Epileptic Seizure Prediction from EEG Using Continual Learning with CNNs

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Abstract **– Epilepsy is a chronic neurological disorder that affects over 50 million people worldwide, with nearly one-third of patients remaining resistant to conventional therapeutic treatments. This study introduces a progressively adaptive seizure prediction framework designed to enhance early detection and clinical decision-making. The proposed model employs a deep learning strategy grounded in continual learning (CL) principles, using Convolutional Neural Networks (CNNs) in combination with knowledge distillation techniques. This enables the model to assimilate new data while retaining previously learned information. The approach was evaluated on the publicly available Bonn University EEG dataset, following a sequential learning process in which each successive model iteration improved prediction performance. The final model version (Model C) demonstrated significantly improved predictive performance, showing strong stability and generalization across sequential learning stages. Its results clearly outperformed conventional machine learning classifiers, including support vector machines, logistic regression, and random forests.**

The results demonstrate that continual learning architectures can effectively manage evolving EEG data streams, offering stable and accurate seizure prediction without retraining from scratch. Overall, this research emphasizes the benefits of continual deep learning in clinical applications, establishing a foundation for intelligent, scalable, and real-time seizure prediction systems for AI-assisted healthcare monitoring.

Keywords **– CNN, knowledge transfer, elastic weight consolidation, FIM, epileptic seizure.**

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1. Introduction

Epileptic seizures (ES) represent one of the most widespread neurological disorders, characterized by sudden and unpredictable bursts of abnormal brain activity that can influence cognition, movement, and consciousness [1], [2]. To date, approximately 50 million people have been affected by various types of ES [3]. These attacks can cause cognitive deviations that may lead to a significant degree of physical disability in the patient. Moreover, patients suffering from ES face psychological torture and an unsuitable position in society. Thus, early diagnosis of ES will be helpful to patients and enhance the quality of their lives. The two major categories of screening techniques employed in diagnosing ES are functional and structural neuroimaging modalities [4].

For medical professionals and neurologists, functional neuroimaging methods offer valuable insights into the brain's activity during epileptic seizure episodes [5]. Structural neuroimaging, on the other hand, provides detailed information about the anatomical organization of the brain in individuals affected by ES [6]. Among functional imaging tools, techniques such as Electroencephalography (EEG) [7], Magnetoencephalography (MEG) [4], Positron Emission Tomography (PET) [8], Single-Photon Emission Computed Tomography (SPECT) [9], Functional Magnetic Resonance Imaging (fMRI) [10], Electrocorticography (ECoG) [11], and Functional Near-Infrared Spectroscopy (fNIRS) [12] are considered especially important for assessing brain function.

Conversely, Diffusion Tensor Imaging (DTI) and Structural MRI (sMRI) remain the most powerful techniques for examining the brain's structural properties [10], [11], [12].

Functional neuroimaging modalities are used more frequently than structural modalities for diagnosing ES [8], [5], [13], [14]. According to existing research, EEG is the most frequently utilized method by healthcare professionals for diagnosing ES [15].

EEG is the primary method employed for the detection of ES. This technique is a moderately non-invasive means of documenting cerebral activity by sensing voltage fluctuations arising from the ionic flow generated by neurons. Historically, medical inference from EEG signals requires neurologists to perform visual scanning, an extensive and demanding effort that often involves reviewing countless hours of recordings. Consequently, the accuracy of ES detection via EEG remains highly contingent on the individual neurologist's expertise [15]. The conventional process for detection typically begins with feature extraction, focusing on time, frequency, or time-frequency domains. Domain specialists frequently apply signal processing methods such as the Fast Fourier Transform, Short-Time Fourier Transform, or wavelet transforms to analyze the frequency content and engineer hand-crafted features from the raw EEG data. These manually derived features are then fed into classifiers in a subsequent phase for final EEG data categorization. However, the efficacy of this two-stage modeling approach is intrinsically tied to the skill and domain knowledge required to define these optimal characteristics. To overcome this reliance on manual feature engineering, the field has increasingly shifted the responsibility of ES signal analysis toward automated Machine Learning (ML) and Deep Learning (DL) paradigms.

Some reasons making the use of traditional ML approaches difficult to use include:

(i) Inability of machine learning to model data for time series and is computationally inefficient [16],
(ii) Scaling the model itself is challenging [17],
(iii) Representation learning as well as fitting capacity are poor; and
(iv) Designing the feature extractor, which transforms raw data into patterns suitable for recognition, requires the expertise of a domain specialist [18], [19].

On the other hand, the rise of powerful computing resources and access to large-scale datasets has enabled DL to overcome many of the limitations associated with traditional ML methods [18]. Unlike ML models, which often rely on human experts for manual feature extraction, DL techniques learn directly from raw data, automatically identifying relevant patterns without the need for predefined features [20].

Currently, the most effective deep neural network for diagnosing ES in health informatics is DL.

However, these models have a challenge in that they are unable to effectively learn and apply their existing knowledge to new ES cases, often termed the problem of catastrophic forgetting.

To overcome the challenges outlined above, this study introduces a continual deep learning framework utilizing a CNN model for predicting epileptic seizures in patients, which combines CNN, and knowledge distillation using elastic weight consolidation (EWC), and built a novel solution for ES prediction. Furthermore, this work contributes to the field of ES prediction by introducing, to the best of current knowledge, the first epileptic seizure prediction model that leverages a continual deep learning framework combined with knowledge distillation, demonstrating effectiveness in learning from EEG signals. Moreover, this study aims to investigate the feasibility and efficiency of continual deep learning for epileptic seizure prediction through the following research questions (RQs):

- *RQ1: Can a continual deep learning framework be effectively developed to enhance ES prediction using EEG signals?*
- *RQ2: Does knowledge acquired from one DL model transfer effectively to subsequent models without requiring manual retraining or human intervention?*
- *RQ3: Can the proposed continual learning framework effectively mitigate catastrophic forgetting while sequentially learning new EEG tasks for ES prediction?*

The proposed approach empowers the model to maintain and refine its predictive accuracy over time, effectively integrating previously learned knowledge with new data, which is particularly critical in dynamic clinical environments.

The structure of this paper is organized to facilitate a clear understanding of the study's contributions. Section 2 outlines prior research efforts in ES prediction. Section 3 introduces the proposed framework, elaborating on the methodology, model architecture, and experimental configuration. Section 4 presents the evaluation results alongside a detailed discussion of the model's performance followed by examining potential threats to the validity of findings. The paper concludes in Section 5, summarizing the outcomes and suggesting future directions.

2. Machine Learning and Deep Learning Techniques for Handling Epileptic Seizures

This section briefly reveals the recent advances in ES prediction studies and identifies critical gaps in current methodologies, focusing particularly on the last decade of developments in this field.

Several studies have focused on both binary and three-class classification of ES using techniques such as random forests (RF) [21], SVM [22], k-nearest neighbors [23], and decision trees (DT) [24]. Other researchers, like [25], proposed a novel ML-based detection framework designed to increase the sensitivity of wearable devices for ES. Previous work has utilized random forests along with least squares SVM to enhance the performance of EEG signal classification in clinical ES diagnosis [26]. Similarly, SVM and GBDT models have been employed, achieving an accuracy rate of 90.00% for ES classification [27]. Typically, ES detection studies are structured around a two-phase process.

Various techniques have been introduced for the classification of ES, such as feature selection, feature extraction, and dimensional reduction including, principal component analysis [28], [29], partial least squares method [30], and minimum redundancy maximum relevance [31]. Similarly, various features extraction techniques have been identified from ES applications such as time-domain [32], nonlinear features [33],[34], frequency-domain [35], and time-frequency domain [36] features.

As shown in [37], signal preprocessing can support useful feature extraction and noise suppression, although it may also result in the loss of important information required for accurate classification. Since the accuracy of classification depends heavily on the primary data, the raw signal cannot be overlooked when applying classification methods. A framework for detecting ES in both patient and non-patient EEG recordings is presented in [38], where Discrete Wavelet Transform (DWT) is used for EEG analysis and both linear and nonlinear classifiers are integrated to improve detection accuracy.

The SVM algorithm was employed by [28] to develop two techniques: "sub-pattern" and "cross-sub-pattern correlation-based principal component analysis" ("SpPCA" and "SubXPCA"). The binary classification problem examined in this study involves the classification of EEG signals into two categories: Seizure and Non-Seizure signals. The authors conducted a comparison between their results and those of other studies that employed distinct algorithms. These techniques obtained the highest accuracy, 100%, which was higher than the average of other techniques, including "k-nearest neighbor", "SVM," "Decision Tree," and "Nave Bayes".

An automatic ES detection technique for clinical decision-making is presented in [39], where systematic EEG signal analysis is used to support accurate classification. In this approach, the preprocessing phase applies selective threshold denoising using Discrete Wavelet Transform (DWT) to remove noise and artifacts from EEG signals.

Unique statistical features are extracted through multi-scale approximation of each sub-band, followed by dimensionality reduction using robust PCA. A two-class nonlinear SVM classifier implemented with Polynomial and Radial Basis Function kernels - is then employed to distinguish between ictal and interictal EEG signals. The use of a Linear SVM is considered unsuitable for ES classification, as seizure data are often not linearly separable. Table 1 presents a summary of existing ES prediction approaches.

Table 1. Overview of ES detection methods

Ref.	Method	Dataset	Key Results	Limitations
[40]	SVM, RF	CHB-MIT Scalp EEG (163 signals, 256Hz)	90.4% (SVM), 93% (RF) accuracy	Catastrophic forgetting, small dataset
[41]	1D CNN + ML ensemble	Bonn EEG (100×5, 173.6Hz)	98% avg. accuracy	Catastrophic forgetting
[42]	Custom DL network	Bonn EEG + CHB-MIT	98% accuracy	Catastrophic forgetting
[43]	CNN + Bi-LSTM	Bonn EEG (4096×100, 173.6Hz)	93.9% (CNN), 97.2% (Bi-LSTM)	Catastrophic forgetting
[44]	CNN, SVM, LSTM ensemble	CHB-MIT (163, 256Hz)	94.2% sensitivity, 95.8% specificity	Small dataset
[45]	Fuzzy Rules + NN	Bern-Barcelona (750×2, 512Hz)	99% detection, 98% severity	Manual features
[46]	GA + ML classifiers	EEG (14 signals)	ANN outperformed	Manual features
[47]	NB, KNN, MLP, SVM	Bonn EEG (100×5, 173.6Hz)	100% accuracy	Manual features

Despite the extensive body of research conventional machine learning and handcrafted feature-based methods have advanced seizure classification, they often lack adaptability and struggle with evolving EEG patterns. Static models trained on fixed datasets require manual retraining and may not generalize well to new patient data. To overcome these limitations, the proposed work presents a CNN-based CL framework that incrementally updates with new data while retaining the past learned knowledge. This adaptive approach improves prediction accuracy, supports long-term stability, and offers a scalable solution for real-time ES monitoring addressing a key gap in existing research.

3. Methodological Framework and Experimental Design

This section outlines the proposed methodology together with the experimental configuration employed in the study. The overview illustrated (Figure 1) and detail mathematical steps are described in algorithm 1.

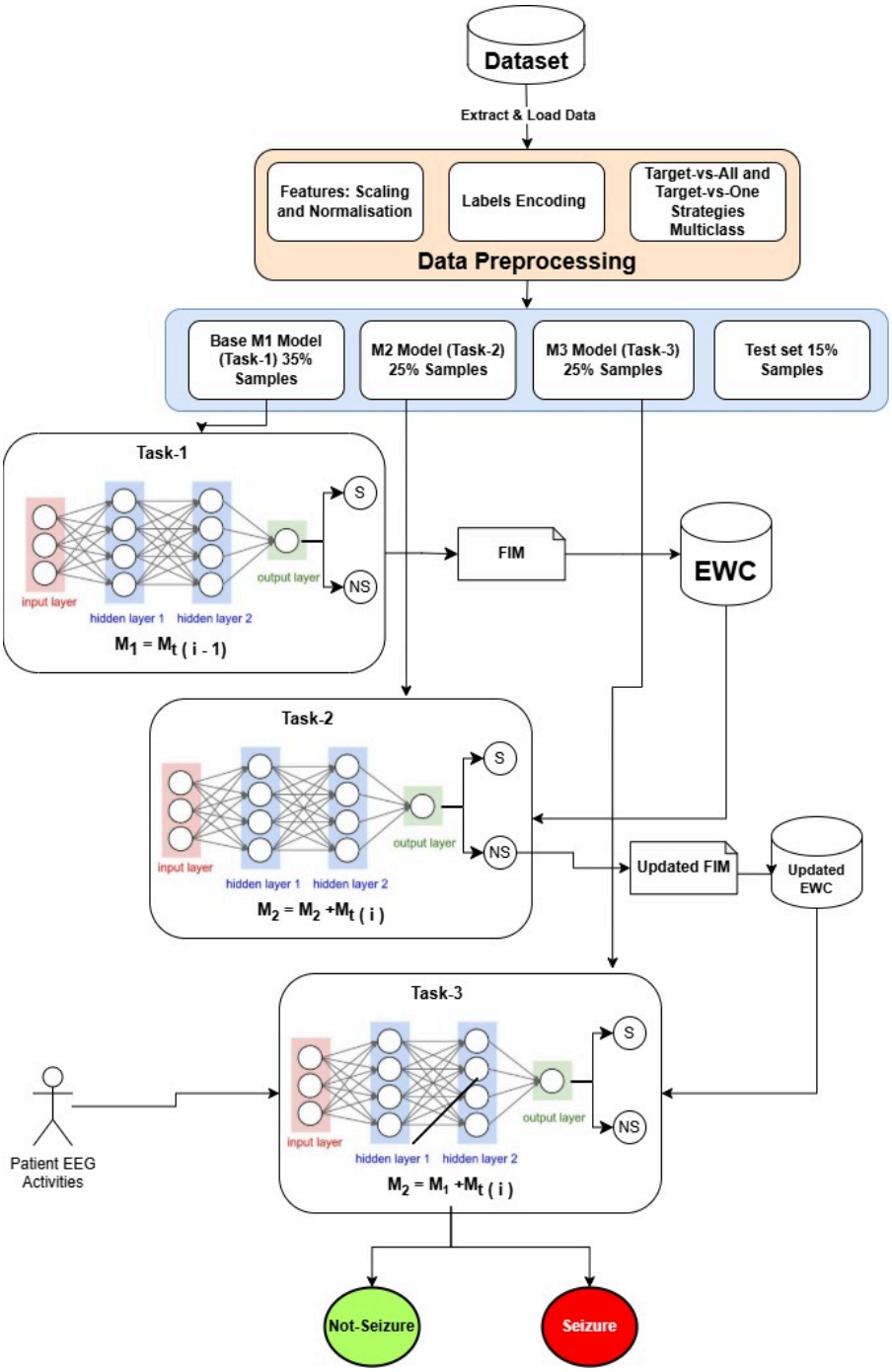


Figure 1. The proposed methodological framework and experimental design

Algorithm 1: *ES Prediction using Continual CNNs*

INPUT: EEG dataset D_0, D_1, D_2 and Deep learning (DL) models architecture

OUPUT Trained DL models M_1, M_2, M_3 produce an accurate seizure prediction while preserving past knowledge

Step 1: # Train base model M_1 using DL on initial task
1.1. Initialize deep learning model M_1 with random weights θ_0
1.2. Train M_1 on dataset D_0 using binary cross-entropy loss.

$$L_0 = -\sum_i y_i \log\left(f_{\theta_0}(x_i)\right) \quad (1)$$

Step 2: 2.1. Extract important parameters using Fisher Information Matrix (FIM)

$$F_i = E\left[(\frac{\partial L}{\partial \theta_i})^2\right] \quad (2)$$

2.2. Save DL model parameters (θ_0) and FIM (F) for future knowledge transfer.

Step 3: # Continual Learning in Model_B (M_2) with EWC
3.1. Initialize Model_B (M_2) with pretrained weights from M_1 (θ_1=θ_0).
3.2. Train M_2 on new EEG dataset D_1 while applying Elastic Weight Consolidation (EWC)

$$L_2 = L_{new} + \lambda \sum_i F_i(\theta_i - \theta_i^*)^2 \quad (3)$$

L_{new} is the new task loss
λ is the regularization strength
$\theta i*$ is the original parameter from M_1
F_i is the Fisher Information score for each parameter

3.3. Use convolutional layers to extract spatial features from EEG data while preserving past knowledge.
3.4. Apply Batch Normalization and Dropout to prevent overfitting.
3.5. Evaluate M_2 on both D_0 and D_1 to ensure knowledge retention.

Step 4: # Continual Learning in Model_C (M_3) with Further Adaptation
4.1. Initialize Model_B (M_2) with pretrained weights from M_1 (θ_2=θ_1).
4.2. Train M_3 on new EEG dataset D_2 while applying EWC using Equation 3.
4.3. Compute new FIM for M_3 to update parameter importance.
4.4. Evaluate M_3 on all previous datasets D_0, D_1, D_2 to verify continual learning effectiveness.

Step 5: Validate that M_1 (trained on initial data), M_2, and M_3 (adapted to new data), achieves the highest performance while retaining past knowledge.

3.1. Subject Dataset's Description

The data used in this research is obtained from a publicly available source provided by Bonn University, and it was initially analysed to identify its distinguishing characteristics [48], [49]. Although the recording system operated within a spectral range of 0.5–85 Hz, the EEG signals were sampled at a frequency of 173.61 Hz. Time-series data captures the frequency spectrum. Table 2 reflects the description of the subject dataset while further detail about multi-class problem into binary class problem [47].

Table 2. Summary of Bonn EEG dataset files

Set	Archive	Individual Files	Size	Samples per File	Description
A	Z.ZIP	Z000.txt – Z100.txt	564 KB	4096	Surface EEG from healthy volunteers with eyes open (non-seizure)
B	O.ZIP	O000.txt – O100.txt	611 KB	4096	Surface EEG from healthy volunteers with closed eyes (non-seizure)
C	N.ZIP	N000.txt – N100.txt	560 KB	4096	Interictal EEG from epileptic patients recorded from the hippocampal formation (non-seizure)
D	F.ZIP	F000.txt – F100.txt	569 KB	4096	Interictal EEG from epileptic patients from within the epileptogenic zone (non-seizure, but pathological)
E	S.ZIP	S000.txt – S100.txt	747 KB	4096	Ictal EEG recordings during active seizures (seizure class)

3.2. Data Preprocessing

The data preprocessing comprises four major steps:

(i) Normalization - All the features of the subject dataset were normalized to a range of [0, 1] to improve model convergence.
(ii) Reshaping - The EEG signals were reshaped into a format compatible with CNN, where each instance was structured as a 2D array.

(iii) The dataset was divided into training, validation, and test sets with balanced class proportions.
(iv) To improve model robustness, augmentation strategies including random cropping and Gaussian noise addition were applied to increase variability within the dataset.

3.3. Continual Learning (CL)

CL aims to enable models to incrementally acquire knowledge across a sequence of tasks without losing previously learned information, a challenge commonly referred to as catastrophic forgetting [50]. The first category, referred to as consolidation-based methods [51], restricts parameter updates that are vital for previously learned tasks, typically by imposing constraints on gradient directions or learning rates. The second group involves dynamic architectures [52], which modify the model's structure on-the-fly to integrate new information while retaining past capabilities. The third type, memory-based techniques [53], stores representative samples from earlier tasks in a buffer and reintroduces them during training to reinforce prior learning during future task adaptation.

3.4. Fisher Information Matrix (FIM)

FIM is an important structure in the proposed study, a key component in EWC. The Fisher Information Matrix (FIM) is a square matrix defined by the number of trainable parameters in the model [54]. It is symmetric, meaning that the (i, j)th element equals the (j, i)th, and positive semi-definite, as all eigenvalues are non-negative. Every entry in the FIM measures the model's output sensitivity with respect to small variations in the respective parameters, with larger values representing higher significance. Because the FIM is task-dependent, it will change based on the data set and training objectives. Following training of a base model on a first task, the FIM is calculated to reflect the value of every parameter. The model is trained on new tasks, the FIM of the base model is incorporated in the EWC loss function to maintain learned knowledge. This mechanism protects important parameters from over-modification, thus mitigating catastrophic forgetting and enabling the model to hold previous knowledge while learning new tasks. It can be mathematically defined as in Equation 4:

$$FIM(\theta) = E\left[\left(\frac{\partial logp(x|\theta)}{\partial \theta}\right)\left(\frac{\partial logp(x|\theta)}{\partial \theta}\right)^{T}\right] \quad (4)$$

Where θ represents the trainable parameters of the neural network, $p(x \mid \theta)$ is the likelihood of the data given the parameters, $\frac{\partial logp(x|\theta)}{\partial \theta}$ is the gradient of the log-likelihood w.r.t the parameters, and E [ ] denotes the expectation over the data distribution.

Since computing full expectation is often infeasible in deep learning, the diagonal approximation of the FIM is commonly used in EWC. It can be expressed as Equation 5:

$$F_{ii} \approx E\left[\left(\frac{\partial logp(y|x,\theta)}{\partial \theta_i}\right)^2\right] \quad (5)$$

Where y is the class-label, and θ_i is the i-th parameter of the model. This diagonal approximation reduces computational complexity by considering only individual parameters contributions rather than full covariance between parameters.

3.5. EWC

EWC was applied to alleviate the problem of catastrophic forgetting during continual learning. The method enables the model to learn new information while retaining previously acquired knowledge by penalizing large updates to key parameters. Both FIN+EWC prevents catastrophic forgetting in neural networks by penalizing modifications to crucial model parameters estimated via the FIM (section 3.3) and regularization term (equation 3). Choosing the right optimizer is important to find a balance between stability and plasticity in sequential learning [54]. In the proposed study, EWC adds a regularization term to the loss function using FIM. It can be mathematically expressed (Equation 6):

$$L_{EWC} = L(\theta) + \frac{\lambda}{2}\sum_i F_i(\theta_i - \theta_i^*)^2 \quad (6)$$

Where the $L(\theta)$ is the standard loss function using cross-entropy, λ is the hyperparameter controlling the strength of the regularization, θ^* represents the optimal parameters from the previous task such as Model B (M_2), and $F_i$is the FIM value for each parameter.

3.6. Mathematical Formulation of the EWC and FIM

In the proposed study, EWC is applied across three models in a series one after another: Namely, (i) the Base model (M_1) is trained on the initial task; (ii) the Model B (M_2) is trained on the new task while retaining knowledge from the previous model M_1. Similarly, (iii) Model C (M_3) is trained in another new task while retraining knowledge from both M_1 and M_2. Table 3 reflects the key hyperparameter setting.

Table 3. The key hyperparameters setting

Property	Value
Learning-rate	0.002
Batch size	64
Epochs	50
Optimizer	Adam
Dropout layers rate	0.4
Activation function	ReLU
Dense layers	128 units

3.6.1. Base Model (M_1)

The base model applies a CNN to extract relevant features for epileptic seizure prediction. Its architecture includes convolutional layers (3×3, 5×5, 7×7) with ReLU activations, max-pooling for spatial reduction, dropout (0.4) for regularization, and two dense layers -one with 128 ReLU units and one sigmoid output unit for binary classification. Training was conducted for 50 epochs using the Adam optimizer and binary cross-entropy loss.

Initially, calculate standard loss function of the trained M_1 on task 1 using Equation 7.

$$L_1(\theta) = -\sum_{(x,y)\epsilon D_1} \log p\ (y\ |x;\ \theta_1) \qquad (7)$$

After training the M_1 model then computed the FIM using Equation 8:

$$F_i^{(1)} = E\left[\left(\frac{\vartheta \log p\ (y\ |x;\theta_1)}{\vartheta \theta_i}\right)^2\right] \qquad (8)$$

Finally, stored the already learned parameters θ_1^*.

3.6.2. Model B (M_2)

The M_2 integrated EWC with the base CNN architecture to enable continual learning. The fine-tuning of the CNN model is designed through transfer learning by freezing the initial convolutional layers and training the dense layers with task-specific data. This approach leveraged pre-trained features while adapting to the nuances of new tasks. The fine-tuning process involved additional optimization to ensure that the features learned by the initial layers remained effective while customizing the dense layers for task-specific predictions. The model was iteratively refined to learn new tasks while retaining important parameters from previous ones using Fisher Information. A regularization penalty was added to the loss function to ensure that these key parameters remained stable throughout the learning of new tasks. M_2 model trained on task 2 with EWC regularization where the standard loss on the new task is calculated through Equation 9 as given:

$$L_2(\theta) = -\sum_{(x,y)\epsilon D_2} \log p\ (y\ |x;\ \theta_2) \qquad (9)$$

And Equation 10 EWC regularization helped in preventing the forgetting of previously learned parameters (e.g., θ_1^*).

$$L_{EWC}^{(2)} = \frac{\lambda}{2}\sum_i F_i^{(1)}(\theta_i - \theta_i^*)^2 \qquad (10)$$

Next, calculated the total loss using Equation 11:

$$L_{total}^{(2)} = L_2(\theta) + L_{EWC}^{(2)} \qquad (11)$$

Finally, the model retained its ability to generalize across new tasks by balancing stability through the EWC framework; for the purpose trained M_2, computed new FIM $F_i^{(2)}$, and stored the new parameters θ_2^*.

This experiment utilizes a second neural network model that is analogous to the initial baseline task and is designed to inherit the knowledge that the Base Model has already acquired. In order to facilitate the efficient advancement of deep learning, this model is specifically engineered to transfer acquired knowledge from a previous task and refine it on a new task. In doing so, it proactively reduces the risk of catastrophic forgetting that may occur when training the model on novel data, such as Task-B data. Analogous to the namely M_1, and M_2 necessitates input data in the form of a series of 178 data points, each representing a distinct feature, in the form of the number of variables (e.g.: 178) and a target variable.

3.6.3. Model C (M_3)

M_3 model trained on task 3 with EWC regularization where the standard loss on the new task is calculated through Equation 12 as given:

$$L_3(\theta) = -\sum_{(x,y)\epsilon D_3} \log p\ (y\ |x;\ \theta_3) \qquad (12)$$

The fine-tuned CNN model was trained on datasets requiring adaptation, utilizing frozen pre-trained layers and updating dense layers. In order to prevent forgetting knowledge of the already gained from M_1 and M_2 through The EWC regularization can be computed using Equation 13:

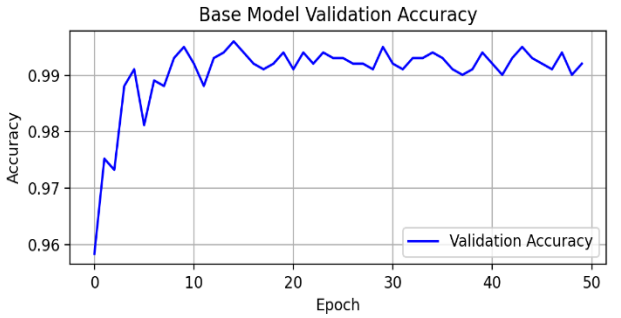
$$L_{EWC}^{(3)} = \frac{\lambda}{2}\sum_i \left[F_i^{(1)}(\theta_i - \theta_1^*)^2 + F_i^{(2)}(\theta_i - \theta_2^*)^2\right] \qquad (13)$$

The Fisher Information Matrix was updated iteratively based on the new task data and calculated the total loss using Equation 14:

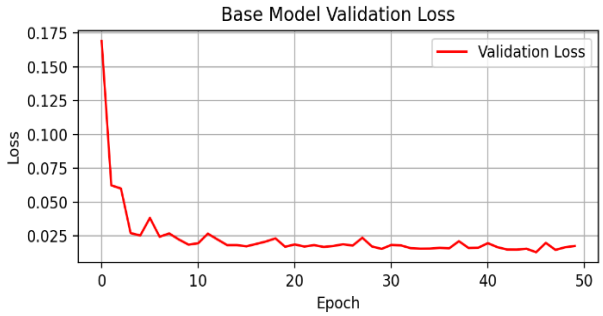
$$L_{total}^{(3)} = L_3(\theta) + L_{EWC}^{(3)} \qquad (14)$$

4. Results and Discussion

This section provides a detailed analysis of the experimental findings, evaluating the performance of the proposed continual learning framework for EEG-based epileptic seizure prediction. The performance of M_1 demonstrates robust performance across both validation and test sets, establishing a strong foundation for continual learning as shown (Figure 2 (a) and (b) for the M_1 accuracy and validation loss on epochs 1-50, respectively).



(a) Accuracy of M_1



(b) Loss of M_1

Figure 2. Performance (accuracy, loss) of M_1 on validation set for 0-50 epochs

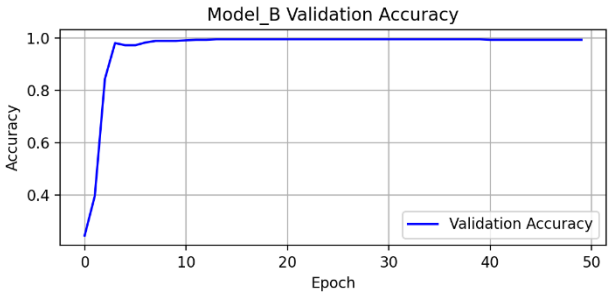
Table 4 reflects the base model performance on the test data and achieved 96.0% accuracy with perfect seizure recall (1.00) and 85.8% precision. The F1-score of 0.923 indicates an excellent balance between sensitivity and positive predictive value. These metrics collectively suggest the model is particularly effective at identifying true seizure events, though with some compromise in specificity as evidenced by the precision score.

Table 4. Performance of M_1 on test set data

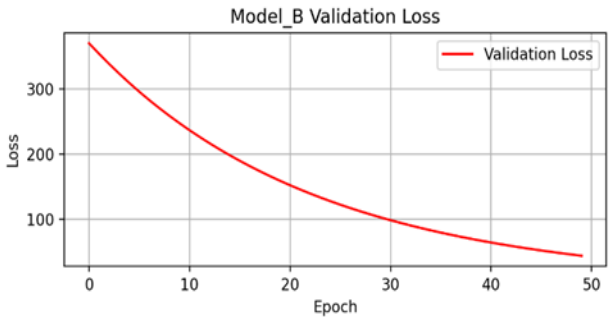
Measure	Value
Precision	0.858
Recall	1.000
F1-Score	0.923
Accuracy	0.960

Next, the experimental findings of M_2, as shown in Figure 3 (a) and (b) for validation accuracy and validation loss, respectively, show a quantifiable improvement in the classification performance of M_2 over that of the M_1, validating the efficacy of the continual learning approach. Table 5 reflects the M_2 performance on the test set. While the M_1 reached 96.0% accuracy (1039 correct non-seizure and 343 correct seizure predictions), M_2 showed better performance with 99.6% accuracy (1096 correct non-seizure and 337 correct seizure classifications).

The absolute 3.6% enhancement attests to effective knowledge fusion during the implementation process of the proposed approach.



(a) Accuracy of M_2



(b) Loss of M_2

Figure 3. Performance (accuracy, loss) of M_2 on validation set for 0-50 epochs

M_2 demonstrates two important improvements as shown in Table 5. First, it entirely eliminated false positive predictions (from 57 to 0), resulting in perfect specificity for non-seizure detection. Second, while retaining 98.3% recall for seizure events (337/343 correct identifications), it added only six false negatives. This is an important clinical trade-off, where M_1 sacrifices less detection sensitivity for fewer unnecessary alarms. Precision-recall metrics imply M_1 might be specifically apt for applications with high false-alarm costs associated with operations.

Table 5. Performance of M_2 on test set data

Measure	Value
Precision	1.000
Recall	0.983
F1-Score	0.991
Accuracy	0.996

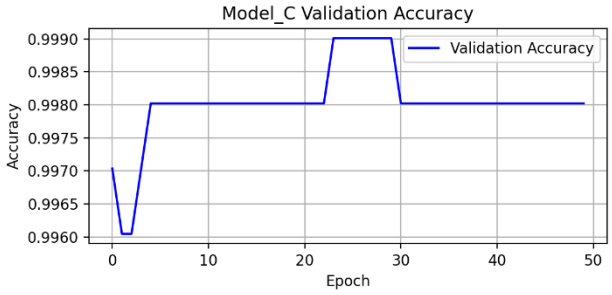
Table 6 analysis provides empirical support for adopting continual learning in clinical EEG applications.

Table 6. Comparative advantages of model M_2 over M_1

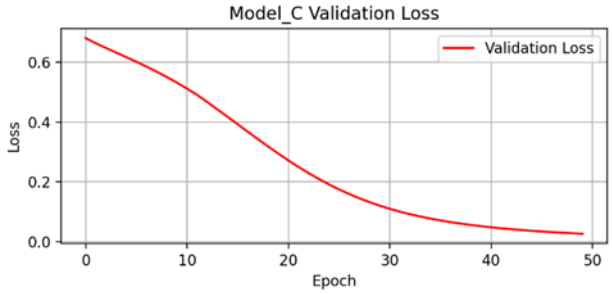
Aspect	Traditional (M_1)	Continual Learning (M_2)
Computational Cost	High ($O(n^2)$)	Efficient ($O(n)$)
Data Dependency	Full dataset required	Incremental updates
Adaptation Speed	Slow	Rapid
Knowledge Retention	None	Preserved

The validation accuracy plot in Figure 4(a) reveals several critical aspects of M_3 learning behaviour. The curve demonstrates remarkable stability, achieving 99.9% accuracy within 50 epochs and maintaining this performance consistently through subsequent training. This rapid convergence suggests that the FIM and EWC approach effectively preserves knowledge from previous tasks while efficiently adapting to new information. Notably, the absence of significant fluctuations in the accuracy trajectory indicates robust protection against catastrophic forgetting - a key challenge in continual learning systems.

Examination of the validation loss curve Figure 4(b) provides complementary insights into the model's learning dynamics. The loss decreases smoothly from 0.6 to approximately 0.2, showing no signs of divergence or instability.



(a) Accuracy of M_3



(b) Loss of M_3

Figure 4. Performance (accuracy, loss) of M_3 on validation set for 0-50 epochs

The higher initial loss compared to earlier models may reflect the increased complexity of the accumulated tasks, while the successful convergence demonstrates the effectiveness of the EWC constraints in managing this complexity.

As a result, the models were able to adapt new information while preserving prior task performance, demonstrating the efficacy of automatic knowledge transfer mechanisms in continual learning setups reported in the RQ2.

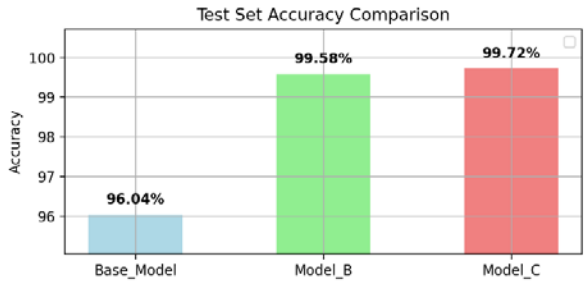
Table 7 describes the most compelling performance of M_3 clinical viability. With only 1 false positive (1095 correct non-seizure predictions) and 3 false negatives (340 correct seizure identifications), the model achieves near-perfect classification performance.

Table 7. Performance of M_3 on test set data

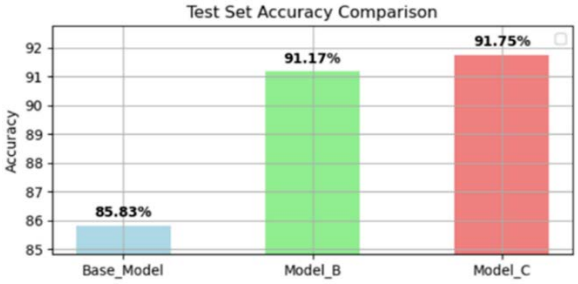
Measure	Value
Precision:	0.997
Recall:	0.991
F1-Score:	0.994
Accuracy:	0.997

4.1. Comparative Performance Analysis in CL Context

The experimental findings provide compelling evidence of the effectiveness of the proposed CL framework for EEG-based ES detection. Three sequential models: M_1, M_2, and M_3 were developed using CNN and RNN frameworks, and their performance was assessed based on key metrics: precision, recall, f1-Score, and accuracy as shown in Figure 5.



(a) Performance of CNN in CL context for ES



(b) Performance of RNN in CL context for ES

Figure 5. Comparison of the M_1, M_2, and M_3 on test set data

Both M_2 and M_3 implement EWC with FIM, demonstrating how progressive optimization of the same core algorithm yields enhanced performance. The evolutionary improvement becomes evident when examining validation set trajectory of both models as described in Table 8.

Table 8. Performance comparison: model B vs Model C

Metric	Model B	Model C	Δ (Change)
Peak Accuracy	0.996	0.997	+0.3%
Final Loss	0.15	0.20	+33.3%
Training Stability	Moderate	Excellent	—

Among the evaluated models as described in Table 8, M_3 (CNN) demonstrated the highest overall performance. It achieved an accuracy of 0.997, correctly classifying seizure events 99.7% of the time. M_3 attained an almost perfect F1-score of 0.994, indicating an excellent balance between precision (0.997) and recall (0.991). This indicates that M_3 not only made highly accurate seizure predictions but also effectively detected most true seizure events with minimal false negatives. Furthermore, the progressive improvement across models - M_3 outperforming M_2, which in turn surpassed the Base Model, highlights the effectiveness of continual learning in retaining prior knowledge while adapting to new tasks. These experimental findings strongly affirm this RQ1. Through a continual learning architecture employing CNN, the system demonstrated progressive improvements in predictive performance across models.

While RNNs produced competitive performance, as shown in Table 9, CNN outperformed them in all metrics of performance for each model. For instance, M_3 (RNN) recorded an accuracy of 0.917 and a precision of 0.863 - far lower than the CNNs 0.997 accuracy and 0.997 precision. These results show that CNN perform better at identifying spatial EEG patterns within the suggested continual learning framework.

Table 9. Performance evaluation of proposed models on unseen data

Metric	CNN (M_1)	RNN (M_1)	CNN (M_2)	RNN (M_2)	CNN (M_3)	RNN (M_3)
Precision	0.858	0.911	1.000	0.909	**0.997**	0.863
Recall	1.000	0.986	0.983	0.980	0.991	**1.000**
F1-Score	0.920	0.950	0.991	0.940	**0.994**	0.927
Accuracy	0.960	0.858	**0.994**	0.917	**0.997**	0.917

The findings of this study affirm research question (RQ3) that the proposed continual learning framework successfully mitigates catastrophic forgetting during sequential task learning, as new EEG-based seizure prediction tasks were introduced in M_2 and M_3, the framework retained performance on earlier tasks without significant degradation.

This was achieved through the incorporation of EWC, which preserved important parameters identified by the FIM. The gradual and statistically significant improvement in performance culminating in M_3 superior accuracy (0.997) and f1-score (0.994), demonstrates that prior knowledge was maintained while adapting to new data. These findings validate the capability of framework to support lifelong learning in dynamic EEG environments, ensuring that previously acquired knowledge is not overwritten, which is a key challenge in deep neural networks. Further analysis of Table 10 reveals that the models generalize exceptionally well to unseen data.

Table 10. Proposed model generalizes performance

Metric	Model B	Model C	Improvement
Precision:	**1.000**	0.997	−0.3%
Recall:	0.983	**0.991**	**+0.8%**
F1-Score:	0.991	**0.994**	**+0.3%**

4.2. Statistical Significance Analysis

To ensure that the performance improvements of the proposed models were reliable and consistent, the Wilcoxon signed-rank test was applied to evaluate the significance of differences in both accuracy and F1-score measures. Statistical significance was produced for all the comparisons between the models ($p < 0.05$) as obtained by analysis, establishing significant evidence supporting the fact that the continual learning mechanism adds meaningfully to enhancing seizure prediction performance by utilizing EEG data. The Wilcoxon signed-rank test comparing performance across continual learning models ($M_1 \rightarrow M_2 \rightarrow M_3$) targeting the metrics F1-score and accuracy. Table 11 reflects the Wilcoxon signed-rank (WSR) test results.

Table 11. WSR test results (CNN architectures)

Metric	Comparison	p-value	Significance
F1-Score	Base vs M_2	0.0019	Statistically significant
F1-Score	M_2 vs M_3	0.0019	Statistically significant
F1-Score	Base vs M_3	0.0019	Statistically significant
Accuracy	Base vs M_2	0.0019	Statistically significant
Accuracy	M2 vs M_3	0.0183	Statistically significant
Accuracy	Base vs M_3	0.0019	Statistically significant

4.3. Threats to Validity Analysis

While the proposed approach demonstrates strong performance in EEG-based ES prediction, several threats to validity required careful consideration to contextualize these findings which are the following.

- Models may show performance gains due to optimized EWC λ values rather than actual continual learning benefits.
- Improvements from Base to Model C could result from a sequence where later tasks are naturally easier.
- Overlap in patient features or time-linked attributes between training and validation sets can lead to inflated accuracy.
- A binary outcome overlooks subtle variations between seizure states, which are important in medical decision-making.
- A small number of seizure instances (343) could lead to unstable performance across validation splits.

5. Conclusion

This study investigated that continual learning using CNN-based deep learning models significantly improves the prediction of ES from EEG signals. By applying a sequential learning strategy, the system adapts to new data without forgetting prior knowledge, an essential requirement for ES prediction. Among the tested architectures, M_3 achieved the highest accuracy among all tested architectures - 99.7% accuracy, 99.7% precision, 99.1% recall, and an F1-score of 99.4% - clearly outperforming conventional ML models such as SVM, RF, and GB. The framework's ability to preserve previous learning while incorporating new EEG patterns highlights its robustness and suitability for evolving clinical environments. Overall, the integration of continual learning, CNN architectures, and knowledge distillation techniques presents a compelling case for the next generation of personalized, AI-assisted healthcare solutions.

Future studies should investigate the integration of the proposed continual learning framework with Internet of Things (IoT) systems to enable real-time processing and deployment on-device seizure prediction. Such integration would support continuous, autonomous monitoring in real-world settings, particularly benefiting patients in remote areas with limited access to healthcare providers.

Additionally, further investigations could examine the framework's adaptability across diverse EEG datasets and its performance in multi-patient, heterogeneous environments, aiming to enhance generalization and clinical applicability.

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