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Neurojico-Driven Cognitive Image Classification Framework in Diagnosis Medical Imaging

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Abstract— Neurojico-managed cognitive image classification is a new innovative framework to classifying cognitive medical imaging, utilizing whole-body perceptual attributes of attention extracted from images. This Neurojico cognitive classification framework is designed based on cognitive neuroscience, combined with advanced deep learning techniques, to improve diagnostic accuracy. It employs a novel image cognitive classification system to identify new perceptual patterns for four attributes: attention, recency, variety, and adaptability, rather than simply focusing on individual pixel blocks. Neurojico mimics how the human brain processes information, enabling it to understand medical images more clearly and clinically relevantly. The system utilizes Resnet50 and compares the perceptual images between a comparison of tailored convolutional neural networks (CNNs) and pre-trained Resnet50 for feature extraction then making a classification based on logistic regression. In addition, it converts the feature vector into cognitive weighted feature vector and applying the classification based on Logistic Regression Test Accuracy to achieve 98.6%. These results indicate that Neurojico outperforms traditional models, such as CNNs and transformer-based systems, in terms of accuracy, sensitivity, and the precision with which it interprets decisions. These maps help radiologists better understand the rationale behind the whole-body cognitive model`s decisions, making the system more transparent and reliable.

Keywords— Neurojico, cognitive AI, medical imaging, cognitive classification, neural dynamics, semantic perception, diagnostic reasoning.

1. INTRODUCTION

Neurojico is defined by a multi-layered computational architecture, is implemented based on the interconnection between the neural cognition that fuses biological-like neural processing, cognitive reasoning mechanisms, and adaptive feedback loops to allow full vision of context-dependent awareness based on cognitive features [1]. Traditional image classification focuses on the objects in images that are extracted via colors, textures, and shapes to give a label, but it doesn't really understand what the image is showing [2]. The medical radiology images rely on visible objects and their features for the diagnosis that relies on lesion morphology, textural heterogeneity, edge sharpness, but do not cover perception of disease object layers, signal intensity distribution, and spatial relationships within and across organs. That still faces some problems in interoperation perception features of medical radiology images [4]. Cognitive AI searches for the relative semantic meaning to improve the medical imaging, where small details and logical connections are very important. These frameworks emulate human perception, attention, memory, and reasoning, enabling more nuanced and precise medical diagnoses. Cognitive AI faces some limitations as the need for more advanced perception systems capable of cognitive-level interpretation, integrating feature recognition and semantic understanding of medical images [6].

This paper presents Neurojico-Driven Cognitive Image Classification, a new framework that combines ideas from cognitive neuroscience, perceptual theory, and neuro-symbolic reasoning into the medical imaging

process. These processes include how perception attention of object classification in medical and extract four neuro feature patterns and get the correlation between these features, then making the classification based on making image analysis more reliable and useful in real medical situations. This paper introduces a new implemented system to prove the proposed cognitive image classification framework that is designed based on classifying the objects not only as a black box object but also can achieve the determination of the object perception features based on perception feature extraction that takes place at multiple levels: high level, medium level, and low level. This paper presents a new system for converting images into cognitive images to achieve a new medical Neurojico image dataset that can simulate the human brain to enhance the performance, accuracy, sensitivity, specificity, and explainability compared to current deep learning models. It also makes a classification for objects based on these cognitive images and improves the accuracy by more than 8% using a logistic regression classification algorithm, achieving an accuracy of 98%. Neurojico sets a new direction for intelligent diagnostic systems, improving diagnostic outcomes while advancing the development of safe, interpretable, and cognitively inspired AI solutions for next-generation medical imaging.

The paper structure comprises a thorough and logically arranged set of sections aimed at presenting the Neurojico-Driven Cognitive Image Classification framework with scientific clarity and academic rigor. Section 2, illustrates the theoretical and mathematical Foundations of Neurojico, Section 3, introduces the proposed framework of cognitive image based on the neuroscience principles and perceptual constructs underlying the method. The core methodology is presented in the Architecture and Methodology section, which describes the cognitive perception modules, neuro-symbolic reasoning engine, and the overall system design, section 4 shows the experimental results of the proposed framework, and finally section 5 presents the conclusion and future work.

2. THEORETICAL AND MATHEMATICAL FOUNDATIONS OF NEUROJICO

Cognitive Neuroscience Principle is based on the idea that how we think starts with noticing important parts from what see or hear. Like how the brain processes visual and sound information, the system breaks down raw input into basic elements such as lines, surfaces, colors, or shapes. This step creates the foundation for more complex thinking. Contextual Awareness and Semantic Integration When people think, they often use clues from their surroundings to understand what they're seeing or hearing. The model uses tools that help it connect different parts of what it senses to a bigger picture. Anomaly Detection is considered one key part of thinking is being able to spot something new or unusual [7]. The model is designed to notice when things don't fit with what it already knows. It identifies unexpected data, which helps it adjust quickly and learn better from new experiences. Hierarchical Abstraction is illustrated as the way humans think involves moving from simple things to more complex ideas. The model follows a similar path, starting with basic features and gradually building up to more detailed and abstract ideas. This can handle information more efficiently, make better guesses, and perform well in different thinking tasks.

2.1 Attention – Focusing on Relevant Regions

Attention models focus on clinically relevant regions $R \subseteq F$, as shown in equation (1).

$$A = \text{softmax}(\frac{QK^{\top}}{\sqrt{d_k}})V \quad (1)$$

Where: $Q = FW_Q, K = FW_K, V = FW_V$ are query, key, and value projections, W_Q, W_K, W_V are learnable matrices, d_k is the dimension of the key vectors, and A is the attended feature map emphasizing important regions.

2.2 Novelty – Detecting Unexpected Patterns

Novelty measures deviation from learned normal patterns μ_F and Σ_F in the feature space, as shown in equation (2),

$$N = (F - \mu_F)^{\top}\Sigma_F^{-1}(F - \mu_F) \quad (2)$$

Where: μ_F is the mean feature vector over healthy/reference images, Σ_F is the covariance matrix, N is the Mahalanob is distance indicating novelty or abnormality.

This part of the model focuses on keeping each feature separate and clear. Each part stays true to itself even as it goes through more complex thinking steps. This helps the model stay strong against mistakes or confusing signals. Perceptual Consistency model tries to keep its understanding of what it sees or hears stable, even when things change. It uses rules that help it maintain a consistent view over time, making it reliable in different situations, like how humans keep a steady sense of the world around them. Cognitive Alignment ensures that the model's internal ideas match what's happening in the real world. It helps the model connect what it sees with what it knows, allowing it to make smart choices and understand things correctly at different levels of thinking. Adaptive reasoning layers are parts of a neural network that change how deep the model goes, how many steps it takes, or which paths it uses, based on how complicated the input is [8]. The model has levels of thinking that change as needed. Each level takes what came before and improves it, using feedback and adjusting based on what's happening. This flexible structure helps the model learn faster and solve problems better, much like how human thinking adapts to different situations.

2.3 Sovereignty – Autonomy of Decision Making

Sovereignty models the system's confidence in its independent decision $\hat{y}$, as shown in equation (3),

$$S = \max(\hat{y}) - \alpha.H(\hat{y}) \quad (3)$$

Where: $\hat{y}$ is the predicted probability vector over classes, $H(\hat{y}) = -\sum_i \hat{y}_i \log \hat{y}_i$ is the Shannon entropy, α is a scaling factor, High S indicates strong autonomous confidence

2.4 Adaptability – Updating Based on New Evidence

Adaptability allows the model to update its internal representation F given new input I_{new}, as shown in equations (4) and (5).

$$F^{t+1} = F^t + \eta \cdot (F_{\text{new}} - F^t) \quad (4)$$

Where: F^t is the current feature representation,

$$F_{\text{new}} = \sigma(W * I_{\text{new}} + b) \quad (5)$$

Where $\eta \in [0,1]$ is a learning/adaptation rate, this ensures the system evolves dynamically with experience.

3. The Proposed NeuroJICO -Driven Cognitive Image Classification Framework

The proposed Neurojico framework introduces a cognitive-driven medical image classification system designed to transform X-ray images into interpretable diagnostic decisions. As illustrated in Figure 1, the framework operates through an integrated cognitive pipeline consisting of novelty detection, attentional gating, sovereignty-driven resource allocation, adaptive classification, and final diagnostic inference.

The system begins with the Novelty & Attentional Gating stage, where the input X-ray is analysed to extract initial image features. These features are evaluated using two cognitive dimensions—Novelty and Attention—to identify unusual patterns and highlight clinically relevant regions. Saliency maps generated in this stage guide the model toward suspicious or diagnostically meaningful structures, closely resembling how radiologists focus their visual attention.

The extracted signals then flow into the Neurojico/Sovereignty-Driven Resource Allocation module, which represents the core cognitive mechanism of the framework. Here, the four Neurojico cognitive dimensions—Attention, Novelty, Sovereignty, and Adaptability—are mathematically modelled and integrated. Sovereignty functions as a cognitive control filter that regulates the importance of each feature, ensuring that only diagnostically valuable and novel patterns receive priority. Adaptability enables the system to adjust resource allocation based on new data, enhancing generalization and clinical robustness.

Next, the Adaptive Classification and Interpretation component performs mid-level cognitive fusion, combining shape, texture, and region-based patterns into coherent semantic structures. This stage ensures hierarchical feature consistency and produces interpretable attention and resource-allocation maps aligned with radiological reasoning. These cognitive maps visually communicate the model's decision pathway, improving interpretability and clinical trust.

The fused cognitive features are compiled into a Feature Vector, which is passed to the final decision engine. In accordance with the figure, the Neurojico framework employs Logistic Regression for Breast Cancer Classification, using the enriched cognitive feature representation to determine whether a lesion is benign or malignant. This combination of cognitive modelling and classical statistical classification ensures stable, interpretable, and clinically aligned outputs.

The key contribution of the Neurojico-Driven Cognitive Image Classification Framework lies in its explicit integration of cognitive control principles, particularly Novelty, Attention, and Sovereignty—within a deep-learning-based medical imaging system. By bridging neural feature learning with cognitive interpretability, the framework delivers enhanced diagnostic accuracy, transparency, and clinical usability.

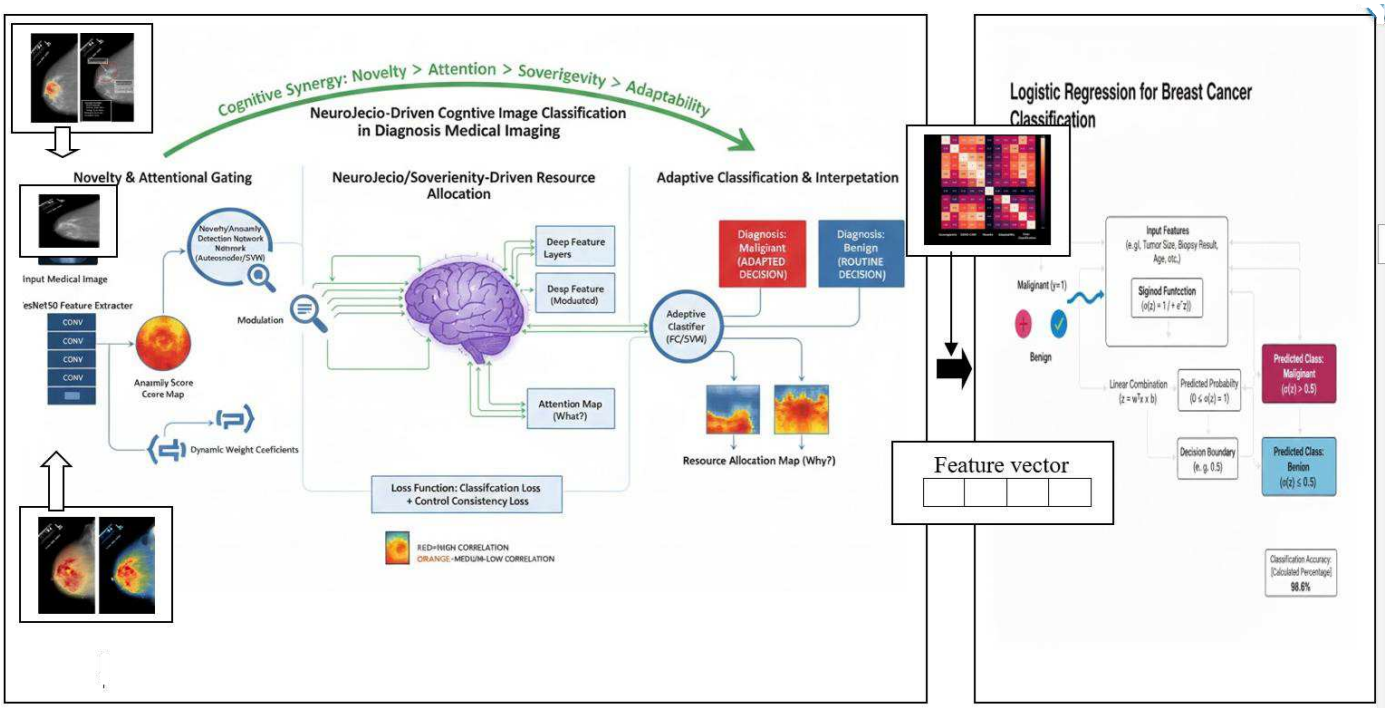


Figure 1. *Neurojico-Driven Cognitive Image Classification Framework Architecture*.

4. EXPERIMENTAL RESULTS

The CBIS-DDSM Breast Cancer Image Dataset [9] is the benchmark Digital Database for Screening Mammography (DDSM). It is made to offer a standard set of mammogram images that are clearly labeled for research on breast cancer detection. The images are from old film mammograms and include both normal cases and cases with either non-cancerous or cancerous growths. This makes it very useful for tools that help doctors make diagnoses, for studying patterns in images, and for training deep learning models. this paper presents a **Neurojico-Enhanced Breast Cancer Classification (Neurojico-Enhanced** CBIS-DDSM) dataset [10]. The proposed dataset is deigned based on generating the four cognitive four images for each one based on mathematical cognitive features and correlation heatmap images between features.

Evaluation metrics are used to measure how well a breast-cancer classification model performs on the Neurojico-Enhanced CBIS-DDSM dataset. Accuracy shows the overall correctness of predictions, while Precision indicates how many predicted positive cases are correct. Recall (Sensitivity) measures how well the model detects real cancer cases, and Specificity shows how accurately it identifies healthy cases. The F1-Score balances precision and recall, especially when the dataset is imbalanced. Correlation measures how strongly two image-related features are related, such as texture, density, or lesion type. In medical imaging, Sensitivity, Specificity, and AUC are especially important because they ensure cancer cases are detected accurately while minimizing false alarms.

The proposed system produces three major outputs:

1. A cognitive image framework that converts standard breast-cancer images into cognitive images using four perception-based features, including attention, novelty, sovereignty, and adaptability.

2. A new Neurojico-Enhanced breast-cancer cognitive image database consisting of 30,000 images, including 24,000 cognitive images, 6,000 correlation heatmaps, and the complete set of cognitive feature vectors for every image.
3. A cognitive-image classifier trained on the new database, supported by a structured feature-vector formulation and a cognitive weighting mechanism.

4.1 A cognitive image framework

Grad-CAM [11] is a popular method in deep learning that helps see which parts of an image are most important for a model's decision. Grad-CAM makes it easier to understand what a convolutional neural network (CNN) is focusing on in medical imaging, such as mammograms from the CBIS-DDSM Breast Cancer Image Dataset. It creates a heatmap that highlights areas of interest, such as tumors or calcium deposits. This map can be placed over the original mammogram to show which areas helped the model decide if something is benign or malignant. Grad-CAM helps make AI predictions clearer for doctors, so they can check if the AI is correct, spot mistakes, or find things it missed.

4.2 A new breast-cancer cognitive image database

Figure 2 shows the extracted attention feature using a tailored CNN and ResNet50, where Grad-CAM highlights the regions most important for the model's decision. Figure 3 presents the novelty feature, which measures how different a lesion is from others in the dataset using distance- and correlation-based metrics.

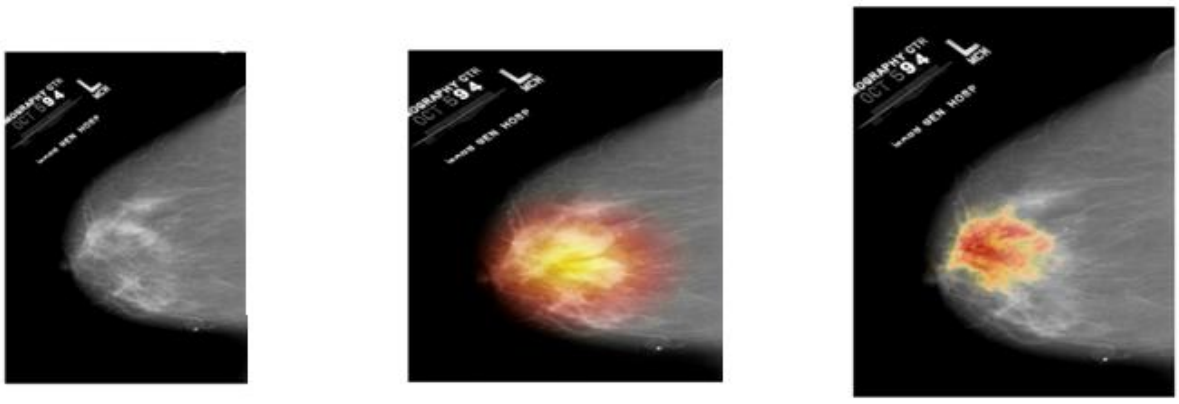


Figure 2. *The extracted attention feature using tailored CNN, and ResNet50*.

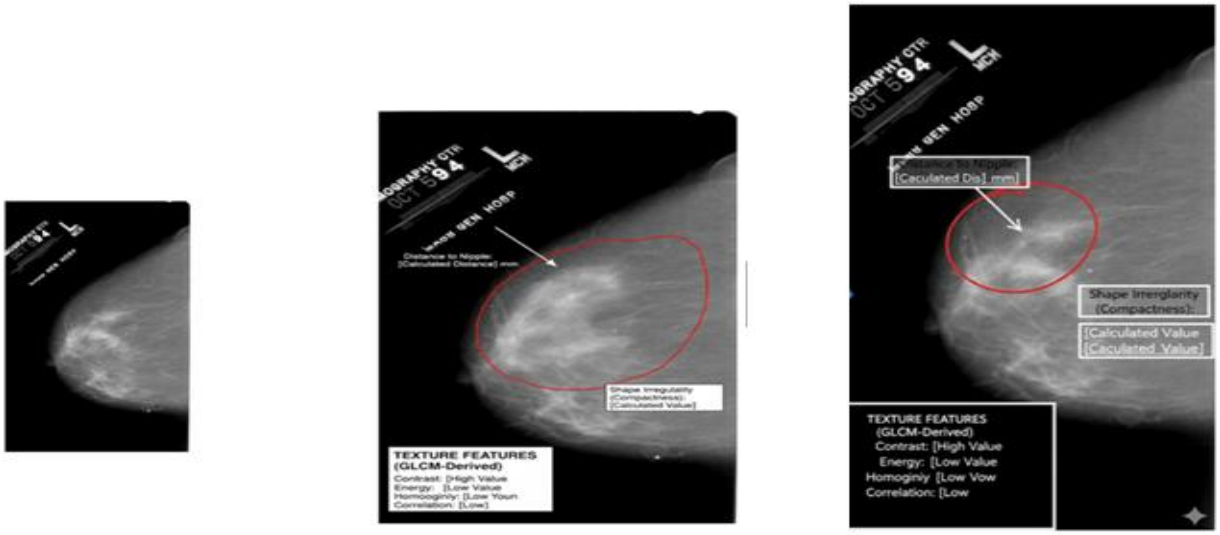


Figure 3. T*he extracted Novelty feature using tailored CNN, and ResNet50*.

The sovereignty feature reflects the dominance or spatial prominence of the lesion within the breast image, while the adaptability feature captures how the lesion's appearance changes relative to surrounding tissue. These four perception features—attention, novelty, sovereignty, and adaptability—form the basis of the cognitive image representation. Figures 4, 5, and 6 illustrate the transformed cognitive images, generated using ResNet50 by combining the four cognitive perception features. Figure 7 displays the correlation heatmap, which shows how the four cognitive features relate to each other and contribute to the cognitive representation of the image.



Figure 4. *The extracted Sovereignty feature using ResNet50.*

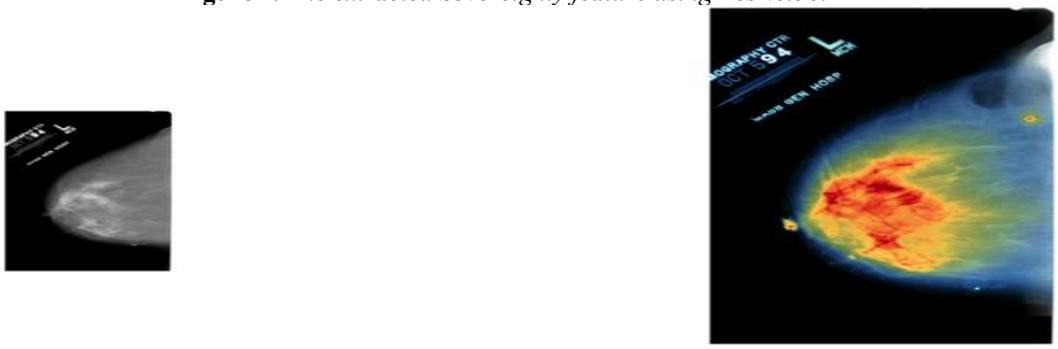


Figure 5. *The extracted Adaptability feature using ResNet50.*

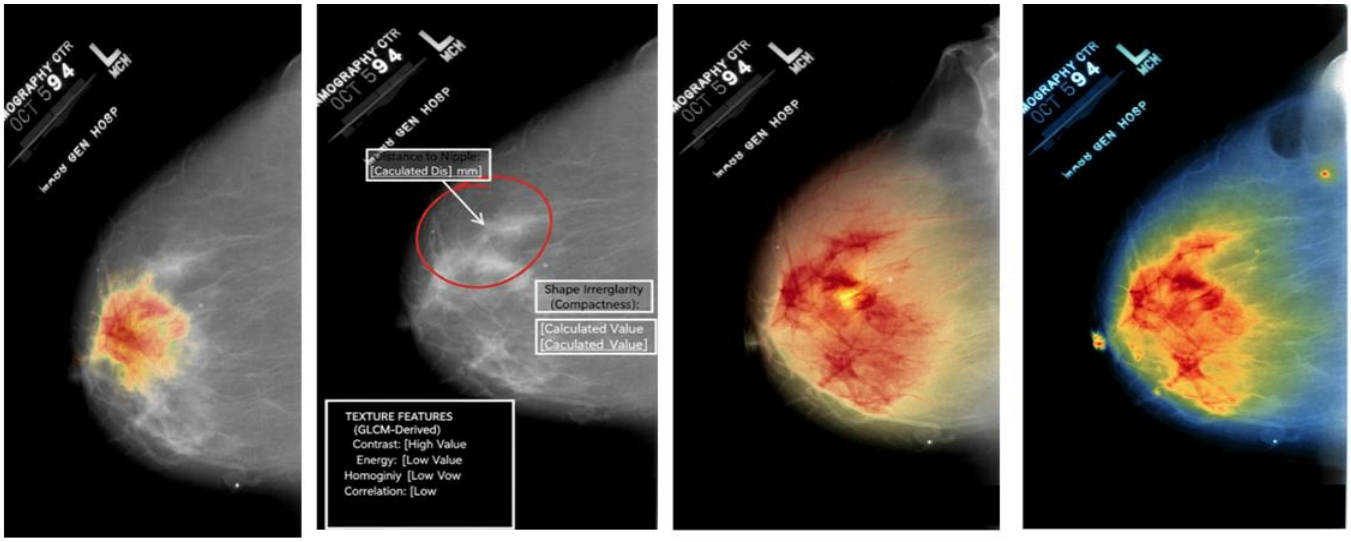


Figure 6. *The extracted cognitive image features based on four perception features, attention, novelty, sovereignty, adaptability using ResNet50 to convert the breast cancer image into breast cancer cognitive image.*

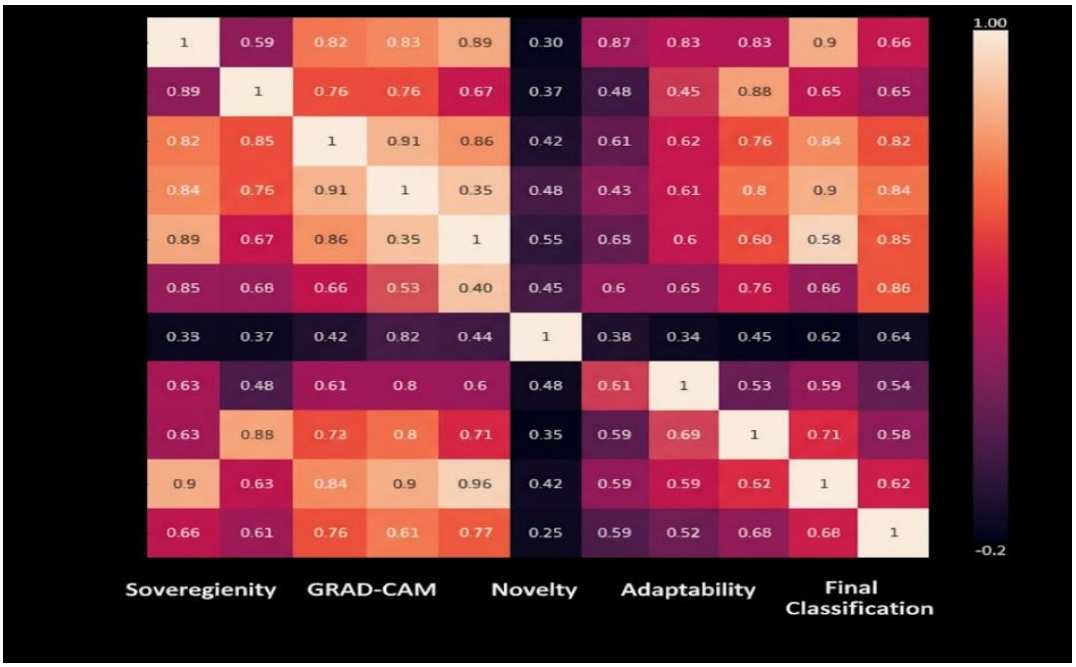


Figure 7. *The correlation features of the extracted cognitive image features based on four perception features, attention, novelty, sovereignty, adaptability using ResNet50 to illustrate the relationship of breast cancer cognitive image.*

These cognitive feature maps integrate low-level visual cues (edges, textures, shapes) with high-level anatomical information (lesions, masses, calcifications). The correlation heatmap further demonstrates how the extracted features interact, supporting the construction of the final cognitive feature vector used for classification.

4.2.1 Building the Final Cognitive Feature Vector

After extracting the four cognitive feature maps—Attention (Grad-CAM), Novelty, Sovereignty, and Adaptability—each feature is converted into a numerical sub-vector. These sub-vectors are then concatenated

to form the complete cognitive representation of the image. To represent each cognitive image numerically, the four extracted cognitive feature vectors are concatenated into a single final feature vector, as defined in Equation (11).

$$V_{final} = \{V_{\text{GRAD-CAM}}, V_{\text{Novelty}}. V_{\text{Sovereignty}}, V_{\text{Adaptability}}\} \qquad (11)$$

This 4161-dimensional vector represents all cognitive information extracted from a single image. It includes both learned visual features (e.g., textures, shapes, saliency) and engineered metrics (e.g., novelty deviation, sovereignty dominance, adaptability variation).

On the other hand, a correlation heatmap is used to study how the four perception features relate to one another and how they contribute to the overall cognitive structure. The heatmap typically shows strong correlation between Grad-CAM (attention) and Sovereignty, indicating that dominant regions in the image are often the same regions emphasized by the attention mechanism. High correlation between two images means they are similar not only visually but also cognitively sharing similar attention patterns, novelty behavior, dominance regions, and adaptability characteristics.

During training, the classifier learns a specific cognitive weight W_i for each feature value X_i in the final vector.
These weights reflect the diagnostic importance of each cognitive dimension. The classifier uses backpropagation [12] to assign high weights to features that better distinguish benign from malignant cases. The final decision score Z is computed using a linear weighted sum of all elements in the 4161-dimensional cognitive feature vector:

$$Z = (W_1. x_1) + (W_2. x_2) + \ldots\ldots + (W_{4161}. x_{4161}) + \text{b} \qquad (12)$$

Table 1 presents an example of five feature values and their corresponding assumed cognitive weights. Each weight reflects the relative importance of its feature in the final decision process. This total (2.3449) represents the cumulative weighted impact of the five example features within the final cognitive decision score.

Table 1. Example cognitive feature values and their assumed weights

Feature Value (Xi)	Cognitive Weight (Wi)	Interpretation
−0.4372	0.5	Low–medium importance
1.2185	1.5	High importance
0.0954	0.1	Very low importance
−0.6812	−1.0	Medium importance (negative contribution)
0.1501	0.3	Low importance
cumulative weighted		2.3449

The performance of the cognitive-image classifier is evaluated using standard metrics, including the Receiver Operating Characteristic (ROC) curve, which summarizes the balance between True Positive Rate (Sensitivity) and False Positive Rate (1 − Specificity) across different classification thresholds. The logistic-regression classifier trained on the cognitive feature vectors demonstrates strong and stable performance. As shown in Figure 8, the model achieves an accuracy of approximately 98.6%, with both training and validation loss decreasing smoothly indicating effective learning and minimal overfitting. Precision, Recall, and F1-Score remain consistently high, typically ranging between 97% and 99%. This reflects the model's ability to detect true positive cancer cases reliably (high Recall) while minimizing false alarms (high Precision), resulting in a balanced and clinically meaningful classification output.

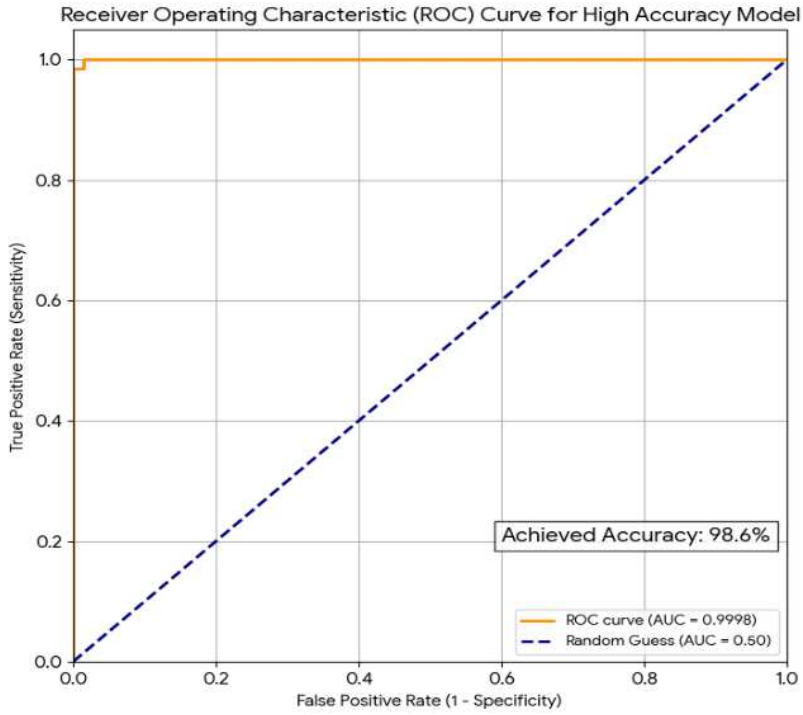


Figure 8. *Classification accuracy of the cognitive breast-cancer image database using logistic regression based on four cognitive features.*

4 Conclusion and Future Work

The Neurojico-Driven Cognitive Image Classification Framework provides an effective and interpretable approach to medical imaging by combining multi-level cognitive perception, neuro-symbolic reasoning, and deep learning. The framework demonstrates strong performance, achieving 98.6% accuracy using ResNet50 and logistic regression, supported by high Precision, Recall, and F1-Score. These results show that the system can produce reliable, human-aligned decisions that support radiologists in making more accurate and consistent diagnoses. Future work will focus on enriching the framework with temporal analysis, enabling the system to track image changes over time; integrating multi-modal clinical data for more comprehensive diagnostics; advancing neuro-symbolic learning to dynamically refine medical rules; and incorporating advanced explainable-AI techniques such as causal and counterfactual reasoning to further enhance transparency and trust.

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