

Enhancing Multiclass Dementia Detection with EEG Signals: A Feature-Driven LSTM Approach

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Received: 26 September 2025 | Revised: 14 October 2025 and 2 November 2025 | Accepted: 3 November 2025

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ABSTRACT

Early and accurate differentiation of dementia subtypes remains a major challenge in clinical neurophysiology and is crucial for timely intervention and personalized care. This study introduces a novel EEG-based deep learning framework for classifying Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), Subjective Cognitive Decline (SCD), and Healthy Controls (HC). Resting-state EEG data from 139 participants (>45 years) were analyzed through spectral and connectivity features, focusing on Theta-Beta activity linked to cognitive dysfunction. A feature-enriched Long Short-Term Memory (LSTM) model integrated Pearson's correlation-based connectivity measures with optimized dimensionality reduction techniques to enhance class separability and computational efficiency. The proposed PCC-PCA-LSTM model achieved 99.47% classification accuracy and an AUC of 1.00 across all classes, significantly outperforming conventional EEG-based diagnostic approaches. These findings demonstrate the model's potential as a clinically viable and scalable tool for early detection, continuous monitoring, and decision support in dementia care, bridging the gap between neurophysiological insight and practical diagnostic utility.

Keywords-Electroencephalography (EEG); dementia detection; Alzheimer's; Mild Cognitive Impairment (MCI); feature engineering; PCA; LDA; LSTM

I. INTRODUCTION

Dementia encompasses a range of neurodegenerative disorders characterized by progressive cognitive decline that impairs memory, reasoning, behavior, and daily functioning. Among its subtypes, Alzheimer's Disease (AD) is the most prevalent, followed by Mild Cognitive Impairment (MCI) and Subjective Cognitive Decline (SCD) [1]. MCI is often regarded as a transitional stage between normal aging and AD, marked

by noticeable but subclinical deficits that do not yet meet dementia criteria [2]. However, it is irreversible and progressive, making it a key target for early intervention. SCD, defined as self-perceived decline in cognitive ability despite normal test performance, has gained recognition as a potential precursor to future cognitive impairment. With the global number of dementia cases expected to exceed 152 million by 2050 [3], especially in resource-limited regions, the need for

early detection and accurate subtype classification, particularly of SCD and MCI, is critical since no curative therapy currently exists.

Electroencephalography (EEG) has emerged as a promising, non-invasive, and low-cost method for early identification of cognitive decline [4], as its high temporal resolution captures subtle neural oscillatory changes associated with dementia progression. However, traditional Machine Learning (ML) methods, though effective in certain scenarios, often face limitations in handling the high-dimensional, noisy nature of EEG data and struggle to generalize across individuals. Neuropsychological assessments and neuroimaging methods, while informative, remain expensive and less scalable, further motivating the exploration of EEG-based automated diagnostic tools. Integrating EEG with advanced Deep Learning (DL) models presents a feasible and powerful direction for reliable multiclass dementia diagnosis.

EEG data are complex and require robust preprocessing and feature extraction [5]. Techniques such as time-frequency decomposition, entropy analysis, and wavelet transforms reveal dementia-related abnormalities. Conventional ML algorithms, including Support Vector Machines (SVMs) and Decision Trees (DTs), rely heavily on such handcrafted features but often suffer from inter-subject variability and noise sensitivity, reducing generalizability [6]. Frequency bands such as Alpha, Beta, Delta, Theta, and Gamma are closely linked with attention, memory, and perception, functions typically disrupted in dementia [7]. Extracted features such as power spectral density, wavelets, and connectivity-based measures like Pearson correlation and phase synchronization serve as critical biomarkers [8].

Connectivity analysis further enhances discrimination power. Coherence quantifies inter-regional phase synchrony, while Pearson's Correlation Coefficient (PCC) captures temporal dependencies, both useful in identifying disrupted communication in neural networks. Advances in DL have transformed this domain by enabling automated learning of spatial-temporal EEG patterns. LSTM networks, for instance, effectively model sequential dependencies [9], while CNN-LSTM hybrids capture both spatial and temporal features [10]. Inclusion of attention mechanisms and transfer learning improves interpretability and reduces data dependency [11]. Recent studies have demonstrated remarkable results: In [12], 98.97% accuracy was achieved using MSPCA with Bi-LSTM; In [13], 94.4% was achieved with a two-layer ANN; In [14], 97.4% was reported for a CNN-LSTM-attention model; In [15], 96.41% was achieved for MCI detection; In [16], accuracy was improved by approximately 5% using RPCA-LSTM; and in [17], 99.2% accuracy and 98.2% F1-score were obtained with a lightweight LSTM-RNN framework.

Hybrid ML-DL strategies have also been proven effective. SVMs augmented with ResNet-18 features reached 98.6% accuracy in schizophrenia detection [18], while CNNs such as DenseNet and Inception ResNet v2 achieved up to 96.65% [19]. Sequential EEG data benefit from CNN-LSTM and ensemble learning frameworks [20], and end-to-end CNN-LSTM models eliminate manual feature engineering [21].

Despite progress, challenges remain in overfitting, generalization, and interpretability. This study aimed to overcome these by integrating band-specific EEG features, PCC-based connectivity, and PCA/LDA-driven dimensionality reduction under k-fold cross-validation. A feature-enriched LSTM framework is proposed for early multiclass dementia classification (AD, MCI, SCD, HC), optimized through coherence validation, confusion matrices, and ROC analysis.

II. METHODOLOGY

A. Proposed Model

The proposed pipeline begins with EEG acquisition from AD, MCI, SCD, and HC participants, followed by preprocessing and frequency band decomposition. Inter-channel correlations are extracted using PCC, then reduced via PCA and LDA to improve separability and efficiency. K-fold cross-validation ensures generalization, while coherence tests validate neural consistency. LSTM classifiers were applied to both PCA- and LDA-transformed features, with PCA on the Theta-Beta (Bands 1, 3) combination yielding the highest accuracy, establishing the optimal setup.

- Data acquisition: EEG data from 139 participants (>45 years) representing AD, MCI, SCD, and HC stages were collected by GAADR and Aristotle University of Thessaloniki with ethical approval [22]. Recordings used the 10–20 system (20 channels, 250 Hz) and were segmented into 4-s windows, yielding 9900 (HC), 6900 (SCD), 12,300 (AD), and 12,600 (MCI) samples.
- Preprocessing: Using Net Station 4.3, data were filtered, segmented, and corrected for poor channels. Artifacts (eye blinks, muscle, noise) were removed via bandpass filtering and ICA. Clean EEGs were decomposed into Delta, Theta, Alpha, and Beta bands, with Theta–Beta features providing the highest discrimination.
- Feature engineering: PCC captured inter-channel correlations ($400 \times n$ matrix), and coherence quantified phase synchrony. Both were computed for all bands. Dimensionality reduction with PCA and LDA improved reliability; PCA yielded superior accuracy, validation loss, and ROC-AUC, and was used for LSTM classification.
- Training and validation: Data were split 70:20:10 for training, validation, and testing. The LSTM was trained for 50 epochs using categorical cross-entropy and Adam optimization with early stopping to avoid overfitting. Experiments ran on standard desktop hardware (TensorFlow/Keras, Python). Metrics included accuracy, F1-score, specificity, sensitivity, and top-2 accuracy, with Theta–Beta bands performing best.
- K-fold cross-validation: PCC-PCA features were evaluated using stratified k-fold validation, preserving class proportions and confirming classification robustness and stability.
- LSTM classification: PCA-reduced EEG sequences were input to an LSTM capturing temporal dependencies. The gated architecture retained relevant signals while

suppressing noise, and the final hidden states fed a softmax layer (Figure 1) for multiclass classification of AD, MCI, SCD, and HC.

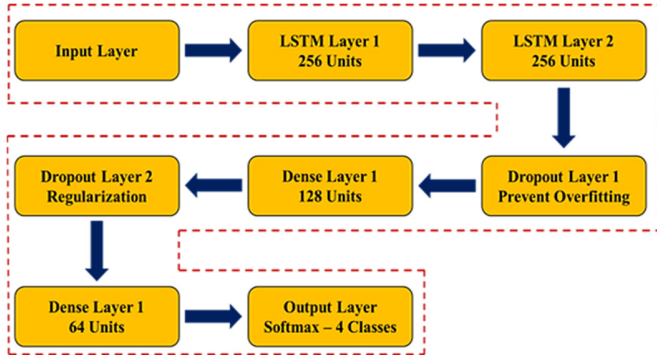


Fig. 1. LSTM model architecture.

- LSTM model architecture: Table I details the network configuration that includes two LSTM layers, dense layers, dropout, and a final softmax layer for four-class output.

TABLE I. LSTM ARCHITECTURE INCLUDING LAYER CONFIGURATIONS AND PARAMETERS

Layer	Type	Output shape	Parameters
Input layer	Input	(None, 15, 600)	0
LSTM layer 1	LSTM	(None, 15, 256)	877,568
LSTM layer 2	LSTM	(None, 256)	525,312
Dense layer 1	Dense	(None, 128)	32,896
Dropout layer	Dropout	(None, 128)	0
Dense layer 2	Dense	(None, 64)	8,256
Dense output layer	Dense	(None, 4)	132

- Evaluation: Model performance was assessed using accuracy, precision, F1-score, and class-wise sensitivity and specificity. Confusion matrices and ROC values confirmed reliable multiclass classification, particularly with the Theta and Beta (1,3) bands.

B. Mathematical Model

PCA projects data onto principal components by maximizing variance while minimizing dimensionality:

$$\bar{X} = X - \mu \quad (1)$$

$$\Sigma = \frac{1}{n-1} X^T X \quad (2)$$

$$X' = X v_k \quad (3)$$

where eigenvalues (λ) and eigenvectors (v) define the reduced feature space. LDA maximizes class separability by optimizing the ratio of between-class to within-class scatter:

$$J(\omega) = \omega^T S_B \omega \quad (4)$$

TABLE III. PERFORMANCE OF THE LSTM MODEL ON PCC-PCA FEATURE SELECTION ON BANDS 1, 3

Feature selection	Analysis type	Accuracy	Sensitivity	Specificity	Precision	F1-score	Time
100%	Training	99.91	99.89	99.97	99.91	99.90	328.04
	Test	99.46	99.55	99.82	99.39	99.47	-
50%	Training	99.82	99.81	99.94	99.81	99.81	197.34
	Test	99.46	99.47	99.81	99.56	99.51	-

with scatter matrices defined as:

$$S_B = \sum_{i=1}^c N_i (\mu_i - \mu)(\mu_i - \mu)^T \quad (5)$$

$$S_W = \sum_{i=1}^c \sum_{x_j \in C_i} N_i (x_j - \mu_i)(x_j - \mu_i)^T \quad (6)$$

The LSTM avoids vanishing gradients via gated mechanisms, learning temporal dependencies through Backpropagation Through Time (BPTT). With categorical cross-entropy loss

$$L = -\sum_{i=1}^N y_i \log(\hat{y}_i) \quad (7)$$

the PCA-LSTM pipeline ensures optimal dimensionality reduction, class separability, and accurate EEG-based dementia classification.

III. RESULTS AND DISCUSSION

The proposed model was evaluated with PCA and LDA Feature Selection (FS), with PCA consistently outperforming LDA. PCC-based PCA features trained the LSTM model under both full and k-fold validation, reducing training time and confirming robustness.

A. Performance of Coherence and PCC

On Bands 2 and 3, PCC-PCA achieved 99.28% accuracy, surpassing coherence (97.12%) with superior sensitivity (99.28%), specificity (99.74%), precision (99.40%), and F1-score (99.33%) (Table II). These results highlight PCC-PCA's effectiveness in extracting relevant neural patterns and reducing false positives.

TABLE II. COMPARING COHERENCE AND PCC OUTCOMES

Feature extraction	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)	Accuracy (%)
PCC	99.28	99.74	99.40	99.33	99.28
COH	96.87	99.00	97.21	97.03	97.12

B. Performance of the LSTM Model on PCC-PCA Feature Selection (FS)

Using PCA-reduced Theta and Beta band features, the LSTM achieved ~99% accuracy on both training and validation within five epochs (Figure 2). With 50% PCC-PCA features, accuracy remained above 99% (Figure 3). Classification metrics (Table III) showed 99.91% training accuracy and 99.46% test accuracy across both feature sets. Dimensionality reduction halved training time (328.04 ms \rightarrow 197.34 ms) without any loss of accuracy. Confusion matrices (Figure 4) confirmed negligible misclassifications, while ROC analysis yielded a perfect AUC (1.00) for all classes under both 100% FS and 50% FS conditions, validating the model's strong discriminative capability.

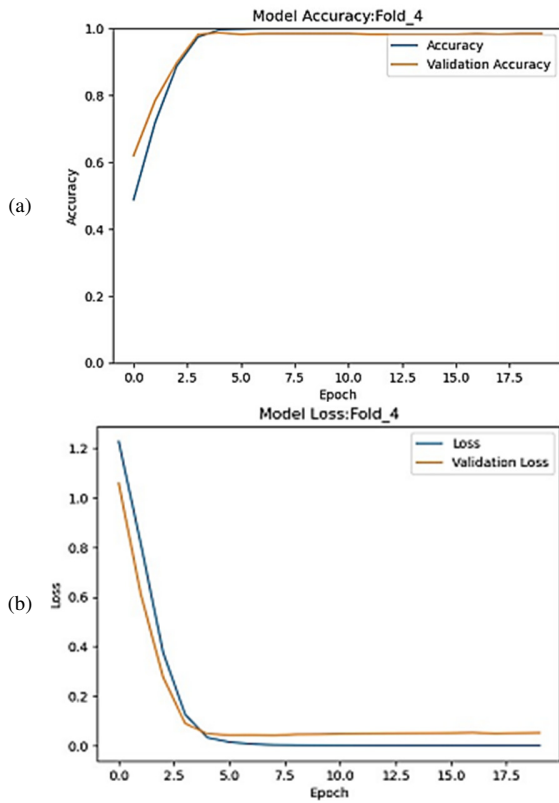


Fig. 2. Accuracy (a) and Loss (b) for PCC-PCA 100% FS.

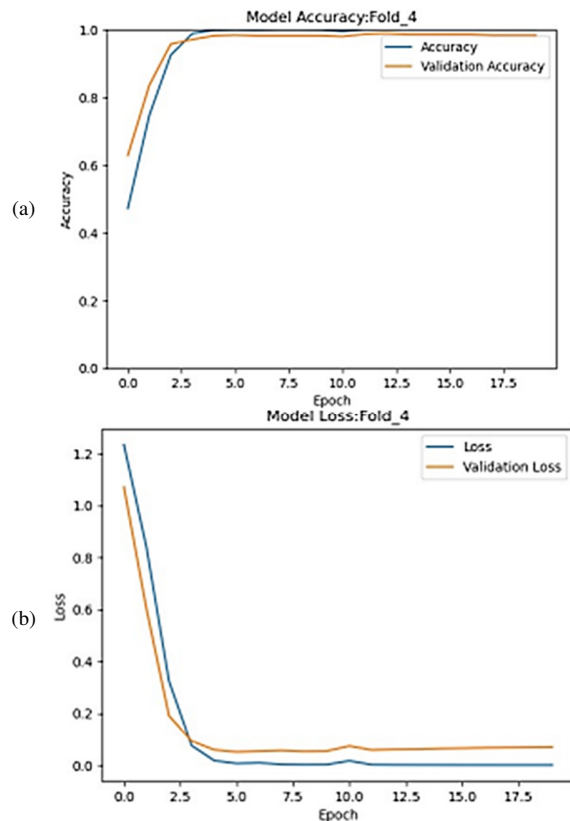


Fig. 3. K-fold accuracy (a) and loss (b) for PCC-PCA 50% FS.

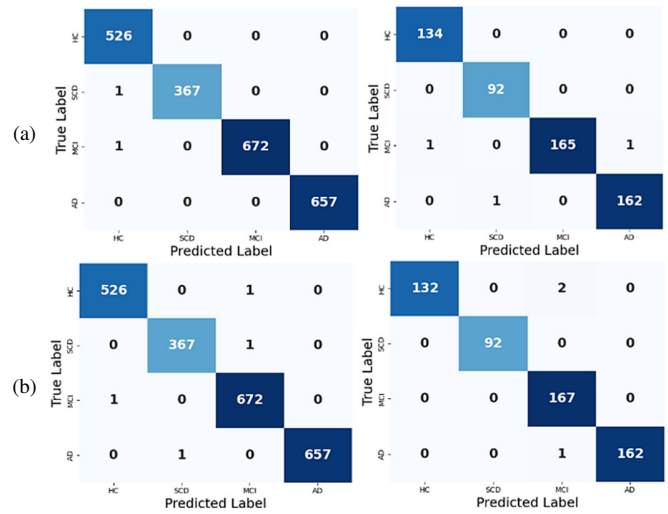


Fig. 4. Confusion matrices: (a) 100% FS training and testing (b) 50% FS training and testing.

C. Performance of Bands with and without K-Fold

As shown in Table IV, test accuracy (99.46%) and F1-score (99.47%) remained stable with or without k-fold. Sensitivity and specificity slightly improved under k-fold, confirming enhanced generalization.

TABLE IV. COMPARISON OF CLASSIFICATION RESULTS OF PCC-PCA FEATURE EXTRACTION MODEL TESTING WITH AND WITHOUT K-FOLD ON BANDS 1, 3

Parameters	Without K-fold	With K-fold
PCA FS (%)	25	100
Band	1,3	1,3
Band weight %	30,90	100
Sensitivity (%)	99.43	99.55
Specificity (%)	99.81	99.82
Precision (%)	99.51	99.39
F1-score (%)	99.47	99.47
Overall accuracy (%)	99.46	99.46

D. Performance of K-Fold LSTM Channels

Temporal and parietal electrodes (T3', C3', C4', T4', T5', P3', P4', T6') yielded the best results (Table V), with 91.4% overall accuracy, underscoring the importance of these spatial regions in dementia detection.

TABLE V. TESTING RESULTS ACHIEVED FOR K-FOLD LSTM CHANNELS FOR PCC-PCA FEATURE SELECTION

Lobe/channel	FS (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)	Accuracy (%)
T3', C3', C4', T4', T5', P3', P4', T6'	100	90.6	96.9	92.1	91.2	91.4

E. Discussion

The PCC-PCA-LSTM model achieved 99.28% accuracy, surpassing coherence-based approaches and maintaining stable performance under k-fold validation with a perfect AUC (1.00).

Reducing PCA dimensions by 50% improved computational efficiency without loss of accuracy, as PCC preserved key Theta and Beta correlations and LSTM effectively captured temporal dependencies. Overfitting was mitigated through PCA-based feature compression, early stopping, and cross-validation, ensuring stable learning rather than memorization.

Nevertheless, since the experiments were conducted on a single dataset, some risk of dataset-specific bias remains, underscoring the need for external validation on independent or multicentre data. Comparative analysis (Table VI) further confirms that the proposed model achieved the highest overall accuracy (99.46%) and F1-score (99.47%) among existing methods, with a superior balance across performance metrics.

TABLE VI. COMPARATIVE ANALYSIS OF EXISTING MODELS WITH THE PROPOSED MODEL

Ref.	Focus	FS/ processing	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)
[12]	MCI	MSPCA + DA	Bi-LSTM + ML	98.97	98.34	99.67	99.70	99.02
[14]	AD	CNN-LSTM	CNN-LSTM-	97.4	97.42	-	97.44	97.43
[15]	MCI	-	-	96.41	96.55	95.95	-	-
[16]	AD	Robust-PCA	LSTM RNN	99	-	-	-	-
[17]	ND	DKLT, PCA+DA	Lightweight LSTM RNN	99.2	98.5	-	98.3	98.2
This study	AD, MCI, SCD, HC	PCC-PCA	LSTM	99.46	99.55	99.82	99.39	99.47

In general, the proposed PCC-PCA-LSTM framework demonstrates optimal accuracy, efficiency, and interpretability, advancing EEG-based dementia detection and supporting its potential for early clinical application.

IV. CONCLUSION

This study demonstrates that combining EEG-based functional connectivity, PCA-driven dimensionality reduction, and LSTM classification enables highly accurate differentiation of healthy controls, subjective cognitive decline, mild cognitive impairment, and AD. The model achieved more than 99% accuracy with strong sensitivity, specificity, and perfect AUC, while dimensionality reduction improved efficiency without loss of precision. Overfitting was mitigated through PCA compression, early stopping, and cross-validation; however, as results are based on a single dataset, external validation on larger multicentre cohorts remains essential. Future work will integrate multimodal biomarkers such as MRI and PET and explore explainable and real-time implementations to enhance clinical usability.

ACKNOWLEDGMENT

The authors thank the Greek Association of Alzheimer's Disease and Related Disorders (GAADR) and Aristotle University of Thessaloniki (AUTH) for providing ethically approved EEG datasets, and CERTH-ITI for maintaining open-access dementia research resources. The authors also appreciate the constructive input and institutional support of their colleagues.

DATA AVAILABILITY

The EEG datasets used in this study are available from the Centre for Research and Technology Hellas - Information Technologies Institute (CERTH-ITI) and the Greek Association of Alzheimer's Disease and Related Disorders (GAADR), Thessaloniki, Greece [22], with access granted upon request.

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