Literature review on AI model and Alzheimer Disease predictions

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Abstract: In recent times, biosensors have become advanced tools in medical diagnostics, utilizing artificial intelligence (AI) to detect specific biological disorders promptly. AI in the form of Open-Pose models with wearable biosensors improves the patient's daily routines and physiological changes in Alzheimer patient diagnostics. AI based patient routine analysis covers complex patterns and offers fast processing with higher accuracy for physiological changes in Alzheimer patients. This model advances the detection of health condition changes, such as understanding patient routines, suggesting disease progression, and improving healthcare outcomes.

Keywords: Artificial Intelligence; Alzheimer; Activity Recognition; Open Pose AI; Healthcare.

Introduction

Alzheimer's disease (AD) is the leading cause of dementia in the elderly, affecting more than 35 million people worldwide. Aging populations in developed countries ensure that AD will reach epidemic proportions unless therapies are developed to cure or prevent it. Unfortunately, to date nearly all "disease-modifying" experimental interventions for AD have failed to demonstrate clinical benefits in individuals with symptomatic AD. The most 16 likely explanations for these failures are that the drugs were administered too late in the course of the AD neuropathological processes. It is plausible to assume that these therapies will be more effective when applied before major brain damage has occurred which makes the identification of biomarkers sensitive to preclinical or early clinical stages of AD crucial. Early-stage identification may also help to develop new treatments that are more effective at this stage as it can facilitate monitoring of the response to the intervention. In addition, a positive early diagnosis gives the patients and their family the necessary time to understand the disease, to decide on the life and financial burdens of the disease, and to arrange for the future needs and care of the patients.[1]

The artificial intelligence model can look at a lot of different ways to show how a patient's personality changes, like MRI scans, MCI neuroimaging, and manual testing with a classifier. In this study, we use a video recording of an Alzheimer's patient's day-to-day activities and a lightweight open pose AI model to track their activity. The model uses biomarker activities like walking, talking, and using a phone as a global estimator to map their pose geometry to markers in their whole body so that we can look at their daily activities and store them as a measure of their activity. A lightweight visual transformer is used to find the different activity or missed activity processed by the patient after collecting the data to find which activity was missed by the user.

Current monitoring and diagnostic systems for Alzheimer's patients suffer from several limitations. They are reactive and depend on observable symptoms. They rely heavily on clinical visits and caregiver feedback. They lack continuous, personalized monitoring.
There is a critical need for a proactive system that can detect subtle behavioral and physiological changes allowing for early diagnosis and timely intervention. The solution must be real-time, wearable, cost effective, and non-invasive. [2].

Related work

In the recent era, machine learning artificial intelligence models have played a significant role in identifying patient conditions and their activity analysis in various forms. These models include manual questionnaire models, data interpretation models, and object and video-based activity analysis, all of which are used to predict the severity of Alzheimer's patients with varying accuracy ranges. This analysis focuses on those models and their preprocessing steps explained in Table 1 and Table 2 defines different senor work and Table 3 defines the different dataset function.

Table 1. Compares of different AI model in preprocessing function

Data Source	**Feature Type**	**Preprocessing Technique**	**Extracted Features**
Wearable Sensors [3]	Physiological signals	Normalization, smoothing, filtering	Heart rate, temperature, sleep duration, activity level
OpenPose Video Input[4]	Skeletal movement	Frame sampling, joint alignment, denoising	Gait cycle length, step symmetry, limb velocity
DAPHNet Gait Dataset[5]	Motion data	Resampling, dimensionality reduction	Stride interval, walking speed, leg stiffness
Simulated Biosensor Data[6]	Synthetic physiological data	Noise injection, standardization	Simulated heart rate/temperature, synthetic motion
ADNI Dataset[7]	Imaging and cognitive scores	Image preprocessing, score scaling	Brain volume, hippocampus size, MMSE score

Table 2. Compares of different data from different sensors

Component	Input Type	Process/Transformatio n	Output for Model
Wearable Biosensors[8]	Heart rate, temperature,	Wireless capture, time-stamped	Raw physiological dataset

	movement		
OpenPose[9]	Video footage	Skeletal keypoint extraction	Joint coordinate sequences
Data Normalization Layer [10]	Raw signals & pose data	Smoothing, filtering, standardization	Cleaned, aligned dataset
Feature Engineering Module[11]	Preprocessed multi-source data	Gait metrics, HRV, temperature variance	Structured feature vectors
Synchronization Engine[12]	Physiological + Skeletal Features	Time-aligned fusion	Unified multimodal vector
AI Classifier (RF/SVM/RNN)[13]	Feature vectors	Classification & detection	Alzheimer stage classification/alert trigger

Table 3. Compares of different datatypes and contribution

Data Type	Description	Role in Alzheimer's Detection
MRI Scans[14]	High-resolution brain imaging	Detects brain atrophy and structural changes
PET Scans[15]	Brain activity/metabolism imaging	Identifies amyloid plaques and tau protein deposits
Clinical Assessments[16]	Cognitive tests and physical exams	Tracks memory, orientation, and problem-solving capabilities
Cognitive Scores	Standardized cognitive scales	Quantifies disease severity and progression

Key Contribution

The key contribution of this research is to explore different artificial intelligence models in detecting Alzheimer's disease from the patients using different approaches, mostly based on brain images and some activity analysis. But effectively analyzing is not possible with these two ways; for that, we are processing video-based motion analysis to identify Alzheimer patient activity and defining which activity they forgot to analyze the severity range of the disease with the help of an AI model. The activity categorization helps analyze the missed behavior of the patients, which leads to cognitive decline. The major activities used for categorization are walking, taking, sitting, sleeping, and using electronic gadgets. This patient activity recognition improved patient supervision, reducing the need for medical experts by processing regular care and attention to patient activity.[18]

Method, Experiments and Results

a) Methods

The signal processing feature include heart rate variability for interval variance and next feature is extracted by using the time series-based signal processing technique. The ML model trained to process the data from the real-world data source like ADNI dataset with both image and cognitive scores are trained to process the prediction accuracy. The next dataset is DAPHNet dataset is simulated with biosensor reading with temperature of body and heart rate with disease stage as abnormal pattern detected.

Training data is used to analyses the pattern of progression based on labelled inputs, testing of data a separate subset of data not seen during testing for evaluation of performance metrics to achieve high robustness of model in predicting the disease.

Some traditional models like random forest, neural networks and support vector machine extract the initial feature by ensuring data with cross validation and process more testing to ensure system performance under unknown conditions.

The input from the model is extracted as feature input for identifying behavioral changes in patient by matching both classifier and biosensor data to predict the disease progression.

The multimodal validation supported by comparing the readings from the biosensors and patient activity data. They help for refine more accurate process for stage analysis to progress the disease progression with stage-oriented detection. For improving the identification and detection clinical data many research utilizes the ADNI dataset which is publicly available with MRI, PET scan details with disease progression score.[18]

This research utilizes the above dataset and simulates it with cloud environment by accessing the motion activity of patients and synthetic data from the biosensors to efficiently simulate the change in behavior of patients with different parameter like body motion, temperature and heart rate with different ranges of stages progression of Alzheimer disease. The video activity of the patient forward to open pose tracking model to analyses the activity of the patients.

The system is developed with initial layer of open pose model with motion tracking then it is forwarded into biosensors for additional tracking with different stages of disease progression data. The fused model enables the system to capture the activity of patients with motion and body sensor data for enhancing the diagnostics function which is mostly effective in training the model. Initial data are collected from the biosensor fixed with the patients including heart rate signs. Next open pose model is process to note the motion activity of the patients. Next pattern recognition is classified by the machine learning model to predict the change in activity of the patients. Finally a alert will send to the care taker regards the abnormal activity process by the Alzheimer patient.

The final classification shows the fused model is having different prediction mechanism to analyses the Alzheimer symptoms in the patients and their activity changes are noted with an average accuracy rate of 93% with the abnormal activity associated with the patient daily routine. for Alzheimer's patients are expressed in Figure 1.

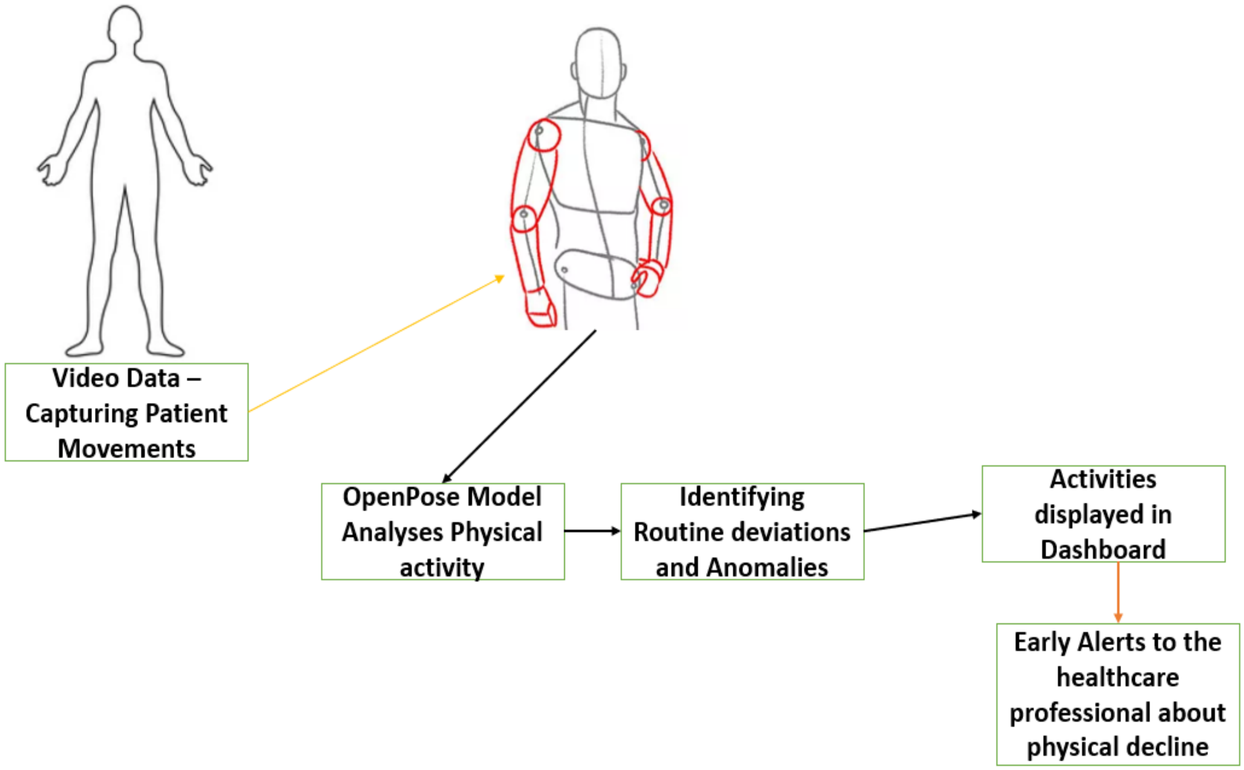

Figure 1. analyze future patient activity

b) Experiments and Results

The comprehensive review above indicates that MRI-based image analysis and biosensor-based data analysis require significant computational time and recommendations from medical experts to confirm the severe status of the patients expressed in table 4.

Table 4. Compares of different parameter used for testing

Parameter	Normal Range	Detected Abnormalities
Heart Rate (bpm)	60–100	<60 or >100 (brady/tachycardia)
Body Temperature (°C)	36.5–37.5	<36.0 or >38.0 (hypo/hyperthermia)
Activity Level	Moderate Daily Movement	Low mobility over extended periods
Sleep Duration	6–8 hours/night	<5 or >9 hours, or frequent awakenings

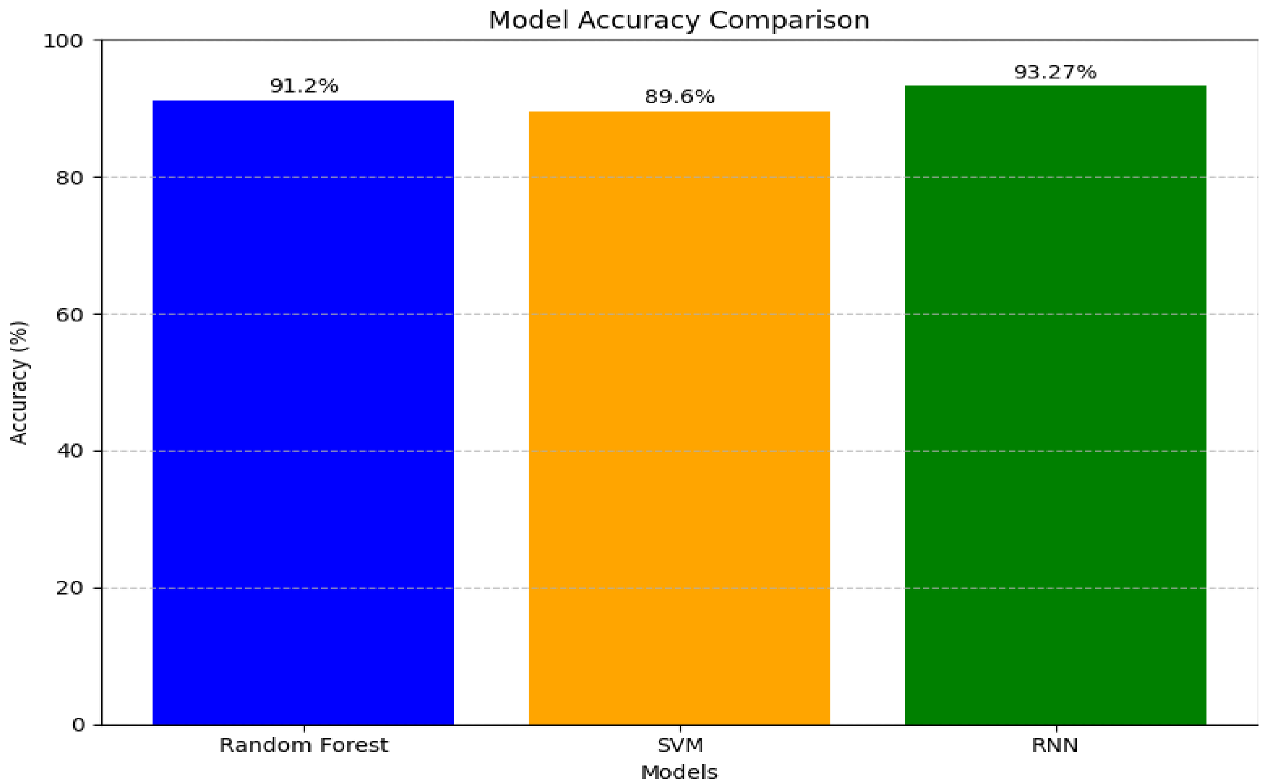

Figure 2. existing model Accuracy range in prediction.

These outcomes validate the system's effectiveness in supporting both early diagnosis and real-time monitoring. Real-Time Monitoring in Continuous tracking of health and behavior. Personalized Insights in AI tailors recommendations based on individual data. Cost-Effective to reduces hospitalization and unnecessary clinical interventions finally Data-Driven Decision Making Which Empowers clinicians with accurate and timely insights.

Discussions

This study looks at a number of different artificial intelligence models used in video capture and machine learning. The proposed model is better than some traditional models because it adds markers to video activity to easily find routine and missed activities.[18]

Conclusions

The integration of wearable biosensors and Open-Pose offers a significant advancement in Alzheimer's care. By providing real-time, AI-assisted monitoring of physiological and behavioral patterns, the proposed system facilitates early detection, enhances personalized care, and supports better treatment planning. As healthcare continues to adopt AI innovations, this system sets a foundational model for chronic disease management through smart technology.

Limitations

1.Data security improvement needed to handling of sensitive health data.

2.Ethical Concerns towards human element in AI-driven care.

3. Effective model is required to reduce false positives/negatives in behavioral classification.

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