

Continual Learning for Enhancing Personal Assistants Using Machine Learning

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ABSTRACT

The ability to learn and adapt continuously is a hallmark of human intelligence, yet artificial intelligence (AI) systems often struggle with catastrophic forgetting, where new learning disrupts prior knowledge. This limitation is particularly critical for personal AI assistants, which must refine user preferences, adapt to new commands, and retain past interactions in order to deliver context-aware and personalized responses. To address this, we apply the Elastic Weight Consolidation (EWC) method to enhance continual learning in personal assistants. By selectively constraining important network parameters, EWC mitigates forgetting while enabling the integration of new information. Using the 16 Personality Types dataset from Kaggle, we compare EWC against established incremental and machine learning approaches, including BLSTM, LwF, iCARL, hybrid neural circuits, and gradient boosting models. Experimental results show that EWC achieves 98.4% test accuracy and

98.3 validation accuracy, outperforming competing methods, and significantly improving the scalability and adaptability of AI assistants. These findings highlight the potential of EWC as a practical solution for building more intelligent, user-centered personal assistants.

1- Introduction:

Learning in humans occurs progressively, where new experiences build upon prior knowledge. For example, a child's understanding of animals develops over time as they encounter new species. This gradual accumulation of knowledge contrasts with most machine learning (ML) systems, which are often restricted to learning from a fixed dataset in a single phase. These models tend to be specialized for specific tasks and struggle to adapt when new data becomes available. In recent years, artificial intelligence (AI) has become deeply integrated into everyday technologies, particularly through advances such as the generative pre-trained transformer (GPT) architecture (OpenAI et al., 2023).

Also, despite these advancements, many AI systems are unable to update their knowledge incrementally without compromising previous learning. This issue, known as catastrophic forgetting, poses a challenge in applications that require adaptability, such as real-time data processing or personal assistant systems. To address this limitation, researchers have proposed various continual learning techniques. These approaches aim to allow models to learn sequentially from new tasks while preserving knowledge from earlier ones. However, many methods still depend on explicitly identifying tasks or storing large amounts of past data, which may not be practical in real-world scenarios.

With developing lightweight, adaptive models that can maintain performance across tasks remains an active area of research. Current methods, despite notable advancements, continue to encounter challenges such as the necessity for explicit task identification during inference and the growing

memory requirements for storing samples or features from prior tasks or classes. The identified limitations substantially impede the effective implementation of continual learning in dynamic, real-world contexts. Incremental learning, in contrast, is a dynamic model learning technique that enables models to continuously acquire new knowledge and facilitate knowledge accumulation.

The incremental learning must address catastrophic forgetting, specifically the ability to acquire new knowledge while retaining previously learned information (Käding et al., 2016). The performance of conventional neural network models declines significantly on previously learned tasks when trained on sequential tasks with samples that become progressively available over time (Kamra, Gupta and Liu, 2017). The (Doyle, Noe and Michaels, 2000) introduced the concept of incremental learning, and in 2001, (Polikar et al., 2001) formalized its definition, which gained widespread acceptance. In 2017, the (Kirkpatrick et al., 2017) introduced the EWC method, facilitating continuous learning across multiple tasks for deep neural network models. Modifying the learning rule enables the model to acquire new tasks while retaining knowledge of previous tasks.

Also in the same year, (Li and Hoiem, 2018) introduced an alternative method known as learning without forgetting (LwF), which can be regarded as a synthesis of Distillation Networks and fine-tuning (French, 1999). The iCaRL method, as proposed by (Rebuffi et al., 2017), enhances the LwF method and demonstrates superiority over many existing incremental learning approaches. The significance of smartphones and smart home devices in daily life has grown. This trend is driven by virtual personal assistants (VPAs) that utilize artificial intelligence to streamline routine tasks (Madani et al., 2018). Virtual personal assistants such as Apple's Siri, Amazon's Alexa, and Google Assistant are advanced AI systems capable of interpreting and responding to natural language commands, controlling smart home devices, delivering weather information, sending messages, making phone calls, and performing various other tasks.

The Virtual Personal Assistants (VPAs) can adapt based on user interactions, modify their responses according to user interests, and anticipate

user needs through the application of artificial intelligence. Natural language processing (NLP) and machine learning enable virtual personal assistants (VPAs) to understand spoken or written language, interpret it, and generate appropriate responses (Zerouaoui and Idri, 2021). Virtual Personal Assistants (VPAs) can efficiently organize notes, meetings, and to-do lists, thereby alleviating users from monotonous administrative tasks also recommendations for movies, music, and books may be provided based on individual preferences (Praveena et al., 2024).

The Internet of Things is centered on AI-run Virtual Personal Assistants. Their expertise encompasses lighting, heating systems, and security systems (Zaher and Eldakhly, 2023). Users can control their home through voice commands. Houses increase in efficiency and functionality. AI-powered virtual personal assistants may enhance accessibility. These systems offer voice-activated controls, enhancing the usability of digital devices for individuals with impairments. This enhances the lives of individuals with impairments and fosters digital inclusion, enabling universal access to technology (Mohamed, 2020). AI-operated virtual personal assistants exhibit limitations. They may misinterpret instructions, encounter difficulties comprehending complex requests, and face challenges with accents or languages (Kashyap and Kashyap, 2022).

Although several continual learning approaches such as Learning without Forgetting (LwF), iCARL, and BLSTM have been studied extensively, their application to personal assistant systems remains limited. Most existing works evaluate continual learning in generic classification or computer vision benchmarks, but they rarely address the specific requirements of adaptive, user-facing assistants. Moreover, the potential of Elastic Weight Consolidation (EWC), a promising technique for mitigating catastrophic forgetting, has not been comprehensively explored in this domain.

To address these gaps, this study makes the following contributions:

- Application of EWC to personal assistants: We propose integrating EWC into the continual learning framework for personal AI assistants, ensuring knowledge retention while enabling adaptation to new tasks.

- **Comprehensive evaluation:** Using the 16 Personality Types dataset, we conduct extensive experiments comparing EWC against leading incremental and machine learning methods, including BLSTM, LwF, iCaRL, hybrid neural networks, and gradient boosting models.
- **Demonstrated improvements:** Our findings show that EWC achieves 98.4% accuracy, outperforming existing approaches and significantly enhancing the adaptability and scalability of AI assistants.
- **Practical implications:** We highlight how EWC-driven continual learning can advance the development of intelligent, user-centered assistants capable of evolving alongside users.

This paper is organized as follows and shown in the figure-1: Section 1 presents the introduction, while Section 2 reviews related work, summarizing the methods and findings of previous research. Section 3 describes the methodology and implementation details, and Section 4 outlines the data preparation and experimental procedures. Section 5 reports the experimental

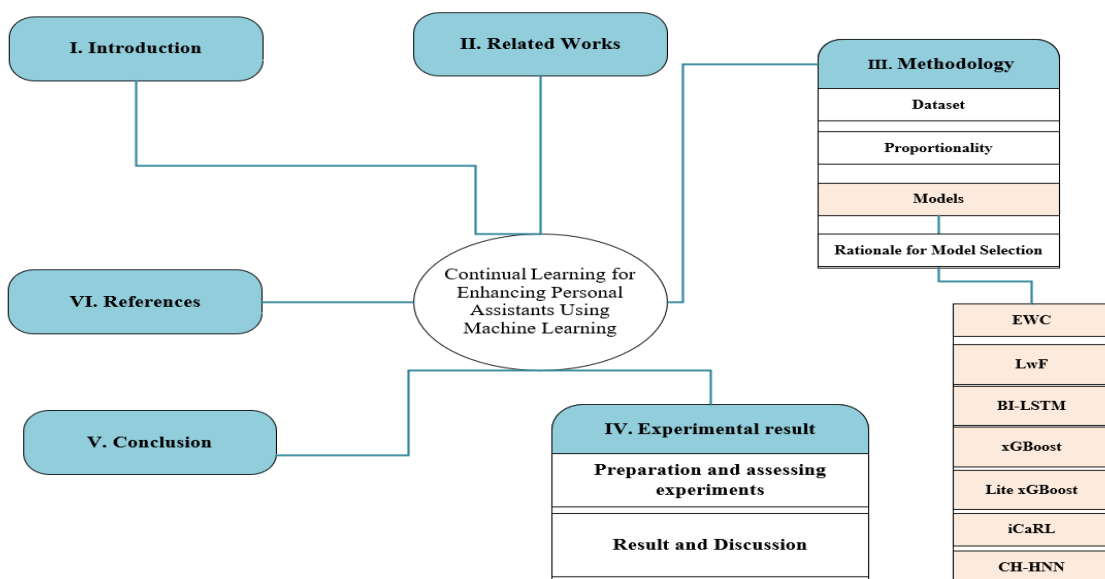


Figure 1:Diagrammatic of the subjects discussed in this paper

results and provides a comparative analysis with existing approaches. Finally, Section 6 concludes the paper by summarizing the key findings.

2- Related Works:

Machine learning (ML) methods have been widely adopted across various domains, including the development of virtual personal assistants (VPAs) that support users in everyday tasks. As these systems become more integrated into daily life, there is growing interest in enabling them to learn continuously without forgetting previously acquired information. This challenge known as *catastrophic forgetting* is a central issue in incremental and continual learning research.

A significant challenge in incremental learning is the prevention of catastrophic forgetting (Kashyap and Kashyap, 2022). For instance, AlphaGo (Silver et al., 2017), which was trained specifically for the game of Go, possesses no knowledge or capability to play chess. If AlphaGo is trained to learn chess, it is likely to lose its knowledge of Go, which is undesirable. The prediction of personality traits utilizing datasets from Facebook and Twitter is a well-established area of research. The author (Belouadah, Popescu and Kanellos, 2021) present a thorough examination of fixed-size models in the realm of picture categorization.

Their research concentrates on class incremental learning, a framework wherein the model lacks awareness of the specific task associated with an input during evaluation, while each task introduces novel classes. To address this, models generally generate more output neurons for each new type. The authors illustrate that a simple fine-tuning technique utilizing a memory of previous assignments, referred to as a Replay Buffer, can attain competitive accuracy relative to more intricate systems. The paper (van de Ven and Tolias, 2019) presents a unique framework termed domain-incremental learning, which is examined within the realm of computer vision.

In this configuration, each subsequent task incorporates inputs from novel classes associated with prior ones. Research conducted by (Yang et al., 2019) utilized an open-source Facebook personality dataset known as

MyPersonality, comprising 250 users along with their status data and traits, which correspond to the Big Five personality model. Simultaneously, an alternative investigation utilizing a Twitter dataset in Bahasa, conducted by (Jeremy, Prasetyo and Suhartono, 2019), employed a distinct technique for constructing the personality prediction model. Recent advancements in technology have seen the widespread application of deep learning to enhance the accuracy of personality prediction.

The experiment conducted by (Cui and Qi, 2017) utilized a different dataset, specifically Personality Café, which highlights variations in personality modelling through the Myers-Briggs Type Indicator (MBTI) approach. In a study(Wan et al., 2014), Naïve Bayes and Support Vector Machine (SVM) techniques were employed to estimate an individual's personality type based on their word choice. The author (Komisin and Guinn, 2012) employed correlation analysis and principal component analysis to accurately predict individuals' Big Five personality types based on their posts on the Chinese social network inWeibo.

The author (Ramakrishna et al., 2023) examines how intelligent personal assistants (IPAs) can transform our methods of learning and engaging with information. They emphasize the sophisticated computing technology and natural language processing (NLP) skills of IPAs that facilitate individualized and collaborative learning experiences. The authors present a persuasive argument for the implementation of IPAs in education and training, highlighting their capacity to revolutionize our methods of acquiring and engaging with knowledge.

Also, the author (Gunasekaran et al., 2023) have emphasized the importance of language and speech as communication tools, as well as the critical role of speech technology in facilitating machine comprehension of human speech. Their research concentrates on the identification of speech, its fundamental model, applications, and methodologies for the speech recognition system. The research underscores the increasing significance of voice recognition technology and its varied uses across multiple domains.

The author(Devarajan et al., 2022) Conducted research on speech analysis, utilizing a pattern recognition technique to ascertain if the voice input constitutes voiced speech, unvoiced speech, or silence based on signal dimensions. Nevertheless, the system possesses constraints, including the necessity for the algorithm to be trained on the designated set of dimensions and the requirement for consistent recording settings. Table-1 shown summary of comparison other works with our work.

Table 1: COMPARISON, RESULTS AND RELATED WORK SUMMARY

Ref.	Purpose/Summary	Dataset Used	Proposed/Used Model(s)	compared with models and accuracy	Year	Accuracy
(Jin, Liang and Yang, 2020)	Prevent the catastrophic forgetting that usually occurs in neural networks due to continuous learning.	sonar image	double consolidation class-incremental learning (DCCIL)	LwF 34.21% iCaRL 85.41%	2020	87.44%
(Dutta, Athilakshmi and Amulya, 2023)	built a personality characteristic extraction model that learns feature representations and cluster assignments collectively.	Kaggle personality dataset	Semi-Supervised Deep Embedded Clustering (Semi-supervised DEC)	RNN 47.19% LSTM 90.5% GRU 95%	2023	95.90%
(Anusha et al., 2024)	To build deep learning-based ensemble model and trained from scratch for classification and machine learning-	Kaggle personality dataset	Long short-term Memory (LSTM) combined with Gated Recurrent Unit (GRU)	CNN 42.8% RNN 40.1% KNN 38.9% SVM 75.8% Naïve Bayes 58.6%	2024	97.80%

Ref.	Purpose/Summary	Dataset Used	Proposed/Used Model(s)	compared with models and accuracy	Year	Accuracy
	based classifier models for better performance					
(Doğan et al., 2024)	To demonstrates a neural network-based identification of human presence using raw data obtained directly from the UWB radar	radar dataSet	convolutional neural network (CNN)	N/A	2024	98.90%
(Praphulla et al., 2023)	to predict the personality type of a user related to their posts and to explore the usability of the test in the study and classification of human behavior using Learning models	Kaggle personality dataset	XGBoost	LR 77.7% SVM 77.04%	2020	75.15%
(Xiao, 2023)	The purpose of this study is to investigate the possibility of using machine learning in psychology, meanwhile	Kaggle personality dataset	Random Forest and Logistic Regression	N/A	2023	71.60%

Ref.	Purpose/Summary	Dataset Used	Proposed/Used Model(s)	compared with models and accuracy	Year	Accuracy
	enlarging the ways of predicting one's personality.					
(Kumar R, Mohan G and Sai, 2023)	the method is recalls previous tasks by slowing learning on the weights that are essential for them selectively.	Kaggle personality dataset	logistic regressions	Random Forest 62.8% Naïve Bayes 67.8% SVM 69.3%	2024	69.80%
(Yang, Lau and Abbasi, 2023)	build the DeepPerson, a text-based personality identification design artifact that blends these two areas by leveraging insights from the relevant psycholinguistic paradigms in combination with advanced deep learning methods	PANDORA	DeepPerson	CNN 65.2% KNN 63.0% SVM 61.7% XGBoost 62.9%	2022	69.9%
(Shi et al., 2025)	mitigating catastrophic forgetting during task-incremental as well as class-	CIFAR-100	corticohippocampal circuits-based hybrid neural network (CH-HNN)	iCaRL 63.0% ANN 70.41% XGBoost 47.23%	2025	82.0%

Ref.	Purpose/Summary	Dataset Used	Proposed/Used Model(s)	compared with models and accuracy	Year	Accuracy
	incremental training scenarios.					
Our	mitigate catastrophic forgetting that typically occurs in neural networks while continually learning and expanding personal assistants.	Kaggle personality dataset	EWC	BI-LSTM 98% xGBoost 93.1% xGBoostLite 86.6% iCaRL 95% LwF 95.3% CH-HNN 91.6	2025	98.4

3- Methodology:

The proposed model, illustrated in Figure 2, focuses on evaluating the effectiveness of Elastic Weight Consolidation (EWC) within a continual learning framework, applied to a personality classification task. The experimental setup involved training multiple models on the 16 Personality Types dataset from Kaggle, which contains user-generated text labeled according to the Myers-Briggs Type Indicator (MBTI). The dataset was preprocessed, cleaned, and split into training (80%), validation(10%) and testing (10%) subsets. To ensure fair comparisons, identical data splits were used for all models.

The experiments were implemented in PyTorch, enabling flexible model design and efficient training. Seven models were compared: Bidirectional Long Short-Term Memory (BLSTM), Learning without Forgetting (LwF), Incremental Classifier and Representation Learning (iCaRL), Corticohippocampal circuits-based Hybrid Neural Network (CH-HNN), Extreme Gradient Boosting (XGBoost), Lite XGBoost, and the proposed EWC-based model.

All models were trained for 50 epochs using a batch size of 32, with the Adam optimizer set at a learning rate of 0.0002. The cross-entropy loss function was used during training. Key metrics, including training loss, validation loss, and accuracy, were tracked throughout the training phase to monitor convergence and model performance.

After training, models were evaluated on the test set using multiple metrics: accuracy, precision, recall, F1-score, and confusion matrix analysis to assess both overall and class-specific performance. The results indicated that the proposed EWC model achieved the highest overall accuracy while successfully preserving knowledge from previously learned tasks, demonstrating its effectiveness for continual learning in personal assistants.

The experiments were conducted on a CPU-equipped workstation (intel Core I7 Gen10) with 16 GB of RAM. EWC introduces additional computation due to the calculation of parameter importance, but this overhead is moderate and does not significantly increase training time. Its selective parameter regularization allows the model to scale to larger datasets and additional tasks without storing all previous data, making it practical for real-world personal assistant applications that require continual adaptation.

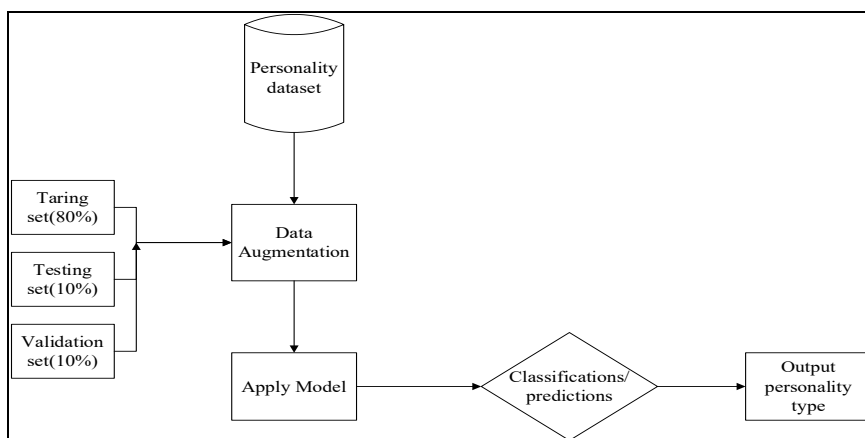


Figure 2: Architecture of the proposed model

3.1 - Dataset:

The research drew its data from the "16 personality test" dataset accessible on Kaggle. Each observation in the dataset presents the textual responses from authors together with their Myers-Briggs type classification through four unique letters. A graphical depiction in Figure 3 shows the sixteen

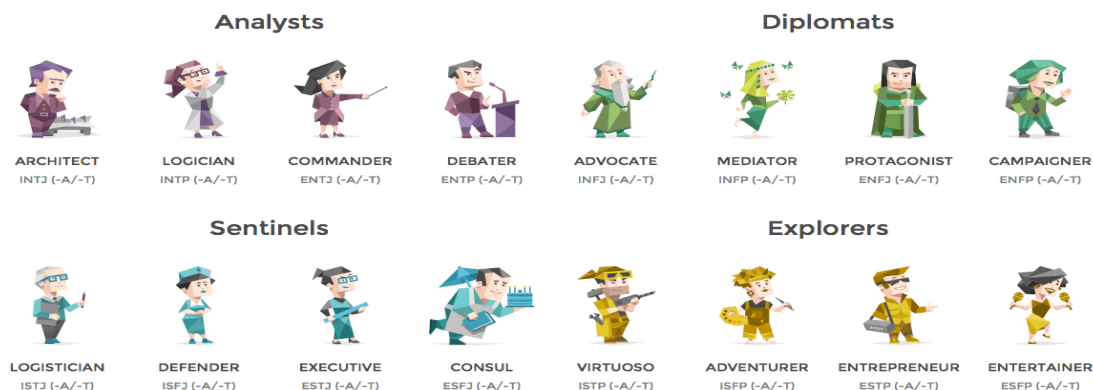


Figure 3: 16 personality type

MBTI personality types and description in table 2.

Table 2: 16P Personality Dataset Description

Feature	Description
Dataset name	16P Personality Dataset
Source	Kaggle Public dataset (16 personalities questionnaire responses)
Number of samples	60,000
Number of classes/labels	16 personality types (MBTI categories)
Class distribution	Stratified to ensure balanced representation across the 16 classes
Input features	Questionnaire responses
Feature type	Numerical (scaled responses)
Train/Validation/Test split	80% Training, 10% Validation, 10% Testing
Preprocessing	StandardScaler applied to features; LabelEncoder applied to class labels

3.2 - Proportionality:

The value counts() function defines frequency for each personality type and the data preview is illustrated through Matplotlib and Seaborn which serve as Python plotting libraries. A visualization of MBTI personality type count exists in Figure 4 and meaning of the MBTI in the figure-5.

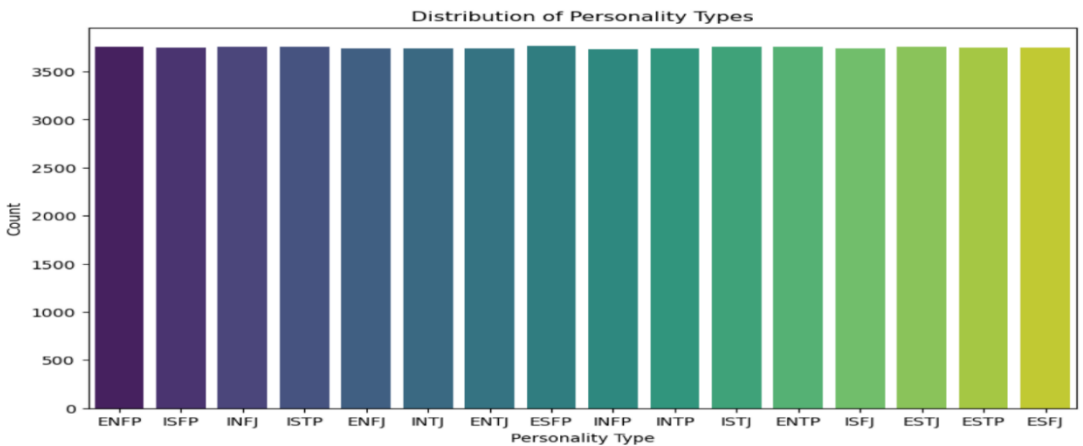


Figure 4: Distribution of the dataset

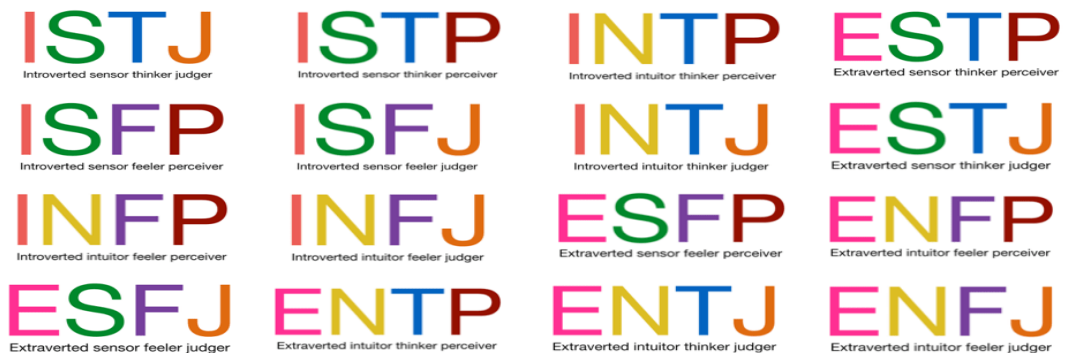


Figure 5: MBTI personality meaning

3.3 - Models:

3.3.1 - Elastic Weight Consolidation (EWC): Bayesian Regularization serves as a continual learning approach which reduces forgetting events through its ability to embed model uncertainty into Bayesian formulations. The method protects saved knowledge from prior tasks through Bayesian framework implementation while enabling adaptation to later tasks integrates parameter uncertainty within a Bayesian framework (MacKay, 1996). The procedure of sequential Bayesian estimation enables the derivation of new task prior T from the old posterior distributions of tasks $t < T$ thus providing an approach to distribute previous task significance weights. The actual posterior distribution remains unattainable so the approach uses Laplace approximation to create an approximation while FIM controls the precision level. When close to a minimum this Fisher Information Matrix (FIM) equates to the positive semi-definite second-order loss function (Pascanu and Bengio, 2013), derivative as practitioners commonly calculate empirical FIM to avoid additional backward passes (Martens, 2020). Importance weight measurement occurs following the completion of task T . A single penalty allowance could solve the problem because it initially demanded one FIM per work. The FIM obtains its estimates from optimized tasks because gradient values decrease which leads to minimal regularization effects. The precision of posterior distributions depends on the Fisher Information Matrix as the fundamental component in this approximation. The FIM measures how sensitive a model's parameters become when loss function changes serve as an indicator for parameter importance. The empirical version of Fisher Information Matrix serves as a practical approximation alternative since it eliminates the need for performing extra backward propagation (Huszár, 2018).

Bayesian Regularization reduces forgetting by assigning an importance weight to each model parameter based on how critical it was for previous tasks. These weights are derived from the Fisher Information Matrix (FIM), which measures how sensitive each parameter is to changes in the loss

function. During learning of a new task, parameters with higher importance weights are updated more conservatively, preserving prior knowledge while still allowing adaptation. Using the empirical FIM provides a practical and efficient approximation, eliminating the need for additional backward passes. This approach ensures that the model can continually learn new tasks without catastrophic forgetting, making it suitable for applications like personal assistants.

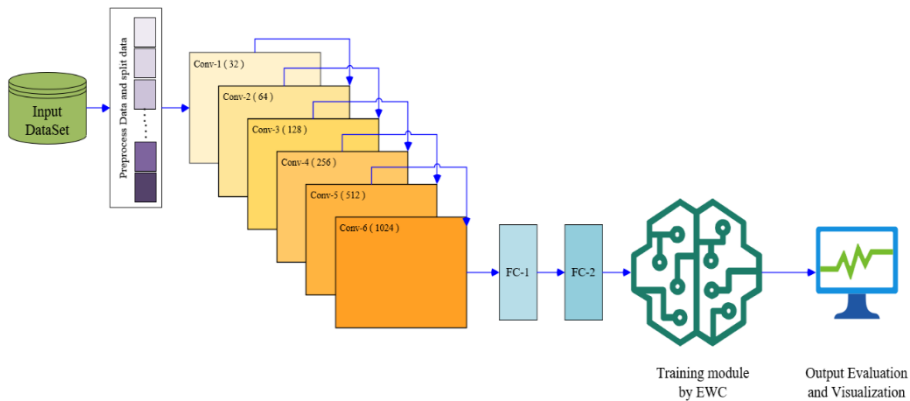


Figure 6: EWC module aarchitecture

3.3.2 – Learning without Forgetting (LwF): retains knowledge of prior tasks through the process of knowledge distillation. Prior to training on the new task, the network's outputs for the new task data are documented and then utilized during training to extract information from the previous task. The efficacy of this strategy is significantly contingent upon the new task data and its relevance to preceding tasks. Distribution shifts concerning previously learned tasks may lead to a progressive accumulation of errors in those tasks as increasingly dissimilar activities are introduced (Ramapuram, Gregorova and Kalousis, 2020). This accumulation of errors is equally relevant in a class-incremental framework, as demonstrated in (Shmelkov,

Schmid and Alahari, 2017). A further disadvantage lies in the extra burden of transmitting all new task data and storing the outcomes.

3.3.3 - BI-LSTM: The main constraint of LSTM cells restricts their ability to

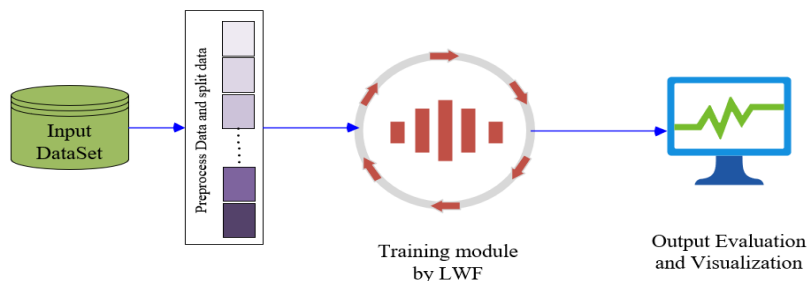


Figure 7: Learning without forgetting architecture

handle information from the future time steps. A new method introduced the utilization of bidirectional recurrent neural networks consisting of two LSTM hidden layers that generated matching outputs but through inverse processing paths. The system includes previous data input as well as forthcoming information in its output component. In Bi-LSTM, an input sequence $X = (X_1, X_2, \dots, X_n)$ happens in forward and backward sequences within this method. The end output derives from the combination of both parts working together (Yu et al., 2019) as shown in the figure 8.

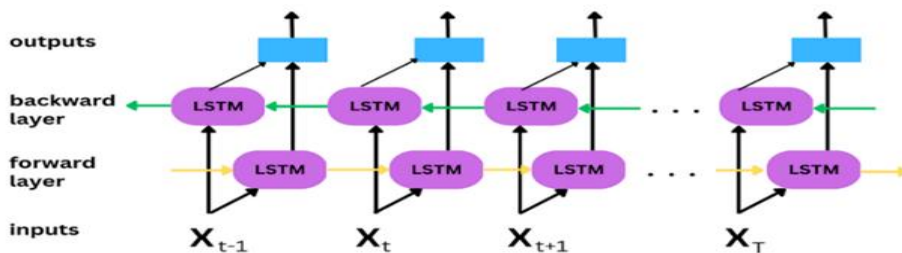


Figure 8: BI-LSTM module architecture

3.3.4 – XGBoost: XGBoost means a machine learning family that relies on decision trees for implementation through gradient boosting as its core algorithm. Researchers at the University of Washington created XGBoost algorithm during a research project. The publication of XGBoost appeared in 2016 through the work of Tianqi Chen and Carlos Guestrin. The platform establishes a remarkable reputation through both Kaggle competition victories as well as field-leading commercial complex applications. An extensive number of data scientists actively support the open-source XGBoost project through GitHub commits (Niu et al., 2019). XGBoost generates efficient gradient tree boosting decisions through its production of sequential decision trees. Relevant computations with XGBoost operate

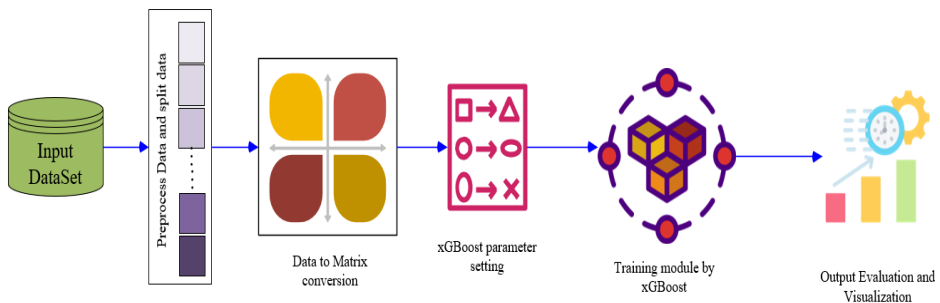


Figure 9: xGBoost module architecture.

at maximum efficiency in any computer environment. XGBoost serves as an algorithm which both creates new features and does label classification tasks. XGBoost algorithm currently maintains widespread popularity because it generates remarkable results for tabular and structured data types. (Uenoyama, Yoshiura and Ichino, 2019).

3.3.5 - LiteXGBoost: This method was developed by (Thai, 2022), emphasizing computing efficiency while maintaining an acceptable degree of accuracy. The term "Light" signifies that this technique is exceptionally rapid in comparison to other boosting algorithms, such XGBoost, which requires considerable time to train when processing extensive datasets. The main difference of LightGBM from other boosting algorithms appears in its

approach to tree growth. The leaf-wise (best-first) tree technique of LightGBM generates trees by expanding the leaf with the maximum loss (see Figure. 10). The two enhancements implemented in LightGBM for speed acceleration consist of gradient-based one-side sampling (GOSS) and exclusive feature bundling (EFB). The sophisticated sampling technique of GOSS uses random selection solely on instances with low gradient values to minimize sample numbers whereas EFB works as a feature bundling method to reduce feature dimensions (Thai, 2022). The implementation of GOSS and EFB accelerates training time because the discovery time of splits directly corresponds to the number of items and characteristics used in the process. The optimization of LightGBM focuses on big data applications yet this same design trait leads to extreme sensitivity towards overfitting problems when implementing it on small datasets.

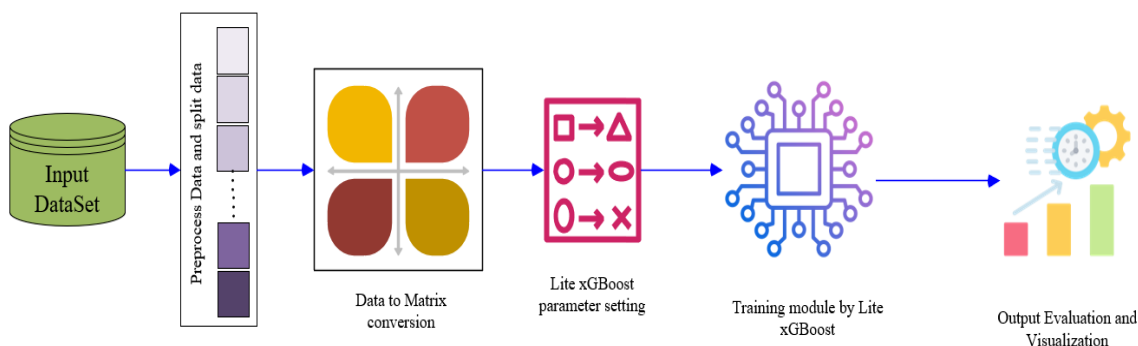


Figure 10: Tree growth methods used in LightGBM

3.3.6 iCaRL: the (Rebuffi et al., 2017) construct an incremental classifier with the purpose of satisfying two requirements. Firstly, the system should be able to provide a reasonable classification performance for the classes that have been observed up to this point at any given moment. A second consideration is that the system's memory and compute needs should be kept within a certain envelope. Specifically, they suggest a hyper parameter K that they refer to as the memory-budget of the classifier in order to establish the memory bound of the system. The maximum number of occurrences of the outdated data that the system is permitted to store at any given time is specified by this budget.

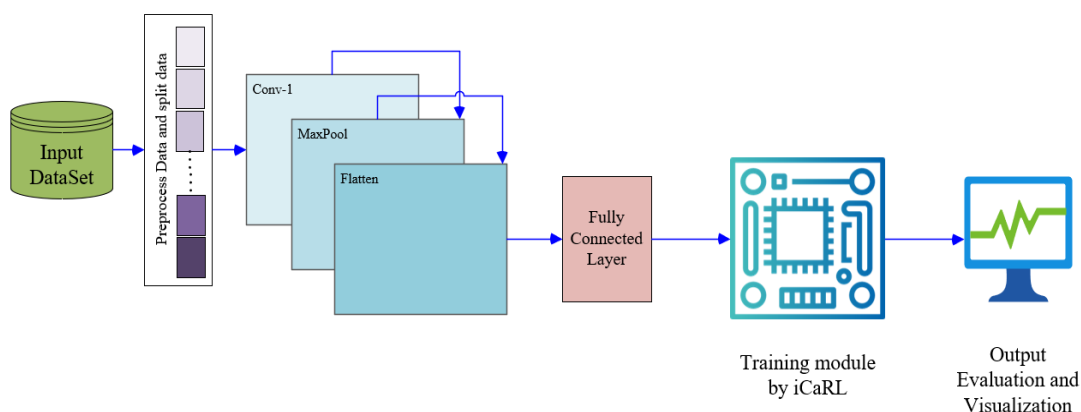


Figure 11: iCaRL module architecture

3.3.7 Corticohippocampal circuits-based hybrid neural network (CH-HNN)

The (Shi et al., 2025) has developed a corticohippocampal circuits-based hybrid neural network (CH-HNN) that replicates the recurrent loop cycle in the human brain to alleviate catastrophic forgetting in artificial intelligence systems, enabling them to learn incrementally without losing previously stored information within datasets. The CH-HNNs integrate artificial neural networks (ANNs) and spiking neural networks (SNNs) to facilitate the algorithms' acquisition of new concepts via periodic inference. The CH-HNN functions as a task-agnostic system, facilitating a decrease in memory overheads. This renders the continuous acquisition of new information in real-world contexts more pragmatic. The model exhibits minimal power consumption due to the implementation of SNNs, rendering it an energy-efficient algorithm capable of continuous learning in dynamic contexts while retaining information for future utilization inside the model.

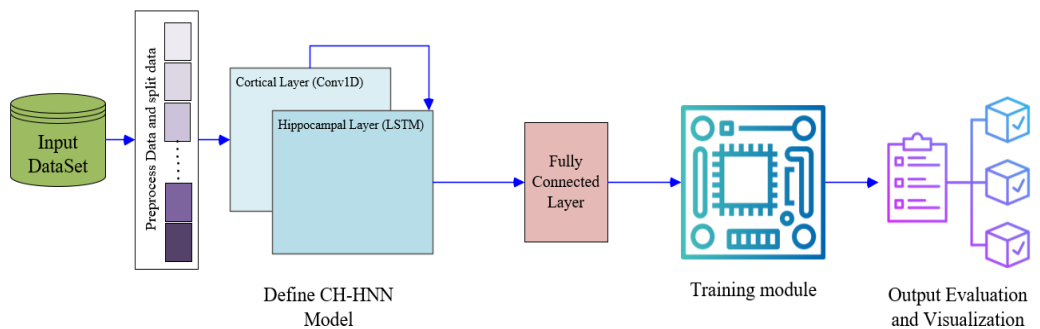


Figure 12: CH-HNN Architecture

3.4 Rationale for Model Selection

To evaluate the effectiveness of the proposed Elastic Weight Consolidation (EWC) approach, a diverse set of baseline models was selected. These models were chosen not only for their prevalence in continual learning and incremental learning research but also for their complementary methodological characteristics. Together, they provide a comprehensive

benchmarking framework to assess the robustness and adaptability of the proposed method.

- **Bidirectional Long Short-Term Memory (BLSTM):** BLSTM networks are widely used in sequence modelling tasks, making them particularly relevant for personal assistants that frequently process sequential and text-based data. Their inclusion allows an assessment of how recurrent architectures perform in continual learning scenarios.
- **Learning without Forgetting (LwF):** LwF represents a regularization-based approach to continual learning. It aims to retain prior knowledge by constraining parameter updates during the learning of new tasks. As such, it provides a direct comparison with EWC, which also adopts a regularization strategy but differs in how parameter importance is calculated and preserved.
- **Incremental Classifier and Representation Learning (iCARL):** iCARL is a rehearsal-based method that combines memory replay with representation learning. Its inclusion serves to benchmark against strategies that explicitly retain samples from past tasks to mitigate catastrophic forgetting.
- **Corticohippocampal Circuits-Based Hybrid Neural Network:** This bio-inspired model draws from neurocognitive mechanisms to address lifelong learning. By integrating it into the comparison, the study evaluates how biologically motivated architectures perform relative to parameter-regularization methods such as EWC.
- **Extreme Gradient Boosting (XGBoost) and Lite XGBoost (LxGBoost):** These models represent strong traditional machine learning baselines. While not specifically designed for continual learning, they provide insight into how non-neural, tree-based classifiers handle incremental tasks and offer a performance contrast with deep learning approaches.

Finally, each baseline model plays a specific role in the evaluation framework: BLSTM tests sequential learning capacity, LwF provides a direct regularization-based comparison, iCARL represents rehearsal-based methods, the hybrid network introduces a bio-inspired perspective, and

XGBoost/LxGBoost serve as traditional machine learning benchmarks. This diversity ensures that the superiority of EWC is demonstrated across multiple methodological paradigms, highlighting its suitability for continual learning in personal assistant applications.

4.Experimental result:

4.1- Preparation and assessing experiments

This experiment employed the 16 Personality Types dataset from Kaggle, consisting of 60,000 samples, to evaluate and compare the performance of all baseline models against the proposed Elastic Weight Consolidation (EWC) approach. All models were trained and tested using identical dataset splits to ensure consistency and fairness in evaluation. A batch size of 32 was selected based on preliminary experiments as the optimal setting for achieving the best overall performance across all models. Hyperparameters for each model, summarized in Table 3, were determined through a combination of grid search and validation set performance, ensuring that each model was tuned optimally for fair comparison. Performance was assessed using accuracy as the primary metric, as it effectively captures the overall correctness of the personality type predictions, providing a straightforward and widely accepted measure for classification tasks.

Table 3: hyperparameter specifications of the models and used
Hardware/software

Measuring evaluation and performance	Evaluating measurement results
Batch size	32
Optimizer	Adam
Number of epochs	50
Learning rate	0.0002
Evaluation criterion	cross-entropy loss function
Training	confusion matrices
Function activation	Adaptive learning rate(min test loss)

Core	Core i7 Gen8
RAM	16 GB
GPU	Intel 8 GB
OS	Windows 10 pro

The evaluated models demonstrated that EWC achieved the lowest testing loss of 0.01205 at epoch 50, together with a testing accuracy of 98.4%. Among the assessed models with stable accuracy, BI-LSTM shown the lowest testing loss of 0.1407 at epoch 3, although it exhibited the greatest variability in testing accuracy. The model attained a testing accuracy of 97.9%. XGBoost demonstrated satisfactory performance, achieving a testing accuracy of 93.2% and a loss of 0.46261 at epoch 50. LiteXGBoost also exhibited good results, with a testing accuracy of 87.2% and a loss of 0.15 at epoch 50. LwF demonstrated promising outcomes, achieving a testing accuracy of 94.5% and a loss of 0.718 at epoch 49. iCaRL yielded commendable results, attaining a testing accuracy of 94% and a loss of 0.206 at epoch 50. CH-HNN exhibited excellent performance, reaching a testing accuracy of 97.5% and a loss of 0.118 at epoch 50. The subsequent Figures (13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41 and 42) illustrate the results of each model across epochs and result values in the table 4.

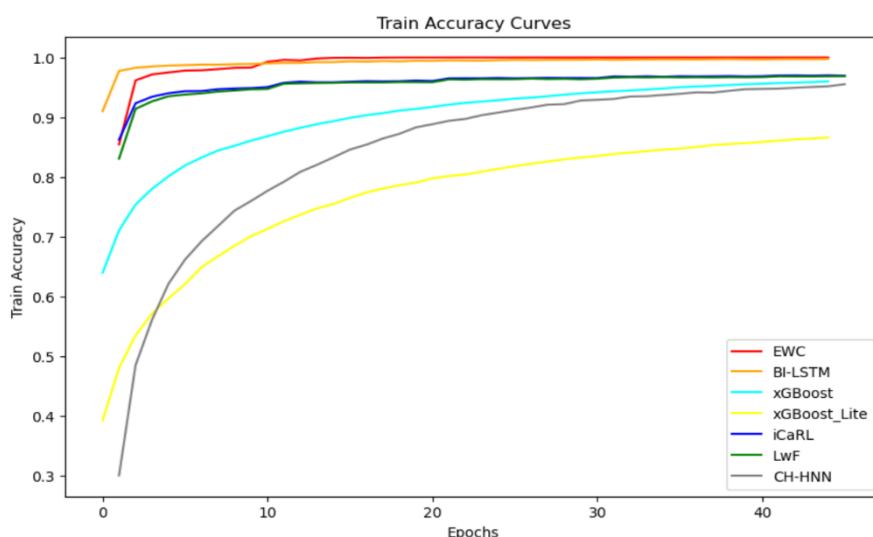


Figure 13: Training accuracy of models for each epoch

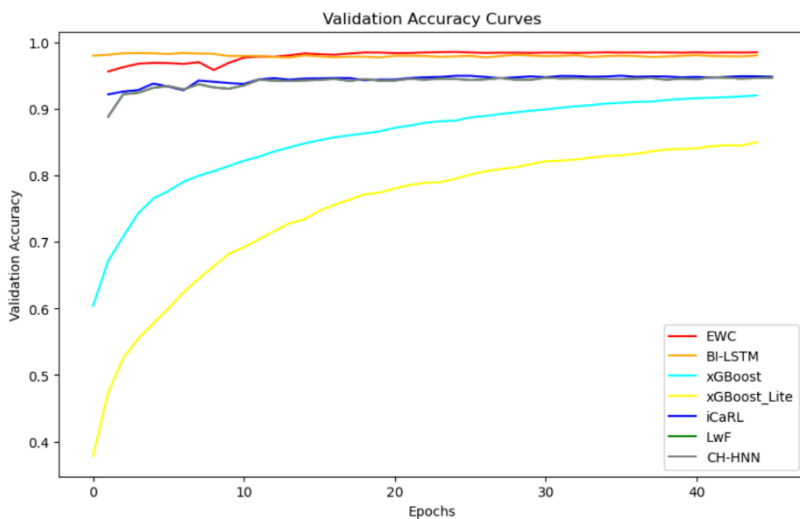


Figure 15: Validation Accuracy of models for each epoch

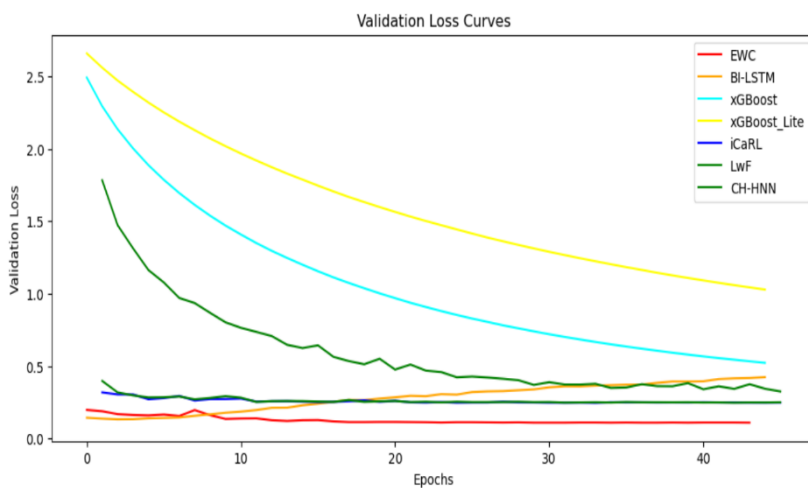


Figure 16: Validation Loss of models for each epoch

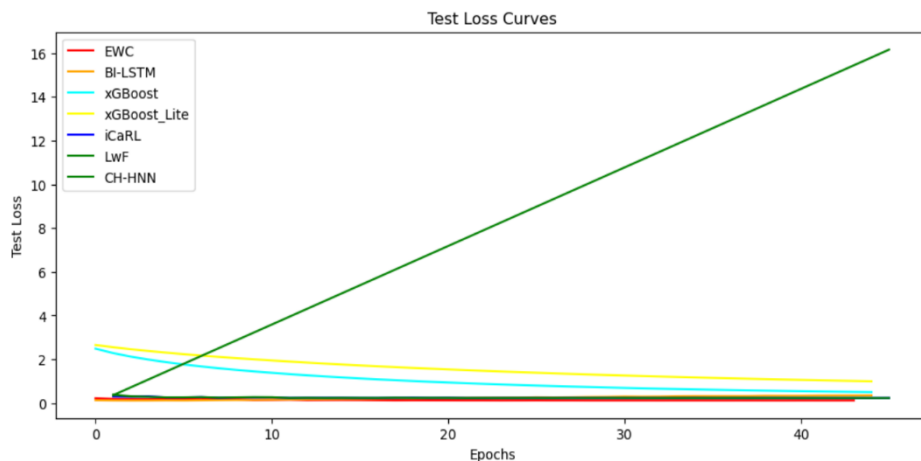


Figure 17: Testing Loss of models for each epoch

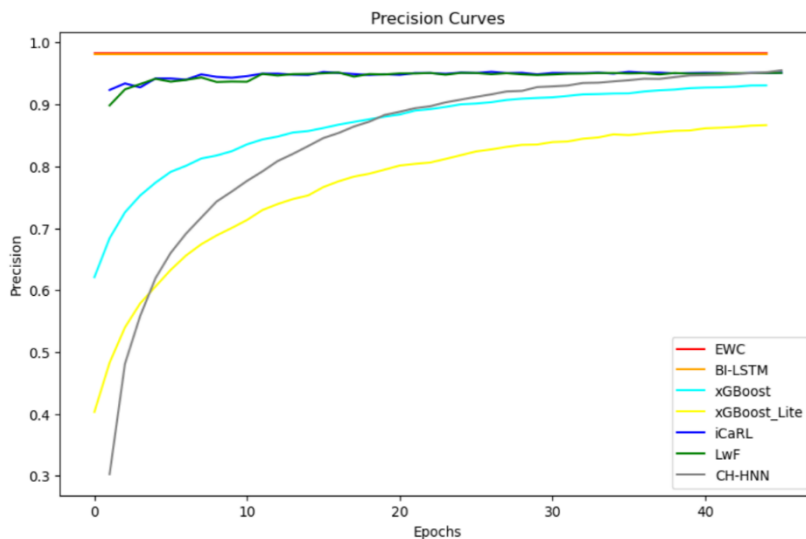


Figure 18: Precision of models for each epoch

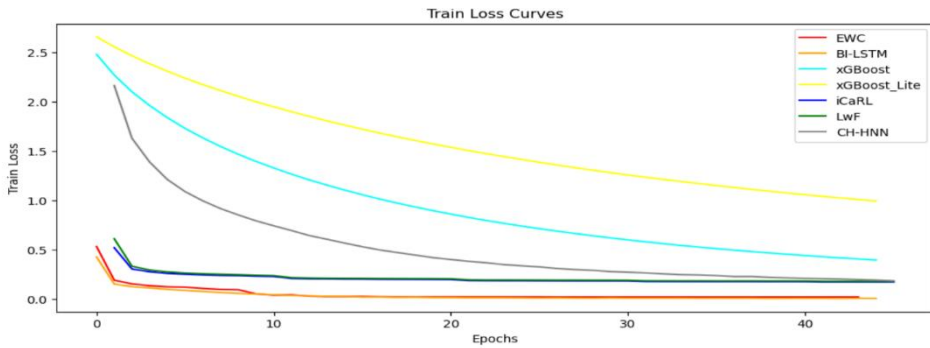


Figure 19: Training Loss of models for each epoch

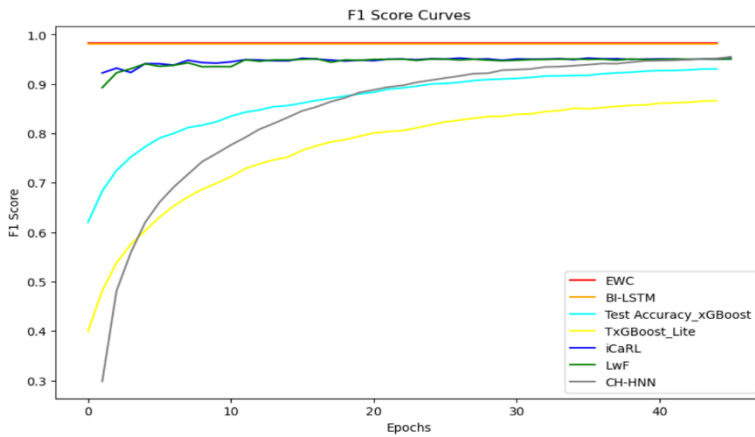


Figure 20: F1-Score of models for each epoch

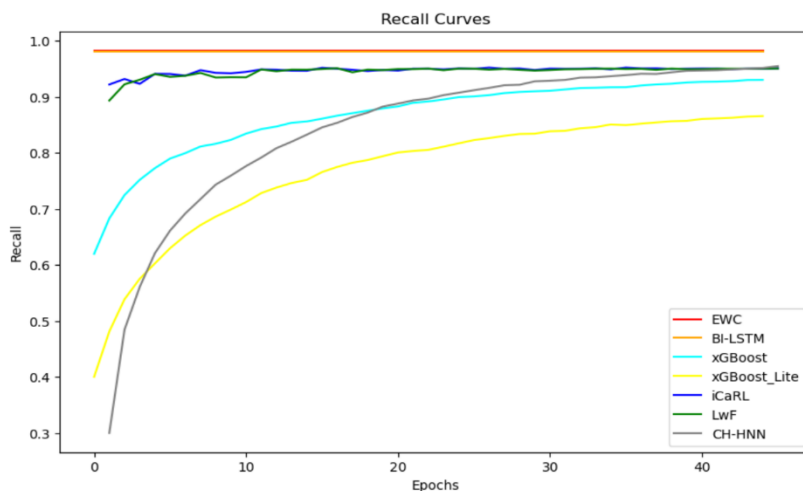


Figure 21: Recall of models for each epoch

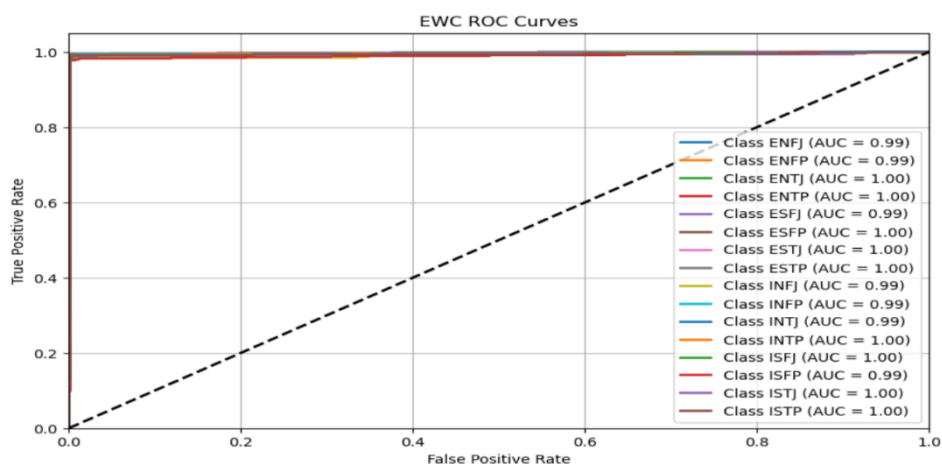


Figure 22: EWC ROC Curves

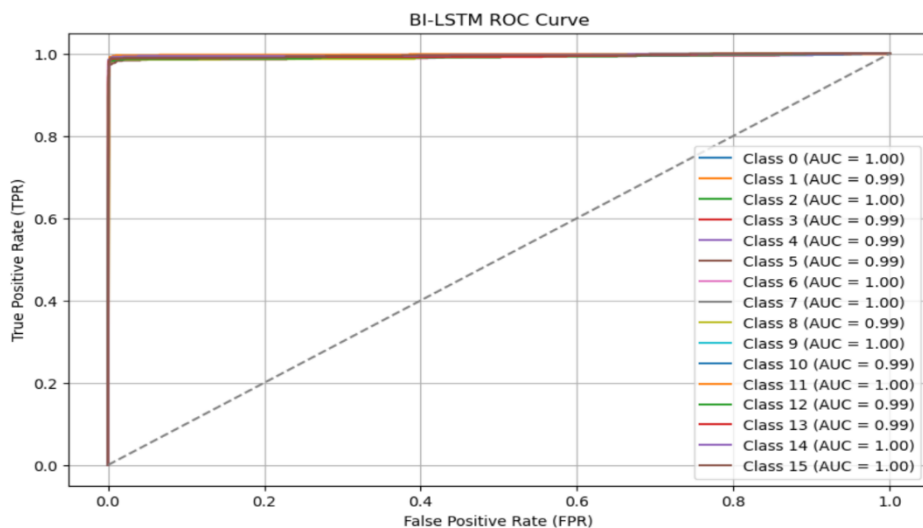


Figure 23:BI-LSTM ROC Curves

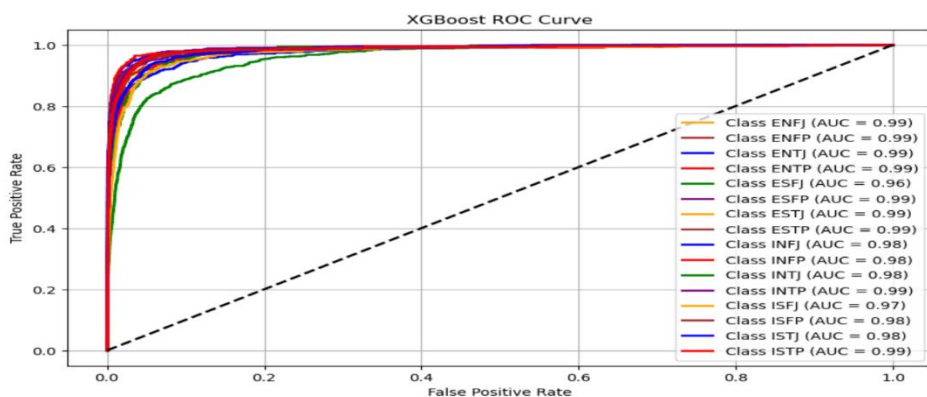


Figure 24: xGBoost ROC Curves

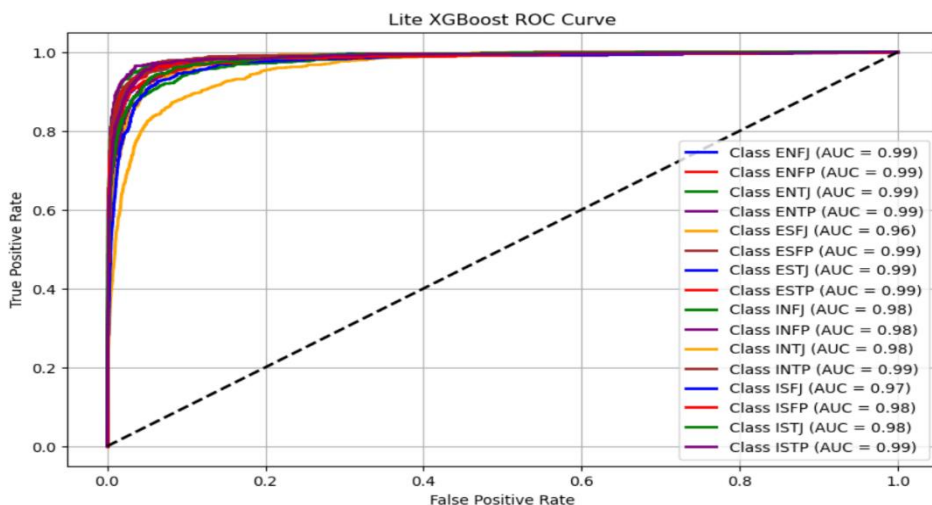


Figure 25: Lite xGBoost ROC Curves

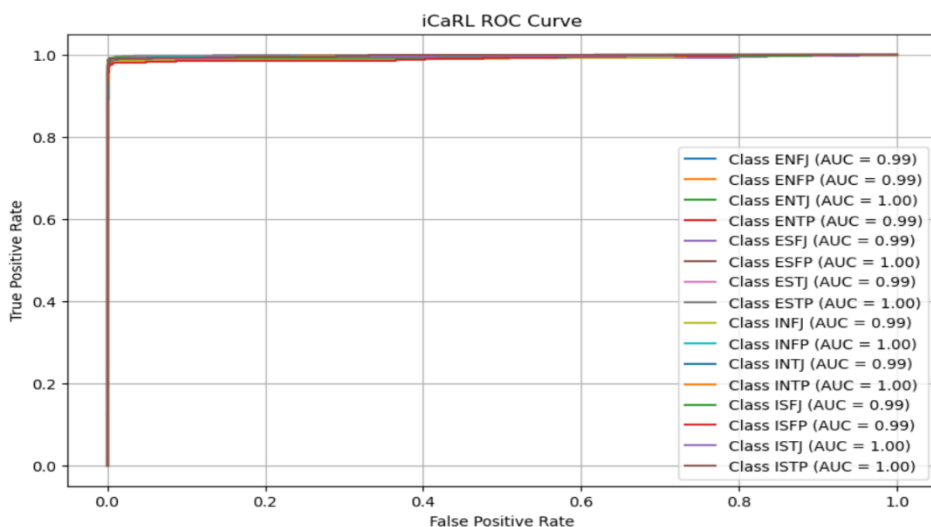


Figure 26 : iCaRL ROC Curves

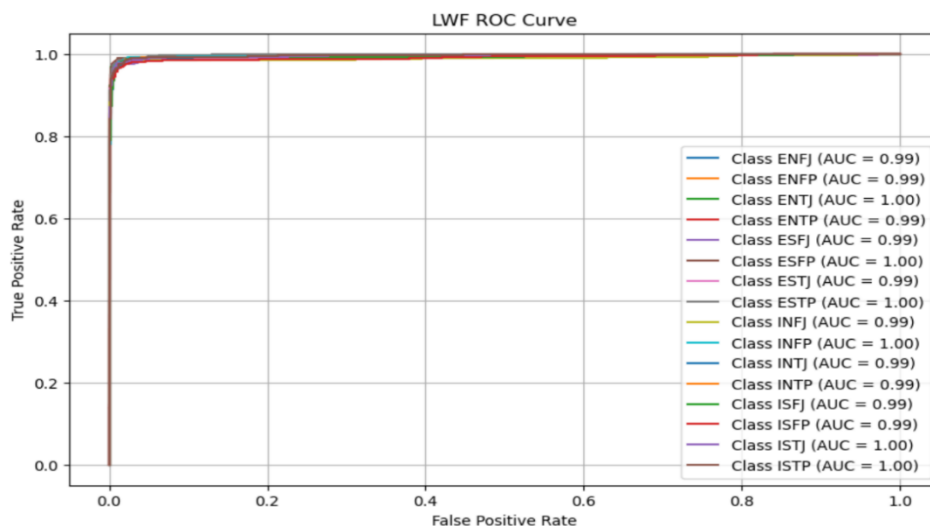


Figure 27 :LwF ROC Curves

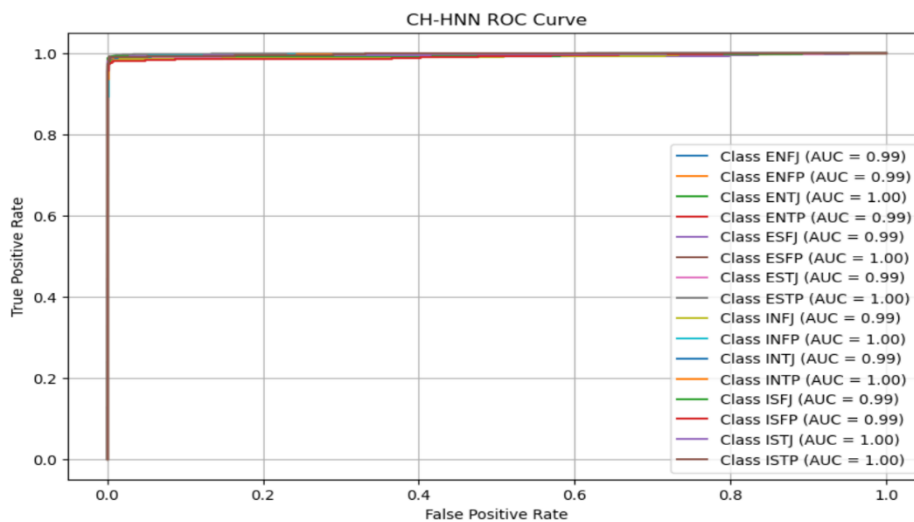


Figure 28: CH-HNN ROC Curves

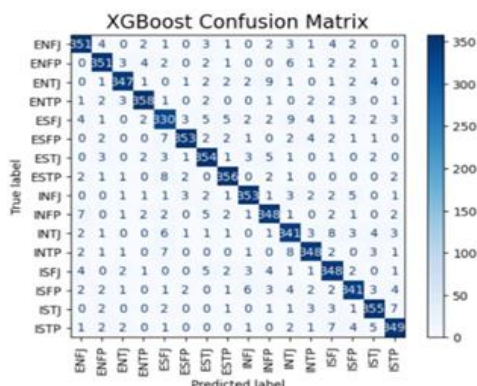


Figure 31: xGBoost Confusion Matrix

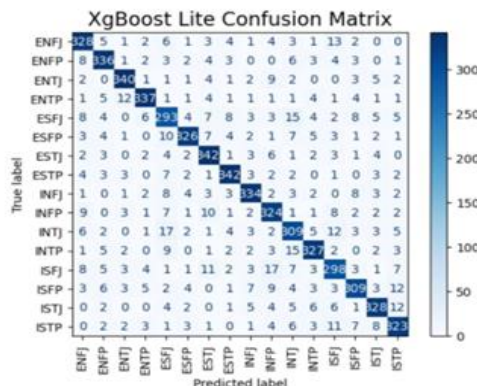


Figure 32: xGBoost Lite Confusion Matrix

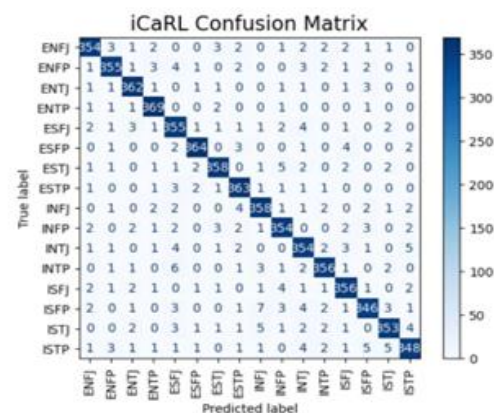


Figure 33: iCaRL Confusion Matrix

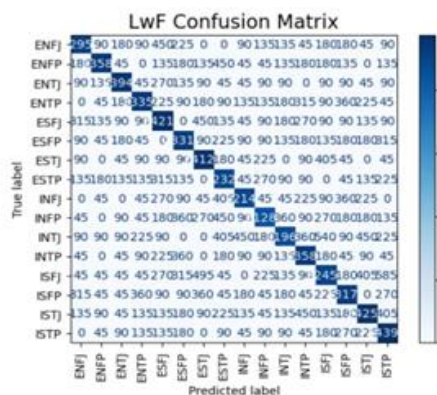


Figure 34: LwF Confusion Matrix

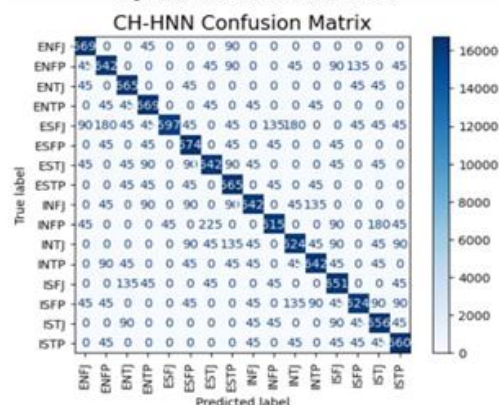


Figure 35: CH-HNN Confusion Matrix

Classification Report(EWC):

	precision	recall	f1-score	support
ENFJ	0.98	0.99	0.99	374
ENFP	0.98	0.98	0.98	376
ENTJ	0.98	0.99	0.99	374
ENTP	0.98	0.99	0.99	376
ESFJ	0.98	0.97	0.98	375
ESFP	0.99	0.99	0.99	377
ESTJ	0.99	0.98	0.98	376
ESTP	0.99	0.99	0.99	375
INFJ	0.98	0.98	0.98	376
INFP	0.98	0.99	0.99	373
INTJ	0.98	0.98	0.98	374
INTP	0.98	0.98	0.98	374
ISFJ	0.98	0.98	0.98	374
ISFP	0.98	0.98	0.98	375
ISTJ	0.99	0.98	0.99	376
ISTP	0.98	0.98	0.98	375
accuracy			0.98	6000
macro avg	0.98	0.98	0.98	6000
weighted avg	0.98	0.98	0.98	6000

Figure 36: EWC Classification Report

Classification Report(BI-LSTM):				
	precision	recall	f1-score	support
ENFJ	1.00	0.98	0.99	374
ENFP	0.97	0.98	0.97	376
ENTJ	0.99	0.99	0.99	374
ENTP	0.99	0.98	0.98	376
ESFJ	0.97	0.98	0.97	374
ESFP	0.98	0.97	0.98	377
ESTJ	0.99	0.99	0.99	376
ESTP	0.97	0.99	0.98	375
INFJ	0.99	0.98	0.99	376
INFP	0.98	0.98	0.98	374
INTJ	0.97	0.99	0.98	375
INTP	0.97	0.98	0.98	374
ISFJ	0.98	0.98	0.98	374
ISFP	0.98	0.98	0.98	375
ISTJ	0.98	0.97	0.97	375
ISTP	0.99	0.98	0.99	375
accuracy			0.98	6000
macro avg	0.98	0.98	0.98	6000
weighted avg	0.98	0.98	0.98	6000

Figure 37: BI-LSTM Classification Report

Classification Report(XGBoost):				
	precision	recall	f1-score	support
ENFJ	0.93	0.94	0.94	374
ENFP	0.94	0.93	0.94	376
ENTJ	0.96	0.93	0.94	373
ENTP	0.96	0.95	0.96	376
ESFJ	0.89	0.88	0.88	375
ESFP	0.96	0.94	0.95	377
ESTJ	0.92	0.94	0.93	376
ESTP	0.95	0.95	0.95	375
INFJ	0.95	0.94	0.94	376
INFP	0.92	0.93	0.92	374
INTJ	0.89	0.91	0.90	375
INTP	0.94	0.93	0.93	374
ISFJ	0.90	0.93	0.91	374
ISFP	0.92	0.91	0.92	374
ISTJ	0.93	0.94	0.94	376
ISTP	0.93	0.93	0.93	375
accuracy			0.93	6000
macro avg	0.93	0.93	0.93	6000
weighted avg	0.93	0.93	0.93	6000

Figure 38: xGBoost Classification Report

Classification Report(XGBoost Lite):				
	precision	recall	f1-score	support
ENFJ	0.85	0.88	0.87	374
ENFP	0.88	0.89	0.89	376
ENTJ	0.91	0.91	0.91	373
ENTP	0.92	0.90	0.91	376
ESFJ	0.78	0.78	0.78	375
ESFP	0.92	0.86	0.89	377
ESTJ	0.86	0.91	0.88	376
ESTP	0.90	0.91	0.91	375
INFJ	0.90	0.89	0.89	376
INFP	0.83	0.87	0.85	374
INTJ	0.80	0.82	0.81	375
INTP	0.89	0.87	0.88	374
ISFJ	0.81	0.80	0.80	374
ISFP	0.87	0.83	0.85	374
ISTJ	0.89	0.87	0.88	376
ISTP	0.85	0.86	0.86	375
accuracy			0.87	6000
macro avg	0.87	0.87	0.87	6000
weighted avg	0.87	0.87	0.87	6000

Figure 39: xGBoost Lite Classification Report

Classification Report(iCaRL):				
	precision	recall	f1-score	support
ENFJ	0.95	0.95	0.95	374
ENFP	0.97	0.94	0.95	376
ENTJ	0.96	0.96	0.96	373
ENTP	0.96	0.98	0.97	376
ESFJ	0.94	0.93	0.93	375
ESFP	0.95	0.98	0.96	377
ESTJ	0.95	0.97	0.96	376
ESTP	0.96	0.95	0.96	375
INFJ	0.97	0.92	0.95	376
INFP	0.92	0.95	0.94	374
INTJ	0.95	0.94	0.94	375
INTP	0.96	0.96	0.96	374
ISFJ	0.95	0.94	0.94	374
ISFP	0.93	0.93	0.93	374
ISTJ	0.95	0.98	0.96	376
ISTP	0.94	0.95	0.94	375
accuracy			0.95	6000
macro avg	0.95	0.95	0.95	6000
weighted avg	0.95	0.95	0.95	6000

Figure 40: iCaRL Classification Report

Classification Report(LwF):				
	precision	recall	f1-score	support
ENFJ	0.96	0.95	0.95	374
ENFP	0.96	0.94	0.95	376
ENTJ	0.96	0.97	0.97	373
ENTP	0.96	0.98	0.97	376
ESFJ	0.92	0.95	0.93	375
ESFP	0.97	0.97	0.97	377
ESTJ	0.96	0.95	0.96	376
ESTP	0.95	0.97	0.96	375
INFJ	0.94	0.95	0.95	376
INFP	0.94	0.95	0.95	374
INTJ	0.93	0.94	0.94	375
INTP	0.96	0.95	0.95	374
ISFJ	0.95	0.95	0.95	374
ISFP	0.95	0.93	0.94	374
ISTJ	0.96	0.94	0.95	376
ISTP	0.95	0.93	0.94	375
accuracy			0.95	6000
macro avg	0.95	0.95	0.95	6000
weighted avg	0.95	0.95	0.95	6000

Figure 41: LwF Classification Report

Classification Report(CH-HNN):				
	precision	recall	f1-score	support
ENFJ	0.98	0.99	0.99	374
ENFP	0.97	0.97	0.97	376
ENTJ	0.97	0.99	0.98	373
ENTP	0.98	0.99	0.98	376
ESFJ	1.00	0.95	0.97	375
ESFP	0.97	0.99	0.98	377
ESTJ	0.98	0.97	0.97	376
ESTP	0.96	0.99	0.97	375
INFJ	0.98	0.97	0.98	376
INFP	0.98	0.96	0.97	374
INTJ	0.97	0.97	0.97	375
INTP	0.98	0.98	0.98	374
ISFJ	0.97	0.98	0.97	374
ISFP	0.98	0.96	0.97	374
ISTJ	0.97	0.98	0.97	376
ISTP	0.98	0.98	0.98	375
accuracy			0.98	6000
macro avg	0.98	0.98	0.98	6000
weighted avg	0.98	0.98	0.98	6000

Figure 42: CH-HNN Classification Report

The following pseudocode shows the procedure for model preparation and execution.

Algorithm: Model Preparation and Execution

1. Define the dataset path.
2. Load the dataset and split it into sets(training (80%), validation (10%) and testing (20)).
3. Create DataLoaders for the training, validation and testing sets.
4. **For** each model_type $\in \{\text{EWC, BI-LSTM, XGBoost, Lite XGBoost, LwF, iCaRL, CH-HNN}\}$:
 - a. Define the model structure for model_type.
 - b. Modify the final layer to match the number of classes.
 - c. Initialize the model and move it to CPU/GPU.
 - d. Set training parameters: number of epochs, learning rate, loss function, optimizer.

End For

5. **For** epoch = 1 to max_epochs:
 - For** each model $\in$ models:
 - a. Set the model to training mode.
 - b. **For** each batch in training data:
 - i. Perform forward pass and compute loss.
 - ii. Backpropagate loss and update weights.
 - iii. Track training loss and accuracy.
 - End For**
 - c. Set the model to evaluation mode.
 - d. **For** each batch in testing and validation data:
 - i. Perform forward pass and compute loss.
 - ii. Track predictions and calculate test accuracy.
 - End For**
 - e. Store training, validation and testing metrics.

End For End For

6. Plot accuracy and loss curves for all models over epochs.

7. **For** each model $\in$ models:

- a. Compute confusion matrix, accuracy, and classification report.
- b. Display training, validation and testing results. **End For**

4.2- Result and Discussion:

The principal objective of the provided learning technique is to generate many models in this study. The models EWC, BI-LSTM, XGBoost, Lite XGBoost, LwF, iCaRL, and CH-HNN exemplify a particular continual learning methodology. The accuracy, specificity, and sensitivity calculated during the testing and validation in this study function as the assessment metrics for all models assessed in this system. Table (3) presents evaluation measures for the performance of the EWC, BI-LSTM, XGBoost, Lite XGBoost, LwF, iCaRL, and CH-HNN models on training and testing datasets, distinguishing across personality types. These measurements include precision, F1 score, and recall.

- **Accuracy:** denotes the proportion of true patterns to the total number of patterns. It can be articulated as

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positives} + \text{False Positives} + \text{True Negative} + \text{False Negative}} \times 100$$

- **Precision:** The proportion of accurately predicted positive observations out of all predicted positives.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positives} + \text{False Positives}}$$

greater accuracy means fewer false positives.

- **Recall:** The proportion of correctly predicted positive observations to actual total positives.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positives} + \text{False Negative}}$$

greater recall shows less false negatives.

- **F1-Score:** The harmonic means of precision and recall.

$$F1_{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

A high F1-score shows that the model balances between precision and recall in a perfect way.

The evaluation results presented in Table (4) demonstrate that all models achieved strong performance across training, validation, and testing, but with clear differences in their ability to generalize.

The EWC model achieved the best overall results, with 100% training accuracy, 98.2% validation accuracy, and 98.4% testing accuracy. It also maintained the lowest losses across all phases (training: 0.01, validation: 0.11, testing: 0.12). With precision, recall, and F1-score all around 98.35%, EWC confirms its effectiveness in mitigating catastrophic forgetting and maintaining stability across validation and testing.

The Bi-LSTM model also performed excellently, with 99.7% training accuracy, 98.1% validation accuracy, and 98.0% testing accuracy. It achieved the highest recall (98.24%) and an F1-score of 98.08%, highlighting its strength in capturing sequential dependencies. However, its validation and testing loss (0.13) were slightly higher than EWC, and its precision (97.93%) was marginally lower, suggesting a tendency toward over-classification.

The XGBoost model demonstrated an interesting profile: although its training accuracy (96.0%) and validation accuracy (92.1%) were lower than those of the deep learning models, it achieved testing accuracy of 93.1 %. However, this came at the cost of much higher loss (0.50) with precision (93.2%) and recall (93.1%).

The CH-HNN delivered strong and balanced results, with 96.0% training accuracy, 92.3% validation accuracy, and 91.6% testing accuracy. While its testing accuracy was slightly lower than EWC and Bi-LSTM, it achieved consistent precision, recall, and F1-scores (97.5%). Its validation loss (0.33) and testing loss

(0.34) were higher than EWC but still competitive, reinforcing the advantage of combining (CNN) and (LSTM) layers.

Among other continual learning strategies, iCaRL achieved 97.1% training, 94.8% validation, and 95.3% testing accuracy, with balanced precision and recall (94.2%) and moderate validation/testing losses (0.26 / 0.23). LwF, on the other hand, achieved 97.0% training accuracy, 95.0% validation accuracy, but only 86.6% testing accuracy. Despite strong precision (94.36%), its much lower testing performance and relatively higher losses.

Finally, Lite XGBoost underperformed compared to all other models, with 86.6% training accuracy, 85.0% validation accuracy, and 93.1% testing accuracy. Its high losses (training: 0.99, validation: 1.03, testing: 0.99) and the lowest precision/recall (87.2%) confirm the limitations of lightweight boosting methods for complex, high-dimensional tasks such as personality classification.

Overall, the comparative analysis reveals that EWC outperforms all other approaches, followed by Bi-LSTM and CH-HNN.

Although the top-performing models achieved accuracies above 98%, some misclassifications remain. Errors were most common among personality types with overlapping behavioral features, where models struggled to differentiate variations. This led to occasional reductions in precision, particularly in Bi-LSTM, which tended to over-predict certain dominant classes.

Another limitation was observed in iCaRL and LwF, where higher losses despite solid accuracy scores suggest instability in knowledge retention when handling imbalanced data distributions. Similarly, Lite XGBoost underperformed due to its reduced model complexity, which may have limited its ability to capture the nonlinear dependencies in personality features.

These findings indicate that while continual learning strategies such as EWC are highly effective for mitigating catastrophic forgetting, future work should explore techniques like contrastive learning, prototype alignment, and data augmentation to further reduce confusion between closely related personality types.

Table 4: our model evaluation comparisons

Model	Average accuracy%			min Loss%			classification report		
	Trainin g%	Validati on%	Testin g%	Trainin g%	Validati on%	Testin g%	Precisio n%	Recal l%	F1- score%
EWC	100	98.2	98.4	0.01	0.11	0.12	98.36	98.35	98.355
BI-LSTM	99.7	98.1	98	0.02	0.13	0.13	97.93	98.24	98.0848
XGBoost	96	92.1	93.1	0.4	0.52	0.5	93.2	93.1	93.15
LiteXGBoost	86.6	85	86.6	0.99	1.03	0.99	87.25	87.23	87.24
LwF	97	95	95.3	0.17	0.25	0.23	94.36	94.33	94.345
iCaRL	97.1	94.8	95	0.18	0.26	0.23	94.25	94.24	94.245
CH-HNN	96	92.3	91.6	0.17	0.33	0.34	95.55	95.53	95.54

Table 5 Other paper model comparisons

Model	Accuracy%	Loss%
BI-LSTM(Anusha et al., 2024)	97.8	N/A
XGBoost(Praphulla et al., 2023)	75.15	0.8
LiteXGBoost(Uenoyama, Yoshiura and Ichino, 2019)	69.9	1.2
LwF(Jin, Liang and Yang, 2020)	87.44	N/A
iCaRL(Rebuffi et al., 2017)	68.6	N/A
CH-HNN(Shi et al., 2025)	82	N/A

5. Conclusion:

Artificial intelligence continues to reshape human interaction with technology, particularly through the development of intelligent and context-aware virtual personal assistants (VPAs). Modern VPAs are increasingly capable of managing both personal and professional tasks by integrating personalization, contextual understanding, and adaptive learning.

This study investigated the use of Elastic Weight Consolidation (EWC) as a continual learning strategy to address the problem of catastrophic forgetting in AI-driven systems. Using the 16 personality type dataset, EWC was benchmarked against state-of-the-art models including Bi-LSTM, LwF, iCaRL, CH-HNN, XGBoost, and Lite XGBoost. Experimental results showed that EWC achieved the highest test accuracy (98.4%) and validation accuracy (98.2%) while maintaining stability across sequential tasks, outperforming all alternative approaches in retaining previously acquired knowledge.

These findings demonstrate that EWC provides a practical and effective solution for applications requiring long-term adaptability, such as virtual personal assistants that continuously learn from user interactions and dynamic information. By enabling continual learning without sacrificing prior knowledge, EWC supports the development of more responsive, personalized, and intelligent AI systems.

Future research should extend this approach to larger and more diverse datasets, as well as evaluate its effectiveness in multitask and multi-domain environments, thereby advancing the real-world applicability of continual learning in intelligent assistants.

References:

- ANUSHA, M. et al. (2024) Text-Based Personality Assessment Using Deep Learning Techniques. *International Conference on Emerging Technologies in Computer Science for Interdisciplinary Applications, ICETCS 2024*, pp. 1–6.
- BELOUADAH, E., POPESCU, A. and KANELLOS, I. (2021) A comprehensive study of class incremental learning algorithms for visual tasks. *Neural Networks*, 135, pp. 38–54.
- CUI, B. and QI, C. (2017) Survey Analysis of Machine Learning Methods for Natural Language Processing for MBTI Personality Type Prediction. *Leland Stanford Junior University*.
- DEVARAJAN, D. et al. (2022) Cervical Cancer Diagnosis Using Intelligent Living Behavior of Artificial Jellyfish Optimized With Artificial Neural Network. *IEEE Access*, 10, pp. 126957–126968.

- DOĞAN, E.B. et al. (2024) Neural Network-Based Human Detection Using Raw UWB Radar Data. In: *2024 IEEE Workshop on Microwave Theory and Technology in Wireless Communications (MTTW)*. pp. 37–42.
- DOYLE, M., NOE, A. and MICHAELS, G.S. (2000) Visible Embryo Project: a platform for spatial genomics. In: OLIVER, W.R. (ed.) *28th AIPR Workshop: 3D Visualization for Data Exploration and Decision Making*. SPIE, pp. 248–255.
- DUTTA, I., ATHILAKSHMI, R. and AMULYA (2023) Personality Prediction Using Deep Learning. *2023 3rd International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies, ICAECT 2023*, pp. 1–5.
- FRENCH, R.M. (1999) Catastrophic forgetting in connectionist networks. *Trends in Cognitive Sciences*, 3(4), pp. 128–135.
- GUNASEKARAN, K. et al. (2023) Smart Decision-Making and Communication Strategy in Industrial Internet of Things. *IEEE Access*, 11(February), pp. 28222–28235.
- HUSZÁR, F. (2018) Note on the quadratic penalties in elastic weight consolidation. *Proceedings of the National Academy of Sciences*, 115(11), pp. E2496–E2497.
- JEREMY, N.H., PRASETYO, C. and SUHARTONO, AND D. (2019) Identifying Personality Traits for Indonesian User from Twitter Dataset. *The International Journal of Fuzzy Logic and Intelligent Systems*, 19(4), pp. 283–289.
- JIN, L., LIANG, H. and YANG, C. (2020) Class-Incremental Learning of Convolutional Neural Networks Based on Double Consolidation Mechanism. *IEEE Access*, 8, pp. 172553–172562.
- KÄDING, C. et al. (2016) Fine-Tuning Deep Neural Networks in Continuous Learning Scenarios. In: *ACCV Workshops*.
- KAMRA, N., GUPTA, U. and LIU, Y. (2017) Deep Generative Dual Memory Network for Continual Learning. [Online] Available from: <http://arxiv.org/abs/1710.10368>.
- KASHYAP, R. and KASHYAP, R. (2022) Machine Learning, Data Mining for IoT-Based Systems. In: *Research Anthology on Machine Learning Techniques, Methods, and Applications*. IGI Global, pp. 447–471.

- KIRKPATRICK, J. et al. (2017) Overcoming catastrophic forgetting in neural networks. *Proceedings of the National Academy of Sciences*, 114(13), pp. 3521–3526.
- KOMISIN, M. and GUINN, C. (2012) Identifying personality types using document classification methods. *Proceedings of the 25th International Florida Artificial Intelligence Research Society Conference, FLAIRS-25*, pp. 232–237.
- KUMAR R, P., MOHAN G, B. and SAI, G.D. (2023) Ensemble Machine Learning Models in Predicting Personality Traits and Insights using Myers-Briggs Dataset. *Proceedings of the 2nd IEEE International Conference on Advances in Computing, Communication and Applied Informatics, ACCAI 2023*, (May 2023), [Online] Available from: doi.org/10.1109/ACCAI58221.2023.10199294.
- LI, Z. and HOIEM, D. (2018) Learning without Forgetting. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 40(12), pp. 2935–2947.
- MACKAY, D.J.C. (1996) Bayesian Methods for Backpropagation Networks BT - Models of Neural Networks III: Association, Generalization, and Representation. In: DOMANY, E., VAN HEMMEN, J.L. and SCHULTEN, K. (eds.) New York, NY: Springer New York, pp. 211–254.
- MADANI, A. et al. (2018) Fast and accurate view classification of echocardiograms using deep learning. *npj Digital Medicine*, 1(1), pp. 1–8.
- MARTENS, J. (2020) New insights and perspectives on the natural gradient method. *Journal of Machine Learning Research*, 21, pp. 1–76.
- MOHAMED, E. (2020) The Relationship between Artificial Intelligence and Internet of Things: A quick review. *Journal of Cybersecurity and Information Management*, 1(1), pp. 30–34.
- NIU, W. et al. (2019) Using XGBoost to Discover Infected Hosts Based on HTTP Traffic. *Security and Communication Networks*, 2019, [Online] Available from: doi.org/10.1155/2019/2182615.
- OPENAI et al. (2023) GPT-4 Technical Report. 4, pp. 1–100.
- PASCANU, R. and BENGIO, Y. (2013) Revisiting natural gradient for deep networks. *1st International Conference on Learning Representations, ICLR 2013 - Workshop Track Proceedings*, pp. 1–18.

- POLIKAR, R. et al. (2001) Learn++: an incremental learning algorithm for supervised neural networks. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 31(4), pp. 497–508.
- PRAPHULLA, G.L. et al. (2023) Personality Prediction Using Machine Learning Techniques. *AIP Conference Proceedings*, 2794(1), [Online] Available from: doi.org/10.1063/5.0174316.
- PRAVEENA, K. et al. (2024) Investigating the Applications of Artificial Intelligence in Enhancing Virtual Personal Assistants. *2024 OPJU International Technology Conference on Smart Computing for Innovation and Advancement in Industry 4.0, OTCON 2024*, pp. 1–5.
- RAMAKRISHNA, M.T. et al. (2023) HCoF: Hybrid Collaborative Filtering Using Social and Semantic Suggestions for Friend Recommendation. *Electronics (Switzerland)*, 12(6), pp. 1–23.
- RAMAPURAM, J., GREGOROVA, M. and KALOUSIS, A. (2020) Lifelong generative modeling. *Neurocomputing*, 404, pp. 381–400.
- REBUFFI, S.A. et al. (2017) iCaRL: Incremental classifier and representation learning. *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, 2017-Janua, pp. 5533–5542.
- SHI, Q. et al. (2025) Hybrid neural networks for continual learning inspired by corticohippocampal circuits. *Nature communications*, 16(1), p. 1272.
- SHMELKOV, K., SCHMID, C. and ALAHARI, K. (2017) Incremental Learning of Object Detectors without Catastrophic Forgetting. *Proceedings of the IEEE International Conference on Computer Vision*, 2017-Octob, pp. 3420–3429.
- SILVER, D. et al. (2017) Mastering the game of Go without human knowledge. *Nature*, 550(7676), pp. 354–359.
- THAI, H.-T. (2022) Machine learning for structural engineering: A state-of-the-art review. *Structures*, 38, pp. 448–491.
- UENOYAMA, D., YOSHIURA, H. and ICHINO, M. (2019) Personal Authentication of Iris and Periocular Recognition using XGBoost. In: *2019 IEEE 8th Global Conference on Consumer Electronics (GCCE)*. pp. 186–187.
- VAN DE VEN, G.M. and TOLIAS, A.S. (2019) Three scenarios for continual learning. pp. 1–18.
- WAN, D. et al. (2014) Personality Prediction Based on All Characters of User Social Media Information. In: *National Conference on Social Media Processing*.

- XIAO, B. (2023) Identifying 16 Personalities Based on Daily Writing by Random Forest and Logistic Regression. *Highlights in Science, Engineering and Technology*, 38, pp. 113–118.
- YANG, K., LAU, R.Y.K. and ABBASI, A. (2023) Getting Personal: A Deep Learning Artifact for Text-Based Measurement of Personality. *Information Systems Research*, 34(1), pp. 194–222.
- YANG, Z. et al. (2019) XLNet: Generalized autoregressive pretraining for language understanding. *Advances in Neural Information Processing Systems*, 32(NeurIPS), pp. 1–18.
- YU, Y. et al. (2019) A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures.
- ZAHER, M.A. and ELDAKHLI, N.M. (2023) Cyber Attack Detection in Wireless Adhoc Network using Artificial Intelligence. *International Journal of Wireless and Ad Hoc Communication*, 6(2), pp. 18–33.
- ZEROUAOU, H. and IDRI, A. (2021) Reviewing Machine Learning and Image Processing Based Decision-Making Systems for Breast Cancer Imaging. *Journal of Medical Systems*, 45(1), p. 8.

پوخته:

مروّف و ئازەلّ خاوەنی توانای فیربوونی بەردەوام و پالۆتن و گواستەنەوهی زانستن بە درێژایی ژیاڤیان. ئەم پرۆسەی فیربوونی تەواوی ژیاڤی پشت بە میکانیزمە دەمارییەکانی مەعریفی دەبەستێت کە پشتگیری لە پەرەپێدانی کارامەیی، چەسپاندنی بیرەوهری و گونجاندن دەکەن. لە زیرەکی دەستکرددا، فیربوونی تەواوی ژیاڤی بۆ ئەو مۆدیلانە زۆر گرنگە کە دەبێت پرۆسێس بکەن و خۆیان لە گەڵ زانبارییە هەمیشە گۆراوەکاندا بگونجێن. بەلام سببە مەکانی AI لە گەڵ "لەبیرکردنی کارەساتبار" دا کێشەیان هەیه، کە داتا تازە فیربووەکان زانیاری پێشوو دەنوسنەوه، ئەمەش تەحەدایەکی گەوره بۆ فیربوونی گونجاوی دروست دەکات. یاری دەدەرانی AI ی کەسی، بە تاییەتی، سوودمەندن لە فیربوونی بەردەوام، ئەمەش توانای ئەو هیان پێدەدات کە هەلبژاردەکانی بەکارهێنەر وردتر بکەنەوه، رێنماییە نوێیەکان هەلبمژن و کارلیکەکانی رابردوو بپاریزن. ئەمەش توانای ئەوان بەرز دەکاتەوه بۆ پیشکەشکردنی وەلامی کەسی و ئاگاداری کۆنتیکست، دلیابوون لە ئەزموونیکێ بێ کێشه و ئینتیلیکتیی بەکارهێنەر. ئەم توێژینه وهیه

شیوازی Elastic Weight Consolidation (EWC) پیشینار دهکات له کاتی پرۆسهی فیربووندا، پارامیتهرهکانی تۆرکه دهستکاری دهکریڻ و پالاوته دهکریڻ بۆ بهرزکردنهوهی مانهوهی تواناکانی ناسینهوه بۆ پۆلهکانی ئیستا له کاتییدا که پۆله نوێیهکان ئاسمیه دهکریڻ. تاقیکردنهوهکه ریکخراوه و شیوازی پیشینارکراوی به تهکنیکهکانی زیاده و فیربوونی ئامیری هه ن هه لسه نگیندراوه، له وانه Bidirectional LSTM (97.9%)، Learning without Incremental Classifier and Representation (94.3%)، Corticohippocampal circuits-based hybrid neural network (94%)، Extreme Gradient Boosting (97.5%)، و Lite Extreme Gradient Boosting (87.2%) له سه ر داتا سیته که که له سه ر “Kaggle” به ناوی “16” جوړی که سایه تی “ به رده سه ته. دۆزینه وه تاقیکارییه کان ئاماژه به وه ده که ن که ته کنیکه پیشینار کراوه که ی Elastic weight consolidation (EWC) به رزتره له وردی ئه لگۆریتمه کان فیربوونی زیاده و فیربوونی ئامیری باو که 98.4% یه، هه ربۆیه به شیوه یه کی به رچاو قه باره دانان و زیره کی مۆدیلی پۆلینکردنه که به رز ده کاته وه.

ملخص:

يملك البشر والحيوانات القدرة على التعلم المستمر، وتحسين المعرفة، ونقلها طوال حياتهم. تعتمد عملية التعلم مدى الحياة هذه على آليات عصبية معرفية تدعم تطوير المهارات، وتقوية الذاكرة، والقدرة على التكيف. في مجال الذكاء الاصطناعي، يُعد التعلم مدى الحياة أمراً بالغ الأهمية للنماذج التي يتعين عليها معالجة المعلومات المتغيرة باستمرار والتكيف معها. ومع ذلك، تعاني أنظمة الذكاء الاصطناعي من "النسيان الكارثي"، حيث تحل البيانات المكتسبة حديثاً محل المعرفة السابقة، مما يشكل تحدياً كبيراً للتعلم التكيفي. تستفيد مساعدات الذكاء الاصطناعي الشخصية، على وجه الخصوص، من التعلم المستمر، مما يُمكنها من تحسين تفضيلات المستخدم، واستيعاب التعليمات الجديدة، والاحتفاظ بالتفاعلات السابقة. وهذا يُعزز قدرتها على تقديم استجابات شخصية واعية بالسياق، مما يضمن تجربة مستخدم سلسة وبديئية. تقترح هذه الورقة البحثية أسلوب Elastic Weight Consolidation (EWC) أثناء عملية التعلم، حيث يتم تعديل معلمات الشبكة وتحسينها لتعزيز الاحتفاظ بقدرة التعرف على الفئات الحالية مع استيعاب الفئات الجديدة. تم تنظيم التجربة وتقييم الطريقة المقترحة باستخدام تقنيات التعلم التدريجي والآلي الحالية، بما في ذلك Bidirectional Long Short-Term Memory (97.9%)، Learning without Incremental Classifier and Representation (94.3%)، Corticohippocampal circuits-based hybrid neural network (94%)، Extreme Gradient Boosting (97.5%)، و Lite Extreme Gradient Boosting (87.2%).



(87.2%) على مجموعة البيانات المتوفرة على منصة Kaggle باسم "16 نوع شخصية". تشير النتائج التجريبية إلى أن تقنية Elastic weight Consolidation (EWC) المقترحة أعلى من دقة خوارزميات التعلم التدريجي والآلي السائدة حاليًا والتي تبلغ 98.4%، مما يعزز بشكل كبير قابلية التوسع وذكاء نموذج التصنيف.