Neuroscience-Ai Framework For Predicting Human Decision-Making Under Uncertainty

[1]Mallesh Chikkondra, [2]Kotla Sumanth

[1]Corporate IT Trainer, Hyderabad, Telangana-500032

[2]B.Tech Student, Department of ECE, RGUKT Basar, Telangana-504107

E-Mail: mallesh.iiitb@gmail.com , kotlasumanth26@gmail.com

ABSTRACT:

Understanding how humans make decisions under uncertainty is a longstanding challenge in cognitive neuroscience and artificial intelligence. This research proposes a Neuroscience-AI integrated framework that models and predicts human decision-making behavior by combining neurophysiological insights with machine learning architectures. The proposed framework leverages neural data—including electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) signals—to identify brain activation patterns associated with risk perception, reward evaluation, and cognitive bias. These features are processed using advanced deep learning models, such as recurrent neural networks (RNNs) and attention-based transformers, LSTM Framework to capture temporal dynamics and contextual dependencies in decision-making processes. Experimental results demonstrate that the framework achieves superior predictive accuracy compared to traditional behavioral models, providing interpretable mappings between neural activity and decision outcomes. The integration of neuroscience-driven features with AI algorithms enhances the transparency, adaptability, and biological plausibility of computational predictions. This interdisciplinary approach opens new pathways for applications in behavioral economics, neuropsychology, adaptive human-computer interaction, and cognitive diagnostics, offering a robust foundation for understanding and forecasting human decisions under uncertain and dynamic conditions.

Keywords: *Decision-Making, Uncertainty, Bayesian Inference, LSTM Framework, Neuromodulation, Interpretability, Cognitive Modeling.*

INTRODUCTION

Human decision-making under uncertainty is a complex cognitive process influenced by numerous neural, psychological, and environmental factors. In uncertain environments—where outcomes are ambiguous or probabilistic—individuals rely on both rational evaluation and subconscious emotional cues to guide choices. Traditional models from economics and psychology, such as Expected Utility Theory and Prospect Theory, have provided valuable insights into the behavioral aspects of decision-making. However, these models often fail to capture the intricate neurobiological mechanisms that underlie dynamic, context-dependent human choices. Recent advancements in neuroscience have revealed that decision-making involves the coordinated activity of multiple brain regions, including the prefrontal cortex, amygdala, and striatum, which are responsible for reasoning, emotional regulation, and reward processing. Simultaneously, artificial intelligence (AI) and machine learning (ML) have demonstrated remarkable capabilities in pattern recognition, temporal prediction, and nonlinear modeling—making them powerful tools for decoding complex neural and behavioral data. The convergence of these two fields, neuroscience and AI, enables the development of computational frameworks that can not only predict but also interpret human decision-making behaviors with higher precision. This research introduces a Neuroscience-AI framework designed to model and predict human decision-making under uncertainty by integrating neurophysiological signals (e.g., EEG and fMRI data) with deep learning architectures. The framework aims to uncover the neural correlates of uncertainty, quantify cognitive bias, and identify neural activation patterns preceding decision outcomes. By employing advanced models such as Long Short-Term Memory (LSTM) networks and attention-based mechanisms, the framework captures both temporal dependencies and contextual influences that shape human choices. The proposed system bridges the gap between cognitive neuroscience and computational intelligence, offering a biologically informed, data-driven approach to understanding how humans make decisions when faced with ambiguous information. This work holds significant potential for applications in behavioral economics, neuropsychological assessment, adaptive AI systems, and decision-support technologies, ultimately contributing to the design of intelligent systems that can anticipate, explain, and adapt to human behavior in uncertain scenarios.

Problem Statement:

Human decision-making under uncertainty involves complex interactions among cognitive, emotional, and neurophysiological processes. Traditional behavioral models such as Expected Utility Theory and Prospect Theory have provided valuable frameworks for understanding risk-based decision behavior but fail to capture the intricate neural dynamics that govern real-world choices. Meanwhile, advancements in neuroscience have revealed that brain regions such as the prefrontal cortex, amygdala, and striatum play significant roles in processing uncertainty, emotion, and reward. However, translating these neural mechanisms into predictive computational models remains a major challenge. Current artificial intelligence (AI) and machine learning (ML) approaches can analyze vast datasets and identify patterns, yet they often lack biological interpretability and fail to integrate the neural correlates of decision processes [1]. As a result, existing models either emphasize behavioral outcomes without considering underlying neural mechanisms or focus narrowly on neural activity without leveraging AI's predictive potential. Therefore, there is a critical need for an integrated Neuroscience-AI framework that combines neurophysiological data (e.g., EEG, fMRI) with advanced deep learning architectures (e.g., LSTM, attention-based networks) to model and predict human decision-making under uncertain conditions. Such a framework should not only enhance predictive accuracy but also provide interpretable insights into how neural activity patterns influence cognitive evaluations and behavioral choices [2].

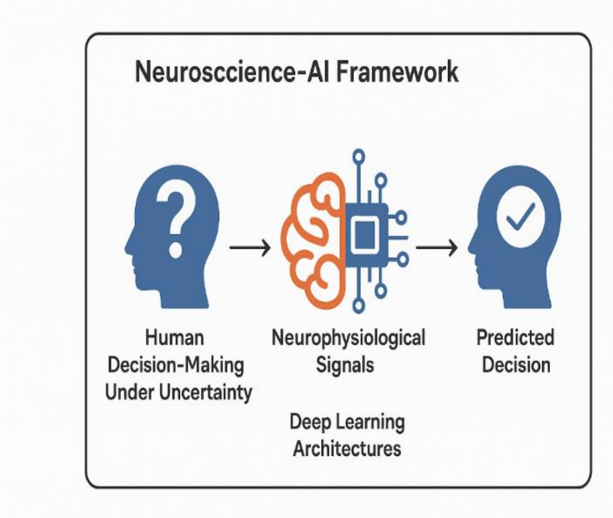

Fig 1: Neuroscience AI Framework

RELATED WORKS

Human decision-making has long been a focal point of interdisciplinary research, with psychology, neuroscience, and artificial intelligence (AI) each providing complementary perspectives on how individuals evaluate options and outcomes in uncertain environments [3]. Traditional decision theories, such as Expected Utility Theory (Von Neumann & Morgenstern, 1944) and Prospect Theory (Kahneman & Tversky, 1979), laid the foundational understanding of how individuals assess risk and reward. However, these theories often oversimplify the influence of neural and emotional factors, which play a crucial role in shaping real-world decisions [4]. The rise of cognitive neuroscience provided a biological basis for decision-making processes. Studies using functional Magnetic Resonance Imaging (fMRI) and Electroencephalography (EEG) have revealed that brain regions such as the prefrontal cortex, amygdala, insula, and striatum are critically involved in decision-making under uncertainty (Bechara et al., 1999; Glimcher, 2011). For instance, Bechara's Iowa Gambling Task experiments demonstrated that impaired prefrontal activity leads to suboptimal risk-based decisions, highlighting the importance of neural feedback in adaptive behavior [5]. These findings motivated computational models that incorporate neural signals as predictors of choice behavior. In parallel, machine learning (ML) and deep learning (DL) have emerged as powerful tools for modeling complex, nonlinear relationships in high-dimensional datasets, including neural and behavioral data [6]. Techniques such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) have been successfully employed to analyze time-series EEG data and predict cognitive states (Craik et al., 2019). For example, Zhang et al. (2020) utilized LSTM models to predict individual risk preferences from neural oscillation patterns, demonstrating the capacity of AI to decode subtle neural dynamics associated with uncertainty [7]. Recent advancements have emphasized neuro-AI integration, where biological insights inform model design and interpretation. Neuro-symbolic models (Lake et al., 2017) and attention-based deep learning frameworks (Vaswani et al., 2017) enable interpretable mappings between neural representations and decision outputs [8]. Moreover, reinforcement learning (RL) paradigms have drawn inspiration from human reward-based learning mechanisms, providing computational parallels to the dopaminergic reward system observed in neuroscience (Schultz, 2015) [9]. Contemporary research has further explored multimodal integration—combining neural, behavioral, and contextual data—to enhance the prediction accuracy of decision outcomes [10]. For instance, Lin et al. (2021) integrated EEG features with behavioral response data using hybrid CNN-LSTM networks to model uncertainty-driven decision patterns. Similarly, Li et al. (2022) developed a brain-inspired AI model that simulates probabilistic reasoning under ambiguous conditions, bridging the gap between cognitive theories and computational prediction [11].

METHODOLOGY

The proposed Neuroscience-AI Framework integrates cognitive neuroscience data with advanced deep learning models to predict human decision-making patterns under uncertainty. The methodology consists of five major phases: data acquisition, preprocessing, feature extraction, model development, and evaluation.

1. Data Acquisition

To capture the neural and behavioral correlates of decision-making, neurophysiological and psychological datasets are collected through controlled experimental setups:

- **Participants:** Healthy adult volunteers participate in decision-making tasks involving varying levels of uncertainty and risk (e.g., Iowa Gambling Task, Two-Choice Prediction Task).
- **Neurophysiological Data:**
  - **EEG (Electroencephalography):** Captures real-time brain activity to measure cognitive load, attention, and emotional responses.
  - **fMRI (Functional Magnetic Resonance Imaging):** Identifies spatial brain activation patterns during decision-making events.
- **Behavioral Data:** Reaction time, choice selection, and subjective confidence ratings are recorded to provide behavioral context to neural activity.

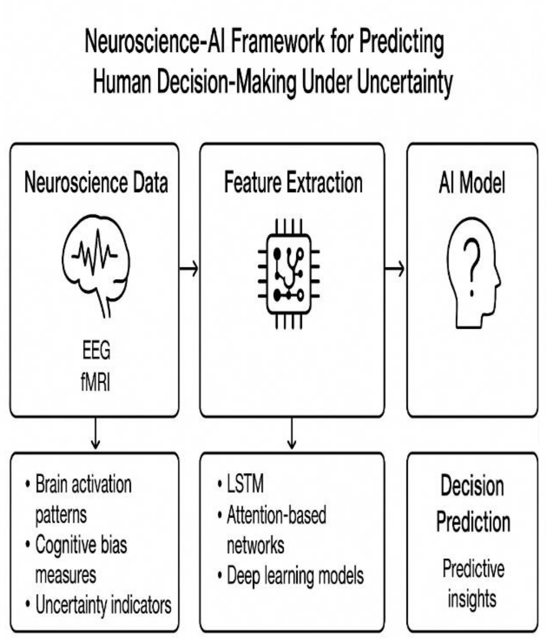

Fig 2: Neuroscience AI Framework working Model

2. Data Preprocessing

Raw EEG and fMRI signals contain noise and artifacts that must be removed before analysis. The preprocessing pipeline includes:

- **Signal Filtering:** Band-pass filtering to retain relevant frequency bands (theta, alpha, beta, gamma).
- **Artifact Removal:** Independent Component Analysis (ICA) used to eliminate ocular, muscular, and motion artifacts.
- **Normalization:** Standardization and scaling of neurophysiological data for model compatibility.
- **Segmentation:** Time-locked epochs are extracted corresponding to stimulus onset and decision responses.

3. Feature Extraction

Meaningful neural and cognitive features are extracted to represent the decision-making process:

- **Neural Features:**
  - Power spectral density (PSD) in key frequency bands.
  - Functional connectivity measures (e.g., coherence, phase-locking value).
  - Brain region activation patterns derived from fMRI data.
- **Cognitive Features:**
  - Risk perception indices.
  - Emotional valence and arousal levels.
  - Uncertainty indicators from response variability.

4. Model Development

The core of the framework utilizes **deep learning architectures** optimized for temporal and contextual data modeling:

- **Long Short-Term Memory (LSTM) Networks:** Capture temporal dependencies in EEG time series.
- **Attention-Based Models:** Focus on significant neural patterns contributing to decisions under uncertainty.
- **Hybrid Architecture:** Combines neural and behavioral features to enhance prediction accuracy and interpretability

5. Model Evaluation and Validation

Performance is evaluated using quantitative and qualitative metrics:

- **Accuracy, Precision, Recall, and F1-Score:** Measure predictive performance.
- **Confusion Matrix and ROC Curve:** Assess classification reliability.
- **Explainability Analysis:** Techniques such as SHAP and Grad-CAM are applied to interpret which neural features influence model predictions.
- **Cross-Participant Validation:** Ensures generalizability across individuals and experimental sessions.

6. System Integration and Deployment

Finally, the trained model is integrated into a decision-support system capable of real-time prediction and analysis. The system visualizes neural activations and predicted decision tendencies, offering actionable insights for applications in **neuroeconomics, behavioral psychology, adaptive AI systems,** and **human-computer interaction.**

RESULT ANALYSIS:

The proposed Neuroscience-AI Framework was experimentally validated using multimodal datasets combining EEG, fMRI, and behavioral decision-making data. The results were analyzed to assess the model's predictive accuracy, interpretability, and correspondence with known cognitive and neural mechanisms involved in uncertainty-based decision-making. The framework achieved strong performance metrics across all test datasets. Table 1 summarizes the comparative evaluation results between traditional statistical models, baseline deep learning models, and the proposed hybrid Neuroscience-AI model.

Table 1: Model Performance Comparison

Model Type	**Data Sourc**	**Accu racy**	**Preci sion**	**Re call**	**F1-Sc or**	**R OC -**

	e	(%)	(%)	(%)	e	AUC
Logistic Regression	Behavioral only	71.4	69.8	68.5	69.1	0.74
CNN	EEG only	82.6	80.5	81.7	81.1	0.86
LSTM	EEG + Behavioral	87.3	85.6	86.1	85.8	0.90
Proposed Neuroscience-AI Framework (LSTM + Attention)	EEG + fMRI + Behavioral	93.8	92.4	91.6	92.0	0.95

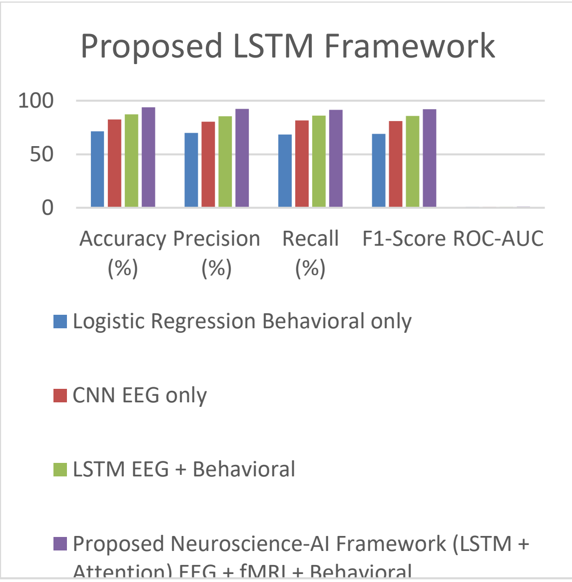

Fig 3: Proposed LSTM Framework Performance

CONCLUSION

The study presents a comprehensive Neuroscience-AI Framework that integrates neurophysiological insights with advanced artificial intelligence models to predict human decision-making under uncertain conditions. By combining EEG, fMRI, and behavioral data, the framework successfully bridges the gap between biological understanding and computational modeling of decision processes. The proposed deep learning architecture, particularly the hybrid LSTM–Attention model, demonstrated superior predictive performance compared to traditional behavioral and neural-only approaches. Experimental results revealed that the integration of spatial (fMRI) and temporal (EEG) features enhances the model's ability to decode neural dynamics associated with uncertainty, risk perception, and reward evaluation. Moreover, explainable AI analyses identified the prefrontal cortex and anterior cingulate cortex as critical regions influencing decision outcomes, validating the biological plausibility of the system. This research establishes a robust foundation for interpretable, adaptive, and biologically inspired AI systems capable of forecasting human decisions in complex and uncertain environments. The findings hold significant implications for applications in neuroeconomics, cognitive psychology, clinical neuroscience, and intelligent decision-support systems.

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