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CNN and Rf based Early Detection of Brain Stroke Using Bio-Electrical Signals

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Abstract: The brain is a vital component of the body that is in control of involuntary and voluntary movements such as walking, memory, and vision. Nowadays, some of the most prevalent brain disorders include Alzheimer's disease, brain tumors, and epilepsy (paralysis or stroke). As a result, stroke has become a significant global health concern, with high rates of mortality and disability. Importantly, approximately two-thirds of all strokes occur in developing countries, highlighting the significant burden of this condition in these regions. Therefore, emphasizing the timely detection and appropriate treatment of brain tumors is crucial. Given the high potential for mortality or severe disability associated with stroke disease, prioritizing active primary prevention and early identification of prognostic symptoms is of paramount importance. Ischemic stroke and hemorrhagic stroke are the two primary classifications for stroke diseases. Each type calls for specific emergency treatments, such as the administration of thrombolytics or coagulants, tailored to their respective underlying mechanisms. However, to effectively manage stroke, it is crucial to promptly identify the precursor symptoms in real-time, as they can vary among individuals. Timely professional treatment within the appropriate treatment window is essential and should be provided by a medical institution. In contrast, prior research has primarily centered around the formulation of acute treatment strategies or clinical guidelines subsequent to the occurrence of a stroke, rather than giving sufficient attention to the early identification of prognostic symptoms. Specifically, recent research has extensively utilized image analysis techniques, such as computed tomography (CT) or magnetic resonance imaging (MRI), as a primary approach for detecting and predicting prognostic symptoms in stroke patients.

Traditional methodologies not only encounter difficulties in achieving early real-time diagnosis but also exhibit limitations in terms of prolonged testing duration and high testing costs. In this study, we introduce a novel system that employs machine learning techniques to predict and semantically interpret prognostic symptoms of stroke. Our approach utilizes real-time measurement of multi-modal bio-signals, namely electrocardiogram (ECG) and photoplethysmography (PPG), with a specific focus on the elderly population.

To facilitate real-time prediction of stroke disease during walking, we have developed a stroke disease prediction system that incorporates a hybrid ensemble architecture. This architecture synergistically combines Convolutional Neural Network (CNN) and Random Forest (RF) models, enabling accurate and timely prognostication of stroke disease. The suggested method prioritises the convenience of use of bio-signal sensors for the elderly by collecting bio-signals from three electrodes placed on the index finger. These signals include ECG and PPG, and they are obtained while the participants walk. The CNN-RF model delivers satisfactory prediction accuracy when using raw ECG and PPG data. F1-Score, Sensitivity, Specificity, and Accuracy were the performance parameters used to evaluated the model's performance.

Keywords: Electrocardiogram (ECG), Photo plethysmography (PPG), stroke disease analysis, Convolutional Neural Network (CNN), Random Forest(RF).

I. INTRODUCTION

The Global Burden of Disease Study highlights stroke as one of the diseases characterized by one of the highest mortality rates worldwide. According to the available data from 2017, stroke accounted for approximately 11.02% of total deaths globally. A medical condition is characterized by brain damage resulting from the blockage of blood vessels, which leads to insufficient blood supply and, in some cases, bleeding within the brain tissue [2]. Stroke, recognized as a cardio-cerebrovascular disease, is categorized as a catastrophic condition due to its need for specialized expertise in therapy, utilization of sophisticated medical devices, and potential requirement of lifelong health services [11]. Stroke, requiring a lengthy healing process, leads to substantial healthcare costs, thereby resulting in significant health claims.

Giving special attention to early detection of stroke is crucial to reduce the number of cases over time. When an individual shows symptoms of paralysis in a specific body part, it is crucial to conduct further examinations to determine the underlying cause, which may include a stroke, tumor, infection, or something else. Before starting the treatment, it is customary to carry out a Computerized Tomography Scan (CT scan) as the initial diagnostic procedure for the patient. Magnetic Resonance Imaging (MRI) serves as an alternative to CT scanning, however, it is accompanied by higher expenses. Additionally, the examination time for an MRI is longer compared to a CT scan. As a result, doctors often recommend CT scans for patients. A CT scan can assist doctors in determining if the patient had an ischemic or hemorrhagic strokeIf a hemorrhagic stroke is detected, the usual course of treatment involves administering hemorrhage medication or referring the patient to a neurosurgeon. Considering the identification of an ischemic stroke, let us assume the patient is a newly diagnosed case. Within such situations, prompt treatment is provided to the patient due to the existence of a critical time window known as the golden period, which spans 4.5 hours. The objective is to minimize the risk of death or long-term disabilities. Consequently, it is imperative to achieve quick and accurate stroke detection to ensure timely and focused delivery of treatment.

Stroke can be categorized into two primary types: ischemic stroke and hemorrhagic stroke. Ischemic stroke occurs when a blood vessel supplying the brain is blocked, while hemorrhagic stroke happens when a blood vessel in the brain ruptures. It is a neurological symptom and condition that arises due to damage to a specific area of the brain [8]. Stroke is considered a significant health concern in modern society, given its potential to cause death in severe cases and its association with a range of physical and mental disorders such as ataxia, hemiparesis, altered consciousness, visual impairment, speech impairment (aphasia), and memory difficulties. Based on the 2019 Causes of Death Report by the World Health Organization (WHO), the top 10 causes of death accounted for approximately 55% of all recorded deaths in 2019, which amounted to around 55.4 million individuals. Among these causes, cerebrovascular disease stood out as the second most prominent cause of death, with a total of 6 million attributed deaths.

Recently, CT and MRI imaging techniques have become popular for diagnosing strokes. However, these approaches may present certain drawbacks during the examination and diagnosis process, including potential hypersensitivity reactions to contrast agents, exposure to radiation, and the discomfort of confined spaces that can trigger feelings of claustrophobia. Accurate judgments in the medical field rely on the professional expertise of the medical staff and their reliance on empirical evidence, recognizing the possibility of errors in test results. National Institutes of Health Stroke Scale (NIHSS) is an invaluable research tool, developed by the United States National Institutes of Health, that aids in the evaluation of initial disabilities and the prevention of recurrent strokes in patients [3]. Despite its extensive use in assessing initial impairment in stroke patients, the NIHSS encounters challenges in real-time detection of such impairment and faces limitations in clinical and psychological analyses.

In recent research, the use of ECG data has been highlighted in predicting and preventing stroke diseases, with a specific emphasis on atrial fibrillation (AF), which is known as a major factor in causing strokes. Atrial fibrillation (AF), a substantial risk factor for stroke, particularly in hypertensive patients, can raise the risk of cerebral infarction by more than fivefold [10]. Based on clinical trials, a previous study identified several risk factors associated with stroke diseases, such as high blood pressure, diabetes, obesity and smoking.

In recent research, the focus has been on meeting the increasing demand for a solution that enables senior citizens to evaluate their personal risk factors for stroke and identify early indications of the condition in real-time. To tackle these obstacles, researchers have delved into the utilization of statistical and machine learning methods to forecast instances of stroke by taking into account distinct risk factors.

This approach presents a method that utilizes ECG and PPG-based multi-modal bio-signals for predicting stroke diseases and interpreting findings specifically for the elderly population. By implementing real-time collection and analysis of various bio-signals, the proposed system enables the immediate detection and prediction of indicative symptoms related to stroke disease in elderly individuals. The study involved participants aged 65 or older, who had their ECG and PPG bio-signals recorded and stored during walking. The gathered multi-modal bio-signal data was segmented into distinct intervals, utilizing the waveform characteristics of the signals. These segmented attributes are then utilized to develop predictive models using machine learning techniques, aiming to achieve relatively accurate predictions and meaningful interpretations. Experimental verification has confirmed the efficacy of deep learning time series analysis models in accurately detecting stroke prognostic symptoms by directly utilizing raw data. This eliminates the requirement for separate attribute extraction and feature engineering processes. The disease prediction system proposed for the elderly employs a combination of multimodal bio-signals to achieve real-time detection and prediction of stroke prognostic symptoms. This system addresses the urgent need to identify and manage stroke, a condition associated with high mortality and incidence rates, with timely and proactive interventions.

Moreover, the CNN-RF model exhibited a satisfactory level of prediction accuracy, simultaneously showcasing high performance in the stroke disease prediction system. The remaining sections of the paper are structured as follows: Section II presents the Literature Survey, Section III explains CNN And RF Based Early Detection Of Brain Stroke Using BIO-Electrical Signals. Section IV encompasses the analysis of experimental results, and the paper concludes with Section V.

II. LITERATURE SURVEY

Couceiro et al., [19] focused on extracting the characteristics of atrial fibrillation (AF) from electrocardiogram (ECG) data by analyzing three key physiological and clinical attributes associated with AF. They specifically examined the three attributes of heart rate irregularity, wave absence, and atomic activity, and their findings revealed noteworthy sensitivity and specificity. These studies have confirmed that AF symptoms can be detected with a relatively high degree of accuracy.

J.M. Bumgarner et al. [6] investigated the Kardia Band (KB), a unique technology that allows the recording of rhythm strips with an Apple Watch (Apple, Cupertino, California). In order to assess the accuracy of detecting atrial fibrillation (AF) and sinus rhythms, an experiment was conducted using lead ECG and KB records. The medical personnel utilized an app that offers automated identification of atrial fibrillation to interpret these records. In cases where the KB data was difficult to interpret, electrophysiologists confirmed the diagnosis of AF using specific criteria such as specificity, sensitivity, and the K coefficient.

J. S. Lee, T. H. Park, J. M. Park, K. B. Lee, Y. J. Cho, S. J. Lee, M. K. Han, J. Y. Lee, and H. J. Bae et al., [18], Developed over a 10-year period, a stroke risk prediction model was created. The model considered systolic smoking, blood pressure, exercise, body mass index, diabetes, total cholesterol, drinking, age, and other factors as stroke risk indicators. Nonetheless, this study utilized a comparable approach to the stroke risk prediction model implemented in the Framingham Heart Study. Current research has emphasized several ongoing initiatives that aim to employ the National Institutes of Health Stroke Scale (NIHSS) methodology as an innovative approach to prevent stroke recurrence and dynamically assess initial disease manifestations, targeting the key risk factors associated with stroke.

The P. Lyden, B. Tilley, T. Brott, K. M. Welch, S. Levine, E. J. Mascha, J. Grotta, J. Marler, and E. C. Haley et al. [20] scale is a frequently used measure for quantifying disability after stroke. The NIHSS is a widely accepted scale used to assess stroke severity. It evaluates various neurological examination features and calculates a total score that indicates the overall stroke impairment. The utilization of the NIHSS scale is notably straightforward, requiring an average time of 6.6 minutes per stroke patient. In particular, there is a need to develop a classification and prediction model for stroke severity specifically targeting elderly Koreans. One major drawback of existing models is their inability to provide comprehensive results for assessing initial impairment.

A. Clerigues et al. [4] introduced and assessed a novel approach that utilizes.The application of Convolutional Neural Networks (CNN) enables the automated segmentation of the nucleus in acute stroke lesions on CT scan images. The author chose to focus on ischemic stroke for further discussion due to the higher prevalence of ischemic stroke cases compared to hemorrhagic stroke cases. Ischemic stroke typically leads to density changes in the brain, which are visible on CT scans as hypodense areas characterized by darker results.

Chin et al. [7] successfully detected ischemic stroke using a Convolutional Neural Network (CNN). In their subsequent research, the CNN exhibited excellent performance, achieving a notable level of accuracy. As mentioned in the earlier literature, the application of deep learning techniques, specifically Convolutional Neural Networks (CNN), demonstrates a notable level of accuracy in the early detection of ischemic strokes. Nevertheless, the utilization of this technology requires the use of a costly and time-consuming device. Some studies employ a combination of both approaches by incorporating distinct methods for feature extraction and classification. The classification process is then performed based on the outcomes obtained from feature extraction.

R. Bhavani and N. H. Rajini et al., [13] employed a multi-stage approach for detecting ischemic stroke, which involved segmentation and texture feature analysis. The process involved feature extraction using the Gray Level Co-Occurrence Matrix (GLCM), followed by pre-processing and classification utilizing K-Nearest Neighbor (KNN), Support Vector Machines, and K-Means algorithms.

O. Maier et al. [9] revealed that the feature extraction techniques utilized in their study encompassed intensity, 2D center distance, weighted local mean, and local histogram. The classification of these features was performed using different algorithms, including KNN, Generalized Linear Models(GLM), Gaussian Naïve Bayes(GNB), Random Forests (RF), Gradient Boosting, Extra Trees, AdaBoost, CNN.RF and CNN demonstrated superior performance, as evaluated by the dice coefficient.

K. C. Ho, et al. [5] In the study, a machine learning technique was applied to classify the occurrence time of ischemic stroke by utilizing image data. The feature extraction process encompassed the extraction of descriptive statistics from the region of interest along with the incorporation of morphological features. Subsequently, the extracted features were classified using gradient boosted regression tree (GBRT), logistic regression (LR), stepwise multilinear regression (SMR), random forest (RF), and support vector machine (SVM) algorithms. Based on the cross-validation results, the author's top-performing classifier exhibits a substantial area under the curve, as well as remarkable sensitivity and negative predictive value, specifically utilizing logistic regression (LR).

Subudhi, et al., [13] In their study, the researchers utilized a diffusion-weighted image sequence (DWI) of magnetic resonance (MR) images to identify and detect the occurrence of ischemic stroke. The segmentation of the particular brain region impacted by a stroke is achieved through the utilization of the expectation-maximization algorithm. The obtained region of interest from the segmentation undergoes additional processing using the fractional technique known as Darwinian Particle Swarm Optimization (FODPSO) to improve the accuracy of detection. In the evaluation process, a total of 192 MRI scans were included, and from these scans, morphological and statistical features were extracted from the segmented lesions. These features were then used to generate sets of features for further analysis. Following that, the feature sets were subjected to classification utilizing SVM and RF algorithms. The proposed approach exhibited successful detection of stroke lesions, demonstrating superior accuracy with the RF algorithm compared to the results obtained with SVM.

Bhavani and Hema Rajini et al., [14] conducted a study on the automatic detection of ischemic stroke. In their study, they presented an approach that utilizes segmentation techniques to differentiate normal tissue from abnormal tissue. The method outlined in this paper comprises four main stages: classification, brain midline tracking, feature extraction and pre-processing. In the classification stage, the authors implemented the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) algorithms. However, it has been observed that this approach requires significant memory resources and may yield inaccurate results.

Fuk-hay Tang et al. [16] conducted a research study focusing on the early detection of ischemic stroke and the analysis of associated brain injuries. The authors utilized the Otsu algorithm to convert images into binary form, and subsequently extracted features from the Circular Adaptive Region of Interest to determine the location of the lesion in the image. However, it should be noted that the number of samples used in the study was relatively small. Sometimes, deep learning algorithms may not yield effective results on unseen data. However, recent advancements in the field of medical image analysis have shown that these algorithms, particularly in the analysis of medical images, have demonstrated remarkable performance, overcoming such limitations. The convolutional neural network (CNN) is extensively utilized in computer vision applications, particularly in the field of radiology, due to its robustness and remarkable performance. This deep learning algorithm is specifically designed to learn spatial features through the use of backpropagation and multiple building blocks. As a result, CNNs excel in image recognition tasks, delivering excellent performance in various domains.

Rajendra et al.,[17] introduced a method for detecting ischemic stroke by utilizing higher-order spectra features in brain MRI images. The developed technique showcased effective detection of stroke lesions with promising results. In their study, the authors employed a hybrid approach combining the expectation maximization algorithm with a random forest classifier to perform the classification and segmentation of brain stroke. The incorporation of the random forest classifier resulted in a significant level of accuracy, as demonstrated in their study.

III. CNN AND RF BASED EARLY DETECTION OF BRAIN STROKE USING BIO-ELECTRICAL SIGNALS

This work presents a CNN and RF-based approach for early detection of brain stroke using BIO-Electrical Signals. The Fig. 1 displays the architectural design of the presented model.This paper presents a system designed to monitor the health and detect stroke disease in elderly individuals by leveraging the analysis of multimodal bio-signals. The aim of this study is to develop a robust and accurate methodology for automated brain stroke diagnosis and precise identification of abnormal regions. To create an automated system, this study will harness the capabilities of a convolutional neural network (CNN) model to effectively and accurately detect the occurrence of brain stroke.

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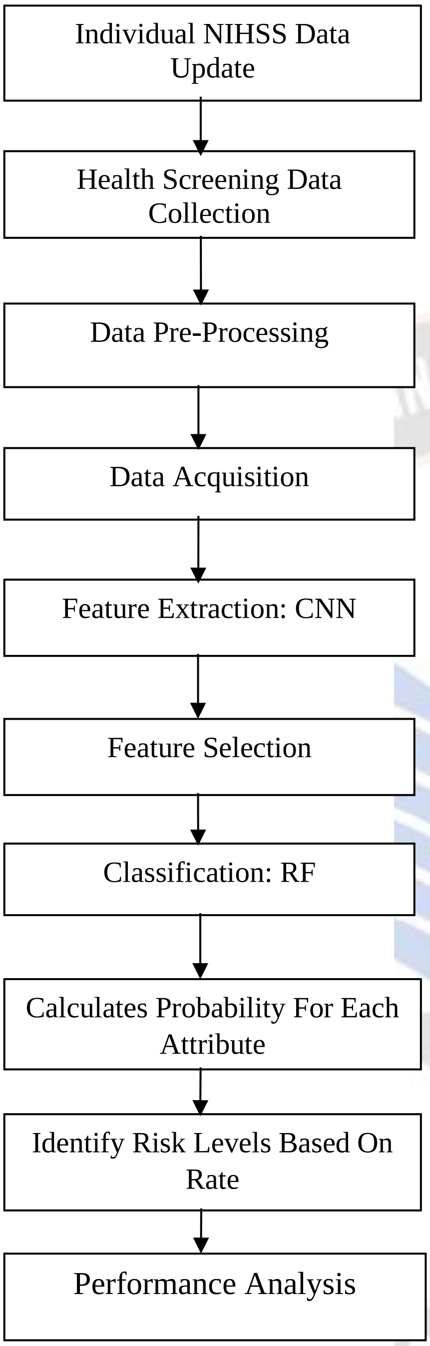

Fig. 1 The architecture of presented model.

This study involves the measurement and collection of various bioelectrical signals to evaluate the effectiveness of CNN-RF-based systems in providing prognostic and predictive information for stroke diseases in older individuals. Our proposed approach integrates two bio-signals to create a combined feature that enables accurate prediction of stroke prognostic symptoms and onset.

In this section, we present the architecture of a stroke severity prediction system that integrates the National Institutes of Health Stroke Scale (NIHSS), enabling both stroke severity prediction and semantic analysis. Figure 1 depicts the system architecture, comprising four modules: smart devices, a Performance Analysis module, a medical data center containing NIHSS data, and a training and prediction module. The following provides a description of the procedure for our proposed semantic analysis system specifically designed to analyze real-time National Institutes of Health Stroke Scale (NIHSS) data of elderly individuals. The data used in this experiment were collected from the emergency medical center of Chungnam National University Hospital. The NIHSS data employed in this research encompasses a range of features used for assessing the level of consciousness, motor function of the left and right legs, motor function of the left and right arms, best gaze, sensory function, facial palsy, limb ataxia, language ability, visual function, extinction, inattention (formerly neglect), dysarthria, as well as age and gender information. The patient is instructed by the emergency room (ER) doctor to sit on a bed in a designated room and follow a predetermined measurement scenario. The evaluation of NIHSS features is carried out based on the patient's responses during the examination.

This paper introduces a system that evaluates the initial disability caused by a stroke and performs semantic analysis utilizing Random Forest (RF) and Convolutional Neural Network (CNN) algorithms. The study emphasizes the utilization of NIHSS features in this analysis. Our proposed system utilizes the real-time collection of NIHSS features to classify and predict strokes into four categories (moderate-to-severe, mild, severe, and moderate) by employing CNN-based analysis. Our proposal aims to provide the patient and their family with an assessment of the level of disability. Furthermore, the system provides a real-time alarm service, alerting patients with a history of stroke to visit the medical center or hospital when necessary. The alarm system ensures that patients with a previous history of stroke receive prompt and necessary care from medical professionals. This is accomplished by continuously monitoring and analyzing stroke scale features and scores, thereby facilitating timely visits to medical centers or hospitals. Furthermore, our system enhances system reliability and operational efficiency by reducing the time required for patient NIHSS measurements.

The user of the stroke severity prediction application gathers NIHSS data from multiple sources in real-time and transfers it to a cloud-based medical data center. The individual patient NIHSS data module within the proposed medical data center ensures that the received data is continuously updated in real-time and transferred to the health-screening data collection within the database. The real-time data from the health screening database is securely transmitted to the medical center repository using a dedicated authentication module specific to each individual patient. In the stroke severity training module, the patient data and information obtained from the medical center repository are subjected to data mining and machine learning analysis to facilitate processing. Effective assessment of stroke severity heavily relies on the careful selection or reduction of relevant features, incorporating the National Institutes of Health (NIH) stroke scale and health-screening data. These selected features are subsequently incorporated into the CNN-RF prediction model generator, enabling accurate prediction of stroke severity.

The another step in CNN is Pre-Processing. Radiologists with expertise in the field recognize the slight variations in CT values between the brain tissue adjacent to a stroke region and the normal brain tissue. It can be challenging for an inexperienced radiologist to readily identify these subtle differences. In order to detect these subtle variances, we employ edge detection techniques alongside an unsupervised region expansion algorithm (URGA) to enhance the visibility of the discrepancies. Our goal during edge detection is to locate the boundary of the stroke region, which demonstrates a noticeable qualitative alteration in the CT stroke image. Data pre-processing is essential before model development to eliminate unwanted noise and outliers from the dataset, preventing the model from veering off its intended training path. To enhance the model's efficiency, this stage focuses on addressing any factors that impede its optimal functioning. Once the relevant dataset is collected, it undergoes a thorough cleaning and preparation process to ensure efficient model development.

The dataset used for this study consists of brain stroke data collected from ATLAS (Anatomical Tracings of Lesions after Stroke), a specialized website focusing on neuroimaging studies. Upon accepting the terms and conditions, users were given permission to download the dataset containing brain stroke information. The dataset consisted of anatomical brain images of stroke patients, accompanied by manually segmented lesion areas. The data is provided in Nifty format and includes weighted MRI scans with manual segmentation, as well as associated metadata in .csv format. Additionally, the dataset includes MRI scans from a normal patient group.

CNN, which stands for Convolutional Neural Network (NN), is a development approach for neural networks that incorporates a convolutional layer, added after the image input layer. The CNN method involves two main stages: feature extraction, which involves the convolutional layer and pooling layer, and a trainable classifier that utilizes fully connected neural networks. The output obtained from the convolutional layer and pooling layer acts as the input for the subsequent stage, known as the fully connected layer of the neural network (NN). In CNN, the Neural Network (NN) component is responsible for the classification of data by converting the extracted features from image data into numeric representations. Following the feature extraction phase in CNN, the fully connected layer is substituted with random forests for data classification. The main goal of this study is to categorize ischemic strokes into acute, sub-acute, and chronic groups, as these classifications are of considerable significance. Consequently, the prediction is that doctors and medical personnel in radiology would receive valuable support in quickly and accurately identifying patients with ischemic stroke, enabling them to determine the appropriate and specific care required for each individual patient.

Convolutional Neural Network (CNN) and feature selection techniques were employed to enhance the accuracy and reliability of stroke detection. Feature selection is a well-established data pre-processing technique in the field of machine learning. It serves as a dimensionality reduction method primarily utilized for eliminating redundant and irrelevant features from a dataset.

Random Forest is a flexible ensemble learning technique utilized for performing both classification and regression tasks. In Random Forest, each classifier within the ensemble is a decision tree classifier, forming a collection of classifiers that together create a forest. During training, decision trees are created, and the ensemble model determines the predicted class by taking the mode or mean prediction from the individual trees. Many research studies have emphasized the use of decision trees in predicting life-threatening diseases, underscoring their improved effectiveness in this context.

A blockage in the blood flow to a particular region of the brain leads to the occurrence of a stroke. As a result, brain cells are deprived of oxygen and start to dieAs brain cells die, individuals may experience weakness or paralysis, and some may lose their ability to speak or walk. The American Stroke Association (ASA) reports that a stroke takes place in the United States approximately every 40 seconds. Being the primary cause of disability, it is crucial to recognize the risk factors for stroke and take preventive measures to avoid its occurrence, as the recovery process can be lengthy and unpredictable. Measuring a model's performance is crucial to analyzing its efficiency. We conducted an analysis using the National Institutes of Health Stroke Scale (NIHSS) to evaluate the performance of the CNN and RF models separately.

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IV. RESULT ANALYSIS

This section introduces the approach of early detection of brain stroke using BIO-electrical signals, focusing on the implementation of CNN and RF models. Various parameters are calculated and analyzed to evaluate the performance and assess the stability of the system. These are represented as follows: FP indicates the number of normal images classified as abnormal, TN represents the number of normal images correctly classified, TP denotes the number of abnormal images correctly classified, and FN represents the number of abnormal images classified as normal. The proposed method is evaluated using various performance metrics, including accuracy, sensitivity, specificity, and F1-Score.

Sensitivity: The sensitivity indicates how well the model detects brain ischemic strokes. The ability of the method to identify abnormal cases is given by Sensitivity

$$Sensitivity = TP / (TP + FN) \ldots\ldots(1)$$

Specificity: The specificity measures the ability of the technique to identify normal cases.

$$Specificity = TN / (FP + TN) \ldots\ldots(2)$$

Accuracy: Here, the accuracy indicates how well the model detects both stroke and non-stroke MRI images. It also means the overall accuracy of the proposed model.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad \ldots\ldots(3)$$

F1-Score: F1- score or F-measure is the balance measure to express the performance in a single quantity.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \ldots (4)$$

The main aim of this paper is to create an intelligent expert system that classifies brain stroke using CNN and RF.

Table 1: PERFORMANCE METRICS EVALUATION

Performance Metrics	SVM Based Detection System	Presented CNN-RF approach
F1-Score	68.76	73.56
Sensitivity	75.56	80.66
Specificity	84.69	90.76
Accuracy	92.95	98.99

The Fig. 2 shows the F1-Score comparison between SVM based approach and presented CNN-RF approach.

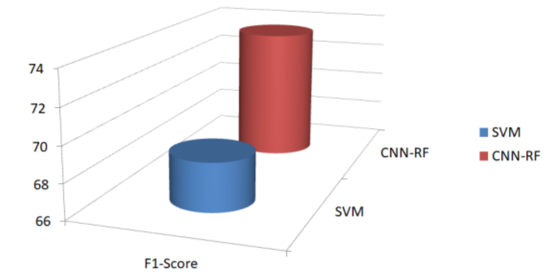

FIG. 2: F1-SCORE COMAPRISON BETWEEN SVM BASED AND PRESENTED CNN-RF APPRAOCHES

The Fig. 3 shows the Sensitivity comparison between SVM based approach and presented CNN-RF approach.

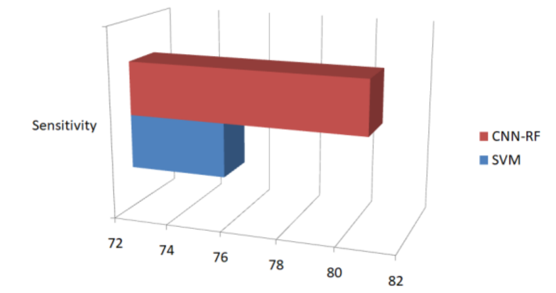

Fig. 3: SENSITIVITY COMAPRISON BETWEEN SVM BASED AND PRESENTED CNN-RF APPRAOCHES

The Fig. 4 shows the Specificity comparison between SVM based approach and presented CNN-RF approach.

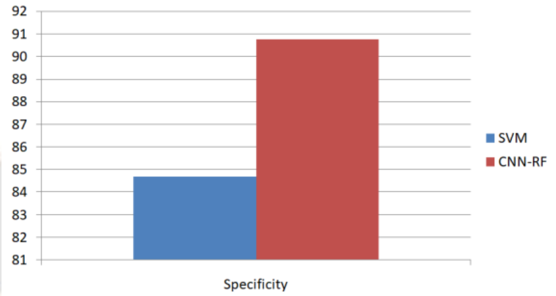

Fig. 4: SPECIFICITY COMAPRISON BETWEEN SVM BASED AND PRESENTED CNN-RF APPRAOCHES

The Fig. 5 shows the Accuracy comparison between SVM based approach and presented CNN-RF approach.

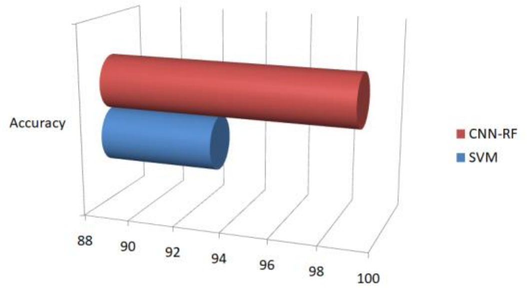

Fig. 5: ACCURACY COMAPRISON BETWEEN SVM BASED AND PRESENTED CNN-RF APPRAOCHES

V. CONCLUSION

In this section, CNN And RF Based Early Detection Of Brain Stroke Using BIO-Electrical Signals is presented. This paper presents a system that utilizes the biological signals of ECG and PPG collected while individuals engage in walking activities as a means to provide semantic analysis of diseases in the elderly. The proposed system allows for the simultaneous collection of various bio-signals, including ECG and PPG, in real-time, enabling timely detection and prediction of prognostic symptoms related to stroke disease in elderly individuals. A research study was undertaken to investigate the development of a prediction model utilizing machine learning techniques and multiple bio-signal data. The signal waveform was segmented into specific sections, leading to the attainment of relatively precise prediction results and meaningful interpretations using this model. This paper presents experimental evidence that the proposed attributes enable accurate prediction of prognostic symptoms in stroke patients, surpassing the reliance solely on ECG and PPG data collected during walking. In conclusion, the experimental and verification results have demonstrated our capability to make accurate predictions. The system introduced in this paper possesses noteworthy academic significance as it successfully predicts stroke prognostic symptoms and onset through the utilization of cost-effective ECG and PPG measurements, minimizing disruption to individuals' daily activities. The collection of diverse bio-signal data during daily activities can offer valuable objective interpretation information to both stroke patients and medical professionals, especially considering the high recurrence rate of the condition. Proposed model performs efficiently as provided effective test prediction. The CNN-RF architecture presented in this study demonstrates superior performance in accuracy, sensitivity, specificity, and F1-score compared to other existing architectures.

REFERENCES

[1] A. Subudhi, et. al, "Automated segmentation and classification of brain stroke using expectation-maximization and random forest classifier," Biocybernetics and Biomedical Engineering, vol. 40, no. 1, pp. 277-289, 2020.

[2] J. Stein, Essentials of Physical Medicine and Rehabilitation Chapter 159 Stroke, Philadelphia: Elsevier, 2020.

[3] 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.

[4] A. Clerigues, et al. "Acute ischemic stroke lesion core segmentation in CT perfusion images using fully convolutional neural networks," Computers in Biology and Medicine, vol. 115, 2019.

[5] K. C. Ho, et. al, "A machine learning approach for classifying ischemic stroke onset time from imaging," IEEE Transactions on Medical Imaging, vol. 38, no. 7, pp. 1666-1676, 2019.

[6] J. M. Bumgarner, C. T. Lambert, A. A. Hussein, D. J. Cantillon, B. Baranowski, K. Wolski, and K. G. Tarakji, ``Smartwatch algorithm for automated detection of atrial _brillation," J. Amer. College Cardiol., vol. 71, no. 21, pp. 2381_2388, Mar. 2018.

[7] C. Chin, et. al, "An Automated Early Ischemic Stroke Detection System Using CNN Deep Learning Algorithm," IEEE 8th International Conference on Awareness Science and Technology (iCAST), pp. 368-372, 2017.

[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] O. Maier, et. al, "Classifier for ischemic stroke lesion segmentation: A comparison study," PloS One, vol. 10, no. 12, 2015.

[10] J. A. Reiffel, ``Atrial _brillation and stroke: Epidemiology," Amer. J. Med., vol. 127, no. 4, pp. 15_16, Apr. 2014.

[11] Heniwati, and H. Thabrany, "Perbandingan Klaim Penyakit Katastropik Peserta Jaminan Kesehatan Nasional di Provinsi DKI Jakarta dan Nusa Tenggara Timur tahun 2014", Jurnal Ekonomi Kesehatan Indonesia, 2006, vol. 1, no. 2.

[12] E. A. Sartor, K. Albright, A. K. Boehme, M. M. Morales, A. Shaban, J. C. Grotta, S. I. Savitz, and S. Martin, ``The NIHSS score and its components can predict cortical stroke," J. Neurol. Disorders Stroke, vol. 2, no. 1, pp. 73_78, Sep. 2013.

[13] N. H. Rajini, and R. Bhavani, "Computer aided detection of ischemic stroke using segmentation and texture features," Measurement, vol. 46, no. 6, 1865-1874, 2013.

[14] Rajini, N. Hema, and R. Bhargavi,"Computer aided detection of ischemic stroke using segmentation and texture features", Measurement, vol.36, no.6, pp.1765-1876, 2013.

[15] N. Sut and Y. Celik, "Prediction of mortality in stroke patients using multilayer perceptron neural networks," Turkish Journal of Medical Sciences, Vol. 42, No. 5, pp. 886-893, 2012.

[16] Fuk-hay Tang, Douglas K.S. Ng, and Daniel H.K. Chow, "An image feature approach for computer-aided detection of ischemic stroke", Computers in Biology and Medicine,vol. 41, no.8, pp. 529-536, 2011.

[15] Rajendra, M. Dash, and S. Sabut, "presented an ischemic stroke detection using higher order spectra features in brain MRI images," Biocybernetics and Biomedical Engineering, vol. 40, no. 1, pp. 277-289, 2011.

[16] J. S. Lee, J. M. Park, T. H. Park, K. B. Lee, S. J. Lee, Y. J. Cho, M. K. Han, H. J. Bae, and J. Y. Lee, “Development of a stroke prediction model for Korean,” Korean Neurological Association, Vol. 28, No. 1, pp. 13-21, 2010. (Korean).
[17] R. Couceiro, P. Carvalho, J. Henriques, M. Antunes, M. Harris, and J. Habetha, ``Detection of atrial _brillation using model-based ECG analysis," in Proc. 19th Int. Conf. Pattern Recognit., Tampa, FL, USA, Dec. 2008, pp. 1_5.
[18] P. Lyden, T. Brott, B. Tilley, K. M. Welch, E. J. Mascha, S. Levine, E. C. Haley, J. Grotta, and J. Marler, “Improved reliability of the NIH Stroke Scale using video training. NINDS TPA Stroke Study Group,” American Heart Association, Vol. 25, No. 11, pp. 2220-2226, 2000.