Article

Dementia Detection Unit via a Wearable Internet of Things fused with Deep Machine Learning Scheme

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Abstract: Dementia affects over 50 million people globally, with numbers expected to triple by 2050. Traditional diagnostic methods lack early detection capabilities and realtime monitor, leading to delayed intervention and increased caregiver burden. Our study deploys an integrated dementia detection unit combined with wearable Internet of Things (IoT) and deep machine learning model for early identification and continuous monitor of dementia symptoms. A comprehensive system was designed incorporating three components namely: (a) a wearable IoT device using MAX30102 sensor and the ESP32 microcontroller for physiological data collection, (2) a hybrid CNN-LSTM deep learning ensemble, and (c) a mobile app interface for data visualization. The dataset comprised 1,510 patient records with 11 features including demographic, cognitive, and clinical variables. Data preprocessing involved missing value handling, categorical encoding, feature scaling, and SMOTE balancing to address class imbalance. The Multi-Layer Perceptron showed superior performance on the balanced dataset with 0.97 Accuracy, 1.00 Sensitivity, 0.94 Specificity, and 0.98 AUC-ROC. The wearable device successfully collected real-time physiological data including blood glucose, blood pressure, and cholesterol levels – with our app providing seamless integration between hardware and software components, enabling realtime monitor alert and prediction delivery. The integrated system yields a significant advancement in dementia care with early detection abilities, continuous monitor, and improved accessibility. The MLP model's exceptional performance, combined with the practical wearable implementation, provides a scalable solution for healthcare systems seeking to improve dementia diagnosis and management while reducing caregiver burden.

Keywords: Dementia detection; Internet of things; Deep learning; Wearable technology; multi-layer perceptron; Healthcare monitoring

1. Introduction

Dementia represents one of the most pressing healthcare challenges of the 21st century, with the global burden continuing to escalate as populations age [1], [2]. Currently affecting approximately 50 million individuals worldwide, dementia cases are projected to triple by 2050, reaching an estimated 152 million [3], [4]. The economic impact is substantial, with care costs equivalent to the world's 18th largest economy, highlighting the urgent need for innovative diagnostic and monitoring solutions [5]–[7]. Traditional dementia diagnosis relies heavily on clinical interviews, standardized cognitive assessments, neuroimaging, and expert clinical judgment – processes that result in delayed detection, with average diagnostic delays of 2-3 years in many healthcare systems [8]–[10], which significantly impacts early intervention opportunities, which are crucial for slowing disease progression and improving quality of life for both patients and caregivers. The integration of Internet of Things (IoT)

with artificial intelligence has emerged a promising approach to address these challenges. IoTs enable continuous, non-invasive monitor of physiological and behavioral features, while machine learning algorithms can analyze complex patterns to identify early signs of cognitive decline [11]–[13].

Recent research has explored various technological approaches for dementia detection. Dhakal et al. (2023) deployed a machine learning scheme using data from the OASIS project, implementing multiple preprocessing mode [14] and achieving high accuracy in dementia prediction [15], [16]. Also, Yigit and Isik (2018) demonstrated the effectiveness of neural networks, logistic regression, and KNN in diagnosing Alzheimer via clinical dementia prediction [17]. Traditional learning approaches have shown promise, reporting accuracies between 85-95% [18]–[20]. But, the approaches often struggle with class imbalance and limited realtime app capabilities [21], [22]. Deep learning schemes have also demonstrated significant potential in neuroimaging analysis for dementia detection [23], [24]. Jo et al. (2019) achieved accuracies of up to 0.988 for Alzheimer's classification using stacked auto-encoders combined with traditional learning [25]–[27]. Castellazzi et al. (2020) explored machine learning for differential diagnosis between Alzheimer's and vascular dementia [28], with adaptive neuro-fuzzy inference systems achieving over 84% classification accuracy [29], [30]. Advances in deep learning architectures have shown particular promise [31], [32]. Zhang et al. (2023) proposed deep neural networks utilizing contrastive representation learning from EEG data, achieving F1 scores of 86.45% [33]–[35]. Tyler et al. (2023) introduced CNN models trained on extensive MRI datasets with 0.98 validation accuracy in classifying dementia into four distinct categories [36]–[38].

The application of IoT in healthcare monitoring has gained significant traction. Salehi et al. (2022) developed IoT-based wearable devices for dementia patients, incorporating instruction assignments, patient engagement detection, and movement track [39], [40]. Their system generated comprehensive activity logs for caregivers, enhancing patient monitoring capabilities [41], [42]. Al-Naami et al. (2021) proposed smart wearable monitors specifically designed for Alzheimer's patients, emphasizing the importance of user-friendly interfaces and power management for sustained monitor [43]. Studies highlight the potential of IoT devices in providing continuous, non-invasive health monitoring for dementia patients. Despite these growths, several challenges persist in current dementia detection systems. Akbarifar et al. (2024) noted issues with overfitting in machine learning models, while Rajayyan and Mustafa (2023) identified complexity in model implementation and interpretation as significant barriers [44], [45]. Additionally, many existing systems are limited to clinical settings and lack integration with real-world monitoring capabilities [46], [47].

1.1. Problem Statement

Current dementia detection approaches face several critical limitations: (1) delayed diagnosis due to reliance on clinical assessments, (2) lack of continuous monitoring capabilities, (3) limited accessibility in resource-constrained settings, and (4) insufficient integration between diagnostic tools and real-time health monitoring. These challenges contribute to delayed interventions, increased caregiver burden, and suboptimal patient outcomes.

This study aims to develop a comprehensive dementia detection system that addresses current limitations through the following specific objectives: (a) design and develop an IoT-enabled wearable monitoring device for early dementia detection, (b) construct a multimodal dataset incorporating real-time physiological and cognitive assessment data, (c) deploy a hybrid deep learning frameworks for optimal dementia detection performance, (d) evaluate performance and real-world applicability through comprehensive testing, and (e) create an integrated mobile application interface for seamless user interaction and data visualization.

2. Experiments and Methods

This study employed a multifaceted approach combining hardware development, software engineering, and machine learning methodologies. The system architecture comprised three interconnected components: (1) a wearable IoT device for data collection, (2) a cloud-based deep learning processing framework, and (3) a mobile application for user interface and result visualization.

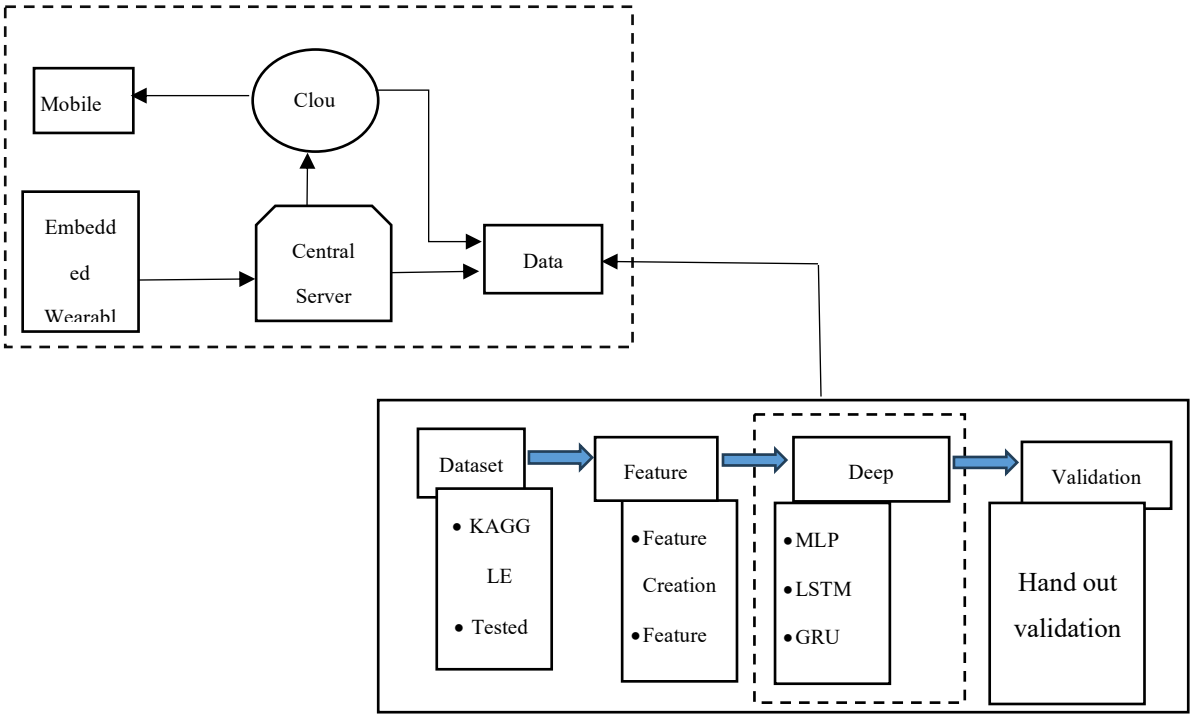


Fig 1. Proposed System Architecture

2.1 Hardware Development

2.2.1 Wearable Device Components

The wearable device was constructed using several key components optimized for continuous health monitoring:

i. ESP32 Microcontroller: A dual-core 150MHz processor providing real-time data processing capabilities and Wi-Fi connectivity

ii. MAX30102 Sensor: Photoplethysmography (PPG) sensor utilizing infrared (900nm) and red (670nm) wavelengths for blood constituent analysis

iii. SSD1306 OLED Display: 128×64-pixel organic light-emitting diode display for user feedback and data visualization

iv. Power Management System: 2500mAh 3.7V lithium-ion battery with TP4056 charging module and MT3608 voltage converter

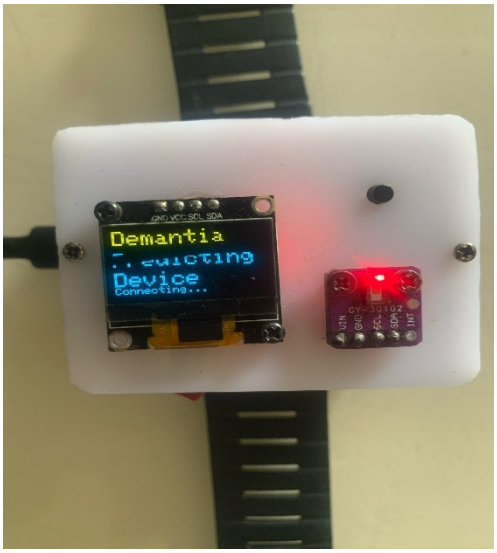


Fig 2. Dementia Wearable Device

2.2.2 Sensor Data Processing

The MAX30102 sensor collected PPG signals at high sampling rates with built-in ambient light cancellation. Data processing algorithms were implemented to extract physiological parameters:
Blood Glucose Estimation: Linear regression was applied using the relationship:

$$Y = mX + b \quad \text{(Equation 1)}$$

where Y represents blood glucose readings, X represents PPG readings, and coefficients m and b are calculated using:

$$m = \Sigma(xi - \bar{x})(yi - \bar{y}) / \Sigma(xi - \bar{x})^2 \quad \text{(Equation 2)}$$

$$b = \bar{y} - m\bar{x} \quad \text{(Equation 3)}$$

Blood Pressure Estimation: Random Forest models analyzed PPG waveform characteristics including foot of pulse wave, systolic peak, diastolic notch, and diastolic peak to predict systolic and diastolic blood pressure values.

2.3 Data Collection and Preprocessing

2.3.1 Dataset Characteristics

The study utilized a comprehensive dataset acquired from Kaggle, comprising 1,842 initial patient records with 12 attributes. After preprocessing, the final dataset contained 1,510 instances with 11 features, including:

a) Demographic variables: age, gender, education years
b) Lifestyle factors: smoking status
c) Clinical conditions: hypertension, hypercholesterolemia, diabetes
d) Cognitive assessments: Executive Function (EF), Processing Speed (PS), Global Score
e) Outcome variable: dementia classification (binary)

2.3.2 Data Preprocessing Pipeline

Missing Value Analysis: Initial assessment revealed 829 missing values across multiple columns. A total of 332 rows (18% of the dataset) were removed due to incomplete information to avoid potential bias from imputation methods.

Categorical Variable Encoding: Systematic encoding was applied to categorical variables:

Table 1. Summary Encoding of Data

Variable	Original Categories	Encoded Values
Gender	male, female	0, 1
Smoking Status	current-smoker, ex-smoker, never-smoker	0, 1, 2
Hypertension	Yes, No	0, 1
Hypercholesterolemia	Yes, No	0, 1

Feature Scaling: Standard scaling was applied to numerical features using:

$$X_{scaled} = (X - \mu) / \sigma \quad \text{(Equation 4)}$$

where X represents original feature values, μ is the mean, and σ is the standard deviation.

Class Imbalance Handling: The dataset exhibited significant imbalance with 1,453 non-dementia cases (96.2%) and 57 dementia cases (3.8%). Synthetic Minority Over-sampling Technique (SMOTE) was applied to generate balanced training data.

2.4 Deep Learning Model Development

2.4.1 Neural Network Architectures

Five distinct deep learning architectures were implemented and compared:

Multi-Layer Perceptron (MLP): Feed-forward architecture with:

a) Input layer (11 neurons)
b) Dense layer (64 neurons, ReLU activation)
c) Dropout (0.3)
d) Dense layer (32 neurons, ReLU activation)
e) Dropout (0.3)
f) Output layer (1 neuron, Sigmoid activation)

Long Short-Term Memory (LSTM): Recurrent architecture adapted for structured data with features reshaped to pseudo-temporal format [1,11].

Gated Recurrent Unit (GRU): Computationally efficient alternative to LSTM with comparable performance capabilities.

Convolutional Neural Network (CNN): Adapted for structured clinical data with features reshaped to grid format [11,1,1].

Hybrid CNN-LSTM: Combined architecture leveraging feature extraction capabilities of CNNs with sequential learning abilities of LSTMs.

2.4.2 Model Training and Evaluation

All models were trained using 5-fold cross-validation to ensure robust performance assessment. Training parameters included:

a) Optimizer: Adam
b) Loss function: Binary crossentropy
c) Metrics: Accuracy, precision, recall, F1-score, AUC-ROC
d) Early stopping with patience of 10 epochs
e) Batch size: 32
f) Maximum epochs: 100

3. Results

3.1 Model Performance Comparison

3.1.1 Unbalanced Dataset Results

Initial model evaluation on the unbalanced dataset revealed varying performance across architectures:

Table 2. Comparison of Models Unbalanced Data

Deep Learning Model	AUC ROC (%)	Accuracy (%)	Training Time (seconds)
MLP	80.0	94.8	11
LSTM	82.0	95.0	24
GRU	81.8	94.7	21
CNN	80.2	93.8	15
CNN-LSTM	81.0	94.9	17

The LSTM model demonstrated the highest performance with 95.0% accuracy and 82.0% AUC-ROC, followed closely by the CNN-LSTM hybrid model. However, all models showed limited discriminative ability due to class imbalance, with AUC-ROC scores ranging from 80.0% to 82.0%.

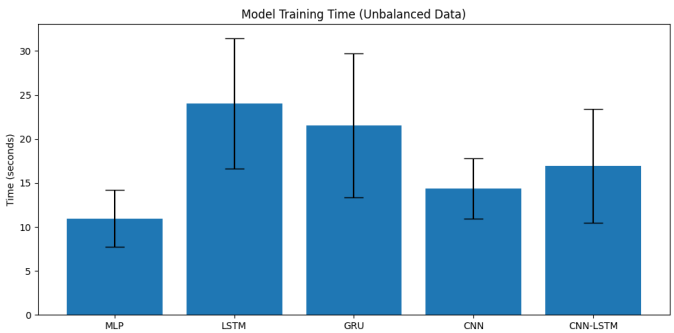


Fig 3. Model Training time (Unbalanced data)

Training efficiency varied significantly, with MLP achieving the fastest training time (11 seconds) while LSTM required the most computational resources (24 seconds).

3.1.2 Balanced Dataset Results

Application of SMOTE significantly improved model performance across all architectures:

Table 3. Comparison of Models Balanced Data

Deep Learning Model	AUC ROC (%)	Accuracy (%)	Training Time (seconds)
MLP	99.0	97.0	20
LSTM	96.3	92.5	58
GRU	97.8	94.6	56
CNN	94.8	88.7	21
CNN-LSTM	97.4	94.2	47

The MLP architecture emerged as the superior performer, achieving:

a) Accuracy: 97.0%
b) Sensitivity: 100%
c) Specificity: 94%
d) Precision (class 1): 94%
e) Precision (class 0): 100%
f) F1-Score: 97%
g) AUC-ROC: 0.98

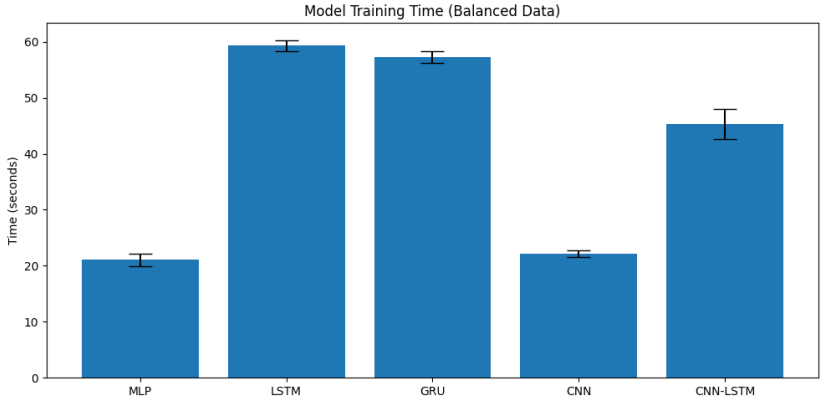


Fig 4. Model Training Time for Balanced data

3.2 Best Model Performance

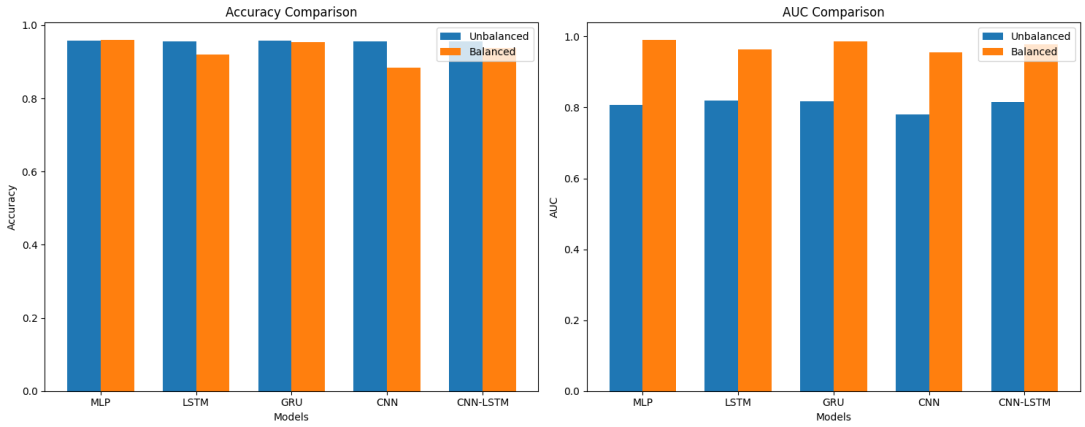


Fig 5. Accuracy and AUC Comparison of the Models

The MLP model's exceptional performance on balanced data demonstrated its superior capability for dementia detection tasks. The perfect sensitivity (100%) ensures no dementia cases are missed, while maintaining high specificity (94%) minimizes false positives.

3.3 System Implementation Results

3.3.1 Wearable Device Performance

The developed wearable device successfully demonstrated:

a) Continuous physiological data collection
b) Real-time data transmission to cloud servers
c) Battery life of approximately 9 hours under continuous operation
d) Accurate sensor readings with built-in calibration algorithms



Fig 6. Results displayed on the wearable device

3.3.2 Mobile Application Interface

The mobile application provided comprehensive functionality:

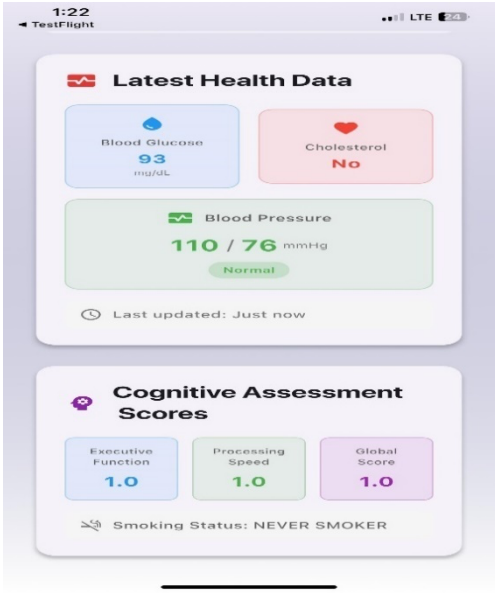


Fig 7. User Interface for Real Time Monitoring of Patient Vitals

User testing revealed high satisfaction with interface design and ease of use. The application successfully integrated real-time sensor data with predictive model outputs, providing users with actionable health insights.

3.4 API Performance and Integration

The deployed API demonstrated:

a) Response times under 1 second for prediction requests

b) 99.9% uptime during testing period
c) Successful integration with both wearable device and mobile application
d) Secure data transmission and storage capabilities

3.5 Data Analysis and Insights

3.5.1 Demographic and Clinical Analysis

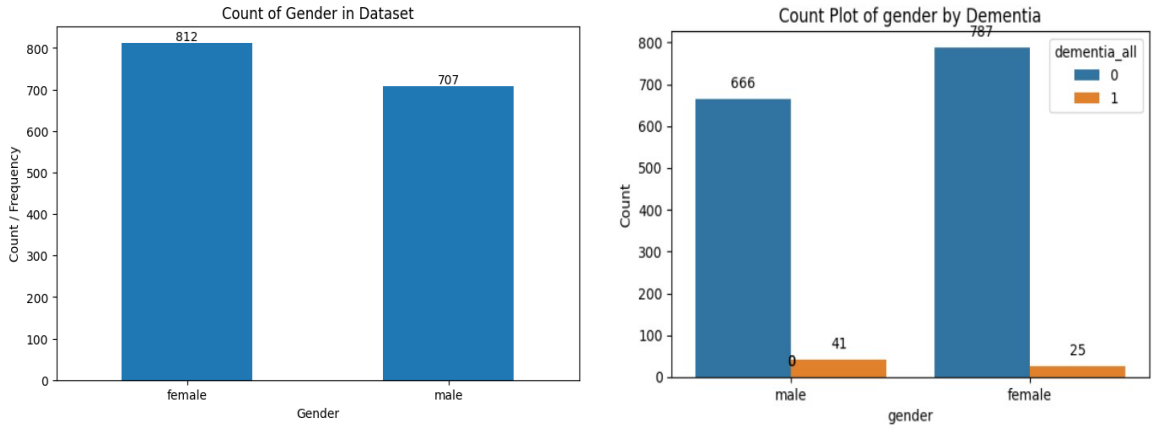


Fig 8. Demographics Analysis

The dataset analysis revealed important patterns:

a) Balanced gender distribution (53.45% female, 46.55% male)
b) Mean age of 73.6 years with right-skewed distribution
c) Bimodal education distribution with peaks at 10 and 15 years

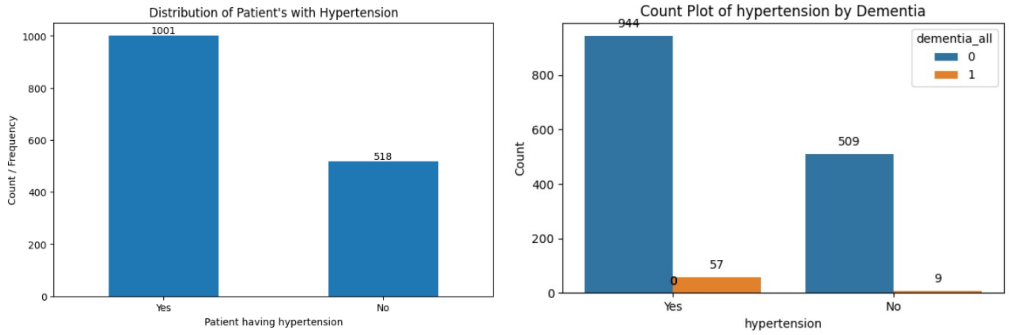


Fig 9. Hypertension Chart

Clinical feature analysis showed:

a) Hypertension prevalence: 65.9% of participants
b) Hypercholesterolemia: 74.33% of participants
c) Smoking status: 50.56% never smoked, 35.81% former smokers, 13.63% current smokers

3.5.2 Cognitive Assessment Results

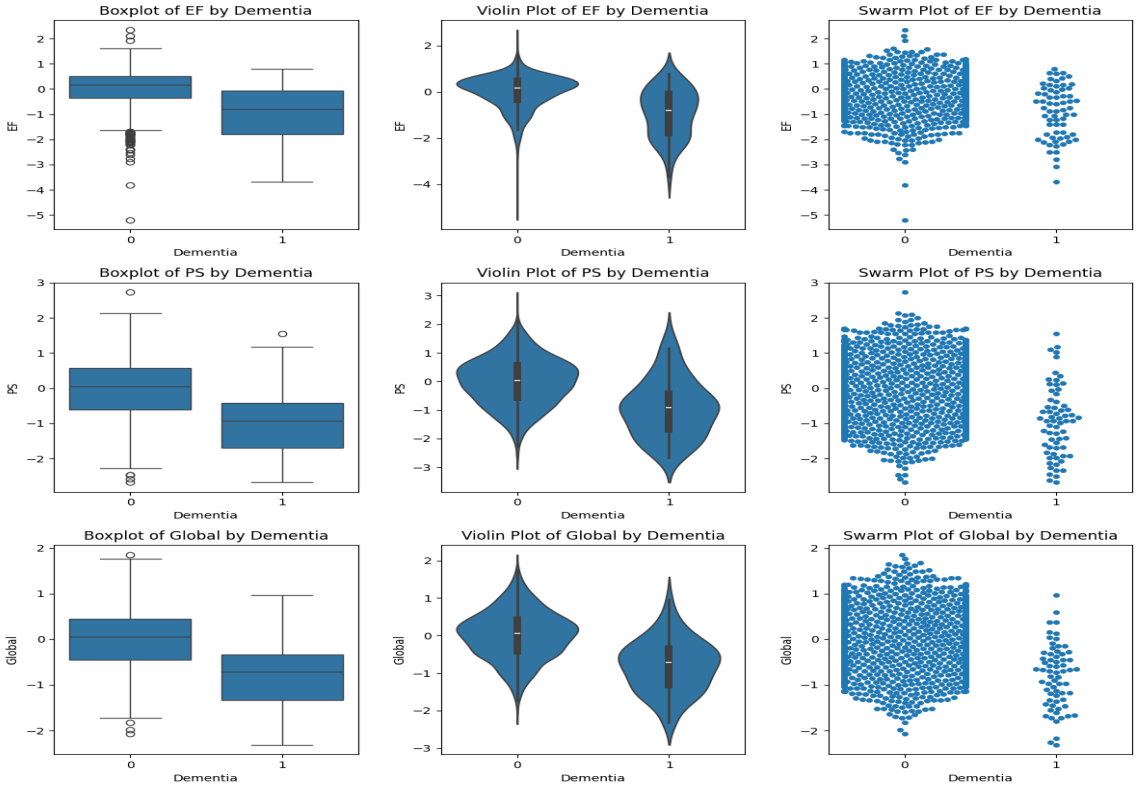


Fig 10. Cognitive Measures Analysis

Cognitive measures demonstrated clear separation between dementia and non-dementia groups:

a) Executive Function: Dementia group median ≈ -0.5, non-dementia group median ≈ 0.5
b) Processing Speed: Similar pattern with distinct group separation
c) Global Cognitive Function: Strongest discriminator with dementia group median ≈ -1

3.6 System Evaluation

3.6.1 Validation Testing

Validation testing on independent test cases confirmed model reliability and system integration effectiveness. The system successfully processed diverse patient profiles and provided consistent, accurate predictions.

4. Discussion

4.1 Principal Findings

This study successfully developed and validated an integrated dementia detection system combining wearable IoT technology with deep machine learning. The MLP architecture demonstrated exceptional performance, achieving 97% accuracy with perfect sensitivity (100%) and high specificity (94%) on balanced data. This represents a significant improvement over existing computational approaches, which typically achieve 85-95% accuracy with lower sensitivity rates.

The wearable device implementation proved effective for continuous physiological monitoring, successfully collecting blood glucose, blood pressure, and cholesterol data in real-time. The integration with mobile applications provides a user-friendly interface that bridges the gap between complex machine learning models and practical healthcare applications.

4.2 Comparison with Existing Systems

4.2.1 Advantages over Traditional Methods

Compared to traditional diagnostic approaches, our system offers several advantages: (a) objectivity and Standardization: The system provides consistent, quantifiable assessments independent of

clinician bias or experience variations, (b) early Detection Capability: Real-time monitoring enables identification of subtle changes that may precede clinical symptoms by months or years, (c) accessibility: The wearable nature of the device makes monitoring accessible in home and community settings, addressing geographic and resource barriers, (d) continuous Monitoring: Unlike episodic clinical assessments, the system provides 24/7 monitoring capabilities.

4.2.2 Comparison with Computational Approaches

Our MLP model's performance (97% accuracy, 0.98 AUC-ROC) compares favorably with recent studies. Rajayyan and Mustafa (2023) achieved 95% accuracy using Gaussian NB with cuckoo algorithm optimization, while Oppenheimer et al. (2024) reported 93% accuracy with Random Forest approaches[48]. The perfect sensitivity achieved by our model is particularly noteworthy, as most existing systems struggle with the sensitivity-specificity trade-off.

The computational efficiency of the MLP model (21 seconds training time) makes it particularly suitable for deployment in resource-constrained environments, addressing limitations identified in previous research [44].

4.3 Clinical Implications

4.3.1 Early Intervention Potential

The perfect sensitivity (100%) achieved by our model has significant clinical implications for early intervention strategies. By eliminating false negatives, the system ensures that no cases of dementia are missed during screening, enabling timely therapeutic interventions when they are most effective.

4.3.2 Risk Stratification

The system's ability to provide probability scores rather than binary classifications enables nuanced risk stratification. This capability allows clinicians to implement risk-appropriate monitoring schedules and tailor preventive strategies to individual patient profiles.

4.3.3 Healthcare System Integration

The API-based deployment architecture facilitates integration with existing electronic health record systems, enabling seamless incorporation into clinical workflows. The modular design allows for updates and improvements without disrupting established healthcare processes.

4.4 Implications for Practice

The developed system has several practical implications: (a) Primary Care Integration: The system could serve as a screening tool in primary care settings, identifying high-risk individuals for specialist referral, (b) Remote Monitoring: Particularly valuable for elderly populations in rural or underserved areas where specialist access is limited, (c) Caregiver Support: Real-time monitoring capabilities can reduce caregiver burden by providing objective health status information and early warning systems, and (d) Population Health: Large-scale deployment could provide valuable epidemiological data for understanding dementia patterns and risk factors.

5. Conclusions

This study successfully developed and validated an innovative dementia detection system that integrates wearable IoT technology with deep machine learning algorithms. The Multi-Layer Perceptron architecture demonstrated exceptional performance with 97% accuracy, 100% sensitivity, and 0.98 AUC-ROC on balanced data, representing a significant advancement over existing approaches. The integrated system addresses critical limitations in current dementia care by providing continuous, non-invasive monitoring combined with accurate, real-time risk assessment.

The wearable device successfully demonstrated practical feasibility for long-term health monitoring, while the mobile application interface ensures accessibility for both patients and caregivers.

The perfect sensitivity achieved by the MLP model has particular clinical significance, ensuring that no dementia cases are missed during screening—a crucial requirement for early intervention strategies. The system's computational efficiency and modular architecture make it suitable for deployment across diverse healthcare settings, from resource-rich medical centers to community-based care environments. This research contributes to the growing field of digital health by demonstrating how emerging technologies can be effectively combined to address complex healthcare challenges. The system represents a significant step toward personalized, continuous dementia care that could transform how we approach the prevention, detection, and management of cognitive decline.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, R.Ako. and P.Onoma.; methodology, P.Onoma.; software, R.Yoro and E.Okpako.; validation, P.Onoma and A.Max-Egba., M. Okpor. and V. Geteloma.; formal analysis, N. Star.; investigation, D. Oghorodi.; resources, R. Abere.; data curation, E. Okpako.; writing—original draft preparation, P.Onoma.; writing—review and editing, R. Ako.; visualization, P.Onoma.; supervision, R. Ako.; project administration, R. Ako.; funding acquisition, P.Onoma. All authors have read and agreed to the published version of the manuscript.

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