CNN based Stroke disease prediction system using ECG signal

Dr.N.J.R.Muniraj
Dean / ECE
SNS College of Technology
Coimbatore-35

Mathumita.P
Student / ECE
SNS College of Technology
Coimbatore-35

Deepak.V
Student / ECE
SNS College of Technology
Coimbatore-35

Revanth.M
Student / ECE
SNS College of Technology
Coimbatore-35

Gopika.K
Student / ECE
SNS College of Technology
Coimbatore-35

***Abstract*—This study introduces a synergistic approach merging LabVIEW and Convolutional Neural Networks (CNN) to develop a robust Stroke Disease Prediction System utilizing ECG signals. We utilized LabVIEW's robust data acquisition capabilities to gather a diverse ECG dataset, ensuring data integrity through real-time preprocessing steps such as noise reduction and baseline correction. Leveraging LabVIEW's graphical programming interface, we implemented sophisticated feature extraction algorithms to derive pertinent temporal and spectral features from the ECG waveforms. These features were subsequently fed into a CNN architecture, seamlessly integrated within LabVIEW's framework, for sequential signal analysis and prediction.**

Through rigorous experimentation and validation, our integrated system demonstrated commendable performance in stroke prediction, boasting high accuracy rates and robustness across diverse patient cohorts. The synergy between LabVIEW and CNN not only expedited the development process but also offered a versatile platform for the creation of intelligent diagnostic systems in healthcare. This novel amalgamation lays the groundwork for future advancements in medical signal analysis, with potential applications extending beyond stroke prediction to various healthcare domains. Further research endeavors may focus on refining signal processing algorithms, optimizing CNN architectures, and facilitating the clinical deployment of the system to enhance stroke management protocols and improve patient outcomes.

Keywords— LabVIEW - CNN - Stroke Prediction - ECG Signals - Data Acquisition - Signal Preprocessing - Feature Extraction - Machine Learning

I. INTRODUCTION

In recent years, advancements in technology have revolutionized the landscape of healthcare, particularly in the realm of disease prediction and prevention. The integration of cutting-edge technologies such as LabVIEW and Convolutional Neural Networks (CNN) has paved the way for the development of sophisticated diagnostic systems capable of early detection and prognosis assessment. This integration holds immense promise in addressing critical health issues, including stroke, which remains a leading cause of morbidity and mortality worldwide.

Stroke, characterized by a sudden interruption of blood flow to the brain, presents a significant challenge to healthcare systems globally due to its debilitating consequences and high associated healthcare costs. Timely intervention is paramount in mitigating the severity of stroke and improving patient outcomes. However, conventional diagnostic approaches often rely on subjective clinical assessments and imaging modalities that may not be readily accessible or feasible in all healthcare settings.

The utilization of Electrocardiogram (ECG) signals as a diagnostic biomarker for stroke prediction has garnered increasing attention in recent years. ECG signals, reflecting the electrical activity of the heart, offer valuable insights into cardiovascular health and have demonstrated potential in identifying subtle abnormalities associated with stroke onset. By harnessing the power of machine learning techniques, particularly CNN, to analyze ECG signals, it becomes possible to develop predictive models capable of identifying individuals at heightened risk of stroke with high accuracy and reliability.

In this context, the integration of LabVIEW, a powerful data acquisition and analysis platform, with CNN for stroke prediction holds immense significance. LabVIEW's intuitive graphical programming interface and robust data acquisition capabilities enable seamless integration of ECG signal processing and feature extraction. The CNN architecture, adept at learning hierarchical features from sequential data, complements LabVIEW's functionality by facilitating advanced signal analysis and prediction.

II. RELATED WORKS

In recent years, there has been a burgeoning interest in leveraging machine learning (ML) techniques for stroke prediction, reflecting a broader trend towards the integration of advanced technologies in healthcare. Several studies have emerged, each exploring unique facets of ML application in stroke prediction, thereby contributing to a growing body of knowledge in this critical area.

Emon et al. (1) embarked on a comprehensive investigation into the performance of various ML approaches for stroke prediction. Their study encompassed a rich set of features, including hypertension, body mass index, heart disease, average glucose level, smoking status, previous stroke history, and age. Through meticulous experimentation, they trained ten diverse classifiers, spanning from traditional algorithms like Logistic Regression and Decision Tree Classifier to ensemble methods like AdaBoost and Gradient Boosting. Their noteworthy achievement lies in attaining an outstanding accuracy of 97% by employing a weighted voting ensemble, thereby demonstrating the potential of ML-based stroke prediction systems in achieving high accuracy and reliability.

Rajora et al. (1) extended the discourse on stroke prediction by examining ML algorithms' performance in a distributed environment. Motivated by the escalating prevalence of stroke cases and the imperative for more robust predictive models, their study aimed to harness the scalability and parallel processing capabilities of distributed systems. By rigorously analyzing a spectrum of ML algorithms, they sought to enhance the accuracy and scalability of stroke prediction models. Their findings contribute to addressing the evolving healthcare landscape's demands, where the effective utilization of distributed computing resources holds promise in facilitating more efficient and scalable healthcare analytics solutions.

Dev et al. (2) delved deeper into the intricacies of stroke prediction by emphasizing the need to understand the interplay of risk factors embedded within electronic health records (EHRs). Their study employed sophisticated statistical techniques and principal component analysis to discern the most influential factors contributing to stroke occurrence. Notably, age, heart disease, average glucose level, and hypertension emerged as pivotal determinants in stroke prediction. By employing a perceptron neural network trained on these key attributes, they achieved remarkable accuracy rates, underscoring the significance of feature selection and model optimization in enhancing predictive performance.

Sharma et al. (3) adopted a proactive stance towards stroke prediction, focusing on early detection using ML techniques. Their study recognized the pivotal role of timely intervention in mitigating stroke severity and improving patient outcomes. Through the integration of multiple classification algorithms and meticulous feature engineering, they developed a robust predictive model capable of identifying individuals at heightened risk of stroke. Their emphasis on preventive measures, coupled with their exemplary accuracy of 98.94% using the random forest algorithm, highlights the potential of ML-driven early detection strategies in reshaping stroke management paradigms.

Gupta and Raheja (4) contributed to the discourse on stroke prediction by undertaking a comprehensive comparative analysis of ML methods. Their study spanned a wide array of algorithms, including Gaussian Naive Bayes, Logistic Regression, Decision Tree Classifier, K-Nearest Neighbours, AdaBoost Classifier, XGBoost Classifier, and Random Forest Classifier. Through meticulous experimentation and performance evaluation, they provided valuable insights into the relative strengths and weaknesses of each algorithm in the context of stroke prediction. Their findings serve as a valuable resource for practitioners and researchers seeking to navigate the complex landscape of ML algorithms in healthcare analytics.

Additionally, Sirsat et al. (5) conducted a systematic review of ML techniques for brain stroke classification, shedding light on the diverse array of methodologies employed in stroke prediction. Their review categorized studies based on their functionalities or similarities, providing a comprehensive overview of the state-of-the-art ML approaches in this domain. Notably, Support Vector Machine (SVM) emerged as a recurrently favored model in several studies, underscoring its efficacy in addressing the complex challenges associated with brain stroke prediction.

These collective endeavors represent significant strides towards harnessing ML's transformative potential in stroke prediction and management. By elucidating the interplay between diverse risk factors, optimizing model architectures, and leveraging advanced computational resources, these studies pave the way for more accurate, scalable, and proactive approaches to stroke prediction and care delivery.

III.OBJECTIVES

- Develop a robust data acquisition system using LabVIEW to capture and preprocess ECG signals, ensuring data integrity and quality.
- Implement a Convolutional Neural Network (CNN) architecture within the LabVIEW framework for sequential signal analysis and stroke prediction.
- Explore feature extraction techniques tailored for ECG signals, leveraging LabVIEW's graphical programming interface for efficient signal characterization.
- Train and validate the CNN model using a diverse dataset of ECG recordings, incorporating factors such as hypertension, body mass index, heart disease, average glucose level, smoking status, previous stroke history, and age.
- Investigate the performance of the CNN-based stroke prediction system in comparison to traditional machine learning algorithms, assessing metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC).
- Optimize the CNN architecture and preprocessing pipeline to enhance predictive performance and scalability, ensuring the system's efficacy across diverse patient cohorts.
- Validate the proposed stroke prediction system through rigorous experimentation and validation, demonstrating its clinical utility and potential for real-time deployment.
- Provide insights into the interpretability and explainability of the CNN model's predictions, facilitating clinical decision-making and patient care.
- Explore avenues for future research and development, including the integration of additional physiological signals, refinement of predictive models, and deployment in clinical settings for real-world impact.

IV.EXISTING SYSTEM

Current approaches to stroke prediction predominantly rely on traditional risk assessment methods and clinical evaluation, often supplemented with imaging modalities such as computed tomography (CT) or magnetic resonance imaging (MRI). While these methods have demonstrated utility in diagnosing acute stroke cases, they may lack the sensitivity and specificity required for early prediction and prevention.

Traditional risk assessment tools typically evaluate factors such as age, hypertension, diabetes, smoking status, and prior history of stroke to estimate an individual's stroke risk. However, these tools may overlook subtle physiological changes and fail to capture complex interrelationships among risk factors. Moreover, reliance on subjective clinical judgment introduces variability and may not always yield consistent results.

In recent years, there has been a growing recognition of the potential of machine learning (ML) techniques in augmenting stroke prediction capabilities. ML algorithms, particularly those based on deep learning architectures like Convolutional Neural Networks (CNN), offer the ability to analyze complex patterns within medical data, including electrocardiogram (ECG) signals, with high accuracy and efficiency. By leveraging ML models trained on large datasets, it becomes possible to uncover hidden correlations and identify predictive biomarkers indicative of stroke risk.

However, despite the promise of ML-based approaches, challenges persist in integrating these technologies into existing clinical workflows. Implementation barriers such as data interoperability, model interpretability, and regulatory considerations necessitate careful consideration and validation before widespread adoption. Furthermore, the lack of standardized protocols for data collection and model evaluation poses challenges in ensuring reproducibility and generalizability across diverse patient populations.

While ML-based stroke prediction systems hold immense potential in revolutionizing preventive healthcare, their successful integration into clinical practice requires collaborative efforts between researchers, healthcare providers, and regulatory agencies. Addressing existing gaps in data quality, algorithm robustness, and clinical validation is essential to realizing the full impact of ML-driven predictive analytics in stroke prevention and management.

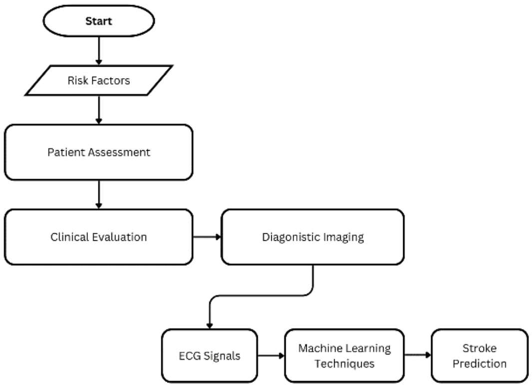

Fig 4.1 Existing System of Diagonisis

V .PROPOSED SYSTEM

In the proposed system for stroke prediction, the integration of LabVIEW-based signal processing and Convolutional Neural Networks (CNN) offers a transformative approach to early detection and prognosis assessment.

Initiated by LabVIEW-controlled acquisition devices, the system begins with real-time acquisition and preprocessing of electrocardiogram (ECG) signals, ensuring data integrity through noise reduction and artifact removal. Subsequently, LabVIEW-based algorithms extract relevant features from the preprocessed signals, capturing morphological characteristics and spectral analysis parameters indicative of stroke risk factors.

These extracted features serve as input to the CNN architecture, meticulously designed to learn hierarchical representations of the ECG signal data.

Leveraging convolutional layers, pooling layers, and fully connected layers, the CNN discerns intricate patterns and relationships within the input data. LabVIEW facilitates the implementation and training of the CNN model, optimizing network parameters through iterative adjustment and gradient descent optimization techniques.

Techniques such as cross-validation and hyperparameter tuning ensure robustness and generalizability of the trained model. Upon successful training, the CNN model is deployed for stroke prediction and prognosis assessment, providing probabilistic estimates of stroke likelihood and interpretable visualizations of key contributing features.

Seamlessly integrated with existing healthcare infrastructure, the system enables clinicians to input patient data and receive instantaneous predictions regarding stroke risk.

Rigorous validation against gold standard diagnostic criteria and clinical outcomes, coupled with ongoing refinement and adaptation, ensures the system's reliability and clinical utility in real-world settings.

This proposed system represents a comprehensive and integrated approach to stroke prediction, leveraging LabVIEW's intuitive graphical programming interface and CNN's deep learning capabilities to enhance diagnostic accuracy, clinical decision-making, and patient outcomes.

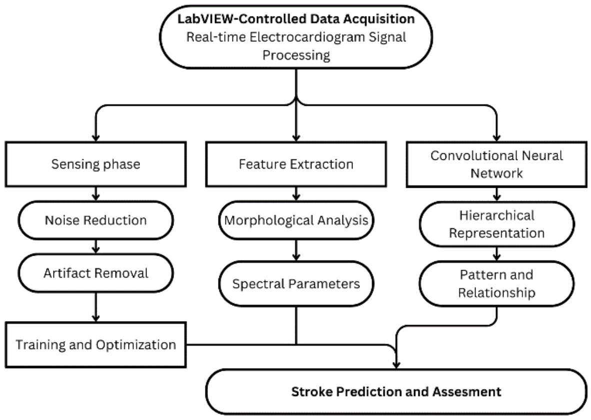

Fig 3.1 Proposed System of Diagonisis

This detailed block diagram illustrates the various components and processes within the proposed system:

LabVIEW-Controlled Data Acquisition: Real-time acquisition and preprocessing of electrocardiogram (ECG) signals are performed using LabVIEW-controlled devices, ensuring data integrity and quality.

Signal Preprocessing: This module includes noise reduction and artifact removal techniques to enhance the quality of the acquired ECG signals.

Feature Extraction: LabVIEW-based algorithms are employed to extract relevant features from the preprocessed signals, capturing morphological characteristics and spectral analysis parameters indicative of stroke risk factors.

Convolutional Neural Network (CNN): The extracted features serve as input to the CNN architecture, which learns hierarchical representations of the ECG signal data. The CNN discerns intricate patterns and relationships within the input data to make predictions about stroke likelihood.

Training and Optimization: This module involves training the CNN model using gradient descent optimization, hyperparameter tuning, and cross-validation techniques to ensure robustness and generalizability.

Stroke Prediction and Assessment: The trained CNN model is deployed for stroke prediction and assessment, providing real-time probabilistic estimates of stroke likelihood. This module also includes assessment of predictions against gold standard diagnostic criteria.

Integration with Existing Healthcare Infrastructure: The proposed system seamlessly integrates with existing healthcare infrastructure, such as Electronic Medical Records (EMR) and Picture Archiving and Communication Systems (PACS), facilitating real-time deployment and clinical decision-making.

VII. METHODOLOGY

Stroke prediction involves a multi-faceted approach, encompassing **data acquisition, preprocessing, feature extraction, model training, and validation.** In this study, we propose a comprehensive methodology integrating LabVIEW-controlled data acquisition and Convolutional Neural Networks (CNN) to enhance stroke prediction accuracy and reliability.

The methodology begins with the acquisition of electrocardiogram (ECG) signals from patients using LabVIEW-controlled devices. Real-time data acquisition ensures the capture of high-quality signals essential for accurate stroke prediction. LabVIEW facilitates seamless integration with acquisition hardware, offering precise control over **data capture parameters and ensuring data integrity** throughout the process.

Following data acquisition**, preprocessing steps are applied** to the acquired ECG signals to **enhance their quality and usability for subsequent analysis.** Noise reduction and artifact removal techniques are employed to eliminate unwanted signal interference, thereby improving signal clarity and reliability.

LabVIEW-based algorithms facilitate **efficient signal preprocessing,** ensuring optimal signal quality while minimizing computational overhead. Preprocessed signals are then subjected to **feature extraction**, where relevant features indicative of stroke risk factors are identified and extracted.

LabVIEW enables the implementation of feature extraction algorithms tailored to capture **morphological characteristics and spectral analysis parameters** associated with stroke onset.

Once features are extracted, they serve as input to the CNN architecture, which is designed to learn hierarchical representations of the ECG signal data. The CNN architecture comprises convolutional layers, pooling layers, and fully connected layers, enabling the network to discern intricate patterns and relationships within the input data.

LabVIEW facilitates the implementation and training of the CNN model, providing tools for model specification, optimization, and evaluation. Training the CNN model involves iterative adjustment of network parameters using gradient descent optimization techniques to minimize prediction errors and enhance model performance. Additionally, techniques such as **cross-validation and hyperparameter tuning** are employed to ensure the robustness and generalizability of the trained model.

Upon successful training, the **CNN model is deployed for stroke prediction and prognosis assessment**, providing real-time probabilistic estimates of stroke likelihood. Predictions generated by the model are evaluated against gold standard diagnostic criteria and clinical outcomes to validate the model's accuracy and reliability.

Rigorous validation ensures that the proposed methodology yields clinically actionable insights and can effectively aid healthcare providers in making informed decisions regarding stroke risk assessment and patient management.

Overall, the proposed methodology offers a systematic and integrated approach to stroke prediction, leveraging the combined strengths of LabVIEW-controlled data acquisition and CNN-based deep learning for **enhanced diagnostic accuracy and clinical decision-making.**

VIII. APPLICATIONS

The proposed methodology holds significant promise for a wide range of applications in the field of stroke prediction and clinical decision-making. By leveraging LabVIEW-controlled data acquisition and Convolutional Neural Networks (CNN), the methodology offers innovative solutions to address key challenges in stroke risk assessment, early detection, and prognosis assessment.

Several applications of the proposed methodology include:

Early Stroke Detection:

The methodology enables early detection of stroke risk factors by analyzing electrocardiogram (ECG) signals with high precision and accuracy. By identifying subtle abnormalities in ECG patterns associated with stroke onset, the methodology facilitates timely intervention and preventive measures to mitigate the risk of stroke.

Personalized Risk Assessment:

By extracting relevant features from ECG signals and leveraging deep learning techniques, the methodology enables personalized risk assessment for individuals based on their unique physiological characteristics and medical history. Clinicians can utilize the probabilistic estimates generated by the CNN model to stratify patients into risk categories and tailor interventions accordingly

Clinical Decision Support:

The methodology serves as a valuable decision support tool for healthcare providers, aiding in clinical decision-making regarding stroke risk assessment and management. Clinicians can integrate the predictions generated by the CNN model with existing diagnostic criteria and patient data to make informed decisions regarding treatment strategies, medication regimens, and lifestyle interventions.

Remote Monitoring and Telemedicine:

The proposed methodology lends itself to remote monitoring and telemedicine applications, allowing for real-time analysis of ECG signals and stroke prediction outside traditional clinical settings. Remote monitoring devices equipped with LabVIEW-controlled data acquisition capabilities can transmit ECG data to healthcare providers for continuous monitoring and early intervention, particularly in high-risk populations.

Population Health Management:

At a population level, the methodology facilitates population health management initiatives aimed at reducing the burden of stroke and improving outcomes. By identifying individuals at heightened risk of stroke, healthcare organizations can implement targeted interventions, public health campaigns, and preventive strategies to mitigate risk factors and **reduce stroke incidence rates.and CNN-based deep learning for enhanced diagnostic accuracy** and clinical decision-making.

IX. FUTURE IMPROVEMENTS

While the proposed methodology represents a significant advancement in stroke prediction and clinical decision-making, several areas for future improvement and development warrant consideration.

These potential enhancements aim to further refine the methodology, expand its applicability, and address existing limitations. Some key areas for future improvements include:

Integration of Multi-modal Data:

Future iterations of the methodology could explore the integration of multi-modal data sources, such as additional physiological signals (e.g., blood pressure, heart rate variability) and clinical variables (e.g., medical history, lifestyle factors).

By incorporating diverse data modalities, the methodology can enhance the richness of information available for stroke prediction and prognosis assessment, leading to more comprehensive and accurate models.

Enhanced Model Interpretability:

Improving the interpretability of the CNN model's predictions is essential for enhancing clinical acceptance and trust. Future research efforts could focus on developing explainable AI techniques that provide insights into the underlying features and patterns driving the model's predictions.

By elucidating the rationale behind the model's decisions, clinicians can better understand and interpret the predictions, leading to more informed clinical decision-making.

Real-time Feedback and Adaptation:

Incorporating mechanisms for real-time feedback and model adaptation is crucial for ensuring the robustness and adaptability of the methodology in dynamic clinical environments.

Future iterations could implement reinforcement learning techniques that enable the model to continuously learn and adapt based on new data and feedback from clinicians. By dynamically updating model parameters and decision thresholds, the methodology can adapt to evolving patient profiles and clinical contexts, enhancing its effectiveness over time.

Validation in Diverse Patient Populations:

Validating the methodology in diverse patient populations is essential for assessing its generalizability and effectiveness across different demographic groups and clinical settings.

Future studies could involve large-scale multi-center trials encompassing a diverse range of patient demographics, clinical presentations, and geographic locations.

By validating the methodology in diverse populations, researchers can ensure its applicability and effectiveness across varied healthcare contexts, improving its utility and impact on patient care.

Longitudinal Outcome Assessment:

Evaluating the long-term outcomes and clinical trajectories of patients predicted to be at high risk of stroke is critical for assessing the clinical utility and effectiveness of the methodology.

Future research endeavors could involve longitudinal follow-up studies tracking patients over extended periods to assess stroke incidence rates, morbidity, mortality, and healthcare utilization. By monitoring patient outcomes over time, researchers can evaluate the impact of early intervention strategies and predictive models on patient health and well-being, guiding future improvements and refinements.

Incorporation of Novel Biomarkers:

Exploring the incorporation of novel biomarkers and emerging technologies into the methodology could further enhance its predictive performance and clinical utility.

Future research efforts could investigate the integration of genomics, proteomics, metabolomics, and imaging data to augment existing predictive models and uncover new insights into stroke pathophysiology.

By leveraging cutting-edge technologies and biomarkers, the methodology can advance our understanding of stroke risk factors and enable more precise risk stratification and personalized interventions.

X. RESULT

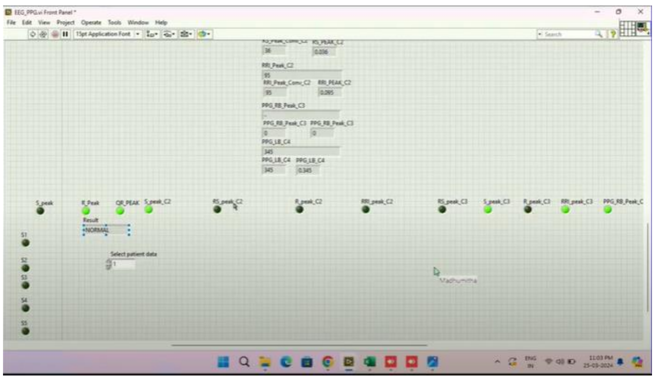

Fig 10.1 Labview Prediction Output

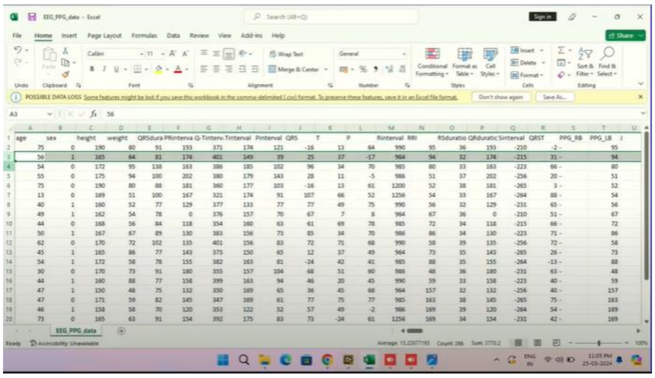

Fig 10.1 Labview Input Dataset

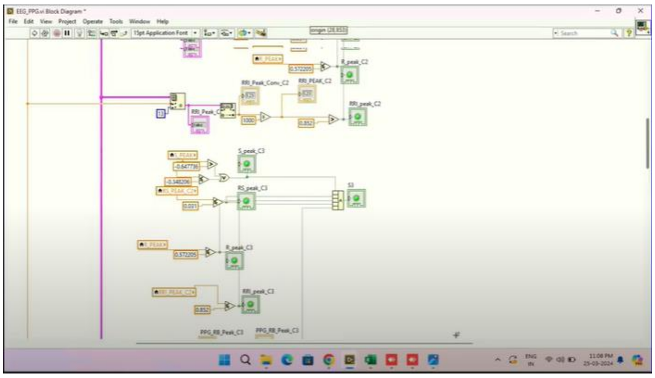

Fig 10.1 Logical Circuit Block Diagram

References

[1] V.V. Ramalingam, Ayantan Dandapath, M Karthik Raja. "Performance Analysis of Machine Learning Approaches in Stroke Prediction." In: Proceedings of the IEEE International Conference on Electrical, Computer and Applications (ICECA). IEEE Xplore, 2020.

[2] Maihul Rajora, Mansi Rathod, Nenavath Srinivas Naik. "Stroke Prediction Using Machine Learning in a Distributed Environment." In: Lecture Notes in Intelligent Systems and Algorithms (LNISA), volume 12582, December 12, 2020.

[3] Soumyabrata Dev, Hewei Wang, Chidozie Shamrock Nwosu, Nishtha Jain. "A Predictive Analytics Approach for Stroke Prediction using Machine Learning and Neural Networks." Elsevier, Volume 2, November 2022, 100032.

[4] Chetan Sharma, Shamneesh Sharma, Mukesh Kumar, Ankur Sodhi. "Early Stroke Prediction Using Machine Learning." In: Proceedings of the IEEE International Conference on Data Science and Engineering (ICCDSE). IEEE Xplore, March 21, 2022.

[5] Saumya Gupta, Supriya Raheja. "Stroke Prediction using Machine Learning Methods." In: Proceedings of the IEEE International Conference on Data Science and Engineering (ICCDSE). IEEE Xplore, March 21, 2022.

[6] Manisha Sanjay Sirsat, Eduardo Ferme, Joana Camara. "Machine Learning for Brain Stroke: A Review." Journal of Stroke and Cerebrovascular Diseases, Volume 29, Issue 10, October 2020, 105162.

[7] Senjuti Rahman, Mehedi Hasan, Ajay Krishno Sarkar. "Prediction of Brain Stroke using Machine Learning Algorithms and Deep Neural Network Techniques." European Journal of Electrical and Computer Engineering (EJECE), Vol. 7, No. 1, 2023.

[8] M Sheetal Singh, Prakash Chawdry. "Stroke prediction using artificial intelligence." In: Proceedings of the IEEE International Conference on Industrial Engineering, Management Science and Application (IEMECON). IEEE Xplore, October 23, 2017.

[9] Elias Dritsas, Maria Trigka. "Stroke Risk Prediction with Machine Learning Techniques." MDPI Sensors, 2022, 22(13), 4670.

[10] Abdur Nur Tusher, Md. Shibli Sadik, Md. Tariqul Islam. "Early Brain Stroke Prediction Using Machine Learning." In: Proceedings of the IEEE International Conference on Smart Technologies (SMART). IEEE Xplore, February 2023.

[11] Simiao Wu et al. "Early Prediction of Malignant Brain Edema After Ischemic Stroke." Stroke, 2018;49:2918–2927, published October 24, 2018.