Embedded System for ECG Signal Monitoring and Fatigue Detection in Elderly Individuals Using Machine Learning Models

Chokri Baccouch[1]*, Chaima Bahar[2]
LIGM, University Gustave Eiffel, Marne-la-Vallée, France[1]
LR-Sys' Com-ENIT, Communications Systems LR-99-ES21 National Engineering School of Tunis, University of Tunis, Tunisia[1]
MACS Laboratory LR16ES22 National Engineering School of Gabes, University of Gabes[2]

Abstract—**Ascertaining fatigue in elderly people is crucial both for preventing future health complications and for enhancing their quality of life. In this paper, we present an embedded system for real-time fatigue detection and monitoring based on electrocardiogram (ECG) signals, leveraging cost-effective sensors and advanced deep learning architectures. The proposed framework integrates an AD8232 ECG sensor with an ESP32/Raspberry Pi platform for continuous signal acquisition, followed by preprocessing through a 4th-order Butterworth bandpass filter, feature extraction, dimensionality reduction with PCA, and classification using recurrent neural network models. Unlike previous studies relying on multi-sensor or image-based approaches, our solution demonstrates high efficiency, scalability, and affordability by employing a single low-cost ECG sensor. Three neural architectures were evaluated: standard Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). Among them, the GRU model achieved the highest accuracy (98.86%), followed by LSTM (97.73%), whereas standard RNNs lagged behind (82.76%). Experimental results confirm the robustness of GRU in capturing temporal dependencies in ECG data, outperforming other models in both accuracy and computational efficiency. This study highlights the feasibility of deploying lightweight yet powerful AI models in embedded healthcare systems for elderly individuals. By enabling early detection of fatigue as a critical risk factor for falls, cardiovascular incidents, and reduced autonomy. Our approach offers significant societal benefits, including preventive care, reduced hospitalization costs, and improved independence. Future work will extend the dataset and validate system robustness in real-world environments to enhance clinical applicability.**

Keywords—Fatigue; ECG; AI; classification; GRU; LSTM; RNN

I. Introduction

Fatigue is a manifestation that is commonly bred from reproductive responses to stressors, situations, experiences, or psychological conditions. It is typically described as the individual's experience of energy exhaustion, either physical or mental, that hinders them in completing necessary or wanted tasks (energy deficiency). Fatigue may present as general tiredness, or more specifically, symptoms such as muscle soreness. Physical fatigue is the inability to maintain activity at normal levels, and mental fatigue occurs when the brain runs out of energy stores and can no longer continue working as normal. The literature identifies six main categories of fatigue: social, emotional, physical, pain-related, mental, and induced by chronic illnesses. These categories are often grouped into physical and mental fatigue to highlight their distinct effects [1].

Mental fatigue (MF) is a widespread phenomenon in daily lives and work-related activities that are characterized by sustained attention demand and long-lasting efficiency [2]. It is described as a psychobiological condition triggered by prolonged cognitive work [3]. Globally, overwork is linked with diseases such as cerebrovascular and cardiovascular disease, diabetes, and cancer, and is considered a horizontal public health problem [4,5]. Moreover, fatigue as a symptom, affects not only individuals with pre-existing disease, but also healthy individuals [6].

Cardiovascular diseases (CVDs) are among the leading health hazards among the older populations and among the primary causes of mortality, and their prevalence rates increase with the aging of the global population.In 2020, CVDs accounted for approximately 32\% of total deaths globally, with nearly 18 million people dying of CVDs worldwide [7]. The risk is especially clear in people older than 65, as 60% of those aged 75 and up showing signs of CVD. The main risk factors are hypertension, diabetes, smoking and genetic predisposition [8].

One such common manifestation of cardiovascular issues are cardiac arrhythmias, which includes tachycardia (heart rate >100 bpm) and bradycardia (heart rate <60 bpm) [9]. Detection of these anomalies reduce the risks of severe outcomes like heart attacks or strokes. With treatments expensive and care often outside the reach of many, the screening and monitoring of older adults is essential as those older than 70 tend to present with atypical features [9].

As with non-invasive heart function monitoring, electrocardiography (ECG) is an irreplaceable tool for the detection of arrhythmia and assessment of fatigue in the elderly population. One of the most vital signs of worsening health is fatigue, which can be measured effectively through ECG signals with physiological indices related to cardiovascular burden. Compared to image-based approaches, ECG can be used with fewer sensors, is less affected by environmental noise, and requires less computation to implement, making it an efficient and reliable modality for fatigue detection and monitoring in aging populations.

Considering the importance of fatigue measurement in older adults, a method that uses less sensors/electrodes, is less affected by other environmental factors and requires less computation and storage than image-based methods is necessary. Among the physiological measurements, ECG is one of the most promising methods for monitoring elderly fatigue.

Electrocardiograms (ECG) have been and still are the workhorse for assessing and analyzing arrhythmias through recording the electrical activity of the heart. Electrocardiogram (ECG) signals are utilized extensively in clinical diagnostics based on P wave, QRS complex, and T wave, which characterize cardiac function [11]. These signals are produced by the electrical activity of the heart, which radiates not just in the heart but through the body. The sinus node, under the influence of sympathetic and parasympathetic nerves, which regulate this activity. The uniqueness of an individual's ECG, shaped by the size, structure, and orientation of their heart and valves, has also led to its growing use in biometric human identification.

Therefore, under this framework, ECG signals are considered as a dual-use tool for providing important information on cardiovascular health [30] and fatigue in elderly people. There is a great potential of improving health and better quality of life for the elderly by using the state-of-the-art ECG sleep state detection using the newly evolved machine learning methods.

The uniqueness of this work lies in the integration of an embedded system (ECG AD8232 sensor + ESP32/Raspberry Pi) with advanced deep learning models (GRU, LSTM, RNN) for real-time fatigue detection in elderly individuals. Unlike prior works that mainly focused on fall detection or general health monitoring using wearable devices, our study specifically targets continuous ECG-based fatigue monitoring, which is both less invasive and computationally efficient compared to image-based or multi-sensor approaches.

In this work, more specifically, we highlight the difficulty of accurately detecting fatigue in older adults using ECG signals and machine learning. We emphasize the reliability of advanced deep learning models, including GRU and LSTM, applied to ECG signals, in order to provide a reliable and cost-effective solution for real-time fatigue detection in older adults.

The remainder of the article is organized as follows: the second section "Related Work" reviews previous research, while the third section "Materials and Methods" describes the methodology and the proposed dataset. The fourth section "ECG Signal Characteristics and Data Analysis" implements the characteristics of an ECG signal and describes the different steps of data analysis in the form of ECG signals such as signal acquisition, signal filtering, data collection under csv extension until the creation of dataset. The fifth section "Machine Learning Models Used for Fatigue Detection" implements the different learning models used in this work. The sixth section "Results and Discussion" details the experiments conducted and their results. Finally, the seventh section "Conclusion" summarizes the main results and describes the potential directions for future research.

II. Related Work

This section discusses important transdisciplinary studies on ECG signal monitoring and the integration of artificial intelligence techniques to predict and detect the fatigue states of the elderly, highlighting the advances and challenges in this area.

Various non-invasive and cost-effective activity monitoring systems have been reviewed, with a particular focus on sensors integrated into wearable platforms [12,13].

An intelligent mobile environment utilizing integrated sensors embedded in a smartphone is proposed in [14] as one of the Ambient Assisted Living (AAL) methods to recognize the sessions of elderly individuals and their environment. This method uses a layered architectural design made up of a context manager, context reasoner, and service controller.

In [15], the authors developed a context-aware sensor system (CARE) for nurses in nursing homes. This system, available as an application on an Android tablet, uses sensors to improve care services for elderly residents [15].

Due to the serious consequences of falls and fall-related injuries, in [16] a private, real-time, context-aware fall detection system for the elderly was proposed to take into account for this reality. The system consists of a smart carpet with a sensor pad hidden underneath the carpet, which can detect falls and immediately notify the medical staff.

In [17], a fall detection system leveraging smart textiles and a non-linear Support Vector Machine (SVM) has been proposed to classify fall orientations into 11 distinct categories. These categories include activities, such as moving upstairs, running, falling forward, backward, to the right, to the left, and others.

In [18], a unique health monitoring system that uses a single device has been unveiled to monitor the health of senior citizens. This system is to provide healthcare professionals with computer aided decision support to improve the quality and accuracy of medical care.

Eleven elderly individuals were tracked using a Sony wellness tracker in work [19] with data collected on their activities and vital signs. Machine learning helped them anticipate their health and well-being one day before. AAL was also automated to recognize activity, and it was an ambient assisted living system. The system identified the most important characteristics from various sensors and then trained and evaluated various classification models to evaluate their performance.

In [20] a multilayered cloud-based platform for the internet of medical things (IoMT) was proposed to track and collect patient information including vital signs and environmental data for use in AAL. Platform to improve quality of life for older adults and care by aggregating and analyzing real-time sensing data.

Smart home automation system was suggested to promote aging well at home and provide assistance to elderly and sick individuals through continuous health monitoring. Using a range of sensors and technologies, this system can monitor vital signs, identify health problems, and provide assistance to enhance the safety and well-being of older adults around the clock [21].

In [22], a noninvasive ambient intelligence system for older people was suggested to solve the issue of noisy patterns in data collected by multiple wireless sensors installed in the subjects' rooms. Random forest machine learning was used to monitor and analyze regular behavior, such as occupancy and ventilation, in order to ensure adequate monitoring and care for older adults. This method not only provides a safer and more comfortable place to live but also helps identify any patterns of behavior that could indicate potential health issues.

In [23], a fall detection system that uses edge computing has been proposed to enable real time patient monitoring and analysis. Edge computing enables the processing of data on devices, leading to faster fall detection and reduced response times. Fall detection is more reliable and effective, especially in hospitals and medical centers where elderly patients are treated, because it doesn't need to transfer data to the cloud. The system can send immediate alerts to caregivers or healthcare professionals, which can improve the responsiveness of caregivers and potentially reduce the severity of injuries caused by falls.

Real-time data streaming from the wearable sensors, the MetaMotionR in this study, was used in addition to an open-source streaming engine, Apache Flink. Using a long short-term memory (LSTM) network model for fatigue classification, it reported a leading accuracy of 95.8% in detecting fatigues based on real-time streaming data analytics. Immediate notifications were created to support caregivers or clinical staff. Ha et al. used the "MobiAct" public dataset [24] to have a robust learning by able to access different data related to fall.

Besides fatigue detection, a remote health monitoring system for elderly people was suggested, which was monitoring the health by capturing vital signs like pulse, blood oxygen via wearable sensors. This system is used to take care of the elderly by actively monitoring their health to prevent the onset of chronic diseases [25].

Heart rate, blood pressure, and blood oxygen are among the vital parameters that this system continuously measures in [26] via wearable sensors. Healthcare providers receive data via the Internet of Things architecture. Hardware from Arduino and Raspberry Pi is used for communication data collecting and processing, allowing patients with chronic illnesses to receive quick help and remote monitoring.

A body sensor device that continually gathers physiological characteristics from patients was used in a tablet PC-enabled body sensor system that was proposed for rural telemedicine [27].

An automated system in [28] detects unusual situations and instantly alerts medical staff, ensuring timely action when needed. This approach enhances the provision of healthcare in remote areas by enabling timely monitoring and response without necessitating frequent in-person visits. In a different approach, a health monitoring system with RFID sensors was utilized to tag objects using hand gestures, and wireless accelerometers were utilized to classify human body states in order to identify users' daily activities [10]. By tracking and analyzing people's movements and interactions, this technology helps doctors monitor patients' health in real time and provides valuable information about their physical activity.

This study provides an affordable and scalable solution for elderly healthcare. By using low-cost ECG sensors and embedded hardware, the system enables early detection of fatigue, which is a critical risk factor for falls, cardiovascular incidents, and reduced quality of life. Its societal benefit lies in supporting preventive healthcare, reducing hospitalization costs, and enhancing independence for elderly individuals through continuous monitoring.

The manuscript is unique because it demonstrates the feasibility of a real-time, embedded ECG monitoring system for fatigue detection using deep learning. While most previous studies relied on multi-sensor systems, costly equipment, or offline analysis, our approach combines lightweight hardware and optimized AI algorithms for practical deployment in elderly care.

Table I provides a comprehensive comparative analysis of the various approaches discussed in previous work.

TABLE I. PARAMETERS USED DURING RELATED WORKS

Study	Sensor Type	Health Focus	Techniques	Accuracy (%)
[18]	Wearable Smart Band Sensors	Sleep activity and Heart rate monitoring	Lasso regression, ANN, SVM, decision trees	–
[19]	Smartwatch sensors, Smartphone sensors,	Activities Recognition	Random forests, SVM, logistic regression and K-Nearest Neighbors	-
[21]	Motion detection sensor and humidity, ambient Temperature, CO2	Movement detection	Random Forest	68.08%
[22]	Smartphone sensors	Fall Detection	LSTM deep learning technique	98.08%
[24]	Pulse sensor	Heart-rate	LSTM deep learning technique	96.00%
[25]	Pulse Sensor	Heart Rate and Blood Oxygen monitoring	Mobile Application Random Forest	99.00%
Our work	ECG, AD8232 sensor	Activity monitoring	GRU, LSTM, RNN	98.8%

III. MATERIALS AND METHODS

To address the challenges of monitoring cardiac arrhythmias and identifying fatigue in the elderly, our approach focuses on technological innovation and affordability. We offer a hybrid solution comprising an online platform and an embedded system, which leverages cost-effective components such as the Raspberry Pi board, as well as sophisticated artificial intelligence algorithms for accurate abnormality identification (Fig. 1).

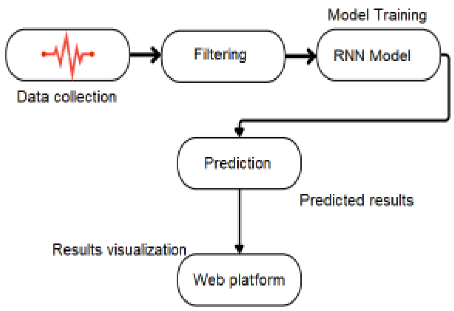


Fig. 1. Proposed framework.

For many years, the electrocardiogram (ECG) has been the gold standard for identifying cardiovascular disease. Arrhythmia can result from any disturbance of electrical impulses that causes the heart to contract. Although people with arrhythmias might not exhibit any symptoms, a doctor may detect arrhythmias during a routine test. As a result, continuous wearable personal monitoring systems are becoming more and more common. The goal of this study is to create and develop a system for both monitoring the ECG signals and predicting arrhythmia (atrial fibrillation). The AD8232 single lead ECG sensor, HC-05 Bluetooth, Raspberry Pi 3, Arduino UNO, biomedical sensor pad, and battery are all used in the system's construction. This method will facilitate remote ECG monitoring and make it simpler for physicians to keep an eye on their patients' ECGs when they are not at the hospital. The core of our system is based on the Raspberry Pi, chosen for its flexibility, low cost, and ability to run AI applications. This embedded system is designed to continuously collect ECG data at home or in any other environment requiring cardiac monitoring. The Raspberry Pi, equipped with ECG sensors and a connectivity module, enables real-time acquisition of cardiac data, which is then preprocessed to extract relevant characteristics before analysis. In real-time systems, the AD8232 sensor ensures adequate data collection by capturing ECG signals without omitting essential information (Fig. 2). These signals are distinct and can be studied after preprocessing using advanced filtering methods to remove noise or artifacts. Appropriate indicators are selected from the processed ECG signals, and then an analysis is performed on these indicators to define different degrees of fatigue.

The uniqueness of study is twofold:

- From the hardware perspective, the system adopts a low-cost ECG AD8232 sensor coupled with ESP32/Raspberry Pi for real-time signal acquisition and processing.
- From the software perspective, we adopted advanced filtering (Butterworth bandpass 10–40 Hz) + PCA + GRU/LSTM to achieve superior fatigue detection performance.

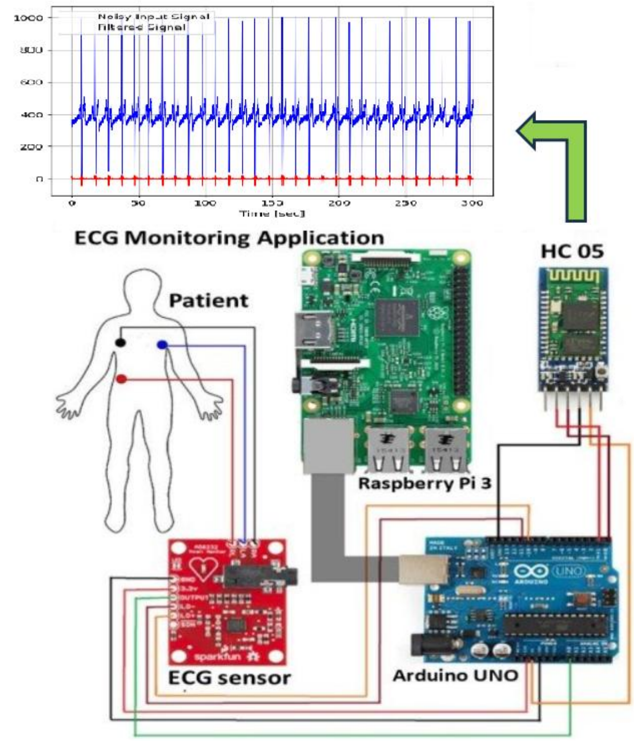


Fig. 2. Embedded system for ECG signal monitoring.

The studies conclude by demonstrating the high accuracy and precision with which deep learning architectures like GRU, LSTM, and RNN can identify fatigue states. By using cutting-edge biomedical signal processing techniques to create methods for quickly determining the elderly's fatigue level, this initiative respects established ethical standards and lessens their load.

IV. ECG Signal Characteristics and Data Analysis

The electrocardiogram (ECG) records the electrical activity of the heart. Each ECG wave corresponds to a specific electrical event. The ECG trace is a form of visualization of the electrical voltages resulting from the heart's excitation. These signals are obtained from specific points located on the skin (leads). The ECG, therefore, expresses the electrical events of cardiac excitation and can provide information on the state of the heart. The heart rate, the nature and genesis of the rhythm, the extent and effects of the excitation, as well as any disturbances, whether anatomical or mechanical in origin.

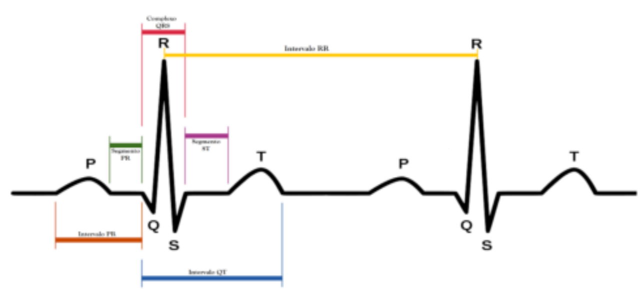


Fig. 3. Representation of an ECG signal.

A. Signal Acquisition

This section shows the realistic assumption of the embedded system which has been developed for the processing of electrocardiogram (ECG) signals for continuous fatigue monitoring and classification. This system consists of two main components, the first is the AD8232 sensor and the second is the ESP32s microcontroller. Fig. 3 shows representation of an ECG signal.

The AD8232 is a sensor which is a compact ECG monitor heart module which is capable to monitor heart electrical activity and display them in ECG graph form. It is intended to isolate, amplify and filter minute biopotential signals in the presence of interference such as muscle contractions or contact bias from lead wires or electrodes. For making these measurements correct electrodes have to be positioned as follows: RA (right arm), LA (left arm), and RL (right leg) [29]. The Espressif Systems ESP32s microcontroller is a System on Chip (SoC), which is based on the technology development of Xtensa LX6 by Tensilica. It has built-in Bluetooth and Wi-Fi modules and a dual-core processor with a clock frequency of 240 MHz. Due to its on-chip connectivity and low power consumption the ESP32s provides many possibilities for Internet of Things and embedded applications.

In capturing ECG signals, the first stage was to configure the ESP32s microcontroller, which was done in a few steps using the Arduino IDE for programming. Initially, the ESP32s was made to record average values of electrocardiogram signals from the AD8232 sensor that monitors the activities of the heart. The processed data was used to derive parameters like heart frequency together with making corrections on the reliability of the parameters computed. This facilitated the storage of data into CSV files for easy retrieval in the data set for heartbeat counts and trends analyses.

Data was collected using the AD8232 ECG sensor module, connected to the ESP32 microcontroller for signal acquisition and preliminary preprocessing. The electrodes were placed at RA (right arm), LA (left arm), and RL (right leg). Signals were sampled at 250 Hz, filtered using a 4th-order Butterworth bandpass filter (10–40 Hz), and stored in structured CSV files. A database of 100 subjects was constructed, comprising 50 segments of 2-minute ECG recordings each, totaling over 180 million labeled data points.

A section of the USB header in this circuit board, where the processing unit is embedded, communicates through a serial plotter (or otherwise logic or protocol analyzer A). This is an effective tool for checking and fixing signals inside the scopes of serial communication systems as it enables the tracking of how the data flows in real time and allows the practitioner to confirm that the heart rate data acquisition process works as intended. This setup allows the users to easily check and repair faults thereby rendering it very effective for processing and analyzing electrocardiogram signal in real time (Fig. 4).

B. Signal Filtering

After getting the data, the next step is filtering to make the results better and more accurate. This step removes unwanted noise or errors, like signals from muscle movements, outside electrical signals, or changes in the baseline that can mess up the original data. For example, with ECG data, we use low-pass filters to remove high-frequency noise, high-pass filters to fix low-frequency baseline changes, and bandpass filters to focus on the heart's important frequency range. This keeps the key details about the heart's electrical activity intact. By using these filters, we get cleaner data, which makes the next steps of analysis and understanding more reliable.

Because of its flat frequency response, smooth transition, ease of design, stability, and robustness, 4th-order Butterworth filter was chosen to bandpass filter of ECG signals. Although some of the filters may offer greater sharpness of transition or better phase response, they generally suffer from the presence of ripples or complexity irrelevant to ECG signal analysis. The Butterworth filter provides a just right compromise for this particular use case, providing faithful representation of the target frequency components without introducing distortions or artifacts.

Bandpass filtering was a key step in analyzing the collected ECG signals. In this filtering method noise and interferences are removed and only target frequency components remain. In the case of ECG signals, useful frequency range is generally within the range of 10 Hz to 40 Hz.

The bandpass filtering was implemented using MATLAB. A 4th-order Butterworth filter was previously designed using the butter function and cutoff/pass frequencies of 10 Hz and 40 Hz, respectively. Such configuration guaranteed that the filter is able to perfectly attenuate the frequencies of the desired ECG signal without contributing to signal distortion and thereby facilitates further analysis.

This method successfully eliminated high- and low-frequency interference while maintaining the essential frequency components of the ECG signals, enhancing the accuracy of detecting key waves such as the P wave, QRS complex, and T wave. This was vital for the later analysis of arrhythmias.

The choice of cutoff frequencies at 10 Hz and 40 Hz was based on the fact that the majority of the energy in ECG signals lies within this frequency range. The lower cutoff frequency of 10 Hz able to filter out base-line wander and low-pass fluctuations with the upper cutoff frequency of 40 Hz, removing high-pass noise from the EM interference and muscle movement sequency range ensuring that the beating features of the ECG signal, P, QRS, and T waves, are retained while removing artifacts that could bias signal analysis accurately.

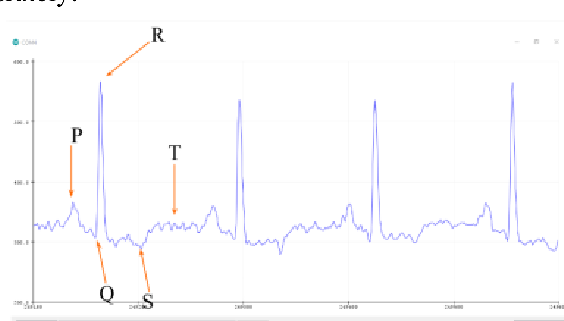


Fig. 4. ECG serial plotter.

As in Fig. 5, the introduction of a 4th-order Butterworth filter with cutoff frequencies of 10 Hz and 40 Hz significantly eliminated undesirable noise and interference while maintaining the main frequency elements of the electrocardiogram (ECG) signal. A comparison of the data prior to and after deconvolving reveals an effective reduction of baseline wander and high-frequency artifacts. Zooming in on the filtered signal clearly shows an improvement in the visibility of the characteristic P, QRS, and T waves, which are crucial for arrhythmia analysis. These findings validate the performance of the Butterworth filter to improve ECG signal quality, enabling analysis to be more accurate and reliable.

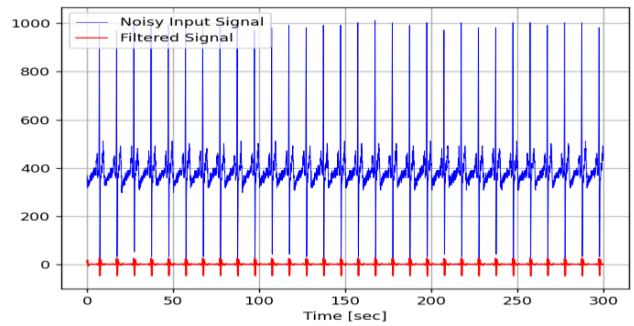


Fig. 5. Real ECG signal before and after filtering.

C. Dataset

Developing a robust database is a essential factor for the success of a machine learning-based solution. In this study, we created a database using data collected from sensors, combined with the outputs from the filtering steps, to ensure optimal quality and relevance of the data for future analyses.

Database structure was designed hierarchically for effective data management. A major collection, "csv files", was generated to store each patient's documents individually. Each patient document was then divided into sub-collections named "Patient+number," where the ECG data was stored in an organized manner.

Our database contains patient data on large volumes of ECG recordings. This encompasses demographic information, medical history, as well as individual ECG data points that were captured during the course. Each patient's data is organized to ensure easy access and retrieval, with clear labeling and structured data points to facilitate analysis. It also permits to analyze patient conditions in detail, and to detect both regular and abnormal patterns in their Electrocardiographic measures, as a means toward improved diagnosis and prognostic care.

Specifically, we indicate that the ECG data was collected using the AD8232 sensor connected to an ESP32 microcontroller, with signals sampled at 250 Hz and filtered using a 4th-order Butterworth bandpass filter. The dataset consists of 100 subjects, with 50 segments of 2 minutes each, totaling over 180 million labeled data points. We have also emphasized that this dataset was built for the purpose of this study and will be further expanded in future work to improve diversity and clinical validation.

V. Machine Learning Models Employed for Fatigue Detection

The study proposes a deep learning-based fatigue classification framework optimized for ECG signals. Specifically, we developed a GRU-based recurrent model with tailored hyperparameters and dropout regularization, which outperformed both LSTM and standard RNN in accuracy and generalization.

Neural networks of the RNN family are used to handle sequential data, including 1D physiological signals. A "memory" of prior inputs might remain in the internal state of an RNN thanks to feedback connections between hidden units [8].

A. Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNN) are the core deep learning frameworks intended for sequential and time-series data. In contrast to conventional neural networks, the RNN model takes into account a feedback mechanism, which allows information retention and thus allows information persistence to model temporal dependence. In the context of ECG data, RNN process sequential heart activity signals by maintaining a "memory" of past information. The design comprises of an input layer, a hidden layer and an output layer, with the hidden layer holding the state to its previous state. On the other hand, by virtue of their tendency to experience vanishing gradient, direct use of RNN is often restricted in the extraction of long-term dependencies in ECG data.

The RNN architecture (Fig. 6) is built on the concept of feedback, where outputs from earlier time steps are looped back into the network, as illustrated in Fig. 6. With this mechanism, the network is able to remember past states and capture temporal long-term dependencies efficiently.

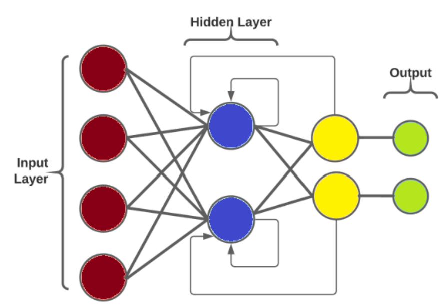


Fig. 6. Architecture of the recurrent neural network.

B. Gated Recurrent Units (GRU)

Group of gated recurrent units (GRU), in Fig. 7, is a generalization of recurrent neural networks (RNN) which is intended to solve the deficiencies of the original models, most notably the vanishing error problem at the time of training. Their simplified architecture utilizes memory units with gates to control the flow of information. In contrast to conventional RNN, GRUs are structurally simpler, more efficient at making use of long-range context in time series data, and thus less computationally demanding. That makes them highly appropriate for any task needing powerful sequential modelling without the expense of a more resource-hungry architecture such as LSTM.

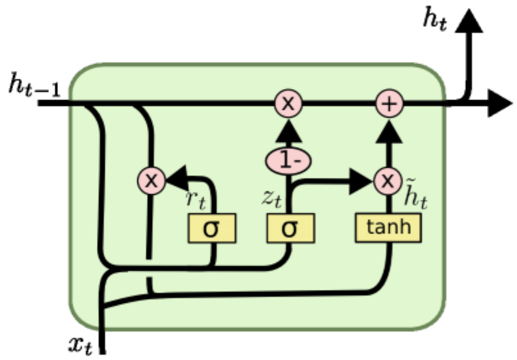


Fig. 7. Architecture of the gated recurrent units (GRU) [31].

C. Long Short-Term Memory Networks (LSTM)

Long Short-Term Memory (LSTM) is a specific type of recurrent neural network (RNN) capable of learning long-term dependencies. It is designed to solve the vanishing and exploding gradient problem often encountered in traditional RNNs. Fig. 8 illustrates the architecture of an LSTM cell. An LSTM cell in recurrent neural networks is much more complex than a traditional RNN cell or a classical neuron. It consists of a memory cell, a forget gate, an input gate, and an output gate, managing a dynamic memory (denoted C) that evolves with the temporal data sequence.

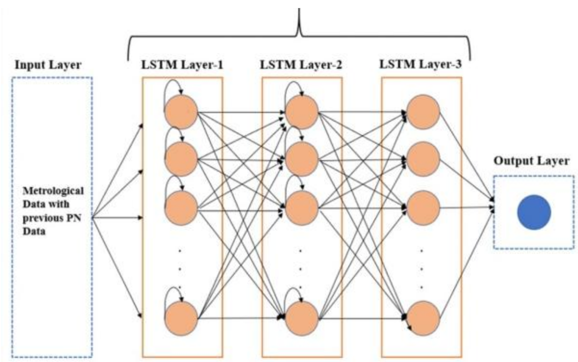


Fig. 8. Architecture of the long short-term memory (LSTM) [32].

The parameters utilized in the experiment are described in Table II.

TABLE II. HYPER-PARAMETER USED AGAINST VARIOUS MODELS

Hyper-parameter	GRU	LSTM	RNN
Number of units	64	128	32
Number of layers	2	2	1
Dropout	0.2	0.3	0.2
Recurrent dropout	0.2	0.2	-
Activation function	tanh	tanh	relu
Optimizer	Adam	Adam	Adam
Learning rate	0.001	0.001	0.001
Batch size	64	32	64
Epochs	50	50	50

D. Performance Metrics

The binary classification of having fatigue produces four outcomes: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

- True Positive (TP): Correct positive prediction
- True Negative (TN): Correct negative prediction
- False Positive (FP): Incorrect positive prediction
- False Negative (FN): Incorrect negative prediction

Eq. 1 provides the model's prediction accuracy, which is the ratio of properly classified samples to total samples.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Eq. 2 provides a precision formula that measures the correctness of the model by dividing the number of successfully identified positive values by the total number of expected positive samples.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Eq. 3 provides the recall of a model, which is defined as the ratio of correctly predicted positive samples to all positive samples.

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

Eq. 4 finds the harmonic mean of Precision and Recall based on the model's F1 score.

$$F1 - Score = \frac{2.Precision.Recall}{Precision+Recall} \tag{4}$$

The novelty does not reside in creating a completely new neural architecture, but in the adaptation and optimization of GRU and LSTM architectures for ECG-based fatigue detection. We designed a hybrid signal processing and classification pipeline combining PCA-based dimensionality reduction with optimized hyperparameters for GRU and LSTM. This configuration significantly improved accuracy (GRU: 98.86%) compared to conventional RNNs and existing methods reported in the literature.

VI. RESULTS AND DISCUSSIONS

A. Results

Some general graphical visualizations of the training of LSTM, RNN, and GRU models were created using various visualization software packages, particularly Matplotlib. These graphs, including loss curves and performance metrics over multiple epochs, provide critical insights into the behavior of each model. Having determined these metrics (based on Fig. 9, 10 and 11), users can also assess the convergence behavior, stability and overall efficacy of the models for learning data patterns. By using this visualization, it is possible to get a global idea of the strengths and weaknesses of each strategy with regard to fatigue detection in older adults.

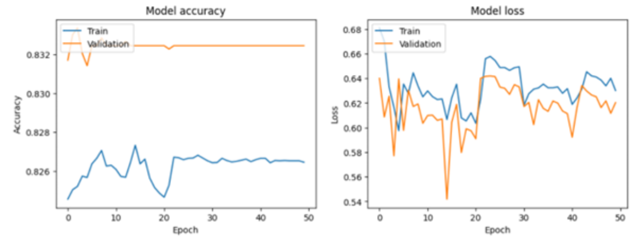


Fig. 9. Accuracy and loss for RNN model.

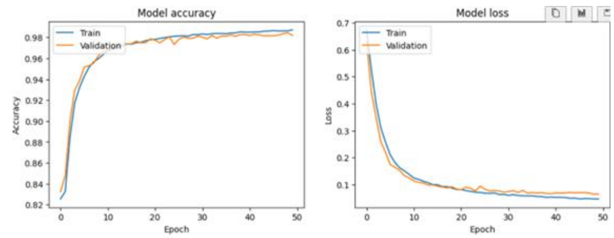


Fig. 10. Accuracy and loss for GRU model.

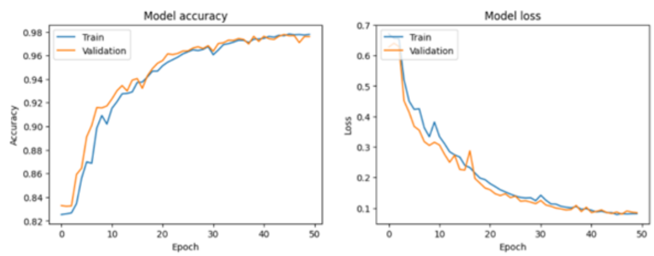
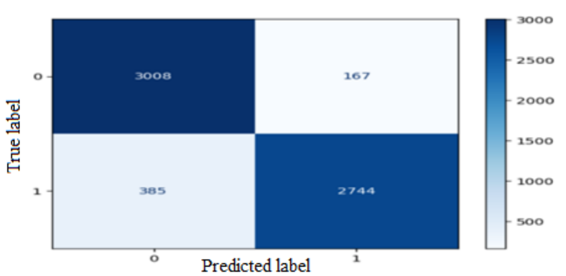
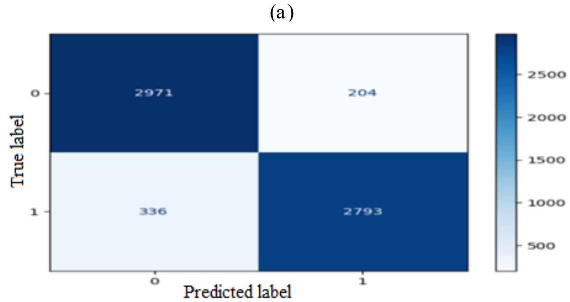


Fig. 11. Accuracy and loss for LSTM model.

The confusion matrix is a visualization technique used to assess the performance of a classification model by comparing actual and predicted values. Fig. 12 presents the confusion matrices of the best-performing models, namely, the GRU and LSTM.



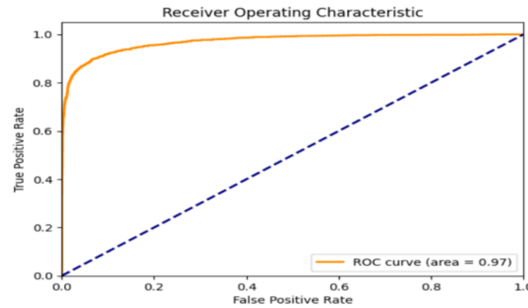
(a)



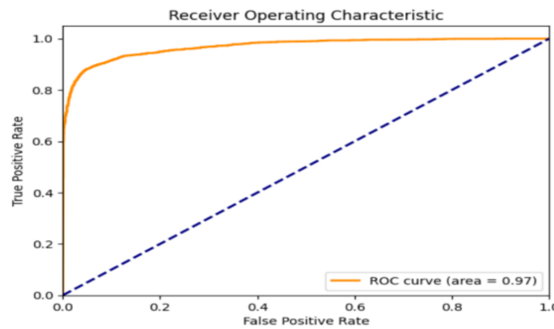
(b)

Fig. 12. Confusion matrix: (a) GRU; (b) LSTM.

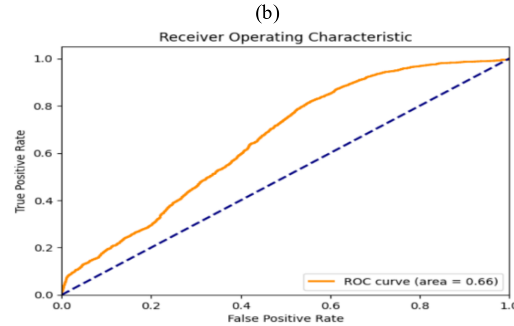
Another parameter we studied is the ROC curve which is a graphical representation used to evaluate the performance of a binary classification model at different decision thresholds. It shows the true positive rate (sensitivity) as a function of the false positive rate (1 - specificity) for each classification threshold. Fig. 13 shows the ROC curves of our GRU, LSTM and RNN models.



(a)



(b)



(c)

Fig. 13. ROC curve: (a) GRU; (b) LSTM; (c) RNN.

B. Discussions

In this section, we review the experimental results used to illustrate the performance of the proposed technique, as well as the outcomes related to fatigue detection. As shown in Table III, we present and compare the performance of the LSTM, GRU, and RNN models.

TABLE III. COMPARATIVE RESULTS

MODEL	ACCURACY	RECALL	F1-SCORE	AUC
GRU	98.20%	0.0649	0.98	0.99
LSTM	97.42%	0.1000	0.97	0.97
RNN	83.24%	0.6203	0.82	0.66

Among the three models evaluated, the GRU achieved the highest overall performance, with training, validation, and test accuracies of 98.86%, 98.20%, and 97.96%, respectively, and the lowest loss values, indicating strong consistency between training and validation. The LSTM model, while slightly less accurate than GRU, still produced very good results, obtaining 97.73% training accuracy, 97.42% validation accuracy, and 97.32% test accuracy, with losses only marginally higher than those of GRU, thereby confirming a reliable data fit. In contrast, the RNN model demonstrated the weakest predictive capability, with training, validation, and test accuracies of 82.65%, 83.24%, and 82.76%, respectively, and the highest loss values, reflecting its poorer agreement with the training and test data compared to GRU and LSTM.

In conclusion, the GRU model stands out as the best choice for our task, with the LSTM model following closely behind. Although RNN model does satisfactory accuracy when used, it is very different in accuracies between the three models.

In particular, we show that the GRU-based model achieves superior performance (98.86% accuracy) compared to both traditional RNNs and LSTMs, while also being computationally more efficient. Additionally, unlike many prior studies that rely on multi-sensor or image-based systems, our approach uses a single low-cost ECG sensor with optimized deep learning models, making it more practical and scalable for real-world elderly healthcare applications.

We conclude that the classification of ECG signals makes it possible to transform continuous physiological measurements into interpretable clinical labels (“fatigue” or “no-fatigue”), which enables real-time monitoring and early intervention in elderly patients.

VII. Conclusion

This study demonstrates the potential of ECG signal monitoring and classification for detecting fatigue states in elderly individuals, leveraging advanced machine learning models. Among the tested algorithms, the Gated Recurrent Unit (GRU) emerged as the most effective, achieving exceptional performance metrics with a test accuracy of 97.96% and minimal loss, indicating a robust ability to capture complex temporal dependencies in ECG signals. The model of Long Short-Term Memory (LSTM) also performed well with similar accuracy and proved its robustness for this task.

In contrast, the traditional type of Recurrent Neural Network (RNN) showed poor performance with significantly reduced accuracy (82.76% and higher loss expressing its unsuitability in the complexity of ECG data as the GRU and LSTM models could. These findings illustrate the necessity of the use of highly developed neural configurations for the effective and accurate classification of physiological signals.

The superior performance of the GRU model shows the applicability of the model as the basis for real-time fatigue detection systems, having significant capability for integration into wearable and remote healthcare monitoring devices. Further research on improving the performance of these models, the use of larger data sets, and the robustness of these models in situations other than the laboratory is necessary to enhance their scalability and generalizability. Through the development of an electrocardiography-based fatigue detection, this work makes a step toward health monitoring and preventive care for aging groups.

We also note the need for extended real-world testing to evaluate long-term robustness, scalability, and integration into healthcare systems. By acknowledging these limitations, we provide a more balanced and comprehensive review of the research while outlining directions for future work.

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