Effective Public Health Assessment: Research on Alzheimer Disease Diagnosis Model With Communication Technology

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KEYWORDS

Alzheimer disease, public health, communication, wearable sensors, chimp search-driven ReLu recurrent network (CS-RRN)

ABSTRACT

Rapid identification and appropriate management of Alzheimer's pose important challenges, particularly within public health contexts. This research introduces a unique framework for diagnosing Alzheimer's disease using communication technologies (such as wearable sensors). Novel chimp search-driven ReLu recurrent network (CS-RRN) strategy is introduced in this study for effectively detecting Alzheimer's disease. The ReLu function is employed in long/short-term memory (LSTM) to learn nonlinear dependencies, and then the chimp optimization strategy is applied to enhance the detection performance of the LSTM network. The gait signal data is collected from various wearable sensor devices to analyze the effectiveness of the suggested CS-RRN m technique. The performance of the proposed method is analyzed through a Python-driven implementation platform in terms of various metrics. The CS-RRN approach effectively achieved the maximum performance in detecting Alzheimer's disease when compared with other existing approaches. Based on the findings of this research, communication technology may substantially boost public health by providing a low-cost and high-performing method for Alzheimer disease identification.

1. Introduction

Alzheimer disease in the elderly causes cognitive decline, memory loss and dysfunction of daily activities for early diagnosis and action accurately to manage the disease and improve patient outcomes [1]. Traditional diagnostic methods, including clinical examination, neuroimaging, and biomarker testing, can be invasive, time-consuming, and expensive. Using electronic devices such as wearables, mobile phones, and tele-health platforms, modern assessment systems collect data on patients mental and physical health functions in real-time [2]. These gadgets are frequently impacted in AD sufferers, consisting of speech patterns, motor abilities, and exceptional sleep [9]. The accumulated records are then sent to cloud-primarily based systems, wherein machine learning algorithms have a look at it to discover minute variations that might be signs and symptoms of dementia in its early stages [12]. These sorts of structures lessen the requirement for repeated trips to the clinic by permitting faraway oversight further to facilitate diagnosis at an early stage [15]. Integration with the conversation era democratizes healthcare [4]. This method, which combines the accuracy of synthetic intelligence with the usability of contemporary technological gear to improve affected person care and executives, marks a good sized progress inside the identity of AD[5].This study aims to improve Alzheimer's disease detection using wearable sensors and advanced computational techniques for enhanced public health results [6].

Related work

Pappagari et al. [13] proposed a language processing algorithm and technology that recognizes voices may be used to predict mini-mental state examination (MMSE) scores and identify Alzheimer disease (AD). The transcription problems demonstrate that acoustic models can yield better outcomes than linguistic models. The most accurate models identify AD with 84.51% accuracy and predict MMSE with 3.85 root mean square error (RMSE).Investigated an Artificial Intelligence (AI) technology with

Magnetic Resonance Imaging (MRI) scans could be used to diagnose and prognosticate AD. Salehi et al. [7]the method outperformed earlier research, with a noteworthy accuracy of 99%. Deep learning techniques might be a superior choice for handling massive amounts of medical data when compared to machine learning methods used in the OASIS datasets. Suggested MRI scans, the proposed DEMentia NETwork (DEMNET) was a Convolutional Neural Network (CNN) that identifies certain features of Alzheimer's disease Murugan et al. [8] with an accuracy of 95.23%, an AUC of 97%, and a dataset, the DEMNET outperforms previous techniques. Datasets were used from the AD Neuroimaging Initiative (ADNI)), DEMNET was also used to predict AD classes. Ghazal and Issa [14] proposed a serious neuronal illness those results in irreversible memory loss. Four levels were identified by the algorithm for images. The accuracy rate of 91.70% in the computer model results was higher than in prior methods. The main cause of memory was AD, which results in mental dependence and the degeneration of brain cells in Nawaz et al. [10] used machine learning techniques such as Random forest (RF). The suggested model beat current state-of-the-art techniques with 99.21% accuracy, surpassing both handmade and deep neural network methods.

2. Methodology

Data Collection

The human gait dataset is gathered from source https://github.com/romanchereshnev/HuGaDB. The information is continuously captured while doing combination activities such as walking, running, climbing and descending stairs, sitting down, and so forth. The information collected is segmented and analyzed. Data was collected via a body sensor network made up of six wearable inertial gauges (gyroscopic and accelerator) on the feet, shins, and thighs of the right and left person. To assess muscle activation, two electromyography sensors were also placed on the quads located on the thighs.

Chimp Search-driven ReLu recurrent network (CS-RRN)

Chimpsearch-driven ReLu recurrent network (CS-RRN) combine’s chimp search with recurrent neural networks (RNNs) for optimization by using improved linear units (ReLu) This hybrid approach combines growth-driven search strategies with RNNs is efficient and scalable together with public health assessment, improving model performance through iterative optimization and dynamic learning capabilities.

Chimp Search

During the process, multiple stages were used to simulate diverse intelligence such as the attacker, barrier, the pursuer, and driver, etc. This approach is inspired by the personal intelligence and emotional drives of chimpanzees in collective hunting and is distinct from that of other social predators. The result is a new nature-prone method called the Chimp optimization Algorithm (ChoA).The suggested algorithm's calculation framework has been broken down into the subsequent stages. The items follow algebraic equations 1 and 2 show driving and pursuing a desired object or victim.

$$C = \left| d.b_{prey}(m) - nb_{chimp}(m) \right| \tag{1}$$

$$b_{chimp}(m+1) = b_{prey} - b.c \tag{2}$$

In this section, $m$stands for the overall amount of repetitions, and the vectors of size that are coefficients are d,$n$and$b$. Using formulas, one may compute the coefficients, m, and b. in equation [(3)–(4)].

$$b = 2.k.q_1 - 1 \tag{3}$$

$$d = 2.q_2 \tag{4}$$

$$n = chotic_{value} \tag{5}$$

In which n represents the chimp vector, q_1 and q_2 are selected at random in the interval [0, 1], and l is lowered non-linearly from 2.6 to 0 by the method of iteration.

The chimps' behaviour has been incorporated statistically during this phase. In this instance, it is assumed that the attacker, driver, barrier, and chaser who are more knowledgeable about the target's location have the first answer. The remaining chimpanzees are compelled to update their places by the optimal chimp positions in the next iteration once four more best practices that have been found so far are saved. The subsequent equations for math have been used to depict equation 6 and 9.

$$c_{attacker} = |d_1 b_{attacker} - n_1 . w| \tag{6}$$

$$c_{barrier} = |d_2 b_{barrier} - n_2 . w| \tag{7}$$

$$c_{chaser} = |d_3 b_{chaser} - n_3 . w| \tag{8}$$

$$c_{driver} = |d_4 b_{driver} - n_4 . w| \tag{9}$$

A chimpanzee's future position can be anywhere between it is exact spot of its intended victim or prey provided the selection matrices are within the range of [−1, 1].

$$w_1 = b_{attacker} - b_1 . c_{attacker} \tag{10}$$

$$w_2 = b_{barrier} - b_2 . c_{barrier} \tag{11}$$

$$w_3 = b_{chaser} - b_3 . c_{chaser} \tag{12}$$

$$w_4 = b_{driver} - b_4 . c_{driver} \tag{13}$$

Equation (14) provides the most recent positioning of the chimpanzees throughout the search procedure based on the total calculations.

$$w_{m+1} = \frac{w_1 + w_2 + w_3 + w_4}{4} \tag{14}$$

Subsequently, the remainder of equation 15 has been used to the updating of the chimpanzees' position throughout the search procedure in the searching domain.

$$b_{chimp}(m+1) = \begin{cases} b_{prey}(m) - w.c, & if \phi < 0.5 \\ chaotic_{value} & if \phi > 0.5 \end{cases} \tag{15}$$

ReLu recurrent network (RRN)

In this study, a time series of power usage is forecasted using an LSTM framework. The ability to simulate the spatial connections of the data is the main feature of recurrent relationships, which frame this design. Because the network is given a set amount of memory, this makes them highly suggested for public health assessment of sequential data issues like language transcription, sound, or series of times. The LSTM algorithm cell gets data collected at the present instant (w_s) and the knowledge modeled about earlier cells(D_{s-1} and g_{s-1}). Based on a set of logic gates for public health assessment, it determined the degree of influence that the knowledge at previous time instants has on the data at the current time immediately to be anticipated, thereby demonstrating the network's conduct. Where it is between the input gate and the output gate, and e_s is the gate that remembers. The data that should be preserved or disposed of is decided by e_s. A number close to 0 denotes that past information has been disregarded, whilst a number close to 1 denotes the opposite. It determines what fresh data to apply to refresh the state of the e_s memory. As a result, j_s and e_s are both used to update. Ultimately $j_s$selects the output value that will serve as the subsequent concealed device's source. The data from the g_{s-1} prior hidden unit and the data from the (w_s) at present are sent via the activation function of ReLuto calculate the new information that will be utilized to update, and the$j_s$sigmoid activation function to calculate all of the gate values. The following is a summary of the equations that define an LSTM unit.

$$\widetilde{D}_s = ReLu(X_d[b_{s-1}, w_s] + a_d)$$

(16)

$$j_s = \sigma(X_v[a_{s-1}, w_s] + a_v) \tag{17}$$

$$e_s = \sigma(X_e[a_{s-1}, w_s] + a_e) \tag{18}$$

$$p_s = \sigma\left(X_p[a_{s-1}, w_s] + a_p\right) \tag{19}$$

$$d_s = j_s * \tilde{d}_s + e_s * d_{s-1} \tag{20}$$

$$b_s = p_s * ReLu(d_s) \tag{21}$$

Where the weights and biases that control the j_s,e_s and p_s gate behavior are represented by X_v, X_e and X_p, while the weights and biases of the ot memory cell candidate are represented by X_d and a_d. A comprehensive explanation of every logic gate and the in-depth workings of the LSTM circuits can be accessed in equation (19).

3. Results and discussion

In this section, we employed ensemble approaches to increase the accuracy of the outcomes evaluated for Alzheimer's disease detection using existing methods are logistic regression, random forest, and SVM [12]. Novel chimp search-driven ReLu recurrent network (CS-RRN) strategy is introduced in a public health assessment for this study effectively detecting Alzheimer's disease communication. Using several parameters, including, recall, accuracy, precision, and F1-score, the study compared the recommended strategy with other existing methods. The findings demonstrated that considering all of these public health evaluation parameters, the recommended solution outperforms other conventional techniques.

Accuracy

The accuracy performance compared the features of the present methodology with our proposed (CS-RRN) method is illustrated in Figure 1. The accuracy level of existing methods of logistic regression, random forest, and SVM achieved 74.7%, 81.3%, and 92.0% respectively. The proposed method (CS-RRN) achieved 94.0% accuracy. Our proposed method has superior performance than the existing methods in Alzheimer's disease detection using communication technology for enhanced public health.

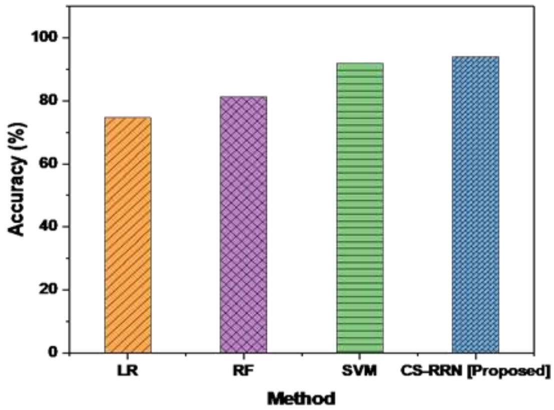

Figure 1. Outcome of Accuracy

Precision

The precision level of existing methods LR, RF, and SVM achieved 76.5%, 84.4%, and 91.9%respectively. Compared to the method of existing, the proposed method (CS-RRN) achieved a 92.1%result of precision. Our suggested solution uses communication technology to improve public health by outperforming the current approach in Alzheimer's disease identification.

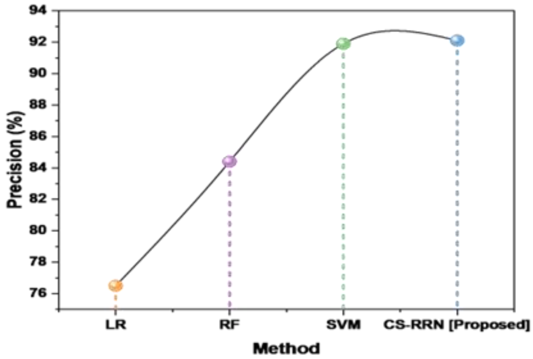

Figure 2. Performance of precision

Recall

A classification model recall is a measure of efficiency that evaluates how well the model finds pertinent samples inside a given class computed as a proportion of positive estimations to the sum of false negatives and true positives. Figure 3 depict the recall process. The recall level of existing methods LR, RF, and SVM achieved 70.3%, 70.3%, and 91.9%respectively. Compared to the method of existing, the proposed method (CS-RRN) achieved a92.0% outcome of recall. Our suggested approach outperforms the current approach in identifying Alzheimer's disease with wearable sensors for improved public health.

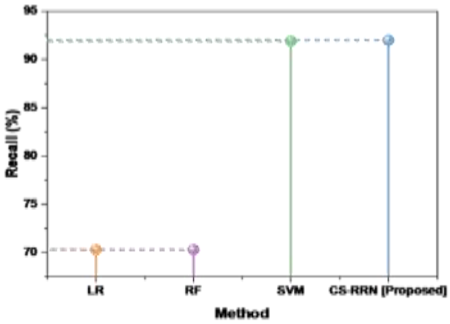

Figure 3. Outcomes of recall

F1-score

When assessing the effectiveness of a model of classification in Alzheimer disease identification based on text, the F1 score is a parameter that is frequently employed in statistics. Figure 4display the output of the F1-score. The F1-score level of existing methods logistic regression, random forest, and SVM achieved 73.3%, 76.7%, and 91.9 respectively. Compared to the method of existing, our proposed method (CS-RRN) achieved 92.1%of the result of the F1-score in health Alzheimer's disease identification using wearable sensors for improved public health.

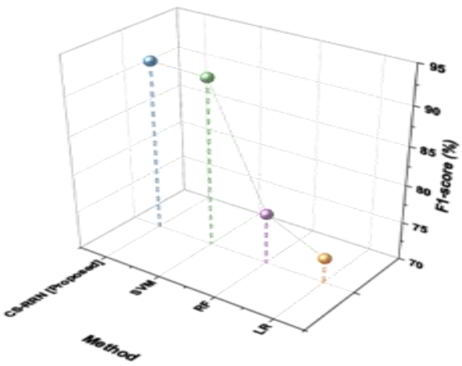

Figure 4. Performances of F1-score

4. Conclusion and future scope

This research CS-RRN framework gives a promising development in Alzheimer disease detection communication using wearable sensors and computational techniques. The integration of ReLu LSTM and Chimp optimization has shown advanced performance over existing methods, highlighting its capacity for cost-effective and accurate diagnosis in public health assessment. Analysis based on the suggested method's performance through a Python-driven implementation platform in terms of various parameters are recall (92.0%), precision (92.1%), F1-score (92.1%), and accuracy (94.0%), are compared to other existing methods during the comparison process. Comparing our suggested strategy to other conventional methods, it performed more effectively. Future work could concentrate on enhancing the robustness of the framework, incorporating more sensor modalities, and resolving real-world issues such as sensor integration and data privacy issues. By removing these obstacles, the framework's use in practical contexts may be improved, and the development of efficient and effective communication technologies may transform the diagnosis and treatment of Alzheimer disease.

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