An Intuitive Approach on Transfer Learning with an IBF+IHP Model for Stroke Classification and Prediction

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ABSTRACT

A cerebral stroke can have significant health ramifications. Efficient stroke prevention requires precise prevention and prompt detection of risk factors. This study introduces a novel predictive modeling technique that uses uncomplicated spatial filter maps and ensemble approaches to enhance stroke risk prediction. The proposed approach utilizes ensemble approaches along with comprehensible spatial filter maps to uncover significant spatial patterns in brain imaging data. The ensemble approach employs a multitude of prediction models to enhance the accuracy of stroke risk forecasts. The experimental findings demonstrate that spatial filter maps and ensemble techniques surpass traditional models in predicting performance. This study showcases the potential of spatial filters to include several patient data to accurately predict stroke risk with a 98% success rate.

Keywords-stroke prediction; ensemble models; spatial filter maps

I. INTRODUCTION

Cerebrovascular disease is an important global public health concern that can result in death or impairment. Early and precise estimation of stroke risk is essential for implementing preventive measures and improving patient outcomes. This study presents a novel predictive modeling method that utilizes spatial filter maps and ensemble approaches to improve the accuracy of stroke risk prediction. Conventional approaches rely on demographic and clinical factors but do not provide a complete understanding of specific brain risk patterns [1]. This method utilizes neuroimaging data to detect intricate spatial patterns in the brain that could suggest an increased likelihood of experiencing a stroke.

Researchers aim to uncover previously undisclosed risk variables using spatial filter maps obtained from neuroimaging [2]. Combining information from spatial filter maps with conventional risk indicators using ensemble learning techniques can enhance the reliability and precision of prediction models. The interpretability of this approach is a unique characteristic that offers healthcare professionals valuable insight into spatial patterns related to the risk of stroke. Spatial filter maps provide visual representations that help physicians understand biological systems and guide individualized preventive care methods. This novel method can transform the evaluation of stroke risk, resulting in early treatments, better patient outcomes, and less cost to the healthcare system [3-7].

Enhancing the precision of survival rates is vital when considering a brain stroke. To achieve this, it is critical to prioritize early identification and precise forecasting of risk variables associated with stroke. However, existing stroke risk assessment approaches are based on traditional clinical and demographic factors, which may not fully capture intricate and nuanced brain-specific risk patterns that contribute to stroke occurrence. To make stroke risk predictions more accurate and easier to understand, more advanced predictive modeling techniques are needed to use neuroimaging data, such as intuitive spatial filter maps and ensemble methods.

Despite notable advances in predictive modeling for brain stroke, there remains a disparity between state-of-the-art research and its practical implementation in clinical settings. The challenge is to efficiently convert the insights gained from these models, especially those featuring spatial filter maps, into actionable recommendations for healthcare professionals. The proposed approach can help progress in the area and eventually alleviate the impact of brain stroke by intervening early and providing tailored treatment.

In [8], a pioneering prototype for ankle neurorehabilitation was proposed. This approach used the heuristic Brain-Computer Interface (BCI) and simplified fuzzy reasoning. This novel technique aimed to improve rehabilitation outcomes by facilitating a more natural relationship between patients and rehabilitation equipment. The framework's dependence on heuristic BCI and simplified fuzzy logic may restrict its adaptation to wider neurorehabilitation settings and various patient demands, although it showed promise in its application to ankle rehabilitation. Using genetic algorithm-based feature selection and stacking approaches, AIBH was proposed in [9], which is a method for accurate diagnosis of brain hemorrhage. This approach focused on the use of sophisticated machine learning algorithms to enhance the diagnostic accuracy of medical imaging. Artificial Intelligence-Based Healthcare (AIBH) aims to improve clinical decision-making and patient outcomes by improving feature selection using genetic algorithms and ensemble learning methods. However, its efficacy could vary depending on the quality and variety of training data, as well as the computational requirements for real-time clinical applications. In [10], a multistep learning-by-examples technique was proposed for the real-time inversion of brain stroke microwave scattering data, contributing to the field of medical imaging by allowing a rapid and precise interpretation of stroke data. This can facilitate prompt interventions and improve prognosis. However, the complicated nature of calibration methods and the requirement for specialized equipment in medical settings might make microwave scattering data inversion techniques difficult to widely use, although they have come a long way.

In [11], the use of automated diagnostics for acute brain stroke was discussed, as well as machine learning approaches that detect stress. Sophisticated methods increase detection accuracy and efficiency, allowing earlier interventions and better results for patients. However, the interoperability of data, the interpretability of models, and the integration into medical workflows continue to be important obstacles to deployment. In [12], the dynamic radiomic characteristics of DSC-PWT were used to diagnose and predict ischemic strokes. Radiomics analysis can shed light on stroke etiology and patient prognosis. Quantitative imaging biomarkers have been used to customize therapy and improve patient outcomes, although different image collection methods and the need to standardize radiomic feature extraction methods limit repeatability and generalizability. In [13], OzNet was proposed, which is a deep learning method for brain CT stroke detection. Deep learning models can automate and improve diagnostic procedures, possibly reducing delays. However, large annotated datasets, computational resources, and additional validation among diverse patient groups can limit its potential in resource-constrained healthcare settings. A-Tuning [14] is an ensemble machine-learning method for predicting cerebral stroke risk, integrating several predictive models to improve risk classification and therapeutic prevention. However, model interpretability and uneven data integration may hinder its use in healthcare.

II. PROPOSED METHOD

A. *Interpolative Linear Spline with Cumulative Adverse Projections (IHP)*

The IHP algorithm, which employs linear spline iteration and cumulative unfavorable projections, is used to identify the possibility of brain stroke by processing data from medical imaging, such as MRI or CT scans. The algorithm extracts features, represented as X, from the imaging data to analyze various qualities. W_i denotes the weights associated with these characteristics, indicating the significance of these aspects in the analysis. The linear spline iteration process is used to interpolate data points that are absent or sampled irregularly. This technique is essential for data filtering and stroke detection. Negative projections, denoted by symbols w_n, α, and β, have a major impact on recognizing stroke-related areas or features. These predictions increase in number at successive iterations, revealing the confirmation of abnormalities. This procedure improves the potential of the method to identify minor indications of stroke, leading to a significant improvement in stroke identification.

B. *Iterative Boost Filter (IBF)*

The IBF technique implements substantial modifications to the use of a boost filter, with a special focus on improving detection performance. This method is specially tailored to analyze medical imaging data and enhance the detection of stroke-specific characteristics. IBF, like IHP, employs data representation using X and W_i , which represent features derived from medical imaging data and weights that indicate their relevance. IBF seeks to improve the detection of stroke-related characteristics on medical images. The repetitive nature of IBF implies a flexible method for recognizing stroke patterns. The H-L boost filter, a component of the algorithm, undergoes repeated updates to enhance its sensitivity to pertinent characteristics related to strokes. This adaptability enables the algorithm to flexibly modify its emphasis based on features of the incoming data, resulting in a substantial impact.

C. *Combined IBF+IHP*

IBF and IHP are essential elements in the field of transfer learning for brain stroke classification and prediction. The fundamental objective is to use preexisting knowledge, expressed as weights and data from csv files, to improve the accuracy and efficiency of stroke prediction models. The IHP algorithm aims to improve forecasts by repeatedly updating cumulative unfavorable projections using a linear spline iteration approach. Preprocessing involves handling missing values and normalizing input, helping to ensure the system's resilience in the presence of diverse data quality. Through dynamic initialization and updating of variables α, δ, β, IHP successfully adjusts to various thresholds, determining if more iterations are necessary to maximize predictions. In the area of predicting brain strokes, this interpolative technique helps to continuously improve models by including the cumulative detrimental effects found in patient data, enhancing the accuracy of predictions.

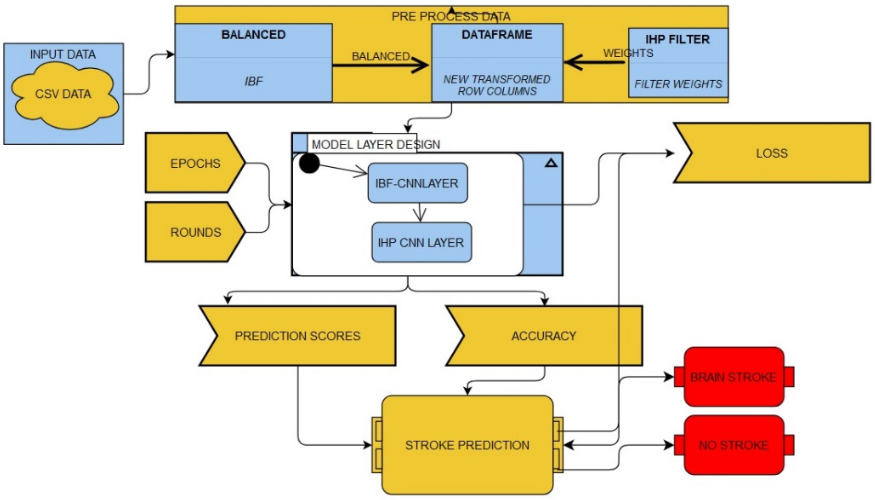

Fig. 1. The overall block diagram for the IBF and IHP with TL modeling.

The IBF method utilizes a boost iteration filter to improve predictions by combining spline iteration with boosting approaches. The weights (k, μ, σ) are initialized to enhance projections, and the filtering methods are adjusted depending on the initial data preprocessing processes. Boosting approaches are very advantageous in transfer learning for brain stroke classification since they increase the sensitivity of prediction models to important aspects of patient data. IBF enhances its predictive capacity by systematically iterating over data, ensuring that adjustments to the H-L boost filter (σ) are made by the model's growing comprehension of stroke-related data patterns.

The incorporation of both IHP and IBF into the IBF+IHP model constitutes a complete approach for transfer learning in the classification and prediction of brain strokes. This integrated method capitalizes on the respective advantages of both algorithms: IHP's interpolative refining of unfavorable projections and IBF's boosting capabilities. The model can efficiently handle diverse data complexity and maximize predicted outputs by using linear spline iteration in conjunction with boosting filters. This integration ensures that the combined negative predictions and methods for improvement are consistently updated, indicating a comprehensive approach to improve the accuracy of diagnoses and the dependability of predictions in clinical settings. Essentially, IBF+IHP is an advanced framework for transfer learning that connects prior knowledge with fresh data insights to continuously enhance stroke prediction models.

The following algorithms describe the IHP, the IBF, and the combined IBF+IHP methods.

Algorithm 1: IHP
Input: $X_{in}W_{in}, w_{ak}, \alpha_n, \beta_n, \sigma_n$
Output: Y_{ik}, Y, P_{hi}
1: Initialize X_{in} and read the samples from the csv data with feature weights as W_{in} and w_{ak}
2: Ensure the normalization of $X \rightarrow X_n$, $W \rightarrow W_n$ to deal with missing values.
3: Encapsulate the different features $w_{ak}, \alpha_n, \beta_n$ for adverse projective transform using cumulative operations
4: Y_i ← Create a Linear Spline interpolative formula through the data (rows or elements) of X and W_i
5: Calculate Y_i based on the iteration method and the values from X and W_i
6: Calculate Y_{pi} using the Y_i values and other relevant factors
7: Update cumulative adverse projections for X and W_i.
8: With an effective threshold (δ), decide whether to loop through the data again or terminate the algorithm.
End Algorithm

Algorithm 2: IBF:
Input: $X_{in}H_{in}, h_{ak}, m_n, n_n, r_n$
Output: Y_i, YP_{hi}
1: Initialize X_{in} and read the samples from the CSV data with feature weights as H_{in} and h_{ak}
2: Ensure the normalization of $X \rightarrow X_n$ and $H \rightarrow H_n$ is operated to deal with missing values
3: Encapsulate the different features $h_{ak}, \alpha_n, \beta_n$, for boost filter operations
4: Y_i← Create a boost iteration filter formula and iterate through the data (rows or elements of X and W_i).
5: Calculate Y_i based on the spline iteration method and the values from X and W_i.

6: Calculate Y_{pi} using the Y_i values and other relevant factors
8: Update the H−L boost filter for X and W_i
9: With effective threshold r, decide whether to loop through the data again or terminate the algorithm.
End Algorithm

Algorithm 3: IBF+IHP:
Input: $X_{in} W_{in}, w_{ak}, \alpha_n, \beta_n, \sigma_n, H_{in}, h_{ak}, m_n, n_n, r_n$
Output: Y_i, YP_{hi}
Initialization:
1. Read Features initializing the different medical parameters as X_{in}
2: Initialize feature weights W_{in}, H_{in}, and respective parameters $w_{ak}, \alpha_n, \beta_n, \sigma_n m_n, n_n, r_n$.
3: Ensure normalization of $X \rightarrow X_n$, $W \rightarrow W_n$ (for IHP) and $X \rightarrow X_n$, $H \rightarrow H_n$ (for IBF) to handle missing values
4: Iterative Processing:
5: Encapsulate features $w_{ak}, \alpha_n, \beta_n$ for adverse projective transform (IHP).
6: Encapsulate features h_{ak}, m_n, n_n, r_n for boost filter operations (IBF)
7: Iterative Calculation (combined):
8: Initialize Y_i using a combination of linear spline interpolative formula (IHP) and boost iteration filter formula (IBF)
9: Iterate through data rows or elements of X_{in}, W_{in} (common to both algorithms)
10: Calculate Y_i based on the iteration method (spline or boost filter) using values from X_n and respective weights W_n and H_n
11: Output Calculation:
12: Calculate Y_{pi} using Y_i values and other relevant factors as per both algorithms
13: Update cumulative projections and filters:
14: Update cumulative adverse projections (IHP) for XXX and WWW
15: Update H−L Boost filter (IBF) for XXX and WWW.
16: Termination Criteria:
17: Use effective thresholds σ (from IHP) and r(from IBF) to decide whether to loop through the data again or terminate the algorithm
End Algorithm

D. Design Process

The IHP method is a systematic approach developed to examine input data X and the corresponding weights W_i to create projections Y_i and Y_{ihp}. The process starts with preparing the data, which involves validating its comprehensiveness and normalizing it to ensure consistency. Subsequently, it calculates Y_i interpolative by the use of linear spline iteration, accounting for each element in X and its corresponding weight in W_i. Subsequently, Y_{pi} is derived from the determined values of Y_i, while considering any other pertinent factors. The approach performs interpolative refining of the output by continually updating cumulative unfavorable predictions for X and W_i. The decision to continue iterating is made dynamically, relying on a pre-established threshold to provide the utmost degree of precision. The IHP algorithm serves as a robust tool in the categorization of brain strokes accompanied by seizures, as it effectively projects data and facilitates the correct diagnosis and treatment planning in urgent medical scenarios when precise and rapid predictions are crucial. The IBF approach operates similarly to the boost iteration filter method, except it produces projections Y_i using a boost iteration filter formula. A sequential approach is used, such as in the IHP technique. It starts with data preparation and proceeds with the calculation of Y_i using spline iteration. The procedure iterates until it reaches the effective threshold r, optimizing the accuracy of the projection. The IBF suggests an enhanced method for data projection that may be used in medical settings, such as the classification of seizures and brain strokes. This approach utilizes boost iteration to enhance the precision and reliability of predictions. This approach is very beneficial for medical applications that require accurate predictions to differentiate between various types of strokes and accurately identify seizure patterns. Consequently, the quality of patient treatment and outcomes is enhanced.

The combined IBF+IHP algorithm integrates the characteristics of both the IHP and IBF algorithms to provide a comprehensive approach to data projection. The calculation of Y_i and Y_{ihp} is achieved by the iterative application of linear spline iteration and BIF formulas. This combination incorporates the favorable characteristics of the two approaches to increase the precision and dependability of the predictions. The proposed classification system for brain strokes, which includes the identification of seizures, leverages the IBF+IHP method to discover intricate patterns in the data. This approach is very efficient in producing precise predictions, allowing physicians to make well-informed judgments about diagnosis and treatment. The system can adapt its criteria and consistently enhance predictions to account for the intricacies of medical data. This allows the framework to convey critical data that could potentially be used to enhance patient care.

III. RESULTS AND DISCUSSION

A. Model Training and Testing

The Stroke Prediction Dataset [15] was used to train and evaluate the performance of the proposed model. This dataset has input parameters such as gender, age, various diseases, and smoking status. The proposed model was trained with 8k samples. Then the trained model was re-trained and tested with

2k samples transfer learning. In addition, existing models, such as the Support Vector Classifier (SVC), XGBoost, Logistic Regression (LR), and Decision Tree (DT), were developed and evaluated. The performance of these models was compared with that of the proposed model.

In the context of stroke prediction, the IHP+IBF method demonstrated remarkable performance, as shown in the classification report in Figure 3, achieving perfect precision, recall, and F1-score of 1.00 for each class, indicating their exceptional accuracy in distinguishing individuals not prone to stroke (class 0) from those at risk (class 1). The overall accuracy of 1.00 underscores the model's ability to make correct predictions throughout the entire dataset. The macro- and weighted averages further validate its consistently high performance across all evaluation metrics, ensuring reliable and robust predictions in stroke risk assessment.

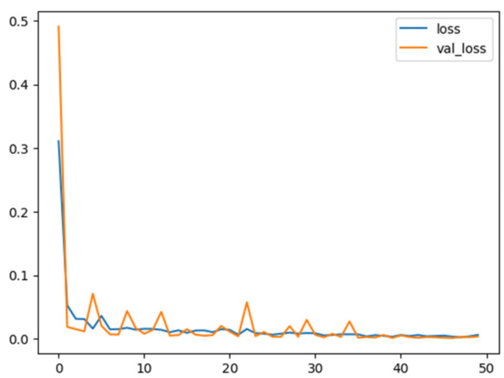

Fig. 2. Training and testing plots for the stroke prediction using the IHP+IBP+TL model.

B. *Performance Evaluation and Model Comparison*

Upon rigorous evaluation, the proposed IBF+IHP+TL model consistently outperformed baseline models and other state-of-the-art approaches. With an accuracy of 98.9% for the 2,000-sample dataset and an astonishing 99.99% for the 8,000-sample dataset, the proposed model demonstrated unparalleled predictive power. These remarkable results underscore the effectiveness of the proposed design in stroke prediction, showcasing its potential for real-world deployment in clinical settings.

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Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       976
           1       1.00      1.00      1.00       968

   micro avg       1.00      1.00      1.00      1944
   macro avg       1.00      1.00      1.00      1944
weighted avg       1.00      1.00      1.00      1944
 samples avg       1.00      1.00      1.00      1944
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Fig. 3. The overall classification report for the proposed design for 2k samples.

The classification report in Figure 3 reveals the outstanding performance of the model in predicting strokes using IHP+IBP+TL. With precision, recall, and F1-score all at 100% for both classes, the model demonstrates flawless accuracy in identifying individuals not prone to stroke (class 0) and those at risk (class 1). Precision signifies that all predictions made by the model for both classes were correct, while recall indicates that the model successfully captured all instances of both classes in the dataset. The F1-score, which combines precision and recall into a single metric, underscores the model's ability to maintain high accuracy while ensuring it comprehensively identifies stroke risks. These metrics are supported by a substantial number of samples for both classes, reinforcing the robustness and reliability of the model's predictions for stroke prediction tasks.

TABLE I. COMPARISON OF THE PROPOSED AND EXISTING METHODS ON THE STROKE 2K CSV DATASET

Algorithms	Accuracy (Training)	Accuracy (Testing)	Precision	Recall	F1-score
SVC	78.875	74.85	72.23	73.178	72.89
XGBoost	82.45	84.96	83.418	92.4774	81.774
Logistic Regression	92.31	85.880	84.67	87.89	82.758
Decision Tree	85.75	87.15	84.82	85.13	84.12
CNN	94.21	92.34	95.127	98.25	96.34
Proposed IBF	95.8	95.6	98.24	94.7	97.6
Proposed IHP	98.8	98.6	98.58	98.71	95.6
Proposed IBF+IHP+TL	98.89	98.65	98.06	98.49	98.69

TABLE II. COMPARISON OF THE PROPOSED AND EXISTING METHODS ON THE STROKE 8K CSV DATASET

Algorithms	Accuracy (Training)	Accuracy (Testing)	Precision	Recall	F1-score
SVC	91.875	84.85	92.896	93.085	92.971
XGBoost	92.45	84.5	93.47	92.874	91.647
Logistic Regression	92.31	82.18	94.67	92.89	92.758
Decision Tree	95.75	86.15	94.37	95.36	94.12
CNN	94.21	94.34	95.127	98.25	96.34
Proposed IBF	99.8	96.6	97.4	98.7	97.6
Proposed IHP	99.8	97.6	0.98	0.987	95.6
Proposed IBF+IHP+TL	99.9	99.9	99.9	99.9	99.9

Tables I and II provide detailed insights into the performance of various machine learning algorithms across the two different-sized datasets for brain stroke prediction. In the smaller dataset (2,000 samples), traditional algorithms such as the Support Vector Classifier (SVC), XGBoost, Logistic Regression, and Decision Tree perform reasonably well, with accuracies ranging from around 74% to 92%. However, they were surpassed by CNN, indicating the superiority of deep learning methods in capturing complex patterns within the data. As observed in Tables I and II, the performance of IHP, IBF, and the integrated IHP+IBF was striking. These methods consistently outperformed traditional algorithms, even CNN, in most metrics across both datasets. For instance, in the 2,000-sample dataset, IBF achieved an accuracy of 95.6%, while IHP achieved 98.6%, demonstrating their effectiveness in improving predictive performance. For the larger dataset (8,000 samples), trends continue, with traditional algorithms maintaining moderate to high accuracy levels. However, the proposed techniques, especially when combined (IBF+IHP+TL), exhibited exceptional performance, achieving accuracy levels of 99.9%. This demonstrates not only the scalability of the proposed approach but also its ability to effectively handle larger datasets.

IV. CONCLUSION

This study proposed a robust and comprehensive approach to stroke prediction, using a combination of innovative algorithms, meticulous optimization techniques, and advanced transfer learning methods. Extensive experimentation and evaluation demonstrated the superior performance of the proposed IBF+IHP model integrated with transfer learning in accurately detecting strokes. When comparing the performance of the proposed with existing models, significant improvements were observed across various metrics. For instance, in the 2,000-sample dataset, traditional algorithms such as SVC achieved an accuracy of approximately 74.85%, while the proposed IBF model achieved 95.6%. Similarly, in the larger 8,000-sample dataset, traditional algorithms such as LR achieved an accuracy of 82.18%, whereas the IBF+IHP+TL model achieved an outstanding 99.9%. These results highlight the remarkable effectiveness of the proposed approach in improving stroke prediction accuracy. Thus, the proposed model outperformed traditional algorithms, even deep learning methods such as CNN, across various datasets and sample sizes. This underscores the robustness and reliability of the proposed model, positioning it as a promising solution for real-world applications in healthcare settings. Furthermore, meticulous optimization techniques, including hyperparameter tuning and transfer learning, contributed to the exceptional performance of the model. Fine-tuning parameters and leveraging knowledge from pre-trained models provided unprecedented levels of accuracy in stroke prediction. Overall, this study demonstrates the transformative potential of advanced machine learning techniques in improving medical diagnostics, particularly in the critical domain of stroke prediction. Further innovation and collaboration should further refine and validate the proposed model for deployment in clinical settings, ultimately improving patient outcomes and advancing the field of precision medicine.

REFERENCES

[1] N. Ottakath *et al.*, "Ultrasound-Based Image Analysis for Predicting Carotid Artery Stenosis Risk: A Comprehensive Review of the Problem, Techniques, Datasets, and Future Directions," *Diagnostics*, vol. 13, no. 15, Jan. 2023, Art. no. 2614, https://doi.org/10.3390/diagnostics13152614.

[2] R. Mia *et al.*, "Exploring Machine Learning for Predicting Cerebral Stroke: A Study in Discovery," *Electronics*, vol. 13, no. 4, Feb. 2024, Art. no. 686, https://doi.org/10.3390/electronics13040686.

[3] M. Ivanenko, D. Wanta, W. T. Smolik, P. Wróblewski, and M. Midura, "Generative-Adversarial-Network-Based Image Reconstruction for the Capacitively Coupled Electrical Impedance Tomography of Stroke," *Life*, vol. 14, no. 3, Mar. 2024, Art. no. 419, https://doi.org/10.3390/life14030419.

[4] Ö. Polat, Z. Dokur, and T. Ölmez, "Classification of brain strokes using divergence-based convolutional neural networks," *Biomedical Signal Processing and Control*, vol. 93, Jul. 2024, Art. no. 106193, https://doi.org/10.1016/j.bspc.2024.106193.

[5] N. Guo *et al.*, "SSVEP-Based Brain Computer Interface Controlled Soft Robotic Glove for Post-Stroke Hand Function Rehabilitation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 1737–1744, 2022, https://doi.org/10.1109/TNSRE.2022.3185262.

[6] T. Janyalikit and C. A. Ratanamahatana, "Time Series Shapelet-Based Movement Intention Detection Toward Asynchronous BCI for Stroke Rehabilitation," *IEEE Access*, vol. 10, pp. 41693–41707, 2022, https://doi.org/10.1109/ACCESS.2022.3167703.

[7] O. Karadima, P. Lu, I. Sotiriou, and P. Kosmas, "Experimental Validation of the DBIM-TwIST Algorithm for Brain Stroke Detection and Differentiation Using a Multi-Layered Anatomically Complex Head Phantom," *IEEE Open Journal of Antennas and Propagation*, vol. 3, pp. 274–286, 2022, https://doi.org/10.1109/OJAP.2022.3150100.

[8] N. Saga, Y. Tanaka, A. Doi, T. Oda, S. N. Kudoh, and H. Fujie, "Prototype of an Ankle Neurorehabilitation System with Heuristic BCI Using Simplified Fuzzy Reasoning," *Applied Sciences*, vol. 9, no. 12, Jan. 2019, Art. no. 2429, https://doi.org/10.3390/app9122429.

[9] D. M. Alawad, A. Mishra, and M. T. Hoque, "AIBH: Accurate Identification of Brain Hemorrhage Using Genetic Algorithm Based Feature Selection and Stacking," *Machine Learning and Knowledge Extraction*, vol. 2, no. 2, pp. 56–77, Jun. 2020, https://doi.org/10.3390/make2020005.

[10] M. Salucci, A. Polo, and J. Vrba, "Multi-Step Learning-by-Examples Strategy for Real-Time Brain Stroke Microwave Scattering Data Inversion," *Electronics*, vol. 10, no. 1, Jan. 2021, Art. no. 95, https://doi.org/10.3390/electronics10010095.

[11] M. A. Inamdar *et al.*, "A Review on Computer Aided Diagnosis of Acute Brain Stroke," *Sensors*, vol. 21, no. 24, Jan. 2021, Art. no. 8507, https://doi.org/10.3390/s21248507.

[12] Y. Guo *et al.*, "A Focus on the Role of DSC-PWI Dynamic Radiomics Features in Diagnosis and Outcome Prediction of Ischemic Stroke," *Journal of Clinical Medicine*, vol. 11, no. 18, Jan. 2022, Art. no. 5364, https://doi.org/10.3390/jcm11185364.

[13] O. Ozaltin, O. Coskun, O. Yeniay, and A. Subasi, "A Deep Learning Approach for Detecting Stroke from Brain CT Images Using OzNet," *Bioengineering*, vol. 9, no. 12, Dec. 2022, Art. no. 783, https://doi.org/10.3390/bioengineering9120783.

[14] M. Alruily, S. A. El-Ghany, A. M. Mostafa, M. Ezz, and A. A. A. El-Aziz, "A-Tuning Ensemble Machine Learning Technique for Cerebral Stroke Prediction," *Applied Sciences*, vol. 13, no. 8, Jan. 2023, Art. no. 5047, https://doi.org/10.3390/app13085047.

[15] "Stroke Prediction Dataset." Kaggle, [Online]. Available: https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset.