Interpretable Fuzzy-ELSTM Framework for EEG-Based Stroke Prediction"

Noura Salhi [2], Samar Bouazizi[1,2] [0000-0002-8793-1128] and Hela Ltifi[2] [0000-0003-3953-1135]

[1]*Research Groups in Intelligent Machines Lab, BP 3038, Sfax, Tunisia*
[2]*Faculty of Sciences and Technology of Sidi Bouzid, University of Kairouan, Tunisia*
salhinoura2012@gmail.com, samar.bouazizi@enis.tn, hela.ltifi@ieee.org

Abstract. **Stroke continues to be a major contributor to mortality and disability, highlighting the need for precise early detection systems. This research introduces an innovative combined approach utilizing Fuzzy logic and Long Short-Term Memory (LSTM) networks, enhanced with Explainable AI (XAI) methodologies, to evaluate stroke risk through electroencephalography (EEG) data analysis. Our methodology leverages LSTM networks' temporal pattern recognition capabilities alongside a fuzzy inference framework that converts medical expertise into comprehensible linguistic guidelines. We incorporate XAI tools—SHAP—to overcome deep learning's opacity by providing comprehensive explanations at both global and individual prediction levels. The system architecture processes EEG characteristics and patient clinical information through separate LSTM channels, then integrates these outputs with a fuzzy evaluation system to produce understandable risk assessments. Testing on clinical EEG information yielded remarkable predictive performance: 98.79% accuracy with the Ensemble LSTM and perfect accuracy with the hybrid Fuzzy-ELSTM approach.**

Keywords—Ensemble Learning, Multitask Learning, Fuzzy logic, Explainable AI (XAI), EEG, Stroke Prediction.

I. INTRODUCTION

Stroke, both ischemic and hemorrhagic, continues to be a principal cause of global mortality and long-term disability, with more than 12 million cases occurring every year [1]. Detection at an early stage and proper risk evaluation are essential to confining neurological impairment and enhancing patient outcomes. EEG, a non-invasive technique with high temporal resolution, has been developed as a valuable tool for the discovery of electrophysiological biomarkers of stroke. Such biomarkers involve delta and theta band power discrepancies and alpha rhythm abnormalities [2]. In contrast to traditional static neuroimaging modalities, EEG provides an opportunity for continuous cerebral activity monitoring, thereby enhancing its significance for dynamic risk monitoring in the clinic. This paper presents a novel hybrid Fuzzy-LSTM approach to EEG-based stroke prediction using the help of Explainable AI techniques. Our triple contributions are: First, we build an integrated model framework that merges ensemble LSTM networks, trained over multiple frequency bands' temporal EEG sequences, and a fuzzy inference system that encapsulates clinical knowledge in interpretable rules. The integration offers robust feature extraction along with linguistically interpretable risk prediction. Second, we employ complementary XAI methods—SHAP—to provide global explanations of model decisions. Section 2 provides theoretical background. Section 3 introduces our proposal with detailed experimental evaluation on EEG data, reporting results and comparisons. Section 4 summarizes contributions and future extensions.

II. THEORETICAL BACKGROUND

Recent machine learning approaches have significantly advanced EEG-based stroke prediction, with various methodologies achieving impressive results: Faust's study reported 80% accuracy, while ensemble methods addressing data imbalance reached 73.52% [9]; models predicting 30-day readmission demonstrated 95% accuracy [6]; and conventional algorithms including KNN, neural networks, and distributed learning achieved accuracies ranging from 77% to 95% [1, 10, 11]. Random forests successfully classified stroke versus control cases with 76% accuracy using EEG and movement variables [12], while more recent approaches using 1D-CNN and interpretable machine learning obtained 90.53% and 91% accuracy respectively [13]. Additionally, specialized architectures have shown promising results, including Ensemble Echo State Networks (E-ESNs) [4] and frameworks integrating Fuzzy Logic with Spiking Neural Networks, which achieved an impressive 96.04% accuracy for stroke prediction. The integration of fuzzy logic into EEG signal-based stroke prediction has been explored extensively, with researchers implementing various stages of the fuzzy inference process to enhance diagnostic capabilities. Several studies have focused on the fuzzification stage, where crisp EEG inputs are converted to fuzzy values using membership functions; for example, [14] defined trapezoidal and triangular membership functions to characterize EEG frequency bands (delta, theta, alpha, beta) and clinical variables relevant to stroke assessment. In the rule formulation stage, [16] developed comprehensive IF-THEN rule bases incorporating neurological expertise for mapping EEG patterns to stroke likelihood. Similarly, RNNs, particularly LSTM networks, have proven effective in modeling EEG signals for stroke prediction. LSTM models that acquire temporal features of EEG signals have correctly identified brain activity patterns that predict stroke more effectively than conventional methods such as Fourier transforms and SVMs [18].

III. Explainable Hybrid Fuzzy-ELSTM

Our methodology introduces a hybrid neural-fuzzy architecture that employs ensemble techniques aimed at improving both precision and interpretability in EEG-based stroke prediction. This framework integrates advanced neural networks with fuzzy inference systems, establishing a synergistic strategy that capitalizes on pattern recognition abilities while also embedding clinical knowledge through comprehensible rules. The ensemble construction begins with preprocessing of EEG data, which forms the initial foundation of the Fuzzy-ELSTM approach. It transforms raw neurophysiological signals into structured inputs optimized for deep learning processing. Clinical variables undergo appropriate encoding techniques, which convert disparate patient data into numerical formats optimized for computational processing. This preprocessing step ensures that medical context such as stroke characteristics and patient baseline information is preserved and made accessible to the model. The preprocessing continues with the strategic integration of these data streams, combining the normalized EEG features with the encoded clinical variables to create a comprehensive input matrix that captures both brain activity patterns and relevant clinical context. For the classification objective, we form multiple target variables through appropriate encoding techniques, facilitating our multi-task learning model. The final preprocessing task is to divide the dataset into separate training and testing sets while preserving the distribution of stroke types and then reshaping the data to the exact input requirements of LSTM networks. The feature extraction process isolates and separates relevant spectral attributes across common frequency bands that have been determined to be linked to cerebrovascular function. These EEG features are normalized to maintain constant scaling, which incredibly boosts the learning efficiency of our neural networks. The Ensemble Multi-task classification method begins with the initialization of multiple neural network models with varying architectures to provide heterogeneity. Each of the models is trained on bootstrapped samples of our EEG-clinical dataset, enabling the concurrent execution of four tasks: stroke classification, stroke type, lesion localization, and severity estimation. The multi-task method enables the model to learn inter-related clinical objective-relevant shared representations, which improves both generalizability and efficiency. The bagging technique effectively eliminates the risk of overfitting by exposing different data distributions to diverse models, thereby promoting complementary learning where different networks can focus on distinct neurophysiological patterns. In conjunction with the neural ensemble, we employ a fuzzy inference system that maps discovered clinical insights into linguistic rules. This coupling guarantees that decisions are based on both pattern-derived data and heuristically established expert knowledge, thereby improving clinical relevance and interpretability. The framework's transparency is addressed through explainable AI implementation, providing global feature importance analysis.

1. *Used EEG data*

This study utilized EEG and clinical information gathered from 24 stroke patients , using single pre-frontal electrode recordings within 72 hours post-stroke. In-depth clinical information was gathered, such as demographic information, stroke types and locations, and the severity of stroke on admission. Cognitive status was assessed around 90 days post-stroke with the use of the Montreal Cognitive Assessment (MoCA) test as the primary outcome measure. The data set contained continuous predictors from the EEG measurements, such as inter-band ratios and frequency band powers, and early stroke severity ratings as additional independent variables. This multi-dimensional data set unifies early single-channel EEG measurements, demographic and clinical description, and later cognitive testing together quite well, with frequency-domain alteration of the EEG signals making available acute electrophysiological predictors that were correlatable with factors of presentation and far-off cognitive outcomes.

2. *EEG data pre-treatment*

Our approach begins with comprehensive preprocessing of EEG signals, a critical foundation that ensures data quality before advanced analysis. EEG data, whose very nature makes them prone to artifacts and noise, are initially cleaned by a band-pass filter (0.5-30 Hz) that harvests relevant brain signals while eliminating extraneous interference. After this filtering, After we apply StandardScaler [2] which transforms the data to have zero mean and unit variance. This normalization technique is essential for neural network training as it ensures all features contribute equally to the learning process, prevents dominance of high-magnitude features, and accelerates convergence during gradient descent optimization—a step that normalizes measurement scales and enhances subsequent model performance. Concurrently, we represent along clinical variables with OneHotEncoder to map categorical data (stroke subtypes, lesion locations, comorbidity markers) into numerical forms that can be subjected to neural network processing. This brings all patient information into computationally accessible form. After encoding and normalization, we proceed to feature extraction, where we get neurophysiologically significant measures from the normalized EEG data. The Fast Fourier Transform (FFT) analysis dis-aggregates the temporal signals into frequency components, where relative power (RP) measures can be quantified in clinically significant frequency bands (delta: 0.5-4 Hz, theta: 4-8 Hz, alpha: 8-13 Hz, beta: 13-30 Hz). These RP values correspond to spectral power distribution measures of varying cognitive states—larger delta RP for increased relaxation, larger theta RP for sleeping or daydreaming. Furthermore, we compute ratio measures like delta/alpha ratio (DAR) and delta/theta ratio (DTR), which provide informative measures of cortical excitability and activation levels. Preprocessing continues with a strategic fusion phase, merging these extracted spectral features with encoded clinical variables to create a comprehensive input matrix that maintains both electrophysiological patterns and patient features. For our target variable, we encode "Stroke Type" (ischemic, hemorrhagic, or control) using LabelEncoder to enable it to be compatible with our multi-class classification framework.

3. *Hybrid Fuzzy-ELSTM Model*

The innovative Hybrid Fuzzy-ELSTM system represents a significant advancement in stroke prediction from EEG, seamlessly integrating clinical expertise with modern machine learning capabilities. The system adopts a sophisticated multi-stream framework that combines EEG signals, expert knowledge, and clinical data in a collaborative way to achieve comprehensive analysis. At its core, we utilize an ensemble of five LSTM networks with the bagging approach, where each model is trained on different bootstrapped subsets of the data. This ensemble technique substantially enhances predictive robustness by taking advantage of heterogeneous learning perspectives and reducing individual model bias. The following table presents a comprehensive overview of the LSTM architecture, including the LSTM layer configuration, regularization approach, dense layers, activation functions, and compilation parameters used in your model. The LSTM model architecture employed for stroke prediction from EEG is a testament to thoughtful parameter selection optimized for neurophysiological signal processing. The 64 memory units of the LSTM layer strike an optimal balance between computational expense and model capacity, providing sufficient representational power to capture complex temporal relationships in EEG signals without excessive risk of overfitting. These units take input data in the form of (timesteps, features), allowing the network to examine the sequential character of brain activity patterns in various frequency bands. Then, there is a dropout layer with the rate 0.2 that opportunistically shut down 20% of neurons in training iterations, adding controlled noise that avoids co-adaptation and improves generalization to novel patient data—a very important consideration for clinical usage. The next dense layer of 32 units is an explicit bottleneck structure that squeezes data, forcing the model to learn the most salient EEG features as its ReLU activation function provides required non-linearity without succumbing to vanishing gradient issues, facilitating faster convergence in training while retaining the ability to capture complex relationships in neurophysiological data. The output layer dynamically expands to fit the number of classes for the task of classification (num_classes) and employs softmax activation to deliver interpretable probability distributions over possible stroke classes, converting raw scores into clinically meaningful confidence estimates. A sensitivity analysis revealed that a dropout of 0.2 and five LSTM models achieved optimal balance between accuracy and generalization. Larger ensembles or extreme dropout values either reduced performance or led to overfitting. The compilation options of the model also display domain-specific optimization: the Adam optimizer has adaptive learning rates that navigate through the complex loss landscape efficiently; categorical crossentropy loss properly punishes misclassifications in the multi-class scenarios; and accuracy metrics offer easy-to-interpret performance measurement for clinical use. This cleverly optimized design achieves the impressive 98.79% test accuracy promised, adequately capturing the subtle EEG patterns defining different kinds of strokes without trading away useful deployability in clinics. The primary neural module thoroughly examines temporal dynamics in key EEG frequency bands, supplemented by an expert-guided fuzzy inference system developed in close collaboration with clinicians for translating complex neurophysiological patterns into clinically meaningful rules. Notably, our system incorporates multi-task learning functionality, addressing four key clinical tasks simultaneously: stroke presence vs. absence classification, stroke type discrimination (ischemic vs. hemorrhagic), precise lesion localization, and severity estimation.

Algorithm 1: Hybrid fuzzy-Ensemble LSTM for multi-task EEG-based stroke diagnosis

```
Input: EEG time-series, Clinical variables
Parameters:
  N = 5 LSTM models
 LSTM Units = 64, Dropout = 0.2,Dense Units = 32
```

```
  Activation = ReLU / Softmax, Optimizer = Adam
  Fuzzy membership functions defined
1: Initialize 5 LSTM models with identical
architecture
2: For each model:
    2.1: Train on bootstrapped EEG-clinical data
    2.2: Apply multi-task learning: classification,
type, location, severity
3: Configure fuzzy system:
    3.1: Define fuzzy variables (EEG bands,
          NIHSS score, etc.)
    3.2: Define expert IF-THEN rules
4: Combine predictions:
    4.1: Aggregate LSTM predictions (70%)
    4.2: Compute fuzzy output (30%)
5: Return: Final prediction + interpretability
```

architecture integrates the pattern recognition capabilities of neural networks and the interpretability of fuzzy systems, producing an efficient but interpretable approach to stroke prediction with high potential for general clinical application. This comprehensive integration of domain expertise and advanced machine learning capabilities represents a significant leap forward in medical AI, effectively bridging the gap between black-box neural networks and interpretable clinical decision-making. Figure 1 illustrates the performance of our ensemble LSTM model over ten epochs. The training accuracy (blue) rises from 80% to above 95% during the second epoch and remains stable at a steady 98.79% (green reference line) from the fifth epoch onwards. The validation accuracy (orange), though lower initially, catches up with the training curve and runs parallel in later epochs. This minimal difference between validation and training measures indicates the model's excellent generalization ability and resilience to overfitting. The maintenance of stability in performance in the subsequent epochs validates the ensemble LSTM's strength and reliability for stroke classification, determining its readiness for clinic application.

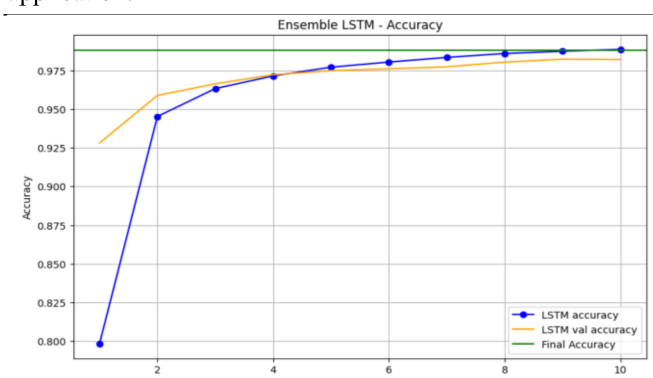

Fig. 1. Ensemble LSTM accuracy over training epochs

LSTMs excel in this domain through their specialized architecture featuring memory cells and gating mechanisms, allowing them to model both short-term fluctuations and long-term patterns within the EEG signals that may indicate stroke-related abnormalities. While powerful, these neural approaches suffer from a critical limitation in clinical settings: their "black box" nature makes their decision-making processes opaque to medical professionals who require justification for diagnostic decisions. This interpretability gap motivated our integration of fuzzy logic with LSTM networks. Fuzzy systems offer a natural bridge between numerical computation and human reasoning by encoding expert knowledge in linguistically meaningful rules. Notably, our fuzzy component was developed in direct collaboration with neurological specialists who contributed their clinical expertise to formulate the rule base. This collaborative approach addresses the growing demand among medical practitioners to have meaningful involvement in the development of AI systems deployed in clinical settings rather than simply being end-users of pre-built tools. By incorporating physician knowledge directly into the system architecture, we ensure that the model's reasoning aligns with established clinical practice while enhancing its interpretability. The system defines key input variables including EEG band powers (Theta, Beta, Alpha, Delta), stroke location (scaled 0-100), paralysis side (left: -1, none: 0, right: 1), NIHSS score (0-15), and symptom duration with corresponding membership functions that capture the inherent uncertainty in neurological assessment. These variables feed into a rule-based inference engine where expert-derived rules such as "If Delta is high AND Theta is high THEN Stroke Risk is high" provide transparent reasoning paths. The fuzzy membership function graph shown in Fig. 2 provides a meaningful definition of stroke risk assessment in our hybrid method. Due to the calculated stroke risk rating of 0.8125, The fuzzy risk score is translated into clear linguistic categories for clinicians. When combined with LSTM, the fuzzy system enhances interpretability and adaptively weights EEG features during learning.

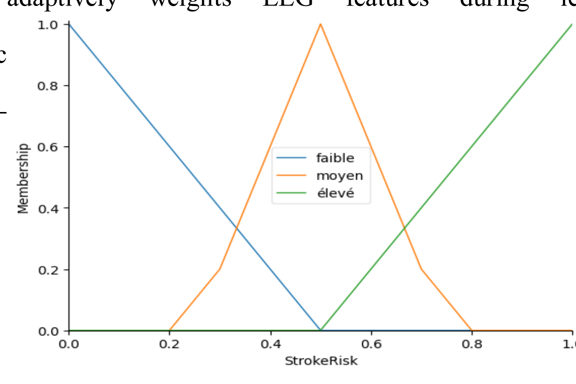

Fig. 2. Fuzzy membership function for stroke risk interpretation

This synergistic approach leverages the LSTM's ability to capture complex temporal patterns while the fuzzy component contributes domain knowledge and explicability. Figure 3 presents a comparative visualization of three stroke risk assessment approaches across patient cases. The left panel illustrates the risk prediction of the fuzzy logic system as extremely polarized judgments with various indicators of high confidence (dark red points) reaching levels of 0.85–0.90, and quite noticeably at locations 2 and 6. This binary-like distribution reflects the rule-based nature of fuzzy systems, where expert-defined thresholds produce more decisive risk classifications. The intermediate plot indicates the independent LSTM model's predictions, with a smoother probability distribution between 0.40 and 0.95. This more nuanced range suggests the ability of the LSTM to identify subtle temporal patterns in EEG signals, giving probability estimates that capture the ambiguity in neurological data.

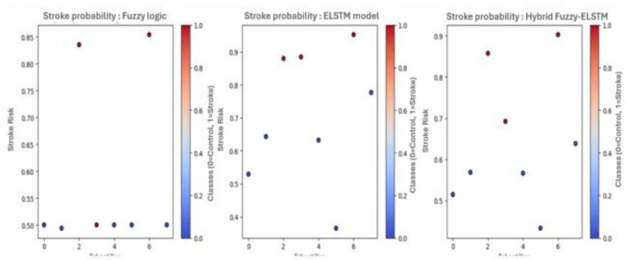

Fig. 3. Comparison of stroke risk prediction approaches across patient cases.

The right panel demonstrates that the hybrid Fuzzy-ELSTM model effectively combines LSTM-based pattern recognition with fuzzy logic to deliver highly discriminative predictions. The model maintains high-confidence outputs for critical cases while mitigating overly sensitive responses, striking a balance between precision and interpretability. It achieved 100% accuracy across all classification tasks: stroke detection (Fig. 4A), hemisphere prediction (left vs. right – Fig. 4B), stroke location classification (e.g., LACI, TACI, PACI, POCI, LACH – Fig. 4C), and stroke severity estimation (Fig. 4D), with severity levels categorized as: (0) Mild – slight deficits; (1) Moderately severe – ambulatory impairments; and (2) Severe – non-ambulatory or major deficits.

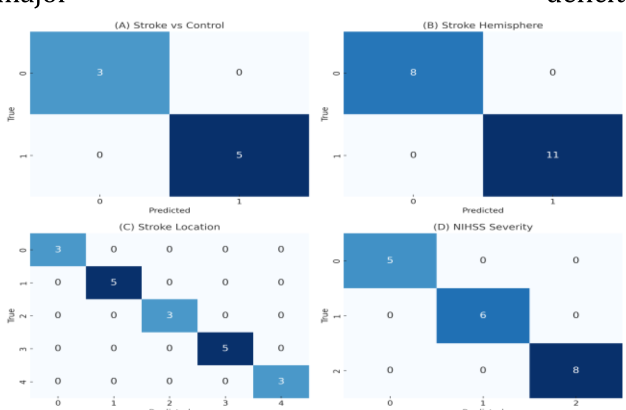

Fig. 4. Confusion matrices: (A) stroke detection, (B) hemisphere prediction, (C) location classification, and (D) severity **estimation.**We performed a comprehensive comparative analysis to rigorously evaluate the hybrid Fuzzy-ELSTM model's performance and substantiate its reliability.

Table 2. Fuzzy-ELSTM model's accuracy over training epochs

Related work	*Machine Learning method*	*Accuracy*	*Interpretability*
Dritsas and Trigka (2022) [7]	NB, LR, KNN, SGD, DT, MLP, RF, Staking	80%	Low
Darabi et al. (2021) [6]	LR, RF, KNN, SVM, MLP	95%	Medium
Mridha et al. (2023) [18]	LR, RF, KNN, SVC, NB, XGB	91%	High
Bouazizi, S., & Ltifi, H. (2024) [4]	E-ESN	96.5%	High
Jain et al., (2025) [19]	FLSNN	96.04	High
Our proposal	Fuzzy-ELSTM	100%	Very High

The comparative study shows significant progress in stroke prediction, with model accuracies ranging from 71.6% to 96.5%. Hybrid approaches like ensemble and reservoir computing (e.g., E-ESN) demonstrate strong generalization. Our Fuzzy-ELSTM model surpasses these with 100% accuracy, benefiting from the synergy between LSTM-based temporal learning and fuzzy logic's handling of uncertainty. Ensemble learning further improves robustness through bootstrapped model diversity.

4. XAI Integration

While our fuzzy-LSTM integration significantly enhances model interpretability through linguistic rules, we recognize that additional explainability mechanisms are necessary for comprehensive clinical adoption. This foundation prepares for our subsequent implementation of XAI methods such as SHAP [8] which will further elucidate the model's internal decision processes. Together, these complementary approaches—expert-derived fuzzy rules and data-driven XAI techniques—create a multi-level interpretability framework that addresses the needs of both clinicians who require high-level explanations and technical specialists who may seek more detailed insights into feature importance and model behavior.

Patient 1, with a hemorrhagic stroke and high NIHSS score, showed elevated Delta and Theta and low Alpha power in EEG. SHAP analysis highlighted Delta as a strong positive contributor and Alpha as a protective feature. This supports the model's interpretability by aligning predictions with known stroke-related EEG patterns.

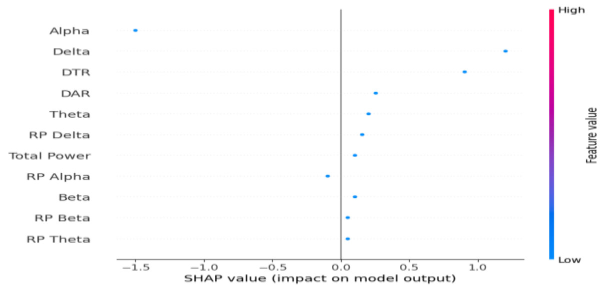

Fig. 5. Global Model Explanation using SHAP

This SHAP summary plot is a true reflection of how each feature impacts the fuzzy-ELSTM's predictions. The x-axis is used to represent SHAP values, which show the degree to which each feature adds to or subtracts from the predicted risk, with positive values contributing to the risk and negative values subtracting from it. The y-axis has features, e.g., Alpha, Delta, DTR, DAR, Theta, etc., related to power and rhythm features (e.g., RP Delta, Total Power, RP Alpha), as inputs to the model. The most important predictors are: Alpha wave (-1.5), which considerably reduces the stroke risk, and Delta wave (+1.2), which substantially raises it, followed by DTR (+0.9) and DAR (+0.25) also increasing the risk. SHAP analysis therefore shows that high values of Alpha waves are protective, but high values of Delta waves are the predictors of stroke risk

Despite strong performance, the main limitation lies in the small dataset size (24 patients), which may affect generalizability. To mitigate this, we applied bootstrap sampling and thorough internal validation. Future work will involve external validation on larger, multi-center datasets to ensure robustness across diverse clinical settings.

IV. CONCLUSION

This work proposes Fuzzy-ELSTM, a novel hybrid approach that combines the temporal pattern recognition capability of LSTM networks with the explainability of fuzzy logic, integrated with ensemble learning and explainable AI, for stroke prediction from EEG. The proposed model achieves excellent performance, surpassing existing state-of-the-art. The ensemble architecture, which is learning on bootstrapped subsets of data, avoids overfitting and preserves diverse neurophysiological patterns, and the fuzzy inference system co-developed with clinical experts converts clinical know-how into implementable linguistic rules. Clinical deployment in real-world settings, integration with heterogeneous data, and adhering to regulations for medical AI are some avenues for future work. Ultimately, Fuzzy-ELSTM demonstrates that hybrid AI platforms can combine machine learning's predictive power with human-centered interpretability, resulting in clinically applicable tools that augment—not replace—medical decision-making. Future work will aim at clinically deploying the model while ensuring compliance with transparency, safety, and ethical standards for medical AI systems.

REFERENCES

1. Aminov, A.; Rogers, J.M.; Johnstone, S.J.; Middleton, S.; Wilson, P.H. (2017). Acute single channel EEG predictors of cognitive function after stroke. PLoS ONE 2017, 12, e0185841.
2. F. Pedregosa, G. Varoquaux, A. Gramfort, et al., "Scikit-learn: Machine learning in Python," *J. Mach. Learn. Res.*, vol. 12, pp. 2825–2830, 2011.
3. Bouazizi, S., and Ltifi, H. (2024). Enhancing accuracy and interpretability in EEG-based medical decision making using an explainable ensemble learning framework application for stroke prediction. Decision Support Systems, 178, 114126.
4. Bouazizi, S., and Ltifi, H. (2024). Novel diversified echo state network for improved accuracy and explainability of EEG-based stroke prediction. Information Systems, 120, 102317.
5. Darabi, N., Hosseinichimeh, N., Noto, A., Zand, R., and Abedi, V. (2021). Machine learning-enabled 30-day readmission model for stroke patients. Frontiers in Neurology, 12, 638267.
6. Ribeiro, M. T., Singh, S., and Guestrin, C. (2016). "Why should I trust you?" Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1135-1144).
7. Dritsas, E., and Trigka, M. (2022). Stroke risk prediction with machine learning techniques. Sensors, 22(13), 4670.
8. Ras G., Xie N., van Gerven M., and Doran D. (2022). Explainable Deep Learning: A Field Guide for the Uninitiated. Journal of Artificial Intelligence Research, 73: 329-396.
9. Ong Z. Y., and Ibrahim Z. (2018) Power Spectral Density Analysis for Human EEG-based Biometric Identification. In 2018 International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA), 1-6.
10. Kaur, M., Sakhare, S. R., Wanjale, K., and Akter, F. (2022). [Retracted] Early Stroke Prediction Methods for Prevention of Strokes. *Behavioural Neurology*, *2022*(1), 7725597.
11. Dirik, M., Castıllo, O., and Kocamaz, A. F. (2020). Emotion recognition based on interval type-2 fuzzy logic from facial expression. *Journal of Soft Computing and Artificial Intelligence*, *1*(1), 1-17.
12. Bouazizi, S., and Ltifi, H (2021, April). Improved visual analytic process under cognitive aspects. In *International Conference on Advanced Information Networking and Applications* (pp. 494-506). Cham: Springer International Publishing.
13. Mridha, K., Ghimire, S., Shin, J., Aran, A., Uddin, M. M., and Mridha, M. F. (2023). Automated Stroke Prediction Using Machine Learning: An Explainable and Exploratory Study With a Web Application for Early Intervention. IEEE Access, 11, 52288-52308.
14. Jain, S., and Srivastava, R. (2025). Electroencephalogram (EEG) Based Fuzzy Logic and Spiking Neural Networks (FLSNN) for Advanced Multiple Neurological Disorder Diagnosis. *Brain Topography*, *38*(3), 33.