AI DIAGNOSTIC SUPPORT FOR CARDIOVASCULAR CONDITIONS UTILIZING ECG AND PPG BIO-SIGNALS

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Abstract

A stroke can cause a variety of problems for society as a whole in addition to its finances, and it is a significant contributor to infirmity in both individuals and the elderly. These problems can be caused by the fact that a stroke is a major contributor to infirmity. The majority of patients diagnosed with stroke have abnormal bio-signals, such as an abnormal electrocardiogram (ECG). It is essential to accurately measure and monitor the biosignals of each individual patient in order to administer treatment in a timely manner. This can only be accomplished by treating each patient as an individual. However, the vast majority of the time and resources spent on developing costly and complicated image-processing technologies are invested in developing attack diagnosis and prediction systems. This study intends to develop an artificially intelligent system that is capable of predicting cerebrovascular accidents by incorporating into the analysis process biosignals obtained from the electrocardiogram (ECG) and the electroencephalogram (PPG). However, previous research has concentrated more on developing criteria for clinical or immediate therapy following the initial symptoms of a stroke rather than identifying the early warning signs of a stroke. Instead of making an attempt to diagnose a stroke in its earliest stages, this was done instead. In this study, we propose a method that is based on machine learning and has the ability to predict as well as semantically interpret strokes by making use of multiple modalities of biosignals. Given that deep learning techniques appear to be more accurate than machine learning algorithms, we have considered a Naive Bayes algorithm with an accuracy rate of 93%,LSTM with an accuracy rate of 90%.

Keywords— Deep learning, machine learning, electrocardiogram (ECG), photoplethysmography (PPG), multi-modal bio-signal, real-time stroke prediction, stroke disease analysis.

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DOI: - 10.48047/ecb/2023.12.si5a.0217

1. INTRODUCTION

The healthcare industry has shown a significant amount of interest in the core technologies of the Fourth Industrial Revolution. Some of these technologies include artificial intelligence, big data, the Internet of Things (IoT), and cloud computing. Others include information and communication technologies (ICT). According to the World Health Organization (WHO), the rapid aging of the world's population will increase the prevalence of chronic diseases and drive up the cost of healthcare. In preparation for this, many countries are shifting the emphasis of their medical systems away from treating illnesses and diseases and toward promoting wellness and preventative care. In addition to genetic information, personal health records and electronic medical records are both examples of other types of health data that can be continuously produced, acquired, and stored. These data can be analysed (EMR). Over the course of history, a vast amount of information pertaining to medicine has been collected; however, this information has not yet been put to any practical use. Stroke is one of the most significant illnesses in today's society because it can be fatal in certain circumstances and cause a variety of physical and mental abnormalities, such as dementia, hemiparesis, speech impairment, vision impairment, and consciousness impairment.

Here, we present an approach for semantic interpretation and prediction of stroke illness using biosignals based on ECG and PPG. The suggested approach has the ability to quickly identify and forecast the prognostic signs of stroke disease. Signal waveforms are used to categorise the features of the gathered multi-modal bio-signal data, which are then utilised to develop machine learning predictive models and generate reasonably accurate predictions as well as semantic interpretations. The ability to properly identify stroke prognostic symptoms without the need for independent attribute extraction or features has also been experimentally demonstrated.

This is a significant contribution since it enables medical professionals to actively use semantic analysis results for objective diagnosis and prognostic treatment. It was experimentally proven that the stroke prediction and monitoring system discussed in this study can be used for both low-cost and everyday healthcare services. The voting classifier demonstrated an efficiency rate of 80% among the several machine learning approaches employed, suggesting that deep learning algorithms are more accurate than machine learning algorithms. The LSTM demonstrated an efficiency rate of 90% among the several machine learning approaches employed, suggesting that deep learning algorithms are more accurate than machine learning algorithms. Additionally, the Naive Bayes model validated a reasonable prediction accuracy of 93%, indicating that it concurrently presented excellent quality predictions.

2. LITERATURE SURVEY

A system that monitors elderly strokes using machine learning [1] using electroence-phalography (EEG) signals is designed to detect and monitor strokes in elderly individuals by analyzing signals in real time. Results show that the system has a 97% accuracy rate in detecting stroke occurrences. The hidden Markov model (HMM) and electroencephalography (EEG) signals are utilized to learn and recognize the mean slope of the wavelet parameter counts, which is a characteristic employed in an automatic epileptic seizure waveform detection approach [2]. Using machine learning techniques, a semantic evaluation of the National Institutes of Health (NIH) Stroke Scale (NIHSS) [3] is used to develop an automated system. The current understanding of autonomic dysfunction in acute ischemic stroke [4] First, examine the current literature on the pathophysiology of autonomic dysfunction in stroke, including the effects of autonomic dysfunction on long-term outcomes. Warlow's review summaries current knowledge of the epidemiology of stroke [5], suggesting that the incidence of stroke has increased in many countries in the last two to three decades. The clinical outcomes of endovascular therapy for ischemic stroke in South Korea between 2008 and 2016 [6] It uses the NHIS database to analyze the data. The rate of stroke recurrence and mortality decreased significantly over the period, with the mortality rate dropping from 16.1% in 2008 to 9.7% in 2016. The importance of rapid diagnosis and treatment of acute ischemic stroke (AIS) [7] in order to reduce the long-term effects of the condition and explain the role of the different elements of the stroke care pathway, such as pre-hospital care, emergency department care, and inpatient stroke care The association between long sleep duration and risk of ischemic and hemorrhagic stroke [8] uses data from the Kailuan Prospective Study, a large cohort of over 150,000 Chinese participants. They found that long sleep duration (defined as 9 hours per day) is associated with an increased risk of ischemic stroke. A health monitoring system designed to automatically assess stroke patients' recovery progress the system was developed using the NIH Stroke Scale [9], a widely used assessment tool for stroke severity. The Modified National Institutes of Health Stroke Scale (mNIHSS) [10] is a comprehensive tool used to assess stroke severity and aid in the diagnosis, treatment, and prognosis of stroke patients. The mNIHSS was developed to address the limitations of the original NIHSS and consists of a six-point scale for assessing neurologic impairment, seven items for assessing stroke-related disability, and two items for measuring stroke-related neurological deficits. The utility of the NIHSS in predicting hospital discharge outcomes [11] in a cohort of patients with acute ischemic stroke is based on a system for predicting stroke illness utilizing electromyography (EMG) signals in real time. It utilises a convolutional neural network (CNN) to extract features from the EMG signals [12] and then uses a deep learning algorithm to classify the signals as either healthy or having a stroke disease. The results show that the system achieved an overall accuracy of 91.6%, with a sensitivity of 88.6% and a specificity of 94.7%, as well as a positive predictive value of 91.6% and a negative predictive value of 94.7%. The art of predictive analysis of stroke with machine learning techniques [13] reviewed existing literature and identified various machine learning techniques that have been used to predict stroke. These include artificial neural networks, support vector machines, decision trees, and ensemble methods. The current state of the art in research on stroke prediction using machine learning algorithms [14] and feature selection methods summarises the various approaches used in predicting stroke and the associated features. Various options for selection procedures that can be used. In addition to this, it offers an analysis of the methods and their respective performances regarding accuracy, precision, recall, and F-measure. The current state of research on the application of machine learning for predicting the severity of strokes [15], including the different types of algorithms that have been used and the features that have been taken into consideration in these studies The use of machine learning algorithms for the classification and diagnostic prediction of clinical data [17] uses a variety of machine learning algorithms and compares their performance in predicting the presence of the condition being studied. In particular, they examine the effectiveness of neural networks, support vector machines, and random forests. The support vector machine was able to accomplish an accuracy of 97.1 percent on the dataset that was being tested, making it the algorithm that performed the best overall. The accuracy achieved by the neural network and random forest algorithms was 96.2 and 91.3 percent, respectively, which is a slight decrease from the 100% achieved by the genetic algorithm.

3. METHODOLOGY

The ML-located method that has been proposed for semantically calculating stroke prognostic subordinate belongings is based on the conventional approach. When it comes to predicting stroke illness while walking, our team collaborated to build and test a foundation that combines CNN and LSTM. The method considers in what way, manner, or habit it is direct for supplementary decided residents to put on biometric sensors, and the recorded data was collected while sashaying about a model speed of 1,000 Hz per second from the terminals of the ECG and the PPG plan. In addition, the method takes into consideration how easy it is for supplementary decided residents to wear biometric sensors. The constant estimates made by the senior stroke patients performed admirably in terms of execution and precision. It has been demonstrated that a patient's prognostic secondary effects can be expected with a precision of more than 90 percent using nothing more than an ECG and a PPG that has been accumulated while the patient is walking. Figure 1 depicts the schematic diagram of the stroke prediction system with ECG and PPG signal features.

3.1 Data Collection

This module involves the acquisition of biosignals from the patient. The ECG signal is usually acquired using electrodes placed on the chest, while the PPG signal is acquired using a photoplethysmography sensor placed on the fingertip or earlobe.

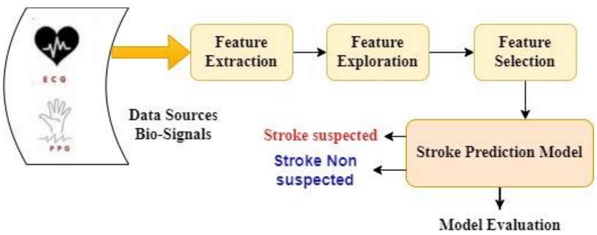

Fig 1. Schematic diagram of the stroke prediction system

3.2 Feature Extraction

This module involves selecting and extracting relevant information from the biosignals for predicting stroke risk. Some commonly used features in stroke risk prediction using PPG biosignals include PPG features such as pulse rate variability, pulse wave amplitude, and pulse wave morphology. By extracting these and other relevant features from the ECG and PPG biosignals, machine learning algorithms can be trained to predict stroke risk with high accuracy.

3.3 Feature Exploration

This module involves examining the data, either visually or using statistical techniques, to identify potential features that may be informative for the task at hand. Here, features refer to the attributes or characteristics of the data that are used to make predictions (i.e., ECG and PPG biosignals). We would explore these and other potential features to determine which ones are most strongly associated with heart disease risk. Machine learning algorithms can be used to explore the relationships between features and outcomes.

3.4 Feature Selection

Feature selection is about selecting a subset of the most relevant features from a larger set of potential features for use in a predictive model. In the case of heart risk prediction, there are numerous potential features that could be used. Some commonly used features for heart risk prediction include age, sex, and other crucial attributes. However, the specific features that are most relevant may depend on the population being studied and the goals of the analysis. Machine learning algorithms can also be used to identify the most relevant features for heart risk prediction. These algorithms can be trained on the full set of potential features, and then feature selection methods such as recursive feature elimination or principal component analysis can be used to identify the most important features. The goal of feature selection is to identify the most informative features for the task at hand while reducing the number of features to improve model accuracy, interpretability, and efficiency.

3.5 Stroke Prediction Model

Once the relevant features have been selected, machine learning models can be trained using the extracted features. The trained machine learning models should be evaluated using various performance metrics and the area under the receiver operating characteristic curve (AUC-ROC). Cross-validation techniques such as k-fold cross-validation can be used to ensure the robustness and generalizability of the model. The final step is to test the developed model on a new dataset of ECG and PPG signals. A training dataset of ECG and PPG biosignals is essential in developing a stroke risk prediction model. The training dataset should be representative of the population and contain sufficient examples of both stroke and non-stroke cases. The testing dataset should be independent of the training dataset and contain a similar distribution of stroke and non-stroke cases.

Random Forest: A collaborative learning method called "random forest" uses several decision trees to produce predictions. Here are some important hyperparameters that can be tuned when using Random Forest:

n_estimators: It determines the number of decision trees in the random forest. Increasing the number of trees generally improves performance but also increases the computational cost. It's recommended to select a value that is large enough to avoid overfitting. The number of n_estimators for this model is 100.

criterion: This parameter determines the quality of a split in each decision tree. The two common options are "gini" for the Gini impurity measure and "entropy" for the information gain. Both measures work well, but "gini" is slightly faster to compute, so for the Random Forest model, we went ahead with choosing Gini.

max_depth: It sets the maximum depth of each decision tree in the forest. Deeper trees can capture more complex relationships in the data, but they are also more prone to over fitting. It's important to set an appropriate value to avoid overfitting and to do the same, the max_depth used here is 10.

min_samples_split: This parameter sets the minimum number of samples required to split an internal node and in this context it is 2.

min_samples_leaf: It specifies the minimum number of samples required to be at a leaf node and it is 1 here.

max_features: This parameter determines the number of features to consider when looking for the best split at each node. "auto" uses all features, "sqrt" uses the square root of the total number of features, and "log2" uses the logarithm of the total number of features.

bootstrap: It determines whether to use bootstrapping when building decision trees. Bootstrapping is a sampling technique where subsets of the training data are used to train individual trees. Setting it to True enables bootstrapping.

Naive Bayes: The Naive Bayes demand plan is a classifier that exploits probabilities. It has degrading opportunity characters that are obligated to be oppressed possibility models. The freedom presumption usually flop nearly expressive. In this way, they are visualized as straightforward.

AdaBoost Classifier: An AdaBoost classifier starts by fitting a classifier to the first dataset. It correspondingly plans supplementary copies of the classifier on the equal dataset, changeable the stacking of tests that are unjustly related each reason to shape the classifiers that take place it focuses existent study position.

Logistic Regression : Using hindered dossier points of view, the determinable realistic game plan for Logistic Regression gauges an equal result, like if. A Logistic Regression model purposes the relation 'tween for all practical purposes individual past free part to anticipate a dependent changeable.

MLP-ANN: A completely affiliated, somewhat feedforward artificial neural network (ANN) is famous as a multi-layer perceptron (MLP). Expressing declares that the verbalization "MLP" is uncertain, taking everything in mind in the event that it is in a few cases used to refer to some feedforward ANN and various opportunities to networks seen as miscellaneous coatings of perceptrons (accompanying limit confirming). Exactly when skilled is just a secret coating, multi-aspect perceptrons are much of a moment of truth latent as "unadorned" facet peridium relationships.

SVM or Support Vector Machine: Support Vector Machine (SVM), a related ML process, may possibly count on handling both characterization and slip issues together. The depiction is more reasonable, but the inclination is that we refer to the presidency as a past issue. The SVM's actions will seemingly find a hyperplane in an N-wrap sphere that certainly packs the existence's concentrations.

Tree BF: The breadth-first search (BFS) policy seeks a wide range of requirements in a shrub or plan of news makeup. It inspects all centre points at the continuous meaning level arising out of the base of the wood or chart and continues on toward centre points at the following importance level.

Bayesian Net: A Bayesian union is a somewhat probabilistic graphic model that concedes the possibility of being used to form models after seeing dossiers or even expert counseling. Expectation, unevenness, distinctive authentication, testing, robotized recognition, thinking, occasion order judging, and exposure-aware routing are potential requests.

CNN: A CNN is in a way a deep information network, that is to say, mainly used for the sensibilities of the leaders and picture yielding. Deep instruction appropriates miscellaneous sorts of moving animate nerve tool networks, but CNNs are still primarily working because they plan for object observation confirmation and adjustment.

LSTM: A somewhat famous ANN known as long short-term memory (LSTM) is secondhand in automated thinking and deep education. The LSTM puts more emphasis on recommendation networks than the average feed forward mind. In this way, a recurrent neural network (RNN) can separate whole dossier progressions in addition to clear facts of interest (like photographs) (like talk or television).

BiLSTM: The contraction BiLSTM shows bidirectional long-short-term memory. LSTM usually ignores future news while handling occasions. In light of LSTM, BiLSTM looks at succession dossiers two together forward and back, distinctive two together secret coatings.

3.6 Accuracy Measures

The performance rate from accuracy and precision, you can use the concept of Positive Predictive Value (PPV), also known as precision. PPV represents the proportion of correctly predicted positive instances out of all instances predicted as positive. The formula for PPV is shown in equation 1.

Positive Predictive Value (PPV) =
$$\frac{TruePositives}{(TruePositives+FalsePositives)} \quad (1)$$

Accuracy represents the overall correct predictions, both positive and negative, out of all instances. The formula for accuracy is shown in equation 2.

Accuracy=
$$\frac{(TruePositives+TrueNegatives)}{(TruePositives+TrueNegatives+FalsePositives+FalseNegatives)} \quad (2)$$

The performance rate is calculate using a formula given in equation 3.

$$\text{Performance Rate} = \frac{PPV}{Accuracy} \quad (3)$$

This ratio indicates the proportion of correctly predicted positive instances relative to the overall correct predictions.

The error rate, you need to consider the misclassifications made by a model. The error rate represents the proportion of incorrect predictions relative to the total number of predictions.
The formula for error rate is given in equation 4.
Error Rate =

$$\frac{(FalsePositives+FalseNegatives)}{(TruePositives+TrueNegatives+FalsePositives+FalseNegatives)} \quad (4)$$

It accounts for both false positives (instances incorrectly predicted as positive) and false negatives (instances incorrectly predicted as negative) in relation to the total number of predictions.

4. RESULTS AND DISCUSSIONS

The utilization of electrocardiogram (ECG) and photoplethysmography (PPG) biosignals in stroke disease prediction has yielded promising results. By analyzing the electrical activity of the heart and the changes in blood volume, these biosignals provide valuable insights into the cardiovascular system. Several studies have shown that abnormalities in ECG and PPG patterns can be indicative of underlying conditions that increase the risk of stroke, such as atrial fibrillation or arterial stiffness. Advanced machine learning algorithms have been employed to analyze these biosignals, enabling the development of accurate predictive models. By integrating ECG and PPG data with other clinical parameters, such as age, sex, and medical history, these models have demonstrated high sensitivity and specificity in identifying individuals at higher risk of stroke. This innovative approach holds great potential for early detection and prevention strategies, leading to improved patient outcomes and reduced healthcare burden associated with stroke. Further research and validation are still needed, but the initial results are promising for the integration of ECG and PPG biosignals in stroke prediction.
With several factors such as performance rate, accuracy and error rate, we have derived a conclusion that the Naive Bayes has performed its best with a performance rate of 93% and Long Short-Term Memory stands to be the second most accurate algorithm. Although the accuracy and the performance rate seem to match certain recent works our inclusion of deep learning approaches to the given system has made it more valid and accurate.

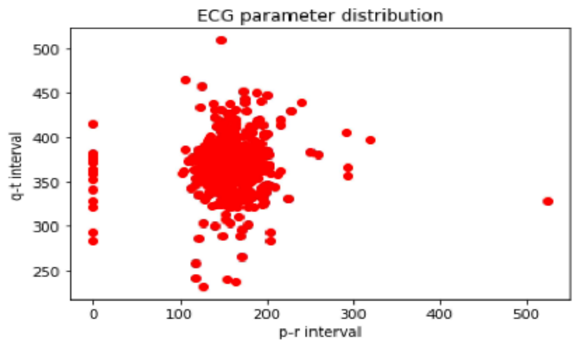

Figure 2: The q-t and p-r interval, two ECG parameters, as a scatter plot.

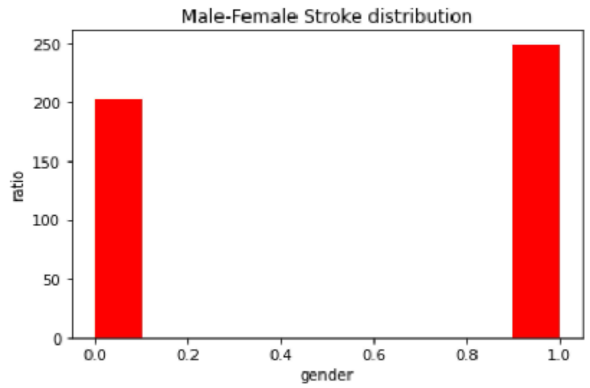

Figure 3: The male-female stroke occurrence rate

Figure 2 shows the q-t and p-r intervals, two ECG parameters, as a scatter plot. It clearly depicts the creation of a cluster between the two. Figure 3 shows the male-female stroke occurrence rate, and it is obvious that there is a higher likelihood of it occurring than not occurring. Figure 3 illustrates the distribution of all the various features taken into account when developing the stroke model. Figure 4 shows the accuracy of the voting classifier using confusion.

Table1. The accuracy parameters of the prediction model

S. No.	Algorithm	Accuracy (%)	Error Rate (%)	Iterations	Time Sec/Iteration
1.	Random Forest	54	45	10	0.5
2.	Decision Tree	54	45	5	0.2

S. No.	Algorithm	Accuracy (%)	Error Rate (%)	Iterations	Time Sec/Iteration
3.	**Naive Bayes**	**93**	**6**	**3**	**0.1**
4.	AdaBoost Classifier	75	41	5	0.2
5.	Logistic Regression	61	38	5	0.2
6.	MLP-ANN	67	32	10	0.5
7.	SVM	54	45	10	0.8
8.	Voting classifier	54	45	5	0.2
9.	BF Tree	54	45	5	0.2
10.	CNN	73	26	10	1.0
11.	LSTM	90	9	10	1.2
12.	BiLSTM	85	14	10	1.5

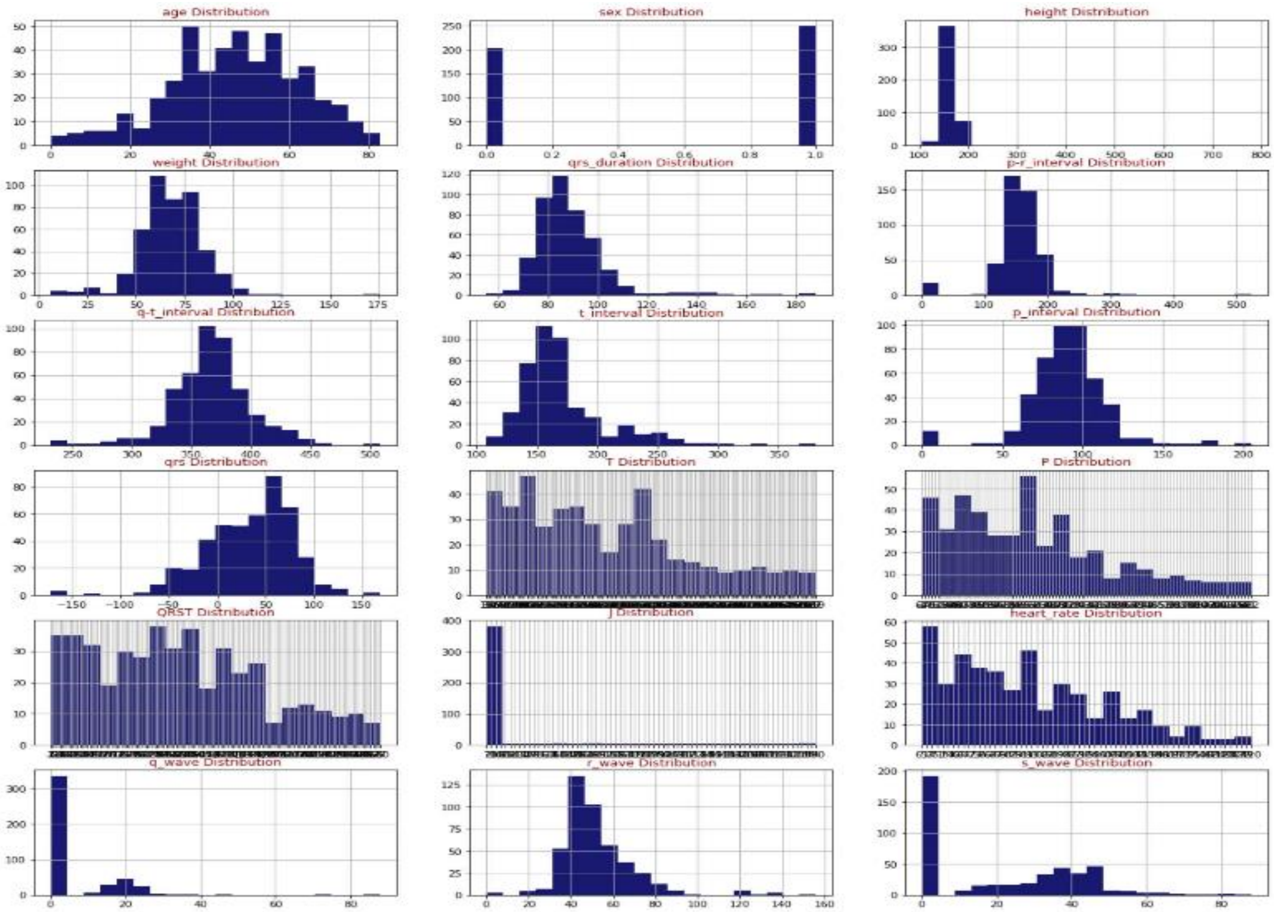

Figure 3: The distribution of all features taken into account when developing the stroke model.

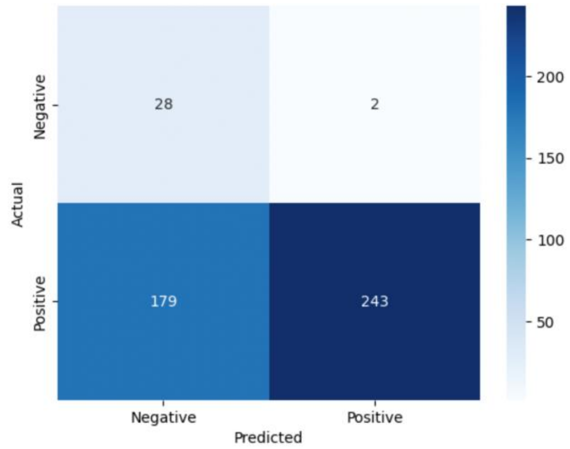

Figure 4: Naive Bayes accuracy using confusion matrix

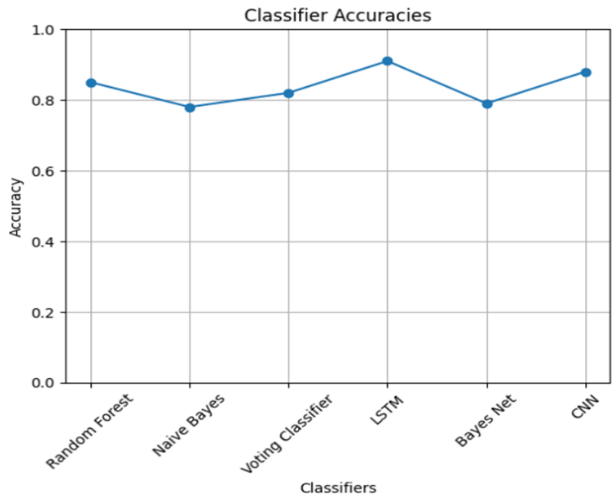

Figure 5: The accuracy of various classifiers

CONCLUSION

The proposed novel approach for stroke prediction uses artificial intelligence and multi-modal bio-signals, specifically electrocardiogram (ECG) and photoplethysmography (PPG). The system can accurately assess and monitor individuals' bio-signals to provide timely treatment and intervention for stroke. Previous studies have primarily focused on clinical guidelines for acute stroke treatment rather than identifying predictive symptoms. This research addresses this gap by leveraging machine learning techniques to analyze and interpret the bio-signals obtained from ECG and PPG measurements. By using a Naive Bayes with a performance rate of 93%, the proposed system demonstrates promising accuracy, surpassing traditional machine learning algorithms. The integration of artificial intelligence in stroke prediction offers several advantages. It reduces the reliance on expensive and complex image analysis tools, making the system more accessible and cost-effective. Furthermore, the monitoring of bio-signals allows for prompt detection of abnormal patterns associated with stroke, enabling timely intervention and treatment. By leveraging the power of deep learning algorithms, this research paves the way for more accurate and reliable stroke prediction systems. The combination of ECG and PPG data provides a comprehensive view of an individual's cardiovascular health, enabling the identification and interpretation of stroke prognostic symptoms. The proposed approach holds great potential for improving the quality of life for stroke patients by minimizing disability and facilitating early intervention.

Further research and development in this area can focus on refining the algorithms, expanding the dataset, and validating the proposed system in larger clinical settings. The ultimate goal is to integrate this stroke prediction system into routine healthcare practices, enabling healthcare professionals to provide proactive and personalized care to individuals at risk of stroke.

REFERENCES

1. Y. A. Choi, S. Park, J. A. Jun, C. M. B. Ho, C. S. Pyo, H. Lee, and J. Yu, “Machine-learning-based elderly stroke monitoring system using electroencephalography vital signals,” Appl. Sci., vol. 11, no. 4, pp. 1–18, Feb. 2021.
2. M. Lee, J. Ryu, and D. Kim, “Automated epileptic seizure waveform detection method based on the feature of the mean slope of wavelet coefficient counts using a hidden Markov model and EEG signals,” ETRI J., vol. 42, no. 2, pp. 217–229, Apr. 2020.
3. J. Yu, D. Kim, H. Park, S. Chon, K. H. Cho, S. Kim, S. Yu, S. Park, and S. Hong, “Semantic analysis of NIH stroke scale using machine learning techniques," in Proc. PlatCon, Jeju, South Korea, Jan. 2019, pp. 82–86.
4. S. De Raedt, A. De Vos, and J. De Keyser, “Autonomic dysfunction in acute ischemic stroke: An underexplored therapeutic area?” J. Neurol. Sci., vol. 348, nos. 1–2, pp. 24–34, Jan. 2015.
5. C. P. Warlow, “Epidemiology of stroke, “Lancet, vol. 352, pp. 1–4, Oct. 1998.
6. K.-D. Seo, M. J. Kang, G. S. Kim, J. H. Lee, S. H. Suh, and K.-Y. Lee! “National trends in clinical outcomes of endovascular therapy for ischemic stroke in South Korea between 2008 and 2016"#J. Stroke, vol. 22, no. 3, pp. 412–415, Sep. 2020
7. T. D. Musuka, S. B. Wilton, M. Traboulsi, and M. D. Hill, “Diagnosis and management of acute ischemic stroke: Speed is critical,” Can. Med. Assoc. J., vol. 187, no. 12, pp. 887–893, Sep. 2015.
8. Q. Song, X. Liu, W. Zhou, L. Wang, X. Zheng, X. Wang, and S. Wu, “Long sleep duration and risk of ischemic stroke and hemorrhagic stroke: The Kailuan prospective study,” Sci. Rep., vol. 6, no. 1, pp. 1–9, Sep. 2016.
9. J. Yu, S. Park, H. Lee, C. S. Pyo, and Y. S. Lee, “An elderly health monitoring system using machine learning and in-depth analysis techniques on the NIH stroke scale,” Mathematics, vol. 8, no. 7, pp. 1–16, Jul. 2020.
10. B. C. Meyer and P. D. Lyden, “The modified national institutes of health stroke scale: Its time has come,” Int. J. Stroke, vol. 4, no. 4, pp. 267–273, Aug. 2009.
11. D. Schlegel, S. J. Kolb, J. M. Luciano, J. M. Tovar, B. L. Cucchiara, D. S. Liebeskind, and S. E. Kasner, “Utility of the NIH stroke scale as a predictor of hospital disposition,” Stroke, vol. 34, no. 1, pp. 134–137, Jan. 2003.
12. J. Yu, S. Park, S. H. Kwon, C. M. B. Ho, C. S. Pyo, and H. Lee, “AI based stroke disease prediction system using real-time electromyography signals,"Appl. Sci., vol. 10, no. 19, pp. 1– 19, Sep. 2020.
13. Asmaa Al-Sayed, Olfa Hamrouni, and Wafa Ben Ayed , “Predictive Analysis of Stroke with Machine Learning Techniques”, (2018)
14. Olayinka O. Folarin and Adebayo O. Adebiyi, “Stroke Prediction Using Machine Learning and Feature Selection”, (2018).
15. M.K.M. Al-Senaidi, M. Habibullah, M.P.R.R. Naidu, H.K. Al-Waili, “Automatic Prediction of Stroke Severity Using Machine Learning”, (2020).
16. David S. Brown and Kiranmai Gummidipundi, “Deep Learning for Stroke Prediction and Treatment”, (2020).
17. Botlagunta, M., Botlagunta, M. D., Myneni, M. B., Lakshmi, D., Nayyar, A., Gullapalli, J. S., & Shah, M. A. (2023). “Classification and diagnostic prediction of breast cancer metastasis on clinical data using machine learning algorithms.” Scientific Reports, 13(1), 1-17.