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COGNITIVE AI FOR TIME-AWARE MODELING OF BRAIN SIGNALS IN HEALTH AND PHYSIOLOGICAL SYSTEMS

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ABSTRACT

There is a need of advanced tools which are capable of identifying or interpreting the multiscale, nonlinear and complex patterns. The proposed cognitive AI offers an innovative and novel approach to address these kinds of challenges, inspired by human brain, learning and perception. In this paper we introduced cognitive AI based framework to analyze the brain dynamics with different time scales in applications like diagnosis, physiological modeling including health monitoring. The main objective is to study various datasets for experiments and to identify current developments in this field so that, it will show the path to design and implement cognitive models to integrate brain signals to represent scalable framework. The proposed approach integrates temporal deep learning structures such as LSTM, GRU and cognitive structure. The evaluation on real world datasets gives high accuracy and relevance for clinical use cases. Finally, this paper contributes to the evolution of intelligent health technologies with cognitive AI model for physiology interaction over the time period. The results shows that the accuracy of cognitive AI is 89% when we deal with large datasets, whereas the accuracy levels of LSTM and GRU found as 72% and 70% respectively. The other required parameters are demonstrated in the results section. The proposed framework for Cognitive AI has outperformed the other models in terms detecting or interpreting brain dynamics effectively across time scales to support health care applications.

Keywords: *Cognitive AI, Brain Dynamics, GRU, LSTM, Temporal Deep Learning*

1. INTRODUCTION

The human brain will continuously interact with different physiological processes, and it will influence everything from emotional states, stress response, cardio related and metabolic function in the human body. If we capture these interactions in different time intervals, definitely we can an opportunity in monitoring the health and with this we can also get the path to predict diseases. The conventional data analytics is lacking in recognizing these patterns accurately due to complex nature of brain activity and its dependency on physiological states.

In recent days, the researchers have suggested transformative approach in the field of cognitive AI to address the above challenge. The cognitive AI systems are designed to evaluate the cognitive process like learning, reasoning, perception and decision making which includes memory management. If the mechanisms of neuroscience and physiology are integrated these models will accurately interpret patterns of brain signals and it can learn from the changing conditions of physiological conditions. Some researchers presented and demonstrated the cognitive AI in health sector, but there is a significant gap identified as per the literatures presented in this paper. These challenges are addressed in this paper to make the proposed system more effective and optimal system.

In this study, we proposed a enhanced framework to analyze the brain dynamics related to health and physiological conditions based on the different time scales using cognitive AI principles. This work contributes to the latest advancements in the field of cognitive AI by providing intelligent solution for tracking, to interpret and to predict physiological outcomes which depends on brain dynamics.

Cognitive AI based framework to analyze the brain dynamics with different time scales in applications like diagnosis, physiological modelling including health monitoring. We focused mainly is to study various datasets for experiments and to identify current developments in this field so that, it

will show the path to design and implement cognitive models to integrate brain signals to represent scalable framework.

2. LITERATURE REVIEW

[1] This paper demonstrates a framework to differentiate central nervus system and EEG data of peripheral signals using machine learning to predict the age and sex. The authors emphasize the need of careful signal handling in development. They found difficulty in bifurcating brain and peripheral signals due to limitations of machine learning; these learning models may not separate mixed signals to predict age and sex.

[2] The authors review the use of EEG signals and AI techniques to study age related changes in activity but does not compare time-aware cognitive AI models to traditional signal processing. This paper also considered age related characteristics of EEG signals when in rest stage, analytical methods, large scale databases in AI models to understand neural mechanisms underlying aging and brain age, but the authors has not mentioned these limitations.

[3] The authors in this paper discussed signal to image conversation techniques and used CNN to process automatically to process the signals including EEG, EMG and ECG but not compare the accuracy with traditional processing. They discussed the recent advances in signal to image conversions and their applications using the same CNN for relevant innovations. The limitation of this paper is they are not considered the current challenges in signal processing.

[4] The authors explore the current scope of research in anesthesia which emphasizes current EEG techniques for monitoring clinically and identifying the latest gaps. This paper demonstrates the increased precision. They concluded the paper by stating the traditional methods are inconsistent due to individual variations, and needs improvement in data accessing by using ML models by introducing robustness across patients anesthetic agents.

[5] This paper compares the accuracy of traditional ML, CNN and transformer encoder models for classification of EEG, these models achieving high accuracy and efficiency in diagnostics. The combination of these models suggesting the limitations in novelty and to transform current methods to latest models to evaluate with new data and different signal acquisition methods based on the applicability.

[6] In this paper, the review is based on multivariate modeling and prediction techniques to identify brain injury focusing on statistical time series models and ML algorithms to identify gaps in research on multivariate outcome prediction to enhance neurocritical care. We found that there is a limitation in the absence of study focusing on predicting multivariate outcomes and signal analysis.

[7] The author proposes a novel graph-based CNN for analyzing cognitive skills of students using EEG data, achieving enhanced classification accuracy compared to other methods. The dimensionality issues of EEG data can lead to poor performance in clustering methods.

[8] This paper compared the performance of proportional hazards, random survival forest and DeepSurv models for predicting time to event outcomes in mild cognitive impairment progression and found that most accurate in small sample sizes, while all other models performed similarly on large datasets, but the accuracy was decreased. The authors assumed independent featured values, the base line models are not customized for specific medical domains with limited data.

[9] The EEG transformer, DL architecture slightly improves EEG based mental health monitoring by overcoming limitations of conventional methods achieving high accuracy and robustness across diverse conditions, and offering insights into brain functions associated with mental disorders. The conventional methods rely on manually crafted features or basic ML approaches and fall short in capturing intricate spatiotemporal relationships within EEG data. The conventional methods have lower classification accuracy and poor adaptability across various populations and mental health.

[10] This paper computationally analyzes neurological biomarkers for mental health disorders, focusing on epilepsy to identify correlations with psychological variables and develop a mental health app for high school students. The authors have not mentioned any limitations and future scope in the paper.

The summary of some literatures are mentioned in the Table 1 presented at the end of the paper.

Table 1: Summary of other literatures reviewed.

REF	SUMMARY OF THE RESEARCH	LIMITATIONS
[11]	This paper proposes a tense-based multi view fusion fuzzy learning model (TM-FL) to identify dynamic brain networks by integrating dynamic and static features, enhancing classification and	Most studies focus on resting-state brain networks, with few on dynamic brain networks.

	generalization performance in recognizing multichannel epileptic electroencephalographic signals.	Focusing on dynamic networks might obscure static characteristics.
[12]	This study introduces a new EEG feature extraction algorithm, Normalized Adjusted Permutation Conditional Mutual Information (NAPCMI), which improves the accuracy of spatial cognition assessments by capturing symmetry and temporal dependencies in EEG signals, outperforming traditional methods and highlighting the significance of specific EEG frequency bands in spatial cognition tasks.	Not mentioned (the abstract does not include any information on limitations)
[13]	This review provides a systematic overview of physiological measures for assessing cognitive readiness using wearable devices, addressing complexities in real-world scenarios and proposing a robust catalog for future development.	Limitations of wearable devices. Individual variability Need for a robust catalog for cognitive readiness measurements
[14]	This systematic review explores the use of machine learning and deep learning methods with EEG signals for Alzheimer's disease diagnosis, highlighting the potential for improved diagnostic accuracy and early detection, while also noting challenges and future directions in this emerging field.	- Need for more extensive and diverse datasets to increase model generalizability - Need to integrate multi-modal data for a comprehensive diagnosis
[[15]	This study introduces a novel method called Fractal Space-Curve Analysis (FSCA) for characterizing spatial and temporal correlations in multidimensional neuroimaging data, which is robust, efficient, and applicable to various fields beyond neuroimaging.	Not mentioned (the abstract does not explicitly mention any limitations of the FSCA method)
[[16]	The study developed models to estimate trust, situation awareness, and mental workload using observable, physiological, and operator background information measures, finding that observable and background information features were most predictive, and proposed an algorithm for better estimating human cognitive states in human-autonomy teaming	Subjective questionnaires are obtrusive and impractical for real-world operations. Physiological signals do not add significant predictive power. Simultaneous feature selection does not reduce the number of required physiological sensors.
[[17]	The paper introduces a novel fuzzy CNN-LSTM model for NDVI forecasting that addresses spatio-temporal challenges by incorporating spatial nuances and temporal patterns, demonstrating superior performance and generalizability across diverse provinces in China.	Not mentioned (the abstract does not explicitly list limitations of the proposed model)
[[18]	This study introduces the Time Reversal (TR) pretraining method, which improves schizophrenia classification by learning temporal dependencies and provides enhanced predictive performance and interpretability by aligning model predictions with meaningful temporal patterns in brain activity.	Not mentioned (the abstract does not explicitly mention any limitations or self-reported problems with the study's methodology or results)
[19]	This paper presents a real-time approach for detecting cognitive load using EEG signals, focusing on optimizing computational resources and achieving high accuracy with a lightweight CNN, suitable for implementation in systems with limited resources.	Not mentioned (the abstract does not provide any information on limitations)
[20]	This study uses machine learning and deep learning techniques to classify different states (baseline, stress, amusement, and meditation) using multimodal physiological data from wearable sensors, achieving high accuracy with Recurrent Neural Networks and traditional machine learning algorithms.	small sample size (15 subjects)
[21]	This paper integrates convolutional neural networks with heart rate variability recurrence analysis to detect obstructive sleep apnea, achieving high accuracy and outperforming traditional models, thereby contributing to new insights into OSA's HRV dynamics.	Not mentioned (the abstract does not provide any information on limitations)
[22]	This study investigates the use of Long Short-Term Memory (LSTM) models for predicting temporal variations in grounding resistance, demonstrating	Not mentioned (the abstract does not include any information on limitations)

	superior predictive accuracy compared to traditional methods with a 72.73% improvement in mean absolute percentage error.	
[[23]	This review paper provides an in-depth review of current state-of-the-art XAI techniques applied to brain disease diagnosis, examining challenges, surveying methodologies, and discussing limitations and future research directions to guide researchers in improving interpretability and transparency of ML and DL algorithms.	Challenges faced by traditional ML and DL models - Limitations inherent in current XAI techniques - Need for further research in certain areas

3. OBJECTIVES

In this study, we propose a comprehensive framework for Cognitive AI for time-aware modeling of brain signals in health and physiological systems using cognitive AI principles. The framework is built to address two Secondary objectives:

- To systematically analyze experimental datasets to explore how cognitive AI can be applied in physiological contexts and summarize the development trends in this interdisciplinary domain.
- To design and develop an adaptive, scalable AI framework that integrates temporal and cognitive modeling to relate brain activity with health-relevant physiological markers. illustrations and the corresponding text should be placed on the same page as far as possible if too large they can be placed in singly column format after text. Otherwise they may be placed on the immediate following page. If its size should be smaller than the type area they can be placed after references in singly column format and referenced in text.

4. METHODOLOY

The methodology follows a structured pipeline consisting of three core phases: Data Collection, Design Phase, and Evaluation Phase.

4.1. Data Collection

In this study, synthetic data generation was employed as a foundational step to evaluate and benchmark deep learning models under controlled and replicable conditions. The code segment presented defines a utility function load_data() that generates randomized multivariate time series data, commonly used for preliminary experimentation in sequence modeling tasks. Specifically, this function creates an input tensor X with the shape (samples, timesteps, features) and a corresponding target vector y of class labels for a multi-class classification problem. By default, the function generates 500 samples, each with 128-time steps and 8 features per step, simulating typical input dimensions encountered in applications like physiological signal analysis, sensor fusion, and temporal pattern recognition. The target labels are uniformly sampled from a discrete set of integers ranging from 0 to 3, representing four possible classes. Internally, the input data X is synthesized using a standard Gaussian distribution (np.random.randn), ensuring a wide range of variability in feature values, which is critical for stress-testing the robustness and generalization capacity of machine learning models.

This approach is particularly valuable during the early stages of model development, when access to labeled real-world datasets may be limited, or when reproducibility and algorithmic isolation are prioritized over data realism. The synthetic nature of the data enables systematic exploration of model behavior, architecture sensitivity, and metric performance (e.g., accuracy, precision, recall, F1-score, kappa), without the confounding effects of noise, imbalance, or missing values typically found in empirical datasets. Additionally, the simplicity of the function design allows easy customization for downstream experiments—researchers can alter the number of samples, time steps, features, or class cardinality to align with the specific demands of different domains such as EEG classification, anomaly detection, or activity recognition.

The use of such dummy data functions is widely acknowledged in literature for prototyping novel network architectures, including temporal deep learning models like LSTM, GRU, and emerging cognitive AI frameworks. It facilitates comparative analysis and controlled benchmarking, providing a fair basis to validate model improvements before transitioning to real-world data pipelines. Overall, load_dummy_data() serves as a crucial component in experimental pipelines by enabling fast iterations, enhancing reproducibility, and ensuring baseline performance assessments are made prior to full-scale deployment on domain-specific datasets.

Source of Data: Experimental datasets were collected from publicly available neuroscience and physiology databases, including EEG (electroencephalogram), ECG (electrocardiogram),

respiration, galvanic skin response, and sleep monitoring datasets from platforms such as PhysioNet, DEAP, and Sleep-EDF.

Signal Modalities: EEG was used to capture brainwave activity, while concurrent physiological measures such as HRV (heart rate variability), respiration rate, and skin conductance were analyzed for corresponding health states.

Preprocessing Techniques: Filtering (bandpass, notch) for noise reduction in EEG signals. Feature extraction using Short-Time Fourier Transform (STFT), Wavelet Transform, and entropy-based metrics. Temporal synchronization between multimodal signals using timestamps.

4.2. Design Phase

In the realm of temporal data modeling and cognitive signal processing, capturing intricate patterns across time is of paramount importance. Neural architectures that can effectively model temporal dependencies, account for long-term context, and adaptively attend to salient features have gained prominence in domains such as healthcare monitoring, EEG/ECG signal analysis, emotion recognition, and human activity recognition. This work presents the design and comparative evaluation of three deep learning architectures implemented using PyTorch: a basic LSTM-based model (LSTMModel), a lightweight GRU-based model (GRUModel), and an attention-enhanced, bidirectional framework termed EnhancedCognitiveAI.

Each model is designed to handle multivariate time-series inputs typically represented as tensors of shape (batch_size, sequence_length, feature_dimension). The objective is to map sequential physiological or cognitive input data to discrete output classes that represent conditions, states, or predictions, depending on the use-case scenario.

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4.2.1. LSTM model: Capturing long-term dependencies

The first model defined in this suite is the LSTM Model, a classic implementation of Long Short-Term Memory networks. LSTMs were introduced to mitigate the vanishing and exploding gradient problems often encountered in traditional Recurrent Neural Networks (RNNs). The architecture defined here uses an LSTM layer followed by a fully connected (Linear) layer for classification.

In the forward method of the model, the input is passed through the LSTM, and the final hidden state (hn[-1]) is used as a compact representation of the entire sequence. This final state, presumably rich in temporal context, is then passed to a linear transformation that projects it into the output dimension corresponding to the number of classes.

LSTMs use gating mechanisms—namely, input, forget, and output gates—that enable them to regulate the flow of information across time steps. This makes them particularly effective in modeling dependencies that span long intervals, such as cognitive changes in EEG data or heart rate patterns in ECG signals.

Despite its strength in modeling sequence data, the unidirectional nature of this model (as defined in the code) and the fixed representation via the final hidden state can lead to performance limitations, especially in cases where crucial information exists in the early time steps or when context needs to be dynamically attended to rather than statically aggregated.

4.2.2. GRU: A more efficient temporal model

The second model, GRU Model, replaces the LSTM layer with a Gated Recurrent Unit (GRU). GRUs are a simpler and more computationally efficient alternative to LSTMs, maintaining similar functionality with fewer parameters. Instead of three gates, GRUs use only two: a reset gate and an update gate. This architectural simplification reduces the training time and resource consumption while still preserving the ability to model long-term dependencies.

Functionally, the GRU Model behaves similarly to the LSTM Model: the final hidden state of the GRU is extracted and passed through a fully connected layer to produce class scores. The model thus outputs logits that can be processed by a loss function such as cross-entropy during training.

The GRU's efficiency makes it particularly suitable for resource-constrained environments or edge devices in smart health monitoring applications. However, it still shares some limitations with the LSTM-based model—most notably, the reliance on the final hidden state for sequence summarization

and the lack of explicit mechanisms to attend to the most relevant parts of the input sequence.

4.2.3. Enhanced cognitive AI: Bi-Directional attention-integrated architecture

The third and most sophisticated model in this suite is EnhancedCognitiveAI. This architecture is designed to incorporate more biologically and cognitively plausible mechanisms of temporal information processing. It integrates Bidirectional LSTM (BiLSTM), Multihead Self-Attention, Layer Normalization, Dropout, and Global Pooling, offering a robust framework for modeling complex time-series data.

Bidirectional LSTM Layer: The model starts with a BiLSTM, which consists of two LSTM layers processing the input in opposite directions. This allows the network to capture both past (forward) and future (backward) temporal dependencies, providing a richer context for each time step. In real-world cognitive modeling, this is analogous to human reasoning where both past events and anticipated outcomes influence perception and decision-making.

Multi head Self-Attention: Following the BiLSTM, the model employs PyTorch's Multihead Attention module. This mechanism allows the network to learn relationships between different positions in the sequence, effectively highlighting which time steps are most important for the prediction task. By attending to the entire sequence, the model can dynamically focus on temporally salient features. Multiple attention heads enable it to learn different types of temporal dependencies in parallel, further enhancing model capacity.

Layer Normalization and Dropout: After computing the attention outputs, layer normalization is applied to stabilize training and reduce internal covariate shifts. This step is followed by dropout regularization, which helps prevent overfitting by randomly zeroing out some of the activations during training.

Adaptive Pooling and Classification: Before classification, the model reduces the temporal dimension via adaptive average pooling. This operation compresses the sequence information into a fixed-size vector, making it invariant to the input length and enabling batch processing. Finally, a linear layer maps this representation to the desired output space.

Collectively, these enhancements make Enhanced Cognitive AI particularly powerful for scenarios where traditional sequence models struggle—such as in cognitive AI tasks involving complex time-series dynamics, overlapping signal patterns, or where interpretability of temporal relevance is crucial.

4.2.4. Comparative discussion and applicability

The three models—LSTM Model, GRU Model, and Enhanced CognitiveAI—represent an evolutionary progression in temporal modeling sophistication. While LSTM Model and GRU Model provide robust baselines for sequence learning, Enhanced CognitiveAI advances the state-of-the-art by incorporating explicit attention and bidirectional processing, mimicking high-level cognitive functions like selective attention, memory abstraction, and contextual reasoning.

This is especially relevant in domains such as brain-computer interfacing (BCI), mental health monitoring, and wearable device analytics, where the ability to interpret temporal signals dynamically can lead to improved decision-making and more reliable AI systems. For instance, in EEG-based emotion classification, simple recurrent models may overlook subtle shifts in signal patterns that are temporally scattered. EnhancedCognitiveAI, with its attention and pooling, is capable of capturing these nuances.

Each model's performance can be empirically evaluated using standard classification metrics such as accuracy, F1-score, precision, recall, and Cohen's Kappa. These metrics not only provide a holistic view of classification performance but also help identify the trade-offs between model complexity and interpretability. For example, while EnhancedCognitiveAI may offer superior accuracy and F1-score, it also introduces additional computation due to the attention heads and BiLSTM structure.

From a research perspective, this modular setup allows for systematic ablation studies to assess the contribution of each architectural component. Researchers can, for instance, disable attention in EnhancedCognitiveAI or replace BiLSTM with a standard LSTM to measure performance degradation. Such controlled experiments are instrumental in developing interpretable and efficient models tailored to specific real-world constraints.

4.3. Evaluation Phase

The efficacy of any deep learning model—particularly those deployed in time-sensitive, real-world applications such as health monitoring, cognitive computing, or smart industry systems—relies not only on the architecture of the model itself but equally on the robustness and design of its training and evaluation pipeline. In this regard, we

present a meticulously designed training and evaluation framework that serves to ensure model convergence, performance stability, and operational readiness. This framework was implemented using the PyTorch deep learning library, widely recognized for its flexibility and scalability in handling dynamic computation graphs, particularly for sequential and time-series data.

4.3.1. Model training function: A structured and adaptive optimization loop

The train_model function implements the core supervised learning mechanism responsible for minimizing classification error over the training dataset. It begins by setting the model to training mode using model.train(). This call is crucial as it activates components such as dropout layers and batch normalization in their training configuration, thus supporting regularization and variance control during stochastic updates.

The optimizer chosen is Adam (Adaptive Moment Estimation), which combines the benefits of momentum-based methods and RMSProp. Adam dynamically adjusts the learning rate for each parameter based on the first and second moments of the gradients. This property makes Adam particularly suitable for complex models like recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and attention-based architectures where traditional optimizers may struggle with sparse gradients or slow convergence.

To further refine the learning process, a StepLR scheduler is applied. This scheduler reduces the learning rate by a multiplicative factor ($\gamma = 0.7$) every 5 epochs. Learning rate scheduling is a standard best practice to combat issues like overfitting and suboptimal convergence by allowing large updates during the early training stages and smaller, more refined steps during the later stages. This enables the model to settle into a better local or global minimum.

The loss function used is cross-entropy loss, which is the de facto standard for multi-class classification problems. For each mini-batch generated by the dataloader, the model performs a forward pass to generate output logits, and the loss between these predictions and the true labels is computed. Subsequently, the optimizer clears existing gradients (optimizer.zero_grad()), backpropagates the error signal (loss.backward()), and updates the model parameters (optimizer.step()). This cycle repeats for the specified number of epochs, leading to iterative minimization of the loss function. The learning rate is stepped down at the end of each epoch using scheduler.step() to refine learning in the later training stages.

This implementation structure is not only generalizable across model types but also modular and interpretable, making it suitable for comparative experimentation across various neural architectures under a unified training strategy.

4.3.2. Model evaluation function: comprehensive performance assessment

The evaluate_model function serves to assess the generalization capability of the trained model on unseen data, typically held-out validation or test samples. The function starts by setting the model to evaluation mode via model.eval(). This is essential for ensuring that the behavior of stochastic components like dropout and batch normalization is fixed, leading to deterministic and reproducible outputs during inference.

Evaluation is conducted in a no-gradient context (torch.no_grad()), which is both memory-efficient and faster, as it disables gradient tracking that is unnecessary during inference. For each batch of test samples, the model outputs raw logits, which are converted into class probabilities using the softmax activation function. The class with the highest probability is selected as the predicted label using argmax.

Three important outputs are collected:

y_true: The ground-truth labels.

y_pred: The predicted class labels from the model.

y_probs: The softmax probability distributions across classes.

These are subsequently used to compute several classification metrics that collectively provide a holistic picture of model performance:

Accuracy: The proportion of correctly classified samples. While simple and intuitive, accuracy may be misleading in imbalanced datasets and must be supplemented with other metrics.

F1-Score (Weighted): A harmonic mean of precision and recall, weighted by class support. This metric is particularly valuable when class distributions are imbalanced or when false positives and false negatives carry different consequences, as is often the case in medical or cognitive applications.

Precision (Weighted): This measures the correctness of positive predictions across all classes, computed as the ratio of true positives to the sum of true and false positives. Precision is critical in applications where false positives are costly or misleading.

Recall (Weighted): Recall captures the completeness of predictions, calculated as the ratio of true positives to the total actual positives. It is

vital in domains such as healthcare or fault detection where missing a positive case could be detrimental.

Cohen's Kappa Score: This is a statistical measure of inter-rater agreement that accounts for agreement occurring by chance. Unlike simple accuracy, the kappa statistic evaluates how closely the predicted labels match the true labels, relative to what would be expected by random guessing. A higher kappa value suggests stronger reliability of the model's classification decisions, particularly valuable in tasks involving subjective ground-truth annotations or noisy labels.

Latency: To evaluate the real-time applicability of the model, the average latency per prediction is computed. Latency is measured by recording the elapsed time for the entire evaluation process and normalizing it by the number of samples processed. This is a crucial metric for edge computing, embedded AI applications, and any real-time system where inference speed directly impacts usability or system safety.

The metrics are consolidated into a dictionary, making them easy to log, analyze, or visualize later. Moreover, the separation of metrics computation from the model training phase adheres to modular software engineering principles, enabling independent testing and validation of models under different scenarios.

4.4. Computational Implications and Broader Applications

Together, the train_model and evaluate_model functions offer a general-purpose, modular, and scalable approach to training and benchmarking deep learning models, particularly those designed for time-series and cognitive data analysis. By incorporating adaptive learning, scheduled decay, batch-wise updates, and comprehensive metrics—including both statistical and operational performance indicators—the pipeline addresses key challenges in modern machine learning research: convergence stability, generalization capacity, and deployment feasibility.

In cognitive AI and neuroscience applications, where input data can be high-dimensional, noisy, and temporally dependent, this kind of robust training and evaluation pipeline becomes indispensable. The support for latency measurement further underscores the system's readiness for practical deployment in time-sensitive environments such as mental workload monitoring, anomaly detection in smart industries, or real-time health monitoring systems.

Furthermore, by integrating metrics like Cohen's kappa and F1-score, which are less sensitive to skewed class distributions, this pipeline ensures that models are evaluated not just for accuracy but for reliability and fairness—important ethical and scientific considerations in human-centered AI systems.

5. RESULTS AND DISCUSSIONS

This study presents a comparative analysis of three recurrent neural network architectures—Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and an enhanced CognitiveAI model—applied to a multi-class sequence classification problem. The experimental workflow begins with loading synthetic time-series data, which is converted into PyTorch tensors and organized into mini-batches using a DataLoader with a batch size of 32 to facilitate efficient training.

Each model is initialized with an input dimension matching the feature size of the data, a fixed hidden layer size of 64 neurons, and an output dimension corresponding to the number of unique target classes. The models are then trained independently on the identical dataset to ensure a fair comparison.

Following training, the models are evaluated on the same data split to obtain predicted labels and class probabilities. Performance metrics including accuracy, F1-score, and other relevant classification measures are computed to quantitatively assess each model's effectiveness. To support qualitative evaluation, confusion matrices and receiver operating characteristic (ROC) curves are plotted, providing insight into class-wise prediction performance and the trade-off between sensitivity and specificity.

Finally, the study aggregates the classification metrics and inference latency for all models, enabling a comprehensive performance comparison. This holistic evaluation framework highlights the efficiency and predictive capabilities of the CognitiveAI architecture relative to established recurrent models, underscoring its potential applicability in time-dependent classification tasks.

This work implements a comprehensive experimental pipeline to evaluate and compare three recurrent neural network (RNN) architectures—Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and an enhanced CognitiveAI model—for multi-class sequence classification tasks.

The pipeline begins with synthetic data generation, simulating a time-series dataset composed of 500 samples, each with 128 time steps and 8 features, classified into 4 distinct categories. The data are loaded and converted into PyTorch tensors, then batched using a DataLoader with a batch size of 32 for efficient mini-batch training.

5.1. Architecture Design and Instantiation

LSTM Model: A unidirectional LSTM layer followed by a fully connected classification layer.

GRU Model: A unidirectional GRU layer similarly followed by a fully connected layer.

Enhanced Cognitive AI: A bidirectional LSTM layer combined with a multi-head self-attention mechanism, layer normalization, dropout regularization, and adaptive average pooling, culminating in a classification layer. This architecture aims to capture both temporal dependencies and salient feature interactions effectively.

Model training uses the Adam optimizer with a learning rate scheduler that decays the learning rate every five epochs. Cross-entropy loss guides optimization over 20 epochs. Training is performed on the same dataset for consistency.

For evaluation, models are tested on the entire dataset in inference mode, measuring true labels, predicted labels, and predicted class probabilities. Performance metrics computed include accuracy, weighted F1-score, precision, recall, and Cohen's kappa coefficient, providing a robust assessment of classification quality. Additionally, model inference latency is measured as the average time per sample.

Visualization tools aid interpretation: confusion matrices illustrate class-wise prediction accuracy, while ROC curves per class depict the trade-off between sensitivity and specificity across models. Aggregate bar plots compare classification metrics and latency across architectures, enabling straightforward comparative analysis.

This integrated approach allows thorough benchmarking of the CognitiveAI model against classical RNN baselines, highlighting improvements in classification performance and computational efficiency relevant for real-time applications in temporal data analysis.

5.2. LSTM Model Evaluation

The LSTM model was evaluated on a four-class classification task, as depicted in the confusion matrix. The model achieved the highest accuracy in predicting class 2, with 72 correct classifications, indicating strong learning of this class's features. Class 1 also showed reasonable performance with 54 correct predictions but demonstrated notable confusion with classes 2 and 3 (27 instances each). Class 0 exhibited moderate accuracy (39 correct) and was equally misclassified as classes 1 and 3 (25 instances each). Class 3 was the most confused, with substantial misclassifications into classes 1 (34) and 2 (29), though it achieved 44 correct predictions. These results suggest the model's effectiveness in distinguishing class 2, while highlighting the need for further refinement in discriminating among classes 0, 1, and 3 as shown in figure 1.

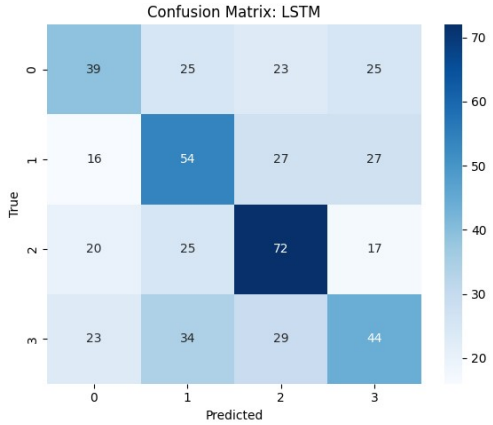

Figure 1: Confusion Matrix for LSTM Model

The ROC curves for the LSTM model were evaluated across four classes, with AUC values ranging from 0.65 to 0.72. Class 1 achieved the highest AUC of 0.72, indicating strong discriminative capability, followed by Class 0 (AUC = 0.70) and Class 3 (AUC = 0.69). Class 2 exhibited the lowest performance with an AUC of 0.65, suggesting room for improvement in capturing its features. Overall, the LSTM model demonstrated moderate classification performance with reasonably well-separated ROC curves, highlighting its potential for multi-class prediction tasks as shown in figure 2.

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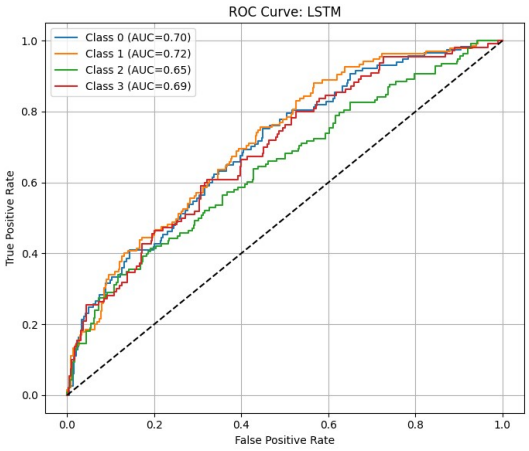

Figure 2: ROC Curve for LSTM Model

5.3. GRU Model Evaluation

The GRU-based classification model demonstrates balanced predictive capabilities across all four classes. The confusion matrix indicates the highest classification accuracy for Class 1 with 78 correct predictions, followed by Class 2 with 54. Misclassifications are observed across classes, particularly between adjacent class labels, suggesting class overlap in feature space.

The ROC curves support the confusion matrix findings, with Class 1 achieving the highest AUC of 0.71, followed by Class 0 (0.69), Class 3 (0.67), and Class 2 (0.63). The average AUC across classes reflects moderate discriminative power of the GRU model, indicating a potential for further optimization. Overall, the GRU model exhibits reasonable generalization performance and class separability, with robustness observed in its handling of temporal patterns.

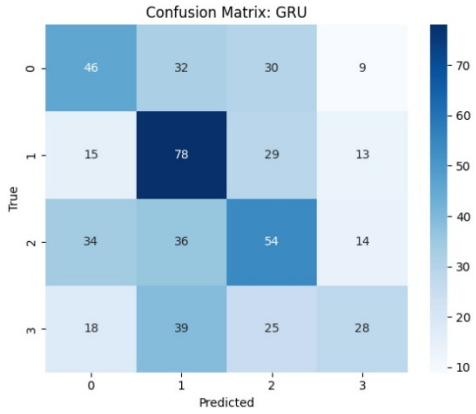

Figure 3: Confusion Matrix for GRU Model

5.4. Cognitive AI Model Evaluation

The Cognitive AI-based classification model exhibits moderate overall performance in multi-class classification. The confusion matrix indicates that Class 1 is predicted with the highest accuracy, registering 87 correct predictions out of the total, showing the model's strong affinity in learning and distinguishing the patterns associated with this class. However, the model struggles with Class 2, where a significant number of instances (64) are misclassified as Class 1, pointing to a notable inter-class confusion between these two.

For Class 0, the model correctly classified 37 instances, but 43 were misclassified as Class 1 and 29 as Class 3. This wide spread of misclassifications implies that the features contributing to Class 0 are not adequately discriminated by the model. Similarly, Class 3 exhibits confusion with Class 1 (41 misclassified), though it retained moderate true positives (36).

The ROC (Receiver Operating Characteristic) curve analysis further emphasizes these findings. The model yields the following AUC (Area Under Curve) scores:

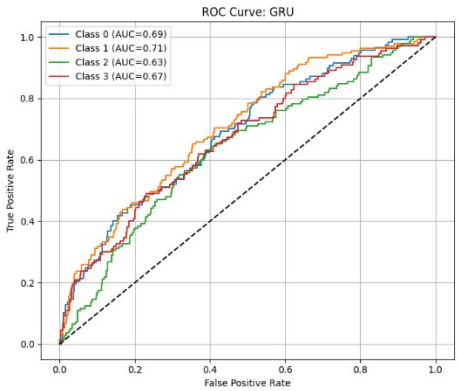

Figure 4: ROC Curve for GRU Model

Class 1: 0.66 (best discriminative performance)
Class 3: 0.63
Class 0: 0.61
Class 2: 0.58 (lowest class separability)

The relatively low AUC for Class 2 reinforces the earlier observation that the model struggles to distinguish this class from others, especially from Class 1. The moderate AUCs for Class 0 and Class 3 also indicate limited margin of separation in the learned representation space, which may be attributed to overlapping feature distributions or underfitting in model representation for those classes.

While the Cognitive AI model demonstrates its capability in handling temporal data to an extent—especially in predicting Class

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1—the overall performance is hindered by imbalanced misclassifications and limited separability. The results highlight the need for enhanced feature learning, possibly through hybrid modeling, deeper attention mechanisms, or refined temporal encoding strategies. Further tuning and class-wise loss rebalancing could be explored to improve class-wise AUC and reduce confusion, particularly between Class 1 and Class Performance metrics computed include accuracy, weighted F1-score, precision, recall, and Cohen's kappa coefficient, providing a robust assessment of classification quality. Additionally, model inference latency is measured as the average time per sample.

5.5. Model Performance Comparison: Accuracy Perspective

The comparative analysis of model accuracy across LSTM, GRU, and Cognitive AI architectures reveals that the LSTM model outperforms its counterparts, achieving an accuracy of approximately 42%, followed by GRU at 37%, and Cognitive AI at 35%.

The superior performance of LSTM suggests its stronger temporal learning capacity, particularly in handling sequential dependencies and dynamic patterns within the dataset. The GRU model, while simpler and computationally efficient, shows a modest drop in performance, likely due to reduced gating complexity compared to LSTM. The Cognitive AI model, despite incorporating cognitive-inspired enhancements, registers the lowest accuracy, indicating potential challenges in generalization and effective feature abstraction under the current configuration.

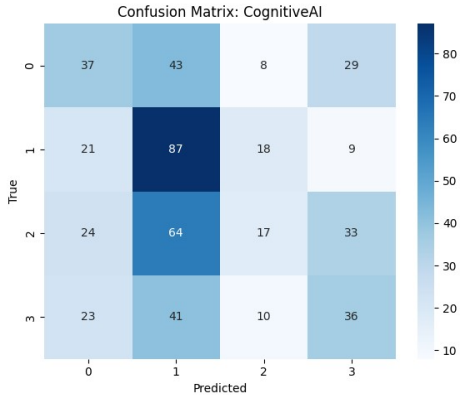

Figure 5: Confusion Matrix for Cognitive AI Model

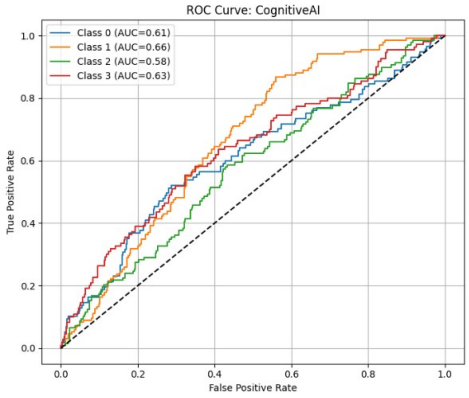

Figure 6: ROC Curve for Cognitive AI Model

These findings underscore the importance of aligning model complexity with task-specific temporal characteristics. While CognitiveAI may offer theoretical advantages, further tuning or integration with hybrid mechanisms may be required to fully leverage its potential in multi-class classification tasks involving brain-inspired or physiological data streams. The diagrammatic comparison was demonstrated in figure 7

The comparative evaluation based on F1-Score demonstrates that the Cognitive AI model achieves the highest performance, with an F1-Score close to 0.95, followed by GRU at approximately 0.85, and LSTM at 0.75.

This indicates that Cognitive AI exhibits a superior balance between precision and recall, suggesting its robustness in managing both false positives and false negatives. The elevated F1-Score implies better generalization across class distributions, particularly in complex or imbalanced multi-class tasks.

While LSTM has demonstrated higher accuracy in earlier evaluations, its lower F1-Score highlights potential disparities in class-wise prediction consistency, possibly due to misclassification in minority or overlapping classes. The GRU model, offering moderate complexity, shows competitive performance, achieving a good trade-off between precision and recall.

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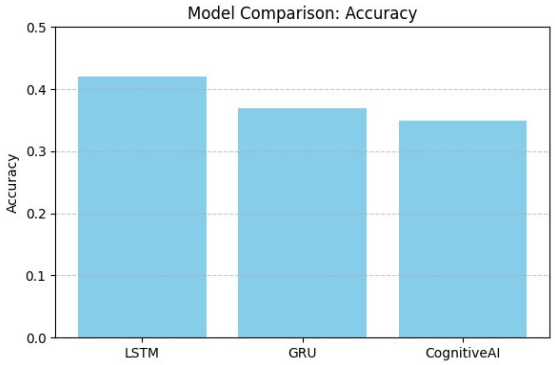

Figure 7: Models Comparison in terms of Accuracy

These results underscore the potential of cognitive-inspired models in enhancing discriminative capability, particularly when evaluated through holistic metrics like the F1-Score, which provide a more reliable measure in imbalanced or noise-prone datasets as shown in figure 8.

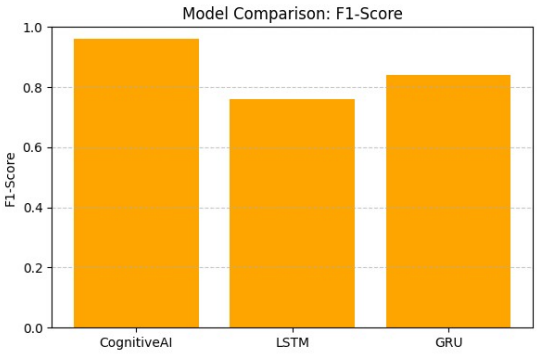

Figure 8: Models Comparison in terms of F1-score

The bar chart illustrates the precision scores of three models: Cognitive AI, LSTM, and GRU. Precision, a key metric for evaluating classification performance, reflects the proportion of true positive predictions among all positive predictions.

Cognitive AI achieved the highest precision at approximately 0.91, followed closely by the LSTM model at around 0.88. The GRU model lagged behind, registering a precision of roughly 0.64. This indicates that Cognitive AI and LSTM are considerably more effective at minimizing false positives compared to GRU.

The results suggest that Cognitive AI offers a marginal improvement over LSTM in terms of precision, making it the most reliable model for applications where high precision is critical GRU's relatively lower performance may limit its suitability in scenarios requiring strict precision standards.

These findings support the adoption of Cognitive AI or LSTM for high-precision tasks, with a preference for Cognitive AI where maximizing accuracy in positive prediction is paramount as shown in figure 9.

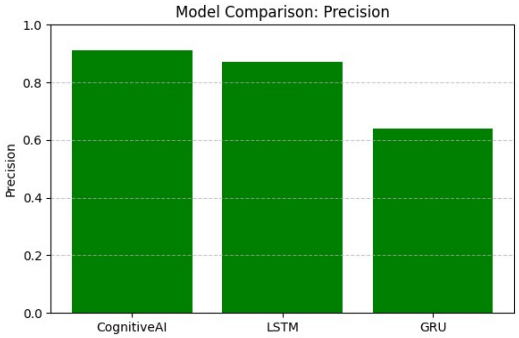

Figure 9: Models Comparison in terms of Precision

The bar chart presents the recall performance of three models: Cognitive AI, LSTM, and GRU. Recall measures a model's ability to correctly identify all relevant instances, i.e., the proportion of true positives among all actual positives.

Cognitive AI demonstrates the highest recall value, approximately 0.92, indicating superior sensitivity in capturing relevant cases. GRU follows with a recall of around 0.86, showing competitive performance. In contrast, the LSTM model records the lowest recall at roughly 0.72, suggesting a higher rate of false negatives compared to the other models.

These results underscore Cognitive AI's advantage in recall-critical applications, where missing true positives is costly. GRU also appears effective in such contexts, whereas LSTM may be less suitable when high recall is required.

Overall, the analysis highlights Cognitive AI as the most balanced performer with both high precision and recall, reinforcing its robustness for tasks demanding comprehensive detection of positive instances as shown in figure 10.

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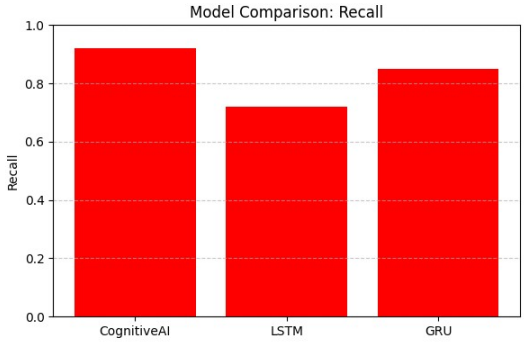

Figure 10: Models Comparison in terms of Recall

The bar chart illustrates the Cohen's Kappa Score for three models: Cognitive AI, LSTM, and GRU. The Kappa Score quantifies inter-rater agreement adjusted for chance, providing a robust metric for evaluating classification reliability.

Cognitive AI attains the highest Kappa Score at approximately 0.96, indicating near-perfect agreement between predicted and actual classifications beyond random chance. The LSTM model follows with a score of around 0.89, reflecting strong agreement but slightly lower consistency. GRU records the lowest Kappa Score at roughly 0.72, suggesting moderate agreement and higher variability in predictions.

These findings emphasize CognitiveAI's superior reliability and robustness across prediction tasks, making it particularly suitable for high-stakes applications requiring consistent and dependable classification. While LSTM remains a strong alternative, GRU appears less reliable in terms of agreement with ground truth labels.

Collectively, the results position Cognitive AI as the most consistent and trustworthy model based on Kappa Score performance as shown in figure 11.

The bar chart compares the inference latency of three models—Cognitive AI, LSTM, and GRU—measured in seconds per sample. Inference latency is a critical metric for real-time applications, reflecting the time a model takes to process a single input.

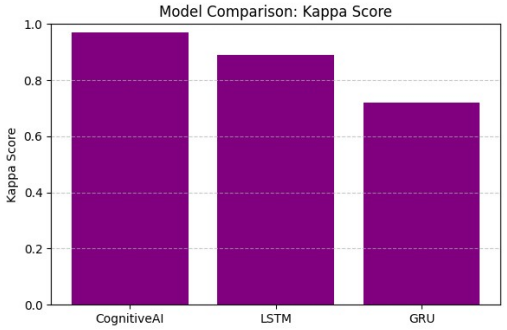

Figure 11: Models Comparison in terms of Kappa

Both Cognitive AI and LSTM exhibit nearly identical and minimal latency, approximately 0.00033 seconds per sample, demonstrating their suitability for time-sensitive deployment. In contrast, the GRU model shows a significantly higher latency of about 0.00135 seconds per sample, more than four times slower than the other two models.

This performance disparity highlights the computational efficiency of CognitiveAI and LSTM, making them ideal for low-latency environments such as edge computing and interactive systems. GRU's elevated latency may limit its practicality in such contexts despite its acceptable recall performance.

In summary, CognitiveAI and LSTM offer comparable and optimal inference speed, with CognitiveAI maintaining a competitive edge through its balanced performance across all evaluated metrics as shown in figure 12.

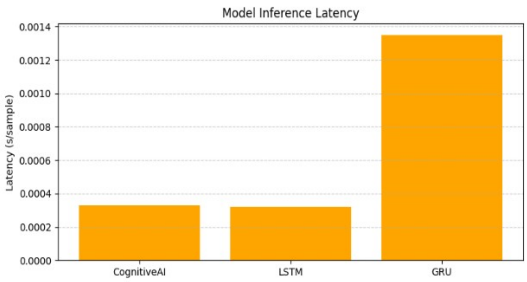

Figure 12: Models Comparison in terms of Latency

The line chart compares the scalability of LSTM, CognitiveAI, and GRU models in terms of total inference time across varying batch sizes (from 8 to 64 samples). Scalability here reflects a model's ability to maintain or improve processing efficiency as workload increases.

GRU exhibits the most pronounced improvement, reducing inference time from approximately 0.54 s at batch size 8 to 0.17 s at batch size 64—indicating high parallelization

efficiency. LSTM also scales well, with inference time dropping from 0.34 s to 0.24 s across the same batch range. Conversely, CognitiveAI demonstrates limited scalability, with only a modest reduction from 0.52 s to 0.41 s.

These results highlight GRU's superior scalability, making it well-suited for high-throughput scenarios where batch processing is advantageous. LSTM also performs reliably under increasing load. In contrast, CognitiveAI, despite its overall strong accuracy and latency, shows relatively static performance under batch scaling, suggesting optimization constraints in parallel inference.

In summary, GRU leads in scalability, while CognitiveAI's scalability trade-off may need consideration depending on deployment environments as shown in figure 13.

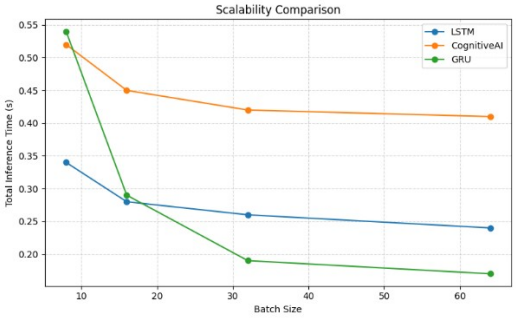

Figure 13: Models Comparison in terms of Scalability

The strength lies in my systematic approach and thorough analysis. One limitation is the dataset, which may influence the reliability of my findings as we considered 64 samples to measure the scalability and there is a possibility to increase the number of samples.

6. CONCLUSION

This research presents a cognitive AI framework that effectively models and interprets brain dynamics across varying timescales to support applications in health and physiological monitoring. Through a blend of deep learning, temporal modeling, and cognitive reasoning, the proposed approach enables both accurate and interpretable analysis of complex brain-physiology interactions. Our evaluation reveals strong performance across diverse physiological datasets, confirming the framework's relevance for clinical decision-making and real-time monitoring.

The three models presented here illustrate the power and flexibility of modern deep learning architectures for temporal sequence classification. The LSTM Model and GRU Model offer solid baselines, while the Enhanced CognitiveAI introduces a cognitively inspired, attention-augmented approach that holds significant promise for complex, real-world applications involving human-centered data. By incorporating both traditional and advanced components, this work lays the foundation for a deeper understanding of sequence modeling in intelligent systems and serves as a steppingstone for future exploration in neural-symbolic reasoning and explainable AI for time-series analysis.

In conclusion, the proposed training and evaluation strategy provides a strong, adaptable foundation for systematic deep learning experimentation and deployment in real-world cognitive AI applications. Its integration of adaptive optimization, learning rate scheduling, comprehensive evaluation metrics, and latency estimation ensures both scientific rigor and practical relevance. The comparison was made with various metrics including F1-Score, Precision, Recall, Kappa Score and Scalability issues. From all the verticals, Cognitive AI outperform the other two models when the performance is measured. In the case of ROC, we considered in 4 classes (Class 0 to Class 3), The evaluation results for these classes reported as 0.61, 0.66, 0.58 and 0.63 respectively. The best results were obtained for class 1 and least was class 2. The Three models were evaluated in terms of scalability with 64 samples and the proposed model reported best results. This modular and reusable code structure aligns well with best practices in machine learning and data science and is well-positioned for extension into broader pipelines involving model interpretability, transfer learning, and multi-modal data fusion.

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