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A solution for early detecting the stroke status of the elderly

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Abstract
Particularly in elderly people, one of the main causes of disability and mortality is stroke, where early detection is essential to minimizing long-term effects and enhancing treatment success. The symptoms of Posterior Circulation Syndrome (PCS) are diverse and vague, making diagnosis difficult. Improving patient outcomes requires prompt and precise detection. The study aims to improve early detection of PCS by utilizing clinical and demographic data and machine learning. The study collects data on elderly individuals aged 60 and above, focusing on risk factors for stroke using wearable sensors to monitor physiological parameters in real-time. In this study, a novel Efficient Osprey Optimized Malleable Random Forest (EOO-MRF) model is proposed for early detection of stroke status in elderly individuals. The collected data was preprocessed using data cleaning, and the noise was removed from the data using in a median filter. The model's performance was evaluated using various kinds of performance metrics, including the parameters accuracy of 95%, sensitivity of 99%, specificity of 96%, precision of 95% and AUC of 99%. The results demonstrate the proposed method outperforms conventional algorithms in the early detection of stroke status in the elderly. The study highlights the effectiveness of a model in predicting stroke risk, enhancing patient care, and reducing healthcare system burden, paving the way for further research and clinical deployment.

Keywords: Early detection, posterior circulation syndrome (PCS), stroke, elderly peoples, efficient osprey optimized malleable random forest (EOO-MRF)

Introduction

Stroke ranks second globally as a leading cause of fatalities and disabilities, and it constitutes one of the most common neurological conditions in adulthood. Recognition and evaluation of stroke severity have an impact on mortality rates, cost of care, treatment, and quality of life following a stroke [1]. The neuro-electrical technique's functioning must be monitored to accurately predict stroke outcomes. The oxygen flow to the neural tissue near the lesion is hampered by ischemia events, such as bleeding strokes, which result in the death of brain cells. The entire nervous system becomes unstable as a result of this neural tissue destruction, which also alters the electrical impulses of the associated local spherical [2]. Stroke is one of the two most common causes of mortality globally and the most prevalent cause of disability according to a 2016 World Health Organization (WHO) investigation [3]. Early identification is crucial for stroke because there is currently no effective treatment for the condition. Because classifications of specific risk factors and the methods for associating them with the likelihood of developing a disease vary, using risk factors to predict stroke outcomes or outbreaks can be challenging [4]. Estimating the prediction of an earlier occurrence or probable occurrence of a stroke disorder based on risk variables that present several challenges specifically. A model for predicting stroke risk was developed from a cohort study on heart disease. In contrast, the use of sensors to monitor mental health and cognition has received relatively less attention in research [5, 6]. The purpose of this research is to use prediction algorithms and cutting-edge monitoring equipment to create a fresh strategy for the early older adults' infarction diagnosis. This method indicators of stroke and risk variables are sought in real time to facilitate prompt medical attention. The ultimate goal of the research is to lessen the impact of stroke-related disability among the elderly and to enhance results.

Remaining of this study: Related work is outlined in Part 2, the methodology is established in Part 3, the performance evaluation is displayed in Part 4, and the conclusion is illustrated in Part 5.

Related work

Electroencephalography (EEG) is a promising prediction technique for stroke development and post-stroke clinical care due to its quick detection. To evaluate the viability of classifying stroke patients with neurological abnormalities from ischemic strokes distinguishing them from healthy adults using handheld EEG equipment. Health SOS, a real-time stroke forecasting system, monitors health using a medical semantic-based health consultant service, data mining, and portable EEG equipment [7]. Research [8] suggested that as life expectancy increases and birth rates decrease, an elderly society is emerging. This necessitates remote medical care and smart medical facilities. Experimental findings show that non-invasive brain activity recording techniques can forecast and track stroke illnesses in real-time, leading to advancements in early stroke identification at a lower cost with less discomfort. These findings are expected to be compared to previous methods. Stroke-related disability is more common in children and older adults, leading to social and economic challenges. Real-time monitoring and evaluation of biological signals can help to provide appropriate treatment. Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are commonly used for stroke evaluation and forecasting, but they are costly and challenging to use. The technology [9] offered an affordable, real-time diagnostic tool that can accurately predict stroke and diagnose other conditions, including heart disease. The government has the power to ensure the elderly's health and well-being, as life expectancies have increased due to technological advancements [10]. By 2030, the number of old people is expected to quadruple, making preventive and early identification crucial. Hyperglycemia and high blood pressure were risk factors for memory loss, and using medical records can help identify dementia risk factors. Aging affects both mentally and physically leads to decreased activity levels and reduced ability to perform daily tasks. Human activity recognition (HAR) methods [11] can help monitor behavior patterns and respond appropriately in case of major incidents or behavioral changes. Machine learning techniques were being used to identify routines in individual activity data. About 25% of patients with brief ischemia and stroke may have unidentified atrial fibrillation (AF) [12], highlighting the need for more controlled studies on continuous cardiac monitoring to assess stroke recurrence. Further investigation is needed into the relationship between AFDAS and stroke recurrence, and a customized strategy for extended cardiac monitoring following ischemic stroke or transient infarction attacks. The research aims to determine if a cyber-physical ventricular tracking device can differentiate between healthy individuals and stroke victims with altered heart activity. The randomized trees model performed best in classifying electrocardiogram (ECG) [13] fiducial factors, potentially aiding healthcare organizations in managing recovery and assessment during post-stroke treatments. Stroke diagnosis and treatment were improved due to the negative impacts of strokes on society. Caregivers can use technology and medical treatment synergy to improve patient care. Researchers analyze digitized healthcare data to predict strokes using principal component analysis and statistical approaches [14]. A well-rounded dataset is provided using subdivision methods, addressing the imbalance in the original dataset on stroke incidence.

Methodology

The approach focuses on creating a way to integrate portable sensor technologies for continual tracking of physiological indicators to build an intervention for the early diagnosis of cerebral infarction status in elderly people. Real-time data is analyzed by machine learning computations, which find trends linked to the risk of stroke predicted using EOO-MRF. This methodology facilitates prompt intervention and enhanced outcomes related to the avoiding strokes.

Data collection

The data that includes extensive physiological data collected from elderly people (60 years of age and older) using wearable sensor that allows for continuous real-time monitoring. Vital signs including blood pressure, heart rate, body temperature, and level of exercise are monitored to offer important health information about the participants. Finding and examining the many risk factors for stroke, such as arrhythmias, hypertension, and physical inactivity, is the major goal. Using this data, medical practitioners can create customized preventive health initiatives and intervention plans with the ultimate goal of lowering the incidence of stroke and enhancing the general health of the elderly people.

Data preprocessing using a median filter

One of the procedures involved in preprocessing information from sensors depending on the suggested method for determining the status of stroke in elderly patients is the order-statistics filter or median filter. In this approach, the median of certain values in a specified window in the neighborhood is used in place of the value of an information point, similar to how a physiological indicator functions. This filtering ensures that configurations of the patterns and indications of the physiological information being processed are kept optimal through successful noise and outlier elimination. To enhance the accuracy of discovering reliable stroke risk characteristics, machine learning techniques are applied in analyzing the processed data expressed in equation (1).

$$e'(w,z) = \underset{(t,s)\in T_{wz}}{Median}\{h(t,s)\} \quad (1)$$

The method for detecting early stroke status in the elderly mentioned earlier includes preprocessing wearable sensor data and addressing random noise in the physiological information. This method retains crucial parameters, allowing for a more precise estimation of the risk of a stroke that can be averted by using this approach. It also incorporates a clipped median noise suppression filter for better data pre-processing to feed into stroke risk estimation methodologies in difficult conditions or in the face of human outside variability.

Early detection of Stroke status using Efficient Osprey Optimized Malleable Random Forest (EOO-MRF)

The EOO-MRF is a method that enhances stroke diagnosis in the elderly by combining advanced optimization techniques with adaptable random forest architecture, utilizing real-time sensor data to accurately identify stroke risk and facilitate proactive treatment measures.

Malleable Random Forest (MRF)

Concerning the performance of MRF algorithm containing both ID3 and CART the expectations are to detect the stroke status of the elderly while avoiding node separation, and to determine if old people can be classified effectively by special physiological parameters. But the results of this type of method may be quite different depending on the presence of various factors. This methodology guarantees the utilization of the most pertinent health indicators for precise categorization and enhanced identification of the possibility of stroke, denoted as equations (2) and (3).

$$Gain(C,b) = Ent(C) - \sum_{u=1}^{U} \frac{|c^u|}{c} Ent(C^u) \quad (2)$$

$$Gain(C,b) = \sum_{u=1}^{U} \frac{|c^u|}{c} Gini(C^u) \quad (3)$$

Where C^u denotes that every sample in the C with a value of u a on the property an contained in the branching node.

$$Ent(C) = -\sum_{l=1}^{|z|} o_l \log_2 o_l \quad (4)$$

$$Gini(C) = \sum_{l=1}^{|z|} \sum_{l' \neq l} olol' = 1 - \sum_{l=1}^{|z|} Ol^2 \quad (5)$$

The goal of the node-breaking concept is to achieve purity in the information set upon division, leading to a formula for separating conjunction nodes and adapting accordingly. The procedure for choosing variables is as follows in equation (4) and (5).

$$G = \min_{\alpha,\beta \in Q} E\{C,b\} = \alpha Gini(C,b) - \beta Gain(C,b) s.t \begin{cases} \alpha+\beta = 1 \\ 0 \le \alpha,\beta \le 1 \end{cases} \quad (6)$$

Here, α and β stand for the attribute separation weight factor. At this moment, G has a very low value. The method of adaptive parameter selection is used to obtain the ideal settings for combination. This implies that ID3 and Both CART and node division criteria are ideal for enhancing the impact of categorization. The sample of categorization error rate C is described in equations (6) and (7).

$$F(e;C) = \frac{1}{n} \sum_{j=1}^{n} \mathrm{II}\left(e(w_j) \neq z_j\right) \quad (7)$$

The accuracy rate is defined as equation (8).

$$acc(e;C) \frac{1}{n} \sum_{j=1}^{n} \mathrm{II}\left(e(w_j) = z_j\right) = 1 - F(e;C) \quad (8)$$

Efficient Osprey Optimized (EOO)

Shortcomings of OOA

The Osprey Optimization Algorithm (OOA) is used for early stroke status detection in the elderly, recognizing high-risk health markers and efficiently integrating physiological information. However, it struggles with large, complex data sets and struggles with local optima. Further improvements are needed to improve OOA's efficacy in identifying stroke risk in the senior population.

Modified Methods

This work introduces three improvements to the EOO algorithm to improve its efficiency in identifying stroke status in elderly individuals. These include the random feature data block selection method, the Brownian motion method for data collection from clothing sensors, and the LFS for examining high-risk health parameters.

Levy Flight Strategy

Variable q_1 in the EOO worldwide search procedure restricts the ospreys' searching area and needs to be adjusted. One useful technique for assisting algorithms for optimization in escaping local minima is the LFS. The value is determined as equation (9).

$$Levy(1) = \frac{v}{|v|^{\frac{1}{\beta}}} \quad (9)$$

$$\sigma_v = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{1-\beta}{2}\right)}} \right)^{\frac{1}{\beta}} \quad (10)$$

When v and u, where $v \sim (0,\sigma_v^2), u \sim (0,\sigma_v^2), \sigma_u = 1, \beta = 1.5$, where Γ is the conventional gamma function. The selected number q_1 in Equation (10) is substituted by the LFS. Equation (11) is a modified version of the original equation for capturing aquariums.

$$W_{j,i}^{O1} = W_{j,i} + Levy(1) \times \left(SF_{j,i} - J_{j,i} \times w_{j,i}\right) \quad (11)$$

Brownian Motion Strategy (BMS)

This modeled after the probabilistic investigation behavior of predators, makes it easier for people to look into potential areas of the environment of health data. As a result, BMS facilitates the procedure for optimization, making it possible for the ospreys to more effectively scan the whole feature space associated with stroke risk. The following is the updated equations (12) and (13) for this deployment:

$$W_{j,i}^{O1} = W_{j,i} + O \times CF \times randm \times \left(randm \times SF_{j,i} - J_{j,i} \times w_{j,i}\right) \quad (12)$$

$$CF = \left(1 - \frac{s}{S}\right)^{\left(2 \times \frac{s}{S}\right)} \quad (13)$$

W is a constant with a value of 0.5 and the arbitrary number that fits the usual typical distribution is called randm.

Results

The suggested approach produced an average ACC of 99.83% and F-Score greater than 92%, and it was relatively less volatile. The Intel Core 2.4 GHz is used for the tests of MATLAB on an i5 processor with 8GB of RAM. Comparing the recommended technique Efficient Osprey Optimized Malleable Random Forest (EOO-MRF) using current methods such as support vector machine (SVM), neural network (NN), and C&R tree with the parameters of accuracy, precision, sensitivity, specificity, and AUC as shown in table 1.

Table 1: Result of accuracy, precision, sensitivity, specificity, and AUC

Methods	Accuracy (%)	Specificity (%)	ACU (%)	Precision (%)	Sensitivity (%)
SVM [15]	93	88	98	89	98
Neural Network [15]	90	94	96	94	86
C&R Tree [15]	92	86	92	87	98
EOO-MRF [Proposed]	95	96	99	95	99

Accuracy: The model's accuracy in accurately categorizing stroke conditions is measured by the ratio of correctly identified stroke and non-stroke cases to the total number of forecasts, indicating its ability to reduce incorrect classifications. Table 1 and Figure 1 present the results of the proposed method (EOO-MRF) was 95% higher than the existing method, such as SVM of 93%, NN of 90%, and C&R tree of 92%.

Precision

The stroke status determination in elderly individuals is based on the percentage of stroke diagnoses among positive forecasts, ensuring accurate stroke recognition by reducing errors. Table 1 and Figure 1 present the results of the proposed method (EOO-MRF) was 95% higher than the existing method, such as SVM of 89%, NN of 94%, and C&R tree of 87%.

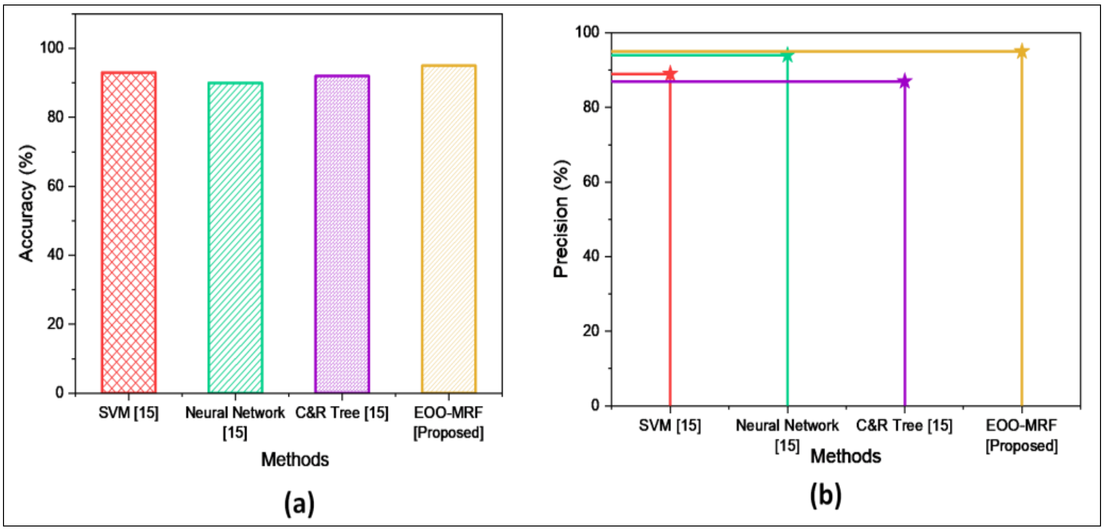

Fig 1: Outcome of the accuracy and precision

Sensitivity: The medical care system's ability to reliably identify patients with acute strokes or early stroke conditions in older people is measured by the percentage of genuine strokes detected, ensuring high sensitivity and reducing false negatives. Table 1 and Figure 2 present the results of the proposed method (EOO-MRF) was 99% higher than the existing method, such as SVM of 98%, NN of 86%, and C&R tree of 98%.

Specificity: The testing solution accurately differentiates stroke patients, reducing false positives by measuring true negatives, thereby reducing unnecessary therapies or concerns in stroke-free individuals, requiring significant accuracy. Table 1 and Figure 2 present the results of the proposed method (EOO-MRF) was 96% higher than the existing method, such as SVM of 88%, NN of 94%, and C&R tree of 86%.

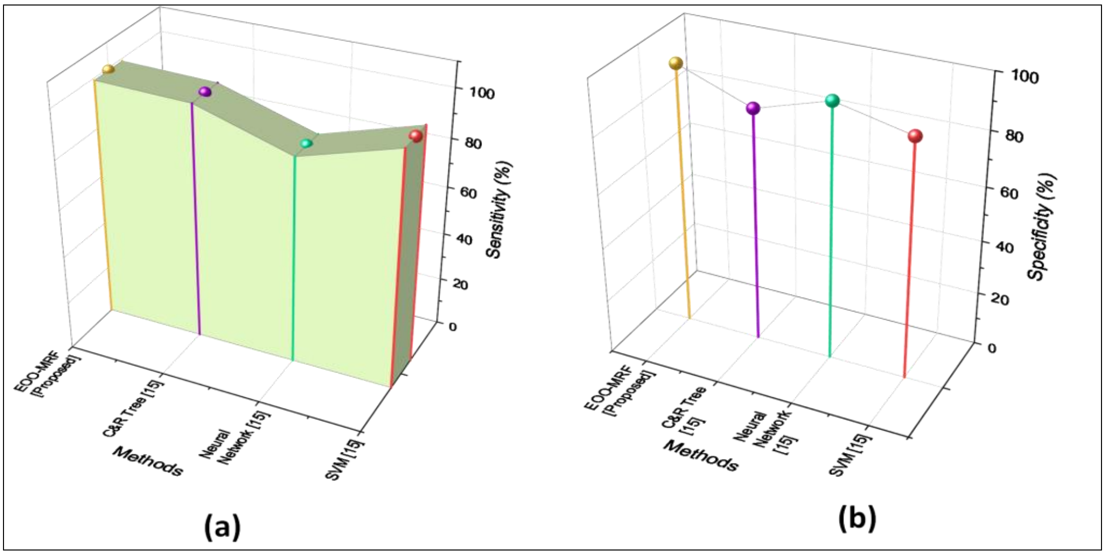

Fig 2: Outcome of the sensitivity and specificity

Area under the Curve: One statistic used to assess the efficacy of the exclusion model was the area under the curve (AUC) in early stroke diagnosis in older adults, with a higher AUC indicating greater discriminatory power. An AUC of 1 indicates optimal specificity and sensitivity in a model. The proposed method (EOO-MRF) achieved a 99% higher than the existing method, such as SVM of 98%, NN of 96%, and C&R tree of 92% as shown in Table 1 and Figure 3.

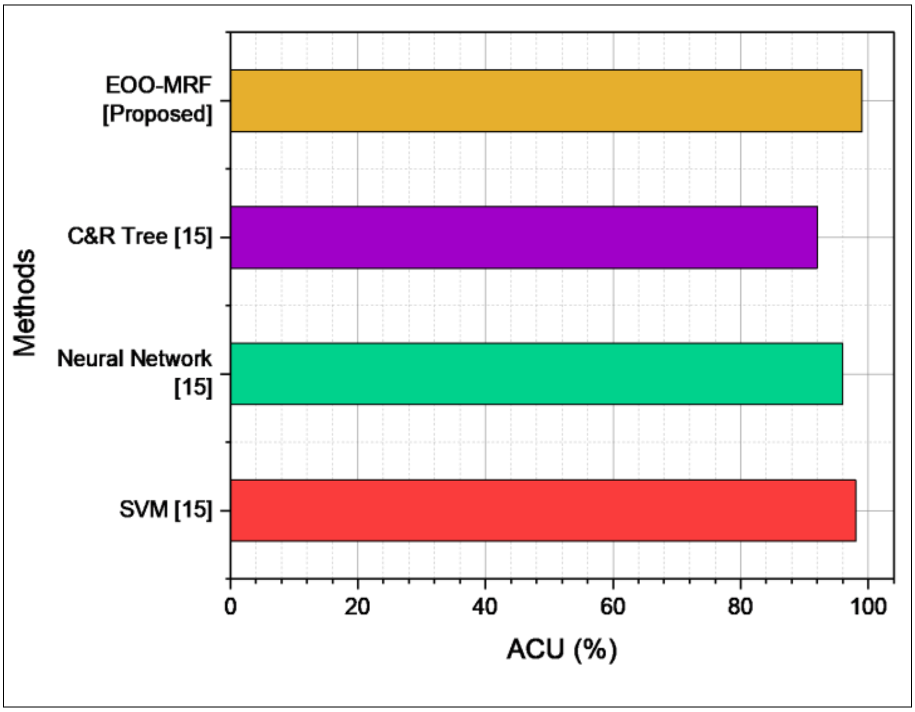

Fig 3: Outcome of the AUC

Conclusion

The development of a rapid identification method for stroke in the elderly is crucial to improving patient outcomes and minimizing long-term effects. By utilizing advanced technologies such as wearable health tracking devices and machine learning computations, healthcare providers can monitor brain function and signs, thereby enhancing the quality of living for senior citizens. Regular health screenings and increased knowledge of stroke symptoms can more effectively manage stroke risk, with the parameters accuracy of 95%, sensitivity of 99%, specificity of 96%, precision of 95%, and AUC of 99%, thereby promoting health and reducing strain on medical systems. Future developments in individualized risk evaluation, telemedicine integration, and outreach programs could further enhance stroke diagnosis for the elderly.

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