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Computer Vison Technique for Stroke Patients

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Abstract*—The emergence of an aging society is inevitable due to the continued increases in life expectancy and decreases in birth rate. These social changes require new smart healthcare services for use in daily life, and COVID-19 has also led to a contactless trend necessitating more non-face-to-face health services. Due to the improvements that have been achieved in healthcare technologies, an increasing number of studies have attempted to predict and analyze certain diseases in advance. Research on stroke diseases is actively underway, particularly with the aging population. Stroke, which is fatal to the elderly, is a disease that requires continuous medical observation and monitoring, as its recurrence rate and mortality rate are very high. Most studies examining stroke disease to date have used MRI or CT images for simple classification. This clinical approach (imaging) is expensive and time-consuming while requiring bulky equipment. Recently, there has been increasing interest in using non-invasive measurable EEGs to compensate for these shortcomings. However, the prediction algorithms and processing procedures are both time-consuming because the raw data needs to be separated before the specific attributes can be obtained. Therefore, in this paper, we propose a new methodology that allows for the immediate application of deep learning models on raw EEG data without using the frequency properties of EEG. This proposed deep learning-based stroke disease prediction model was developed and trained with data collected from real-time EEG sensors. We implemented and compared different deep-learning models (LSTM, Bidirectional LSTM, CNN-LSTM, and CNN-Bidirectional LSTM) that are specialized in time series data classification and prediction. The experimental results confirmed that the raw EEG data, when wielded by the CNN-bidirectional LSTM model, can predict stroke with 94.0% accuracy with low FPR (6.0%) and FNR (5.7%), thus showing high confidence in our system. These experimental results demonstrate the feasibility of non-invasive methods that can easily measure brain waves alone to predict and monitor stroke diseases in real time during daily life. These findings are expected to lead to significant improvements for early stroke detection with reduced cost and discomfort compared to other measuring techniques.

***Keywords*—** electroencephalography (EEG); stroke prediction; stroke disease analysis; deep learning; long short-term memory (LSTM); convolutional neural network (CNN); bidirectional; ensemble

I. INTRODUCTION

Stroke is a condition involving abnormalities in the brain blood vessels that result in dysfunction in certain brain locations [1]. According to a 2016 report by the World Health Organization (WHO), stroke is the second most common global cause of death in the world and the third most common global cause of disability [2]. The incidence of stroke in developing countries has more than doubled over the past 40 years [3]. Since a suitable treatment for stroke has yet to be found, early detection is paramount. CT and MRI techniques are the most common detection methods for stroke disease. However, CT and MRI are expensive and may not be suitable for developing countries or low-income earners. With stroke disease emerging as an important disease worldwide, particularly among low-income and elderly people, healthcare services desperately need a solution to help them accurately and quickly detect stroke diseases at a low cost. Studies on the early detection and prediction of stroke are actively underway.

The 2019 Global Burden Disease (GBD) study estimated cardiovascular disease incidence and patient mortality from 204 countries and regions from 1990 to 2019 [4]. According to that report, the number of deaths from cardiovascular disease in 2019 accounted for one-third of all deaths. While the death toll according to cardiovascular index rose from 11.1 million in 1990 to 18.6 million in 2019, many of the causes from cardiovascular disease were attributed to ischemic stroke. Hier et al. also reported that ischemic stroke had a very high recurrence rate of 14.1% within two years [5]. Further, recent studies have shown a link between COVID-19 and stroke, which is expected to increase the number of stroke deaths [6,7]. Kummer et al. [6] informs us that patients admitted with COVID-19 who had a stroke history were much more likely to die than those without a stroke history, while Zhang et al. [7] reported that patients with a stroke prognosis had a higher incidence of severe pneumonia and subsequent mortality according to Cox regression.

Aside from these prior studies, there is still a significant lack of understanding between experimental data and data collected in real-time for stroke. Stroke disease can be identified using blood tests; brain imaging such as CT, MRI, and X-ray; ECG and EEG; and neurological physiological methods such as induced potential tests [8]. Among these techniques, CT and MRI are most often used to determine stroke, but these involve risks such as exposure to radiation or potential allergic reactions to the contrast agents used. These tools can also be inconvenient as they involve confined spaces and require constant monitoring while also incurring separate medical costs for each examination, all of which increase the difficulty of diagnosis.

New wearable electrodes provide an opportunity to measure EEG in the comfort of a participant's home. These electrodes are attached to the head and measure the activity of brain nerve cells in a more natural setting. Brain signals are also recorded during the different sleep states, thereby allowing for pain-free and rapid examination. EEG data can be contaminated by the patient's movement as well as environmental noises. However, it is possible to collect and test EEG data in real time and in a low-cost manner with fewer side effects than the aforementioned imaging techniques. Due to these advantages, 24-h EEG measurements are considered a useful, low-cost method for monitoring stroke disease with high recurrence rates in daily life.

According to the literature review, a number of studies have analyzed diseases such as seizure, Alzheimer's, and stroke using EEG, while other studies have also correlated the level of sleep and emotions using EEG testing [9–13]. However, most of these studies focused on simple classifications or used preset frequency features extracted for experimentation. Thus, additional time and cost are needed to separate raw data into frequency domains, meaning that real-time health monitoring is not currently feasible with the technology that has been reported to date.

A recent study was able to classify seizure patients using raw EEG data alone, representing a promising step toward real-time health monitoring using EEG [14,15]. Therefore, in this paper, we propose a real-time stroke monitoring system to predict the degree of risk of stroke in real time by collecting raw EEG data. Using real-time EEG data, our system can predict stroke diseases in elderly Koreans. To test this system, we developed a walking protocol that reflects the everyday life of an elderly Korean.

The EEG data used in this work were measured and collected from Korean seniors aged 65 or older. To compare between deep learning models and machine learning models, the collected EEG data were separated into raw data and frequency domain-extracted data, respectively. Each set of raw EEG data from six channels (Fz, T7, C1, C2, T8, and Oz) undergoes a fast Fourier transform (FFT), and 66 values in total were extracted and used in the experiment. The initial results show that the raw data alone could be used to predict stroke disease with high accuracy. To determine which deep learning model is the most suitable for real-time EEG data, a comparison of the predictive accuracies of LSTM, bidirectional LSTM, CNN-LSTM, and CNN-bidirectional LSTM models was conducted.

These algorithms were chosen because they are known to be suitable for realtime data learning based on the characteristics of EEG data. Our experiments showed 94.0% accuracy for CNN-Bidirectional LSTM models with very low false negative rate (FNR) and false positive rate (FPR) at 5.7% and 6.0%, respectively, confirming high confidence in the results.

Meanwhile, using power value, we showed 81.4% accuracy along with 18.5% FPR and 17.3% FNR in CNN-bidirectional LSTM models. Further, experiments using relative value showed 89.2% accuracy as well as FPR and FNR of 12.5% and 8.4%, respectively, in CNN-LSTM models. These experimental results indicate that raw EEG data alone can be used to accurately detect and predict stroke diseases without separating the frequency attribute values.

We also confirmed that the system proposed in this paper accurately predicts the precursor symptoms of stroke disease with very high mortality and recurrence rates in real time, and thus represents a low-cost method that enables health monitoring during the daily lives of the elderly.

The paper is organized as follows. Section 2 examines prior research involved in EEG features in stroke patients as well as computer engineering studies related to stroke prediction. Section 3 explores deep learning-based stroke disease prediction systems with real-time brainwave data proposed in the paper, and also discusses prediction methodologies using raw data and frequency properties of brainwaves. Section 4 discusses the real-time stroke disease prediction experiments conducted in this study and the analysis results with deep learning models specialized in time series signal data prediction, while Chapter 5 concludes and proposes future study directions.

II. METHODOLOGY

Establishing a methodology for this research paper involves outlining the approach taken to achieve the objectives laid out in the study. Considering the nature of the project revolving around the methodology encompasses several key steps.

A. *Literature Review*

Previous research extensively explores EEG features in stroke patients and computer engineering studies related to predicting stroke incidents. However, prevalent methods predominantly rely on frequency domain extraction, posing challenges for real-time stroke prediction leveraging EEG data. These gaps in existing research emphasize the pressing need for methodologies bypassing the laborious process of extracting frequency domains from raw EEG data, enabling swift and accurate stroke prediction.

B. *Proposed System:*

The proposed system aims to confront the challenges inherent in real-time stroke prediction by directly leveraging raw EEG data collected from elderly Korean individuals. Acknowledging the complexities involved in separating EEG data into frequency domains, the study proposes employing deep learning models to directly analyze raw EEG data for swift and effective stroke prediction and monitoring.

C. *Experiment Setup:*

The experiment meticulously gathered EEG data from Korean seniors aged 65 or older. A comparative analysis was conducted between raw EEG data and frequency domain-extracted data to discern the advantages and limitations of each approach. The study focused on specific EEG channels—Fz, T7, C1, C2, T8, and Oz—to ascertain their significance in accurate stroke prediction.

D. *Deep Learning Models Comparison:*

This segment involved an in-depth exploration and comparison of diverse deep learning models tailored for time series data analysis. LSTM, Bidirectional LSTM, CNN-LSTM, and CNN-Bidirectional LSTM models were evaluated for their aptness in processing real-time EEG data. These models were chosen based on their capabilities to efficiently analyze EEG signals for accurate stroke prediction.

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E. Experimental Results:

The experimental findings provided crucial insights into the performance of different models. Remarkably, the CNN-Bidirectional LSTM model demonstrated exceptional success, achieving a 94.0% accuracy rate with notably low false negative and false positive rates. This outcome underscores the potential and efficacy of utilizing raw EEG data for precise stroke prediction.

F. Conclusion and Future Directions:

In conclusion, the study highlighted the significance of the proposed system in enabling real-time stroke prediction during daily life, particularly for the elderly. It recommended avenues for future research, stressing the need for further refinement and validation of the methodology to bolster its effectiveness in stroke prediction and monitoring. Continuing research endeavors are imperative to fine-tune this approach, fostering its application in real-world healthcare settings.

G. Documentation and Reporting

Structured documentation encompassing each phase of the methodology, findings, insights, challenges, and recommendations will be meticulously compiled. A comprehensive research paper will be prepared, encapsulating the entire journey, methodologies employed, outcomes, and prospective recommendations for the seamless implementation and evolution. This documentation ensures transparency, knowledge dissemination, and serves as a guiding document for future enhancements and adaptations.

III. System Analysis

A comprehensive examination of computer vision techniques for stroke patients highlights the existing limitations in traditional stroke diagnosis methodologies. Conventional diagnostic methods often lack precision and timeliness, leading to delayed treatment and prolonged patient suffering. The proposed computer vision techniques aim to revolutionize stroke diagnosis by leveraging image-based analysis to swiftly and accurately detect stroke-related abnormalities. These techniques intend to bridge the gap in current stroke diagnosis systems by offering advanced, non-invasive, and efficient diagnostic tools.

IV. System Architecture

The architectural framework for computer vision techniques in stroke diagnosis entails a multi-layered structure integrating image acquisition systems, preprocessing units, feature extraction algorithms, classification models, and result visualization components. This architecture is designed to facilitate the seamless processing of medical images obtained from stroke patients, employing sophisticated algorithms for analysis and interpretation. It emphasizes real-time image processing capabilities, ensuring rapid and accurate identification of stroke indicators while maintaining patient data privacy and security.

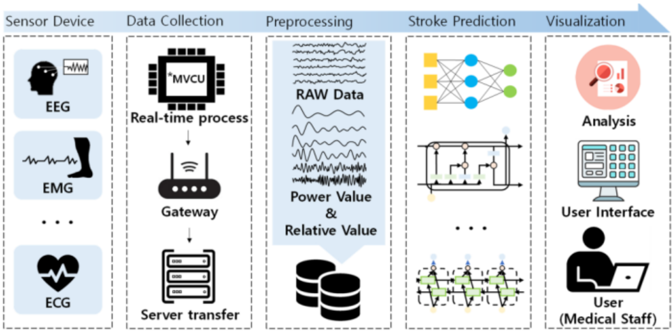

Fig 1: System Architecture for a Computer Vision Techniques for Stroke Analysis

V. System Design

A. System Modules

1) Image Acquisition Module: Describes the process of acquiring medical images of stroke-affected regions, including MRI scans, CT scans, or other imaging modalities.

2) Preprocessing Module: Details image preprocessing techniques such as noise reduction, contrast enhancement, and image normalization to optimize images for further analysis.

3) Feature Extraction Module: Elaborates on algorithms and methodologies to extract relevant features from medical images that signify stroke-related abnormalities.

4) Classification Module: Discusses machine learning or deep learning models used for classification and diagnosis based on extracted image features.

5) *Result Visualization Module:* Explains techniques to visualize and present the diagnostic outcomes to healthcare practitioners for decision-making purposes.

B. Module Description

Image Acquisition Module:

The Image Acquisition Module forms the foundational stage in stroke diagnosis by acquiring high-fidelity medical images. It encompasses diverse imaging modalities like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), or other specialized techniques tailored to capture detailed brain structures and detect stroke-affected regions with precision. Additionally, this module ensures the optimal selection of imaging parameters and protocols to acquire comprehensive and high-resolution brain images necessary for subsequent analysis.

Preprocessing Module:

The Preprocessing Module is pivotal in refining raw medical images to enhance their quality and extract vital information. It involves a spectrum of preprocessing techniques such as noise reduction, artifact removal, contrast enhancement, normalization, and geometric correction. By employing these techniques, it standardizes the images, mitigates inherent imaging artifacts, and enhances their clarity, ensuring consistency and reliability in subsequent analysis stages.

Feature Extraction Module:

The Feature Extraction Module employs sophisticated algorithms and image processing techniques to discern crucial features from preprocessed medical images. It focuses on identifying distinctive patterns, textures, edges, or intensity variations that are indicative of stroke-affected brain regions. Utilizing computational methods such as edge detection, texture analysis, or local feature extraction, this module extracts discriminative features crucial for accurate stroke diagnosis and characterization.

Classification Module:

The Classification Module harnesses the power of machine learning or deep learning algorithms to categorize medical images into stroke or non-stroke categories based on the extracted features. Leveraging trained models, such as Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), or Recurrent Neural Networks (RNNs), this module enables automated diagnosis, providing clinicians with accurate and timely identification of stroke-affected areas, aiding in prompt treatment decisions.

Result Visualization Module:

The Result Visualization Module facilitates the presentation of diagnostic outcomes derived from the classification process. It offers intuitive and comprehensive visual representations of identified stroke-affected regions within medical images. These visual aids, such as heatmaps, overlays, or annotated images, assist healthcare professionals in comprehending and interpreting the diagnostic findings effectively, fostering better communication and decision-making in clinical settings.

Segmentation Module:

The Segmentation Module employs advanced algorithms, including region-based or boundary-based techniques, to delineate and segment stroke-affected regions from surrounding healthy brain tissue. This module precisely identifies and isolates areas of interest, enabling accurate localization and quantification of stroke lesions for detailed analysis and assessment.

Registration Module:

The Registration Module facilitates the alignment and fusion of multiple imaging datasets from different time points or imaging modalities. By employing image registration algorithms like rigid, affine, or non-linear transformations, this module spatially aligns images, ensuring accurate comparative analysis and tracking of disease progression over time. It enables clinicians to observe and assess changes in stroke lesions, crucial for longitudinal studies and treatment evaluation.

Deep Learning-based Analysis Module:

This module incorporates advanced deep learning architectures, such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), or recurrent models like Long Short-Term Memory (LSTM) networks. These deep learning models are designed to learn intricate patterns, textures, and spatial relationships within medical images, enabling comprehensive analysis and feature extraction.

Quantitative Assessment Module:

The Quantitative Assessment Module quantifies and measures specific attributes of stroke-affected regions extracted from medical images. It computes quantitative metrics like lesion volume, intensity distribution, shape descriptors, or spatial characteristics. By quantifying the severity and extent of stroke-related damage, this module provides clinicians with objective and quantitative insights.

Integration with Clinical Data Module:

This module integrates the extracted imaging features with pertinent clinical data, including patient demographics, medical history, symptoms, or other diagnostic test results. By correlating imaging findings with patient-specific information, it augments the diagnostic process, enhancing the accuracy and reliability of stroke diagnosis. This integration empowers healthcare professionals to make more informed and personalized treatment decisions based on a holistic view of the patient's health profile.

Interpretability and Explainability Module:

The Interpretability and Explainability Module aims to elucidate the decision-making process of computer vision models. It generates detailed interpretability reports, highlighting the rationale behind the model's predictions. By identifying influential image features, providing visual explanations, and outlining the reasoning behind diagnostic outcomes, this module enhances clinicians' trust in automated diagnostic results, fostering better adoption and collaboration between machine-assisted diagnostics and healthcare professionals.

Validation and Generalization Module:

The Validation and Generalization Module focuses on assessing the reliability, robustness, and generalizability of the developed computer vision system. It employs rigorous validation methodologies, including cross-validation, transfer learning techniques, or external dataset validations, to ensure the system's consistent performance across diverse patient populations, imaging conditions, and scanner types. This module aims to validate the system's efficacy, ensuring reliable and consistent performance in real-world clinical scenarios.

Scalability and Deployment Module:

The Scalability and Deployment Module optimizes the developed computer vision system for real-time performance, scalability, and practical deployment in clinical environments. It fine-tunes the algorithms, optimizes computational resources, and designs user-friendly interfaces tailored for healthcare practitioners. Additionally, it ensures seamless integration into existing clinical workflows, facilitating widespread adoption and utility of the computer vision system in real-world healthcare settings.

VI. RESULTS AND DISCUSSION

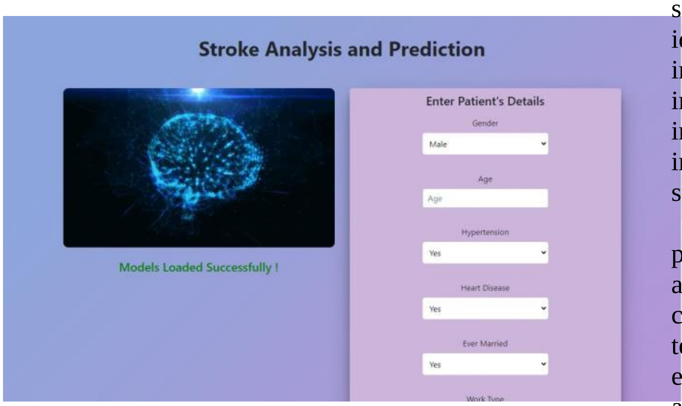

Fig 2: Home Screen

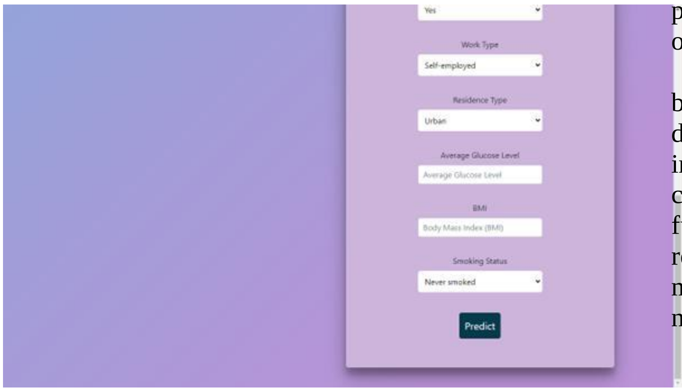

Fig 3: Home Screen

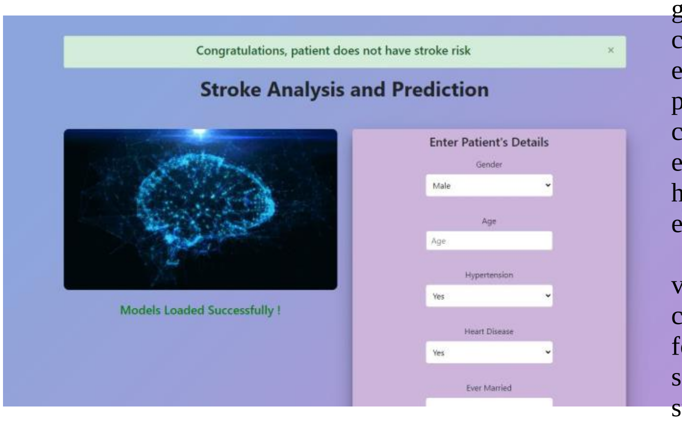

Fig 4: Prediction Page

VII. CONCLUSIONS

The development and integration of advanced computer vision techniques present a transformative approach in the domain of stroke diagnosis and patient care. The comprehensive framework established through this project signifies a significant leap towards automated and precise identification of stroke-affected regions within medical images. The amalgamation of diverse modules, ranging from image acquisition to deep learning-based analysis, culminates in a robust system capable of extracting, analyzing, and interpreting intricate imaging features crucial for accurate stroke diagnosis.

This integrated system not only streamlines the diagnostic process but also empowers healthcare professionals with an augmented understanding of stroke pathology. By leveraging cutting-edge algorithms, sophisticated image processing techniques, and deep learning architectures, the system exhibits promising capabilities in identifying subtle nuances and quantifying the extent of stroke-related damage. Moreover, its interpretability and integration with clinical data foster a holistic approach to patient care, enabling personalized treatment strategies and longitudinal monitoring of patient recovery.

The versatility and scalability of this computer vision-based approach offer a glimpse into the future of stroke diagnosis and management. With continuous advancements in imaging technologies, machine learning algorithms, and clinical integration, this system stands as a foundation for further innovation. As such, it holds the potential not only to revolutionize stroke diagnosis but also to pave the way for more precise, efficient, and personalized interventions in neurological disorders and healthcare at large.

ACKNOWLEDGMENT

The successful culmination of this project owes its gratitude to a multitude of individuals and institutions whose contributions have been instrumental in its fruition. We extend our heartfelt appreciation to the healthcare professionals, radiologists, and neurologists whose insights, clinical expertise, and unwavering support have guided this endeavor. Their invaluable feedback and domain knowledge have been pivotal in shaping the system's development, ensuring its alignment with clinical standards and practices.

We express our deep gratitude to the patients and volunteers who participated in this study, providing access to critical medical data and imaging studies that form the foundation of this research. Their willingness to contribute to scientific advancements in healthcare has been integral to the success of this project.

Furthermore, we extend our appreciation to the academic and research institutions that have facilitated collaboration, provided resources, and fostered an environment conducive to innovation and exploration. Their support, infrastructure, and academic guidance have been indispensable in navigating the complexities of this interdisciplinary project.

Lastly, we acknowledge the dedication and tireless efforts of the research team, comprising engineers, data scientists, and healthcare professionals, whose commitment, expertise,

and collaboration have been the driving force behind the development and realization of this advanced computer vision system for stroke diagnosis. Their collective efforts have propelled this project forward, marking a significant milestone in the intersection of technology and healthcare.

REFERENCES

[1] Mendelow, A.D. Stroke: Pathophysiology, diagnosis, and management. Elsevier Health Sci. 2000, 56, 275–286.

[2] Global Health Estimates. Geneva: World Health Organization. 2012. Available online: http://www.who.int/healthinfo/global_burden_disease/en (accessed on 1 June 2016).

[3] Feigin, V.L.; Forouzanfar, M.H.; Krishnamurthi, R.; Mensah, G.A.; Connor, M.; Bennett, D.A.; Murray, C. Global and regional burden of stroke during 1990–2010: Findings from the Global Burden of Disease Study 2010. Lancet 2014, 383, 245–255.

[4] Roth, G.A.; Mensah, G.A.; Johnson, C.O.; Addolorato, G.; Ammirati, E.; Baddour, L.M.; Barengo, N.C.; Beaton, A.Z.; Benjamin, E.J.; Benziger, C.P.; et al. Global Burden of Cardiovascular Diseases and Risk Factors, 1990–2019: Update from the GBD 2019 Study. J. Am. Coll. Cardiol. 2020, 76, 2982–3021.

[5] Hier, D.B.; Foulkes, M.A.; Swiontoniowski, M.; Sacco, R.L.; Gorelick, P.B.; Mohr, J.P.; Price, T.R.; Wolf, P.A. Stroke recurrence within 2 years after ischemic infarction. Stroke 1991, 22, 155–161.

[6] Kummer, B.R.; Klang, E.; Stein, L.K.; Dhamoon, M.S.; Jetté, N. History of Stroke Is Independently Associated with In-Hospital Death in Patients With COVID-19. Stroke 2020, 51, 3112–3114.

[7] Zhang, L.; Sun, W.; Wang, Y.; Wang, X.; Liu, Y.; Zhao, S.; Long, D.; Chen, L.; Yu, L. Clinical Course and Mortality of Stroke Patients with Coronavirus Disease 2019 in Wuhan, China. Stroke 2020, 51, 2674–2682.

[8] Lee, K. Stroke Diagnosis. J. Korean Med. Assoc. 2002, 45, 1432–1439.

[9] Lee, M.; Ryu, J.; Kim, D. 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. 2020, 42, 217–229.

[10] Acharya, U.R.; Oh, S.L.; Hagiwara, Y.; Tan, J.H.; Adeli, H.; Subha, D.P. Automated EEG-based screening of depression using deep convolutional neural network. Comput. Methods Programs Biomed. 2018, 161, 103–113.

[11] Kim, D.; Kim, L. Detection of Early Stage Alzheimer's Disease Using EEG Relative Power with Deep Neural Network. In Proceedings of the 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 18–21 July 2018; pp. 352–355.

[12] Chambon, S.; Thorey, V.; Arnal, P.; Mignot, E.; Gramfort, A. DOSED: A deep learning approach to detect multiple sleep micro-events in EEG signal. J. Neurosci. Methods 2019, 321, 64–78.

[13] Kwon, Y.H.; Shin, S.B.; Kim, S.D. Electroencephalography based fusion two-dimensional (2D)-convolution neural networks (CNN) model for emotion recognition system. Sensors 2018, 18, 1383.

[14] O'Shea, A.; Lightbody, G.; Boylan, G.; Temko, A. Neonatal seizure detection from raw multi-channel EEG using a fully convolutional architecture. Neural Netw. 2020, 123, 12–25.

[15] Özdamar, Ö.; Kalayci, T. Detection of Spikes with Artificial Neural Networks Using Raw EEG. Comput. Biomed. Res. 1998, 31, 122–142.

[16] Wijaya, S.K.; Badri, C.; Misbach, J.; Soemardi, T.P.; Sutanno, V. Electroencephalography (EEG) for detecting acute ischemic stroke. In Proceedings of the 2015 4th International Conference on Instrumentation, Communications, Information Technology, and Biomedical Engineering (ICICI-BME), Bandung, Indonesia, 2–3 November 2015; 2015; pp. 42–48.

[17] Rahma, O.N.; Wijaya, S.K.; Badri, C. Electroencephalogram analysis with extreme learning machine as a supporting tool for classifying acute ischemic stroke severity. In Proceedings of the 2017 International Seminar on Sensors, Instrumentation, Measurement and Metrology (ISSIMM), Surabaya, Indonesia, 25–26 August 2017; pp. 180–186.

[18] Li, X.; Bian, D.; Yu, J.; Li, M.; Zhao, D. Using machine learning models to improve stroke risk level classification methods of China national stroke screening. BMC Med. Inform. Decis. Mak. 2019, 19, 261.

[19] Adhi, H.A.; Wijaya, S.K.; Badri, C.; Rezal, M. Automatic detection of ischemic stroke based on scaling exponent electroencephalogram using extreme learning machine. J. Phys. Conf. Ser. 2017, 820, 12005–12013.

[20] Djamal, E.C.; Ramadhan, R.I.; Mandasari, M.I.; Djajasasmita, D. Identification of post-stroke EEG signal using wavelet and convolutional neural networks. Bull. Electr. Eng. Inform. 2020, 9, 1890–1898.

[21] Schneider, A.L.; Jordan, K.G. Regional Attenuation WithOut Delta (RAWOD): A distinctive EEG pattern that can aid in the diagnosis and management of severe acute ischemic stroke. Am. J. Electroneurodiagn. Technol. 2005, 45, 102–117.

[22] Finnigan, S.; Wong, A.; Read, S. Defining abnormal slow EEG activity in acute ischaemic stroke: Delta/alpha ratio as an optimal QEEG index. Clin. Neurophysiol. 2016, 127, 1452–1459.

[23] Varelas, P.N.; Hacein-Bey, L. Ischemic Stroke, Hyperperfusion Syndrome, Cerebral Sinus Thrombosis, and Critical Care Seizures. In Seizures in Critical Care; Springer Science and Business Media LLC, 2017; Volume 14, pp. 155–186.

[24] Ip, Z.; Rabiller, G.; He, J.W.; Yao, Z.; Akamatsu, Y.; Nishijima, Y.; Liu, J.; Yazdan-Shahmorad, A. Cortical stroke affects activity and stability of theta/delta states in remote hippocampal regions*. In Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 23–27 July 2019; 2019; pp. 5225–5228.

[25] Kim, J.; Lee, B.; Lee, H.S.; Shin, K.H.; Kim, M.J.; Son, E. Differences in Brain Waves of Normal Persons and Stroke Patients during Action Observation and Motor Imagery. J. Phys. Ther. Sci. 2014, 26, 215–218.

[26] Gautam, A.; Raman, B. Towards effective classification of brain hemorrhagic and ischemic stroke using CNN. Biomed. Signal. Process. Control 2021, 63, 102178.

[27] Kalchbrenner, N.; Grefenstette, E.; Blunsom, P. A Convolutional Neural Network for Modelling Sentences. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Baltimore, MD, USA, 23–25 June 2014; Volume 1, pp. 655–665.

[28] Krizhevsky, A.; Sutskever, I.; Hinton, G.E. Imagenet classification with deep convolutional neural networks. Commun. ACM 2017, 60, 84–90.

[29] He, K.; Zhang, X.; Ren, S.; Sun, J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.

[30] Chin, C.-L.; Lin, B.-J.; Wu, G.-R.; Weng, T.-C.; Yang, C.-S.; Su, R.-C.; Pan, Y.-J. An automated early ischemic stroke detection system using CNN deep learning algorithm. In Proceedings of the 2017 IEEE 8th International Conference on Awareness Science and Technology (iCAST), Taichung, Taiwan, 8–10 November 2017; 2017; pp. 368–372.

[31] Liu, L.; Chen, S.; Zhang, F.; Wu, F.-X.; Pan, Y.; Wang, J. Deep convolutional neural network for automatically segmenting acute ischemic stroke lesion in multi-modality MRI. Neural Comput. Appl. 2019, 32, 6545–6558.

[32] Dourado, C.M., Jr.; da Silva, S.P.P.; da Nobrega, R.V.M.; Barros, A.C.D.S.; Reboucas Filho, P.P.; de Albuquerque, V.H.C. Deep learning IoT system for online stroke detection in skull computed tomography images. Comput. Netw. 2019, 152, 25–39.

[33] Kabir, M.F.; Hossain, A.; Dahal, K. Enhanced classification accuracy on naive Bayes data mining models. Int. J. Comput. Appl. 2011, 28, 9–16.

[34] Pal, S.K.; Mitra, S. Multilayer Perceptron, Fuzzy Sets, and Classification. IEEE Trans. Neural Netw. 1992, 3, 683–697.

[35] Peterson, L.E. K-nearest neighbor. Scholarpedia 2009, 4, 1883.

[36] Pal, M. Random forest classifier for remote sensing classification. Int. J. Remote Sens. 2005, 26, 217–222.

[37] St, J.P.O.E.D.; Dumais, S.; Osuna, E.; Platt, J.; Scholkopf, B. Support vector machines. IEEE Intell. Syst. 1998, 13, 18–28.

[38] Choi, Y.-A.; Park, S.; Jun, J.-A.; Ho, C.; Pyo, C.-S.; Lee, H.; Yu, J. Machine-Learning-Based Elderly Stroke Monitoring System Using Electroencephalography Vital Signals. Appl. Sci. 2021, 11, 1761.

[39] Yu, J.; Park, S.; Kwon, S.-H.; Ho, C.M.B.; Pyo, C.-S.; Lee, H. AI-based Stroke Disease Prediction System Using Real-Time Electromyography Signals. Appl. Sci. 2020, 10, 6791.
[40] Xie, Y.; Yang, H.; Yuan, X.; He, Q.; Zhang, R.; Zhu, Q.; Chu, Z.; Yang, C.; Qin, P.; Yan, C. Stroke prediction from electrocardiograms by deep neural network. Multimed. Tools Appl. 2021, 80, 17291–17297.
[41] Fawaz, S.; Sim, K.S.; Tan, S.C. Encoding Rich Frequencies for Classification of Stroke Patients EEG Signals. IEEE Access 2020, 8, 135811–135820.
[42] Mirza, M.; Osindero, S. Conditional generative adversarial nets. arXiv 2014, arXiv:1411.1784. 2014.
[43] Bebis, G.; Georgiopoulos, M. Feed-forward neural networks. IEEE Potentials 1994, 13, 27–31.
[44] Zhang, S.; Zheng, D.; Hu, X.; Yang, M. Bidirectional long short-term memory networks for relation classification. In Proceedings of the 29th Pacific Asia Conference on Language, Information and Computation, Shanghai, China, 30 October–1 November 2015; pp. 73–78.
[45] Jeong, J.H.; Shim, K.H.; Kim, D.J.; Lee, S.W. Brain-controlled robotic arm system based on multi-directional CNN-BiLSTM network using EEG signals. IEEE Trans. Neural Syst. Rehabil. Eng. 2020, 28, 1226–1238.