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Quest for Ground-Truth or Stochastic Myth by Leveraging the AI-Powered Wearable Device for Dementia Disease Detection: A Pilot Study

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ABSTRACT

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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 tree-based, stacked learning approaches with 3-base classifiers (decision tree, random forest and adaboost) – and a XGBoost meta-classifier, and (3) a mobile app to ease data visualization. The dataset comprised of 2,149 records with 16-features. Preprocessing handled missing values to ensure data quality/integrity – while, normalization was used to address imbalanced dataset. Results showed that the stacked model yielded a 99.7% accuracy, 100% sensitivity, 99.4% specificity, and 99.8% AUC. While IoMT device successfully collected physiological data as displayed over mobile app – model shows that the AI-Powered unit can effectively help detect dementia.

1. INTRODUCTION

The deployment of wearable devices for the identification and classification of disease, vis-à-vis the consequent early warning alert and prevention represents a bold step towards inclusivity for persons living with dementia (PwD) (Obasuyi *et al.*, 2024; Ojugo and Eboka, 2018a, 2018b), In addition, this advances the consequent reachability and availability for and of medicare every time and everywhere, to all. These wearables units (also known as Gerontechnology) advances the utilization of the Internet of Medical Things (IoMT) (Og and Ying, 2021) to yield the convergence of: (a) a wearable technology (Salehi *et al.*, 2022), and (b) adoption of wireless sensors and networks (Akazue, Edje, et al., 2024; Akazue, Okofu, *et al.*, 2024). This fusion advances body-worn, smart devices equipped with

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programmable microcontrollers, sensor observation units, and software that ease data acquisition cum exchange (Brizimor *et al.*, 2024). Examples include smartwatch, fitness-trackers, and medical monitors (Krishna *et al.*, 2023) – that seamlessly provide PwDs and care-support with enhanced realtime monitoring, and alert (Oyemade and Ojugo, 2021) of patients' physiological metrics. It allows uninterrupted data acquisition (Kakhi *et al.*, 2022) – and aids improved analysis that unveils a patient's comprehensive health status and all potential anomalies with early warning (Nahavandi et al., 2022) and identification of disease in its localized state (Aghware *et al.*, 2025). The utilization of IoMT prevents metastasis of the disease (Ako *et al.*, 2025), improves patient's status by initiating of a treatment plan via coordinated prognosis (Pratama et al., 2025), and enhance patient's life status also (Roshan, 2022). Gerontech assist the medi-expert with non-invasive treatment for lessened medical complications (Manickam et al., 2022), less side effects, substantial cost savings (Oladele et al., 2024), and as an expansive tools to help manage the early-stage conditions for a patient's healthcare .

Dementia is a global health menace of the 21st century, with continued burden that escalates as populations of elderly increases (Al-Hammadi et al., 2024; Twait et al., 2023). With over 55-million and counting patients globally, dementia cases are estimated to also triple by 2050, reaching an estimated 152 million people (Ojugo et al., 2021a, 2021b; Ojugo and Otakore, 2018). The economic impact is substantial, with costs that equates to world's 18th largest economy, highlighting the urgent need for innovative diagnostic and monitor (AlSaeed and Omar, 2022; Odiakaose et al., 2025; Ugbotu, Aghaunor, et al., 2025; Ugbotu, Emordi, et al., 2025). Traditional diagnosis relies heavily on clinical interviews, neuro-imaging, modal cognitive assessments, 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, Agboi, *et al*., 2025). This delay significantly impacts early intervention opportunities, which are crucial for slowing disease progression and improving quality of life for both patients and caregivers (Odiakaose *et al.*, 2024).

This fusion of Internet of Medical Things (IoMT) with machine learning schemes and artificial intelligence (AI) has emerged as a promising strategy to address the challenges of learning for these units. IoMTs enable for the non-invasive, continuous monitoring and notification of both PwDs physiological and behavioral parameters (Ojugo *et al.*, 2014; Ojugo, Ugboh, *et al*., 2013), while machine learning algorithms helps to 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

The 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. 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 its inherent benefits, there exists several challenges persist in current dementia detection systems. Akbarifar et al. (2024) noted issues with overfit in machine learning, while Rajayyan and Mustafa (2023) further identified complexities with dynamic feats in model implementation and interpretation as significant barriers (Akbarifar 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).

Yigit and Isik (2018) utilized various neural nets, and traditional learning schemes in diagnosing Alzheimer’s via clinical rating (Yigit and Isik, 2018). These showed promises with accuracy rates between 85-95% (Miah et al., 2021; Rajayyan and Mustafa, 2023). Dhakal et al. (2023) on the OASIS project, explored ML scheme to achieve high performance for dementia classification (Dhakal et al., 2023). However, these performance metrics are also hampered by both feature selection approach, dataset (class) imbalances, and limited nature of accompanying realtime app functionalities (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).

Previous works in dementia detection has continued to face limitations that includes: (1) delayed diagnosis due to PwDs visits and clinical assessments, (2) lack of continuous monitoring and notification, (3) constrained access to environmental, resource settings, and (4) non-fusion of traditional procedures, diagnostic tools and real-time sensor-based PwDs 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).

The study adopts the works of Onoma et al. (2025) to: (a) leverage the wearable unit for monitoring and alert of early dementia disease detection (Muslikh et al., 2023; Safriandono et al., 2024), (b) advance a deep learning scheme with explainable properties (Allenotor et al., 2015; Allenotor and Ojugo, 2017), (c) evaluate performance of the DL model for optima dementia detection (Binitie et al., 2024; Oyemade et al., 2016; Oyemade and Ojugo, 2020), and (d) perform an ablation performance on the proposed model via a comprehensive testing (Jiang et al., 2024; Ojugo et al., 2024; Ojugo, Yoro, et al., 2015; Shome et al., 2021).

3. MATERIALS AND METHODS

3.1. Hardware IoMT Deployed

Our framework leans on the IoMT unit to monitor and alert emergency with accessible smartphone for dementia patients. It advances: (a) an IoMT artifact with GPS to alert support-care, (b) an alert module (Omosor et al., 2025) with daily routines for memory task processing and location service of PwDs, and (c) dementia-friendly, mobile app with customizable features for support-care with efficient monitoring of PwDs as in Figure 1. The GREDDIoMT consists as thus: (a) ESP32 WROOM as its processing nexus (Eboka, Aghware, et al., 2025), (b) Ublox Neo6M GPS (Dwi Rangga Okta Zuhdiyanto and Yuli Asriningtias, 2025) to retrieve satellite coordinate with unique service-provider code, (c) SIM800l for network service (Omede et al., 2024), (d) Max30102 helps acquires the photoplethysmography data to interact with blood constituents, (e) SSD1306 OLED for interactive user display, (f) MT3608 boosts voltage for ESP32, (g) TP4056 protects the battery from overcharge or for over-discharge, (h) 5V battery to power device components, (i) push button for user commands, (j) rocker switch for ON/OFF function, (k) Vero board to hold all the components, (l) wires to ease electrical connections on board, and (m) headers to holds components connected while still allowing them to be detachable (Okofu et al., 2024; Onoma, Ako, Ojugo, Geteloma, et al., 2025). All connected components are powered via the 5V battery.

The proposed GREDDIoMT helps with early detection, continuous monitor, memory functioning, and support access for PwDs as in Figure 2 (Eboka and Ojugo, 2020). The GREDDIoMT is equipped to address physical, emotional, and cognitive tasks (Onoma, Ugbotu, Aghaunor, Agboi, et al., 2025) – its interface explores a dementia-friendly design with refinements to best meet PwDs needs. Its sensors as intra-auricular unit, monitors and acquire physiological feats such as blood pressure, oxygen saturation, and heart rate (David et al., 2023; Ojugo and Eboka, 2018c). Its anatomical and ergonomic features of PwDs in focus, makes for greater comfort with the wearable device. The device supports a non-invasive, continuous monitor and notification of care-support that aligns with United Nation sustainable development goals (Ojugo, Aghware, et al., 2015; Ojugo, Eboka, et al., 2015).

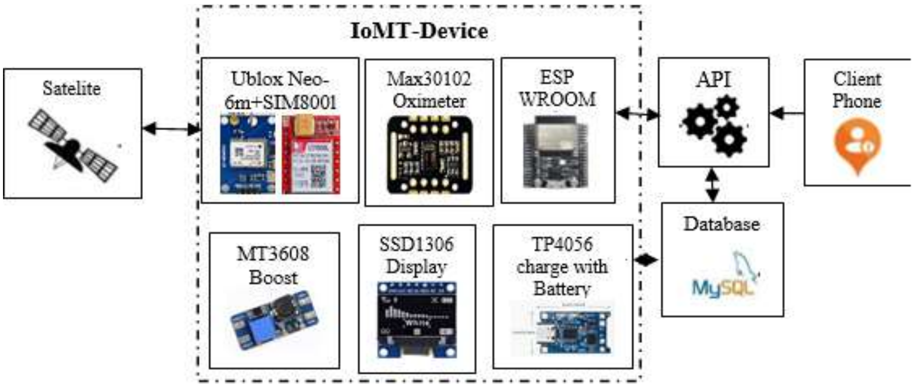

Figure 1. Schematic diagram

3.2. Experimental Proposed Scheme

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) mobile app to interface users (Ojugo, Eboka, et al., 2013; Ojugo, Oyemade, et al., 2015; Ojugo and Oyemade, 2020; Okorodudu et al., 2023).

Step-1 – Data Collection: We explore the Alzheimer disease dataset available on [web]: www.kaggle.com/datasets/rabieelkharoua/alzheimers-disease-dataset (Kharoua, 2024). The dataset consists of 2,149 patient-records distinguishable with features that are sub-grouped into demographic, patient lifestyle, family medical history, clinical observations, cognitive assess, patient observed symptoms, diagnosis data, and healthcare confidential data (Yoro et al., 2025; Yoro and Ojugo, 2019a, 2019b). The dataset records are distributed into groups as 1,061-cases as non-PwD (non-Patients with Dementia, or non-demented), and 1,088-cases as PwDs (demented). The original dataset plot as in Figure 3 (Aghware, Ojugo, et al., 2024).

Step 2 – Pre-processing: The study utilized a comprehensive dataset from Kaggle with 1,842 initial patient records and 12 attributes. After pre-processing, final dataset is seen as in Figure 3 (Ojugo, Akazue, Ejeh, Ashioba, et al., 2023; Ojugo, Ejeh, Akazue, Ashioba, Odiakaose, 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) (Atuduhor et al., 2024; Ejeh et al., 2024; Ifioko et al., 2024).

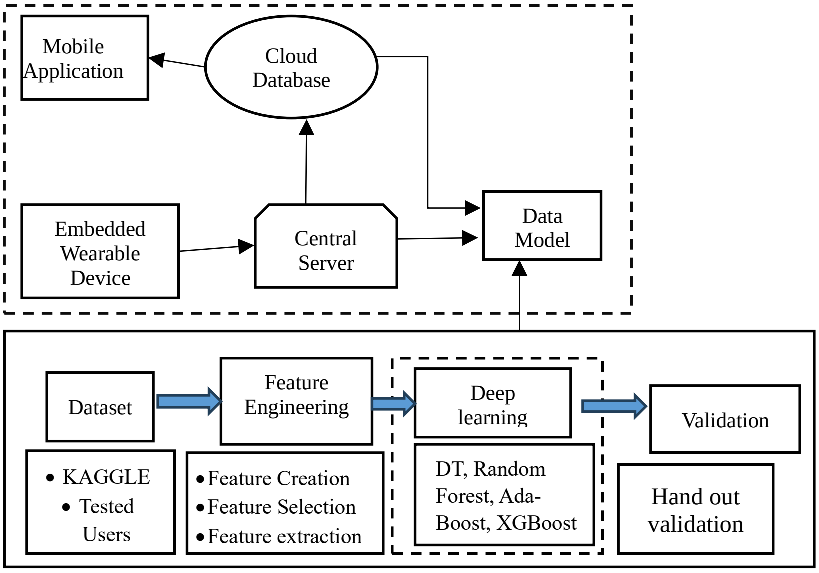

Figure 2. Proposed System Architecture

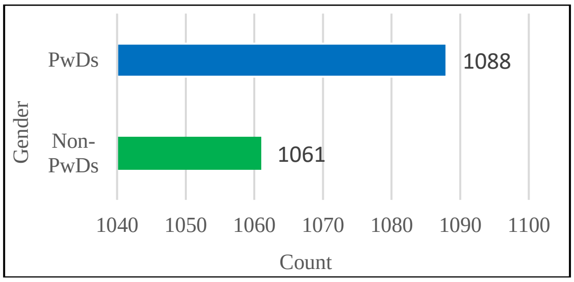

Figure 3. Original Dataset plot

Here: *(a) handling missing values:* the initial assessment reveals 829 missing values across multiple columns. A total of 332 rows (18% of the dataset) were removed due to incomplete data to avoid potential input bias (Setiadi, Muslikh, et al., 2024; Zuama et al., 2025), and (b) *encoding data:* Systematic encoding was applied to categorical variables (Ojugo, Akazue, Ejeh, Odiakaose, et al., 2023; Ojugo, Odiakaose, Emordi, Ako, Adigwe, et al., 2023; Ojugo, Odiakaose, Emordi, Ejeh, Adigwe, et al., 2023):

Step 3 – Chi-Square Feature Selection: We select strictly, only relevant predictors and expunge all docile feats and reduce dataset dimensionality, to aid fastened model construction (Ying, 2019). The chi-square (x^2) feature selection approach is performed as thus (Okpor, Aghware, Akazue, Eboka, et al., 2024; Okpor, Aghware, Akazue, Ojugo, et al., 2024): (a) it assumes all features have same weight/influence on accuracy, (b) identifies the nearest sample from the same class as the nearest hit, and the nearest sample from a varying class as the nearest miss, and (c) uses feature value of nearest neighbour to update its weight(s). It assesses the correlation of all predictors for ground-truth. With a computed threshold of 8.321, the chi-square algorithm ranked features from the original dataset with 16-features to eventually select only 12-predictor features as in Table 1.

Step 4 – Data Split and Normalization: First, dataset is split into train (75% or 1,612-labels), and test (25%, or 537-labels). Our choice of splitting depends on the tradeoff between the need for a more robust model favoring the 75%:25% train-and-test ratio mode, or it can be poised towards the need for improved performance as guided by model complexity, larger dataset size and other feats so as to favour the 80%:20% mode (Malasowe et al., 2023; Malasowe, Aghware, et al., 2024; Malasowe, Edim, et al., 2024; Malasowe, Ojie, et al., 2024; Malasowe, Okpako, et al., 2024). Here, our choice of the 75%:25% ratio leans on the small nature of the explored dataset with 2,149 records so that we can ultimately have a more robust evaluation on diverse unseen held-out (test) dataset, address the issue of flexibility in feature selection with a more adaptive assessment with more accurate, less bias generalization of the model (Otorokpo et al., 2024; Panagoulias et al., 2022).

Table 1. The Chi-Square Threshold computation for the Alzheimer Disease Dataset

Parameters	Description	Data Type	Selected
subjectID	Whether a URL shortening service like bit.ly is used (1=Yes, -1=No)	integer	Yes
mriID	Identification number for the MRI-scans done for the patient	integer	No
group	Group of patient (0=undemented, 1=demented)	binary	No
clinicalVisit	Total number of clinical visits for the patient	integer	No
mrDelay	MR delays experienced	integer	Yes
sex	Sex of patient (0=Male, 1=Female)	float	Yes
handedness	Patient handedness (0: Right, 1: Left)	binary	Yes
age	Range of age from 60-to-90years of old	float	Yes
educationStatus	Educational status (0: None, 1: Primary, 2: Secondary, 3-Bachelors, 4-Higher)	float	Yes
SES	Socio-economic status of the patient	float	Yes
MMSE	Mini-mental state exam score range (0-to-30) with lower score as impairment	float	Yes
CDR	Clinical dementia ratings	binary	Yes
eTIV	Estimated total intracranial volume	binary	Yes
nWBV	Normalize whole brain volume	binary	Yes
ASF	Atlas scaling factor	binary	Yes
alzheimirsClass	Target class as Alzheimer's (0: No Alzheimer's; 1: Alzheimer's)	binary	Yes

Normalization helps resample the dataset, by interpolating its nearest neighbour to create synthetic data-points that eventually repopulates the pool, or by removing data-points from the training subset to create a balanced dataset. Thus, we performed data normalization via z-score normalization as in Equation 1. Figure 3 shows the normalized data plot.

$$z = \frac{x - \mu}{\sigma} \quad (1)$$

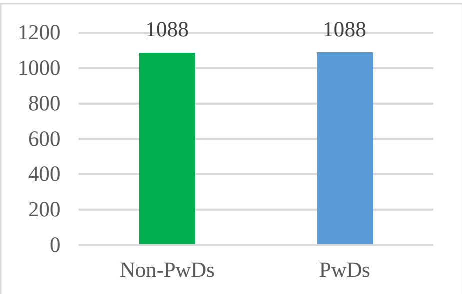

Figure 3. Normalized Dataset

Step-5 – Stacked Ensemble: The utilization of ML schemes in deployment of medical apps for early detection of disease (with dementia as case in point) have sought to explore a variety of techniques poised at improved generalization and performance (Parikh et al., 2019). Previous works for risk behaviour disease detection have explored a variety of dataset (Ojugo and Yoro, 2013) – and also showcased a variety of performance as captured. While, identification of dementia is quite challenging, its performance accuracy have ranged between 0.69-to-0.89 (El Massari et al., 2022). To achieve a perfect score of 1.00 implies model must circumvent critical factors that hinder performance such as: (a) imbalanced dataset due to homogeneity complexity, (b) model must be sensitive enough to identify hidden patterns vis-à-vis become adaptive to capture predictor bias and variations, and (c) model experiencing data leakage(s) (Eboka, Odiakaose, et al., 2025). To study these – we evaluate for Accuracy, Precision, Recall, Specificity, and F1 performance metric via a tree-stacked ensemble:

a. *Decision Tree* is a single-classifier that explores intricate sampling, tailored to mitigate the decision-making issues (Ako et al., 2024; Gaye and Wulamu, 2019). To predict a target class, it starts from its root node to compare the values of the root with the records attribute. With this compared, it branches off to the next node as: (a) begins at a tree with root node S that consists of a complete dataset, (b) finds the best attribute in the dataset via attribute selection measure, (c) divide S into train/test sub-datasets that contains possible values for the best attributes, (d) generate decision tree node, which contains best attributes, and (e) recursively make new decision trees using the subset of the dataset created (Umarani et al., 2021). Then continue this process until the criterion for optimal solution is reached so that the tree can no longer classify the nodes. Such is reached by leaf node via error pruning and/or cost-complex pruning. Its demerits are: (i) it is complex due to its many layers, (ii) may result in overfit, resolved via a Random Forest ensemble, and (c) computational complexity increases for large datasets (Jáñez-Martino et al., 2020). Furthermore, its merits are numerous and the feats used in our DT construction are as in Table 2.

Table 2. Decision Tree design configuration

Parameters	Value	Description
info_gain	120	Number of trees constructed
learning_rate	0.25	Step size learning to update
min_sample_split	10	Minimal number of samples
min_sample_leaf	auto	Number of features considered
eval_set	(x,val, y_val)	Dataset used for evaluation
minWeightLeaf	0.1	DT structure weight assigned
max_depth	5	Max depth of each tree
random_state	25	The seeds for reproduction

b. Random Forest ensemble utilizes the bagging mode to grow successive trees independently. It uses bootstrap aggregation to construct each tree and to sample its train data using a majority vote at its prediction (Satpathi et al., 2023). The RF extends this randomness via an extra layer that changes how it constructs its trees. With a tree, each node is split using the binary-tree predictor – RF splits its nodes and randomly selects the best predictor node from its subset of learner(s) (Bahl et al., 2019). Its recursive structure helps it to capture interactions between various predictors (Udeze et al., 2022). Its drawback is in their flexibility (Abakarim et al., 2018; Zareapoor and Shamsolmoali, 2015) with data diversity and complexity (Xuan et al., 2018) as its outcome can yield lesser performance (Rtayli and Enneya, 2020) for ground truth. To curb this, we adopt hyper-parameter tuning to greatly reduce model overfit, address imbalanced datasets, and enhance accuracy in its quest for ground truth (Saponara et al., 2021) as in Table 3.

Table 3. Random Forest design configuration

Parameters	Value	Description
n_estimators	150	Number of trees constructed
learning_rate	0.25	Step size learning for update
max_depth	5	Max depth of each tree
max_features	5	Max features to construct the RF
min_sample_leaf	auto	Number of feats considered
min_sample_split	10	Minimal samples needed
minWeightLeaf	0.1	DT structure weight assigned
random_state	25	The seeds for reproduction
eval_metric	error, logloss	Performance evaluation metrics
eval_set	x,val, y_val	Train data for evaluation
verbose	True	Determines if ensemble evaluation metric is printed at training
bootstrap	True	Use bootstrap aggregation use

c. Adaptive Boosting combines multiple weak classifiers to build a strong one. Weak learners are called decision stumps as they are DTs with a single split. The ensemble places more weight on hard-to-classify instances and less weight on data operating well. Stumps are produced for every feature iteratively and stored in a list until a lower error is received. Weight(s) assigned to each example determines its significance in the training dataset. Weights are updated with each iteration to yield stumps' performance. Ensemble sequentially trains its predictors so that each predictor tries to correct its predecessor (Otorokpo et al., 2024). Thus, they are more robust against overfitting and yield a more stable and improved performance as in Table 4

Table 4. AdaBoost tree design configuration

Parameters	Value	Description
n_estimators	140	Number of trees constructed
learning_rate	0.25	Learning size to update ensemble
max_depth	5	Max depth of each tree
random_state	25	The seeds for reproduction
eval_metric	"error', 'logloss'	Evaluation metrics for ensemble performance
eval_set	(x,val, y_val)	Dataset used for evaluating ensemble performance at training
verbose	True	Prints ensemble evaluation metric

d. XGBoost is a tree-based leaner that scales the gradient boosting (Paliwal et al., 2022) to classify data points. It yields a stronger classifier by aggregating its weaker (base) learner tree via majority voting schemes over a series of iterations on data points to yield an optimal fit solution. It expands its goal function by minimizing its loss function as Equation 2 to yield an improved model to manage tree complexity more effectively (Ojugo, Ejeh, Odiakaose, Eboka, and Emordi, 2023). For optimality – the XGBoost leverages the predictive power of weak base learners, to yield a better decision tree with each iteration and account for the weak performance that contributes to its knowledge about the task (Al-Qudah et al., 2020). Thus, with each tree trained on the candidate data, it expands the objective function via a regularization term $\Omega(f_t)$ and loss function $l(Y_i^t, \hat{Y}_i^t)$ to ensures an appropriate fit of the ensemble to yield improved generalization. It ensures that both training dataset fits as re-calibrated solution to remain within its solution's set boundaries, and tunes its loss function for higher accuracy (Ojugo and Eboka, 2014, 2019, 2020) as in Table 5.

$$L^t = \sum_{i=1}^{n} l\left(Y_i^t, \hat{Y}_i^{t-1} + f_k(x_i)\right) + \Omega(f_t) \qquad (2)$$

Table 5. XGBoost tree design configuration

Parameters	Value	Description
n_estimators	250	Number of trees constructed
learning_rate	0.25	Step size learning for update
max_depth	5	Max depth of each tree
random_state	25	Minimal samples needed
eval_metric	["error', 'logloss']	The seeds for reproduction
eval_set	x,val, y_val	Performance evaluation metrics

Step 6 – Training: Ensemble learns from scratch using the training dataset. With tree-based models, its trees are iteratively constructed to allow for bootstrap training of each tree to yield the required enhancement using prediction probabilities on the scaled and balanced dataset. This further enhances the trees' collective knowledge and in turn, helps the ensemble to easily and quickly identify all inherent intricate patterns present in each data set since training blends both the newly created synthetic and original samples in its dataset to guarantee all base-learner comprehensive learning. This improves model flexibility and adaptability for reuse in other domain tasks.

Hyperparameter tuning controls how much of the tree's complexity and its nodal weights need to be adjusted in place of gradient loss. The lower the value, the slower we travel on a downward slope – which also ensures how quickly a tree abandons old beliefs for new ones during training. So that as the tree learns – it identifies crucial from unimportant feats. Our meta-learner yields a higher learning rate to imply that our tree ensemble changes quickly as it learns newer features. This flexibility grants it adaptability ease. The ensemble uses regularization terms to ensure it quickly changes as values remain within its lower and upper bounds. It does this to ensure it adequately adjusts its learning and avoids poor generalization. Then we carefully tuned these parameters: max_depth, n_estimator, learning_rate, and booster to ensure optimal performance (Karimi et al., 2013).

Cross-validation is applied with 10 percent of the training dataset to estimate how well-learned skills by the ensemble perform on unseen data. It also evaluates the performance of the ensemble's accuracy on how well it has learned the feats of interest via resampled and balanced dataset technique. We use the stratified k-fold, to rearrange the data so that each fold is a good representation of the dataset (Camargo and Young, 2019; Rukshan Pramoditha, 2020) and ensure our proposed stacking ensemble is devoid of overfit with improved generalization. We tested our resultant ensemble as an embedded system deployed via Flask API and Streamlit to help port the application onto various platforms as an embedded system.

4. RESULT FINDINGS and DISCUSSION

4.1. Performance Evaluation

Table 7 shows performance evaluation metrics for all base-learners (Decision Tree, Random Forest, and AdaBoost) respectively with the meta-learner (i.e. XGBoost). Note that the purpose of the tree-based ensemble learning is to reduce the outcome relations conflict caused therein due to the diversity and computational complexities of the dataset used. And in turn, ensure the ensemble is devoid of overfit considering the 3-base-learners. However, since the stacking ensemble can combine the performance of all 3-predictor classifiers – we decided to ensure simple and non-complex constructs for the tree-based, base-learners used.

Table 6. Classifier performance metrics

Base-Learners	***Accuracy***	***Precision***	**Recall**	**F1**
DT	0.9815	0.9805	0.9745	0.9805
AdaBoost	0,9968	0.9318	0.9848	0.9881
Random Forest	0.9981	0.9541	0.9881	0.9925
Meta-Learner				
XGBoost	1.0000	1.0000	0.9999	1.0000

Table 7 shows that for our base-tree-classifiers – both the Adaboost and Decision Tree underperformed in comparison to the Random Forest. And this agrees with (Aghware, Ojugo, et al., 2024). However, all 3-base leaners (i.e. DT, RF, and Adaboost) yield training accuracy of 0.9815, 0.9968, 0.9981 respectively. With Recall score(s) of 0.9745, 0.9848, and 0.9881 respectively; And Precision of 0.9805, 0.9318, and 0.9541 respectively; And, F1 of 0.9805, 0.9881, and 0.9925 respectively. Conversely, the meta-learner yields perfect scores for its Accuracy, Recall, Precision, and F1 respectively. Thus, our ensemble classifies traffic anomaly in spatiotemporal data accurately as detected (Aghware, Adigwe, et al., 2024) dataset and has proven to efficiently reduce bias and variance as in the confusion matrix of Figure 4 – yielding a more stable and robust heuristic for new data and/or hidden underlying parameters within training dataset.

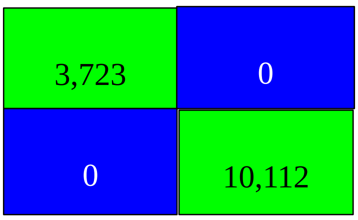

Figure 4. Confusion Matrix

The study supports that SMOTE-Tomek data balancing outperformed both SMOTEEN and SMOTE modes, as it had a greater influence in the quest for ground truth. It greatly impacted the overall performance by identifying features of importance that influence model prediction. It also had enhanced efficiency for differentiating between true-positive and true-negative, and between false-positive and false-negative scores. Figure 5 shows the confusion matrix performance.

4.2. Ablation Report

AUC of 0.997 shows model's capability to differentiate the negative and positive classes. Model accurately identified all 537-records of the test sub dataset. With only one-misclassified and false positives – Specificity of 1.000 implies that no dementia disease case was misclassified. This is quite crucial and critical to avoid misclassification (model sensitivity) in detecting dementia. Thus, proposed model enhances dementia detection performance and generalization on both the training and the held-out test subset(s).

Whilst some domain task datasets have proven much easier to be detected/recognized and classified; Others, have also conversely proven to be more painstaking. Some domain task(s) such as medical and image records – require its chosen ensemble design metric to be strongly impacted by the consequence of diagnostic errors within the captured dataset. Thus, specificity and sensitivity are critical features to be evaluated since they are directly related to the patient clinical outcomes.

5. CONCLUSION

This study successfully developed and validated an innovative dementia detection system that integrates wearable IoT with deep learning algorithms. XGBoost demonstrated exceptional performance with 0.99 accuracy, 1.00 sensitivity, and 0.98 AUC-ROC on balanced data. The system addresses critical issues in dementia care with 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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