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Equipping the GREDDIoMT Device with Early Behavioural Risk Detection of Dementia via a Pre-Activated SENet fused BiGRU

Eferhire Ugbotu[1], Paul Onoma[2], Rita Ako[2], Anne Odoh[3], Duke Oghorodi[4], Ejaita Okpako[5], Tabitha Aghaunor[6], Frances Emordi[7], Emeke Ugboh[8], Joy Agboi[9], Chris Odiakaose[7], Arnold Ojugo[2], Victor Geteloma[2], Reuben Abere[2], Rebecca Idama[4], Andrew Eboka[8], Peace Ezzeh[8], Chris Onochie[8], Amanda Oweimieotu[10] & Bright Ojo[11]

[1]Faculty of Science, Engineering & Environment, University of Salford, Manchester M54WT, United Kingdom
[2]College of Computing, Federal University of Petroleum Resources Effurun, Delta State 330102, Nigeria
[3]School of Media and Communications, Pan-Atlantic University Lekki, Lagos State 332109, Nigeria
[4]Faculty of Computing, Southern Delta University Ozoro, Delta State 334111, Nigeria
[5]Faculty of Computing, University of Delta Agbor, Delta State 334111, Nigeria
[6]School of Data Intelligence and Technology, Robert Morris University, Pittsburg, PA15108, USA
[7]Faculty of Computing, Dennis Osadebay University Asaba, Delta State 320212, Nigeria
[8]School of Science Education, Federal College of Education (Technical) Asaba, Delta State 320212, Nigeria;
[9]Faculty of Computing, Delta State University Abraka, Delta State 330105, Nigeria
[10] Faculty of Science, Edwin Clark University Kiagbodo, Delta State, Nigeria
[11]University of Arkansas, Fayetteville, AR70521, United States.

E-mail: eferhire.ugbotu@gmail.com, kenbridge14@gmail.com, ako.rita@fupre.edu.ng, ojugo.arnold@fupre.edu.ng; geteloma.victor@fupre.edu.ng; aodoh@pau.edu.ng, oghorodid@dsust.edu.ng; ejaita.okpako@unidel.edu.ng, osegalaxy@gmail.com, idamaro@dsust.edu.ng, tabitha.aghaunor@gmail.com, emordi.frances@dou.edu.ng, ugboh1972@gmail.com, ebokaandrew@gmail.com, peace.ezzeh@fcetasaba.edu.ng, xtoline2@gmail.com, abere.reuben@fupre.edu.ng, agboijoy0@gmail.com, oweimieotuamanda@edwinclarkuniversity.edu.ng, brightojo@gmail.com

ABSTRACT

Gerontechnology has marked a transformative shift in healthcare via its fusion of embedded sensor units with Interne of Medical Things (IoMT), which embodies early disease detection and borders on its early warning for prevention. The IoMT equipped with sensors and algorithms, continuously monitors patients' physiological data – provisioning real-time monitoring for early identification of potential health anomalies, and wades in with a personalized healthcare approach. With vast amount of data acquired, the gerontechs can be successfully trained with machine learning (ML) schemes, to gleans off insights via data analytics, and proffer medi-czars with proactive interventions for potential health risks prior its clinical manifestations. We posit a hybrid fusion of the dual channel squeeze-and-excite attention mechanism with bi-directional gated recurrent unit, for identifying the dementia disease. The model output is utilized as input for the GREDDIoMT (wearable) device that senses patient vitals, monitors and alerts on patients with dementia (PwDs), and yield resulting detection of the disease. With appropriate features selected for estimation, and imbalanced explored dataset resolved via SMOTEENN – our study shows that our hybrid (SENet+BiGRU) ensemble yields F1 0.995, Accuracy 0.997, Recall 0.998, Precision 1.000, AUC 0.997, and Specificity 1.000 – to accurately classify all 537-cases of test-dataset. In addition, our proposed hybrid model outperformed the various benchmarks.

Keywords: Dementia, Healthcare, GREDDIoMT, SENet-BiGRU, Data Balancing, Disease detection,

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I. INTRODUCTION

Dementia is chronic, neurodegenerative disease and a major health menace for the elderly (Ejeh et al., 2024; Rajayyan & Mustafa, 2023). Characterized by long-term decrease in the cognitive processing (AlSaeed & Omar, 2022; Ifioko et al., 2024), its early detection has become crucial (Jeon et al., 2021) as the disease features debilitating cognitive impairment with increased mortality risks and a declined quality of life in patients (Twait et al., 2023; Yoro & Ojugo, 2019b). The remarkable complexity of the brain, allows for a variety of vital functioning ranging from problem-solving to critical thinking with decision-making, and memory experience storage (Throm et al., 2025). With over 50 million patients globally, and an expected 2.1 billion patients by the year 2050 – the provision of medicare for patients is estimated to adequately also cater for the world's 18th largest economy (Dhakal et al., 2023; Ojugo, Yoro, et al., 2015). Thus, dementia has become of great medical concern as the elderly population continues to grow. And the quest for its early detection has continued to advance the utilization of cost-effective, embedded units with speech-based, digital biomarkers (Yasin et al., 2021). The quest for protocol standardization with care support units – have continued to bedevil this mode as data corruption and tamper (if and when mishandled) can ruin feedbacks, yielding false-negatives (Panagoulias et al., 2022). In addition, the advent of the large language models have been proposed as learning strategies that can be generalized for the disease's prediction – targeted at the continued provision for both improved care support, and improved quality of lives for patients with dementia (PwD) (Okpor, Aghware, Akazue, Ojugo, et al., 2024; Schulz et al., 2019; Yoro & Ojugo, 2019a).

The deployment of wearable devices represents both a bold step towards inclusivity of PwDs, and the consequent reachability of medicare every time to all (Obasuyi et al., 2024; Onoma, Ako, Anazia, Oghorodi, et al., 2025). The Gerontechnology (or wearables) advances the utilization of the Internet of Medical Things (IoMT) (Og & Ying, 2021) to yield the convergence of: (a) a wearable technology (Salehi et al., 2022), and (b) adoption of wireless sensor networks (Akazue, Edje, et al., 2024). This integration cum fusion advances a body-worn, smart device or unit that is equipped with programmable microcontrollers, sensor observation units, and software that ease data acquisition cum exchange (Brizimor et al., 2024; Ojugo & Eboka, 2019).

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 & Ojugo, 2021) of patients' physiological metrics. It allows the uninterrupted data acquisition (Kakhi et al., 2022) – and aids improved analysis therein as well as unveils a patient's comprehensive health status to uncover 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 helps to prevent a disease's metastasis (Ako et al., 2025), improves patient's condition via initiation of a treatment plan via coordinated prognosis (Pratama et al., 2025), and enhance the quality of the patient's life (Oladele et al., 2024; Roshan, 2022). Gerontechnology assist medi-experts with non-invasive treatments of lessened-complications (Manickam et al., 2022), less side effects, substantial cost savings (Ojugo & Eboka, 2020), and as an expansive tools to help manage the early-stage conditions for a patient's healthcare.

While the continuous monitor by Gerontechs proffer data acquisition approaches to yield a patient's baseline health acquired metrics (Bolívar, 2013) – early warning with such predictors (as symptoms) can improve a first-responders formulation of a tailored treatment plan to stop as close as possible, to the source cum localized region, the disease prior its metastasis (Odiakaose et al., 2025).

The utilization of machine learning (ML) can be applied as data analytics to help the IoMT unit to adequately recognize anomaly patterns that indicates emerging health issues. A sudden but consistent increase in resting heart rate (RHR) may indicate early cardiovascular problem, or an impending disorder. MLs are veritable tools, trained to detect anomalous patterns. MLs can be grouped into: machine learning (ML) (Onoma, Agboi, Geteloma, et al., 2025), deep learning (DL) (Ojugo, Akazue, Ejeh, Ashioba, Odiakaose, et al., 2023; Oppenheimer et al., 2024), and ensemble learning (EL) (Binitie et al., 2024). ML's flexibility and robustness help it to learn intrinsic patterns and decode predictors that fastens model design for eased outlier identification. Its pitfalls are imbalanced dataset and the feature selection mode used.

With DLs to overcome the issues inherent in MLs, DLs utilize recurrent neural networks to capture chaotic, high-dimensioned data (Malasowe, Aghware, et al., 2024; Setiadi, Sutojo, et al., 2025). Its poor generalization is due to the vanishing gradient problem, which also restricts its usage. However, its variant overcomes this via gates to control its input, and eases its adaptability to learned changes as long-term dependency (Schwertner et al., 2022; Tyler Morris et al., 2023). Its inability to handle larger dataset and longer training time required implies the quest for better alternative (Borchert et al., 2023). ELs fuses ML and DL into a stronger classifier with enhanced performance (Nayak et al., 2025; Setiadi, Susanto, et al., 2024). To resolve structural conflicts and data-encoding conflicts – it leans on the merits of both underlying ML and DL to avoid model overfit (Odiakaose et al., 2024). They leverage on the predictive capability of their base (weak) learners (Malasowe, Edim, et al., 2024; Ojugo, Ejeh, Akazue, Ashioba, Odiakaose, et al., 2023) to enhance its generalization performance, which in turn, benefits from their comprehensive knowledge (Islam et al., 2021; Ugbotu, Aghaunor, et al., 2025).

Resolving data imbalance via oversampling has become imperative in ML, as it accounts for the minor class as crucial (Aghaunor et al., 2025). It is opposed to under-samplers that often reduces or ignore as meaningless, the minor class in a dataset. Thus, we use the synthetic minority oversample technique (SMOTE) (Omoruwou et al., 2024), or its variants SMOTE-Tomek and SMOTEEN (Okpor et al., 2025). Our study contributes thus: Section 1 introduces the subject with gaps that motivate the study, (b) Section 2 explores the proposed method – and leans on data collection, pre-processing, dataset split-balance-normalize via SMOTEENN, the hybrid model construction, training and validation, and (c) Section 3 – discusses the experimental results obtained as evidence in a broader context for the hybrid model on the dementia disease dataset.

2. PRELIMINARIES

2.1. Gerontechnology and Machine Learning: A Review

Our framework leans on the condition that there are IoMT solutions to monitor, set reminders, and alert emergency contacts with easily accessible smartphone platforms for dementia patients. This study seeks to provide (Geteloma et al., 2024a): (a) develop an IoMT-based artifact fused with GPS module, specifically tailored to facilitate family and care-support staff monitoring and alert of dementia patients, (b) integration of a reminder module since patients memory often relapse with respect to locations and daily activities that implies the continuous attention and supervision by family and care-support staff, and (c) integration of a dementia-friendly and easy-to-use mobile application cum platform with customizable features such as activity logs, location alerts, etc – provisioning family and care-support with efficient monitoring and alert of patients as in Figure 1, showing the circuit diagram of the proposed device.

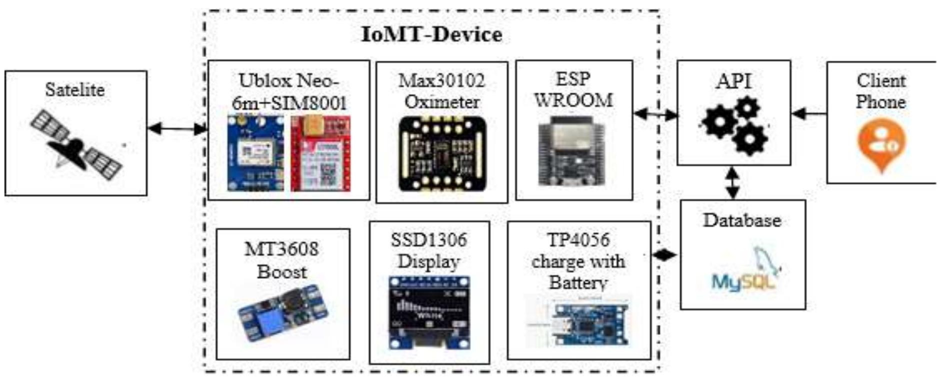

Figure 1. Schematic Diagram of the IoMT Architecture

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 of: (a) ESP32 WROOM as its processing nexus (Eboka, Aghware, et al., 2025), (b) Ublox Neo6M V2 GPS (Dwi Rangga Okta Zuhdiyanto & Yuli Asriningtias, 2025) to retrieve coordinates with uniquely-defined (satellite) service provider code, (c) SIM800l for network service (Omede et al., 2024), (d) Max30102 acquires photoplethysmography (wavelength) data to interact with blood constituents, (e) SSD1306 OLED for interactive display/feedback to users, (f) MT3608 boosts voltage for the ESP32, (g) TP4056 protects the battery from (over)discharge, (h) 5V battery to power device, (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, Akazue, et al., 2024; Onoma, Ako, Ojugo, Geteloma, et al., 2025). Each connected component is powered via a battery.

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The GREDDIoMT helps with early detection, continuous monitor, memory functioning, and support access for PwDs as in Figure 2. Equipped to address requirements for 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, blood oxygen saturation, and heart rate (David et al., 2023; Ojugo & Eboka, 2018c). With the anatomical and ergonomic features of dementia patients in focus, these informed the device's form to ensure a comfortable, continuous unit. The device supports a non-invasive, continuous monitoring and alert of care providers/family that aligns with the United Nations Sustainable Development Goals 3 (Good Health and Well-Being), SDG 9 (Industry, Innovation and Infrastructure), and SDG 10 (Reduced Inequalities) (Ojugo & Yoro, 2021).

3. MATERIAL AND METHOD

The proposed transfer learning approach is seen as in Figure 2.

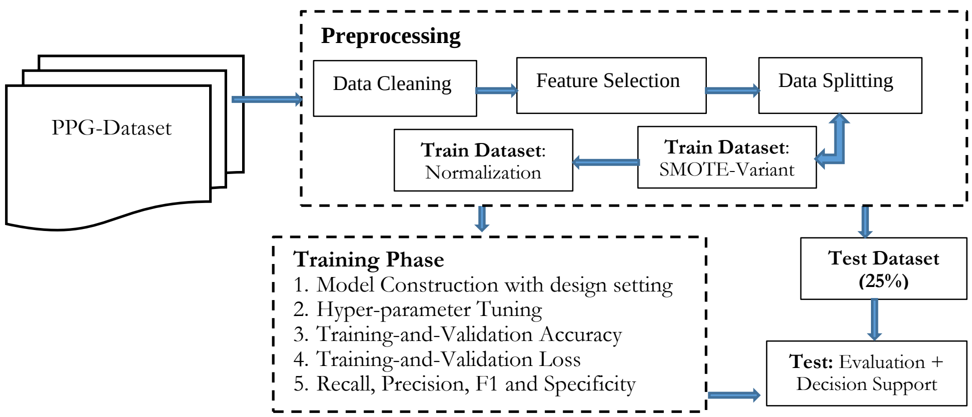

Figure 2. Proposed Stacking Ensemble with Boosted Learner

Step-1 – Data Collection: We explore the Alzheimer's disease dataset (Kharoua, 2024) available on [web]: https://www.kaggle.com/datasets/rabieelkharoua/alzheimers-disease-dataset, which consist of 2,149 patient-records distinguishable with features that are sub-grouped into demographic, patient lifestyle, family medical history, clinical observations, cognitive assessment, patient observed symptoms, diagnosis data, and expert czars confidential data. The dataset records are distributed into groups as 1,061-cases as non-PwDs (non-Patients with Dementia, or non-demented), and 1,088-cases as PwDs (demented). The original dataset plot as in Figure 3.

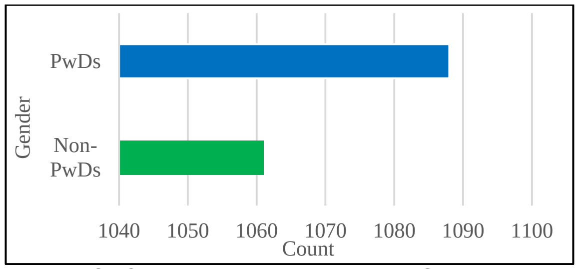

Figure 3. Original Dataset Plot by Gender

Step-2 – Pre-processing cleans up the dataset by expunging redundancies to yield integrity, and removes missing values to yield quality. The dataset had no missing values cum records. Thus, it was then encoded using the one-hot encoding technique mode that transforms categorical data into its equivalent binary forms (Ojugo & Eboka, 2018c; Ojugo & Otakore, 2018).

Step 3 – Relief Rank 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 relief rank feature selection approach is performed as thus: (a) it assumes that all features have same weight and 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) (Geteloma et al., 2024b). It assesses the correlation of all predictors for ground-truth as in Eq. 1 (Okpor, Aghware, Akazue, Ojugo, et al., 2024). With a threshold of 8.321 as computed, algorithm 1 ranked features to choose a total of 20 predictors as in Table 1, from the original UCI dataset with the initial 30 features.

$$Y = 100 * \sum \left|(x_1^2 - x_2^2)^2 + (1 - x_1^2)^2\right| \quad (1)$$

Table 1. Alzheimer's' Disease and Healthy Aging Dataset

Parameters	Description	Data Type	Select
patientID	Patient identity number	integer	Yes
age	Range of age from 60-to-90years of old	integer	Yes
gender	Sex of patient (0=Male, 1=Female)	binary	No
ethnicity	Ethnicity (0: Caucasian, 1: African, 2-Asian, 3-Others)	integer	No
educationStatus	Patient's educational status (0: None, 1: Primary, 2: Secondary, 3-Bachelors, 4-Higher)	integer	Yes
bmi	Body mass index of patient ranging from 15-to-40	float	Yes
smokingStatus	Patient's smoking status (0: No, 1: Yes)	binary	Yes
alcoholConsumed	Alcohol consumption in unit ranging from 0-to-20	float	No
physicalActivity	Weekly physical activities in hours (1-to-10)	float	Yes
dietQuality	Patient's diet quality ranging from 0-to-10	float	Yes
sleepTime	Patient's sleep time and quality ranging from 4-to-10	float	No
familyHistory	Patient's family history of Alzheimer's (0: No, 1: Yes)	binary	Yes
cardioDisease	The occurrence of cardiovascular disease (0: No, 1: Yes)	binary	No

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Parameters	Description	Data Type	Select
diabetes	Presence of diabetes (0: No, 1: Yes)	binary	Yes
depression	Presence of depression (0: No, 1: Yes)	binary	Yes
headInjury	History of head injury (0: No, 1: Yes)	binary	Yes
hypertensionStatus	Presence of hypertension (0: No, 1: Yes)	binary	Yes
systolicBP	Systolic blood pressure range (90-to-180mmHg)	integer	No
diastolicBP	Diastolic blood pressure range (60-to-120mmHg)	integer	No
cholestorolTotal	Total cholesterol levels range (150-to-300mg/dL)	float	No
cholestorolLDL	Level of low-density lipoprotein cholesterol (50–200mg/dL)	float	Yes
cholestorolHDL	Level of high-density lipoprotein cholesterol (20–100mg/dL)	float	Yes
cholestorolTriglyceride	Level of triglycerides range (50-to-400mg/dL)	float	No
MMSE	Mini-mental state exam score range (0-to-30) with lower score as impairment	float	No
Parameters	**Description**	**Data Type**	**Select**
functionalAssessment	Memory function assess ranging from 0-to-10 with lower scores as greater impairment	float	Yes
memoryComplaints	Presence of memory complaints (0: No, 1: Yes)	binary	Yes
behaviouralProblems	Presence of behavioural problems (0: No, 1: Yes)	binary	Yes
adl	Activity of daily living score range (0-to-10) with lower score as greater impairment	float	Yes
confusion	Presence of confusion (0: No, 1: Yes)	binary	Yes
disorientation	Presence of disorientation (0: No, 1: Yes)	binary	Yes
personalityChanges	Presence of personality changes (0: No, 1: Yes)	binary	
difficultyTaskCompletion	Presence of difficulty of completing memory challenge-response tasks (0: No, 1: Yes)	binary	
forgetfulness	Presence of forgetfulness (0: No, 1: Yes)	binary	
doctorInCharge	Doctor-In-Charge confidential report	XXXConfid	Yes
diagnosis	Presence of Alzheimer's (0: No, 1: Yes)	binary	Yes
alzheimirsClass	Target class as Alzheimer's (0: No Alzheimer's; 1: Alzheimer's)	binary	Yes

Step 4 – Data Split/Balance: First, dataset is split into train (75% or 1,612-labels), and test (25%, or 537-labels). The action of balancing seeks to 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 pool (subset) to create a balanced dataset. Using SMOTE-ENN (Ojugo et al., 2014; Ojugo & Eboka, 2018a), we fused the SMOTE-oversampler with ENN-undersampler as in algorithm 2 with Figure 4 showing SMOTEENN plot.

Algorithm 2: SMOTE-ENN Data balancing approach
1. load dataset with trainTestSplit → stratifyShuffleSplit trainset (75%) and testSet (25%)
2. for trainset, use 5-fold split with randomState = 42
3. choose random point from minorClass
4. for each selectedData → compute: relativeDistance && kNearestNeighbour
5. choose randomValue [0,1] && compute randomValue * relativeDistance
6. update minorClassNew && repeat till setThreshold is reached for minorClassNew
7. select randomMinorClass: compute kNearestNeighbor(randomized_data)
8. with selected minorClassNew → evaluate newPool with editedNearestNeighbour function
9. end editedNearestNeighbour

The choice of data 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 favor the 80%:20% mode. 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 and less bias generalization of the model. In addition – with the train-subset still unbalanced, we performed data normalization using the z-score normalization as in Equation 2. Figure 5 shows the normalized data plot.

$$z = \frac{x - \mu}{\sigma} \qquad (2)$$

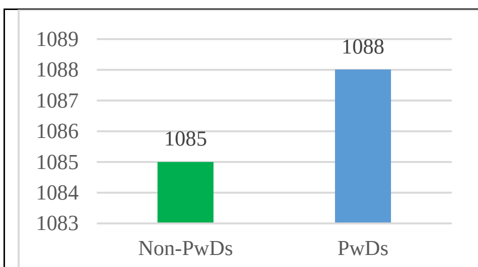

Figure 4. SMOTEENN Data Balancing

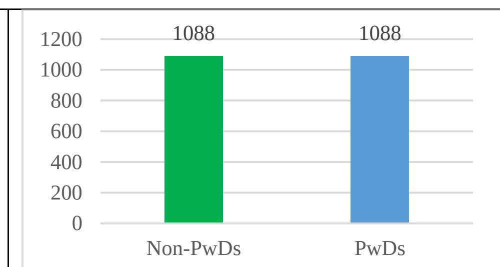

Figure 5. Normalized plot

Step-5 – Fused SENet-BiGRU 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 behavioural risk in disease detection have explored a variety of dataset (Ojugo et al., 2021; Ojugo & Yoro, 2013) – which in turn, also have showcased a variety of performance predictions 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 impact – we evaluate for Accuracy, Precision, Recall, Specificity, and F1 performance metric via a hybrid dual channel squeeze-and-excite network with a bi-directional gated recurrent unit (BiGRU). This is explained as thus (Al-Hammadi et al., 2024; Reinke et al., 2023).

The BiGRU: The LSTM without proper setting is caught up with the challenge of the vanishing problem. BiGRU yields a simpler structure (as a variant RNN) (Yao et al., 2022) and also overcomes the vanishing gradient problem in LSTM as it fuses both the input and forget gates into a single update gate; And in turn, reduces the number of predictors to be trained (Aghware et al., 2025). These speeds up the construction of the model and its training without trading off much of its memory capability. Similar to BiLSTM – the BiGRU yields a 2-way data processing capability to capture the before/after context in each data sequence.

It achieves this via the Update and Reset gates as in Equations (1)-(2) respectively (Otorokpo et al., 2024; Oyemade & Ojugo, 2020) – where u_t is update gate, σ is sigmoid function, W is weight matrix, W_u is weight of update gate, h_{t-1} as hidden state in previous time, x_t is input at time t, r_t is reset gate, $\bar{\bar{h}}_t$ is new hidden state candidate value for the memory cell, and h_t is the updated hidden state at time t. Thus, the model captures bidirectional data context – to yield an improved understanding of all intricate data dependencies with carefully tuned hyper-predictor to help achieve a greater balance for train speed, result convergence, memory requirements, enhanced accuracy, and task distribution. Model configuration is seen as in Table 2.

$$u_t = \sigma(W_u[h_{t-1}, x_t]) \quad (1a)$$
$$r_t = \sigma(W_r[h_{t-1}, x_t]) \quad (1b)$$
$$\bar{h}_t = tanh(W[r_t * h_{t-1}, x_t]) \quad (2a)$$
$$h_t = \left(u_t * h_{t-1}(1 + u_t) * \bar{\bar{h}}_t\right) \quad (2b)$$

Table 2. The BiGRU Design Configuration

Features	Value	Description
RNNLayer	Bidirectional (GRU(64))	Bidirectional RNN: 64-GRU (1st) and 32-GRU (2nd) layer
returnSequence	True (for first layer)	Returns entire output sequence for the first layer
inputShape	xTrainScaledShape[1],1	Same as predictors in xTrainScaled: a feat per timestep
denseLayer	yTrainResampleMax()+1	Same as classes in y_train_resampled / output_layer
activation	Softmax	Output Activation function for multi-class classification
optimizer	Adam	learnRate=0.001, beta1=0.9, beta2=0.999, epsilon-1e-07
lossFunction	categorical_crossentry	Loss function for multi-class classification

1. **The Dual Channel Squeeze-and-Excitation (SENet)** as an attention mechanism, enhances our BiGRU's performance by explicitly modeling inter-channel dependencies (Ucar & Korkmaz, 2020). It recalibrates the importance of each channel, and improves the attention network's capability to selectively focus on relevant features within the dataset (Atuduhor et al., 2024; Zuama et al., 2025). Its actions are steered by three (3) steps namely:

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a. **Squeeze**: Its global average pooling reduces the spatial dimensions of each channel's feature map into one global feature. It yields a vector whose length equals the number of channels. Next, it transforms the spatial data into global features that capture the overall context of each channel using Equation 3 where *Xc* is *c*-th feature map, $H*W$ is the size of the feature map, and $Fsq(x_i)$ is the output value (Akazue, Okofu, et al., 2024; Ojugo, Odiakaose, Emordi, Ejeh, et al., 2023).

$$z_c = F_{sq}(x_i)\frac{1}{H*W}\sum_{i=1}^{H}\sum_{j=1}^{W}X_c\,(i,j) \quad Equation\ 3$$

b. **Excitation**: The global feature vector is sent through a 2-layer fully connected network that first, reduces and then expands its number of channels. In addition, its middle layer uses a ReLU, while its final layer uses a Sigmoid function to generate weights for each channel. The weights show relative importance of each channel, with higher values indicating greater significance as expressed in Equation 4 (Aghware et al., 2024; Okofu, Anazia, et al., 2024).

$$s = F_{ex}\left[F_{sq}(x_c), W\right] = \sigma\left(W_2\delta \cdot \left(W_1F_{sq}(x_c)\right)\right) \quad Equation\ 4$$

c. **Recalibration**: Here, the generated weights are applied to each channel of the original feature map (through channel-wise weighting), adjusting the features of each channel. This allows the network to focus more on the features of important channels.

Attention schemes rely on average/max pooling to extract key knowledge; But a single pooling is quite insufficient to capture a dataset's feature diversity and complexity. We address this limitation via the dual-channel SENet, which splits the feature map channels into two groups based on inherent channel characteristics. Each group computes and applies its own attention weights via a separate excitation net; Which in turn, allows each group of channels to receive different weightings based on their distinct roles therein a task. In addition, the weighted feature maps are aggregated to yield the net final outcome. The network automatically adjusts to focus on the more important channels vis-à-vis suppresses all irrelevant channels. This dual-channel SENet not only adjusts the importance of individual channels – it also offers greater flexibility in weights tuning for the various features (Datta et al., 2021; Jerbi et al., 2023).

Step 6 – Train/Cross Validation is initialized with default configuration as in Tables (2)-(5) to tune hyperparameters. Each tree is iteratively constructed and trained to ensure the collective knowledge to identify intricate data. Training blends synthetic with original data to guarantee its comprehensive learning with improved adaptability to various configurations (Setiadi, Muslikh, et al., 2024).

4. RESULTS AND DISCUSSION

4.1. Ensemble Performance

For a comprehensive evaluation devoid of overfit, we use a 5-fold training partition on the 75% train-subset obtained via SMOTEENN, and a final evaluation carried out via a held-out test (25%) as in Table 6. Proposed hybrid yields average Accuracy 0.997, Recall 0.998, Precision 1.000, F1 0.995, Specificity 1.000 and AUC 0.997.

Table 3. SENet-BiGRU Performance Metrics

Models	5-Fold Training with Validation					Held-Out Test Dataset
	Fold-1	Fold-2	Fold-3	Fold-4	Fold-5	
Accuracy	0.991	0.981	0.997	0.998	1.000	0.997
Recall	0.981	1.000	0.975	0.976	1.000	0.998
Precision	1.000	0.984	1.000	0.996	1.000	1.000
F1	0.991	0.989	0.995	0.985	1.000	0.995
MCC	0.982	0.963	0.955	0.985	1.000	0.986
Specificity	1.000	1.000	0.985	0.998	1.000	1.000
AUC-ROC	0.999	0.999	0.986	0.996	1.000	0.997

Its high MCC implies that model accurately/consistently handles the dataset minority class with SMOTEENN balancing and normalization performed; while the Specificity of 1.00 implies that the model effectively recognizes dementia disease symptoms, and that no benign records were misclassified. The held-out test (25%) assesses the model's generalization ability with unseen data. The AUC of 0.997 implies that the model was able to differentiate between the benign and malignant records.

As in Figure 6, the AUC of 0.997 shows the 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 – a Specificity of 1.000 implies that no dementia disease case was misclassified. This is critical to avoid misclassification (model sensitivity) in detecting dementia (Ojugo, Eboka, et al., 2013, 2015). Thus, proposed model enhances dementia disease detection performance and generalization on both the training and the held-out test subset(s).

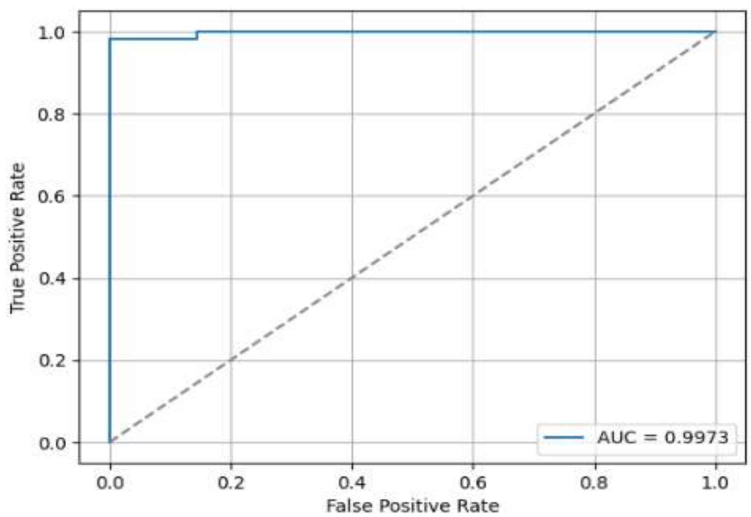

Figure 6. ROC Result of the Held-Out Test Dataset

Figure 7 implies the hybrid SENet-BiGRU ensemble correctly classified all test data. The utilization of both feature selection, SMOTEENN, and z-score normalization did not degrade generalization (Setiadi, Ojugo, et al., 2025). Rather, it focuses on critical feats for model construction to successfully detect the dementia disease predictors with reduced errors (Agboi et al., 2025; Ojugo, Ugboh, et al., 2013; Ojugo & Eboka, 2018b; Ojurongbe et al., 2023).

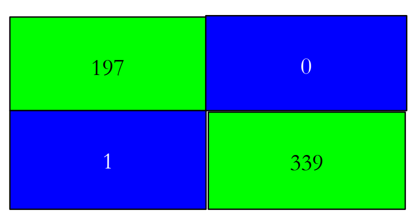

Figure 7. Confusion Matrix

4.2. Ablation Studies with Benchmark Comparison

Table 4 shows ablation report with performance of the base learners applied. Our hybrid ensemble yielded best result with F1 0.699, accuracy 0.697, precision and recall values of 0.685 and 0.684 respectively. Conversely, our benchmarks yield the F1 range [0.611, 0.639], Accuracy range [0.619, 0.637], precision range [0.632, 0.64] and recall range [0.634, 0.64] respectively (Malasowe, Ojie, et al., 2024; Malasowe, Okpako, et al., 2024; Ojugo & Okobah, 2018).

Table 4. Ablation Results Per Components.

Models/ Components	Accuracy	Precision	Recall	F1
RNN	0.619	0.632	0.634	0.611
BiGRU	0.627	0.642	0.653	0.631
Attention Mechanism + BiGRU	0.637	0.640	0.640	0.639
Hybrid SENet + BiGRU	0.697	0.685	0.684	0.699

With the relief ranking feature selection strategy as applied – Table 5 shows performance of our hybrid versus the benchmark models. Results shows that our hybrid ensemble out-performed the benchmark with F1 0.857, accuracy 0.832, Precision and Recall values of 0.846 and 0.847. Conversely, our benchmarks yield F1 range [0.801, 0.839], accuracy range [0.769, 0.826], precision range [0.798, 0.830] and recall range [0.799, 0.845] respectively (Muhamada et al., 2024; Muslikh et al., 2023; Yoro et al., 2025).

Table 5. Performance with and Without Relief Ranking Feature Selection

Components	Without Relief Ranking				With Relief Ranking			
	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1
RNN	0.619	0.632	0.634	0.611	0.769	0.798	0.799	0.801
BiGRU	0.627	0.642	0.653	0.631	0.819	0.842	0.822	0.842
Attention Mechanism + BiGRU	0.637	0.640	0.640	0.639	0.826	0.830	0.845	0.839
Hybrid SENet + BiGRU	0.697	0.685	0.684	0.699	0.832	0.846	0.847	0.857

With the SMOTEENN strategy applied – Table 6 shows our hybrid outperformed the benchmark with F1 0.995, accuracy 0.997, precision 1.000 and Recall 0.998 respectively. Conversely, our benchmarks show various ranges with F1 range [0.921, 0.955], accuracy range [0.921, 0.958], precision range [0.911, 0.951] and recall range [0.911, 0.952] respectively (Okpor, Aghware, Akazue, Eboka, et al., 2024).

Table 6. Performance with and Without SMOTE-Tomek Data Balancing

Components	Without SMOTE-Tomek				With SMOTE-Tomek			
	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1
RNN	0.769	0.798	0.799	0.801	0.921	0.911	0.911	0.928
BiGRU	0.819	0.842	0.822	0.842	0.928	0.944	0.944	0.938
Attention Mech. + BiGRU	0.826	0.830	0.845	0.839	0.958	0.951	0.952	0.955
Hybrid SENet + BiGRU	0.832	0.846	0.847	0.857	0.997	1.000	0.998	0.995

Table 7 shows that the proposed model outperforms others due to its use of BiGRU with the dual channel attention mechanism across the test dataset – achieving its high accuracy 0.997, precision 1.000, recall 0.998, specificity 1.000 and AUC 0.997.It yields best generalization with low false-positives, which is crucial in dementia detection especially (Ako et al., 2024; Ojugo et al., 2024; Ojugo & Otakore, 2020; Ugbotu, Emordi, et al., 2025).

Table 7. Comparison with Related Works

Metrics	SEM + DBN (Al-Hammadi et al., 2024)	DHH + GRU (Noviandy et al., 2024)	BiGRU + FSOR (Luz et al., 2023)	LSTM + CNN (Ntampakis et al., 2024)	GBM + PSO (Miah et al., 2021)	Proposed SENet + BiGRU
Accuracy	0.973	0.919	0.986	0.992	0.969	0.997
Recall	0.974	0.959	0.989	0.989	0.976	0.998
Precision	0.982	0.948	1.000	0.992	0.947	1.000
F1	0.976	0.973	0.991	0.985	0.974	0.995
AUC-ROC	0.938	-	0.928	0.987	0.958	0.997

Models leverage deep learning capabilities – their performance can be seen to be slightly lower in metrics, and the lack thereof of specificity indicates that they are less robust; whereas, our model can be seen to maintain high sensitivity performance, even with its transfer learning architectures (Ojugo, Odiakaose, Emordi, Ako, et al., 2023; Onoma, Agboi, Ugbotu, et al., 2025). We used the SMOTEENN scheme to address class imbalances.

4. CONCLUSIONS

The study affirms that our proposed ensemble, which yields a strong potential with improved performance generalization, and a classification accuracy of 0.997 – fully and functionally equips the GREDDIoMT device with learning intelligence required to identify and classify the dementia disease. The increased early detection rate(s) at its training and validation with its increased accuracy and decreased loss suggest that the proposed hybrid model is quite robust and well-regularized as its success is attributed to the effective fusion of the SMOTEENN data balancing technique, the optimized predictors as selected via feature selection approach, and the suitable deep learning scheme utilized.

These, have revealed Recall 0.998, Accuracy 0.997, Precision 1.000, F1 0.995, Specificity 1.000 and AUC 0.997 respectively. In addition, the proposed ensemble achieved high discriminative capability via statistically fused heuristics mode to successfully mitigate class-imbalance with enhanced evaluation scores for F1, Accuracy, Recall, Specificity and AUC respectively. Study advances a lightweight yet effective framework that avoids complex training and validation that results in overfit or over-parameterization, effectively handles larger data complexities; while offering interpretability and high performance.

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