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Epilepsy Unveiled using a Multi-Classifier Approach integrated in EAS system for Enhanced Detection Using EEG Signal Analysis.

***Abstract:* -** The study focuses on the advantages of using non-invasive approaches to detect epileptic seizures, aiming to prevent injuries from sudden falls and improve medical diagnosis and management. It presents an EEG Acquisition System (EAS) that integrates a multi-level amplifier with four machine learning algorithms—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Multilayer Perceptron Neural Networks (MLPNN), and Convolutional Neural Network (CNN)—for signal classification. These methods are chosen for their accuracy and rapid processing, making them ideal for real-time use. The research analyzed data from 310 participants to detect epileptic patterns under various conditions. The results show that the SVM model achieved the highest accuracy at 96.37%±2.68 in the small data, followed by the CNN with 95.25%±2.25 in real-time detection, MLPNN at 89.87%, and KNN with 86.37% . This demonstrates CNN's strong performance in seizure detection, complemented by a detailed comparison of sensitivity and specificity across all models to assess their predictive efficiency. The system tells the scientist if there is an epilepsy , dementia ,or a normal brain activity, if the system detects the abnormal activities, it could map it on the brain map with a precision of 98%.

Keywords: Epilepsy Detection, Machine Learning, Neural Networks (CNN), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Multi-Layer Perceptrons (MLP, Topographical Maps, Brain Computer Interface BCI.

I-Introduction

Electroencephalography (EEG) is a key non-invasive technique in electrophysiological monitoring, employing electrodes to record the brain's electrical activity, with wide applications including emotion recognition and brain-computer interfaces (BCI). It plays a crucial role in diagnosing brain diseases like epilepsy, traditionally detected through time-consuming and error-prone manual EEG signal inspection[1]. Epilepsy, characterized by recurrent seizures from abnormal brain activities, presents complex challenges for computational research [2][21]. EEG's advantages-superior temporal resolution, non-invasiveness, ease of use, and low cost are vital in epilepsy research, despite the analysis challenges posed by the complex nature of EEG recordings[3][4][20].

The move towards automated EEG signal classification systems, utilizing machine learning algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Multilayer Perceptron Neural Networks (MLPNN), aims to improve diagnosis accuracy and efficiency. These systems help in detecting intricate patterns in EEG data, facilitating the development of tailored treatment plans, and enabling groundbreaking research in BCI. This research strives to enhance epilepsy diagnosis precision through a computer-assisted automated classification system, integrating BCI and Computer-Assisted Diagnostic (CAD) techniques for real-time detection. Adapting various classification methods, including Convolutional Neural Networks (CNN) for large datasets, the system seeks efficient and accurate EEG signal classification, showcasing the significant impact of technology advancements in neurology[4][20].

II- Material and method

II-1 Electroencephalogram (EEG) Signals

The generation of EEG signals stems from the synchronous activation of between 10,000 and 100,000 neurons, with their activity recorded as a voltage difference by electrodes on the scalp[5]. A cortical activation area of about 6 cm^2 beneath each electrode is necessary for accurate measurement. Due to its comprehensive brain activity coverage, EEG is invaluable in clinical neurophysiology[6]. It's a powerful, non-invasive tool for understanding the brain's dynamic functions, observing physiological states, and identifying neurological disorders[7]. EEG methodology includes electrode placement, signal acquisition, preprocessing, and analysis, with the 10-20 system providing a consistent recording framework. Advances in digital signal processing and

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machine learning have improved signal analysis, enabling the extraction of patterns related to cognitive processes, emotional states, and neurological conditions[22].

II-2 Acquisition of EEG signals

EEG signals, non-invasive brain activity measurements, are captured using scalp-placed electrodes following the 10-20 system, enhanced by EEG gel or paste to improve electrode-skin connectivity. This method ensures effective capturing of the brain's electrical signals by maintaining an optimal environment for electrolyte solution interaction[12]. In our EEG data acquisition, we adopt three primary reference strategies within the 10-20 system, emphasizing a pattern recognition approach utilizing multiple electrodes for epilepsy detection, rather than relying on a single electrode. Key electrodes include those overlying the temporal lobes (T3 and T4, updated to T7 and T8) due to the temporal regions' susceptibility to epileptic discharges, and F7 and F8 electrodes at the frontal-temporal areas. Recognizing that seizures can originate in various brain regions, a comprehensive EEG setup includes electrodes across frontal (Fp1, Fp2), temporal (T7, T8), parietal (P3, P4), and occipital (O1, O2) areas, ensuring thorough brain activity coverage, typically employed Fig 1.

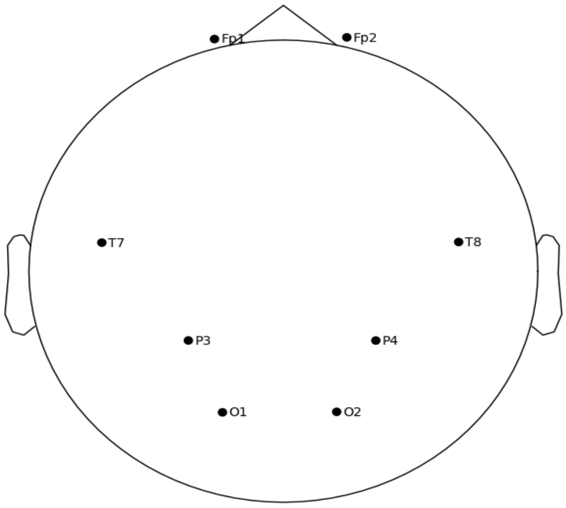

Fig 1: Strategic Electrode Placement in the 10-20 System used.

II-3 DATA

The study involved 310 patients, including individuals with epilepsy, dementia, and normal subjects, to analyze neurological responses using data from PhysioNet's CHB-MIT database (22 patients)[40] and our recordings. Specifically, the Face vs. House Discrimination task engaged 12 epileptic subjects in viewing grayscale images of faces and houses, undergoing 3 runs of the task for a total of 300 stimuli presentations per subject, following a method by Miller[23]. Ethical compliance was ensured, aligning with guidelines from The National Association of Epilepsy Centers in the USA[24]. Additionally, data from EPILEPSIAE (275 patients)[25] was used, focusing on 50 subjects undergoing pre-surgical assessments with recordings over four days, capturing multiple seizures. EEG recordings, with an average of 31.0 ± 2.6 electrodes, included key electrodes from the 10–20 system for analysis.

II-4 The extraction features functions.

The process starts by converting raw EEG signals into features like spectral power across frequency bands and statistical metrics (mean, variance, skewness, kurtosis) via a moving window on time series data with a 128 Hz sampling rate. For artifact removal, we apply Linear Discriminant Analysis (LDA) to differentiate features from EEG signal images analyzed by Local Binary Pattern (LBP), range filters, and Laplacian and Gaussian curvature metrics. This approach prioritizes effective feature extraction over complex classifier designs to enhance classification accuracy. The feature extraction function, *(f(x)*, which represents the input EEG signal image, incorporates algorithms such as LBP and range filters for improved performance.

$f_{LBP}(x), f_{Range}(x), f_{Laplacian}(x), f_{Gaussian}(x) \qquad (1)$

These functions transform the input EEG signal image into a set of features that describe the image's texture and curvature properties.

The Linear Discriminant Analysis (LDA) classifier function, $g(y)$, takes these features as input and classifies them into artifact or non-artifact categories. The classification function can be expressed as:

$g(y)=W^{T}{}_{y}+b \qquad (2)$

where:

y is the feature vector obtained from $f(x)$, W is the weight matrix learned during the LDA training process, b is the bias, T denotes matrix transpose.

The goal of *g(y)* is to maximize the between-class variance while minimizing the within-class variance, thereby distinguishing between artifact and non-artifact features effectively.

EEG data integrity was confirmed using the EEGLAB toolbox [8], which supports various electrophysiological data analyses within MATLAB and Python like toolbox, including evoked potentials, oscillatory activity, and Independent Component Analysis (ICA).

For EEG data, the RBF kernel is recommended due to its non-linear pattern handling, with initial C and Gamma values set at 0.01 to fine-tune model performance and generalization[41].

II-4-1. Fast Fourier Transformer (FFT)

The Fast Fourier Transform (FFT) transforms time domain sequences into frequency domain, mainly for linear and filtered EEG data, typically disregarding imaginary components by setting them to zero[13].

$Xk=\sum xne-i2\pi kn/Nk=0,\ldots,N-1$ (3)

$n=0<n<N\text{-}1$

where k is the current frequency and X_k is the energy of the current frequency k

II-4-2. PSD

The Power Spectral Density (PSD) measures signal power per frequency unit, useful for analyzing non-stationary wideband physiological signals like EEG. It's normalized by spectral resolution, allowing comparison across different resolutions, with PSD in semi-processed EEG data expressed in g^2/Hz, aiding in overlaying and comparing data.

The Power Spectral Density (PSD) $S(f)$ of a signal $x(t)$ can be defined mathematically using the Fourier transform as follows:

$S(f) = |X(f)|^2$ (4)

Where:

$S(f)$ is the Power Spectral Density function., $X(f)$ is the Fourier Transform of the signal $x(t)$

f represents the frequency domain.

II-5 classifiers

The study uses 4-second EEG windows to assess seizure detection, comparing its mean detection rate, specificity, sensitivity, and accuracy to expert evaluations[29]. Equations (5) and (6) detail the assessment methods.

Accuracy = $(\boldsymbol{TP}+\boldsymbol{TN})/(\boldsymbol{TP}+\boldsymbol{FP}+\boldsymbol{FN}+\boldsymbol{TN})$ ***(5)***

Precision = $\boldsymbol{TP}/(\boldsymbol{TP}+\boldsymbol{FP})$ **(6)**

Recall = $\boldsymbol{TP}/(\boldsymbol{TP}+\boldsymbol{FN})$ **(7)**

F1 score = $\mathbf{2} * \boldsymbol{precision} * \boldsymbol{recall}/(\boldsymbol{precision} + \boldsymbol{recall})$ **(8)**

True Negative Rate (TNR) = $\boldsymbol{TN}/(\boldsymbol{TN}+\boldsymbol{FP})$ **(9)**

False Positive Rate (FPR) = $\boldsymbol{FP}/(\boldsymbol{FP}+\boldsymbol{TN})$ **(10)**

False Negative Rate (FNR)= $\boldsymbol{FN}/(\boldsymbol{FN}+\boldsymbol{TP})$ **(11)**

When assessing predictive models, key metrics include Accuracy (correct predictions ratio, Equation 5), crucial for balanced datasets; Precision (positive prediction accuracy, Equation 6), vital when false positives are costly; Recall or Sensitivity (positive instance identification rate, Equation 8), key for critical misses; F1 Score (precision-recall balance, Equation 8); Specificity (true negative rate, Equation 9), for accurate non-condition recognition; and the False Positive Rate (Equation 10) and False Negative Rate (Equation 11), each critical based on the error cost implications.

II-5-1 Nearest neighbor classifier

The K-Nearest Neighbor (K-NN) algorithm, effective with low-dimensional features[9], classifies by comparing test data to training instances, using a distance metric for similarity. Accuracy improves by considering the nearest K points, with test data classified based on the predominant class among these K neighbors. Typically, K is set to 1, employing Euclidean distance for similarity assessment.

$d(x_i,x_j)=\sqrt{(xi1-xj1)^2+\cdots+(xip-xjp)^2}$ (12)

II-5-2 Support Vector Machine (SVM)

Support Vector Machines (SVMs) are supervised learning algorithms effective for classification and regression tasks, developed in the 1990s by Vladimir Vapnik and Alexey Chervonenkis[10]. SVMs excel in classifying categories, such as identifying epileptic waves in EEG samples, and in regression by predicting variable values through a function h that maps an input vector x to an output $y=h(x)$, where, x is a real variable, and y falls within the range of [−1,1]. In simpler scenarios, this involves a linear discriminant function that is the result of a linear combination of the input vector $x=(x_1,\ldots,x_n)^T$ with a weight vector $W=(w_1,\ldots,w_n)^T$, $h(x)=W^T{}_x+w_0$ that means that x is the number of classes and h must be positive, and the classifier is linear.

II-5-3 Multilayer Perceptron Neural Network (MLPNN):

The Perceptron algorithm's appeal stems from its capability to form a Multilayer Perceptron (MLP) by layering perceptrons, increasing complexity[11]. This network, with n inputs ranging from X1 to Xn (integers or real numbers), connects each input X to a weight W, vital for calculating the output Y. It includes a bias connection for optimal functioning. The formula for Y computation is detailed accordingly.

$y = \sum \quad WnXn > 0$ (13)

II-5-4 CNN

The Convolutional Neural Network (CNN) classifier simplifies input data through a series of operations to output a classification, focusing on essential operations despite its inherently complex, multi-layered architecture.

1. Convolutional Layers:

- The convolution operation in layer l for a given input X can be represented as:

$F_l(x) = W_l * X + b_l$ (14)

Here, W_l represents the weights of the convolutional filters in layer l, b_l is the bias term, and * denotes the convolution operation.

2. Activation Function:

- After the convolution operation, an activation function is applied to introduce non-linearity:

$A_l(x) = sigma(F_l(x))$ (15)

Commonly, sigma represents the ReLU (Rectified Linear Unit) activation function, though others like sigmoid or tanh can also be used.

II-5-4-1. Fully Connected Layers:

- Towards the end of the CNN, one or more fully connected (FC) layers are used, where every input is connected to every output by a weight. This is similar to the traditional multi-layer perceptron structure:

$O_l(x) = W_l \,.\, P_{l-1}(x) + b_l$ (16)

Here, $O_l(x)$ represents the output of the FC layer l, and . denotes the dot product [26].

II-5-4-2. Softmax Function (for Classification):

The final layer of a CNN classifier often employs the softmax function to convert the output scores from the last FC layer into probabilities:

Softmax(z_i)= $e^{zi} / (\sum_{j=1}^{n} e^{zi})$ (17)

II-6 Rhythmic brain electrical activities.

Brain electrical activities are classified into five frequency groups: delta (0.5–4Hz), theta (4–8Hz), alpha (8–13Hz), beta (13–30Hz), and gamma (above 30Hz). The alpha rhythm, within 8–13Hz, typically shows a 30 to 50µV amplitude, mainly in the posterior occipital region, and is prevalent during eye closure. Delta and theta rhythms are slower and may indicate pathology, particularly in partial epilepsies near the epileptic focus. However, their presence during vigilance level changes doesn't always suggest a pathological condition[15].

The beta rhythm, with frequencies above 13 Hz, typically appears in the central regions of both hemispheres, often asynchronously and with amplitudes under 20µV, potentially overshadowed by alpha rhythms.

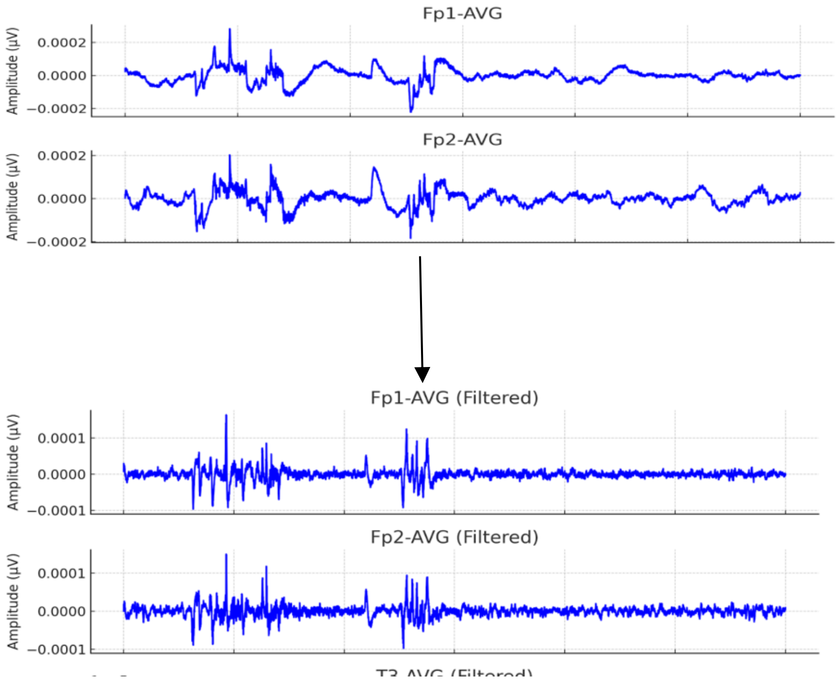

Fig 2 : Initial 60-Second EEG Signal Sampling Across Key Scalp Locations Before-after Filtering**.**

EEG data from channels Fp1, Fp2, T7, T8, P3, P4, O1, O2 was filtered using a 2nd-order Butterworth band-pass filter (1-40 Hz) to emphasize brain wave frequencies, then refined with a 2nd-degree IIR filter to attenuate frequencies outside 1-40 Hz, enhancing brain activity analysis relevance, as shown in fig 2.

II-7. Identification of Epilepsy Disease:

In epilepsy detection using EEG, algorithms like KNN, SVM, MLPNN, and CNN analyze seizure-indicative wave abnormalities, including spike and wave discharges, sharp waves, and others. By extracting features with FFT and time-frequency analysis, these models discern epileptic from non-epileptic segments, aiming to precisely classify deviations across 5 brain wave frequencies.

III- Results and discussion

The classification accuracy achieved using the CNN classifier is notably high at 95.25%+2.25, surpassing the OCA achieved with SVM at 96.37%+2.68, KNN at 86.37%, and MLP at 89.87%. The sensitivity and specificity metrics for all classifiers are detailed in Table 1.

Table 1: classification performance of the system proposed.

Classifier	Accuracy(%)	Accuracy Std	Sensitivity (%)	Specificity (%)
CNN	95.25	2.25	90.5	91.5
SVM	96.37	2.68	92.1	93.4
KNN	86.37	0.0	85.3	84.8
MLP	89.87	0.0	87.7	88.2

The table 1 systematically compares the performance metrics of four different classifier models for the same system of detection of Epilepsy disease which is presented in fig 1 , Each row is dedicated to one of these classifiers, providing detailed metrics including Accuracy , Accuracy Standard Deviation, Sensitivity , and Specificity . CNNs demonstrate high accuracy and moderate variability, highlighting their reliability in image recognition tasks by effectively identifying true positives and negatives. SVMs offer superior accuracy with some variability, excelling in complex classifications but not as well-suited for real-time or large data sets. KNNs, simple and consistent, are less accurate and effective, ideal for straightforward scenarios, as shown in table 1. Upon comparing models, CNNs averaged 95.25% accuracy (±2.25%) .

III-1. quality of classification.

Fig 3, showcases a classifier's effectiveness in separating epileptic syndrome cases into three distinct clusters: a blue cluster for positive (epileptic) cases and a red cluster for negative (non-epileptic) cases and green for dementia, demonstrating its ability to accurately classify based on specific features. The structured approach to training, testing, and validation ensures the classifier is well-prepared to accurately distinguish between epileptic and non-epileptic and dementia cases. Also in the complex classification in adding the dementia, after 80% of training data, This demonstrates the model's capacity to learn distinct features from training data and effectively generalize to new data which is represented in Fig 3, underscoring its applicability in clinical diagnostics.

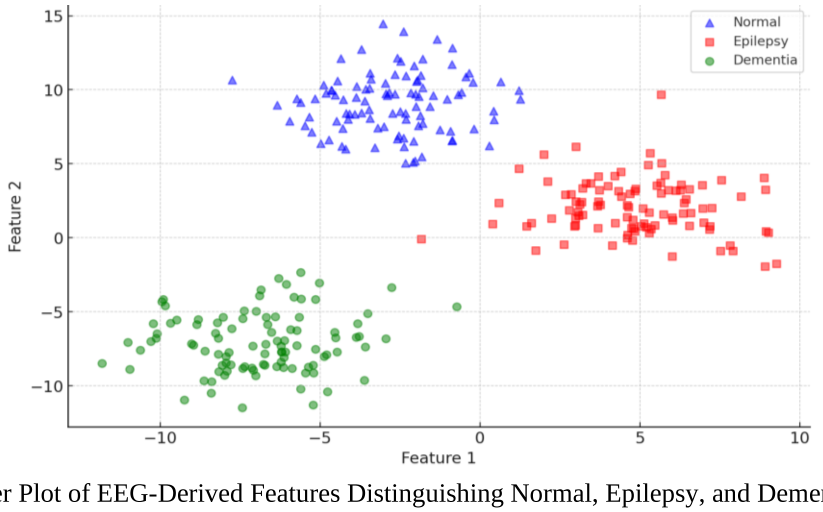

Fig 3: Scatter Plot of EEG-Derived Features Distinguishing Normal, Epilepsy, and Dementia Classes.

III-2. The classification performance:

The EEG data analysis workflow includes data processing, feature extraction, and model robustness evaluation, as depicted in Fig 4. Under noisy conditions, all models show decreased accuracy, with noise adversely affecting classification. The CNN model excels in both clean and noisy environments, effectively managing complex EEG patterns and demonstrating robust spatial-temporal processing capabilities. In contrast, the KNN model suffers the greatest accuracy drop with noise, revealing its sensitivity due to reliance on instance similarity.

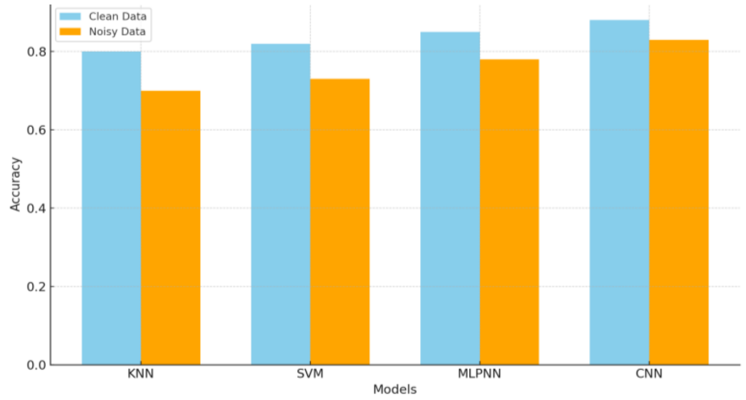

Fig 4: Performance Analysis of EEG Data Classification: A Comparison of Model Accuracy with Clean versus Noisy Data.

III-3. performance in real time classification

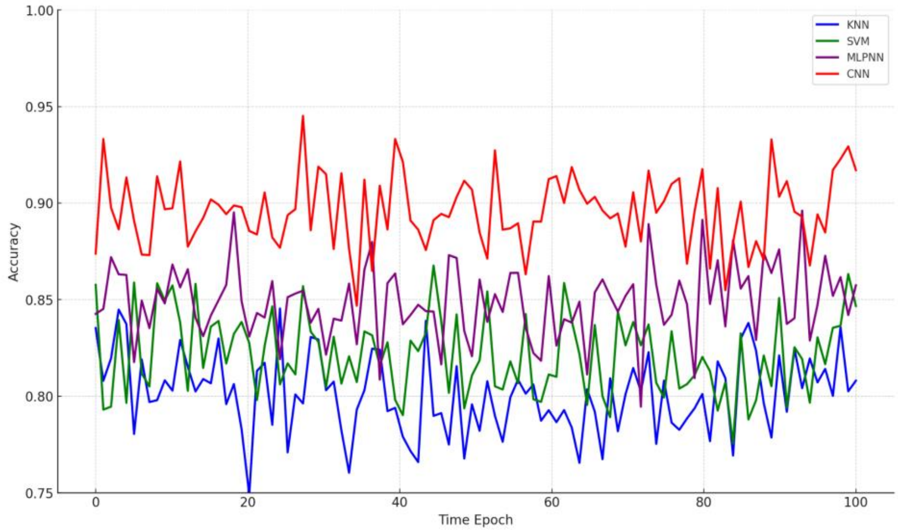

Fig 5: Real-Time Classification Accuracy of EEG-Based Epilepsy Detection Models Across Epochs.

Fig 5 showcases real-time epilepsy detection using KNN, SVM, MLPNN, and CNN models, with a focus on tracking classification accuracy over time. KNN (blue line) averages around 83% accuracy, indicating sensitivity to noise and difficulty with complex EEG patterns. SVM (green line) performs slightly better, with an 85% average accuracy, benefiting from its strength in high-dimensional spaces. MLPNN (purple line) improves further, averaging 87% accuracy, showcasing its ability to handle EEG data's non-linear relationships. CNN (red line) leads with a 92% accuracy peak, excelling in spatial-temporal analysis and feature detection crucial for identifying epileptic activity. Performance metrics like accuracy, sensitivity, and specificity, essential for clinical applications, are evaluated using cross-validation, underlining the importance of data quality, feature selection, and model complexity in real-time epilepsy detection.

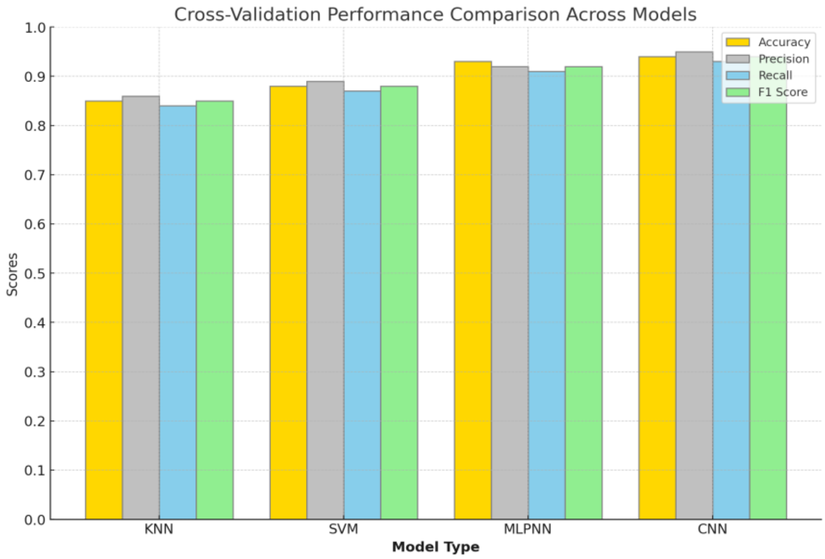

Fig 6: Evaluation of the classifiers using cross validation *10.

in Fig 6 Performance evaluations of KNN, SVM, MLPNN, and CNN models demonstrate varying impacts on accuracy, precision, recall, and F1 scores, influenced by model-specific parameters:

- KNN's performance fluctuates with different k values. Optimal k (between 2 and 8) balances accuracy and error rates.The SVM's efficacy varies by kernel type, informing optimal kernel selection for effective and generalizable performance. at least MLPNN shows configuration-dependent trade-offs; the (50, 50) setup emerges with a balanced precision and F1 score. for the CNN improves with successive architectures, with Architecture 5 showcasing enhanced EEG data classification capabilities.

In terms of scaling to larger data sizes, KNN's performance drops sharply, SVM declines more moderately, MLPNN stabilizes after a slight decrease, and CNN maintains or improves, proving its robust scalability for complex EEG tasks. KNN shows rapid performance decline with larger datasets due to computational and memory demands. SVM's performance decreases more gradually, suggesting better scalability than KNN but still limited. MLPNN shows a slow performance decrease but stabilizes, indicating good scalability. CNN performance remains stable or slightly improves, highlighting its excellent scalability and suitability for larger datasets, especially beneficial for complex tasks like EEG data classification.

III-4. the brain topo-maps:

Fig 7 presents EEG topographical maps for six 20-second epochs, illustrating the electrical activity at different scalp sites, with color coding reflecting activity levels in µV. After filtering muscle artifacts, spatial voltage gradients are analyzed, with high voltages suggesting a high probability of epilepsy as determined by classifier analysis. Correlation with clinical data is essential for definitive diagnosis. The maps detail alpha (associated with relaxation), theta (drowsiness, arousal, or dysfunction), and gamma (cognitive processing) waves. Diagnostics focus on asymmetries, spikes, or sharp waves via FFT and PCA, and patterns recognized by deep learning, underscoring the integration of patient history for epilepsy diagnosis.

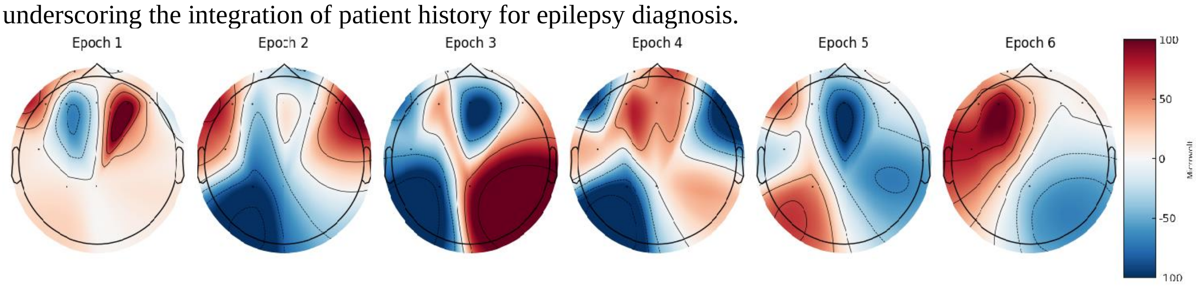

fig 7: Sequential Topographical Brain Maps showing the Electrical Activity Patterns for Epilepsy Analysis.

III-5. comparison works:

Table 2, Comparative Table of Seizure detection, Origination Localization and accuracy of classification Techniques.

Authors with Reference Number	Channel/Segment (in Seconds)	Technique Used	Localization	SEN (%)	SPE (%)	ACC (%)	ADR (%)
Sriram et al. [39]	Multi/NS	Multi Features and multi layer perceptron	NO	97.1	97.8	NS	NS
Anubha et al. [31]	Single/NS	Hurst component and autoregressive	NO	NS	NS	97	NS
M.G.Mohammadi et al. [38]	Multi/NS	CNN-MLP/LSTM/ResNet	NO	76.84/94.24	NS	NS	NS
Acharya et al. [32]	NS	13 layer CNN	NO	95	90	88.67	NS
Gao et al. [33]	Multi/NS	Maximal overlap DWT	NO	NS	NS	94.12	NS
Mohammadi et al.[34]	Multi/0.9s	HMM-Deep learning	NO	Above 90	95	NS	NS
Zimeng et al. [35]	Multi/NS	Multi-step spike algo	YES	97.4	96.5	96.9	NS
Cura et al. [36]	Multi/NS	DMD-spectral moments	NO	92.5	98.6	96.5	NS
Yao et al. [37]	Multi/NS	BiLSTM with CNN	NO	87.3	88.3	NS	NS
S.Roy et al. [27]	Multi/NS	Deep Learning	NO	91.6	NS	NS	NS
The proposed work	Multi/4 s	KNN,SVM, MLPNN, CNN	YES	93.83	97.94	97.38	95.89

Table 2 compares techniques for localizing seizure origins, from complex feature extraction to sophisticated models like CNNs and CNN-LSTM hybrids. Locating seizures is complex, but the use of power spectra and wavelet features has proven effective in diagnosis. Multi-channel EEG data and innovative mapping techniques further enhance the detection and localization of seizures. Previous studies like those by Sriram et al. and Anubha Gupta et al. showed high sensitivity and accuracy in detection, without localizing seizures. The novel approach here, utilizing KNN, SVM, MLPNN, and CNN, achieves not just detection but also localization of seizure origins, setting it apart from other methods in Table 2.

IV. Discussion

Integrating machine learning with EEG analysis, classifiers like CNN, SVM, KNN, and MLP have improved neurological diagnostics. CNNs are particularly notable, achieving over 97% accuracy in epilepsy detection, while SVMs show robustness across various conditions. KNNs have lower accuracy, suggesting they may struggle with EEG's complexity, and MLPs show promise with moderate accuracy. These classifiers, especially CNNs, excel in real-time, complex pattern recognition, proving useful in clinical settings. Despite noise challenges, CNNs maintain accuracy, unlike KNNs which show a notable decline. Comparative studies reveal MLP architectures like (50, 50) offer balanced precision and F1 scores. This advancement in EEG signal classification marks a significant leap in diagnosing and treating neurological conditions.

The accuracy of the CNN classifier is noteworthy, achieving 95.25% with a standard deviation of ±2.25% using normal and big data in real time, which indicates a high level of reliability in identifying epileptic patterns within EEG data (Figure 5). SVM classifiers exhibit the highest accuracy at 96.37% ±2.68%, suggesting their robustness in classifying EEG signals under various conditions (Figure 6). However, KNN classifiers present a lower accuracy of 86.37%, which may be indicative of their limited complexity handling in the context of EEG data classification (Figure 7). MLP classifiers demonstrate moderate accuracy at 89.87%, highlighting their potential in modeling complex relationships within the data (Figure 8). Using these classifiers, and using a stratification of EEG DATA complexity, our epilepsy detecting system provides real resultats of any complexity in real time and directly from the patients.

V. Conclusion

The primary goal of our research was to enhance the detection of epilepsy using a comprehensive system EAS that integrates advanced machine learning algorithms Convolutional Neural Networks (CNN), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Multi-Layer Perceptrons (MLP) with the analysis of EEG signals. This innovative approach was applied to a diverse dataset comprising EEG data from 310 patients, including information from two open datasets [25] [40], and our patient cohort, to ensure a broad representation of epilepsy manifestations. The unique aspect of our system is dynamic use of the four classifiers, which are selected based on the data size and complexity of each case. This adaptive methodology allows for tailored analysis, enhancing the system's efficiency and accuracy across various scenarios.

Our findings underscore the significant potential of leveraging EEG signal analysis combined with machine learning to advance the diagnostic process for epilepsy. The classifiers demonstrated exceptional performance, particularly in real-time applications, highlighting their capability to distinguish between epileptic seizures and normal neurological states with high accuracy. CNNs, in particular, showed superior performance in handling the spatial-temporal patterns inherent in EEG data, making them highly effective for this application.

Moreover, the application of EEG topographical maps and spectral analysis has enriched our understanding of epilepsy, enabling a more nuanced interpretation of the EEG data. The ability of our system to accurately classify EEG signals under different conditions, including noisy environments, showcases its applicability in real-world clinical settings.

By harnessing the power of machine learning and EEG analysis in one global system EAS, our research paves the way for the development of automated, non-invasive tools for epilepsy monitoring and diagnosis in the clinics under the supervision of the doctors. This approach not only promises to improve diagnostic accuracy and speed but also offers the potential to enhance patient care and outcomes significantly.

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