**A HYBRIDIZED MACHINE LEARNING BASED CRISIS PERIOD PREDICTION SYSTEM FOR EPILEPTIC PATIENT**

**Abstract**

Epileptic seizures are unpredictable and can severely impact the quality of life of patients. To address this challenge, this research presents a hybridized machine learning-based crisis period prediction system designed to predict seizure occurrences with high accuracy. The system leverages a comprehensive dataset that integrates physiological signals, environmental variables, and behavioural patterns, offering a holistic approach to seizure prediction. The methodology follows the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, ensuring a structured approach to data pre-processing, model development, and evaluation. Object-Oriented Analysis and Design Methodology (OOADM) principles were employed to modularize and optimize the implementation, facilitating scalability and maintainability of the system. The dataset underwent rigorous pre-processing, including normalization, feature selection, and handling of missing values, to ensure the quality and reliability of the input data. A Support Vector Machine (SVM) classifier was employed due to its robustness in handling high-dimensional data. The evaluation of the model yielded an accuracy of 85%, demonstrating its effectiveness in predicting crisis periods for epileptic patients. This system represents a significant step forward in predictive healthcare for epilepsy management. By integrating diverse data sources and leveraging advanced machine learning techniques, it offers a promising tool for real-time crisis period prediction, potentially improving patient safety and autonomy. Future work will focus on enhancing the model's accuracy and integrating real-time monitoring capabilities to enable proactive interventions.

**Keywords:** Epilepsy; Hybrid Machine Learning; Support Vector Machine; SRISP-DM

**Introduction**

Patients with epilepsy, a common neurological condition marked by periodic abnormalities in the activity of brain nerve cells, present several difficulties to medical personnel. The World Health Organization (WHO) estimates that 0.6% of people worldwide suffer from epilepsy, with developing nations accounting for a sizable majority of those affected. "Epileptic seizures," which are characterized by abrupt and fleeting disruptions in perception or behavior, are a significant way that epilepsy is detected (Halawa *et al.*, 2022). Technological developments in recent years, especially in the area of machine learning, have created new opportunities for the study and treatment of epilepsy. With its capacity to analyze large volumes of data and identify intricate patterns, machine learning techniques have exciting prospects for early detection, precise diagnosis, and customized treatment plans (Halawa et al., 2022). The application of machine learning in epilepsy detection and prediction has gained significant attention due to its potential to revolutionize clinical practices. Machine learning techniques have been increasingly utilized to develop automated epilepsy detection and prediction models, leveraging various data sources such as physiological signals, environmental variables, and behavioral patterns. These applications aim to improve the accuracy and efficiency of epilepsy diagnosis, seizure detection, and prediction of treatment outcomes (Ahmed et al., 2019).

Machine learning has significantly advanced the field of epilepsy prediction and diagnosis. Several studies have demonstrated the potential of machine learning in automated epilepsy detection techniques. For instance, machine learning algorithms have been used to predict epilepsy duration based on brain network metrics, showing a high correlation with actual epilepsy duration. Furthermore, advanced machine learning methods have been applied to assist in the diagnosis and prediction of treatment responses in individuals with epilepsy and other neurological illnesses. Additionally, machine learning approaches have been utilized to predict the outcome of epilepsy surgery, incorporating clinical, pathological, and neuro-psychological evaluations. Moreover, the application of machine learning in neuroimaging for the diagnosis and prognosis of epilepsy has been recognized as a promising area of research. Specifically, machine learning models trained with resting-state functional MRI data have shown potential for providing adjunctive methods for the diagnosis and evaluation of epilepsy, aiming to enable timely and appropriate care for patients. Furthermore, a study has presented a machine learning prediction framework using MRI to lateralize hippocampal sclerosis in patients with temporal lobe epilepsy, highlighting the potential of machine learning in leveraging neuroimaging data for epilepsy diagnosis (Araújo et al., 2021).

Epileptic crisis monitoring and prediction of patients has become a huge challenge within the healthcare industry. This is due to the fact that, no system can predict individual responses to antiepileptic medication. Also, prediction is not accurate because diverse physiological and environmental data are underutilized in model building. There is high mortality rates in remote areas due to untimely detection/prediction of epilepsy. This research aimed to develop a hybridized machine learning-based crisis period prediction system for epileptic patients with the following specific objectives;

1. To collect and analyze a diverse dataset encompassing physiological signals, environmental variables, and behavioral patterns.
2. To design hybridized machine learning algorithms to predict the occurrence of epilepsy.
3. Evaluate the performance of the new hybrid model with the results.
4. Develop a user-friendly interface and deploy the trained model.

**Review of Related Literatures**

Machine learning has become a cornerstone in modern healthcare, enabling the development of predictive models that can analyze vast amounts of medical data to identify patterns and make accurate predictions. These models are utilized in various domains, including diagnostic imaging, personalized treatment plans, and predictive analytics (Ekpe et al., 2025). The ability of machine learning algorithms to handle complex, high-dimensional data makes them particularly valuable in medical applications where traditional statistical methods fall short (Rajkomar *et al.*, 2019). Epilepsy, a neurological disorder characterized by recurrent seizures, poses significant challenges in terms of timely diagnosis and effective treatment. Machine learning techniques have shown great promise in addressing these challenges by providing tools for early detection and prediction of seizures. Various machine learning models, including support vector machines, neural networks, and ensemble methods like random forests, have been employed to analyze EEG data and other physiological signals for seizure prediction (Acharya *et al.,* 2018). Adannaya et al., (2024), developed an expert system for outpatients, their findings highlight how expert systems can improve outpatient healthcare by allowing evidence-based treatment decisions and increasing diagnostic accuracy.

Random Forest, an ensemble learning method, has been widely used in epilepsy research for its robustness and accuracy in classification tasks. This algorithm constructs multiple decision trees and merges them to obtain a more accurate and stable prediction. Studies have demonstrated the efficacy of Random Forest in predicting seizure occurrences and identifying epileptic patterns in EEG data (Gupta *et al.*, 2020). K-Nearest Neighbors (KNN) is a simple yet effective algorithm used in epilepsy prediction models. KNN classifies a sample based on the majority class among its k-nearest neighbors, making it suitable for pattern recognition tasks in EEG data. Research has shown that KNN can be effectively applied to detect and predict epileptic seizures with high accuracy (Wang *et al*., 2019). Support Vector Machine (SVM) is a powerful supervised learning model used for classification and regression tasks. In epilepsy prediction, SVM has been utilized to classify EEG signals and predict seizure onset. The ability of SVM to handle high-dimensional data and its effectiveness in separating classes with a clear margin makes it a popular choice in epilepsy research (Basu *et al.,* 2020). The integration of machine learning in epilepsy research has significantly advanced the field, offering new possibilities for accurate diagnosis and effective treatment. Hybridized machine learning approaches, which combine multiple algorithms, hold particular promise for improving the prediction and management of epileptic crises. This literature review highlights the progress made so far and underscores the potential benefits of continued research in this area.

Many studies focus primarily on EEG data for seizure prediction. While EEG is a valuable source of information, relying solely on it can limit the accuracy and generalizability of the prediction models. Some studies have begun integrating physiological signals from wearable devices, but the scope of data remains limited. There is a lack of research utilizing a diverse dataset that combines physiological signals, environmental variables, and behavioral patterns. Our system leverages a comprehensive dataset of 2000 samples that includes Heart Rate Variability (HRV), Skin Conductance, Body Temperature, Stress Level, Sleep Duration, Exposure to Flashing Lights, Physical Activity Level, Ambient Temperature, Humidity, Medication Adherence, and Hydration Level. This multimodal data integration can provide a more holistic view of the factors influencing seizure occurrences and enhance the predictive power of the models.

Previous research often uses single or limited sources of data, which may not capture the full spectrum of factors affecting seizure activity. For instance, studies integrating clinical data with EEG often overlook environmental and behavioural factors. Our system addresses this by incorporating a wide range of data sources, including physiological, environmental, and behavioural parameters. This comprehensive approach ensures that all relevant factors are considered, potentially improving the accuracy and reliability of seizure predictions.

While several machine learning and deep learning techniques have been applied to seizure prediction, the methodologies used are often narrowly focused on specific algorithms or data types. Studies typically employ standard machine learning methods like SVM, Random Forest, or basic deep learning models without integrating advanced methodologies or hybrid approaches. Our system adopts the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology, which provides a structured and systematic approach to data mining and machine learning projects. This methodology ensures that all phases of the project, from understanding the data to deployment, are comprehensively covered. Additionally, by utilizing Object-Oriented Programming (OOP), our system benefits from modularity, reusability, and maintainability, which are often overlooked in existing studies.

Real-time processing and user interface considerations are crucial for practical applications but are often not the primary focus of existing research (Chu et al., 2017). Many studies are conducted in controlled environments and do not address the challenges of real-time implementation and user interaction. Our system emphasizes real-time processing and provides a user-friendly interface developed using the Django web framework. This ensures that healthcare professionals and patients can easily input data, receive timely predictions, and act upon them. Real-time alerts and a seamless user experience are critical for the practical utility of seizure prediction systems.

Validation approaches in current studies are often limited to specific datasets and lack extensive real-world testing. Many models are validated using cross-validation techniques but do not undergo thorough real-world testing with diverse patient populations. Our system aims to implement a comprehensive validation process that includes both cross-validation and real-world testing with diverse patient populations. This will ensure that the model is robust, generalizable, and reliable across different scenarios and patient demographics.

**Methodology**

A mixed research methodology was employed for the development and evaluation of the hybridized machine learning-based crisis prediction system for epileptic patients. This approach integrates both qualitative and quantitative research methods to provide a comprehensive understanding of the system's effectiveness and functionality. Quantitative methods were used to collect and analyse numerical data from the epilepsy dataset. This includes physiological measurements (e.g., heart rate variability, skin conductance), environmental factors (e.g., ambient temperature, humidity), and behavioural patterns (e.g., sleep duration, physical activity). Statistical techniques and machine learning algorithms were applied to this data to identify patterns, build predictive models, and evaluate their performance (Hussain et al., 2019). Qualitative methods were employed to gather feedback from health professionals and patients regarding the usability and effectiveness of the system. This involved conducting interviews and focus groups to understand their experiences, challenges, and satisfaction with the system. The feedback provided valuable insights into the system's real-world applicability and areas for improvement.

The new epilepsy prediction system adopts the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology because of its structured framework, facilitating systematic development and ensuring effective management. In the field of data mining and machine learning projects, using a structured approach is crucial for ensuring systematic and effective development. One widely recognized structured approach in this domain is CRISP-DM. CRISP-DM provides a comprehensive framework that guides practitioners through the various stages of a data mining project, from understanding business objectives and data collection to deployment and maintenance. Its iterative nature allows for flexibility and adaptation, making it particularly suitable for complex projects with evolving requirements.

The system architecture comprises several interconnected components designed to facilitate the prediction of epileptic seizures. At its core, the architecture includes modules for data collection, preprocessing, feature extraction, and predictive modeling. These modules work together to analyze patient data, extract relevant features, and apply machine learning algorithms to predict the likelihood of an epileptic seizure. Additionally, the architecture incorporates mechanisms for data security and patient privacy to ensure the confidentiality and integrity of sensitive health information. Figure 1 depicts the new system architecture.



Fig 1: New System Architecture

**System Design**

This system incorporates real-time data collection and predictive analytics. It leverages advanced machine learning algorithms to continuously monitor patient data and predict seizures with high accuracy. The system is designed to provide timely alerts to patients and healthcare providers, enabling immediate intervention and reducing the risk of severe seizures. Figure 2 depicts the Use Case diagram of the system, which reveals that; User interacts with functionalities like Register, Login, View Profile, Update Profile, View Patient Data. Health Professional interacts with functionalities like Login, View Dashboard, View Patient Data, Analyze Data, Predict Crisis, Review Recommendations, Update Patient Records, and Generate Reports.



Fig 2: Use Case diagram of the system

**System Design**

The system design for the hybridized machine learning-based crisis prediction system for epileptic patients involves defining the specifications, inputs, outputs, databases, hardware, software, and overall program design. The system is designed for use by health professionals and epileptic patients. It integrates real-time data collection, analysis, prediction, and alerting functionalities to provide comprehensive support for epilepsy management.

**System components**

1. **Data Collection Subsystem**: This subsystem collects data from various sensors and user inputs. The data includes physiological signals (e.g., heart rate variability, skin conductance), environmental variables (e.g., ambient temperature, humidity), and behavioural patterns (e.g., sleep duration, physical activity).
2. **Data Pre-processing Subsystem**: This subsystem cleans and pre-processes the collected data, handling missing values, noise reduction, and normalization to ensure the quality and consistency of the input data for analysis.
3. **Feature Extraction Subsystem**: This subsystem extracts relevant features from the pre-processed data, transforming raw sensor readings into meaningful variables that can be used by the machine learning models.
4. **Machine Learning Subsystem**: This subsystem is responsible for training, validating, and deploying machine learning models. It uses hybridized algorithms to analyse the extracted features and predict the likelihood of an epileptic seizure.
5. **Prediction and Alerting Subsystem**: This subsystem generates real-time predictions based on the machine learning models. It provides alerts and recommendations to health professionals and patients when a potential seizure is predicted.
6. **User Interface Subsystem**: This subsystem provides a graphical user interface for data input, monitoring, and interaction. It includes dashboards, forms, and controls for users to manage and view their data and prediction results.

**Functional and Non-Functional Requirements**

The Functional Requirements include;

1. The system must support the input of various types of data, including physiological signals, environmental variables, and behavioural patterns.
2. The system must continuously monitor incoming data and process it in real-time to provide timely predictions and alerts.
3. The system must send immediate notifications and recommendations to users when a potential seizure is detected.
4. The system must store all collected data, prediction results, and user interactions in a database, allowing for easy retrieval and analysis.
5. The system must support user authentication, role-based access control, and personalized settings for health professionals and patients.

**The Non-Functional requirements are;**

1. **Performance**: The system must process and analyse data efficiently to provide real-time predictions without significant delays.
2. **Scalability**: The system must be scalable to handle increasing amounts of data and a growing number of users.
3. **Security**: The system must ensure the confidentiality, integrity, and availability of user data, implementing robust security measures to protect against unauthorized access and data breaches.
4. **Usability**: The system must provide an intuitive and user-friendly interface to facilitate ease of use for health professionals and patients.
5. **Reliability**: The system must be reliable and maintain high availability, minimizing downtime and ensuring consistent performance

**Data Collection:** We gathered data from various sources, including sensors, manual inputs, and external databases. Components include interfaces for connecting to physiological sensors (e.g., heart rate monitors, temperature sensors), user-friendly forms for entering data manually, and utilities for importing data from external sources in various formats (e.g., CSV, JSON).

**Data Pre-processing**: We cleaned and prepared the collected data for analysis, ensuring quality and consistency. Components include functions to handle missing values, outliers, and noise; methods to normalize data ranges for consistency; and techniques to create new features from raw data, enhancing predictive power.

**Feature Extraction**: We extracted relevant features from the pre-processed data that can be used by machine learning models. Components include algorithms to extract features from physiological signals, tools to derive statistical features (e.g., mean, variance) from data, and custom features based on domain knowledge (e.g., stress levels, physical activity patterns).

**Machine Learning:** We trained, validated, and deployed machine learning models for predicting epileptic seizures. Components include functions to train various machine learning models (e.g., SVM, random forests, neural networks) using labelled data; methods to evaluate model performance using cross-validation and other techniques; and tools to deploy trained models for real-time predictions.

**Prediction Module**: This module generates real-time predictions based on the input data and machine learning models. Components include capabilities to process incoming data in real-time, core logic to generate predictions and calculate confidence scores, and mechanisms to trigger alerts and notifications based on prediction results.

**Alert Module**: This module manages and delivers alerts and notifications to users when a potential seizure is predicted. Components include tools to send notifications via various channels (e.g., email, SMS, app notifications), interfaces for users to view and respond to alerts, and contextual recommendations and guidance for users based on alert severity.

**Reporting Module**: This generates reports and summaries based on collected data and prediction results. Components include tools to create customizable reports (e.g., daily, weekly, monthly), graphs, charts, and other visual aids to summarize data and trends, and facilities to export reports in various formats (e.g., PDF, CSV).

**User Interface Module**: This module provides a graphical user interface for interacting with the system. Components include a centralized interface displaying key metrics, real-time data, and system status; user-friendly forms for data input and system navigation; and interfaces for user authentication, profile management, and role-based access control.

**Database Module**: To manage data storage, retrieval, and maintenance. Components include the definition of tables, relationships, and constraints; APIs and utilities for interacting with the database; and mechanisms to ensure data integrity and recovery in case of failures.

In the development of the epilepsy crisis prediction system, the choice and implementation of the database management system (DBMS) are crucial for efficient data storage, retrieval, and management. We oversaw the selection and integration of SQLite as our primary DBMS, complemented by the Django web framework to facilitate seamless interaction between the database and the application. This decision was driven by several factors, including SQLite's lightweight nature, ease of integration with Django, and its adequacy for our project's data requirements.



Fig 3: Database Implementation

Python was chosen for the model implementation its simplicity, readability, and extensive libraries for machine learning and data analysis. Key libraries used for the work are; Django, Scikit-learn, Pandas and NumPy, Matplotlib and Seaborn.

**Testing and Performance Evaluation**

Test data was carefully curated to cover a wide range of scenarios, including normal conditions and edge cases that could affect epileptic patients. The dataset used in testing consists of 2,000 entries, including parameters such as heart rate variability, body temperature, stress level, sleep duration, exposure to flashing lights, ambient temperature, humidity, medication adherence, and hydration level. Table 1 outlines the test cases, data used, expected outcomes, actual results, and status of each test.

**Table 1: The test results of the new system**

| **Test Description** | **Test Data** | **Expected Result** | **Actual Result** | **Status** |
| --- | --- | --- | --- | --- |
| Model Prediction (Normal Conditions) | HRV: 70ms, Temp: 36.5°C, Stress: 3, Sleep: 7 hours, No Lights, Amb. Temp: 24°C, Humidity: 50%, Med: Yes, Hydration: 2L | No crisis predicted | No crisis predicted | Pass |
| Model Prediction (Crisis Conditions) | HRV: 50ms, Temp: 37.5°C, Stress: 8, Sleep: 3 hours, Lights: Yes, Amb. Temp: 30°C, Humidity: 70%, Med: No, Hydration: 1L | Crisis predicted | Crisis predicted | Pass |
| Data Processing Accuracy | Random sampling from dataset | Correct preprocessing | Correct preprocessing | Pass |
| Model Training | Full dataset (2,000 entries) | SVM model trained without errors | SVM model trained without errors | Pass |
| Model Evaluation (Accuracy) | Confusion matrix results | 85% accuracy | 85% accuracy | Pass |
| Model Evaluation (Precision and Recall) | Classification of crisis (1) and non-crisis (0) | High precision and recall for crisis prediction | Precision: 0.89, Recall: 0.91, F1-score: 0.90 | Pass |
| ROC Curve Analysis | Model prediction scores | ROC curve with high AUC | ROC curve with high AUC | Pass |

The performance evaluation focused on assessing the system’s accuracy, response time, and stability under load conditions. The following key metrics were evaluated:

* Accuracy: The system achieved an accuracy of 85%, as detailed in the confusion matrix and classification report, indicating reliable performance in predicting crisis periods.
* Response Time: The average response time for predictions was within 1.5 seconds, ensuring that the system provides timely alerts to users.
* Scalability: During load testing, the system successfully handled up to 1,500 concurrent users without significant performance degradation, demonstrating its scalability for real-world applications.

**Conclusion and Recommendation**

We were able to develop a hybridized machine learning based crisis prediction system for Epileptic patients. We collected and analyzed a diverse dataset encompassing physiological signals, environmental variables, and behavioral signals. We were also able to develop a user-friendly interface and deploy the trained model. The work successfully achieved its objectives by integrating sophisticated machine learning algorithms with a user-friendly web interface, powered by Django framework, and employing rigorous testing methodologies. Overall, this work contributes to the ongoing advancement of predictive healthcare technologies, offering a promising tool for supporting medical professionals in epilepsy management and enhancing patient-centric care strategies.

Based on the findings and outcomes of this work, several recommendations can be made to further enhance the system and its applications. They include;

1. Enhance Prediction Accuracy: Continuously refine and optimize the machine learning models to improve seizure prediction accuracy. This could involve exploring advanced algorithms, fine-tuning model parameters, and incorporating additional relevant features or data sources.
2. Real-time Data Integration: Implement mechanisms for integrating real-time data streams, such as wearable devices or IoT sensors, to enhance the system's ability to provide timely predictions and interventions.
3. Scalability and Performance: Further optimize the system's architecture and backend infrastructure to ensure scalability, especially under high data volume and concurrent user scenarios. This includes refining database queries, implementing caching mechanisms, and leveraging cloud services for enhanced performance.
4. User Interface and Experience: Continuously gather user feedback and iterate on the user interface (UI) design to enhance usability and accessibility. Consider implementing personalized dashboards, intuitive data visualization techniques, and responsive design principles for a seamless user experience.
5. Security and Privacy: Strengthen security measures, including data encryption, secure authentication protocols, and regular security audits, to protect sensitive patient information and comply with healthcare data regulations (e.g., GDPR, HIPAA).

This work demonstrates the effective integration of machine learning algorithms to predict epileptic seizures based on diverse datasets encompassing physiological signals, environmental variables, and behavioral patterns. This contributes to advancing predictive healthcare technologies aimed at improving patient care and management. The system's ability to predict epileptic seizures offers healthcare professionals valuable insights and early warnings, potentially leading to timely interventions and improved patient outcomes. It contributes to enhancing clinical decision-making processes and supports personalized treatment strategies for epileptic patients. It also provides educational value by demonstrating practical applications of machine learning in healthcare, serving as a case study for students, researchers, and healthcare professionals interested in developing predictive healthcare systems. It also encourages further research into optimizing prediction models, integrating new data sources, and exploring interdisciplinary collaborations.

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