International Journal of Modern Computation, Information, and Communication Technology
2025;8(1):11-17.
ISSN: 2581-5954

Patient Health Monitoring in Dementia Using K-Nearest Neighbor Model

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Abstract. Dementia is a progressive neurological condition that severely affects memory, behavior, and everyday functioning, necessitating ongoing surveillance of patients' health state. Conventional healthcare methods often lack timely treatments owing to restricted real-time data analysis. This paper presents a patient health monitoring system using the K-Nearest Neighbour (K-NN) classification model to identify and assess essential health metrics in dementia patients. The system amalgamates sensor-derived physiological data, including heart rate, blood pressure, and activity levels, to categorize patient health situations into normal, warning, or critical categories. The k-NN method is used for its simplicity, versatility, and efficacy in managing non-linear medical data. Experimental findings indicate that k-NN provides dependable accuracy in forecasting health hazards, hence assisting carers and healthcare professionals in their decision-making processes. This methodology enhances patient safety, individualized treatment, and proactive disease management in dementia monitoring.

Keywords: Dementia, Patient Health Monitoring, k-Nearest Neighbor, Machine Learning, Health Risk Prediction, Personalized Care, Physiological Data

INTRODUCTION

Dementia is a chronic neurological disease that significantly impairs cognitive skills, including memory, thinking, and decision-making. As illness advances, patients often encounter changes in behavior, challenges in communication, and a decline in autonomy over everyday tasks. These problems adversely affect patients' quality of life and impose considerable strain on carers and healthcare systems. Ongoing health monitoring is crucial for facilitating prompt interventions and enhancing patient care. In recent years, the amalgamation of sensor technology and machine learning algorithms has revolutionized healthcare monitoring methodologies. Sensors can acquire physiological and behavioral data, including heart rate, blood pressure, sleep patterns, and activity levels, in real time. When analyzed proficiently, this data yields significant insights into the health condition of dementia patients and facilitates the identification of early indicators of health decline. Conventional monitoring techniques are often constrained by human evaluations, delayed reporting, and an absence of predictive functionalities.

Machine learning, especially classification algorithms, has shown potential in overcoming these restrictions. The k-NN model is distinguished by its simplicity, resilience, and efficacy in managing medical datasets. The k-NN algorithm categorizes incoming patient data by juxtaposing it with historical data, facilitating precise classification of health problems into normal, warning, or critical categories. Its non-parametric characteristics render it particularly apt for examining complex, non-linear health patterns prevalent among dementia sufferers. This research investigates the use of k-NN models for monitoring patient health in dementia care. The proposed method combines real-time sensor data and machine learning to assist carers and healthcare professionals in making educated choices. The primary objective is to improve patient safety, facilitate personalized treatment, and mitigate the dangers linked to delayed or insufficient medical responses.

This study shows an AI-driven application to enhance cognitive health and assist carers of dementia patients. The program features a machine learning model for early dementia identification, preventative guidance, location monitoring, memory exercises, digital brain games, and cognitive rehabilitation resources. This solution, developed using Flutter for universal device compatibility and Firebase for backend support, aims to improve patients' quality of life and alleviate the responsibilities of carers. A novel assessment approach and comparative

Received: 21.11.2024 Revised: 09.01.2025 Accepted: 25.01.2025

study demonstrate its efficacy [1]. The proposed system employs intelligent sensing devices, including wearable and ambient sensors, to monitor the health of dementia patients in real-time. Heart rate data, movement metrics, and environmental factors are gathered and sent to a cloud server for analysis. The camera may observe and assess visual data, acquire essential information, and assist in evaluating the patient's condition. The cloud-based system's scalability, accessibility, and storage capabilities enable efficient real-time monitoring of several patients.

An intelligent nursing garment designed for incontinence detection in elderly patients with dementia. The intelligent garment is structurally segmented into a control module, a temperature and humidity detection module, a wireless communication monitor, and a power module, among others, with the APP detection functionality implemented on the mobile device terminal. This paper simultaneously improves the comfort and convenience of donning and doffing smart clothing while also increasing acceptance among elderly patients with dementia through the design of style, structure, and color, as well as demonstrating the virtual effects of smart clothing [3]. The proposed technique detects and rectifies deficiencies in current research to enhance the lives of people in the first phases of dementia and their carers via real-time anomaly identification and alarms derived from patient trajectory data. The technique includes many essential stages: Data collection and transmission include gathering and transmitting patient trajectory data to the cloud; the isolation forest methodology, an advanced anomaly detection tool, discerns deviations from typical behavior within patient trajectories. Real-time anomaly identification and alert creation provide prompt notifications to carers in cases of aberrant patient movements [4].

This study provides a real-time remote healthcare monitoring system with scalable event processing and analytics platforms for healthcare applications using open-source components. They analyzed the system using sample data from individuals with disabilities at the Ontario Shores Mental Health Institute. The system may gather data from wearable devices, such as wristbands, rings, or patches, and use machine learning to categorize agitation in individuals with dementia. The proposed approach furthermore offers significant insights into many health issues. Additionally, it processes continuous data in real-time while classifying with high precision using the Extra Trees model [5]. A comprehensive evaluation of tracking systems in long-term care homes for individuals with dementia. Context: Long-term care institutions are progressively using tracking systems. Their use is contentious, however. This study aims to examine the impact of tracking technology on dementia patients and personnel in institutional environments. Sweat is a normal excretion from the body that contains a reservoir of physiological indicators. The emergence of wearable electronics and soft bioelectronics has created new opportunities for monitoring individual health. The phenomenon of the silver tsunami has recently gained prominence in several affluent nations, raising worries around aged care. Many older individuals have a decline in cognitive function referred to as dementia. This results in their inability to perceive thirst, causing bodily dehydration.

The design and development of a smart e-textile sock with knitted electrodes for the early detection of discomfort in patients with dementia. The sock employs Shima Seiki WHOLEGARMENT® technology, using silver-coated conductive yarns to monitor variations in electrodermal activity (EDA), an indicator of physiological arousal. The research examines different yarn and knitting configurations to develop insulated electrodes that maintain stability throughout laundering and provide sufficient compression to guarantee dependable contact between the electrodes and the skin. Agitation is a significant behavioral and psychological symptom seen in individuals with dementia. These actions may jeopardize the health and safety of the patient with dementia and others. Surveillance cameras in long-term care institutions provide constant monitoring of patients and the identification of risky activities, such as agitation [9]. This study details the design and execution of a PCB board for controlling the display and electrodes in a neural helmet, addressing identified issues. The project has two components: electrical design and IoT for the user interface. The system operates using a helmet equipped with technology that detects variations in the user's pulse, thereby activating different functions such as music playback, audiovisual presentations, and relaxation-focused vibrations, contingent upon the patient's state of agitation [10].

The incidence of Alzheimer's disease (AD) is increasing each year, placing a significant strain on sufferers and society. Consequently, facilitated Alzheimer's disease evaluation is essential. The deterioration of linguistic abilities and the cognitive deficits it signifies are key outward indicators of Alzheimer's disease. Numerous studies have used speech analysis for efficient, non-invasive, and cost-effective Alzheimer's disease diagnosis. While cutting-edge research attains high-precision Alzheimer's disease diagnosis with multimodal information, these studies often overlook relationships across many modalities and fail to provide explanations for complex models [11]. Neuropsychiatric Symptoms (NPS) often occur in Individuals Living with Dementia (PwD), with agitation being among the most prevalent symptoms. Agitated behavior in persons with dementia induces distress and increases the likelihood of damage to both patients and carers [12]. Anomaly detection technologies are progressively used to oversee individuals with dementia in domestic environments, focusing on essential behaviors such as roaming, sleep disruptions, and agitation. This narrative review analyses technology used for identifying behavioral abnormalities, the activities they oversee, and the trade-offs between their advantages and constraints [13]. The digital health monitoring industry is growing swiftly, with technologies that track health information and facilitate access to medical data offering advantages for consumers, especially in regions with few healthcare resources [14]. The coronavirus disease 2019 (COVID-19) pandemic has profoundly affected economic, health, and social dimensions. The illness has resulted in more than 500,000 fatalities globally. Consequently, identifying the variables leading to mortality is crucial for risk factor classification, optimizing hospital resource allocation, and informing public health recommendations and initiatives [15].

PROPOSED SYSTEM

The proposed system aims to provide an intelligent health monitoring framework for dementia patients, using the k-NN algorithm as the primary classification model. Dementia care requires ongoing and dependable surveillance of physiological and behavioral metrics, since patients often undergo unforeseen health fluctuations. The system is engineered to amalgamate sensor-based data collection, health record preprocessing, and machine learning classification to provide carers and healthcare professionals with precise insights into patient problems. The proposed system prioritizes real-time analysis and proactive identification of major health hazards, in contrast to traditional monitoring systems that depend significantly on human reporting or postponed clinical evaluations. Figure 1 shows the proposed dementia monitoring system, which encompasses sensor-based data collection, preprocessing, and k-NN classification, culminating in health status alerts and care guidance for immediate response.

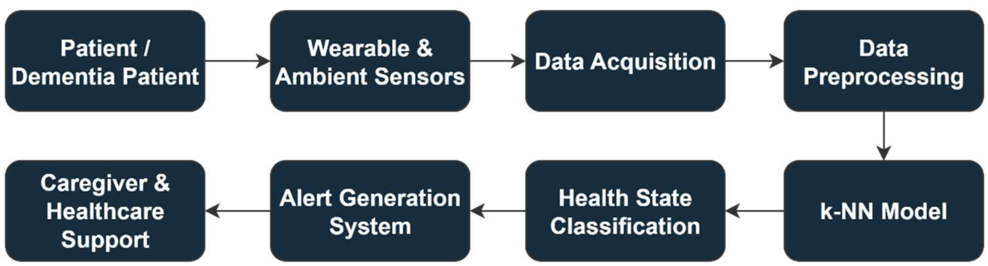

FIGURE 1. Block Diagram of Proposed Dementia Patient Health Monitoring System

The first element of the system is the data collection layer. This layer gathers data via wearable and ambient sensors positioned on or around the patient. These devices record essential physiological parameters like heart rate, blood pressure, oxygen saturation, and body temperature. Also document behavioral patterns, including movement levels, sleep cycles, and everyday activities. Furthermore, emergency indications, such as abrupt falls or irregular inactivity, are seen. The system integrates physiological, behavioral, and emergency data to provide a holistic assessment of the patient's health state. This comprehensive data collecting technique is crucial in dementia care, since even little fluctuations in activity or vital signs can signify early indicators of decline. Upon data collection, it undergoes a preparation phase. Sensor data is susceptible to absent values, noise, and anomalies that may undermine predictive accuracy. Data cleaning techniques are used to eliminate mistakes, normalization methods enable consistent scaling of features, and imputation approaches address missing values. Outliers that may distort the categorization process are removed. Ultimately, feature extraction is conducted to ascertain the most relevant health characteristics for categorization, hence diminishing computing complexity and enhancing model efficacy. This step guarantees that only significant and coherent data is sent to the machine learning phase. Figure 2 shows the systematic process of the proposed dementia health monitoring system. The procedure starts with the gathering of sensor-based patient data, proceeds to preparation for information quality improvements, and finishes in classification using k-NN. Health statuses are recognized, resulting in automatic alarm creation and decision assistance for carers to facilitate prompt action.

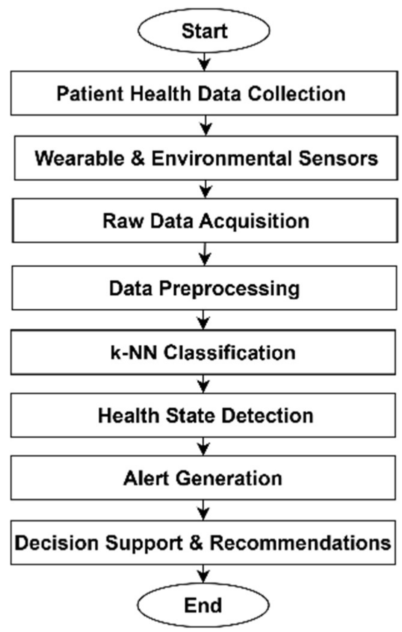

FIGURE 2. Health Monitoring and Classification Process using k-NN

The k-NN algorithm is the core of the proposed system. It is chosen for its simplicity, versatility, and efficacy in categorizing health-related data. The k-NN classifier computes the distance, typically the Euclidean distance, between the new record and the existing data. The algorithm then determines the nearest k neighbors and allocates the new record to the predominant class among these neighbors. In this application, the classifications are designated as normal, warning, and critical. A patient is said to be in a normal condition if vital signs and activity levels are maintained within acceptable parameters. A warning state is designated when there are slight variations from standard circumstances that may pose possible hazards. Critical condition indicates significant anomalies necessitating prompt care. The method aids carers in prioritizing patient needs and executing timely interventions by categorizing health information into three distinct classifications. The system's process commences with the ongoing collection of data via sensors. The data is thereafter sent to a secure monitoring hub, where preprocessing guarantees quality and dependability. The processed data is input into the k-NN model, which examines the patterns and generates categorization outcomes. When a patient is designated as warning or critical, the system autonomously issues warnings to carers via mobile devices or dashboard displays. These alerts may include decision-support advice, including medication reminders, hydration notifications, or advisories for emergency medical intervention. The integration of decision assistance with categorization improves the system's overall efficacy.

RESULTS AND DISCUSSIONS

This dataset sample [16] includes many health-related metrics and lifestyle aspects of people, emphasizing their Dementia status. The dataset encompasses details regarding alcohol concentration, heart rate, blood oxygen saturation, body temperature, weight, MRI latency, prescription information, dosage in milligrams, age, educational attainment, dominant hand, gender, familial medical history, smoking habits, APOE_ε4 genotype status, physical activity levels, depression status, cognitive assessment scores, medication history, nutritional intake, sleep quality, chronic health conditions, and dementia status. Each row represents a distinct person, and the dataset has a varied array of information, providing insights into the relationship between health indicators, lifestyle choices, and medical disorders. The characteristics provide a thorough picture of the patients' general health, facilitating prospective analysis and study of trends linked to diabetes and its associated issues.

The dataset used for monitoring the health of dementia patients comprises 1,000 samples, almost evenly divided between two groups. Class 0 comprises 515 samples, constituting 51.5% of the dataset, whilst Class 1 consists of 485 samples, representing 48.5%. The dataset is partitioned in an 80:20 ratio to provide dependable model training and assessment. This allocates 800 samples to the training set and reserves 200 samples for the testing set. Class 0 provides 412 samples for training and 103 for testing, while Class 1 supplies 388 samples for training and 97 for testing. This stratified division preserves class equilibrium in both subsets, guaranteeing that the k-NN model is trained and evaluated on representative data distributions. This proportionate division improves the accuracy, equity, and generalizability of the proposed health monitoring system.

Figure 3 shows a confusion matrix that captures model performance, with accurate classifications shown along the diagonal and misclassifications positioned off-diagonal, highlighting the pattern of accuracy and errors across classes.

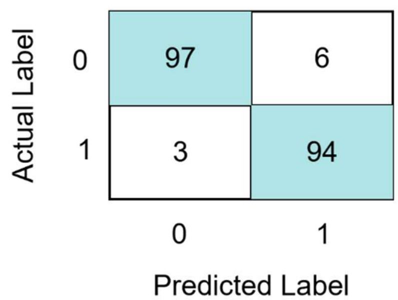

FIGURE 3. Classification Results Represented by a Confusion Matrix

Figure 4 shows the accuracy of the k-NN model at various values, showing improved performance with an increasing number of neighbors, with peak accuracy of 95.5% at k = 9.

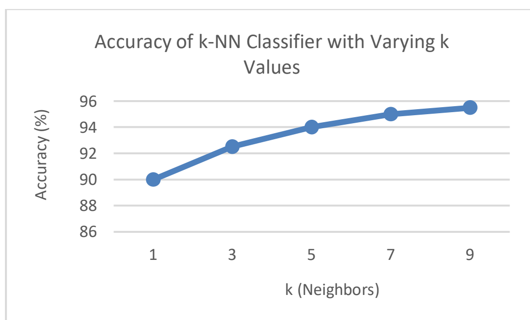

FIGURE 4. Performance Evaluation of k-NN: Accuracy vs. Number of Neighbors

Figure 5 shows the error rates of the k-NN model across various k values, demonstrating a consistent decrease as the number of neighbors increases, ultimately achieving the minimum error rate of 4.5% at k = 9.

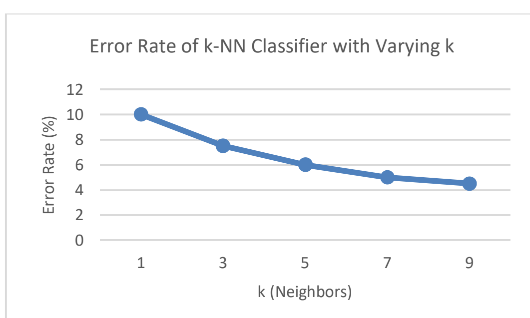

FIGURE 5. Error Rate Comparison for Varying k in k-NN Classification

CONCLUSION

The study proposed a patient health monitoring platform for dementia care using the k-NN algorithm. The system used wearable and ambient sensors to accurately collect physiological and behavioral data, including vital signs, activity patterns, and emergency indications. Data preprocessing guaranteed quality, whereas the k-NN model categorized patient health conditions into normal, warning, and critical classifications. Experimental assessment demonstrated robust performance, with an accuracy of 95.5%, elevated sensitivity, and minimal error rates, with the best parameter set at k = 9.The results highlight the promise of k-NN in healthcare applications due to its simplicity, flexibility, and dependable classification proficiency. The proposed approach facilitates prompt interventions, improves patient safety, and reduces the strain on carers via the provision of real-time notifications and decision-making assistance. While successful, future research may investigate hybrid models, cloud-based integration, and bigger datasets to further augment scalability and predictive capability. This method improves proactive, personalized dementia care and improves quality of life.

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