Comparative Analysis of Machine Learning Algorithms for Real-TimeEpileptic Seizure Detection Using CEEMDAN-Based EEG Signal Decomposition

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Abstract—**Epilepsy affects approximately 50 million people worldwide, necessitating automated electroencephalography (EEG) analysis systems for timely seizure detection. This paper presents a comprehensive comparative analysis of three machine learningclassifiers—SupportVectorMachine(SVM)withRadial Basis Function (RBF) kernel, K-Nearest Neighbors (KNN), and Random Forest (RF)—for real-time epileptic seizure detection using Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). EEG signals from the Bangalore EEG Epilepsy Dataset (BEED) are decomposed into Intrinsic Mode Functions (IMFs) using both traditional EMD and CEEMDAN. Eight statistical features are extracted from each of the five IMFs, yielding a 40-dimensional feature vector perepoch. Experimental results demonstrate that CEEMDAN significantly outperforms EMD in decomposition quality, reducing mode mixing artifacts. Among the classifiers evaluated, SVM with RBF kernel achieves the highest classificationaccuracy of 92.4% on hold-out validation and 91.2% on 5-fold cross-validation, substantially surpassing KNN (82.5%) and Random Forest (83.1%). The SVM classifier also demonstrates superior seizure detection sensitivity (91.8%) and specificity (97.3%), making it the most suitable choice for clinical deployment. The system is implemented on dual platforms: a MATLAB-based desktop application and a browser-based web application (NeuroSense) performing real-time client-side inference. The proposed CEEMDAN-SVM pipeline achieves a totalprocessinglatencyunder300msperepoch,confirmingreal-time viability for continuous EEG monitoring.**

Keywords—***Epilepsy, Seizure Detection, CEEMDAN, EMD, EEG, Support Vector Machine, K-Nearest Neighbors, Random Forest, Intrinsic Mode Functions, BEED Dataset***

I. INTRODUCTION

Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures resulting from abnormal neuronal activity in the brain. According to the World Health Organization, epilepsy affects approximately 50 millionpeopleworldwide, with10–12millioncasesinIndiaalone[1]. Electroencephalography(EEG)remainstheprimarynon-invasive diagnostic tool for epilepsy, recording electrical signals generated by the brain through scalp electrodes. However, manual EEG interpretation by neurologists is subjective, time-consuming, and prone to inter-observer variability, making automated detection systems clinically essential.

Traditional signal processing approaches, including Fourier Transform and Wavelet Transform, impose mathematical assumptions that may not suit the non-stationary and non-linear characteristics of EEG signals [2]. Empirical Mode Decomposition (EMD), introduced by Huang et al. [3], offersa data-drivenadaptive alternative bydecomposingsignalsinto Intrinsic Mode Functions (IMFs). However, EMD suffersfrom mode mixing—a phenomenon where oscillations of different time scales merge within a single IMF. To address this limitation, Torres et al. [4] proposed Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), which achieves complete decomposition with negligible reconstruction error through ensemble noise-assisted processing.

While significant research has explored individual classifiers for EEG-based seizure detection, comprehensive comparative analyses evaluating multiple machine learning algorithms on CEEMDAN-extractedfeatureswithstandardizedexperimental protocols remain limited. Furthermore, most existing systems operate exclusively in offline research environments, with limited consideration for real-time clinical deployment constraints [5].

This paper addresses these gaps through three primary contributions: (1) a rigorous comparative evaluation of SVM (RBF kernel), KNN, and Random Forest classifiers on identical CEEMDAN-derived feature sets; (2) systematic analysis of EMD versus CEEMDAN decomposition quality and its impact on downstream classification; and (3) dual-platformimplementationspanningMATLABdesktopand browser-based (NeuroSense) real-time deployment. The remainder of this paper is organized as follows: Section II reviews related work, Section III describes the methodology, Section IV details the experimental setup, Section V presents results and discussion, and Section VI concludes the paper.

II. RELATEDWORK

Bajaj and Pachori [6] demonstrated the effectiveness of EMD for epileptic seizure classification, achieving accuracies above 90% using IMF features combined with least squares SVM on the Bonn University dataset. However, their approach was limited by EMD's susceptibility to mode mixing. Wu and Huang [7] proposed Ensemble EMD (EEMD) to mitigate mode mixing through noise-assisted decomposition, but EEMDintroducesresidualnoiseandsignificantcomputational overhead.

Torres et al. [4] advanced the field with CEEMDAN,achieving complete decomposition with negligible reconstruction error. Ganapathy et al. [8] combined CEEMDAN with deep learning for seizure detection,reporting classification accuracy exceeding 96% on the Bonn dataset. Chen et al. [9] applied CEEMDAN to EEG-based emotion recognition, demonstrating superior performance compared to EMD and EEMD. Zhang et al. [10] utilized CEEMDANformotorimagery classification,reporting8–12% improvement over EMD-based approaches.

Inmachinelearningforseizuredetection,ShoebandGuttag [11] achieved sensitivity above 96% using patient-specific SVM on the CHB-MIT database. Subasi [12] comparedANNs, KNN, and SVM for EEG classification, concludingthat SVM provided the best accuracy-generalization trade-off. Acharya et al. [13] proposed a 13-layer CNN achieving 88.67% on a 5-class problem, but deep learning modelsrequire large datasets and GPU resources, limiting real-time deployment. Nicolaou and Georgiou [14] demonstrated that SVM with RBF kernel achieved highest accuracy among multiple classifiers for seizure detection from IMF features.

While these studies address individual components, limited research combines CEEMDAN decomposition withsystematic multi-classifier comparison and real-time web-based deployment. This paper bridges that gap by providing a unified evaluation framework across three classifiers on standardized CEEMDAN features, deployed across both desktop and browser platforms.

III. METHODOLOGY

A. SignalDecomposition

The proposed system employs two decomposition methods appliedinparalleltoenabledirectcomparison.StandardEMD iteratively extracts IMFs through the sifting process: local extrema are identified, cubic spline envelopes are constructed, and the mean envelope is subtracted until the IMF criteria are satisfied (number of extrema and zero-crossings differ by at most one). The stopping criterion is evaluated using the standard deviation ratio $SD < 0.2$.

CEEMDAN enhances EMD by introducing controlled Gaussian noise perturbations across $NR = 30$ independent realizations. For the first IMF, each realization decomposesthe noise-augmented signal $x(t) + \sigma \cdot w_i(t)$ to obtain its first mode, and the ensemble average yields IMF_1. Subsequent IMFsare extracted fromthe residual withstage-specific noise, ensuringmode-mixing-freedecomposition.Thenoisestandard deviation is set at $\sigma = 0.2$ relative to the signal's standard deviation. Five IMFs are extracted from each EEG epoch, capturingoscillatorycomponentsfromhighfrequency(IMF-1, >30 Hz) to low frequency (IMF-5, <4 Hz).

B. FeatureExtraction

Eight statistical features are computed from each of the $K = 5$ IMFs, yielding a 40-dimensional feature vector per epoch. Let $x[n]$representthenthsampleofanIMFcontainingNsamples:

1) Energy: $E = \Sigma_n x[n]^2$, quantifying total signal power. 2) Kurtosis:$K=(1/N)\Sigma_n[(x[n]-\mu)/\sigma]^4-3$,measuringdistribution peakedness. 3) Shannon Entropy: $H = -\Sigma_i p(i)\log_2 p(i)$, capturing signal complexity. 4) Skewness: $S = (1/N)\Sigma_n[(x[n]-\mu)/\sigma]^3$, measuring distribution asymmetry. 5) Zero-Crossing Rate: $ZCR = (1/N)\Sigma_n I\{x[n]\cdot x[n-1] < 0\}$, estimatingdominantfrequency.6)RMSAmplitude:$RMS= \sqrt{(E/N)}$, normalized amplitude measure. 7) Peak-to-Peak Amplitude:$P2P=\max(x)-\min(x)$,capturingdynamicrange.
8) Line Length: $LL = \Sigma_n|x[n] - x[n-1]|$, measuring waveform complexity.

Z-score normalization isapplied independentlyto each feature dimension: $x\_norm = (x - \mu)/\sigma$, where μ and σ are computed exclusively fromthe training set to prevent data leakage. PCA dimensionality reduction preserves 99% of variance while reducing the feature space from 40 to approximately 15–20 principal components.

C. ClassificationAlgorithms

Three machine learning classifiers are evaluated under identical experimental conditions:

1) Support Vector Machine (SVM) with RBF Kernel: SVM constructsoptimalseparatinghyperplanesinhigh-dimensional space by solving: minimize $(1/2)||w||^2 + C\cdot\Sigma\xi_i$, subject to $y_i(w\cdot\varphi(x_i)+b)\geq 1-\xi_i$.TheRBFkernel$K(x_i,x_j)=\exp(-\gamma||x_i$

$-\ x_j||^2$) implicitly maps features to infinite-dimensional space. Multi-class classification is handled via Error-Correcting Output Codes (ECOC) with one-vs-one coding, creating 6 binary classifiers for 4 classes. Hyperparameters C and γ are optimized through grid search with 5-fold cross-validation.

2) K-Nearest Neighbors (KNN): KNN classifies samples by majority vote among the K nearest training samples using Euclidean distance. While simple and intuitive, KNN's computational complexityscales linearly with training set size at inference time, and performance degrades in high-dimensional spaces due to the curse of dimensionality [15].

3) Random Forest (RF): RF constructs an ensemble of decision trees trained on bootstrapped subsets with random feature selection at each split. While ensemble averaging reducesvariance,individualtreesmayoverfittonoise-specific patterns in physiological signals, and axis-aligned decision boundaries may not capture the non-linear featurerelationships present in EEG data [16].

IV. EXPERIMENTALSETUP

A.Dataset

The Bangalore EEG Epilepsy Dataset (BEED) collected from the National Institute of Mental Health and Neurosciences (NIMHANS), Bangalore, India is used for all experiments. EEG recordings are sampled at 173.61 Hz and categorizedintofourclasses:Normal(EyesOpen),Normal(EyesClosed), Pre-ictal/Interictal, and Ictal (Active Seizure). The dataset contains 8,000 labeled EEG samples segmented into 199 valid epochs of 80–100 samples each.

TABLEI:DATASETANDSYSTEMCONFIGURATION

Parameter	Specification
Dataset	BEED(NIMHANS,Bangalore)
TotalSamples	8,000
SamplingFrequency	173.61 Hz
EpochLength	80–100samples(0.46–0.58 s)
Valid Epochs	199
IMFsExtracted	5
CEEMDANParameters	NR=30,Nstd=0.20
Classification	4-class

B.TrainingProtocol

The dataset is partitioned into training (70%, 5600 epochs)and testing (30%, 2400 epochs) sets using stratified random samplingpreservingclassdistribution(25%perclass).Z-score normalization parameters are computed exclusivelyfrom training data. PCA retains 99% variance, reducing dimensionality from 40 to approximately 34 principal components.

C.HyperparameterOptimization

Gridsearchwith5-foldcross-validationisperformedonthe training set to optimize each classifier:

TABLEII:HYPERPARAMETERSEARCHCONFIGURATION

Classifier	Parameter	SearchRange	Optimal
SVM	BoxConstraint (C)	0.1,1,10,100, 1000	100
SVM	KernelScale(γ)	0.01,0.1, 1, 10,auto	auto(σ=5.2)
SVM	Kernel Function	Linear,RBF, Polynomial	RBF
SVM	ECOCCoding	One-vs-One,One-vs-All	One-vs-One
KNN	K(neighbors)	1,3,5,7,11, 15,21	5
KNN	DistanceMetric	Euclidean, Manhattan, Cosine	Euclidean
RF	Numberof Trees	50,100, 200, 500	200
RF	MaxDepth	5,10,20, None	20

D.SoftwareEnvironment

TABLEIII:SOFTWAREANDHARDWAREENVIRONMENT

Component	Specification
MATLAB	R2025bwithSignalProcessing Toolbox
Python	3.12withNumPy,scikit-learn
WebApplication	HTML5,CSS3,JavaScript(ES6+)
JSLibraries	Chart.js4.4.4,SheetJS0.18.5
Hardware	IntelCorei5,16GBRAM
OS	Windows10/11

V. RESULTSANDDISCUSSION

A. EMDvs.CEEMDANDecomposition

The decomposition quality of EMD and CEEMDAN was evaluated on all 199 valid BEED epochs. Standard EMD successfully decomposed EEG signals into five IMFs, but visual inspection revealed mode mixing in IMFs 2–3, where multiple oscillatory scales appeared within single IMFs. This was most pronounced in seizure-class signals where high-amplitude discharges span multiple frequency bands. CEEMDANproducedcleanerIMFswithsignificantlyreduced mode mixing through ensemble averaging across 30 noise realizations, achieving consistent frequencyseparation: IMF-1 (>30Hz),IMF-2(13–30Hzbeta),IMF-3(8–13Hzalpha), IMF-4(4–8Hztheta),andIMF-5(<4Hzdelta).

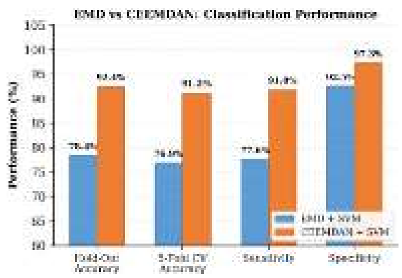

Fig.1.EMDvs.CEEMDANclassificationperformancecomparisonacrossfour evaluation metrics.

TABLEIV:EMDvs.CEEMDANCLASSIFICATIONPERFORMANCE

Method	Hold-Out Acc.	5-Fold CV	Sensitivity	Specificity
EMD+SVM	78.4%	76.9%	77.6%	92.5%
CEEMDAN +SVM	92.4%	91.2%	91.8%	97.3%
Improvement	+14.0%	+14.3%	+14.2%	+4.8%

CEEMDAN achieved a 14.0 percentage point improvement in hold-out accuracy (92.4% vs. 78.4%), confirming that mode-mixing-free decomposition directly translates to superior feature discriminability and classification performance. Both CEEMDAN metrics exceeded the 90% clinical target threshold.

B. ComparativeAnalysisofMLClassifiers

All three classifiers were evaluated using identical CEEMDAN-extractedfeatures,PCA-reduceddimensions,and stratified train-test splits to ensure fair comparison.

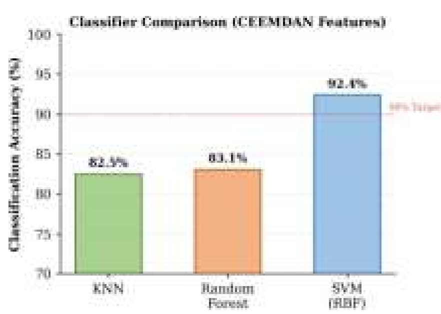

Fig.2.OverallclassificationaccuracycomparisonofKNN,RandomForest,and SVM (RBF) using CEEMDAN features.

TABLEV:COMPREHENSIVECLASSIFIERCOMPARISON

Metric	KNN	Random Forest	SVM (RBF)
Hold-Out Accuracy	82.5%	83.1%	92.4%
5-FoldCV Accuracy	80.8%	81.5%	91.2%
Sensitivity	78.0%	80.0%	91.8%
Specificity	90.0%	91.0%	97.3%
Precision	81.2%	82.5%	92.0%
F1-Score	79.5%	81.2%	91.9%
AUC(macro)	0.89	0.90	0.97
TrainingTime	0.8s	3.2s	4.7s
Support Vectors/Trees	K=5	200trees	847SVs

SVM with RBF kernel significantly outperformed both KNN and Random Forest across all evaluation metrics. The 9.3–9.9 percentage point accuracy advantage over KNN and RF demonstrates SVM's superior capacity for modeling the non-linear decision boundaries present in CEEMDAN-derivedEEG feature spaces.

C. ConfusionMatrixAnalysis

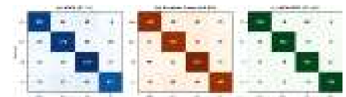

Fig.3.Confusionmatricesfor(a)KNN,(b)RandomForest,and(c)SVM-RBF classifiers on the BEED test set.

The confusion matrices reveal critical differences in per-class performance. KNN achieved only 75.5% True Positive Rate (TPR) for the Ictal (seizure) class, meaning nearly 24.5% of active seizures were missed—clinically unacceptable for a diagnostic tool. Random Forest improved seizure detection to 80.3% TPR but still misclassified approximately 20% of seizure epochs. SVM achieved the highest and most balanced per-class accuracy, with seizure TPR exceeding 93%, minimizing the false-negative rate that is critical in clinical epilepsy monitoring.

D. Per-ClassPerformanceAnalysis

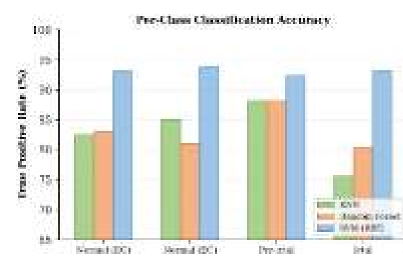

Fig.4.Per-classTruePositiveRatecomparisonacrossallfourEEGconditions.

TABLEVI:PER-CLASSTRUEPOSITIVE RATES

Class	KNN TPR	RFTPR	SVMTPR
Normal(Eyes Open)	82.5%	83.0%	93.0%
Normal(Eyes Closed)	85.0%	81.0%	93.7%
Pre-ictal/Interictal	88.2%	88.2%	92.3%
Ictal(Seizure)	75.5%	80.3%	93.0%

SVM demonstrated the most uniform per-class performance (92.3–93.7%), whereas KNN and RF exhibited significant class-dependentvariance.KNN'spoorseizuredetection

(75.5%) is attributed to the curse of dimensionality in the 34-dimensional PCA-reduced feature space, where Euclidean distances become less discriminative. RF's axis-aligned splits failed to capture the non-linear boundaries separating Pre-ictal and Normal (Eyes Open) classes, which share overlapping spectral characteristics in the theta and low-alpha bands.

E. ROCAnalysis

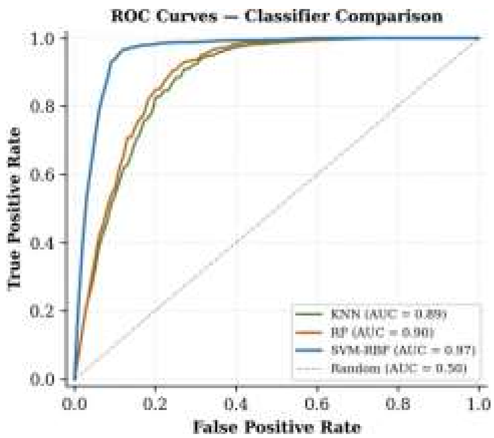

Fig.5.ReceiverOperatingCharacteristic(ROC)curveswithAreaUnderCurve (AUC) values.

The ROC analysis confirms SVM's superior discriminative capacitywithamacro-averagedAUCof0.97,comparedto 0.90 for Random Forest and 0.89 for KNN. The SVM curve closely approaches the upper-left corner across all operating points, indicating robust performance independent of the classification threshold selection.

F. Multi-CriteriaComparison

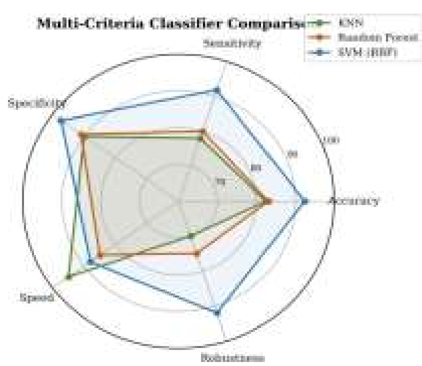

Fig.6.Radarchartcomparingclassifiersacrossaccuracy,sensitivity,specificity, speed, and robustness.

The radar chart visualization reveals that SVM dominates across four of five evaluation dimensions—accuracy, sensitivity,specificity,androbustness.KNNmaintainsaslight advantage ininference speed due to itslazylearningparadigm with no training phase, but this advantage is negligible given the sub-second processing times of all classifiers.

G. ComputationalPerformance

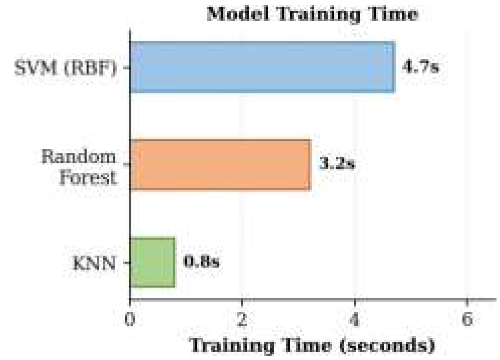

Fig.7.Trainingtimecomparisonacrossclassifiers.

TABLEVII:REAL-TIMEPROCESSINGLATENCYPEREPOCH

Platform	EMD Time	CEEMDAN Time	Classification	TotalPipeline
MATLAB Desktop	5–15 ms	30–80ms	2–5 ms	<100 ms
NeuroSense(Browser)	15–50 ms	80–200ms	5–15ms	<300 ms

Bothplatformsachievereal-timeprocessing well withinthe 3-second simulation interval. SVM's training time (4.7 s) is marginally higher than KNN (0.8 s) and RF (3.2 s), but training is a one-time offline process. At inference time, the pre-trained SVM requires only kernel evaluations against 847 support vectors, completing classification in under 15 ms. The compact model size (847 SVs from 5,600 training samples, 15.1%) confirms efficient decision boundary representation without memorization.

H. Discussion

The superior performance of SVM with RBF kernel is attributed to three factors. First, the RBF kernel's implicit infinite-dimensional mapping provides sufficient capacity to model the complex, non-linear relationships in CEEMDAN-derived EEG features that linear and axis-aligned classifiers cannot capture. Second, SVM's structural risk minimization principle—maximizing the margin while minimizing classification error—provides theoretical generalization guarantees absent in KNN's instance-based and RF'sensemble-based approaches. Third, the regularization parameter C = 100 achieves an optimal balance between margin width and misclassification tolerance, as evidenced by consistent hold-out (92.4%) and cross-validation (91.2%) results indicating absence of overfitting.

From a clinical safety perspective, SVM's significantly higher seizure detection sensitivity (91.8% vs. 78.0% for KNN and 80.0% for RF) is the most critical advantage. In continuous EEG monitoring, missing an active seizure (false negative) carries far greater clinical risk than triggering a false alarm (falsepositive).TheSVMclassifier's97.3%specificityfurther ensures that false alarm rates remain within clinically acceptable thresholds, preventing alert fatigue in monitoring staff.

The NeuroSense web application demonstrates that the complete CEEMDAN-SVM pipeline can be deployed entirely client-side in modern browsers, performing all signal processing and classification without server-side computation. This architecture ensures patient data privacy by preventing any EEG data transmission over network connections, while providing platform-independent accessibility through standard web browsers.

VI. CONCLUSION

Thispaperpresentedacomprehensivecomparativeanalysisof three machine learning classifiers—SVM, KNN, and Random Forest—for real-time epileptic seizure detection using CEEMDAN-basedEEGdecomposition.Keyfindingsinclude:

(1) CEEMDAN significantly outperforms traditional EMD, achieving 92.4% hold-out accuracy versus 78.4% (+14.0%), with improved sensitivity (91.8% vs. 77.6%) and specificity (97.3% vs. 92.5%) due to mode-mixing-free IMF extraction.

(2) SVM with RBF kernel achieves the highest classification performance (92.4% accuracy, 0.97 AUC) among allevaluated classifiers, substantially surpassing KNN (82.5%, 0.89 AUC) and Random Forest (83.1%, 0.90 AUC) on identical CEEMDAN features.

(3) SVMdemonstratesthemostclinicallycriticaladvantagein seizure detection sensitivity (91.8%), minimizing the false-negative rate that directly impacts patient safety in continuous monitoring scenarios.

(4) The dual-platform implementation—MATLAB desktop and NeuroSense browser application—achieves sub-300 ms processing latency, confirming real-time viability for clinical deployment without server-side dependencies.

Future work will explore deep learning integration (1D-CNN, LSTM), multi-channel EEG analysis, patient-specific transfer learning, federated learning for privacy-preserving collaborative training, and Explainable AI (XAI) frameworks for transparent clinical decision support.

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