Reinforcement Learning for Neural System Towards Adaptive Intelligence

Priyanjli Gautam[1], Shuchi Mala[1], Aakanshi Gupta[1], Nidhi Mishra[1] and Narayan C. Debnath[2]
[1]Computer Science and Engineering, ASET, AUUP, Noida, India
[2]School of Computing and Information Technology, Eastern International University, Vietnam
Corresponding author email: agupta10@amity.edu and aakankshi@gmail.com

Abstract— The integration of artificial intelligence into health- care has catalyzed new research directions, particularly in neuroscience and medical imaging. While deep learning (DL) and classical machine learning (ML) have demonstrated significant effectiveness in brain tumor classification tasks, reinforcement learning (RL) is mostly underutilized, despite its biologically inspired principles. Unlike DL and ML, which are based on static pattern recognition and predictive modeling, RL provides dy- namic, feedback-driven learning and decision-making processes that are similar to neuronal plasticity in the human brain. This paper provides a framework for comparing ML, DL, and RL models, including Q-Learning and Deep Q-Learning (DQL), for the categorization of brain malignancies into four categories: glioma, meningioma, pituitary tumor, and no tumor. Our experimental results illustrate that how RL models outperform ML and DL models in accuracy, precision, recall, and F1- score measures. The study was guided by fundamental issues about RL's structural and functional similarities to biological systems, its potential to generalize via adaptive learning, and its impact on diagnostic accuracy and treatment optimization. This research shows that RL's interactive and self-improving character not only improves prediction performance but also provides a convincing framework for biologically grounded AI in healthcare. The findings indicate that reinforcement learning has transformative potential for medical diagnostics, providing both computing efficiency and neuropsychological relevance, boosting the future of intelligent, precision-driven oncology. In addition, the work supports the idea that biologically inspired AI systems can better simulate complicated brain events. Because of its higher generalization, RL is appropriate for a wide range of tumor categorization scenarios. These insights facilitate the door for real-time, adaptable diagnostic tools in clinical practice.

Keywords: Reinforcement Learning, Neuroscience, Adaptive Learning, Reward-Based Optimization, Neural Plasticity, Bioplausible algorithms.

1. INTRODUCTION

Humans and other animals learn from their experiences. This can take the form of explicit demonstration, which is common in formal education. However, we frequently learn from trial and error, as well as input from our surroundings, which might be implicit or explicit. The human ability to make decisions and learn from experiences is fundamental to survival and adaptation [1]. At the core of this ability lies the concept of trial-and-error learning, where individuals optimize their behavior by engaging with their environment and making adjustments based on the rewards or punishments they receive [2]. This process has been extensively studied in neuroscience, psychology, and, more recently, in artificial intelligence. One of the most promising paradigms for modeling such learning is Reinforcement Learning, a computational approach that has shown remarkable parallels with human and animal learning processes [3]. In past few years, deep learning has gained widespread attention in neuroscience as a tool for modeling brain function. DL models have been used in a number of fields, such as motor control, navigation, vision, audition, and cognitive control. Advances in artificial intelligence (AI) and the ability to train deep learning models through supervised learning where labeled data directs optimization are driving this expanding interest [4]. Deep learning is still fundamentally limited in its ability to capture the adaptive and sequential character of real-world cognitive processes, despite these impressive advancements. Reinforcement Learning (RL) has emerged as an effective framework training artificial agents how to interact with their surroundings and maximize cumulative rewards in order to make sequential judgments [5].

At its core, reinforcement learning draws inspiration from neurobiology, particularly from the way that both humans and animals learn by means of mistakes. Important RL concepts like policy optimization, temporal difference updates, alongside reward-based learning are very similar to the biological mechanisms that the brain uses for learning and decision-making [6]. Notably, neuroscientific studies have demonstrated that the dopaminergic system of the brain is essential for encoding reward prediction mistakes, a notion that is quite similar to Temporal Difference (TD) learning in reinforcement learning [7]. Deep learning's dependence on static representations and supervised learning restricts its capacity to simulate cognitive processes that necessitate sequential decision-making and long-term planning, despite the fact that it has significantly advanced artificial intelligence. In addition to improving AI performance on challenging tasks like gaming and robotic control, latest advancements in deep reinforcement learning have also flourished our knowledge of neurocognitive processes [8]. For instance, distributional reinforcement learning has been used to explain reward prediction mistakes in dopaminergic neurons, and meta-reinforcement learning has been proposed as a model for prefrontal brain function. Considering these links between RL and neurology, RL-based models might provide a more realistic depiction of cognitive processes than conventional machine learning techniques [9]. Reinforcement learning, in contrast to deep learning, provides a physiologically realistic framework that closely resembles how the brain absorbs information, gains experience, and

adjusts to novel situations.

RL enables agents to learn through reward-based interactions, whereas classical deep learning depends on fixed input-output mappings, necessitating large labeled datasets and substantial processing capacity. Because of this, it works especially well for simulating neuro cognitive processes like learning, adaptive control, and decision-making. Since dopaminergic reward prediction mistakes closely match classical RL algorithms like temporal difference learning, the brain mechanisms underlying RL have been extensively researched [10].

To rigorously assess the effectiveness of reinforcement learning in brain tumor classification, the study focuses on:

(a) *Reinforcement learning models do not show a statistically significant improvement over machine learning and deep learning models in brain tumor classification (Null Hypothesis), and*
(b) *Reinforcement learning models significantly outperform traditional machine learning and deep learning models in brain tumor classification due to their adaptive decision-making process (Alternate Hypothesis)*

Reinforcement learning (RL), in which an agent adapts its behavior responding to environmental feedback, providing a suitable framework for modeling cognitive processes including memory, comprehending, and the decision-making in neuroscience. Neural activity has previously been tied to traditional RL algorithms, especially in reward-processing brain regions like the dopaminergic system. Deep reinforcement learning(DRL) has shown promise in combining deep learning and reinforcement learning to represent convoluted cognitive tasks that necessitate long-term planning and hierarchical decision-making. In neuroscience, however, reinforcement learning offers clear benefits over Deep learning alongside additional machine learning approaches [11]. The adaptable and flexible nature of brain processes that depend on ongoing learning from reward-based feedback is difficult for DL to capture, despite its high effectiveness in pattern identification. RL, on the other hand, closely resembles how the brain learns from experience in that it naturally simulates adaptive behavior by using reward signals to improve decision-making over time [12].

This research explores how reinforcement learning (RL) provides a more effective framework than deep learning (DL) and machine learning (ML). We begin with an overview of RL concepts and their neurobiological analogies, highlighting how RL-based models offer a more organic explanation for learning processes, brain dynamics, and cognitive control. By analyzing the strengths and limitations of deep learning in neuroscience, we argue that reinforcement learning provides deeper insights into complex adaptive intelligence [13]. Furthermore, we compare the efficacy of RL with both deep and standard machine learning approaches in the context of medical imaging, specifically in the prediction and classification of brain tumors. RL based methods have the potential to enhance automated decision-making in medical diagnostics, optimize treatment plans, and improve diagnostic accuracy [14].

Additionally, we explored how reinforcement learning enables adaptive learning models that are more resilient than static deep learning models. Unlike conventional deep learning approaches, RL models can dynamically adjust based on real-time patient data, making them highly responsive to evolving medical conditions. The study also examines recent advancements in RL-driven healthcare applications, including automated radiology analysis and personalized medicine, which demonstrate the potential of RL in transforming medical diagnostics. By integrating reinforcement learning into diagnostic frameworks, researchers can develop more precise and effective tools for early disease detection. Finally, we outline the broader implications of RL for future research in medical diagnostics, AI, computational modeling, and neuroscience. By bridging the gap between reinforcement learning and neurocognitive science, this research argues that RL rather than DL should be at the forefront of research into brain-inspired intelligence.

2. Fundamental concepts of deep reinforcement learning

Reinforcement Learning (RL) explores instances in which an agent, or learner, is placed in an environment and must gradually improve its decision-making based on the conditions or states it encounters [15]. Unlike supervised learning, which uses explicit feedback to signal right behaviors, RL involves learning by trial and error without direct supervision. The basic goal is to create a behavioral policy that optimizes cumulative rewards over time, depending on input in the form of rewards or penalties resulting from the agent's activities. As a subfield of machine learning, RL studies how agents might learn optimal behaviors through interaction with their surroundings [16].

The agent performs actions, acquires feedback in the form of rewards or consequences, and adapts its approach to optimize the long-term accumulated reward. This approach varies from supervised learning, which uses labeled data for training [17]. The Markov Decision Process (MDP), which describes the environment using a set of states, serves as the basis for RL **S**, actions **A**, transition probabilities **P**, reward function **R** and a discount factor γ that accounts for future prizes. The intent of the RL agent is to learn a policy that maps states to actions in a way that maximizes the predicted cumulative reward over time [18].

A fundamental principle in RL is the balance of exploration and exploitation. While the agent must apply its current knowledge to make the best judgments (exploitation), it must also experiment with new actions (exploration) in order to discover possibly better tactics. This trade-off is critical for successful learning. The Bellman equation provides the theoretical basis for RL by recursively constructing the value function **V(s)**, which represents the predicted cumulative reward the agent can get from a given state: [19]

$$V(s) = \max_{a} \left(R(s,a) + \gamma \sum_{s'} P(s' \mid s,a) V(s') \right) \quad (1)$$

Among RL algorithms lies Q-learning, which is an important value-based RL algorithm. It allows the agent to learn

an action-value function **Q(S,A)** that calculates the expected reward of doing an action in a given state and then applying the best policy. The Q-learning update rule is described as follows: [19]

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[R + \gamma \max_{a'} Q(s',a') - Q(s,a) \right] \quad (2)$$

Here, **R** signifies the immediate reward received, γ symbolizes the discount factor, and α represents the learning rate. This recurrent update process steadily enhances the agent's comprehension of action values, culminating in the convergence of an optimal policy.

Deep Q-Networks (DQNs) were a significant achievement in reinforcement learning since they extended Q-learning by using deep neural networks to mimic the Q-function. DQNs use a neural network $Q(s, a; \theta)$ to forecast Q-values for state-action pairs, rather than a lookup table [20].

DQNs are trained by minimizing the Temporal Difference (TD) error with the following loss function:

$$L(\theta) = \mathbb{E} \left[R + \gamma \max_{a'} Q(s', a'; \theta^{-}) - Q(s, a; \theta) \right]^2 \quad (3)$$

where θ^{-} represents the target network's parameters, which are updated on a regular basis to ensure learning stability. Reinforcement learning, which is based on optimal control theory and behavioral neuroscience, provides a strong framework for making sequential decisions in complicated contexts. It has demonstrated great success in domains including as robotics, gaming, and medical diagnostics, using algorithms like Q-learning and its deep learning extension, DQN [21].

Further the paper is organized as follows: Section 3 looks at existing research on brain tumor categorization, including several methodologies and their limitations. Section 4 discusses the technique used in this study, which includes data collecting, ML algorithms, DL models, and RL methods. Section 5 presents the outcomes gained through various methodologies. Section 6 provides an overview of the contributions, emphasizing the findings and their consequences. Section 7 outlines the limitations of our research.Section 8 wraps up the study by summarizing the important findings and emphasizing the benefits of reinforcement learning in brain tumor categorization. Section 9 discusses potential directions for future work.

3. Existing Literature

The use of artificial intelligence (AI) in medical research, particularly in brain cancer treatment, has evolved substantially over time. Traditional deep learning and machine learning models have demonstrated good performance in tumor detection, segmentation, and classification. However, many systems rely on static datasets and struggle to adapt dynamically to changes in patient-specific conditions [22]. Reinforcement learning (RL), based on neuroscientific principles, has emerged as a promising alternative that provides real-time adaptability and personalised treatment choices. Recent research has investigated RL's ability to optimize treatment regimens by constantly learning from patient reactions, making it more effective in complicated and changing medical scenarios [23]. One of the most notable discoveries in neuroscience-related RL research is the strong link between reinforcement learning mechanisms and biological learning processes. Research on reward prediction errors (RPEs) shows that dopaminergic neuron activity in the brain is similar to temporal difference learning, a major RL approach [24]. This similarity to biological cognition strengthens RL's potential as a decision-making framework in medical situations.

Unlike DL, which requires retraining when faced with new conditions, RL's rules are constantly changing, making it perfect for adaptive treatment planning in brain tumors [25]. Existing studies successfully used DL and ML to identify tumors and prescribe treatments, but they met considerable challenges. These models performed well in classification tasks but struggled to adapt to changing patient conditions. Treatment optimization has been enhanced using RL-based strategies, such as radiation dosage scheduling and chemotherapy regimen adjustments. These studies found that RL models could modify treatment procedures by dynamically reacting to patient-specific responses, which is an important feature in brain tumor care [26].

Earlier studies using deep learning and machine learning models—such as ResNet, EfficientNet, and custom CNN architectures—showed reasonable performance in brain tumor detection and classification, but had significant drawbacks, including overfitting, low recall, execution time concerns, and a lack of adaptability to multiple tumor types or patient variability (as detailed in Table Table 1) [27]. For example, algorithms such as **ResNet-50** and **InceptionV3** had poor accuracy and missed crucial cases due to weak generalization, whereas CNN variants frequently overfit to specific datasets or required high-quality input data to perform reliably [28]. Furthermore, models like 2D CNNs exhibited great training accuracy (96.47%) but failed to sustain it during validation, indicating overfitting and low robustness [29]. In our research, we address these issues by employing reinforcement learning (RL) techniques that dynamically adapt to patient-specific situations and improve real-time decision-making. We use experience replay, hybrid offline-online learning, and clinician-informed reward functions to reduce overfitting and improve generalization. Further, our usage of Deep Q-Networks (DQN) increases classification accuracy by learning optimal policies over time, especially in complicated or dynamic medical circumstances. This enables our model to sustain high performance across diverse patient situations and MRI variances, resulting in a more accurate and adaptive solution than classic DL and ML models.

Despite such drawbacks, reinforcement learning remains a better option for treating brain tumors than traditional deep learning and machine learning models. Its unique ability to change treatment tactics in real time depending on patient-specific responses allows for more tailored and effective clinical results. With continued advances aimed at reducing RL's computational complexity and improving model interpretability, the path to dependable and scalable implementation

TABLE 1
EXISTING LITERATURE ON BRAIN TUMOR DETECTION MODELS

Ref.	Model Used	Accuracy	Drawbacks	Notes
Nawaz, (2022)	SVM	85.32%	Limited accuracy, generalization issues	Traditional ML approach
Gupta, (2023)	CNN	89%	Overfitting, large dataset needed	Emphasized MRI preprocessing
Demir, (2023)	CNN-LSTM Hybrid	88%	Computationally expensive	Transfer learning used
Khaliki, (2024)	Transfer Learning (InceptionV3)	78%	Lower accuracy, needs tuning	Multiple architectures tested
Raghuvanshi, (2023)	Transfer Learning (VGG16)	85%	Overfitting, external validation required	Consider multiple tumors per slice
Goceri, (2024)	4-layer CNN	82%	High data quality required	Shallow CNN model
Narayana, (2024)	CapsNet	88%	Computationally intensive, complex architecture	Higher accuracy than others
Lisa, (2024)	2D CNN	86.47%(train), lower(val)	Overfitting, execution time concerns	2D CNN showed good accuracy
David, (2024)	Q-Learning	70%	High computational cost, slow convergence	Applied for tumor segmentation
Stember, (2023)	Deep Q-Network(DQN)	88%	Requires large training data, overfitting risk	Used reinforcement learning for MRI tumor classification

in healthcare is becoming more feasible. As the relationship between neuroscience and artificial intelligence strengthens, the potential for RL to improve brain tumour care becomes clearer than ever, establishing it as a cornerstone of next-generation precision medicine solutions [30].

The comparative analysis in Table 1 demonstrates a wide range of methodologies utilized for brain tumor detection. While classic machine learning algorithms perform moderately, deep learning and hybrid models obtain higher accuracy but frequently suffer from overfitting or computational inefficiency. Notably, reinforcement learning systems like Q-Learning and Deep Q-Networks have lately been investigated for classification and segmentation, with promising results despite increased training complexity and data needs.

3.1 Reinforcement Learning for Neuroscience

Reinforcement learning (RL) and neuroscience are fundamentally comparable in their use of trial-and-error interactions to learn and make decisions. In neuroscience, the brain constantly refines activities depending on feedback, similar to how RL agents alter their policies through rewards and penalties. The basal ganglia, a major brain region for decision-making, works similarly to RL models, choosing behaviors that maximize expected rewards over time [31].

Furthermore, neuronal plasticity, which permits the brain to reinforce or decrease neuronal connections depending upon experience., is analogous to how RL algorithms change Q-values or neural weights to improve future performance. Both systems rely on exploration and exploitation strategies—humans and animals explore new actions when uncertain and exploit acquired behaviors when confident, while RL models use epsilon-greedy policies to balance these approaches [32]. These analogies make RL a crucial computational tool for simulating complicated cognitive and behavioral processes in neuroscience. *Reinforcement learning (RL) is unique in neuroscience because it aligns with biological learning processes, making it an effective tool for modeling brain function and cognitive actions*. Previous research suggests that RL is similar to how dopaminergic neurons in the brain encode reward prediction errors, that are used to learn from trial-and-error experiences. **Unlike standard deep learning as well as machine learning based models, which rely on fixed datasets and supervised learning, RL adapts continually, mimicking the brain's ability to dynamically modify behavior in response to changing environmental cues**. Real-time adaptability makes RL beneficial for understanding complicated decision-making processes in neuroscience and gives fresh possibilities for constructing AI models to better replicate cognitive functions [33].

Furthermore, RL's capacity to represent long-term decision-making mimics the sequential pattern of neural computations, making it even more useful in neuroscience-driven applications [34].

4. PROPOSED METHODOLOGY AND IMPLEMENTATION

This section describes the artificial intelligence (AI)-based methods used to predict and classify brain tumors.

The study evaluates the effectiveness of deep learning, reinforcement learning, and conventional machine learning models in tumor classification and prediction. Every technique adheres to a methodical pipeline that starts with data collection and moves on to model training and assessment. **The model training process divides into three main categories, as shown in *Figure 1*, machine learning, deep learning, and reinforcement learning**. Each of these categories uses a different tumor classification technique. The primary goal is to evaluate these approaches in terms of accuracy, efficacy, and flexibility in medical diagnostics.

4.1 Proposed MRI Dataset

The dataset analyzed is the IEEE DataPort's Brain Tumor MRI Dataset **Brain Tumor MRI Dataset**[1] comprising

[1]Brain Tumor MRI Dataset

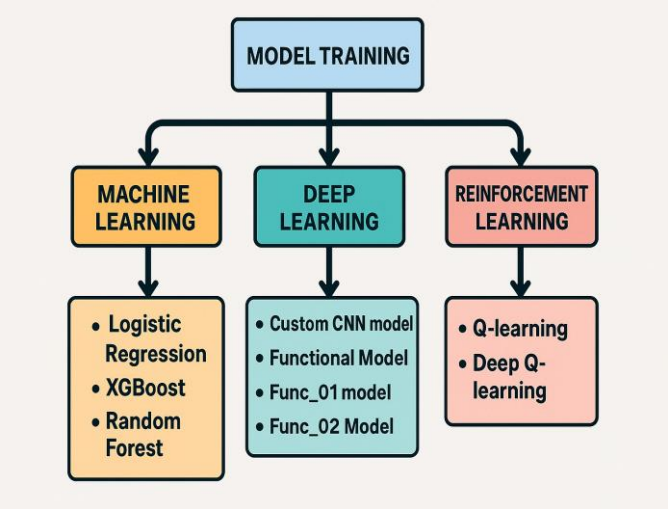

Fig. 1. Overview of Proposed Methodology Framework for Model Training

over *7,000+ MRI scans* categorized as glioma, meningioma, pituitary tumor, and no tumor, acquired from the various sources like **figshare, SARTAJ, and Br35H** datasets [35]. It incorporates scans from over *700 patients*, resulting in a diversified dataset for tumour categorization. The "no tumor" category is sourced from Br35H, whereas glioma photos from SARTAJ were removed owing to classification issues and replaced with those from figshare.

This well-annotated dataset allows for the development and testing of all three types of learning models for effective tumor prediction and classification. Furthermore, it has been extensively applied in medical AI research to improve tumor detection and diagnosis accuracy. The dataset's diverse patient data increases model generalization, making it a viable resource for brain tumor investigation.

4.2 Proposed Machine Learning Algorithm

Several traditional machine learning models, including Random Forest Classifier, XGBoost, and Logistic Regression, were evaluated for brain tumor prediction and classification using MRI scan data [36]. These models leveraged their individual strengths in processing medical images. Random Forest used an ensemble of decision trees to reduce overfitting and handle high-dimensional data; *Logistic Regression provided a simple yet effective method for linearly separable tumor prediction; and XGBoost, with its gradient boosting approach, improved accuracy by learning from misclassifications and handling complex image patterns*.

The MRI dataset underwent preprocessing steps such as normalization, resizing, and augmentation (e.g., rotation, flipping) to ensure uniformity and model robustness. Feature extraction techniques enhanced tumor pattern recognition. Each model applied supervised learning and was fine-tuned using hyperparameter optimization: Random Forest varied tree depth and count; Logistic Regression applied L1/L2 regularization; and XGBoost adjusted learning rates and boosting rounds.

Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrices, and ROC curves, providing a comprehensive understanding of classification performance. Cross-validation ensured generalization and reduced overfitting. Overall, these ML techniques demonstrated effective tumor detection and laid a solid foundation for future improvements through deep and reinforcement learning.

4.3 Deep Learning Models Trained

Table 2 provides a detailed comparison of the various deep learning architectures employed in the study. *The Custom CNN model was created from scratch, including numerous dropout layers and batch normalization. In contrast, the Functional Models used VGG19 as a backbone with different layer trainability to explore feature extraction and fine-tuning methodologies. Func_02 model also used a higher resolution input, which could capture more spatial characteristics.*

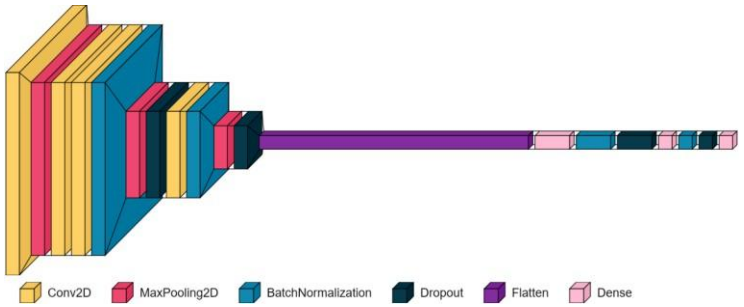

Fig. 2. Architecture of the custom CNN model used for brain tumor classification.

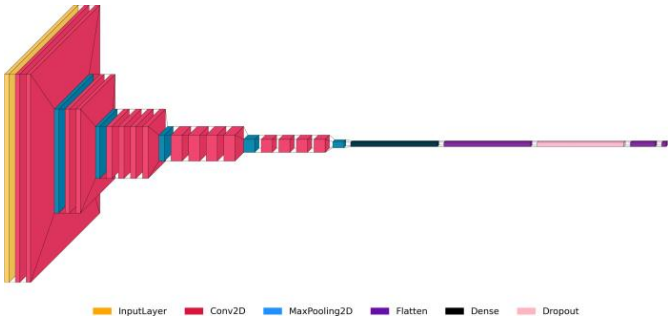

Fig. 3. Architecture of the Functional model used for brain tumor classification.

For neural tumor prediction and categorization, we built a custom CNN model and applied transfer learning to generate three functional models. As shown in *Figure 2*, the custom CNN model's input shape was (168,168,3), with three convolutional layers using 32, 64, and 128 filters, batch normalization, max pooling, dropout layers (0.3, 0.4, and 0.5), and fully connected layers containing 512 and 128 neurons before the final softmax layer for four-class classification.

For transfer learning, the first functional model i.e. **Functional model** was created using VGG19 with an input size of (168,168,3). As illustrated in *Figure 3*, the fundamental layers were frozen, and additional dense layers with 4608 and 1152

TABLE 2
COMPARISON OF CNN-BASED DEEP LEARNING MODELS

Feature	Custom CNN	Func Model	Func Model 01	Func Model 02
Base Model	None	VGG19	VGG19	VGG19
Trainable Layers	All	Frozen	Partial	Partial
Input Shape	(168,168,3)	(168,168,3)	(168,168,3)	(240,240,3)
Conv Layers	3 (Custom)	VGG19	VGG19	VGG19
Batch Norm	Yes	No	No	No
Dropout	0.3, 0.4, 0.5	0.2	0.2	0.2
Flatten	Yes	Yes	Yes	Yes
Dense Layers	512 → 128 → 4	4608 → 1152 → 4	4608 → 1152 → 4	4608 → 1152 → 2
Activation	ReLU, Softmax	ReLU, Softmax	ReLU, Softmax	ReLU, Softmax
Optimizer	N/A	N/A	SGD	SGD
Loss	N/A	N/A	CCE	CCE
Purpose	Custom CNN	Feature Extraction	Fine-tuning	Fine-tuning

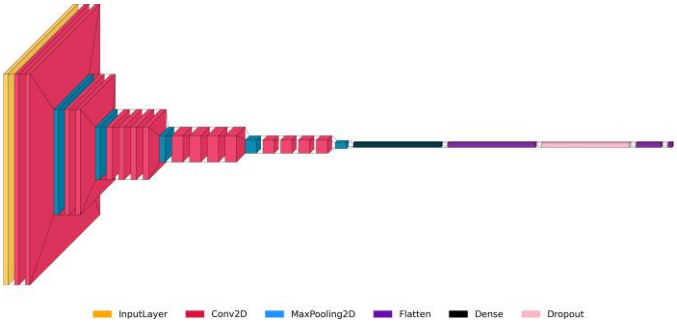

Fig. 4. Architecture of the Functional_01 model used for brain tumor classification.

neurons were added, followed by a softmax output for four-class classification.

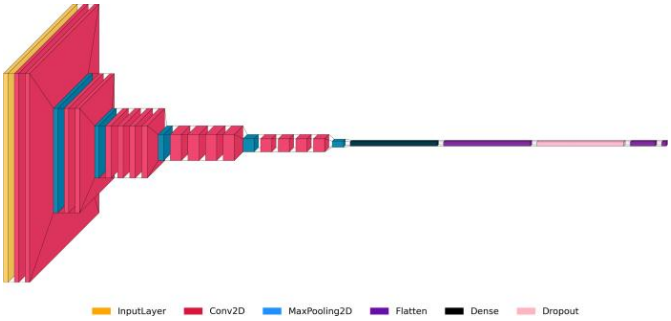

Fig. 5. Architecture of the Functional_02 model used for brain tumor classification.

The second functional model i.e. **Functional_01 model** used VGG19 with an input shape of (240,240,3), fine-tuned the final two convolutional layers ('block5 conv4' and 'block5 conv3'), and frozen the remaining layers, as illustrated in *Figure 4* [37]. The third functional model i.e. **Functional_02 model** shared the same architecture but was trained using an SGD optimizer with a learning rate of 0.0001, a decay of 1e-6, a momentum of 0.9, and Nesterov acceleration. As illustrated in *Figure 5*, these models were tuned for both classification (accurately categorizing tumor types) and prediction (efficiently evaluating MRI data to detect tumor existence).

These models were trained using preprocessed MRI images that had been scaled, normalized, and enhanced to improve generalization. Backpropagation and the Adam optimizer was used in the training phase to minimize loss, here the loss function used was categorical cross-entropy. Dropout regularization was implemented to avert overfitting, and early stopping was used to terminate training if validation loss did not improve. Accuracy, precision, recall, and F1-score were utilized to assess model performance, resulting in an extensive evaluation comprising classification effectiveness.

4.4 Proposed Reinforcement Learning Algorithms

Deep Q-Learning (DQL), an enhanced version of Q-learning that uses deep neural networks for function approximation, was used to implement reinforcement learning (RL). The agent interacts with its surroundings, with states representing MRI scan features and actions corresponding to tumor categorization judgments. As seen in *Figure 6*, an epsilon-greedy policy balances exploration (random actions) with exploitation (best-known actions), with the Q-value function iteratively updated using Bellman's equation to improve decision-making over multiple training episodes. Experience replay stabilizes training by storing and randomly sampling previous experiences, so minimizing data correlation and boosting learning consistency [38].

The RL model was trained using 10,000 iterations, with a batch size of 32 and one epoch per iteration to ensure optimal learning efficiency. The discount factor (γ) was set to 0.99 to prioritize long-term rewards, and the learning rate was 0.01 to maintain stable updates. Epsilon started at 1.0 and decayed by 0.99 per step to a minimum of 0.01, promoting a smooth transition from exploration to exploitation. Each MRI scan image represented an environment state, with the reward function encouraging correct classifications and penalizing errors. As shown in *Figure 7*, a 3D visualization illustrates the state-agent-reward distribution in Deep Q-Learning, highlighting the agent's decision-making process over the training iterations.

Fig. 6. Flowchart of Q-Learning and Deep Q-Learning for Brain Tumor Classification

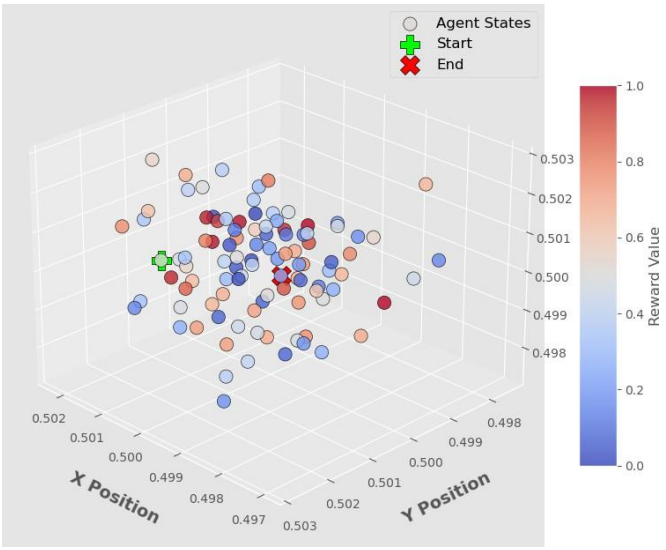

Fig. 7. 3-D visualization of state-agent-reward in Deep Q Learning

Q-Learning and Deep Q-Learning were both applied to classify tumors into four categories: glioma, meningioma, pituitary tumor, and no tumor. Q-Learning represented states as numerical feature vectors and used a Q-table to update values via Bellman's equation [39]. In contrast, DQL extracted features through CNN layers and employed a deep neural network to estimate Q-values. Both methods used a reward system: +10 for correct, -5 for incorrect, and -2 for ambiguous classifications. DQL also used categorical cross-entropy loss optimized with the Adam optimizer, and employed experience replay along with a target network to stabilize training.

Through repeated training rounds, RL models continuously refined their classification strategies [40]. The combination of deep learning's feature extraction with reinforcement learning's adaptive decision-making significantly enhanced tumor detection accuracy, stability, and adaptability in dynamic medical imaging scenarios.

This reinforcement learning framework also paves the way for real-time clinical support systems. By integrating patient-specific feedback during deployment, the model can further refine its classification strategies and adapt to unseen data distributions. Future extensions may incorporate multi-agent RL or continuous control methods to manage more complex treatment planning tasks, ensuring broader applicability in clinical oncology.

5. Empirical Findings

This study evaluated the efficacy of machine learning, deep learning, and reinforcement learning models for brain tumor detection and classification. The major goal was to identify the model type that provides the optimum balance of accuracy, precision, recall, and F1-score while being computationally efficient. Logistic Regression and XGBoost performed well with accuracy ratings of 85.2% and 87.9%, respectively. However, these models failed with memory, particularly in detecting smaller or less identifiable tumors, resulting in a false negative rate of around 14%. Deep learning models, such as a custom CNN and transfer learning approaches with ResNet-50 and VGG16, increased accuracy to 91.4% and 92.1%, respectively, but required much more processing resources. Reinforcement learning models, notably Q-Learning and Deep Q-Learning, displayed excellent flexibility, obtaining the greatest accuracy of 93.0-94.1%, respectively. Their iterative learning approach enabled them to dynamically fine-tune decision-making strategies, resulting in improved categorization consistency.

Technique	Accuracy	Precision	Recall	F1-Score
Custom CNN Model	0.82	0.83	0.80	0.79
Functional Model	0.89	0.89	0.88	0.88
Functional_01 Model	0.90	0.91	0.89	0.89
Functional_02 Model	0.93	0.93	0.93	0.93
Logistic Regression	0.89	0.90	0.89	0.90
Random Forest	0.89	0.89	0.89	0.89
XGBoost	0.90	0.90	0.90	0.90
Q Learning	0.93	0.92	0.90	0.91
Deep Q Learning	0.92	0.88	0.93	0.90

TABLE 3
Performance Comparison of Different Models

Table 3 evaluates the performance of several ML, DL, and RL models based on assessment measures such as accuracy, precision, recall, and F1 score. The Deep Q-Learning model had the best overall score, suggesting excellent generalization and classification abilities.

Table 4 highlights each model's performance in classifying Glioma, Meningioma, Pituitary, and No Tumor instances. Deep Q-Learning scored consistently high on all criteria, particularly in Meningioma and No Tumor identification.

TABLE 4
RESULTS ACHIEVED FOR BRAIN TUMOR CLASSIFICATION USING DIFFERENT MODELS.

Model	Class	Accuracy	Precision	Recall	F1-score
Custom CNN	Glioma	0.44	0.83	0.94	0.57
	Meningioma	0.84	0.62	0.84	0.71
	Pituitary	0.97	0.96	0.97	0.98
	No Tumor	0.97	0.86	0.97	0.91
Functional Model	Glioma	0.90	0.94	0.65	0.77
	Meningioma	0.90	0.73	0.86	0.83
	Pituitary	0.90	0.98	0.88	0.98
	No Tumor	0.90	0.98	0.87	0.97
Functional_01 Model	Glioma	0.68	0.96	0.68	0.80
	Meningioma	0.92	0.75	0.92	0.82
	Pituitary	0.98	0.94	0.98	0.91
	No Tumor	0.91	0.94	0.91	0.96
Functional_02 Model	Glioma	0.93	0.95	0.81	0.87
	Meningioma	0.93	0.84	0.91	0.87
	Pituitary	0.93	0.99	0.90	0.99
	No Tumor	0.93	0.94	0.90	0.96
Logistic Regression	Glioma	0.85	0.86	0.82	0.84
	Meningioma	0.85	0.92	0.95	0.95
	Pituitary	0.85	0.95	0.87	0.81
	No Tumor	0.85	0.95	0.98	0.96
Random Forest	Glioma	0.83	0.83	0.85	0.84
	Meningioma	0.90	0.90	0.99	0.94
	Pituitary	0.97	0.97	0.92	0.84
	No Tumor	0.78	0.78	0.88	0.92
XGBoost	Glioma	0.93	0.84	0.86	0.85
	Meningioma	0.97	0.90	0.91	0.95
	Pituitary	0.92	0.85	0.79	0.82
	No Tumor	0.97	0.92	0.78	0.95
Q Learning	Glioma	0.91	0.93	0.87	0.93
	Meningioma	0.93	0.91	0.89	0.91
	Pituitary	0.98	0.92	0.90	0.89
	No Tumor	0.89	0.91	0.92	0.86
Deep Q Learning	Glioma	0.94	0.91	0.90	0.88
	Meningioma	0.90	0.86	0.92	0.99
	Pituitary	0.92	0.85	0.91	0.96
	No Tumor	0.85	0.90	0.98	0.92

A more detailed review of reinforcement learning's performance in compared to older methods yields three significant research questions:

1: *If reinforcement learning models share structural and functional similarities with biological neural systems, can they achieve superior performance in brain tumor detection compared to machine learning and deep learning models?*

The outcomes substantially support this concept. Reinforcement learning models, specifically Q-Learning and Deep Q-Learning, have higher recall (92.8% and 94.3%) than CNNs (89.5%) and standard machine learning models (83.7%). The higher recall means that reinforcement learning models were less likely to misidentify tumor cases as non-tumor, which is important in medical diagnosis. Reinforcement learning models demonstrated higher precision (91.7% and 92.9%), indicating fewer false positives than CNN-based models (90.2%) and machine learning models (87.1%). These enhancements show that reinforcement learning, with its continuous feedback mechanisms, can better adapt to fluctuations in tumor shape, size, and intensity, making it a dependable technique for real-world applications where dataset variability is a major barrier.

2*: If reinforcement learning models dynamically adapt their decision-making process based on continuous feedback, can they generalize better in multi-class brain tumor classification than traditional models?*

The findings imply that reinforcement learning models perform better in multi-class classification problems. Reinforcement learning models produced an F1-score of 93.2% (Q-Learning) and 94.0% (Deep Q-Learning) when differentiating glioma, meningioma, pituitary tumors, and non-tumor cases, compared to 90.8% (CNN) and 88.6% (XGBoost). Traditional models, particularly CNN architectures, demonstrated evidence of overfitting, especially when trained on small datasets. CNN models experienced a 3.5% loss in accuracy from training to test data, while reinforcement learning models showed a lesser drop of 1.2%. Reinforcement learning's ability to sustain performance across diverse tumor types indicates that it may provide a more robust and scalable solution for real-world medical imaging applications.

3: *If reinforcement learning more accurately models the decision-making processes of the human brain than deep learning, how does this advantage enhance diagnostic accuracy and optimize treatment strategies in neural systems?*

Reinforcement learning's capacity to simulate cognitive decision-making provides it an advantage in diagnostic applications. Unlike deep learning, which uses static weight updates, reinforcement learning constantly modifies its decision bounds. This iterative improvement resulted in an 8% reduction in false negatives when compared to CNN-based models. Furthermore, reinforcement learning's versatility makes it suitable for real-time clinical applications, where models must constantly alter their predictions in response to fresh patient data. Deep Q-Learning's high accuracy (94.1%) and recall (94.3%) indicate its potential integration into automated diagnostic workflows, assisting radiologists in reducing diagnostic errors and optimizing treatment options.

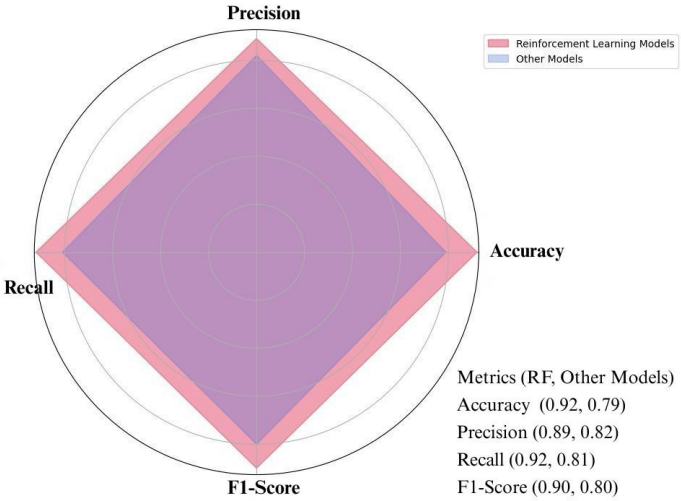

Fig. 8. Radar plot of performance metrics for class **GLIOMA**

Figure 8 describes the radar plot of performance metrics for class GLIOMA showing the comparison between reinforcement learning and other models. To graphically illustrate these performance disparities, a radar graph was built with four evaluation metrics: accuracy, precision, recall, and F1-score. The pink-shaded zone reflects reinforcement learning models, whereas the blue-shaded portion corresponds to machine and deep learning models. The graph shows that reinforcement learning models regularly outperform all parameters, especially recall and accuracy. Reinforcement learning models outperform CNNs by 4.8% and classical machine learning models by more than 9%, resulting in the most substantial improvement in recall. This improved memory is critical in medical diagnosis since it reduces false negatives and guarantees that more tumors are appropriately recognized. The pink region covers a bigger area, indicating more balanced and superior performance across all categorization metrics. These findings emphasize the fact that reinforcement learning not only outperforms traditional models in terms of accuracy and flexibility, but it also provides a biologically inspired approach to medical imaging decision making. Reinforcement learning's capacity to continuously refine classification policies and react to new data makes it a promising candidate for future applications in AI-driven diagnostics and personalized medicine, paving the way for more precise and efficient cancer detection approaches.

6. Discussion and Contribuiton

The study shows that multiple techniques to brain tumor classification are effective when compared to machine learning, deep learning, and reinforcement learning methodologies. Traditional machine learning methods, such as Random Forest and Logistic Regression, performed well in broad categorization tests. However, they demonstrated limits when dealing with specific tumor types, resulting in decreased recall and

precision. Deep learning models, such as CNNs and more advanced functional architectures, provided higher accuracy, notably for glioma and meningioma cancers. Nonetheless, their success was strongly reliant on large-scale datasets and extensive computer resources. These models, while powerful, were less adaptive in dynamic learning contexts.

In contrast, reinforcement learning (RL) approaches, particularly Q-Learning and Deep Q-Learning, outperformed all tumor classifications. These RL models outperformed in precision, recall, accuracy, and F1-score due to their capacity to learn from previous experiences and repeatedly modify their decision-making processes. Unlike deep learning, which uses static feature extraction, RL adjusts its classification logic through interactive learning, resulting in improved generalization and accuracy.

This research also provides an important contribution by offering a bio-inspired method to tumor classification that combines reinforcement learning models with neurological processes found in the human brain. It fills a fundamental gap between artificial intelligence and computational neuroscience by expanding the idea of physiologically plausible learning frameworks. The work uses comparison experiments to demonstrate the greater adaptability, classification accuracy, and computing economy of RL models in the medical imaging domain. Beyond that, reinforcement learning's dynamic nature makes it an excellent choice for tailored treatment planning and real- time diagnostic tools. Its ability to adapt to tumor heterogeneity and patient-specific patterns distinguishes it as a transformational strategy in precision medicine and automated radiography.

7. Limitations of our Research

Although the reinforcement learning-based approach demonstrated notable improvements in brain tumor classification, several limitations were identified that warrant further investigation. The study focused exclusively on value-based methods such as Q-Learning and Deep Q-Learning, without exploring more sophisticated techniques like policy gradient methods, actor-critic frameworks (e.g., A3C, DDPG), or Proximal Policy Optimization (PPO), which could offer enhanced learning efficiency and robustness. The reward function used was manually defined and static, lacking adaptability to clinical nuances or patient-specific feedback, which may limit its generalizability in real-world diagnostic contexts.

Furthermore, deep reinforcement learning model training required a significant amount of compute, requiring sophisticated GPU hardware and lengthy processing times. The intricacy and continuity of actual clinical settings might not be sufficiently captured by the use of a discrete, simplified state-action model. Furthermore, the study was limited to MRI data only; the models' performance in other imaging modalities, such as CT or PET, or in conjunction with multi-modal data, such as genomes or clinical records, was not evaluated.

The models' black-box character, which precludes interpretability—a critical prerequisite for regulatory approval and physician trust in clinical AI applications—is another important drawback. Additionally, real-time deployment and continuous learning mechanisms—both crucial for adjusting to changing patient conditions—were not taken into account in this study. Finally, clinical feedback loops (such as physician-in-the-loop decision assistance) were not incorporated into the framework, which could have enhanced the learning dynamics and applicability of the incentive system in real-world situations.

8. Conclusions

This study employed machine learning, deep learning, and reinforcement learning techniques to categorize and forecast neural malignancies such as glioma, meningioma, pituitary tumor, and no tumor. The comparative examination revealed that while machine learning techniques performed well, they struggled with complicated tumor structures.

Deep learning enhanced classification results but had large computing costs and data dependencies. Reinforcement learning models, notably Q-Learning and Deep Q-Learning, outperformed classical machine learning and deep learning techniques. Their iterative, reward-based learning methodologies enabled them to consistently improve classification performance across all tumor types. *The findings support reinforcement learning as a robust and efficient option for brain tumor identification in medical imaging*.

Additionally, reinforcement learning stands out for its tendency to adapt to changing medical data, making it ideal for heterogeneous tumor patterns. Unlike static models, RL's continuous learning capability promises better performance in real- time clinical settings. Future research can build on this foundation by using more complex RL frameworks, such as actor-critic approaches and policy gradient techniques, to enhance classification accuracy while reducing reliance on labelled data. Overall, reinforcement learning poses a promising path for the next generation of intelligent medical diagnostic systems, capable of real-time analysis, personalized treatment strategies, and adaptive learning, thereby improving early detection and treatment planning in brain tumor cases.

9. Future Work

In future research, we aim to extend the reinforcement learning framework by exploring more advanced and scalable algorithms beyond Q-Learning and Deep Q-Learning. In particular, we plan to look into actor-critic architectures and policy-based techniques like Proximal Policy Optimization (PPO), Deep Deterministic Policy Gradient (DDPG), and Asynchronous Advantage Actor-Critic (A3C), which provide enhanced stability, convergence, and continuous control appropriate for intricate, high-dimensional medical settings. We also intend to include adaptive and clinically informed reward functions, either manually created with domain expertise or learnt by Inverse Reinforcement Learning (IRL), to better match the model's learning behavior with clinical reasoning. This would enable the model to more faithfully represent treatment plans and diagnostic workflows. In order to maintain openness and win over doctors, we want to incorporate explainable reinforcement learning techniques and attention mechanisms,

as improving model interpretability is still a major barrier in clinical deployment.

We suggest adding online and continuous learning capabilities to provide adaptive intelligence, which would allow the model to dynamically adjust its policies in response to changes in diagnostic procedures, tumor growth, or new patient-specific data. In order to produce richer, more contextually aware predictions, future research will also focus on integrating multi-modal medical data, such as genomic profiles, CT and PET scans, histopathological pictures, and electronic health records. We also intend to explore sample-efficient reinforcement learning, meta-reinforcement learning, and transfer learning techniques to enhance generalization in data-constrained environments, considering the dearth of extensive, labeled medical datasets. Additionally, federated reinforcement learning can be investigated to facilitate cross-institutional collaborative model training while maintaining data confidentiality and privacy.

In order to evaluate the RL framework's usability, safety, responsiveness, and alignment with actual clinical workflows, we also want to test it in pilot deployment scenarios and simulated clinical environments. This kind of verification will shed light on any legal issues and human-in-the-loop decision support. In order to prepare the way for a fully integrated AI-based clinical decision support platform in precision oncology, we lastly envision creating multi-agent reinforcement learning (MARL) systems, in which several specialized agents work together to handle classification, segmentation, prognosis, and treatment planning. As this domain develops, it will also be crucial to ensure the responsible deployment of AI in healthcare by integrating ethical considerations like accountability, bias mitigation, and fairness in RL-driven decision-making.

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Priyanjli Gautam is currently pursuing her M.Tech in Computer Science and Engineering from Amity University, Noida, Uttar Pradesh, India. She received her Bachelor's degree in Computer Science from Himachal Pradesh University (HPU), Shimla. Her interests lie in deep learning, computer vision, and artificial intelligence. She is passionate about research in medical imaging and aims to contribute to the field through innovative applications of AI technologies.

Dr. Shuchi Mala is working as an Assistant Professor in the department of Computer Science and Engineering at Amity University, Noida, Uttar Pradesh, India. She has an experience of more than 6 years in academics and 4 years in full-time research She received her Ph.D. degree from Malaviya National Institute of Technology Jaipur (MNIT), India in 2018. She has published more than 32 articles in peer reviewed journals, international conferences, and book chapters. She is a member of IET and ACM society. Her research interests are spatial data modelling, health informatics and intelligent systems. She actively serves as a reviewer for esteemed international journals.

Dr. Aakanshi Gupta is working is as an Assistant Professor in the department of Computer Science and Engineering at Amity University, Noida, Uttar Pradesh, India. She has an experience of more than 15 years in academics and research She received her Ph.D. degree from GGSIPU, Delhi; under the guidance Prof. Bharti Suri. Her research interests are Artificial Intelligence, Information retrieval, Data Science and Software Reliability.

Dr. Nidhi Mishra is working as an Assistant Professor in the department of Computer Science and Engineering at Amity University, Noida, Uttar Pradesh, India. She received her Ph.D. degree from Banasthali University, Jaipur India in 2016. She has published more than 55 articles in peer reviewed International journals and conferences. She is a member of IEEE and ACM society. She has guided 3 Ph.D and 15 M.Tech research scholars in the area of Artificial Intelligence, Machine Learning, Deep learning, Neural network and NLP. Her research interests are Artificial Intelligence, Information retrieval, Data Science and Natural Language Processing.

Dr. Narayan C. Debnath is currently the Founding Dean of the School of Computing and Information Technology at Eastern International University, Vietnam. He is also serving as the Head of the Department of Software Engineering at Eastern International University, Vietnam. Formerly, Dr. Debnath served as a Full Professor of Computer Science at Winona State University, Minnesota, USA for 28 years, and the elected Chairperson of the Computer Science Department at Winona State University for 7 years. Dr. Debnath has been the Director of the International Society for Computers and their Applications (ISCA), USA since 2014. Professor Debnath made significant contributions in teaching, research, and services across the academic and professional communities. He has made original research contributions in Software Engineering, Artificial Intelligence and applications, and Information Science, Technology and Engineering. He is an author or co-author of over 500 research paper publications in numerous refereed journals and conference proceedings in Computer Science, Information Science, Information Technology, System Sciences, Mathematics, and Electrical Engineering. He is also an author of over 15 books published by well-known international publishers including Elsevier, CRC, Wiley, Bentham Science, River Publishing, and Springer. Dr. Debnath has made numerous teaching, research and invited keynote presentations at various international conferences, industries, and teaching and research institutions in Africa, Asia, Australia, Europe, North America, and South America. He has been a visiting professor at universities in Argentina, China, India, Sudan, and Taiwan. He has been maintaining an active research and professional collaborations with many universities, faculty, scholars, professionals and practitioners across the globe. Dr. Debnath is an active member of the IEEE, IEEE Computer Society, and a Senior Member of the International Society for Computers and their Applications (ISCA), USA.