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A Data-Driven Framework for Epileptic Seizure Prediction Using Wearable Physiological Data and Optimized LSTM Models

Asma B. Shahin[1], Deepa S. Deshpande[2]
Assistant Professor, Department of Computer Science & Engineering, MGM University [1]
asma141182@gmail.com
Professor & Head of Department, Department of Computer Science & Engineering, MGM University [2]
ddeshpande@mgmu.ac.in

I. Introduction

Both wearable technology of today and traditional EEG-based methods have been employed in recent developments in seizure prediction and detection. Thompson et al. [1] demonstrated the application of wearable sensors and deep learning models to predict seizures by detecting complex temporal patterns in physiological signals. Comparable to this, Tang et al. [2] established a benchmark for machine learning-based wearable seizure detection by systematically evaluating a number of algorithms and summarizing the pros and cons of real-world applications. Rasheed et al. [3] provided an exhaustive review of EEG-based approaches, including feature extraction, classification strategies, and challenges to clinical translation, to complement wearable-centered approaches. This perspective was further developed by Lucas et al. [4], who explored the broader role of AI in epilepsy and outlined the ways of integrating predictive systems into practice. McKee et al. [5] showed the utility of standardized EEG data stored in electronic medical records in a clinical environment by employing it to develop neonatal seizure prediction models. Karoly et al. [6] emphasized that the risk of seizures often is multi-day and circadian, enabling probabilistic forecasting methods in conjunction with detection. Last but not least, Kuhlmann et al. [7] examined the development of seizure prediction research and made the case that new developments in computational techniques, wearable technology, and algorithms herald a new era for accurate, practical seizure forecasting. In order to detect temporal and spatial dependencies in EEG signals for seizure prediction, Zhu et al. (2024) [8] developed a multidimensional fusion model that combines Transformer encoders with LSTM/GRU layers. Using benchmark datasets such as CHB-MIT and Bonn EEG, the study demonstrated remarkably high performance, obtaining 98.24% sensitivity and 97.27% specificity on CHB-MIT. This hybrid model enhanced temporal feature representation while successfully lowering false positives. However, real-world, ambulatory validation is still a challenge, and the study was restricted to public, controlled datasets. One of the biggest hospital-based studies on wearable seizure detection was carried out by Yu et al. (2023) [9], who used multimodal physiological data (blood volume pulse, accelerometery, and electrodermal activity) from 166 patients with 900 recorded seizures. Multimodal sensor fusion, as opposed to individual signals, produced the best results for the proposed CNN–LSTM hybrid, which had a mean sensitivity of 83.9%. The study proved that non-invasive, wrist-worn seizure detection devices are clinically feasible. The false positive rate (~35%) is still a real obstacle to ongoing monitoring, though. A thorough analysis of current machine learning and deep learning methods for seizure forecasting, prediction, and detection was presented by Kerr et al. [10] in 2024. The authors talked about how the field is moving away from binary classification models and towards probabilistic forecasting frameworks that incorporate contextual, wearable, and EEG data. The review identified a critical research gap between laboratory accuracy and real-world reliability and underlined the significance of clinical validation, interpretability, and patient-specific modelling.

The following sections comprise the remainder of this paper: The dataset and exploratory data analysis are described in Section 2, and data preprocessing, feature engineering, and model selection are covered in Section 3. The suggested architecture is highlighted in Section 4, and the fine-tuning and optimisation process is described in Section 5. The Model Architecture is explained in Section 6, and the findings are covered in Section 7.

A. *Gaps Identified in the Existing Literature*

Although there has been significant advancement in seizure prediction using wearable sensor analysis and EEG, current methods are still limited by a lack of multimodal integration, high false alarm rates, and little real-world validation. Existing models frequently work well in controlled settings but fall short in real-world settings and with patients. Furthermore, clinical translation is limited by the lack of patient-specific, adaptable frameworks and energy-efficient wearable implementations. In order to fill these gaps, this study suggests a data-driven, real-time framework for seizure prediction that makes use of optimised LSTM models and wearable physiological signals. This allows for low-latency, personalised prediction for early

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intervention in real-world healthcare settings.

B. Research Objectives

Framework Development and Validation: Using the MMASH dataset as a proof-of-concept environment, a data-driven analytical framework for real-time seizure prediction utilising multimodal physiological data obtained from wearable sensors will be developed and validated.

Optimized LSTM Model Design: Long Short-Term Memory (LSTM) networks that can capture intricate temporal dependencies in physiological signals (such as HR, HRV, EDA, activity, and stress indicators) linked to preictal patterns are to be designed and optimised.

Feature Engineering and Signal Processing: Implementing reliable feature extraction, preprocessing, and noise-handling strategies that enhance model dependability and lower false positives under dynamic, real-world circumstances is the goal of feature engineering and signal processing.

II. Description of the Dataset and Exploratory Data Analysis (EDA)

A. Description of the Dataset

The Multilevel Monitoring of Activity and Sleep in Healthy People (MMASH) [11] dataset consists of behavioural and physiological information gathered from 22 participants. Its multi-modal design provides a comprehensive view of health and stress indicators that can be extended for seizure prediction research. In order to present a comprehensive picture of the patient's health and seizure-related patterns, it integrates several modalities.

Among the primary data categories are:

- Physiological signals: Heart rate, stress levels, RR intervals, and sleep patterns.
- Behavioural indicators: Information on physical activity gleaned from movement sensors and actigraphy.
- Biomarkers: Saliva samples that have biochemical signs of neurological activity and stress.
- Responses to the questionnaire: Lifestyle, stress, and health evaluations provided by the patient.
- Age, gender, and further clinical background information are examples of demographic and clinical data.

A number of crucial components are included in the suggested system to guarantee precision, usability, and accessibility in actual healthcare settings. An easy-to-use graphical user interface (GUI) facilitates involvement by allowing physiological data visualisation, time window customizability, and concise prediction summaries to facilitate informed decision making. Wearable technology enables data acquisition. Parameters such as heart rate and stress are captured and then enhanced via preprocessing techniques such as normalisation, missing value imputation, and systematic feature selection to enhance prediction accuracy. To enhance the early identification of epileptic seizures, feature engineering plays a pivotal role in the extraction of clinically relevant properties like heart rate variability, markers of stress, and temporal trends. Due to the cross-device nature of the framework, numerous wearable technologies would be available. This safeguards sensitive health data during both historical analysis and real-time monitoring.

B. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was carried out to gain a deeper understanding of the dataset prior to model development. The process focused on uncovering statistical properties, temporal patterns, anomalies, and interrelationships among variables, all of which informed subsequent feature engineering and model optimization. Distribution Analysis: Descriptive statistics such as mean, median, variance, and standard deviation were used to evaluate the distributions of physiological features including heart rate (HR), electrodermal activity (EDA)[12][13], and sleep-related [14] variables. Visualizations such as histograms and boxplots provided further insights into the range, skewness, and variability of the data. These baselines established the normal operating ranges for different physiological parameters.

Pattern Identification: Temporal analyses spotlighted periodic trends and rhythms, including circadian patterns of heart rate and stress variability. Detection of such time-dependent behaviours was essential to appraise the inherent variability in physiological signals and its possible relationship with seizure onset.

Outlier Detection: Outliers and anomalies were detected and treated employing statistical techniques such as Z-scores and the interquartile range (IQR). Deleting or adjusting these abnormal values ensured the dataset better represented real physiological conditions, thus avoiding biases during model training.

Correlation Analysis: Pairwise correlation analysis, supplemented with scatter plots and heatmaps, identified interdependencies between features. For instance, high correlations between the levels of activity, HR variability, and stress indicators [15] pointed towards this potentiality serving as significant predictors for seizure prediction.

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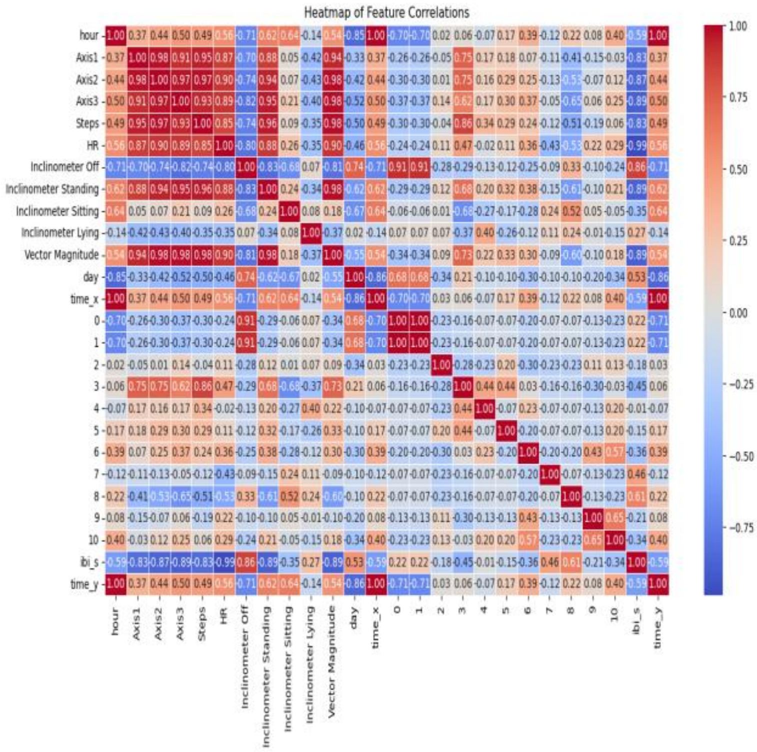

Figure 1: Heatmap of Feature Correlations

Correlation Heatmap Analysis The correlation heatmap (Figure 1) provides insights into interdependencies between features, with values ranging from –1 (blue, strong negative correlation) to +1 (red, strong positive correlation).

Several key observations were identified: Strong Positive Correlations: Axis1, Axis2, Axis3, Steps, and Vector Magnitude are highly correlated [16] [17], suggesting redundancy due to overlapping accelerometer information. This indicates potential for dimensionality reduction techniques such as PCA to remove redundancy without losing predictive power. Mutually Exclusive States: Inclinometer Off and Inclinometer Standing display a strong negative correlation, consistent with their representation of distinct postural states. Similar negative correlations between other inclinometer variables and the hour of the day suggest temporal variations in posture. Temporal Features: Day and time_x exhibit low correlations with most physiological features, indicating that they provide independent contextual information useful for temporal modelling. Multicollinearity Concerns: Strong correlations among accelerometer axes and activity features raise the possibility of multicollinearity, which can distort model training. Proper feature selection or dimensionality reduction is therefore recommended. Low-Correlation Features: Certain features with weak correlations (e.g., stress levels, heart rate) may provide unique predictive value despite limited linear associations, making them valuable for inclusion in nonlinear models like LSTMs.

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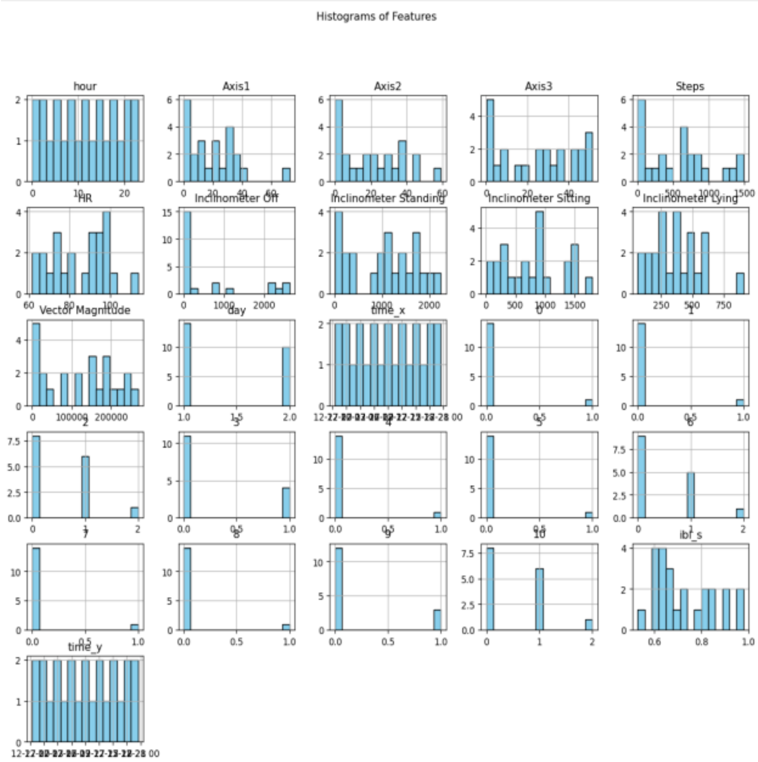

Figure 2: Histogram Analysis

Histogram analysis reveals each feature's distributional characteristics (Figure 2). The hour variable shows a roughly uniform distribution, suggesting uniformly sampled time intervals, whereas the Steps and Vector Magnitude variables show right-skewed distributions, with a higher frequency of lower values. This skewness indicates that in order to improve feature representation for next machine learning models, transformation strategies like logarithmic or square root scaling are required. Histograms can also be used to spot unusual trends or possible outliers that could need extra research. At the same time, Axis1, Axis2, and Axis3 are the focus of feature relationship analysis, which looks at their temporal patterns and relationships with the target variable, epilepsy occurrences.

Time-series visualisations draw attention to patterns and oscillations in activity, providing information about variances that could be signs of seizure-prone times. To find abnormalities in physiological measurements like heart rate (HR), outlier detection was done using both statistical methods, like z-scores, and visual aids, like boxplots.

Clinically relevant occurrences were linked to outliers, which were carefully assessed for removal or additional research. By confirming total data integrity across all features, missing value assessment removed the requirement for imputation and made sure the dataset was clean and prepared for direct analysis. Furthermore, posture-related patterns that could affect seizure prediction were found using frequency analysis of categorical variables, including Inclinometer Standing and Inclinometer Sitting. These observations emphasise how crucial it is to include environmental and behavioural characteristics in addition to physiological data in order to increase model accuracy. Inter-variable relationships were examined through scatterplot matrix analysis, which provided additional clarity on feature interactions. A strong positive correlation was observed between steps and heart rate (HR), indicating that higher levels of physical activity are consistently associated with elevated heart rates. Similarly, steps demonstrated a positive correlation with vector magnitude, reflecting greater movement intensity during periods of increased activity. Conversely, steps showed a negative correlation with inter-beat interval (ibi_s), suggesting that higher activity levels are linked to shorter inter-beat intervals—an outcome consistent with physiological expectations. These patterns align with normal cardiovascular responses to exertion, where HR typically ranges between 70 and 90 bpm, while ibi_s peaks around 0.7 seconds.

TABLE 1. ADF TEST RESULTS

Test Case	ADF Statistic	Critical Value (5%)	p-value	Stationarity Conclusion
Series 1	-2.128	-2.999	0.2335	Non-stationary
Series 2	-2.207	-2.999	—	Non-stationary
Series 3	-3.178	-3.104	—	Stationary
Series 4	-3.012	-3.104	—	Stationary

To assess the suitability of time-series features for modelling, the Augmented Dickey-Fuller (ADF) test was applied. Results

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reveal mixed stationarity across the series segments. Series 1 and Series 2 exhibit ADF statistics greater than the 5% critical value and, in the case of Series 1, a p-value above 0.05. This indicates a failure to reject the null hypothesis, confirming non-stationarity. Conversely, Series 3 and Series 4 have ADF statistics more negative than the 5% threshold, leading to rejection of the null hypothesis and confirming stationarity.

These findings suggest that while some segments can be modelled directly, others require transformations (e.g., differencing or detrending) before inclusion in time-series analysis or predictive modelling.

III. Data Preprocessing and Feature Engineering

A. Preprocessing of Data

In machine learning and predictive modelling, data preprocessing is a critical step, particularly in the Predictive Modelling of Epilepsy Using Wearable Technology research. Wearable sensors generate raw, heterogeneous signals that must be transformed into a clean, structured, and analysis-ready format suitable for machine learning models.

1) Data Cleaning

One of the most important steps in getting the dataset ready for predictive modelling is data cleansing. Missing values are common in real-world situations and can skew results or affect model performance if ignored. In order to preserve underlying patterns, these were addressed by employing techniques like deleting incomplete records, applying sophisticated imputation techniques like regression or KNN, or imputing values using statistical measures (mean, median, or mode). Particular attention was paid to physiological variables like heart rate and stress indicators. Statistical techniques like the Interquartile Range (IQR) and Z-scores were used to identify outliers, which are extreme values that substantially vary from normal distributions. In order to guarantee representative distributions and decrease distortion in model training and evaluation, physiologically implausible or incorrect values were eliminated. Lastly, in order to avoid distorted results and exaggerated model confidence, duplicate entries—which are frequently caused by device sampling faults or repeated transmissions in wearable datasets—were methodically found and removed. When combined, these procedures made guaranteed the dataset was dependable, clean, and suitable for precise predictive modelling.

2) Data Transformation

To prepare the dataset for time-series modelling and predictive analysis, data transformation was done. Normalisation (scaling to [0,1]) or standardisation (rescaling to zero mean and unit variance) were used to make sure that all features contributed proportionately during model training because physiological variables like heart rate and stress levels are recorded in different units and ranges. This was especially important for algorithms like LSTMs that are sensitive to input magnitude. The dataset was organised into fixed-length rolling or sliding time windows to preserve both short- and long-term temporal correlations between physiological signals and capture sequential dependencies that are essential for epilepsy prediction. Furthermore, raw sensor timestamps were converted from seconds to hours via time unit conversion, which highlighted long-term temporal trends and allowed for easier comparison between datasets as well as exploratory analysis and interpretability.

B. Feature Engineering

Feature engineering was used to derive clinically relevant features from wearable sensor data, such as heart rate variability, patterns of stress, and statistical summaries. Temporal patterns (e.g., rolling average, time-of-day corrections), frequency-domain measures (spectral entropy, Fourier coefficients), and window-based statistics tracked sequential and incremental physiological changes. Posture from inclinometer data, cross-feature interactions, and detection of anomalies (Z-score, IQR) added predictive strength. For the support of LSTM models, one-hot encoded categorical variables were utilized, and PCA-based dimensionality reduction helped minimize redundancy and complexity. Then, the dataset was divided chronologically into training, validation, and test sets to avoid leakage, and class-weighted losses through resampling helped manage imbalance, enhancing sensitivity to infrequent but clinically relevant seizure episodes.

HRV measures from RR-interval signals [18], the addition of temporal and circadian trends [19], and standardized preprocessing pipelines involving noise removal, dimensionality reduction, and feature selection [20]; [21] [22] have all been found to be valid feature engineering for wearables-based seizure prediction.

A strong epilepsy prediction pipeline is highly dependent on good data preprocessing and feature engineering. Preprocessing provided data integrity in terms of cleaning, normalization, temporal structuring, and handling missing values, thus making the dataset ready for significant analysis. Feature engineering additionally enhanced the data with the addition of statistical descriptors, frequency-domain transformation, temporal dynamics, and domain activity correlations. These designed features pick up subtle physiological and behavioral signs that potentially precede seizure onset. Cumulatively, these processes greatly enhance data quality, relevance, and predictive capability, creating a robust basis for model training, validation, and execution in real-time seizure detection networks.

C. Choosing a Model

The collection includes time-stamped physiological information from wearable devices, such as heart rate (HR), stress indicators, activity levels (steps, inclinometers), and derived metrics like inter-beat intervals (IBI) and vector magnitude. Models that can capture time-dependent patterns and correlations are necessary due to its sequential and temporal character. Both continuous variables (such as HR, Axis1, and Axis2) and categorical variables (such as posture states like standing or sitting) are present in the multivariate data. Class imbalance, where epileptic episodes are far less common than non-epileptic ones, and possible noise or missing values due to device constraints and user mobility are further difficulties.

Given these attributes, the selected model needs to:

- Capture Temporal Dependencies: Effectively manage time-series data (e.g., by employing RNN or LSTM architectures).
- Easily handle both continuous and categorical variables by supporting multivariate inputs.
- Address Class Imbalance: To enhance the detection of infrequent seizure occurrences, use weighted loss or resampling.
- Be Resilient to Inaccurate Data: Preserve precision in the face of noise, artefacts, or absent signals.
- Assure Scalability and Interpretability: Make effective real-time predictions while providing lucid explanations of the predictive variables.

Long Short-Term Memory (LSTM): A subset of recurrent neural networks (RNNs), LSTM networks are very useful for time-series analysis with long-range patterns since they are made to capture temporal dependencies in sequential data. This experiment uses LSTMs to analyse sequential changes in physiological data including heart rate, stress levels, and activity metrics in order to identify minor antecedents of epileptic seizures. They are ideal for producing accurate and customised predictions from wearable sensor data because of their capacity to retain pertinent information over long periods of time.

Transformer Models: Unlike step-by-step models like LSTMs, transformers use a self-attention mechanism to process complete sequences in parallel, which allows them to more effectively capture intricate patterns and long-range dependencies. Transformers can concurrently model interactions between several physiological signals in the context of this research, including mobility data, stress indicators, and heart rate variability. This feature facilitates real-time prediction and makes it possible to spot tiny pre-seizure signals. Transformers are especially useful for giving prompt, useful insights in wearable-based epilepsy management systems because of their efficiency and scalability.

IV. PROPOSED ARCHITECTURE

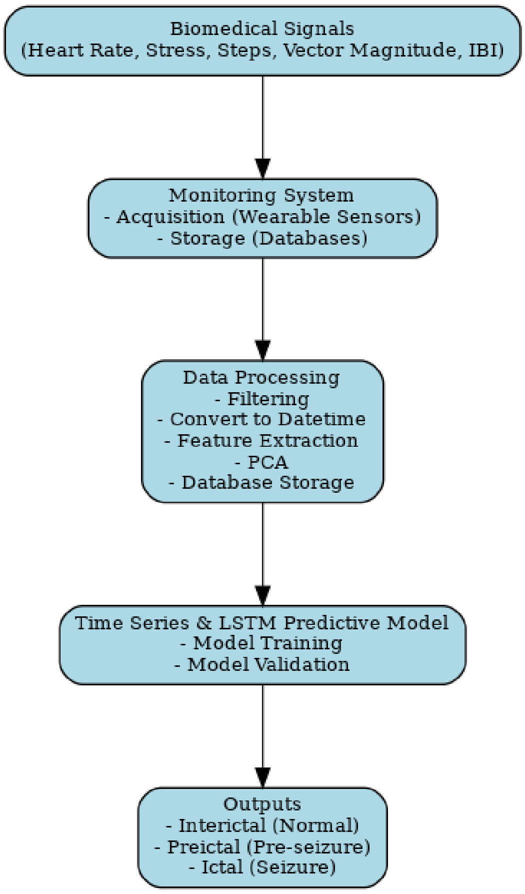

Figure 2: Workflow for seizure prediction using wearable signals, integrating data acquisition, processing, LSTM-based modelling, and classification into interictal, preictal, and ictal states.

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A. Signals from Biomedicine

The main inputs for predictive modelling are biomedical signals, which capture states related to both activity and physiology. The inter-beat interval (IBI), which measures the time interval between successive heartbeats, steps that reflect physical movement, vector magnitude that represents combined movement across multiple axes, stress levels derived from physiological parameters, and heart rate (HR), which indicates cardiovascular activity, are important inputs. When combined, these signals offer a thorough depiction of a person's health dynamics and serve as the basis for seizure prediction.

B. System of Monitoring

The monitoring system is in charge of gathering and storing wearable sensor data in real time. While structured storage methods, such temporary caches or databases, guarantee that data is organised, retrievable, and prepared for additional analysis, continuous signals are gathered and sent to processing units. This stage makes it possible for downstream processing and raw data acquisition to work together seamlessly.

C. Information Processing

Raw sensor outputs are converted into organised, analysis-ready inputs by data processing. This entails feature extraction to obtain clinically significant metrics like mean heart rate or stress patterns, filtering to eliminate noise, and temporal alignment to synchronise signals. PCA and other dimensionality reduction techniques are used to minimise computing overhead and redundancy while preserving important variance. Lastly, organised repositories are used to systematically manage processed data for predictive model training and validation.

D. Validation and Predictive Modelling

Long Short-Term Memory (LSTM) networks are used in the modelling stage to identify temporal dependencies in sequential physiological data. Prediction accuracy is increased by these algorithms' ability to detect minute changes in patterns that precede seizures. The model's robustness across a range of patient data is maintained by rigorous validation using performance metrics, which guarantees that it consistently distinguishes between various seizure-related states.

E. Classification of Output

The last step converts model predictions into results that have therapeutic significance. Signals are categorised by the system as either ictal (active seizure state), preictal (early warning stage), or interictal (normal state). Insightful visual cues, such alerts or warnings, are used to convey outputs, allowing patients, carers, or physicians to take prompt action. This phase guarantees that the system's forecasts are applicable and in line with actual medical requirements.

V. Fine-tuning and Optimization

Systematic optimisation and fine-tuning across parameters, architecture, and training methodologies are necessary to maximise the seizure detection model's predicted accuracy and robustness.

A. Optimisation of Parameters

The main objective of optimisation is to minimise loss functions like Binary Cross-Entropy or Mean Squared Error (MSE) in order to match predictions with real labels. For effective weight updates, adaptive optimisation algorithms such as Adam (a favoured method for time-series), RMSProp, or Stochastic Gradient Descent (SGD) are used. By using annealing or warm restarts, learning rate tuning guarantees steady convergence and avoids overfitting.

B. Adjusting Hyperparameters

In order to balance computational efficiency, generalisation, and temporal dependence capture, important hyperparameters are adjusted, including batch size, sequence length, number of LSTM layers/units, and dropout rate. To find the best configurations, methods like Grid Search and Random Search are employed; Random Search frequently yields faster results with comparable performance.

C. Generalisation and Regularisation

Early halting, dropout, and L1/L2 regularisation are included to prevent overfitting and improve adaptability. When validation loss stagnates, early stopping stops training; regularisation penalises model complexity and promotes weight sparsity. Cross-validation, especially time-based cross-validation, ensures robustness for sequential biological data by maintaining temporal order and confirming consistency over folds.

D. Measures of Performance

Metrics designed for seizure detection tasks, such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) for interpretability, and Mean Squared Error (MSE) for average deviation from real values, are used to evaluate model performance. These offer supplementary perspectives on the precision of predictions.

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E. Use in the Real World

The model can handle multivariate, noisy, and imbalanced biological signals by integrating robust validation, hyperparameter tweaking, and parameter optimisation. The framework is dependable for wearable health monitoring and seizure prediction in clinical and personal care contexts because to these methodologies, which also improve precision, dependability, and real-time application.

VI. Model Architecture Overview

In order to efficiently capture both short- and long-term temporal dependencies within multivariate physiological data, an LSTM-based time series prediction model was proposed. For improved feature learning and prediction accuracy, the architecture consists of two stacked Long Short-Term Memory (LSTM) layers followed by dense layers that are fully connected. To prevent overfitting, the first LSTM layer uses an L2 regularisation term ($\lambda = 0.001$) and has 50 memory units. The second layer uses 25 units to further refine the temporal representations. The model can balance nonlinearity and gating control because both layers internally use the hyperbolic tangent and sigmoid activations. After every LSTM layer, dropout regularisation is applied at a rate of 0.3, randomly deactivating 30% of the neurones during training to guarantee robust generalisation. With this setup, the network minimises noise amplification and model overfitting while maintaining crucial sequential information. Multivariate regression is made easier by an output layer whose dimensionality corresponds to the number of input features, after which the dense layer with 25 neurones and a ReLU activation adds more nonlinearity to map learnt temporal embeddings into higher-level representations.

To stabilise training and avoid exploding gradients, which are common in recurrent architectures, the model was optimised using the Adam optimiser with a gradient clipping value of 1.0 and a learning rate of 0.001. The loss function used was Mean Squared Error (MSE), which works well for forecasting tasks involving continuous-valued time series. Two adaptive mechanisms, Early Stopping and ReduceLROnPlateau, were added to improve training efficiency and convergence even more. After ten epochs of monitoring the validation loss, early stopping automatically lowered the learning rate by half if there was no improvement for five consecutive epochs. Once convergence was achieved, the best-performing model weights were restored. To ensure there was enough data for model evaluation during training, the dataset was divided using an 80:20 training-to-validation ratio (validation_split = 0.2). The LSTM framework for time-dependent physiological signal modelling has stable convergence and high predictive reliability thanks to a combination of dynamic optimisation controls, regularisation techniques, and precisely calibrated architecture parameters.

VII. Discussion

The MMASH dataset offers a useful basis for early work in seizure prediction, despite the fact that it was initially created to examine psycho-physiological interactions in healthy persons. Numerous physiological and behavioural signals generated from wearables are included in the dataset, such as heart rate, heart rate variability, activity levels, posture, stress indicators, and sleep metrics. These signals are also known to be significant correlates of epileptic occurrences in clinical literature. Even while MMASH lacks real seizure recordings, its multimodality and richness make it appropriate for testing and creating feature engineering plans, time-series modelling structures like LSTMs, and pipelines for preparing data. Before applying the analytical framework to clinical epilepsy cohorts, we first build and validate it under controlled conditions using MMASH as a proof-of-concept dataset. When used in patient-specific seizure prediction research, this method lowers translational hurdles by guaranteeing that model optimisation, robustness testing, and scalability evaluations are completed beforehand.

This research presents a real-time, scalable epilepsy prediction system that leverages physiological data from wearable devices. The technology uses optimised Long Short-Term Memory (LSTM) models to visualise temporal patterns associated with epileptic episodes in real-time through an intuitive user interface. The framework is designed to be easily integrated into clinical and personal healthcare settings, with an emphasis on minimising overfitting and false positives while maximising prediction accuracy and speed. It also makes it easier to build new features in the future. The main topics covered include stringent privacy regulations, restrictions on wearable technology, the need for population-level generalisation, the availability and calibre of information, and the inherent challenges of erratic real-time data transfer. The research suggests a real-time framework for seizure detection that combines optimised Long Short-Term Memory (LSTM) models with physiological inputs from wearable technology. With a focus on optimising predictive accuracy, reducing false positives, and utilising efficient feature engineering, the system uses an easy-to-use graphical user interface (GUI) to present alerts and visualisations. Achieving strong generalisation across a variety of patient populations, tolerating device restrictions, protecting data privacy, minimising the impact of noisy or missing data, and guaranteeing real-time performance are some of the major issues addressed. This study supports the growing need for wearable health solutions that facilitate prompt medical intervention, offering chances to improve patient outcomes, lower healthcare expenses, and aid in the management of chronic illnesses. Enhancing accessibility through cross-device interoperability, adaptive functionality, and user-centred design, as well as optimising LSTM model performance through sophisticated preprocessing and feature selection, are key goals. Patients, carers, medical professionals, researchers, and wearable technology developers are all considered to be stakeholders. In order to enable proactive patient care and further the integration of AI-driven health monitoring into clinical practice and personal healthcare environments, this work's main contribution is the provision of dependable, real-time seizure prediction with timely notifications.

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