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Dementia Detection and Management Using Wearable Device fused Deep Learning Scheme

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ABSTRACT

Dementia affects over 50 million people worldwide, with numbers expected to triple by 2050. Traditional diagnostic methods often lack early detection capabilities and real-time monitoring, leading to delayed interventions and increased caregiver burden. This study aimed to develop an integrated dementia detection system combining wearable Internet of Things (IoT) with deep learning for early identification and continuous monitor of dementia. The system has three core components: (1) a wearable IoT using ESP32 and MAX30102 sensors to collect data, (2) a deep learning scheme to compare five neural network approaches (MLP, LSTM, GRU, CNN, and hybrid CNN-LSTM), and (3) a mobile app to ease data visualization. The dataset comprised of 1,510 records with 11 features. Preprocessing handled missing values, categorical encoding, and feature scaling; while, SMOTE was used to address class imbalance. Results showed that the MLP demonstrated superior performance with a 97% accuracy, 100% sensitivity, 94% specificity, and 0.98 AUC-ROC. Device successfully collected physiological data as displayed over mobile app – enabling real-time monitor and prediction. Device yields a significant advancement in dementia care with early detection, continuous monitoring, and improved accessibility. MLP offered exceptional performance with the practical wearable implementation, provides a scalable solution for healthcare systems seeking to improve dementia diagnosis and management while reducing caregiver burden.

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 (Al-Hammadi et al., 2024; Twait et al., 2023). With over 50 million patients worldwide, dementia cases are projected to triple by 2050, reaching an estimated 152 million people (Ojugo et al., 2021a, 2021b; Ojugo and Otakore, 2018). The economic impact is substantial, with care costs equivalent to the world's 18th largest economy, highlighting the urgent need for innovative diagnostic and monitor (AlSaeed and Omar, 2022; Odiakaose et al., 2025; Ugbotu et al., 2025). Traditional diagnosis relies heavily on clinical interviews, standard cognitive assessments, neuroimaging, and expert clinical judgment that often result in delayed detection, with diagnostic delays of 3years (Aghaunor et al., 2025; Borchert et al., 2023; Onoma, Agboi, Geteloma, et al., 2025; Onoma, Agboi, Ugbotu, et al., 2025; Onoma, Ugbotu, Aghaunor, et al., 2025). This delay significantly impacts early intervention opportunities, which are crucial for slowing

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disease progression and improving quality of life for both patients and caregivers (Odiakaose et al., 2024, 2025).

The integration of Internet of Things (IoT) technology with artificial intelligence has emerged as a promising approach to address these challenges. IoT devices enable continuous, non-invasive monitoring of physiological and behavioral parameters, while machine learning algorithms can analyze complex patterns to identify early signs of cognitive decline (Addae et al., 2024; Okpor et al., 2025; Sheikhtaheri and Sabermahani, 2022).

2. LITERATURE REVIEW

2.1 Review of Literatures

Studies explore various approaches for dementia detection. Dhakal et al. (2023) deployed a machine learning model with data from OASIS project, implementing multiple pre-processing to achieving high accuracy in dementia (Dhakal et al., 2023). Yigit and Isik (2018) showed effectiveness of neural nets, logistic regression, and KNN in diagnosing Alzheimer's via clinical rating (Yigit and Isik, 2018). Traditional approaches have shown promise with accuracy rates between 85-95% (Miah et al., 2021; Onoma, Agboi, Geteloma, et al., 2025; Rajayyan and Mustafa, 2023). However, these struggle with class imbalance issues and limited realtime app capabilities (Agboi et al., 2025; Eboka, Odiakaose, et al., 2025; Javeed et al., 2023; Reinke et al., 2023).

Deep learning successfully demonstrates potential in imaging for dementia detection. Jo et al. (2019) achieved accuracies of up to 98.8% for Alzheimer's classification using stacked auto-encoders combined with traditional machine learning (Jo et al., 2019). Castellazzi et al. (2020) explored machine learning approaches for differential diagnosis between Alzheimer's and vascular dementia, with adaptive neuro-fuzzy inference systems achieving over 84% classification accuracy (Castellazzi et al., 2020). Recent advances in deep learning architectures have shown particular promise. Zhang et al. (2023) proposed deep neural networks utilizing contrastive representation learning from EEG data, achieving F1 scores of 86.45% (Zhang et al., 2023). Tyler et al. (2023) introduced CNN models trained on extensive MRI datasets, reaching 98% validation accuracy in classifying dementia into four distinct categories (Geteloma et al., 2024a, 2024b; Tyler Morris et al., 2023).

Use of IoT in healthcare has gained significance. Salehi et al. (2022) used IoT wearable for dementia patients, incorporating instruction assignments, patient engagement detection, and movement tracking (Salehi et al., 2022). This, generated a comprehensive activity log for caregivers, enhancing patient monitor capabilities. Al-Naami et al. (2021) used wearable monitor unit specifically designed for Alzheimer's patients with a user-friendly interface and power management for sustained monitoring (Al-Naami et al., 2021) to showcase the potentials of IoT in providing continuous, non-invasive health monitor for dementia patients (Al-Nbhany et al., 2024; Muhamada et al., 2024; Og and Ying, 2021; Ojugo and Yoro, 2020b, 2020a, 2020c).

Despite promising developments, 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 (Akbarifar et al., 2024; Oladele et al., 2024; Omede et al., 2024). Additionally, many existing systems are limited to clinical settings and lack integration with real-world monitoring capabilities (Wagner and Borycki, 2022).

2.2. Study Motivation

Current dementia detection face several critical limitations: (1) delayed diagnosis due to reliance on clinical assessments, (2) lack of continuous monitoring, (3) limited access for resource-constrained settings and environ, and (4) insufficient integration and fusion between diagnostic tools and real-time health monitoring. These risks, result in the delayed interventions, increased caregiver burden, and suboptimal patient outcomes (Setiadi, Nugroho, et al., 2024; Setiadi, Ojugo, et al., 2025; Setiadi, Susanto, et al., 2024; Setiadi, Sutojo, et al., 2025).

Study develops comprehensive dementia detection system to address the limitations via these specific objectives:

1. Design and develop an IoT-enabled wearable monitoring device for early dementia detection (Muslikh et al., 2023; Safriandono et al., 2024).
2. Construct a multimodal dataset with real-time physiological and cognitive assessment data (Akazue, Asuai, et al., 2023; Akazue, Debekeme, et al., 2023).
3. Compare deep learning frameworks for optimal dementia detection (Allenotor et al., 2015; Allenotor and Ojugo, 2017).
4. Evaluate performance with realtime app via a comprehensive testing (Binitie et al., 2024; Oyemade et al., 2016; Oyemade and Ojugo, 2020, 2021).
5. Create an integrated mobile application interface for seamless user interaction and data visualization (Jiang et al., 2024; Ojugo et al., 2024; Ojugo, Yoro, et al., 2015; Shome et al., 2021).

3. MATERIALS AND METHODS

3.1. The Proposed System

Study employed a multifaceted approach combining hardware development, software engineering, and machine learning method (Ojugo and Nwankwo, 2021b, 2021c, 2021d, 2021a). Its architecture utilized three (3) units namely: (1) wearable IoT for data collection, (2) a cloud-based deep learning processing framework, and (3) a mobile application for user interface and result visualization (Ojugo, Eboka, et al., 2013; Ojugo, Oyemade, et al., 2015; Ojugo and Oyemade, 2020; Okorodudu et al., 2023).

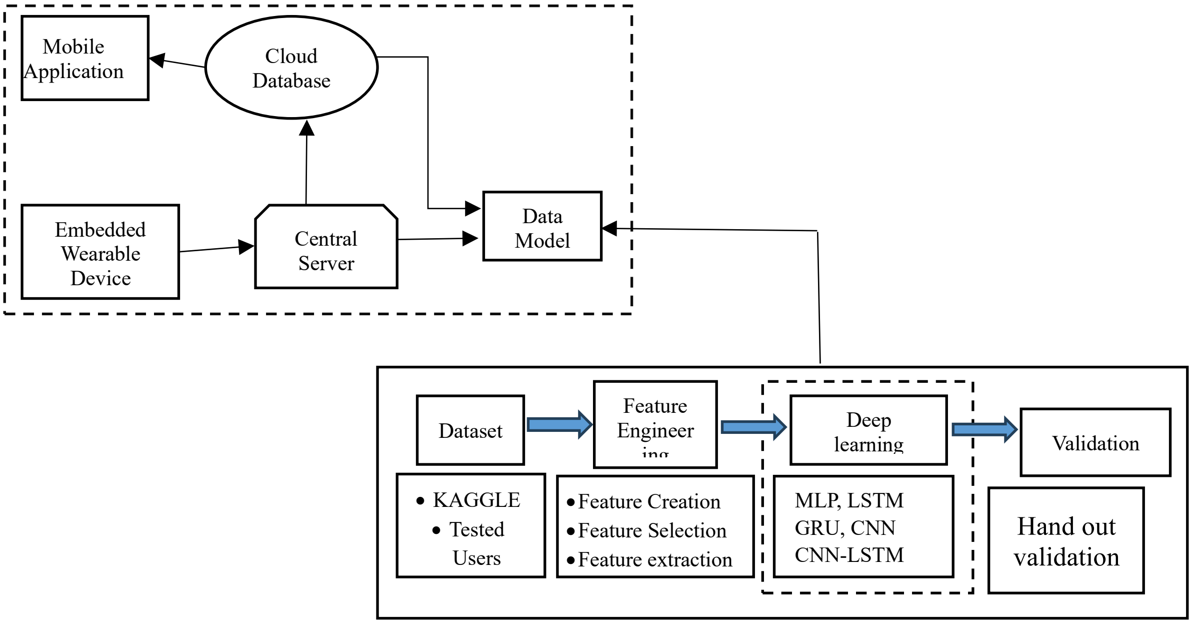

Figure 1. Proposed System Architecture

3.1. Hardware Development

The system implementation follows a modular approach with a 2-layer architecture (Ojugo, Aghware, et al., 2015; Ojugo, Eboka, et al., 2015). The wearable device/unit was constructed using several key features optimized for continuous health monitoring and alert scheme as thus: (a) the ESP32 microcontroller: A dual-core 150MHz processor offers realtime data processing and Wi-Fi connectivity, (b) MAX30102 Sensor: Photoplethysmography sensor uses infrared (900nm) and red (670nm) wavelengths for blood constituent analysis, (c) the SSD1306 OLED Display: 128×64-pixel organic light-emitting diode display for user feedback and data visualization, (d) power management system: 2500mAh 3.7V lithium-ion battery with TP4056 charging module and MT3608 voltage converter (Eboka, Aghware, et al., 2025; Eboka, Odiakaose, et al., 2025; Eboka and Ojugo, 2020).

3.2. Sensor Data Processing

The MAX30102 sensor collected PPG signals at high sampling rates with built-in ambient light cancellation. Data processing extracted physiological parameters (Aghware et al., 2024, 2025; Ako et al., 2025):

1. The Blood Glucose Estimate: Linear regression was applied using the relationship: where Y represents blood glucose readings, X represents PPG readings, and coefficients m and b are calculated using (Yoro et al., 2025; Yoro and Ojugo, 2019a, 2019b):

$$Y = MX + b \quad Equation\ 1$$

$$m = \sum \frac{(x_i - \bar{x})(y_i - \bar{y})}{(x_i - \bar{x})^2} \quad Equation\ 2$$

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

2. 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 (Brizimor et al., 2024; David et al., 2023; Otorokpo et al., 2024; Panagoulias et al., 2022).

3.3. Data Collection and Pre-processing

Study utilized a comprehensive dataset from Kaggle with 1,842 initial patient records and 12 attributes. After pre-processing, final dataset contained 1,510 cases with 11 feature-classes (Ojugo, Akazue, Ejeh, Ashioba, et al., 2023; Ojugo, Ejeh, Akazue, Ashioba, et al., 2023; Okonta et al., 2013, 2014; Wemembu et al., 2014): (a) demographics, (b) lifestyle status, (c) clinical conditions, (d) cognitive assessments, and (e) class target (binary).

For pre-processing – we acted as follows: *Phase-1 – 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 (Pratama et al., 2025; Setiadi, Muslikh, et al., 2024; Zuama et al., 2025).

Categorical Variable Encode: Systematic encoding was applied to categorical variables (Ojugo, Ugboh, et al., 2013; Ojugo, Akazue, Ejeh, Odiakaose, et al., 2023; Ojugo, Odiakaose, Emordi, Ako, et al., 2023; Ojugo, Odiakaose, Emordi, Ejeh, et al., 2023):

Table 1. Data Encoding

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

Phase 2: Feature Scaling: Standard scaling was applied to numerical features using (Okpor et al., 2025; Okpor, Aghware, Akazue, Eboka, et al., 2024; Okpor, Aghware, Akazue, Ojugo, et al., 2024):

$$x_{scaled} = \frac{x - \mu}{\sigma} \quad Equation\ 4$$

Phase 3: Class Imbalance: Dataset shows imbalance with 1,453 non-dementia (96.2%) and 57 dementia (3.8%). Synthetic Minority Over-sample Technique (SMOTE) was used to generate balanced training data (Malasowe et al., 2023; Malasowe, Aghware, et al., 2024; Malasowe, Edim, et al., 2024; Malasowe, Ojie, et al., 2024; Malasowe, Okpako, et al., 2024).

3.4. Deep Learning Model Deployment

Five (5) models were implemented: (a) a feedforward multilayer perceptron (MLP) with 11-input neurons, 2-dense layer with 64 and 32 neurons respectively with the ReLU activation function, 2 dropout with (0.3), and an output layer with a neuron and Sigmoid activation, (b) the Long Short-Term Memory

(LSTM): Recurrent architecture adapted for structured data with features reshaped to pseudo-temporal format [1,11], (c) the Gated Recurrent Unit (GRU): Computationally efficient alternative to LSTM with comparable performance capabilities, (d) the Convolutional Neural Network (CNN): Adapted for structured clinical data with features reshaped to grid format [11,1,1], and (e) hybrid CNN-LSTM that leverages feature extraction abilities of CNNs with sequential learning abilities of LSTMs (Atuduhor et al., 2024; Ejeh et al., 2024; Ifioko et al., 2024).

All the models were trained using 5-fold train/validation to ensure robust performance assessment. The training parameters include: (a) Adam optimizer, (b) loss function: Binary cross-entropy, (c) early stop criterion of 10-epochs with batch size of 32, and maximum epoch of 100, and (d) evaluation metrics are Accuracy, precision, recall, F1-score, AUC-ROC.

4. RESULT FINDINGS and DISCUSSION

4.1. Artifact Construction / Performance

Our wearable device demonstrated its purpose as unit for continuous physiological data collection, realtime data transmission to cloud servers, battery life of approximately 9 hours under continuous operation, and an accurate reading with built-in calibration algorithms as seen in Figure 2 with Figure 3 respectively showing the mobile app used to provide comprehensive functionality to patients cum users.

Figure 2. Display for the wearable device

Figure 3. User Interface for monitor of Patients

Results on user testing showed high user 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. In addition, the deployed API demonstrated a response time under 1 second for prediction requests, an uptime of 99.9% during testing period, a successful integration with both wearable device and mobile application, and secure data exchange and storage capabilities

4.2. Dataset 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, and (c) Bimodal education distribution with peaks at 10 and 15 years as seen in Figure 4 and Figure 5 respectively.

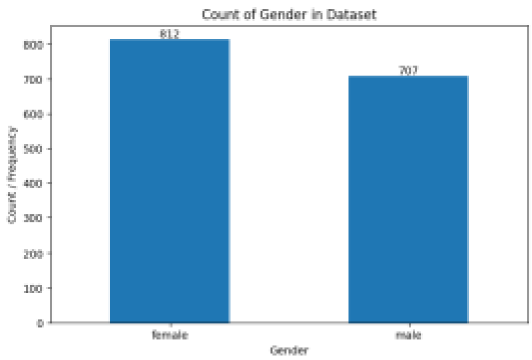

Figure 4. Dataset by Gender

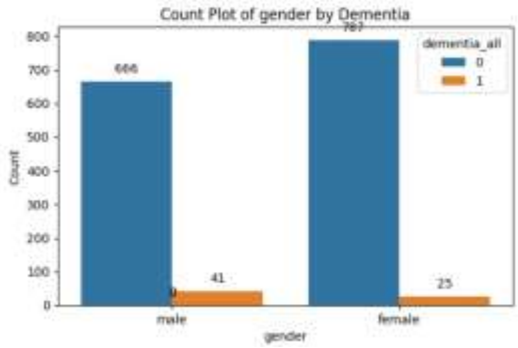

Figure 5. Dataset plot by Dementia Gender

In addition, the 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 as seen in Figure 6 and 7 respectively.

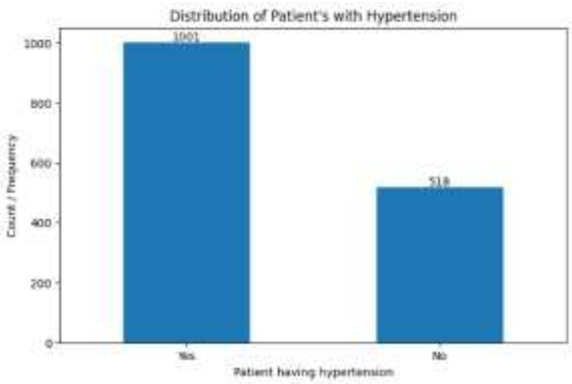

Figure 6. Patient Distribution by hypertension

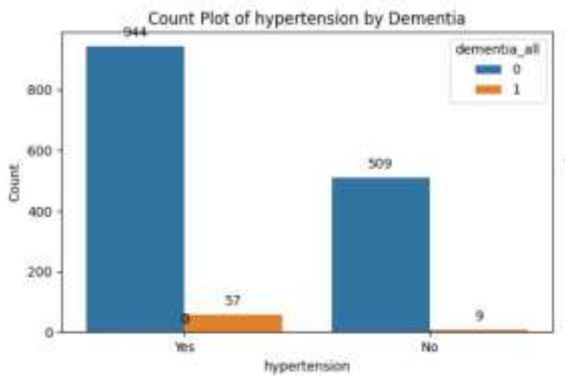

Figure 7. Dementia Patients by hypertension

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 (Akazue, Edje, et al., 2024; Akazue, Okofu, et al., 2024; Okofu, Akazue, et al., 2024; Okofu, Anazia, et al., 2024).

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.

4.3. Clinical Implications

The system yields several clinical implications namely: (a) early intervention: with its 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, and (b) Risk Stratification: with its 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.

4.4. Discussion of 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.

4.5. Practical Implications

System yields several 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, (d) Population Health: Large-scale deployment could provide valuable epidemiological data for understanding dementia patterns and risk factors.

5. CONCLUSION

This study successfully developed and validated an innovative dementia detection system that integrates wearable IoT technology with deep machine learning algorithms. MLP 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 issues in current dementia care by providing continuous, non-invasive monitoring combined with accurate, real-time risk assessment. The wearable unit demonstrated practical feasibility for long-term health monitoring, while the mobile application interface ensures accessibility for both patients and caregivers.

Its sensitivity shows 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 centres 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. System represents a significant step toward personalized, continuous dementia care that could transform how we approach the prevention, detection, and management of cognitive decline.

Conflict of Interest

The authors declare that there is no conflict of interest.

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