AI-driven technologies in Digital Health & Well Being: early detection and intervention strategies

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Abstract

Artificial Intelligence (AI) is increasingly central to scientific research, especially in digital health and well-being. Technological advancements enable early detection of health issues and personalized treatments, facilitating real-time monitoring, promoting healthy lifestyles, and providing rehabilitation aids. The adoption of AI technologies requires reliability and promotes the development of symbiotic artificial intelligence systems, wherein humans and AI collaborate synergistically. This paper provides valuable insights into the study areas explored by our team. Our primary focus has centered on employing AI and explainable AI (XAI)-based methodologies to enable early detection and decision-making processes regarding treatments and rehabilitation for conditions such as skin melanoma, heart disease, and neurological disorders. It is crucial to recognize the importance of symbiotic systems and diagnostic support tools that rely on reliable technologies such as AI and XAI. The integration of these technologies not only improves the effectiveness of treatments and rehabilitation but also promotes greater transparency and understanding in the decision-making processes, underscoring their crucial role in the future of healthcare.

Keywords

Artificial Intelligence, eXplainable Artificial Intelligence, Symbiotic Artificial Intelligence, Mental Health, Alzheimer disease

1. Introduction

Artificial Intelligence (AI) is becoming increasingly prominent in scientific study, particularly in the field of digital health and well-being. Indeed, the European community, recognizing the importance of the convergence of technology and health, has adopted substantial investments to promote the development of cutting-edge technologies that leverage AI to improve the quality of life and overall health of the population. Recent deployments under the coordinated AI framework make possible the adoption of a new generation of technologies in digital wellness, with an emphasis on health. Thanks to rapid advances in AI, computer systems have acquired analytical and predictive capabilities that can facilitate early detection of potential health problems by helping to identify risky conditions while avoiding pathological degeneration. In parallel, the use of these technologies has drawn attention to the critical role of Explainable AI (XAI) in ensuring transparency and trustworthiness in the decision-making processes of these systems [1]. The practical applications of AI in digital health and wellness are heterogeneous. Among these emerge: 1) Early detection and intervention: analyzing extensive data aids in identifying precursor signs, enabling timely interventions; 2) Personalized treatment: AI tailors treatment plans to individual characteristics, enhancing effectiveness and patient satisfaction; 3) Real-time monitoring: continuous vital sign monitoring provides instant data for informed decision-making. 4) Promotion of healthy lifestyles: AI offers personalized advice through apps and devices, fostering better habits. 5) Rehabilitation: AI assists in designing tailored rehabilitation programs, and improving outcomes.

Despite the significant inherent benefits, accepting and adopting AI-driven technologies in the digital health and wellness fields may need more awareness and trust among users. Thus, such technologies must be designed with deep consideration of the specific needs of the end users and be able to adapt dynamically to their changing status and needs. The integration of AI systems with human users creates a mutually beneficial relationship promoting the design of Symbiotic AI (SAI). In SAI, humans and AI work together synergistically, each leveraging the strengths of the other to achieve common goals. This collaborative approach emphasizes trust, transparency, and effective communication between humans and AI systems. Symbiotic AI has the potential to enhance decision-making, problem-solving, and productivity across var-

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ious domains while maintaining control and oversight over the decision-making process [2].

In this context, our projects represent significant progress in the development of innovative strategies for early disease diagnosis and intervention methods.

2. Research Fields

Our primary research focus is medical image analysis, emphasizing the development of AI-driven and XAI algorithms to understand their decisions. We aim to improve diagnoses and outcomes across cardiovascular, skin cancer (melanoma), Alzheimer's (AD), and Parkinson's diseases (PD). Our research focuses on utilizing XAI techniques to establish a trustability index for AI models analyzing melanoma images and PVC signals. Through SAI systems, we aim to create reliable Computer-Aided Diagnosis (CAD) systems. Additionally, we employ neurogenetic Recurrent Neural Networks (RNNs) to identify PVCs and Deep Learning (DL) to classify COVID-19 individuals using Electrocardiogram (ECG) signals. Our research group designs and implements innovative AI methods, focusing on mental health. Our proposed research aims to enhance the diagnosis of schizophrenic syndrome [3] and rehabilitation of neurodegenerative disorders like Alzheimer's [4]. Our goal is to build decision support tools for mental health professionals' clinical diagnoses to reduce health care expenditures and promote early diagnosis and intervention. Additionally, we are creating AI-based cognitive and emotional rehabilitation solutions for AD patients to improve their quality of life and reduce cognitive impairment through individualized systems that take into account their unique traits.

These activities were developed at the University of Salerno, particularly at the CAIS Lab[1].

3. Skin Cancer

Melanoma is one of the most common types of skin cancer worldwide. In 2023, the American Cancer Society recorded 97,610 new cases, affecting 58,120 men and 39,490 women [2]. Despite representing just 1% of skin cancers, melanoma sustains a high mortality rate, underscoring the essential need for early diagnosis enabled by CAD systems.

3.1. XAI on melanoma images

One of the crucial aspects that makes building reliable CAD systems difficult is the fact that differences in neural network structures might undermine confidence in AI methods, highlighting the importance of reliable and resilient models. There is a need for trustworthiness in establishing confidence in AI systems, specifically in the context of Digital Health. A transparent AI system helps to build confidence among users by highlighting the significance of understanding AI decisions from the perspective of SAI systems. To address this issue, we employed the GRADient-weighted Class Activation Mapping (Grad-CAM) algorithm to show how five Convolutional Neural Networks (CNNs), AlexNet, GoogleNet, ShuffleNet, MobileNetV2, and SqueezeNet, perform in identifying the most relevant features in images for the final decision of the model [5]. Table 1 highlights that, overall, the best performance is obtained by AlexNet, which reached an 82%, 87.4%, 75.8%, 81.5%, and 84.3% of Accuracy (ACC), Sensitivity (SN), Specificity (SP), Precision (PRE) and F1 SCORE (F1), respectively. In Figure 1, the behavior of networks on the same images demonstrates how distinct networks learn vastly different features when the Grad-CAM algorithm is applied. The results highlighted the necessity for consistency and robustness in AI models and allowed us to define a trustability index, defined as (Λ), in the range ($\Lambda \in [0, 1]$), where a value near 1 indicates max trustability. We calculate the trustability index across all pairs and globally for all of the networks. Results, validated by Λ calculation, indicate that relying on only one AI model for melanoma detection lacks reliability without common shared patterns. It underscores the importance of collaborative approaches, considering network interactions and synergies.

Table 1
Performance results of the five CNNs

CNN	ACC (%)	SN (%)	SP (%)	PRE(%)	F1 (%)
Alexnet	**82**	**87.4**	**75.8**	**81.5**	**84.3**
GoogleNet	75	91.9	54.9	71.3	80.3
ShuffleNet	76	89.2	59.3	72.8	80.2
MobileNetV2	76	82	68.1	75.8	78.8
SqueezeNet	85	92.8	67	75.8	78.8

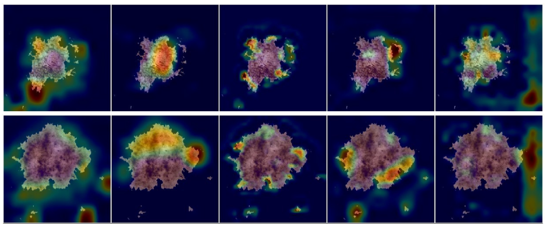

Figure 1: Two different networks learn very different features from Benign and malignant skin lesions (1 lesion at row).

[1]https://caislab.di.unisa.it
[2]https://www.cancer.org/cancer/melanoma-skin-cancer/about/key-statistics.html

Table 2
Final Results

Models	ACC	RE	SP	PRE	F1	gmean	AUC
ResNet-18	**98,9%**	**95,3%**	**100%**	**100%**	**97,6%**	**97,6%**	**99,4%**
ResNet-50	98,5%	96,9%	99%	96,7%	96,8%	97,9%	99,4%
SqueezeNet	98,8%	95,8%	99,7%	99,1%	97,4%	97,7%	99,4%
MobileNetV2	87,7%	93,5%	86,7%	55,5%	69,7%	90,1%	98,3%
AlexNet	86%	94%	84,6%	51,9%	66,9%	89,2%	98,1%
OurCNN	75,2%	91,3%	72,4%	37%	52,6%	81,3%	97,5%

4. Cardiovascular Diseases

The prevalence of cardiovascular disease (CVD) is rapidly increasing over the world. According to the World Health Organization (WHO), CVD accounted for 17.9 million deaths in 2019. This data underscores the global effects of CVD and highlights the significance of preventive actions to reduce its impact on individuals and society.

4.1. SARS-CoV-2 detection through DL

The uncontrolled transmission of the COVID-19 pandemic required the adoption of preventive measures such as surgical masks, hand sanitization, and social distancing. Although molecular swabs and X-rays are recognized as the most accurate diagnostic methods, they have disadvantages in terms of time, expense, and invasiveness. Therefore, the significance of researching alternate methods, such as ECG signals, increased. The objective of this study was to establish a correlation between ECGs and COVID-19 infection in a dataset of 1937 images divided into: patients with COVID-19 (COVID), with Myocardial Infarction (MI), with Previous History of Myocardial Infarction (HMI), Abnormal Heartbeat (ABN) and healthy (N). The study applied different Deep Learning algorithms, such as MobileNetV2, ResNet-18, ResNet-50, AlexNet, SqueezeNet, and a proprietary neural network. Training sessions progressed through comparisons of all five classes, then four (COVID-19, N, ABN, HMI), followed by three (COVID-19, N, ABN), and finally in a binary comparison (COVID-19 vs. N). The results (see Table 2) demonstrated a high level of accuracy in classification, with ResNet-18 having an approximate accuracy of 98.94%, both for multiclass and binary classification. The study suggests a correlation between ECG signals and COVID-19 infection, potentially enabling the integration of proposed neural networks into healthcare monitoring systems for real-time detection.

4.2. Design of RNN with neuroevolution approach

PVCs disrupt normal heart rhythms, particularly the QRS complex but their identification in ECG signals is crucial for avoiding misdiagnosis. We started from two main hypotheses: first, different types of PVCs correlate with distinct patterns in the electrical signal; second if various PVC types exist, it is feasible to divide an ECG dataset into clusters, each associated with a potential outcome. In this work [6], we investigated the potential of the Extended Genetic Algorithms (EGA) approach to design RNNs. In particular, Long Short-Term Memory (LSTM) and bidirectional LSTM (BLSTM) models are employed to examine QRS complexes in the MIT-BIH Arrhythmia Database, which includes both non-PVC and PVC data, to understand the typical features of standard QRS signals and learn to reproduce them. Genetic algorithms (GAs) are optimization techniques inspired by biological principles of the evolutionary theory. The neuroevolution approach employs these evolutionary algorithms to produce artificial neural networks (ANN), parameters, and rules. They enable the discovery of optimal solutions to optimization problems by emulating natural selection, iterating through generations to improve candidate solutions. Consequently, these trained RNNs can accurately assess new ECGs with normal QRS complexes by minimizing Root mean square error (RMSE) between predictions and actual values. These architectures allow us to achieve a Root Mean Square Error (RMSE) of 15. Initial results suggest that PVC patterns likely reside in the central segments of ECG signals (Figure 2). RSME values in these segments support this observation, emphasizing their importance for precise PVC detection.

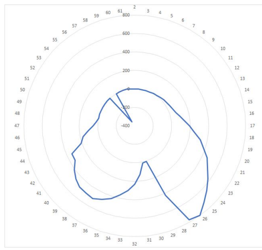

Figure 2: Estimated ECG signal zones related to PVC with higher RMSE variability compared to normal QRS complexes.

4.3. CardioView: A XAI framework for detecting PVCs

In this study, we proposed a visual framework, called *CardioView*, that integrates a human-in-the-loop (HITL) approach, ensuring continuous engagement and oversight of cardiologists during the PVC detection process. In this initial phase of the work, our focus was on PVC classification, the implementation of XAI algorithms, and their clustering. Figure 3 outlines the workflow of the proposed framework, beginning with pre-processing on

[2]https://www.who.int/health-topics/cardiovascular-diseases

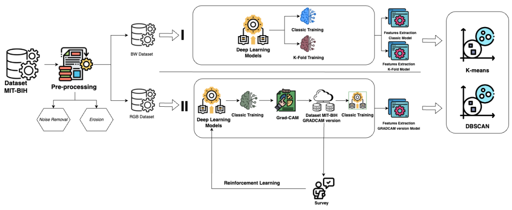

Figure 3: CardioView workflow

the MIT-BIH Arrhythmia Database to enhance data quality. It involves two phases: training a CNN model on a black-and-white (BW) dataset using classic and k-fold methods, followed by feature extraction. The RGB (red, green, and blue) dataset is then trained using the classic method, with the resulting model applied to the Grad-CAM algorithm for dataset modification and retraining. Trained models extracted vital features, employed in k-means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering algorithms to identify patterns of PVC and non-PVC for early diagnosis. Grad-CAM facilitated the visualization of ECG waveform segments, effectively distinguishing between PVC and non-PVC, highlighting potential multiple PVC classes, indicating diverse outcomes. The proposed CNN achieved 96.21% of ACC, 98.09% of recall (RE), 94.74% of PRE, and 99.28% of Area under the ROC Curve (AUC) on the GRADCAM dataset, highlighting promising results in PVC detection. CardioView integrates cardiologist surveys, crucial for the human-in-the-loop process integral to reinforcement learning (RL). This approach emphasizes the active participation of cardiologists, enhancing the reliability and accuracy of PVC detection. CardioView is structured to collect data via surveys distributed to cardiologists, assisting in algorithm refinement. The dynamic survey involving experienced cardiologists to express confidence levels in the AI model outcomes (see Figure 4). Cardiologists evaluate 20 images, providing feedback on XAI efficacy and suggesting improvements if needed, promoting iterative refinement in PVC detection.

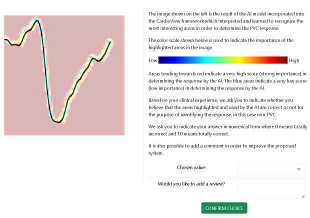

Figure 4: Step of the survey in CardioView

5. Neurological Diseases

Alzheimer's disease (AD) is a condition characterized by the gradual accumulation of abnormal proteins, particularly amyloid-β (Aβ) and hyperphosphorylated tau, within the brain. This accumulation causes progressive impairment of synaptic function, neuronal health, and axonal integrity [7]. Regarding cognitive features, AD mainly affects episodic memory (EM), semantic memory (SM), and spatial abilities (SA). However, the clinical presentation may vary in moderate or early cases. AD patients not only experience memory and visuospatial disorders but also a range of symptoms that affect their emotional well-being. These symptoms include difficulties in problem-solving, feelings of sadness, and lack of motivation, which substantially impact the patient's daily functioning.

5.1. Technology-driven rehabilitation strategies

In recent years, due to advances in AI, research has turned increasing attention to the analysis and design of rehabilitative interventions targeting AD patients based on the use of advanced technologies such as computerized cognitive training (CCT) and interventions that exploit social robotics.
These approaches are aimed at providing adequate therapeutic support to counter the decline of cognitive function in AD patients, presenting themselves as complementary or alternative options to traditional therapies.
The connection between sophisticated technological tools and targeted rehabilitation methodologies is a growing area of research in digital health and, in particular, in caring for the elderly with neurodegenerative diseases.

5.2. Mosaic of Memory: a serious game for Alzheimer's patients

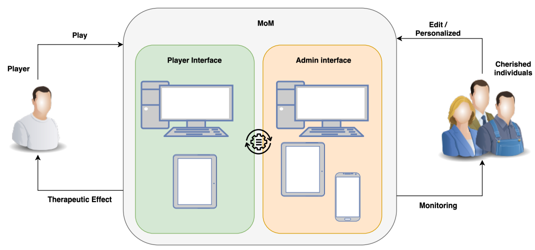

Figure 5: MOM experimental flow

Mosaic of Memory (MoM) is a serious game designed for AD patients inspired by the traditional "memory" card game. The game's objective is to make correct matches of cards presented on a virtual grid, depicting the faces of the patient's loved ones. MoM falls within the scope of CCTs and aims to slow down the deterioration of (i) spatial memory, as it is necessary to memorize the spatial positions of cards to proceed with the game, and (ii) autobiographical memory, due to the personalized content of the game. MoM leverages a multimodal approach that combines visual and auditory stimuli to achieve its therapeutic goals and facilitate memory reinforcement. While the cards convey visual stimuli, the auditory stimuli consist of audio recordings of the people depicted on the cards. This feature gives the game a high level of customization, reinforced by MoM's ability to dynamically adapt to the user's cognitive abilities through different game difficulty levels (easy, medium, expert) or by selecting the automatic mode, which automatically adapts the game to patient capacity. This ensures that the game is always challenging but not frustrating for the player. When players experience high frustration levels, this negatively influences the gaming experience, leading to anger and stress. For this reason, MoM is equipped with AI, particularly an AU R-CNN model, designed to detect facial microexpressions through a multi-label classification approach [8]. This improves MoM's ability to detect and respond to player frustration during gameplay. An additional distinguishing feature of the application is the dedicated patient profile for gaming and an administrative interface explicitly aimed at a loved one or the AD patient's therapist. This interface allows you to customize the user experience by changing the background color and cards and modifying the game content (images, names, and audio recordings of loved ones). The system also records detailed data from each session, including games played and completed, average frustration rate, aids used, average play times, and number of games played by difficulty. These features allow healthcare providers to monitor the patient's progress and tailor the gaming experience to her needs.

5.3. RetroMind: a support tool for reminiscence therapy.

RetroMind framework is preliminary study which combines Large Language Models (LLMs) and social robots to enhance reminiscence therapy for Alzheimer's disease patients. Aims to support mental health professionals by providing visual representations of patients' life memories, facilitating personalized and empathic interactions tailored for each of them.

The RetroMind framework procedure consists of five steps as shown in figure 6:

1) Traditional Therapy: Mental health professionals administer the Autobiographical Memory Interview (AMI)[9] and the Cornell Scale for Depression in Dementia (CSDD)[10] tests to Alzheimer's disease patients, col-

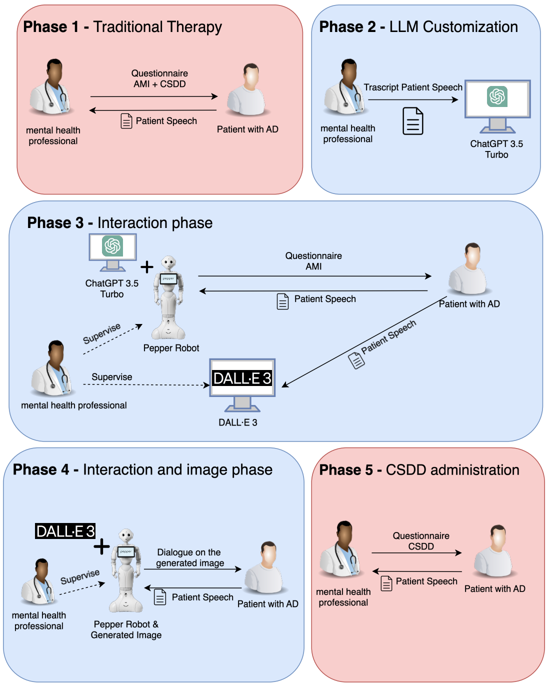

Figure 6: RetroMind Framework

lecting and transcribing patient responses to understand their cognitive functioning and emotional well-being.
2) LLM customisation: Healthcare professionals personalise ChatGPT 3.5 Turbo based on the information collected in phase one. enabling ChatGPT 3.5 Turbo to personalise patient interaction.
3) Interaction phase: The robot Pepper, adapted to the needs of the patient, supports the therapist in administering the AMI test. The robot captures the patient's speech, converts it into text and sends it to ChatGPT 3.5 Turbo. Simultaneously, the content of the patient's speech is transformed into visual representations by DALL-E3, providing an image as output.
4) Interaction and image phase: Pepper presents the patient with the images generated by DALL-E3 in the previous phase. With the support of the image, the patient's narration is stimulated, reinforcing the memory of the events by arousing positive emotions.
5) CSDD Administration: In the final phase, the mental health professional administers the CSDD to monitor changes in the patient's emotional state compared to baseline levels, ensuring an ongoing assessment.
RetroMind is an innovative system that aims to improve the effectiveness of reminiscence therapy. It acts as a narrative support tool using generated images, while continuously monitoring the patient's cognitive performance and emotional state. What distinguishes Retro-

Mind from other existing solutions in the literature is its unique ability to recreate representations of memories for individuals who may not have access to actual images of their past.

5.4. Dynamic Visualization of Gene Ontology Terms in AD and PD

In the domain of systems biology, where intricate networks of biological molecules interact to regulate the processes of an organism, the use of visual and interactive data representations is a critical aspect to aid in intuitively communicating complex knowledge. This is particularly true when navigating through vast multilevel data sets that encompass various *omics* sciences such as genomics, transcriptomics, proteomics, and metabolomics. This study introduced a human-interaction system for visualizing similarity data based on Gene Ontology (GO) functions (Cellular Component -CC, Molecular Function -MF, and Biological Process-BP) related to AD and PD proteins/genes [11]. Similarity data was generated using Lin and Wang distance measures across all three areas of GO. The data was then clustered using the K-means algorithm, and a dynamic, interactive view was developed using SigmaJS to allow users to customize the analysis workflow interactively. To deepen our understanding of the functional relationships between GO terms, we introduced a spatial distance metric, denoted as *SD*, specifically utilized for visualization purposes in the rendering routines (see Figure 7). This approach provides a more immediate visualization, enabling users to capture the most relevant information within the three vocabularies of GO. It facilitates an omic view and enables multilevel analysis with finer details, compared to the traditional cluster view, enhancing understanding of end-user knowledge.

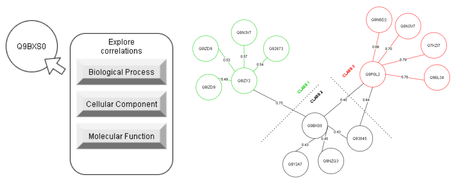

Figure 7: The contextual menu and an use case

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