: Adam, LR: 0.001, Batch Size: 32, Epochs: 100
Proposed GA+LSTM	LSTM Layers: 2, Hidden Units: 64, Dropout: 0.3, Activation: tanh, Optimizer: Adam, Learning Rate: 0.001, Batch Size: 32, Epochs: 100, Loss Function: Binary Crossentropy

Confusion matrix is provided in Fig 8 which evaluates the performance of our model in predicting AD progression stages based on gait analysis data. We have four disease progression stages: Normal (N), Mild Cognitive Impairment (MCI), Moderate Alzheimer's Disease (AD) and Severe Alzheimer's Disease (SAD).

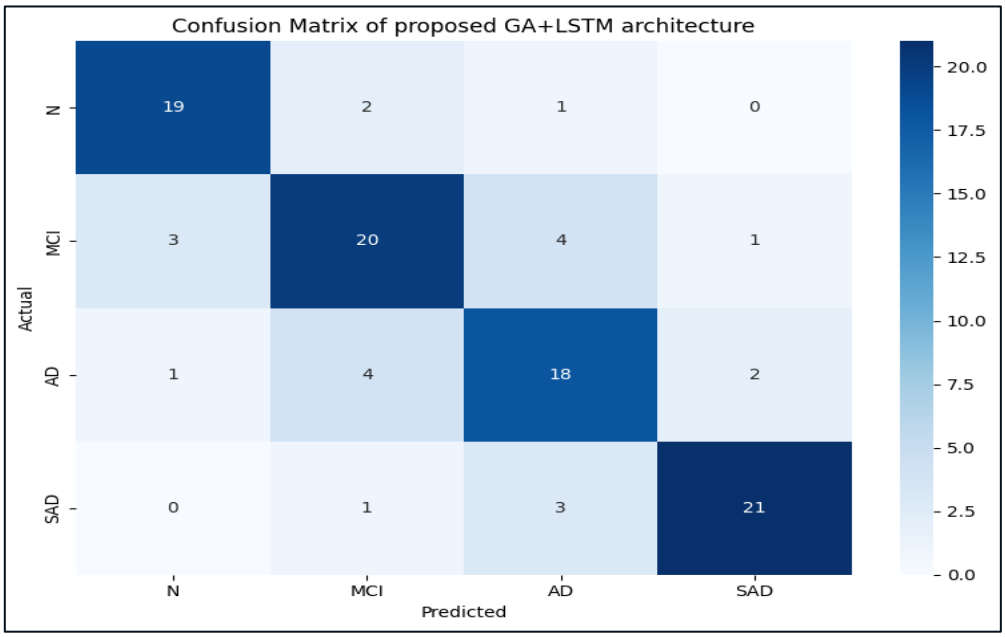


Figure 8. Confusion Matrix for the Proposed Model

Data collected from a cohort of individuals at various stages of AD progression includes their walking pattern, step length, step width, gait speed, and cadence. GA parameters can be used to categorize them into different disease stages.

1. **Gait Speed:** Slower values are commonly associated with cognitive decline and can indicate the presence of MCI or AD.
2. **Stride Length:** Shorter stride lengths are observed in patients with SAD and AD in comparison to those with normal cognition.
3. **Stride Width:** Increased variability or irregularity can be observed in individuals with cognitive impairment.
4. **Cadence:** Irregular or inconsistent step timing, may be indicative of cognitive impairment. Patients with SAD often exhibit alterations in cadence compared to those with MCI or normal cognition.

Participants wear ankle-mounted IMUs during a standardized 5M walk. Raw data is processed using a 5-layer LSTM (Python/PyTorch) to extract gait biomarkers such as stride variability, and swing asymmetry etc., Results visualize on a clinician dashboard (Plotly Dash) with alert thresholds set at ±2SD from age-matched norms.

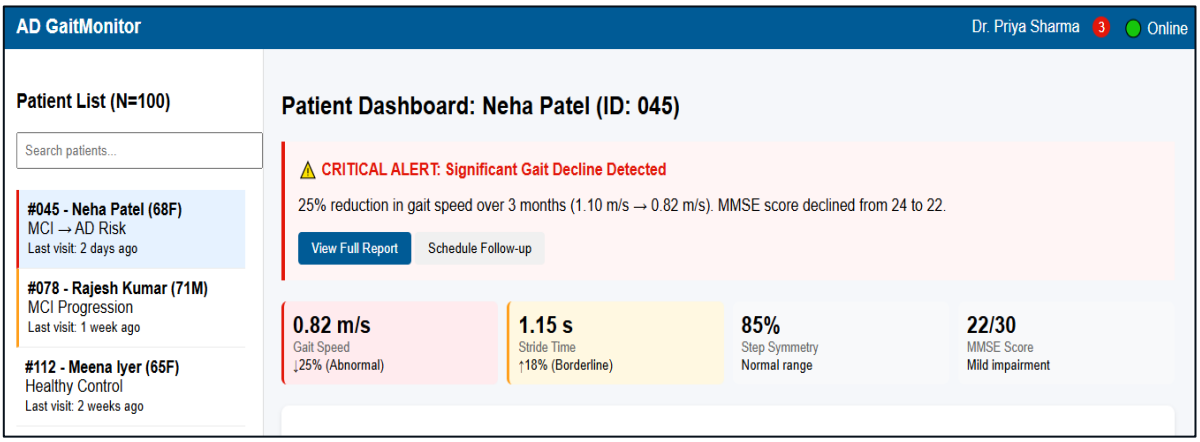
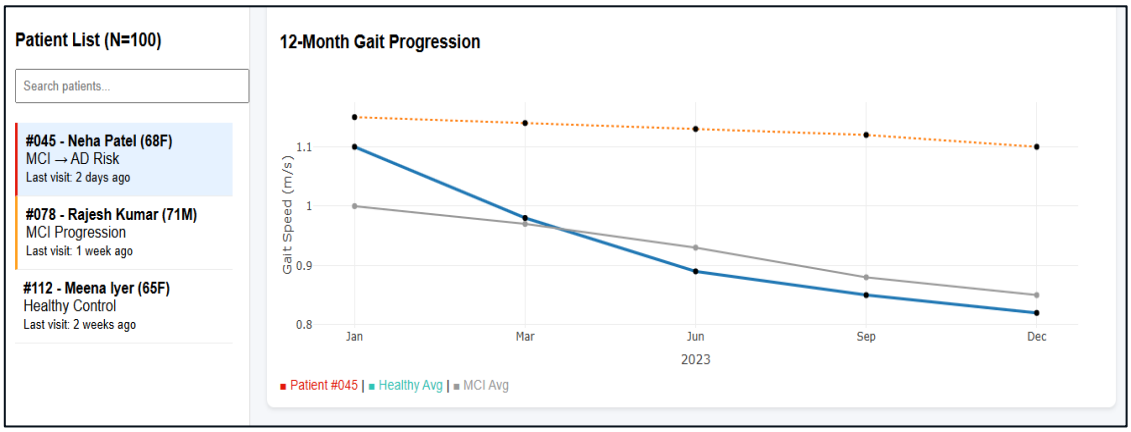


Figure 9. ADGaitMonitor Clinical Dashboard

Fig.9. provides the interface shown for patient Neha Patel (ID: 045) highlighting a critical alert indicating a 25% reduction in gait speed over three months (from 1.10 m/s to 0.82 m/s) alongside a decline in MMSE score from 24 to 22, suggesting and increased risk of progression from MCI to AD. The dashboard displays key gait metrics, including stride time (1.15 s) marked as borderline abnormal and step symmetry (85%) within the normal range.



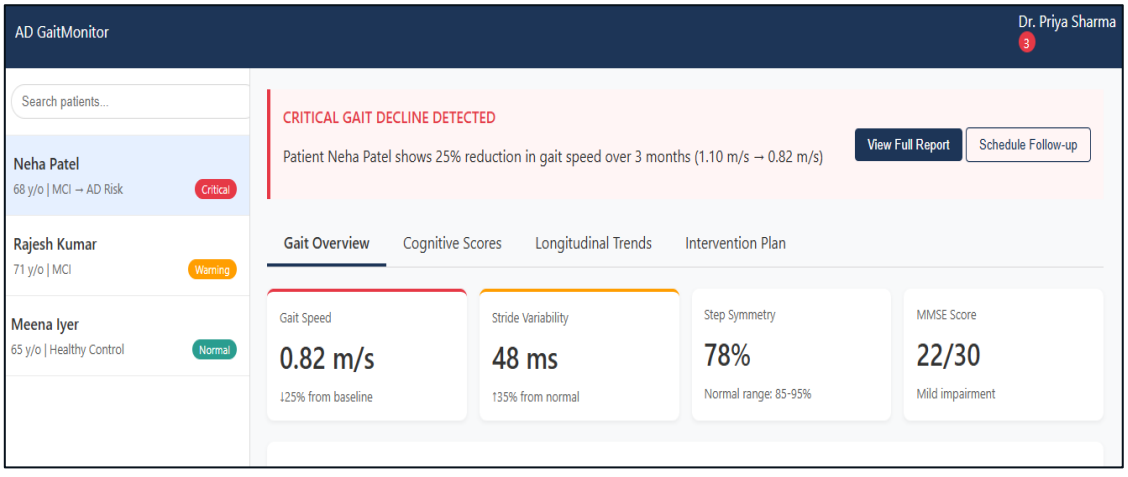


Figure 10. Patient Interface Showing Critical Alert

Fig.10 indicates critical gait decline detected over a 3-month period. Her gait speed dropped by 25% and stride variability increased to 48 ms, which is 35% above normal, both indicators of motor-cognitive decline. Step symmetry fell to 78%, below the normal threshold (85–95%), further supporting motor irregularities. The MMSE score declined to 22/30, indicating MCI. The interface in Fig 11 presents the gait sessions and their duration statistics which allows clinicians to quickly assess risk progression, view longitudinal trends and initiate timely intervention planning for early AD detection.

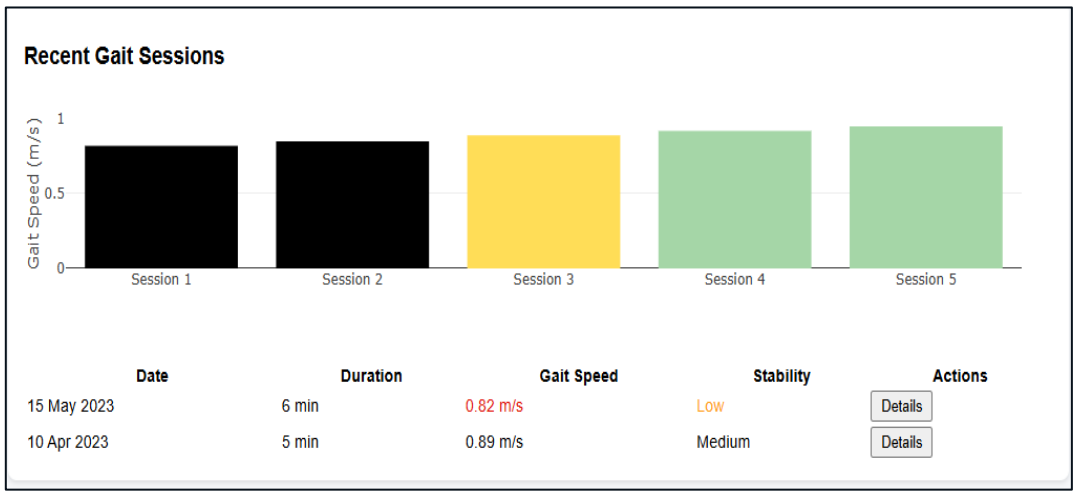


Figure 11. Gait Sessions Window

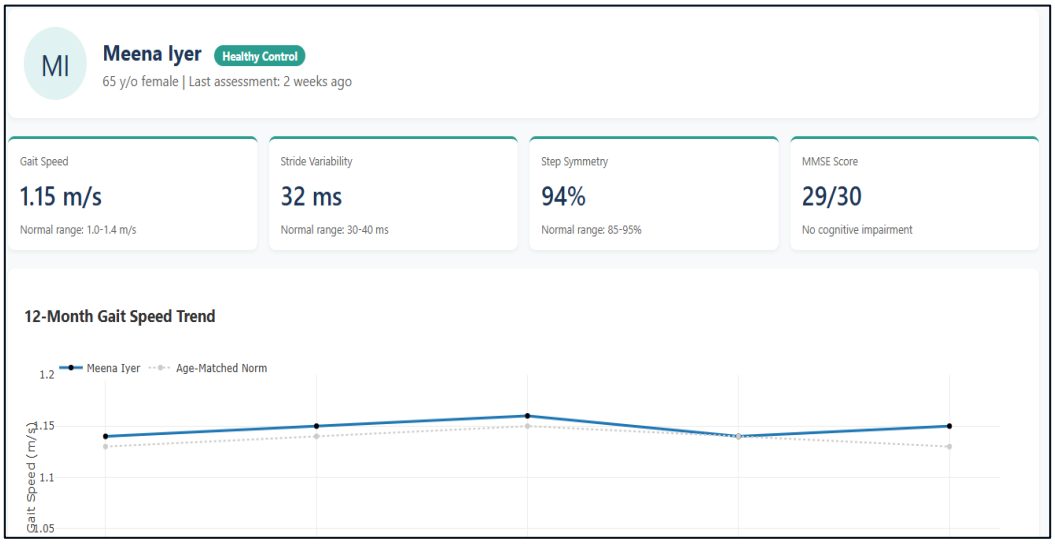


Figure 12. Healthy Controls Dashboard

Fig.12 shows stable gait and cognitive metrics of a patient with a gait speed is 1.15 m/s, well within the normal range and stride variability is 32 ms, indicating consistent walking rhythm. A high step symmetry score of 94% (normal: 85–95%) reflects balanced bilateral leg movement. Her MMSE score of 29/30 confirms no cognitive impairment. The 12-month trend chart demonstrates stable gait speed over time, closely aligned with age-matched normative data, reinforcing her low risk for neurodegenerative progression. This profile serves as a reference benchmark for comparison with at-risk patients.

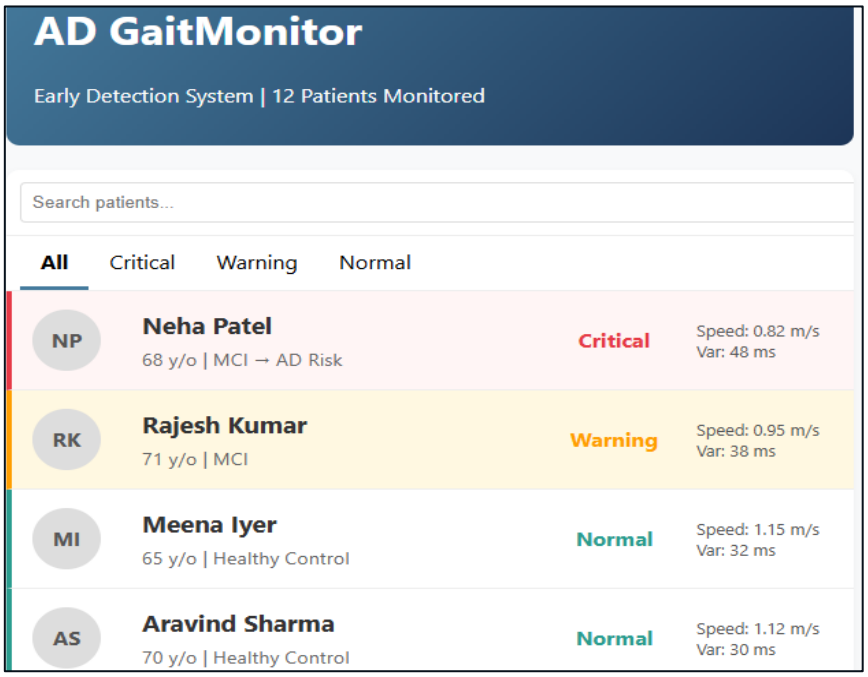


Figure 13. Gait Metrics

Fig.13 provides clinicians with real-time visualization of gait-cognitive metrics. The interface compares individual patients (e.g., 68 y/o MCI patient with 0.82 m/s gait speed) against healthy controls (e.g., 65 y/o female, 1.15 m/s), with automated alerts for deviations >2SD from age-matched norms. Data streams from wearable IMUs (100Hz sampling) are processed via an LSTM pipeline, generating progression trends and risk scores. To enhance the interpretability of our model, we incorporated SHAP analysis to quantify the contribution of each input feature such as gait speed, stride length and MMSE to the model's decision-making process [Fig.14]. SHAP values were computed post-hoc on the trained model using our dataset. The results revealed that decreased gait speed, increased stride variability and lower cognitive scores were the most influential predictors of early-stage Alzheimer's classification [Fig.15].

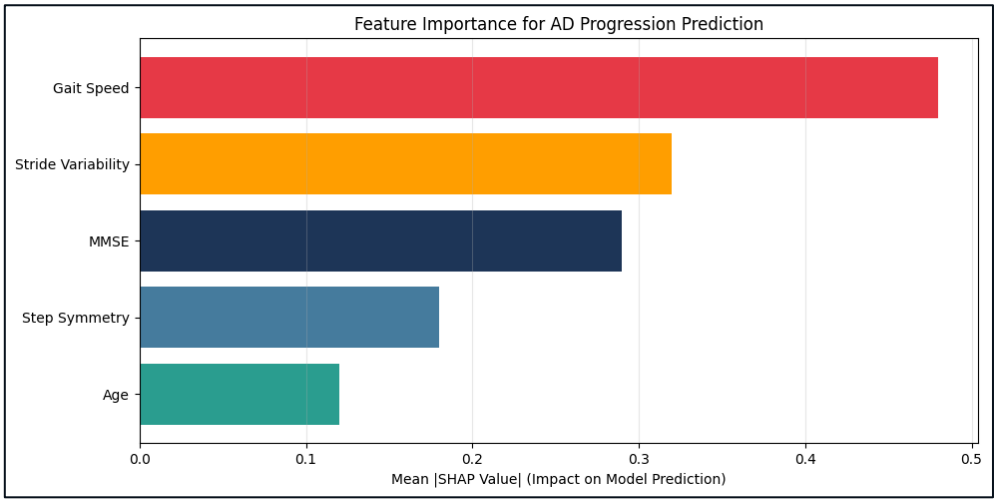


Figure 14. Feature Importance SHAP Plot

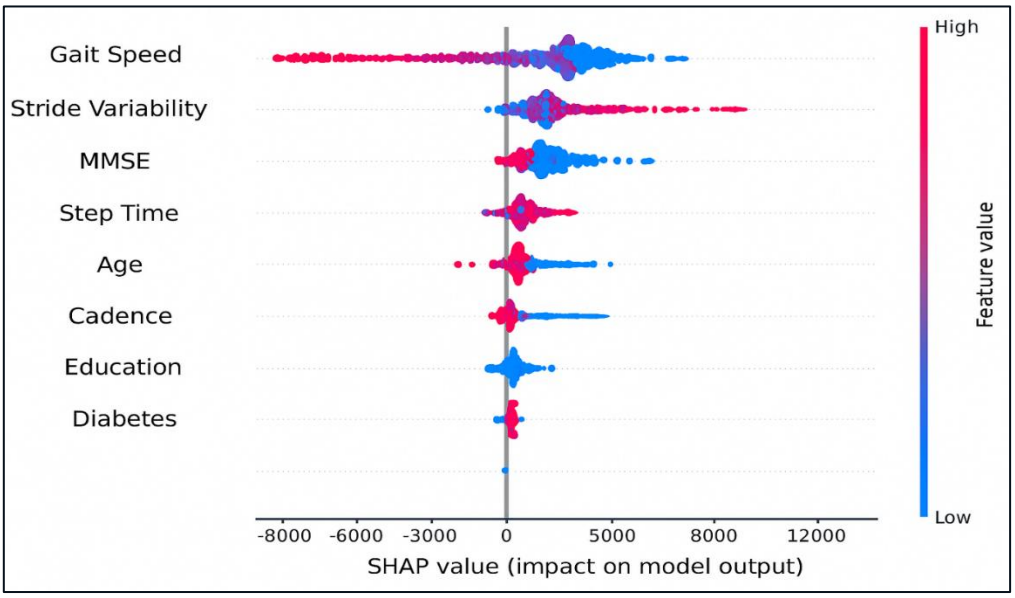


Figure 15. SHAP Summary Plot

Temporal progression of AD was quantified by analyzing longitudinal changes in spatiotemporal gait features across multiple sessions per participant and by comparing patterns across cognitive stages. Key gait metrics such as gait speed, stride variability and step time asymmetry were used to track cognitive decline. In our LSTM framework, this information is captured as subtle deviations accumulated across time steps. These findings suggest that gait pattern changes can reflect the temporal trajectory of Alzheimer's, offering a non-invasive biomarker for early monitoring and disease staging. The effectiveness and performance of our proposed framework were evaluated using metrics such as accuracy, precision, recall F1-score and AUC-ROC (Table 7).

Table 7. Performance Comparison

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
Gait+LSTM based proposed model	0.98	0.98	0.99	0.98	0.99
CNN [Khan et al, 2021]	0.90	0.92	0.95	0.94	0.94
CNN+LSTM [Singh et al, 2024]	0.95	0.95	0.96	0.95	0.96
LR [Tolea et al, 2025]	0.92	0.94	0.96	0.93	0.94
SVM	0.91	0.93	0.94	0.93	0.92
RF	0.93	0.95	0.95	0.94	0.95

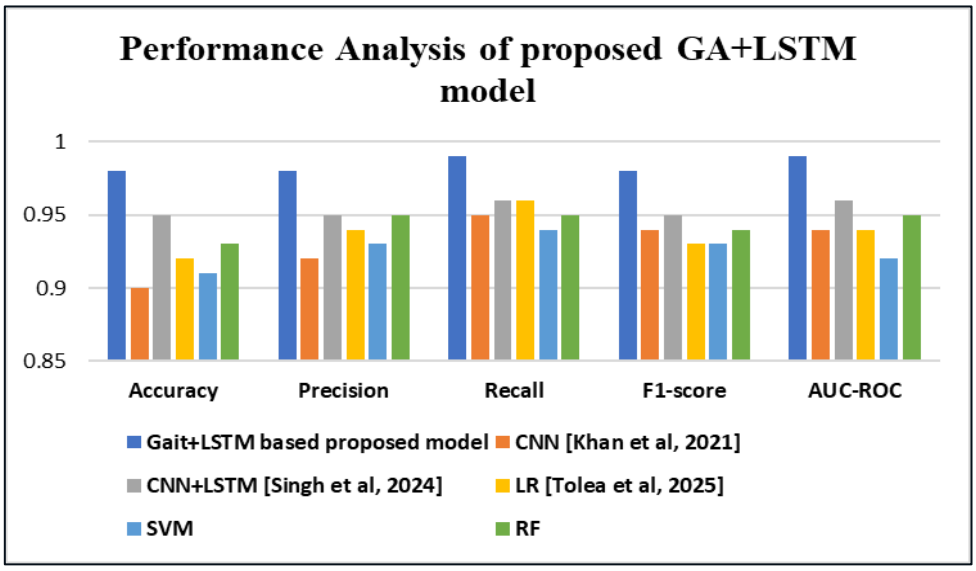


Figure 16. Performance Comparison Chart

Based on the graphical illustration of performance metrics of our proposed model (Fig 16), its performance was compared against both existing DL models from recent literature and widely used baseline classifiers. Specifically, the proposed model achieved superior results across all evaluation metrics, with an accuracy of 98%, precision of 98%, recall of 99% and an AUC-ROC of 0.99. The model's accuracy improved from 0.95 to 0.98 after applying stepwise feature selection, and the AUC-ROC score increased from 0.93 to 0.99. These results highlight the robustness and predictive capability of the proposed Gait+LSTM architecture in accurately identifying and distinguishing between various cognitive conditions.

5. Conclusion

Our proposed model utilizes the GA and LSTM models for monitoring AD and has demonstrated high performance with an accuracy and precision of 98 %. By showcasing a remarkable ability in accurately classifying gait patterns associated with different stages of AD progression, our model can be effectively adopted in real time therapeutic applications. Through achieving recall score of 99 %, the model's effectiveness in capturing positive instances within the dataset has been demonstrated. Gait abnormalities have been detected effectively, as evidenced by an F1-score and AUC-ROC score of 99%. Discrimination between FPR and TPR instances, further validates its utility in actual clinical settings. These empirical validations suggest hopeful prospects for the model's application in early diagnosis and intervention strategies for AD. Future enhancement involves deploying our GA+LSTM model in tangible biomedical environments where multi-modal data is utilized to ensure its everyday usefulness.

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