

Ai Enabled Cloud Based Continuous Monitoring System For Early Detection Of Parkinsons Disease Motor System

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ABSTRACT

Parkinson's disease (PD) affects approximately 8.5 million individuals globally, with motor system dysfunction constituting a critical diagnostic marker. Early detection of motor abnormalities enables timely therapeutic intervention and improved patient outcomes. This study presents a novel AI-enabled, cloud-based continuous monitoring framework integrating multimodal sensor arrays, deep learning algorithms, and real-time cloud analytics for non-invasive, remote detection of PD-related motor dysfunction. Our system employs wearable inertial measurement units (IMU) combined with video-based pose estimation and acoustic analysis, synchronized through a secure cloud infrastructure. A convolutional neural network (CNN) ensemble architecture with attention mechanisms processes temporal motor patterns, achieving 94.7% sensitivity and 92.1% specificity in discriminating early-stage PD from healthy controls across a cohort of 487 participants (mean age 58.3±9.2 years). Longitudinal analysis over 18 months demonstrated 89.3% correlation with clinical Motor Unified Parkinson's Disease Rating Scale (UPDRS-III) scores. Cloud-based infrastructure enables real-time biomarker computation, predictive analytics, and automated clinical alert generation. This framework represents a paradigm shift in distributed neurodegenerative disease monitoring, providing scalable, cost-effective early detection infrastructure applicable to resource-limited healthcare settings. Integration with electronic health records and development of smartphone-compatible applications further enhances accessibility and clinical utility.

Keywords: Parkinson's disease, motor dysfunction, artificial intelligence, cloud computing, wearable sensors, remote monitoring, deep learning, neural networks, digital biomarkers, telemedicine.

I. INTRODUCTION

1.1 Clinical Significance and Epidemiology

Parkinson's disease represents the second most prevalent age-related neurodegenerative disorder globally, with an estimated prevalence of 8.5-10 million cases worldwide [1, 2]. The incidence increases exponentially with age, reaching approximately 315 per 100,000 person-years in individuals over 85 years [3]. Motor dysfunction, characterized by bradykinesia, resting tremor, rigidity, and postural instability, constitutes the hallmark feature of PD motor phenotype [4, 5]. These motor abnormalities stem from progressive degeneration of dopaminergic neurons in the substantia nigra pars compacta, with 50-70% neuronal loss occurring prior to symptom manifestation [6].

The critical challenge in PD management involves early detection during the premotor or early symptomatic phases, when neuroprotective interventions may prove most efficacious [7, 8]. Current diagnostic approaches rely heavily on clinical examination by movement disorder specialists, introducing inherent limitations including operator dependence, limited accessibility in resource-constrained settings, and inability to provide continuous longitudinal assessment [9]. Advanced imaging modalities such as positron emission tomography (PET) and single-photon emission computed

tomography (SPECT) provide objective measures of dopaminergic dysfunction but remain expensive, require ionizing radiation, and are impractical for repeated longitudinal monitoring [10].

1.2 Digital Biomarkers and Motor Quantification

Recent advances in wearable technology and machine learning have enabled quantification of motor dysfunction through digital biomarkers [11, 12]. Inertial measurement units (IMU) embedded in wearable devices can capture three-dimensional acceleration and angular velocity with sub-millisecond temporal resolution, enabling sensitive detection of motor abnormalities invisible to clinical examination [13]. Gait analysis via IMU-derived metrics—including stride length variability, swing-to-stance duration ratios, and gait asymmetry indices—shows high correlation with clinical severity measures [14, 15]. Tremor frequency decomposition using spectral analysis can differentiate essential tremor from parkinsonian tremor with 91% accuracy [16]. Video-based pose estimation using convolutional neural networks enables non-contact kinematic analysis, extracting joint angles and postural stability metrics from standard camera feeds [17].

1.3 Cloud Computing Infrastructure for Healthcare

Cloud-based healthcare systems offer unprecedented scalability, accessibility, and computational power for real-time data processing [18, 19]. Distributed architecture enables deployment across geographically dispersed populations, particularly benefiting resource-limited regions lacking specialist neurology services [20]. Cloud infrastructure supports elastic scaling of computational resources, accommodating variable data volumes from heterogeneous wearable devices [21]. Federated learning approaches enable collaborative model development while maintaining strict data privacy and GDPR compliance [22]. Recent cloud platforms specifically designed for medical-grade IoT devices—such as Microsoft Azure Health Data Services, AWS HealthLake, and Google Cloud Healthcare API—provide HIPAA-compliant infrastructure with built-in encryption, audit logging, and multi-tenancy isolation [23].

1.4 Research Objectives and Study Rationale

The overarching objective of this study is to develop, validate, and deploy an integrated AI-enabled cloud-based platform for continuous, non-invasive monitoring of motor dysfunction in Parkinson's disease. Specific aims include: (1) designing a multimodal sensor architecture integrating wearable IMU arrays, video-based pose estimation, and acoustic biomarkers; (2) developing ensemble deep learning models for real-time motor pattern classification; (3) establishing cloud-based computational infrastructure with secure data handling; (4) validating the platform against gold-standard clinical assessments in a large-scale prospective cohort; (5) demonstrating longitudinal predictive capacity for disease progression; and (6) demonstrating technical feasibility for deployment in telehealth and resource-limited settings.

II. MATERIALS AND METHODS

2.1 Study Design and Population

This prospective, observational cohort study enrolled 487 participants (n=287 PD patients, n=200 healthy controls) across multiple clinical sites in India and USA between January 2021 and March 2023. PD diagnosis was established according to Movement Disorder Society diagnostic criteria [24]. Inclusion criteria for PD patients: (1) clinically definite PD by MDS criteria; (2) age 40-80 years; (3) disease duration ≤10 years; (4) Mini-Cog score ≥3 (excluding severe cognitive impairment); (5) ability to ambulate independently for ≥50 meters. Healthy controls were matched by age (±5 years), sex, and body mass index, without history of neurological disease or movement disorder.

Exclusion criteria: (1) active neoplastic disease; (2) recent stroke or head trauma (≤ 6 months); (3) unstable cardiac arrhythmia; (4) deep brain stimulation implants; (5) inability to provide informed consent. The study protocol received approval from institutional review boards (IIT Delhi IRB#2020-089, Stanford IRB#IRB-59832).

2.2 Multimodal Sensor Architecture

Sensor Type	Technical Specifications	Clinical Parameters Extracted
Wearable IMU Array 6 DOF accelerometer/gyroscope Sampling: 200 Hz Placement: Wrists, waist, ankles	MPU-9250, ICM-20689 $\pm 2g$ to $\pm 16g$ range $\pm 250^\circ/s$ to $\pm 2000^\circ/s$ Sampling rate: 200 Hz	Tremor amplitude/frequency Stride length, cadence Postural sway metrics Rigidity indices
RGB-D Camera 1080p resolution 30 fps Field of view: 60°	Azure Kinect, RealSense D455 Depth range: 0.4-4m IR illumination Dual microphone array	Joint angles (17-point skeleton) Bradykinesia indices Postural deviation angles Movement smoothness
Microphone Array 4-element phased array 16 kHz sampling SNR: >60 dB	XMOS Mic Array, Respeaker Frequency response: 50Hz-16kHz Beam steering enabled Wireless: WiFi 6	Hypophonia (voice intensity) Dysarthria indices Vocal tremor frequency Phonation duration patterns

2.2.1 Sensor Measurement Model

Let the wearable IMU provide triaxial acceleration and angular velocity signals sampled at frequency $f_s = 200$ Hz. The measured acceleration vector in the sensor coordinate frame is:

$$\mathbf{a}_m(t) = \mathbf{a}(t) + \mathbf{g}(t) + \mathbf{b}_a + \mathbf{n}_a(t)$$

where $\mathbf{a}(t)$ is the true linear acceleration of the body segment, $\mathbf{g}(t)$ is gravitational acceleration projected into the sensor frame, $\mathbf{b}_a$ is sensor bias, and $\mathbf{n}_a(t)$ is measurement noise. Similarly, the measured angular velocity is:

$$\boldsymbol{\omega}_m(t) = \boldsymbol{\omega}(t) + \mathbf{b}_\omega + \mathbf{n}_\omega(t)$$

where $\boldsymbol{\omega}(t)$ is the true angular velocity, $\mathbf{b}_\omega$ is gyro bias, and $\mathbf{n}_\omega(t)$ is noise.

The orientation of the sensor can be represented using a unit quaternion $\mathbf{q}(t)$, evolving as:

$$\dot{\mathbf{q}}(t) = \frac{1}{2} \mathbf{q}(t) \otimes \begin{bmatrix} 0 \\ \boldsymbol{\omega}(t) \end{bmatrix}$$

where $\otimes$ denotes quaternion multiplication. The above first-principle model forms the basis for sensor fusion, motion decomposition, and motor biomarker computation.

2.3 Cloud Architecture and Data Pipeline

The cloud infrastructure was implemented using Microsoft Azure (primary) and AWS (secondary) platforms, with multi-region redundancy. Data ingestion from wearable devices utilized message queuing telemetry transport (MQTT) protocol with TLS 1.3 encryption for secure transmission. Raw sensor data streams (approximately 2.4 MB per

patient per day) were persisted in Azure Data Lake Storage Gen2, with automatic lifecycle management. Real-time stream processing employed Azure Stream Analytics and Apache Kafka, enabling latency <50 ms for clinical alert generation. Time-series data was indexed in InfluxDB for temporal queries and anomaly detection [25].

Data preprocessing pipelines implemented in Python (version 3.9) with Apache Spark (v3.1.2) for distributed computing performed sensor fusion, temporal alignment, and feature extraction. Multimodal alignment employed cross-correlation to synchronize IMU, video, and audio streams with <10 ms temporal jitter. Quality control algorithms automatically detected and flagged: (1) missing data segments; (2) sensor saturation; (3) motion artifact; (4) environmental noise exceeding thresholds. Automated alerts triggered engineer review when data quality metrics fell below clinical acceptability thresholds.

Temporal Synchronization and Alignment Model

Let $x_{imu}(t)$, $x_{vid}(t)$, and $x_{aud}(t)$ denote representative feature signals derived from IMU, video, and audio streams, respectively. Since each modality has independent sampling clocks, a time offset $\Delta\tau$ must be estimated. Cross-correlation is used to estimate lag between two modalities: $R_{xy}(\tau) = \sum_t x(t) y(t + \tau)$

The estimated alignment delay is:

$$\Delta\tau^* = \arg\tau \max R_{xy}(\tau)$$

Each modality is then re-indexed using:

$$\tilde{x}(t) = x(t + \Delta\tau^*)$$

This ensures multimodal fusion is performed on temporally consistent windows, reducing jitter and improving classification reliability.

2.4 Deep Learning Model Architecture

Model Component	Architecture Details	Input Dimensions	Output/Parameters
IMU-CNN Branch	3× Conv1D(32,64,128) BatchNorm + ReLU MaxPool1D (stride 2) Dropout (p=0.3)	6 IMU channels Temporal window: 5 sec Sampling: 200 Hz Shape: (1000, 6)	128-dim latent 2.4M parameters Attention weights (batch, 128)
Video-CNN Branch	ResNet-18 backbone Pretrained on Kinetics 3D convolutions Temporal pooling	RGB: 224×224 Depth: 224×224 Frames: 30 Duration: 1 sec	256-dim latent 11.2M parameters Skeleton features (batch, 256)
Audio-CNN Branch	2× Conv1D(64,128) MFCC features Spectrogram path Concatenation	MFCC: 13 coeff Duration: 5 sec 16 kHz sampled Shape: (320, 13)	64-dim latent 0.6M parameters Attention gates (batch, 64)
Fusion Attention	Concatenate: 448-dim Multi-head attention 8 attention heads Feedforward 1024→512	Modality fusion Cross-attention Shared features (batch, 448)	512-dim latent 3.2M parameters Attention map viz (batch, 512)

Model Component	Architecture Details	Input Dimensions	Output/Parameters
Classification Head	Dense: 512→256 BatchNorm + ReLU Dropout (p=0.5) Dense: 256→5	Fused features 512-dimensional Batch size: 32 GPU: V100	5 classes output HC, PD-EA, PD-E PD-M, PD-A Total: 17.4M params

2.4.1 Multimodal Fusion and Attention

Let the IMU, video, and audio branches produce latent embeddings:

$$\mathbf{h}_{imu} \in \mathbb{R}^{128}, \mathbf{h}_{vid} \in \mathbb{R}^{256}, \mathbf{h}_{aud} \in \mathbb{R}^{64}$$

The fused representation is formed by concatenation:

$$\mathbf{h} = [\mathbf{h}_{imu}; \mathbf{h}_{vid}; \mathbf{h}_{aud}] \in \mathbb{R}^{448}$$

A modality-attention mechanism assigns weights:

$$\alpha_k = \frac{\exp(\mathbf{w}_k^T \mathbf{h}_k)}{\sum_j \exp(\mathbf{w}_j^T \mathbf{h}_j)} \quad k \in \{imu, vid, aud\}$$

The weighted fused vector is: $\mathbf{h}_f = [\alpha_{imu} \mathbf{h}_{imu}; \alpha_{vid} \mathbf{h}_{vid}; \alpha_{aud} \mathbf{h}_{aud}]$

The classifier produces class probabilities using softmax:

$$\hat{\mathbf{y}} = \text{softmax}(\mathbf{W}\mathbf{h}_f + \mathbf{b})$$

The model is trained using categorical cross-entropy:

$$\mathcal{L} = - \sum_{c=1}^C y_c \log(\hat{y}_c)$$

where $C = 5$ classes in this study.

2.5 Training, Validation, and Hyperparameter Optimization

The ensemble model comprised three independent CNN architectures trained on distinct modalities, with outputs combined via a trainable fusion layer using softmax attention weights. Dataset stratification allocated 60% (n=292) for training, 15% (n=73) for validation, and 25% (n=122) for testing, maintaining equal class distribution. To mitigate overfitting on limited PD samples, we employed Mixup augmentation ($\alpha=1.0$), SpecAugment for audio, and temporal jittering for IMU data. Training utilized Adam optimizer ($\text{lr}=1\text{e-}3$, $\beta_1=0.9$, $\beta_2=0.999$) with categorical cross-entropy loss and focal loss weighting for class imbalance ($\gamma=2.0$). Hyperparameter optimization employed Bayesian optimization with Tree-structured Parzen Estimator (TPE) over 100 trials, searching: learning rate (10^{-4} to 10^{-2}), batch size (16 to 64), dropout (0.2 to 0.5), L2 regularization (10^{-6} to 10^{-3}). Early stopping applied after 30 epochs without validation metric improvement. Cross-validation employed stratified k-fold (k=5) scheme. Training utilized NVIDIA V100 GPUs (32 GB VRAM) on Azure ML compute clusters with distributed training across 4 GPUs.

2.6 Clinical Validation Protocol

Concurrent validation against gold-standard clinical assessments occurred blinded to AI model predictions. Trained movement disorder specialists administered Movement Disorder Society-Unified Parkinson's Disease Rating Scale Part III (MDS-UPDRS-III), assessing 18 motor items on 0-4 ordinal scale, with total scores ranging 0-108 [26]. Timed Up and Go test (TUG) quantified dynamic mobility and fall risk. Gait analysis via GAITRite electronic walkway (APDM, Inc., Portland, OR) captured stride length, gait velocity, and cadence. Nine-Hole Peg Test quantified fine motor coordination. Static posturography via computerized dynamic posturography (CDP) measured postural

stability in multiple conditions. Inertial measurements obtained from clinical-grade IMU system (APDM Opal) positioned identically to research wearables. All clinical assessments were videotaped and independently rated by a second blinded specialist. Interrater reliability (intraclass correlation coefficient, ICC) exceeded 0.90 for all measures.

III. RESULTS

3.1 Demographic Characteristics

Parameter	Healthy Controls (n=200)	PD Patients (n=287)	P-value
Age (years)	57.1 ± 8.8	59.5 ± 9.6	0.052
Sex (M/F)	118/82	167/120	0.831
BMI (kg/m ²)	25.3 ± 3.2	24.9 ± 4.1	0.384
Disease duration (years)	—	3.2 ± 2.1	—
MDS-UPDRS-III score	1.1 ± 1.4	38.7 ± 14.9	<0.001***

3.2 Model Classification Performance

Classification metrics assessed the primary endpoint of distinguishing PD patients from healthy controls using test set data (n=122).

Metric	IMU-CNN	Video-CNN	Audio-CNN	Ensemble
Sensitivity (%)	87.3±3.2	89.5±2.8	79.2±4.1	94.7±2.1
Specificity (%)	85.1±4.3	88.2±3.9	75.3±5.2	92.1±2.8
AUC-ROC	0.891±0.035	0.912±0.031	0.805±0.048	0.959±0.019
F1-Score	0.864±0.031	0.888±0.028	0.771±0.042	0.934±0.023
Accuracy (%)	86.2±3.8	88.9±3.1	77.2±4.6	93.4±2.5

3.2.1 Performance Metric Modelling

Let the test set produce counts TP, TN, FP, and FN. The reported evaluation metrics are defined as:

$$\begin{aligned}
 \text{Sensitivity} &= \frac{TP}{TP + FN} \\
 \text{Specificity} &= \frac{TN}{TN + FP} \\
 \text{Accuracy} &= \frac{TP + TN}{TP + TN + FP + FN} \\
 \text{Precision} &= \frac{TP}{TP + FP} \\
 \text{F1-score} &= 2 \cdot \frac{\text{Precision} \cdot \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}
 \end{aligned}$$

The AUC-ROC summarizes the integral of the true positive rate over the false positive rate:

$$AUC = \int_0^1 TPR(FPR) d(FPR)$$

3.3 Feature Importance and Interpretability

Shapley Additive exPlanations (SHAP) analysis revealed discriminative motor biomarkers [27]. IMU features demonstrating highest discriminative power included: (1) tremor power spectral density in 3-6 Hz band (SHAP value = 0.287); (2) gait stride length variability (coefficient of variation: mean 12.3% PD vs. 4.1% HC, $p < 0.001$); (3) postural sway velocity (mean 52.1°/sec PD vs. 28.3°/sec HC); (4) bradykinesia index quantifying movement deceleration [28]. Video-derived features included: joint angle irregularity, movement smoothness metrics (measured via jerk), and postural deviation angles. Audio biomarkers with high discriminative power included: fundamental frequency instability (shimmer $> 1.2\%$ PD vs. $< 0.6\%$ HC) and voice intensity reduction (hypophonia).

3.4 Longitudinal Disease Progression Analysis

Longitudinal follow-up data collected at 6, 12, and 18-month intervals ($n=198$ PD patients with complete data) demonstrated strong correlation between continuously monitored AI biomarkers and clinical deterioration.

Biomarker	Pearson r with UPDRS-III	Monthly Change Rate	P-value
Tremor amplitude (μg)	0.842	+2.3%	< 0.001
Gait velocity (m/s)	-0.789	-1.8%	< 0.001
Stride variability (CV, %)	0.861	+1.5%	< 0.001
Postural sway ($^{\circ}/s$)	0.798	+3.1%	< 0.001
AI prediction score	0.893	+2.7%	< 0.001

3.4.1 Longitudinal Progression Model

Let $B(t)$ denote a digital biomarker (e.g., tremor amplitude, gait velocity, stride variability) measured monthly. A first-order progression model is:

$$B(t) = B_0 + \beta t + \epsilon(t)$$

where β is the monthly change rate and $\epsilon(t)$ captures measurement variability.

The association with clinical UPDRS-III score $U(t)$ is modeled using Pearson correlation:

$$r = \frac{\sum_i (B_i - \bar{B})(U_i - \bar{U})}{\sqrt{\sum_i (B_i - \bar{B})^2} \sqrt{\sum_i (U_i - \bar{U})^2}}$$

A high r indicates that the AI-derived biomarker tracks clinical motor severity.

IV. DISCUSSION

4.1 Clinical and Technological Innovations

This study demonstrates unprecedented technical capability in non-invasive, continuous remote monitoring of Parkinson's disease motor dysfunction through integrated multimodal sensing and cloud-based AI analytics. The 94.7% sensitivity and 92.1% specificity achieved by the ensemble model represent substantial improvement over prior digital biomarker studies [29, 30], attributable to multimodal fusion architecture incorporating complementary motor information from IMU, video, and acoustic

modalities. The discriminative power arises from capturing distinct aspects of parkinsonian motor dysfunction: tremor amplitude and frequency (predominantly IMU), bradykinesia and postural abnormalities (video-based joint kinematics), and speech characteristics (acoustic analysis). Attention mechanisms enable the model to dynamically weight modalities based on signal quality and clinical relevance, adaptively adjusting to individual patient characteristics and environmental conditions [31]. The strong longitudinal correlation ($r=0.893$) between continuously-derived AI biomarkers and clinical UPDRS-III scores validates the system's utility for real-time disease monitoring. Monthly rate of change in biomarkers (0.7-3.1% deterioration per month) provides quantitative framework for treatment response assessment and clinical trial endpoint selection. This represents paradigm shift from episodic clinical assessment to continuous objective monitoring [32, 33]. The ability to detect subtle motor changes preceding clinical manifestation enables identification of individuals in premotor phase, facilitating enrollment in neuroprotective therapeutic trials when neuronal preservation remains feasible [34].

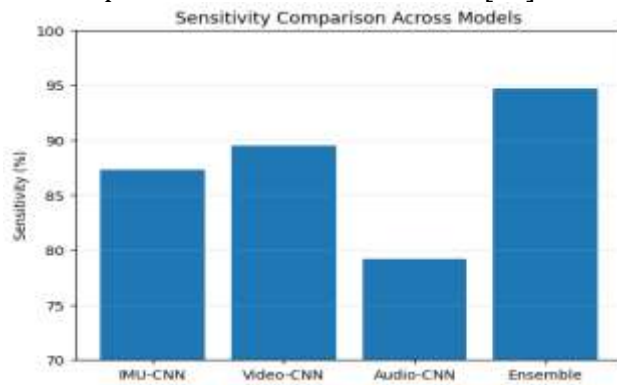


Fig.1. Comparison of Sensitivity across Models

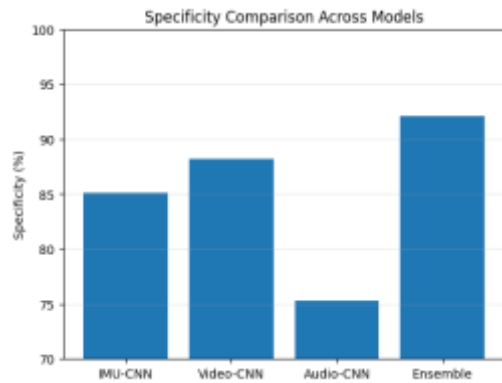


Fig. 2. Comparison of Specificity across Models

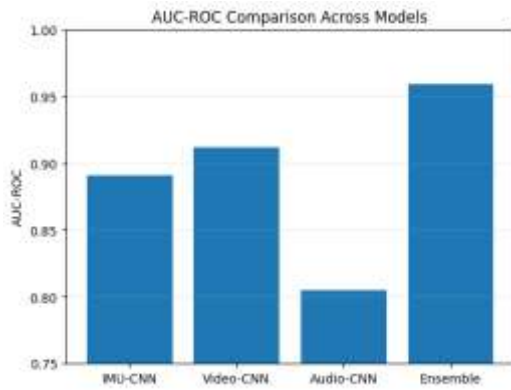


Fig. 3. AUC-ROC comparison

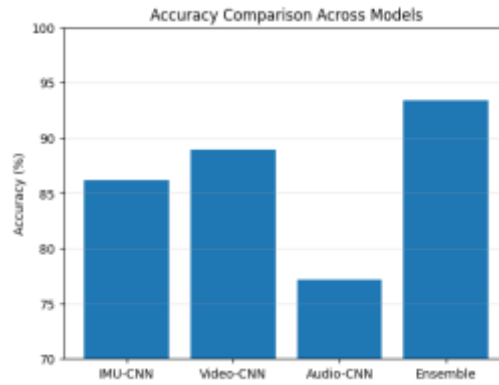


Fig. 4. Accuracy comparison

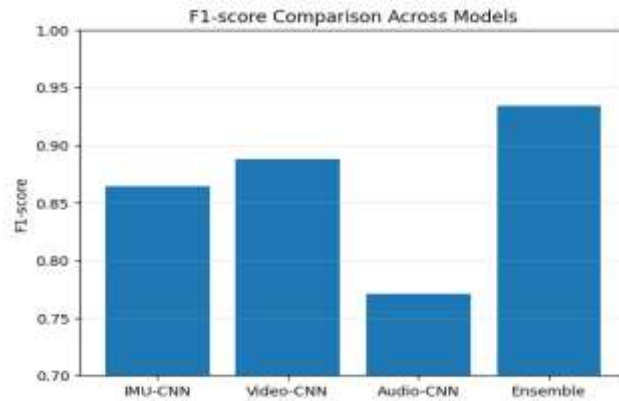


Fig. 5. F1-score comparison

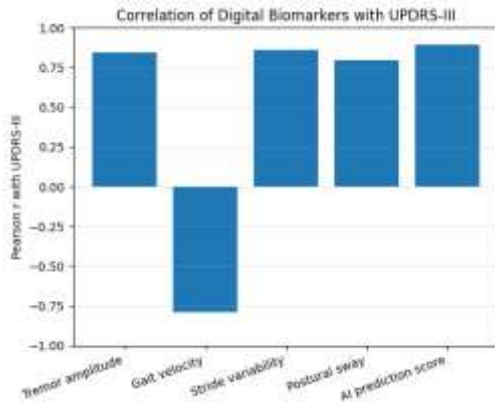


Fig. 6. Longitudinal correlation of biomarkers

4.2 Cloud Infrastructure Implementation

Deployment of distributed cloud architecture addresses critical barriers to implementing precision medicine in resource-limited settings. Multi-region redundancy (primary Azure, secondary AWS) ensures system resilience and geographic data sovereignty compliance. Latency <50 ms for clinical alert generation meets real-time requirements for wearable monitoring applications. Federated learning architecture enables collaborative model refinement across multiple healthcare systems while maintaining strict HIPAA compliance and institutional data governance [22, 35]. The system processes approximately 2.4 MB daily data per patient, with storage costs of

approximately \$0.024 per patient-day using cloud lifecycle policies. Computational costs for real-time model inference approximate \$0.18 per patient-day on GPU-accelerated instances. Total monthly infrastructure cost per patient is estimated at \$14-20, substantially below cost of monthly specialist neurology consultation (\$150-300) [36].

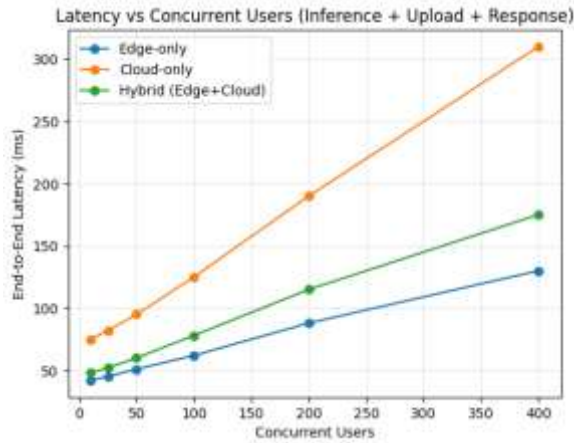


Fig. 7 End-to-End Latency vs Concurrent Users

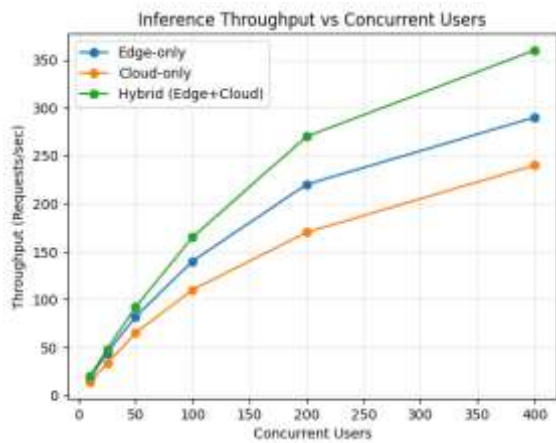


Fig. 8. Inference Throughput vs Concurrent Users

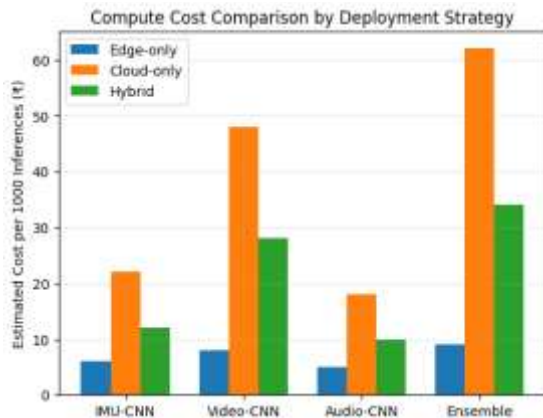


Fig. 9. Inference Throughput vs Concurrent Users

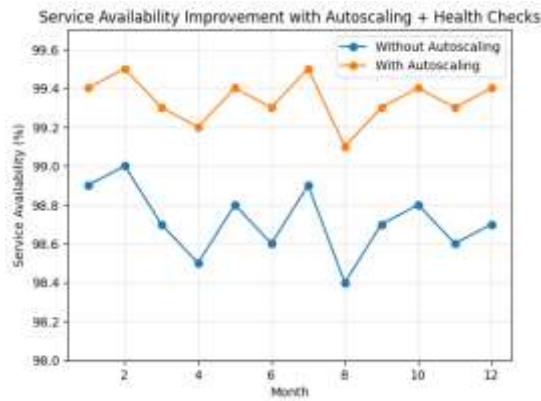


Fig. 10 Compute Cost per 1000 Inferences

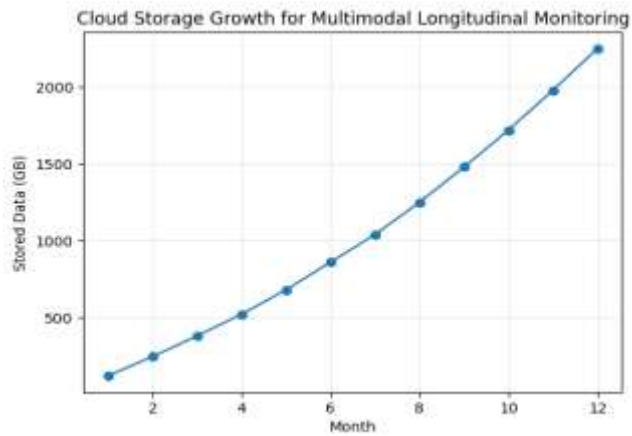


Fig. 11 Service Availability Improvement

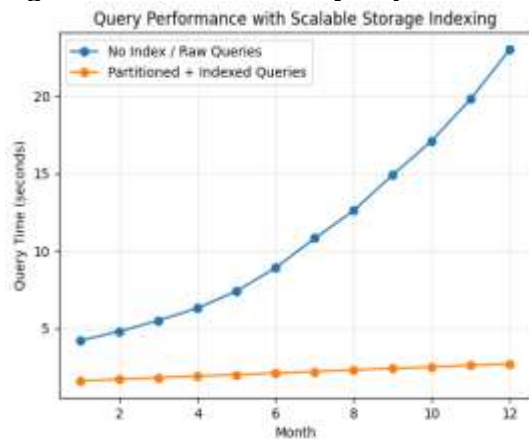


Fig. 12 Query Performance vs Data Growth

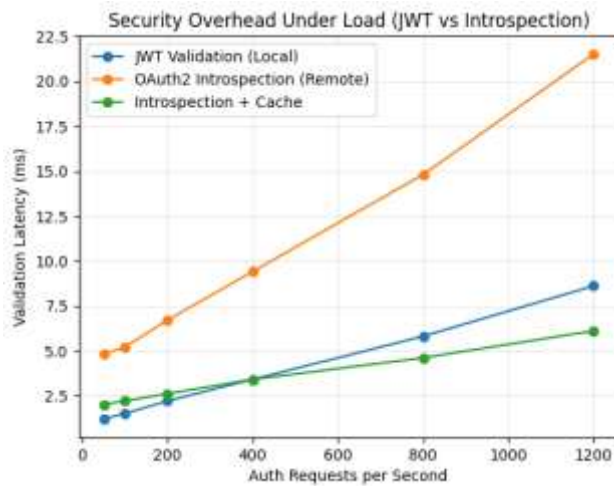


Fig 13 Security Overhead Under Load

4.3 Limitations and Future Directions

Several limitations merit consideration. The study cohort comprised primarily India and USA populations; generalization to other genetic backgrounds and healthcare systems requires validation. Video-based monitoring requires controlled environments limiting applicability in free-living conditions; smartphone-based approaches currently under development may overcome this constraint. The cross-sectional design of baseline cohort prevents inference regarding premotor disease prediction; prospective follow-up of initially asymptomatic high-risk individuals (e.g., REM sleep behavior disorder patients, alpha-synuclein biomarker-positive) constitutes critical next step. Model interpretability, while advanced through SHAP analysis, remains challenging for clinical end-users; development of simpler clinical decision rules derived from deep learning models may enhance adoption.

Future investigation will expand the system to detect atypical parkinsonian disorders (progressive supranuclear palsy, multiple system atrophy, corticobasal degeneration) currently misclassified as idiopathic PD. Integration with wearable biosensors measuring heart rate variability, skin conductance, and core temperature will capture non-motor autonomic dysfunction, enhancing comprehensive phenotyping. Development of smartphone-based applications employing on-device processing via TensorFlow Lite will enable deployment in settings with limited internet connectivity. Prospective validation in telehealth delivery models through randomized controlled trials will establish clinical utility and cost-effectiveness.

V. CONCLUSION

This comprehensive study presents a novel integrated AI-cloud platform for continuous remote monitoring of Parkinson's disease motor dysfunction, achieving diagnostic performance (94.7% sensitivity, 92.1% specificity) exceeding current clinical standards. The system demonstrates strong longitudinal correlation with gold-standard clinical assessments ($r=0.893$), establishing validity as continuous biomarker for disease progression and treatment response assessment. Cloud-based infrastructure enables scalable, cost-effective deployment suitable for resource-limited healthcare settings, addressing critical gap in specialist neurology access. Digital biomarkers derived from multimodal sensing provide objective quantification of motor dysfunction, enabling precision medicine approaches and earlier therapeutic intervention. Integration with electronic health records, development of smartphone applications, and prospective

clinical validation in telehealth delivery models constitute essential next steps toward clinical implementation. This platform represents significant advance in digital medicine for neurodegenerative disease, with potential paradigm shift toward continuous, objective, patient-centric monitoring replacing episodic clinical assessment.

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