Early Detection of Alzheimer's-like Behavior Using Deep Learning and Sensor Data in a Smart Home Environment

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Abstract

In order to provide effective treatment and management, early detection of Alzheimer's disease is crucial. This study investigates the potential of deep learning models to identify early signs of Alzheimer's-like behavior using sensor data collected in a smart home environment. We employed four deep learning architectures: GRU, LSTM, Bidirectional LSTM, and Conv1D, to distinguish between normal activity patterns and those indicative of Alzheimer's-like behavior. However, the results showed that recurrent neural networks (GRU, LSTM, and Bidirectional LSTM) performed better than the biggest convolutional model (Conv1D) due to their capability in capturing temporal dependencies within sensor data more accurately than any other model. The Bidirectional LSTM had an excellent ROC AUC score suggesting it was capable of taking information from both previous states as well as future ones into account which made it very efficient in detecting Alzheimer's disease. These findings indicate that sensor-based data analysis has the potential for developing non-invasive continuous monitoring systems capable of supporting early diagnosis, improving care and perhaps even better management strategies for this condition over the long term. It is necessary to conduct further research with a view of refining deep learning models and designing sophisticated systems for Alzheimer's detection in real-world smart home settings.

Keywords: Alzheimer, Lstm, and Smart Home

1 Introduction

Due to the aging of the population worldwide, more elderly suffer from Alzheimer's disease [1]. Alzheimer's disease is known as one of the most well-known diseases in the elderly, which is a neurological and irreversible brain disorder that slowly destroys memory, the ability to think, and finally the ability to perform even basic daily tasks [2]. They may also have difficulty communicating with others. All of these barriers affect patients' ability to complete daily activities, reduce their quality of life, and force them to seek help from others.

Alzheimer's disease does not allow a person to do daily activities, that's why a caregiver is needed who is a member of the family or friends and has the most connection and help to the sick person.

Time-consuming documentation of patients' activities is one of the important tasks of caregivers, especially in nursing homes for people with dementia. This documentation should help to understand the stage of disease the patients are in. There are methods that allow access to digital nursing documents with online tools where activities can be collected by checking boxes next to a list of activities. Although such online tools simplify the work of caregivers, they still have to be done manually. To be in addition, there is a possibility that due to the high workload, the staff will neglect certain activities. A smart home equipped with the Internet of Things and a dementia detection system can help caregivers and doctors to obtain medical history, life habits collect daily and change in daily routine pattern of patients [3].

Cognitive diseases such as dementia must be detected at an early stage so that early treatment is possible. Current assessment methods rely mainly on questions from questionnaires or face-to-face examinations that depend on recall of events or brief snapshots of functioning that may reflect a person's normal functioning status. show weak Also, clinical methods have limitations such as episodic nature and the possibility of biased reporting. The main motivation of our work is that cognitive decline can be observed in the daily activities and routines of an elderly person. Real-time monitoring of activities performed by an elderly person in a smart home will be useful for early detection of such decline [4].

Daily activities of dementia patients can be well recognized by sensors technology and machine learning [3]. Today, various advanced technological advancements in medicine have led to a rapid increase in the elderly population worldwide, which in turn has created a major problem in our society, namely the increasing number of people suffering from dementia

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[1]. The increase in life expectancy worldwide has been accompanied by an unprecedented increase in the incidence of dementia, with high socioeconomic costs reaching $818 billion worldwide in 2015. However, its prevalence may nearly triple by 2050 as the number of people aged 65 and older with Alzheimer's disease increases, from 46.8 million to 131 million worldwide, the majority of whom live in an institution [5]. In recent years, special attention has been focused on monitoring technologies for early intervention services and ambulatory case management. Typical solutions include physical assistance and remote monitoring. Assistive living technologies have limited use in the unobstructed diagnosis of activities of daily living (ADL) [6]. These refer to self-care tasks, including exercises that are performed daily and that the individual wishes to perform independently. Cognitive impairment has life-threatening consequences on the patient's independence and quality of life.

ADLs fall into two clusters: those that involve tasks central to regular daily existence, for example, eating, dressing, and washing, are called essential ADLs, and those that involve higher-level complex tasks, such as using and interacting with tools, for example, planning dinners, monitoring funds and using the phone, to name a few [7]. IADL Cognitive diseases such as dementia should be detected in the early stages so that early treatment is possible. However, research shows that 75 percent of dementia cases go unnoticed, and many cases are only diagnosed when the disorder reaches a moderate or advanced stage. The best markers of cognitive decline may not necessarily be determined by an individual's performance at any point in time, but rather by monitoring trends over time and the variability of change over a period of time [8]. The use of smart home technology can significantly Support the lives of people with dementia. This type of technology would also be useful for detecting signs of dementia and alerting caregivers and physicians for further diagnosis. Recent studies show that deviations in activity patterns can be indicators of cognitive decline, behavioral changes such as sleep disorder, night waking, and inability to perform tasks can be indicators of cognitive impairment [6] Current assessment methods mainly rely on questions from questionnaires or face-to-face examinations that recall Events or brief snapshots of performance are dependent that may understate an individual's normal performance status. Also, clinical methods have limitations such as episodic nature and the possibility of biased reporting. The main motivation of our work is that cognitive decline can be observed in the daily activities and routines of an elderly person. Real-time monitoring of activities performed by an elderly person in a smart home would be useful for early detection of such decline. In machine learning, convolutional neural network (CNN) is a class of deep and feedforward artificial neural networks. Recently, CNNs have become popular due to their ability to learn rich representations and capture local dependence and spatial information of grain-level patterns [9].

Therefore, there is a technology that can automatically support Alzheimer's patients in achieving self-sufficiency in their daily lives. The need for an efficient, dynamic, and friendly support system for patients with Alzheimer's disease is urgent. Such technologies have been exploited in many fields, such as monitoring, elderly fall detection, and human activity detection. Therefore, identifying the behaviors and interactions of people with their environment is very important for the development of intelligent systems [2].

Using modern technologies, active and assisted living (AAL) systems offer innovative and cost-effective solutions to increase the safety of residents in order to increase the quality of life [10].

The smart home system has the ability to automatically collect the required data from the person's behavior in daily activities through sensors installed around the patient.

The Internet of Things, which connects smart phones and monitoring devices, can provide security and health for elderly citizens and caregivers. IoT-based smart homes can automatically meet daily needs and notify caregivers and relatives [11]. This research aims to address these gaps by investigating the effectiveness of deep learning models in detecting early signs of Alzheimer's-like behavior using a comprehensive dataset of sensor data. Specifically, we aim to answer the following research questions: Can deep learning models effectively distinguish normal activity patterns from those indicative of Alzheimer's-like behavior using sensor data collected in a smart home environment? How do different deep learning architectures, such as GRU, LSTM, Bidirectional LSTM, and Conv1D, impact the accuracy and robustness of the detection system?

By exploring these questions, this study aims to contribute to the development of a more accessible, non-invasive, and potentially more sensitive approach to early Alzheimer's disease detection. Specifically, we introduce the innovative use of synthetic data simulation to mimic Alzheimer's-like behavior and assess how various deep learning architectures can enhance detection accuracy in smart home environments.

2 Literature Review

2.1 Introduction

In this chapter, we will review a selection of research exploring the diagnosis of Alzheimer's disease using various techniques, including traditional methods and emerging AI-driven approaches. We will focus particularly on studies utilizing sensor data and machine learning for early detection of cognitive decline and activity recognition in smart home environments.

2.2 Alzheimer's diagnosis using daily activities for care

Accurate and early diagnosis of Alzheimer's can play an important role in improving the treatment and management of this disease. The use of sensors such as motion, audio, and visual sensors has been considered as a non-invasive and non-destructive method for Alzheimer's diagnosis.

The use of environmental sensors can reduce the costs and treatment burden related to Alzheimer's. By using these sensors, it is possible to continuously monitor environmental indicators such as movement, sleep, and daily activities. This information can help doctors in the diagnosis, treatment, and management of the disease and, as a result, make better decisions and reduce the costs and burden of treatment.

In 2019, Ting-Ying Li et al. [1] proposed a support system that can rapidly estimate the likelihood of dementia based on a 2–4-hour observation of a behavioral test performed by an elderly person. This paper uses the Naïve Bayes algorithm to train the model, which is used to quickly classify participants into two classes: 'dementia' and 'nondementia.' The proposed system uses environmental sensors instead of wearable sensors or cameras, and the distance between two adjacent sensors is about 1.5 meters so that the elderly feel more comfortable during monitoring. The sensors used in this article include motion sensors, item sensors, door sensors, burner sensors, hot water sensors, cold water sensors, temperature sensors, and electricity consumption sensors for the entire apartment. Passive infrared motion sensors (PIR) are also installed in the corridor. CASAS and ZS senior home datasets were used to evaluate the system's performance. The first dataset achieved 98.3% accuracy, 98.3% readability, and an AUC-ROC of 0.846. The second dataset achieved 89.9% accuracy, 90% readability, and an AUC-ROC of 0.921. Eight activities from the "IADL" list were selected by a professional psychologist, including cleaning rooms, reading medication prescriptions, writing greeting cards, watching news clips, watering plants, answering the phone, baking cookies, and choosing clothes.

Damla Arifoglu and colleagues in 2019 [12] used convolutional neural networks (CNN) and recurrent neural networks (RNN) for activity recognition. They utilized one-dimensional and two-dimensional CNNs, with two-dimensional CNNs together with an LSTM layer (long short-term memory networks) also being tested. The datasets used in this article are the Aruba dataset, including activities such as preparing food, relaxing, eating, working, sleeping, washing dishes, bed to toilet, entering the house, leaving the house, housekeeping, and breathing, and the WSU dataset, including phone call, hand washing, food preparation, eating and cleaning. The Aruba dataset includes 224 days of data with 11 daily activities performed by a single user. The WSU dataset consists of 5 activities performed by 20 students and has normal and non-normal versions to reflect errors. Their findings demonstrated that a twodimensional CNN network achieved 89.67% accuracy, while a two-dimensional CNN network with LSTM achieved 89.72% accuracy. HMM and HSMM models had the lowest accuracy (77.90% and 77.98%, respectively).

Damla Arifoglu et al. in 2020 [6] presented a method to detect abnormal behavior that results from cognitive problems in the elderly. To address the lack of data, they proposed a data generation method to simulate abnormal behavior that reflects the cognitive status of elderly people with dementia. They then used graph convolutional networks (GCN) to detect activities and identify abnormal cases. The dataset used in this paper is obtained from the "Aruba test-bed" of CASAS smart homes, containing information from 3 door sensors, 31 motion sensors, and 5 temperature sensors over 224 days. However, they only used motion sensors and doors in their study. This dataset includes 11 daily activities, including those mentioned above, performed by an adult, excluding any abnormal behavior. To evaluate the model, measures such as precision, recall, overall accuracy, and F-measure were used.

K. S. Gayathri et al. in 2015 [5] used Markov Logic Network (MLN) for activity detection due to its ability to integrate common sense knowledge with a probabilistic model, enhancing the system's detection ability. To incorporate an efficient activity detection and anomaly detection system in smart environments, the usual activities of the occupants are modeled, and any deviation from the activity model is recognized as abnormal. Their Hierarchical Activity Detection and Anomaly Detection System for Dementia Care used a standard smart home dataset provided by the UCI Machine Learning Repository. The sensors used in this article include: a PIR sensor in the shower and sink, a magnetic sensor on the kitchen screen in the main door, refrigerator, and cabinet, a flush sensor in the closet in the toilet, a pressure sensor in the chair and bed, and an electric sensor in the microwave and toaster. Activities used include: leaving the house, toileting, showering, sleeping, breakfast, lunch, snack, leisure TV, and cleaning.

Chennai, INDIA and colleagues in 2020 [13] focused on early detection of Alzheimer's disease (MCI). They adopted a predictive model based on short-term memory recurrent neural networks (RNN), achieving an average test accuracy of 77.5%.

A synthetic dataset representing real-life cognitive/functional decline was obtained from simulation observations of daily life activities of elderly people. They proposed the use of new or existing algorithms to extract contextual meaning and useful features (such as calculating sleeping time, cooking time, and walking speed) from raw sensor data. Their work explored the tradeoffs between wearable sensors (which are more intrusive) and non-wearable sensors (such as motion sensors and door contact sensors), which are less intrusive and can monitor activities naturally. Santos Bringas et al. in 2020 [14] used a convolutional neural network (CNN) model to identify patterns that distinguish different stages of Alzheimer's. They trained their deep learning models using mobility data collected for patients in Santander (Spain). They achieved 90.91% accuracy and 0.897 F1 score using their CNN-based method.

Debraj De et al. in 2015 [15] addressed fine-grained activity detection using multimodal wearable sensors, including those worn on different body positions and Bluetooth beacons placed in the environment. Their solution exploits measurements of the environment and the user's location, combined with movements recorded by accelerometers and gyroscopes. The proposed algorithm is a two-level supervised classifier that operates on a server. In the first level, multi-sensor data from wearables is collected and analyzed using a modified conditional random field (CRF)-based supervised activity classifier. This classified activity status is then combined across all wearables to decide the user's final activity status. They classified activities into four categories: locomotor activities (indoor walking, indoor running), semantic activities (using the refrigerator, cleaning dishes, cooking, sitting and eating, using the bathroom sink), transitional activities (indoor to outside, outside to inside, walking upstairs, walking downstairs), and postural/stationary activities (just stand, lie on the bed, sit on the bed, lie on the floor, sit on the floor, lie on the couch, sit on the couch, and sit on the dresser). The devices used include: Lumo Back, Lumo Lift, Nike+, and Fitbit.

In 2020, Sara Casaccia et al. [9] presented a tool for simulating the home environment with the capability to analyze human movement patterns related to activities of daily living (ADL) and model passive infrared (PIR) sensor networks. They chose PIR sensors due to their non-intrusive and non-contact nature, along with their low cost. The tool is programmed in MATLAB and includes a graphical interface allowing the developer to change key simulation parameters. The researchers installed three wallmounted PIR sensors with a radius of 2 meters and a field of view (FoV) of 140 degrees: PIR1 in the kitchen, PIR2 in the bedroom, and PIR3 in the bathroom. These sensors were used to detect people's wandering patterns. Their results show that a decision tree (DT) algorithm is reliable for distinguishing normal routes from stray routes detected by PIR sensor activation, obtaining an accuracy level of more than 95% using a cross-validation approach. They also found that if the house layout, sensor placement, or sensor characteristics were changed, the classifier could not function properly.

While existing research has demonstrated promising results in activity recognition and anomaly detection using sensor data, it often relies on specific activity sets, smaller datasets, and predominantly focuses on wearable sensors, which can be inconvenient for users. In contrast to this, our work utilizes a comprehensive dataset, simulates Alzheimer's-like patterns in a more realistic way, and explores the potential of deep learning models to learn from complex temporal patterns, which are more likely to be indicative of cognitive decline. This research is more focused on developing a practical, non-invasive, and cost-effective system for detecting early signs of Alzheimer's disease, utilizing a large dataset and various deep learning architectures.

2.3 Alzheimer's diagnosis using medical screening

In 2019, Mostafa Amin-Naji et al. [16] developed a method for Alzheimer's disease diagnosis using a Siamese Convolutional Neural Network (SCNN) with three ResNet-34 branches to distinguish between AD and NC. They used the OASIS dataset, which included 235 subjects, and achieved an accuracy of 98.72%. This research utilizes deep learning for Alzheimer's diagnosis based on brain imaging data, offering insights into the potential of AI in identifying neurological changes related to the disease. However, this method differs significantly from our approach, which concentrates on analyzing sensor data from everyday activities to detect early signs of decline.

In 2018, Hiroki Fuse and colleagues [17] used brain shape information to classify between healthy people and people with Alzheimer's disease, achieving 87.5% accuracy using a support vector machine. This research highlights the potential of using brain shape information as a diagnostic marker for Alzheimer's disease, but it relies on detailed brain scans (MRI or CT). This approach differs from the non-invasive, unobtrusive nature of the sensor-based methods explored in this paper.

In 2020, Dan Pan et al. [18] proposed a CNN-EL approach to identify individuals with mild cognitive impairment (MCI) or Alzheimer's disease (AD) using

MRI. The combined CNN and EL approach successfully captured early AD-related brain changes, demonstrating its potential in early diagnosis.

In 2023, Dr. Chamandeep Kaur et al. [19] proposed a method combining transfer learning (TL) and deep neural networks (DNN) to diagnose Alzheimer's disease (AD). They trained the model using an image dataset from Kaggle, which includes images of different stages of AD, achieving an accuracy of 99.32%. This research utilizes the power of deep learning for image-based diagnosis of Alzheimer's, but it differs greatly from our approach that focuses on sensor-based analysis of activity patterns in a smart home environment.

In 2013, Rigel Mahmood et al. [20] developed a new approach to classify AD using mathematical and image processing techniques. Their approach analyzes MRI scans utilizing diffeomorphism features that map from one MRI to another. They trained a neural network using 230 MRI scans from the OASIS MRI database and tested it on 457 MRIs, achieving close to a 90% accuracy in AD diagnosis and classification.

The techniques of advanced medical imaging processing in this area are examined for the diagnosis of Alzheimer's Disease. Though these approaches provide important information on the illness, they tend to be very costly, need specialized instruments and do not fit well for long-lasting monitoring or prompt identification which is what we are striving for in our inquiry.

3 Methodology

In the era of big data, monitoring the activities of individuals, particularly the elderly, through various data sources has become crucial. This research aims to develop an efficient model for detecting Alzheimer's-like patterns in sensor data using different neural network architectures. The primary objective is to enhance the care of individuals globally by identifying Alzheimer's-like patterns in their sensor data records. Leveraging recent advancements in deep learning, this study focuses on the application of state-of-the-art neural networks to accurately detect these patterns [21].

3.1 Data Description

The dataset used for this study is the Aruba dataset, collected by the Center for Advanced Studies in Adaptive Systems (CASAS) at Washington State University [22][23]. This dataset includes time-series sensor data from a smart home environment, specifically designed to monitor the activities of residents, particularly the elderly. The Aruba dataset comprises various types of sensor data, including Passive Infrared (PIR) binary sensory data, door sensors, and temperature sensors. The data records the states of these sensors over time, capturing the movements and activities within the smart home.

The dataset was collected and labeled by the CASAS team, who are independent of this study's research team. This independence ensures an objective and unbiased labeling process, enhancing the dataset's reliability and credibility for evaluating machine learning models.

Several studies have utilized the CASAS Aruba dataset for different purposes. For instance, Gochoo et al. (2017) focused on detecting travel patterns of a resident living alone using PIR binary sensory data. Their approach involved analyzing the activation patterns of motion sensors to infer the resident's movement within the home [24]. In another study, Gochoo et al. (2018) and MacHot et al. (2017) explored activity recognition by converting temporal sensory events of each activity sample into images. These images were then fed into Deep Convolutional Neural Networks (DCNN) for feature extraction. The extracted features were subsequently used for activity classification using Fully Connected Neural Networks (FCNN). This method demonstrated the potential of using image-based representations of sensor data for accurate activity recognition [25][26].

The floor plan of the smart home, where the Aruba dataset was collected, is shown below. This map illustrates the layout of various rooms and the placement of sensors, including large motion sensors (Mxxx), small motion sensors (Txxx), and door sensors (Dxxx).

For example, a typical entry in the dataset might look like this: "2011-07-14 15:57:29.967596, M031, OFF," indicating the timestamp, sensor ID, and sensor state. This entry signifies that at 15:57:29.967596 on July 14, 2011, the sensor with ID M031 was turned off. Such entries help in tracking the state changes of various sensors over time, providing valuable information for activity recognition and pattern detection [27].

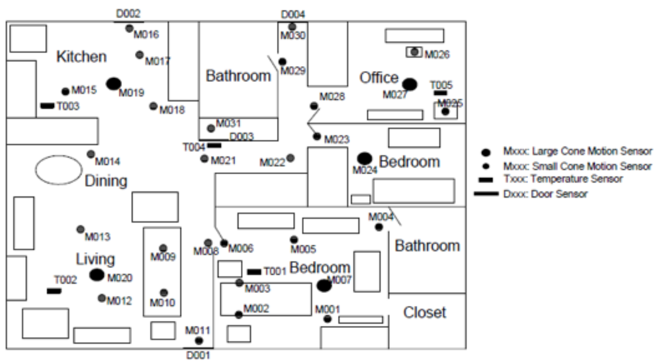

Figure 1: Smart home floor plan in which Aruba dataset is collected

3.1.1 Data Simulation

Simulating Alzheimer's-like behavior in sensor data is a critical step to evaluate the performance of our

model in detecting patterns indicative of Alzheimer's in smart home environments. While the simulation does not represent actual Alzheimer's patient behavior, it provides a controlled framework for creating datasets with characteristics resembling behavioral changes observed in Alzheimer's, such as repetitive actions and reduced activity.
To construct the simulated dataset, we identified sensors associated with repetitive behavior (e.g., M015, M019, M014, M024, M007, and M027) and reduced activity (e.g., M017, M018, and M021). Synthetic data was generated by modifying the frequency of sensor activations. For sensors linked to repetitive actions, the activation frequency was increased using a probabilistic approach, drawing a frequency factor from a normal distribution (mean: 1.5, standard deviation: 0.5). If a sensor's state was 'ON,' its activation was included in the synthetic data with a probability proportional to the frequency factor. Conversely, for sensors linked to reduced activity, the activation frequency was decreased using a normal distribution (mean: 0.5, standard deviation: 0.2), reducing the likelihood of activation.

The synthetic data generation process maintained the structure of the original dataset, preserving timestamps, sensor IDs, and states to ensure compatibility with downstream analysis and enhance data diversity for training and evaluation purposes. For instance, an entry such as "2011-07-14 15:57:29.967596, M031, OFF" reflects a sensor state change at a specific timestamp. We assigned a label of '1' to denote Alzheimer's-like

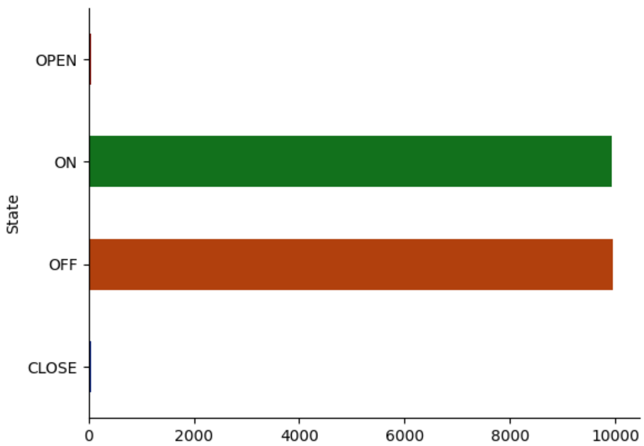

Figure 2: The number of activity records for each sensor

behavior in the synthetic data, enabling supervised learning. Additionally, action frequency for each sensor was calculated over a 10-minute window by grouping 'ON' state occurrences. Sensor activity distributions and label histograms were plotted to visualize the impact of simulation, highlighting the introduced changes and their alignment with Alzheimer's-like behavior patterns.

3.2 Data Preprocessing

Data preprocessing is one of the most important steps in getting the sensor dataset ready for the detection of Alzheimer's disease using a machine-learning model. The original dataset, which is recorded sensor reading over some time, was loaded into a Pandas DataFrame for manipulation. In the first instance, the data was reduced to a manageable size when selecting the first 20,000 rows. The columns in the sensor data show the date, time, sensor ID, and sensor state. A DateTime column was generated from the date and time columns to allow for time-based grouping and analysis [28].

3.2.1 Action Frequencies

To obtain the characteristics of Alzheimer's disease, the frequency of actions by each sensor was calculated. The sensor data was filtered based on the ID of the sensor and its state, which is 'ON'. A count of action concentrations was obtained by grouping data according to the type of sensor and by time window (1 minute); in this way, a time series of action concentrations for a specific sensor was obtained.

$$f(s,t) = \frac{\text{Number of 'ON' states for sensor } s \text{ in time window } t}{\text{Total time window duration}}$$

3.2.2 Simulation of Alzheimer's-like Behavior

The Alzheimer's-like data was simulated by modifying the normal data's action frequencies. Specific sensors were chosen to represent repetitive behavior or reduced activity, which are characteristic of Alzheimer's patients. These modifications were introduced using a probabilistic approach.

For repetitive behavior, the action frequency was increased by a factor sampled from a normal distribution with a mean of 1.5 and a standard deviation of 0.5. Conversely, for reduced activity, the action frequency was decreased using a factor with a mean of 0.5 and a standard deviation of 0.2. The normal distribution $N(\mu, \sigma)$ used for these factors can be represented as:

$$\text{Repetitive behavior factor} \sim N(1.5, 0.5)$$

$$\text{Reduced activity factor} \sim N(0.5, 0.2)$$

These modifications generated a dataset representing Alzheimer's-like behavior, which was then merged with the original normal data.

3.2.3 Labelling and Transformation

The two datasets were thereafter labeled with a binary classification target. Target 0 meant normal behavior, while 1 meant Alzheimer's-like behavior. One-hot encoding independent variables followed, so that our machine learning model could make optimal use of the categorical data contained in Sensor and State columns.

3.2.4 Sequence Generation

To work with sequential models, for example an LSTM or GRU, the data was reshaped into sequences of fixed length, that is, 60-time steps. Each sequence was labeled with respect to the last time step in the sequence. This methodology contributes to the learning of temporal dependencies in sensor data.

3.3 Train-Test Split and Data Normalization

The data was then split into an 80/20 ratio for training and testing, respectively. The training set was used to fit the models, while the testing set was used to measure their performance. Features were normalized as input to make sure that while training the models, convergence was obtained effectively regarding the classes present in the training set. Missing values were replaced using the mean of the respective feature to make the data complete before model training.
All of this complicated preprocessing pipeline made the data well-prepared to the point of training various kinds of deep learning models for detection of Alzheimer's.

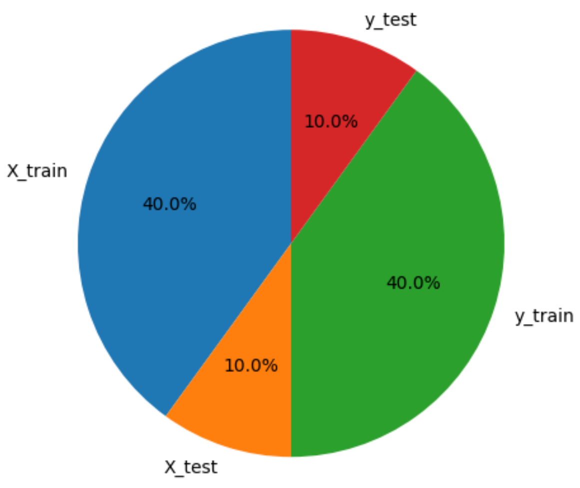

Figure 3: Train-Test Split Dimensions

3.4 Model Architectures

To detect Alzheimer's-like patterns in the preprocessed sensor data, we implemented and compared four different deep learning architectures: Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), Bidirectional LSTM, and 1D Convolutional Neural Network (Conv1D). Each model was designed to capture temporal dependencies in the sequential sensor data, making them suitable for this time-series classification task.

3.4.1 Gated Recurrent Unit (GRU) Model

The GRU model, first introduced by Cho et al. (2014), is designed to capture long-term dependencies in sequential data with fewer parameters than LSTM. Our GRU architecture consists of an input layer shaped to match our sequence length and number of features, followed by two GRU layers with 100 and 50 units respectively, both using `tanh` activation. We incorporated layer normalization and dropout (0.2) after each GRU layer to improve training stability and prevent overfitting. The final layer is a dense output layer with a single unit and `sigmoid` activation for binary classification.

The GRU update equations are as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$

$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t])$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

where z_t is the update gate, r_t is the reset gate, $\tilde{h}_t$ is the candidate activation, and h_t is the final activation [29].

3.4.2 Long Short-Term Memory (LSTM) Model

The LSTM model, introduced by Hochreiter and Schmidhuber [30], is designed to address the vanishing gradient problem in RNNs. Our LSTM architecture incorporates residual connections and batch normalization. It begins with an input layer, followed by two LSTM blocks with 100 and 50 units respectively, each with `tanh` activation and a residual connection. Batch normalization is applied after each block. A final LSTM layer with 25 units and `tanh` activation is followed by a dense output layer with `sigmoid` activation for classification.

The LSTM update equations are:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t$$
$$h_t = o_t * \tanh(c_t)$$

where f_t is the forget gate, i_t is the input gate, o_t is the output gate, $\tilde{c}_t$ is the cell input activation, c_t is the cell state, and h_t is the hidden state.

3.4.3 Bidirectional LSTM Model

The Bidirectional LSTM model, as described by Schuster and Paliwal [31], processes the input sequence in both forward and backward directions. Our architecture includes an attention mechanism. It starts with an input layer, followed by two Bidirectional LSTM layers with 64 and 32 units respectively, both using ELU activation. Dropout (0.3) is applied after each Bidirectional LSTM layer. An attention layer is then applied, followed by global average pooling and a final dense output layer with sigmoid activation.
The attention mechanism is defined as:

$$e_t = \tanh(W_h h_t + b_h)$$
$$\alpha_t = \mathrm{softmax}(e_t)$$
$$c = \sum \alpha_t h_t$$

where e_t is the energy, α_t is the attention weight, and c is the context vector.

3.4.4 1D Convolutional Neural Network (Conv1D)

The 1D Convolutional model, inspired by the work of Yu and Koltun (2016), uses dilated convolutions to capture long-range dependencies [32]. Our architecture begins with an input layer, followed by two Conv1D blocks. The first block has 64 filters with a kernel size of 3 and dilation rate of 1, while the second has 32 filters with a kernel size of 3 and dilation rate of 2. Both use SELU activation and are followed by batch normalization and max pooling. The output is then flattened before passing through a dense output layer with sigmoid activation.
The 1D convolution operation is defined as:

$$y[i] = \sum_k x[i + r \cdot k] \cdot w[k]$$

where x is the input, w is the filter, r is the dilation rate, and y is the output.

3.5 Model Training and Evaluation

In this section, we outline the training and evaluation procedures for the four neural network architectures employed in our study: GRU, LSTM, Bidirectional LSTM, and 1D Convolutional models. Each model was implemented using the Keras framework and trained to predict sensor data labels in a binary classification task, focusing on distinguishing between two classes.

3.6 Training Procedure

All models were trained using binary cross-entropy[35] as the loss function:

$$\mathrm{BCE} = -\frac{1}{N} \sum (y_i \cdot \log(p_i) + (1 - y_i) \cdot \log(1 - p_i))$$

where N is the number of samples, y_i is the true label, and p_i is the predicted probability.

The training process was carried out with a learning rate of 0.001, using the Adam optimizer[33]. An exponential learning rate decay was applied:

$$\eta_t = \eta_0 \cdot \text{decay\_rate}^{(t/\text{decay\_steps})}$$

where η_t is the learning rate at step t, η_0 is the initial learning rate, the decay rate was set to 0.96, and decay steps to 100,000.

We trained the models for a maximum of 50 epochs with a batch size of 32. Early stopping with a patience of 5 epochs was employed to prevent overfitting, monitoring the validation loss during training [34]. Additionally, dropout layers were incorporated into each model to reduce the risk of overfitting by randomly setting a fraction of input units to zero during each update [36].

3.7 Model Structures

The GRU, LSTM, and Bidirectional LSTM models were structured to capture the temporal dependencies within the data, leveraging their respective architectures to process sequences. In contrast, the Conv1D model was designed to identify local patterns in the data, applying convolutional filters across the input sequences. This combination of models allowed for a thorough exploration of the data's characteristics and provided insights into the effectiveness of different architectures in this binary classification task.

3.8 Model Evaluation

Performance was evaluated using accuracy, precision, recall, F1-score, and ROC AUC on the test set. We also utilized confusion matrices, classification reports, ROC curves, and precision-recall curves to assess the models' performance comprehensively. These metrics, along with the early stopping strategy, ensured that our models were both accurate and generalizable, minimizing the risk of overfitting [37][38].

3.9 Results

The GRU (Gated Recurrent Unit) model demonstrated robust performance in classifying Alzheimer's-like patterns in the sensor data. The confusion matrix showed that the model correctly classified 3,740 instances of class 0 and 3,288 instances of class 1, while misclassifying 263 instances of class 0 and 513 instances of class 1.

The classification report further revealed that the model achieved a precision of 0.88 for class 0 and 0.93 for class 1, with corresponding recall values of 0.93 and 0.87. The overall accuracy of the model was 0.90, and both the macro and weighted averages for precision, recall, and F1-score were 0.90. The ROC AUC score, a measure of the model's discriminative ability, was 0.9809, indicating a strong performance in distinguishing between the two classes. The LSTM (Long Short-Term Memory)

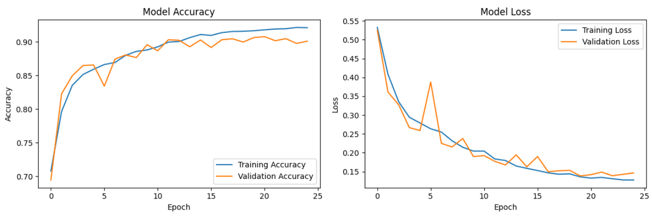

Figure 4: GRU model Evaluation

model also performed well, with results slightly different from the GRU model. The confusion matrix indicated that the model correctly identified 3,501 instances of class 0 and 3,540 instances of class 1, with 502 and 261 misclassifications, respectively. The classification report highlighted a precision of 0.93 for class 0 and 0.88 for class 1, with both classes achieving a recall of around 0.90. The model's accuracy was 0.90, with macro and weighted averages also at 0.90 for precision, recall, and F1-score. The ROC AUC score was 0.9801, suggesting that the LSTM model was nearly as effective as the GRU model in distinguishing between the two classes. The Bidirectional LSTM model, which leverages infor-

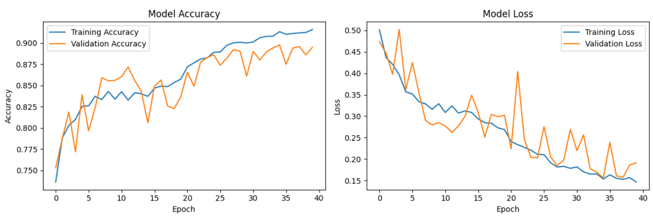

Figure 5: LSTM model Evaluation

mation from both past and future states, provided similar results. The confusion matrix revealed that the model correctly classified 3,646 instances of class 0 and 3,375 instances of class 1, with 357 and 426 misclassifications, respectively. The classification report showed a precision of 0.90 for both classes, with recall values of 0.91 for class 0 and 0.89 for class 1. The accuracy of the model was 0.90, with both macro and weighted averages at 0.90 for precision, recall, and F1-score. Notably, the Bidirectional LSTM achieved the highest ROC AUC score of 0.9820 among the models tested, indicating superior performance in capturing temporal dependencies and distinguishing between the classes. The 1D Con-

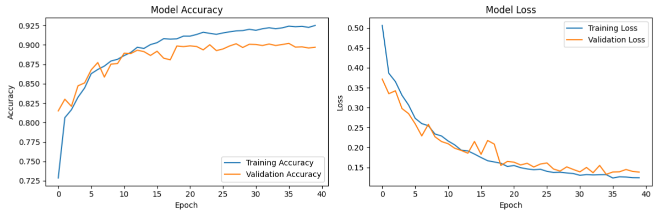

Figure 6: Bidirectional LSTM model Evaluation

volutional Neural Network (Conv1D) model, which applies convolutional layers to extract features from the sequential data, produced different results. The confusion matrix showed that the model correctly classified 3,823 instances of class 0 and 2,129 instances of class 1, but it also misclassified 180 instances of class 0 and 1,672 instances of class 1. The classification report indicated a significant drop in recall for class 1, with a value of 0.56, leading to a lower F1-score of 0.70 for this class. The model's overall accuracy was 0.76, with macro and weighted averages reflecting this decrease in performance, particularly in recall. The ROC AUC score for the Conv1D model was 0.8884, suggesting that while the model still had a reasonable ability to distinguish between the classes, it was less effective at correctly identifying Alzheimer's-like patterns compared to the recurrent models. Among the mod-

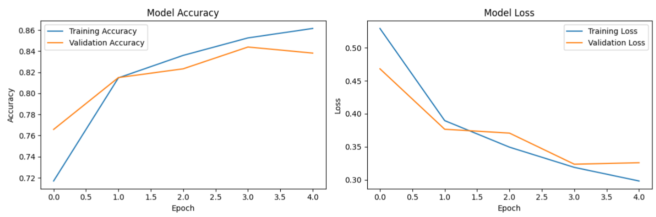

Figure 7: CNN model Evaluation

els tested, the Bidirectional LSTM achieved the highest ROC AUC score, suggesting superior performance in capturing temporal dependencies and distinguishing between normal and Alzheimer's-like patterns. Both the GRU and LSTM models also performed well, showing balanced precision, recall, and F1-scores. However, the Conv1D model demonstrated a significant drop in performance, particularly in recall for class 1, making it less reliable for this specific classification task.

4 Discussion

Results of our study indicates a great promise in detecting Alzheimer-like characteristics in sensor data through different deep learning architectures. All models were accurate enough but among them all, recurrent models

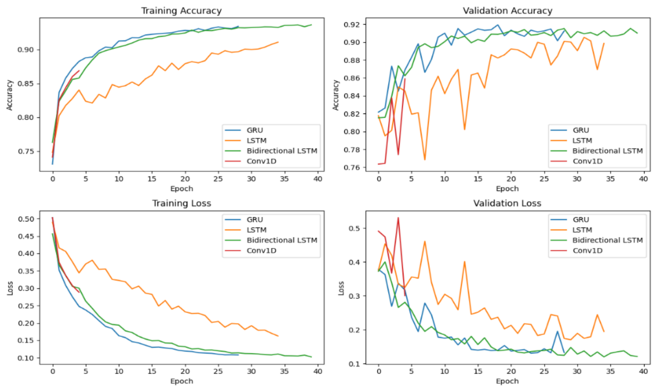

Figure 8: Training and Validation Metrics for Different Models

(trained with GRU, LSTM and Bidirectional LSTM) always outshone Conv1D even on ROC analysis.
Recurrent Neural Networks (GRUs, LSTMs and BiLSTMs): Performed exceptionally well when it comes to building time-based relationships within sensor data due to activity pattern shifts which are usually undetectable meant for cognitive decline while temporally reversing Bidirectional LSTMs had the best ROC AUC score reflecting their ability to utilize data held in both past and future time intervals.
Convolutional Neural Network (Conv1D): However, despite fitting localized correlations effectively Conv1D failed to record sequential dependencies thereby producing poorer recall on class one (that is behaviors resembling Alzheimer's). This implies that understanding an activity change series sequence is key thus making it possible to detect cognitive decline.

The implications for Early Detection: Deep learning models for Alzheimer's disease detection through sensor-based data analysis are promising according to our findings. The reasons are as follows:
Non-Invasive and Unobtrusive: A smart home with sensors gives a non-invasive and unobtrusive method of tracking personal activity patterns that reduces the reliance on alternative methods such as questionnaires or clinical examinations.
Continuous Monitoring: The passive collection of data over extended periods by these sensors allows them to detect subtle changes in one's activity patterns that may go unnoticed during short-term observations.
The Early Warning System: This information can help develop an early warning system for caregivers and health care professionals to aid timely intervention which could eventually slow the course of the illness progression.

5 Conclusion

This research examined how well deep learning models can recognize initial signs suggestive of Alzheimer's disorder based on sensor signals acquired inside a household fitted with intelligent technologies. The outcomes reveal that GRU, LSTM, and Bidirectional LSTM are suitable choices for this assignment, particularly as far as capturing temporality is concerned; hence its best attributes. On the other hand, the convolutional model (Conv1D) had an average performance but exhibited less sensitivity to Alzheimer-like behavior, which implies that there is still room for improving those models used on sequential actions.
This study is significant because it advances non-invasive, unobtrusive, and possibly more sensitive methods for detecting early Alzheimer's disease using deep learning and smart home technology. A system to continuously monitor activities could result in an earlier diagnosis of Alzheimer's disease as well as better care and perhaps even improved management of the illness. Our findings open the door to further investigation regarding this field, such as new sensor technologies, more complex data simulation techniques, and the enhancement of deep learning models to improve Alzheimer diagnosis.

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