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Research Article

Intelligent Gamified Therapy Using Dilated Residual Network and Bayesian Inference Learning Automaton Based Reinforcement Learning for Emotional Regulation

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Abstract: Emotional well-being is essential for maintaining mental health, yet many individuals struggle with regulating negative emotions due to limited access to effective interventions. This study proposes a gamified digital therapy framework using the strategic board game Go to enhance emotional regulation and provide mental health support. The framework integrates a Dilated ResNeXt (Dil-ResNeXt) network for advanced spatial feature extraction and contextual learning, combined with a Bayesian Inference Learning Automaton (BInfLA)-based Reinforcement Learning model to dynamically adapt policies under uncertainty. Additionally, the Predictive Upper Confidence Bound applied to Trees (PUCT) algorithm is employed to improve decision-making efficiency in gameplay. Experimental evaluation demonstrates that the proposed system achieved a 12.8% increase in winning rate stability and improved technical balance scores by 15% compared with conventional AlphaGo-based models. A psychological assessment with 128 participants reported a 20% improvement in emotional regulation and a 17% reduction in anxiety levels. These findings indicate that the proposed framework significantly enhances user engagement and emotional well-being, providing a robust approach to digital mental health interventions.

***Keywords*:** gamified therapy, dilation, residual network, Bayesian inference, learning automaton, reinforcement learning, emotional and mental support

MSC: 68T07, 68T05, 62F15

Abbreviation

AI	Artificial Intelligence
BInfLA	Bayesian Inference-based Learning Automaton
CBT	Cognitive Behavioral Therapy
CNN	Convolutional Neural Network
Dil-ResNeXt	Dilated Residual Network with Grouped Convolutions and Dilated Filters
DL	Deep Learning

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ERL	Enhanced Reinforcement Learning
ERLA	Enhanced Reinforcement Learning Algorithm
HCI	Human-Computer Interaction
MCTS	Monte Carlo Tree Search
PUCT	Predictive Upper Confidence Bound applied to Trees
QL	Q-Learning
RLA	Reinforcement Learning Algorithm
RL	Reinforcement Learning
SAC	Soft Actor-Critic
UCT	Upper Confidence Bound

1. Introduction

Emotional well-being is a vital component of mental health. However, the overall state of emotional health is declining globally, with many individuals adopting a passive approach to emotional regulation due to personal limitations and social or cultural factors [1] . Prolonged negative emotions or heightened emotional responses can lead to psychological disorders [2]. While several programs exist to improve emotional regulation, studies indicate that 70-80% of adolescents and children with mental health challenges do not benefit from these interventions due to barriers such as stigma, lack of accessibility, high costs, and long wait times [3–5].

Because inadequate emotional control is intimately associated with anxiety, depression, and other affective disorders, clinical psychology emphasizes it highly [6]. Clinical evidence shows that treatments like mindfulness-based treatment and Cognitive-Behavioral Therapy (CBT) enhance emotional control by encouraging adaptive coping and minimizing maladaptive responding. Nevertheless, established systems of therapy delivery are frequently confronted with problems such as stigma, long waiting lists, and inaccessibility [7]. Digital treatment platforms, which have proven to substitute in-person therapy successfully, are founded on evidence-supported psychological concepts. For example, evidence has demonstrated that digital Cognitive Behavioral Therapy platforms and cell phone-based mental health applications can effectively lower symptoms of anxiety and depression and improve treatment adherence. This demonstrates how innovation in technology and psychological theory can be merged in order to offer scalable and personalized interventions [8].

The success of virtual mental health interventions, as Human-Computer Interaction (HCI) suggests, rests on their capacity to meaningfully and enduringly engage people. HCI studies show that therapeutic interactive systems are required to strike a balance between accessibility, usability, and emotional connection [9]. Adding playfulness and game-like features to treatment environments, gamification enhances motivation, engagement, and intervention compliance [10]. Past research in affective computing has established that emotionally intelligent systems that are capable of perceiving, understanding, and responding to user emotions [11] are necessary for effective digital therapy. This connection between psychological principles and HCI design underlies modern digital mental health models.

Gamification is the process of incorporating gaming features into non-gaming contexts that has become more popular as a means of enhancing mental and physical health [12]. It was started in 1998 when the exergame Dance Revolution was developed for weight loss and cardiovascular fitness. Since then, gamification concepts have been incorporated into a wide range of games and smartphone applications to improve mental and physical health, as SuperBetter for reaching personal health goals and Nike+ for tracking physical activity [13]. Currently, gamification principles have been most popularly used in mental health interventions with two main uses in contemporary practice. In one strategy, gamified mental health therapies are directly developed to produce new and more interesting treatments. On the other hand, gamification components are included into pre-existing mental health interventions to increase their effectiveness [14, 15].

For example, a group of researchers intended to increase the efficacy of a computerized CBT aimed to change cognitive biases in patients with depression [16]. By combining the six essential gamification elements such as challenges, goals, feedback, progress, incentives, and fun, they specifically aimed to lessen the tedium of repetitive tasks in this intervention. According to their findings, persons responded favorably to all of these new elements, saying that the games used in treatment sessions were enjoyable to play, and the goals and guidelines were obvious. Based on these results, most persons are amenable to the addition of gamification to current therapies aimed at reducing depressed symptoms. The application of gamification components in unsupervised cognitive-behavioral treatment for teenagers with depression was also subjected [17]. These components included riddles, rewarding mini-games, and entertaining tests pertaining to the therapeutic material.

The findings showed strong retention rates and no additional risks to persons when compared to standard depression treatment. Nevertheless, it is remarkable that dropout rates rose when the intervention was used in real-world situations. A significant obstacle for the gamification is highlighted by the adolescent persons' desire for the game format to be as competitive and captivating as commercial games [18]. Thus, persons' expectations for gamification elements in mental health interventions have increased due to the accessibility of high-quality entertainment games, particularly among teenagers who regularly play video games for fun. In these situations, it could be helpful for clinicians to control their users' elevated expectations and make sure they understand the gamified intervention's therapeutic goal, which means, to promote mental health rather than just entertainment. Go is a sport that demands a lot of mental energy and thus Psychiatrists totally agree that playing it can relieve patients of the tiresome daily work and learning [19]. The impact is immediately apparent and thus Go can reduce stress, enhance emotional intelligence, and support positive psychology.

Intelligent agents can be guided by Reinforcement Learning (RL) to learn on their own and develop a strategy system that can address real-world issues [20]. However, high-dimensional environmental conditions, actions, and intelligent agent tactics cannot be adequately encoded by conventional RL techniques. Only minor issues can have positive outcomes. As Deep Learning (DL) has advanced, RL algorithms with decision-making capabilities and advanced neural network model with robust perception capabilities have been integrated in the proposed method for regulating mental health and emotions. One application area for this approach is board games. The AlphaGo series algorithms are examined in order to achieve. It is projected to offer technical and scientific backing for psychotherapy. Go games can help patients focus better, forget about social issues in real life, and efficiently manage negative emotions while enhancing their cognitive abilities.

Numerous digital therapy models integrating gamification, clinical psychology, and Artificial Intelligence (AI) have been proposed, including gamified CBT exercises delivered via mobile platforms, AI-driven chatbots that provide real-time emotional support, and serious games designed for cognitive training in individuals with anxiety and depression. [21, 22]. These models illustrate how gamified interventions can enhance emotional outcomes when built with clinical rigor and user-centered design principles. Most current systems, however, are confined to static rule-based interactions or are unable to respond dynamically to users' emotional states. Even with development in digital mental health tools, there remains limited paradigms combining DL systems, clinically informed therapy principles, and adaptive policy updates [23]. This is resolved through the proposed framework, which builds a dynamic, gamified emotional regulation therapy system through a combination of a Dilated ResNeXt model for context learning with Reinforcement Learning from Bayesian inference.

This limitation allows more advanced models that employ DL, Reinforcement Learning, and probabilistic reasoning to provide customized therapeutic experiences.

The major contributions of the proposed method are provided below:

• To propose a novel framework through digital board game applications for improving emotional regulation and mental health support.

• To offer improved feature extraction through Dilated ResNeXt (Dil-ResNeXt) that combines residual connection, grouped convolution and dilated filter for enhancing spatial representation and contextual learning.

• To incorporate RL with Bayesian Inference-based Learning Automaton (BInfLA) for allowing dynamic policy adaptation through probabilistic reasoning.

• To present empirical validation in mental health assessment with proposed and existing algorithms for determining the superiority.

The research is organized as follows: Section 2 deals with related works. Section 3 describes the proposed model in mental health and emotional regulation. Section 4 indicates the result and discussion. Lastly, Section 5 shows the conclusion and future work.

2. Related works

Eun et al. [24] presented a personalized serious game powered by AI to improve elderly persons' cognitive and physical abilities. This method would provide relative scoring and difficulty level adjustment to encourage the player to continue playing the game with enjoyment. A 3-month empirical evaluation of user happiness and performance was created in this model. The experimental findings demonstrated the appropriateness and usefulness of presented serious game as a digital healthcare application by showing all three features of performance, satisfaction, and immersion records improved when compared to other currently available. However, this model failed to acquire full complexity of cognitive or physical states and limited accuracy.

Joypriyanka and Surendran [25] suggested using checkers game therapy with chatbots to improve cognitive function in dementia patients. The main objective was to discover policies to stimulate peoples' brain suffering from dementia for enhancing their cognitive capabilities like problem-solving, memory, and observational skills. The potential of RL was used to enhance the checker-playing experience for individuals with dementia in a therapeutic gaming setting. The Soft Actor-Critic (SAC) RL system was used to train an agent that could support both offensive and defensive strategies. The outcomes demonstrated that the SAC algorithm had outperformed the existing models. However, the effectiveness of the model was limited due to game complexity and lack of clinical validation.

Almgren et al. [26] presented a Machine Learning (ML)-assisted detection of longitudinal cognitive decline using multimodal features. Four sets of input features were identified such as brain volumes, Cerebrospinal Fluid (CSF) biomarkers, clinical test scores, and genetic variations. A basic model comprising baseline cognition and demographics was expanded to include all possible amalgamations of input feature sets. To find the set of prognostic features and assess model performance for every combination of input feature sets, an iterative approach utilizing support vector regression, RReliefF-based feature ranking, and tenfold cross validation had employed. However, this model would exhibit limitations like overfitting issues, affected by irrelevant features, poor global model understanding.

Zamani et al. [27] described a gamified AI-driven system for managing and monitoring depression. The suggested platform supported context-aware and personalized depression monitoring and self-regulation by integrating sensor data, AI analytics, adaptive surveys, and micro-games. This system continuously monitored cognitive, behavioral, and environmental patterns in contrast to conventional static models. Then, customized interventions were delivered using this data that metacognitive principles form the foundation of the system. Through interactive reflection and feedback, it encouraged user engagement and self-awareness. According to evaluation results, neural networks achieved a Receiver Operating Characteristic-Area Under the Curve (ROC-AUC) of 0.931, indicating strong classification accuracy across models. However, the model should enhance model generalizability, evaluate long-term user engagement and improve robustness.

Pavithra et al. [28] recommended the cognicare framework and an AI-enabled Internet of Things (IOT) intervention for improving cognitive capacities in autistic children. This system, which used AI and IoT technologies, had collected data from Electroencephalogram (EEG) and heart rate sensors. A Radial Basis Function Network (RBFN) was employed for classification, and quick geometric assembling for feature extraction. The device provided a predictive model for behavioral and emotional states by integrating heart rate sensors to track the child's physiological condition. Enhancing eye contact and reducing social barriers were facilitated using 3D models. Improving adaptive mechanisms while addressing communication difficulties and social skill deficiencies was the main intension of this model. The system's ability to detect and communicate a child's state, promote good interactions, and tear down barriers of fear through creative virtual surroundings was demonstrated by the results. However, this model would need to enhance the performance in terms of various assessment metrics.

3. Proposed methodology

In the age of Internet, games are a significant development trend. Gamification is used in this work to address mental health issues, with emotional regulation as the primary objective. Experiencing several senses, including sight, sound, and smell, helps individuals control their emotions. Go is a game that demands focus and composure, which helps individuals with psychological distress, irritability, and other symptoms feel less stressed. This study specifically focuses on college-aged young adults (18-25 years) with self-reported mild to moderate anxiety symptoms, representing a general population group at high risk for emotional regulation challenges rather than individuals with clinically diagnosed psychiatric or developmental disorders such as Autism Spectrum Disorder (ASD) or Attention-Deficit/Hyperactivity Disorder (ADHD). In order to address these issues, a novel hybrid Enhanced Reinforcement Learning (ERL)-based BInfLA model is proposed to regulate mental health and emotions. Here, the Predictive Upper Confidence Bound applied to Trees (PUCT) algorithm and ensemble learning are used to develop a board game. The strategies and approaches for game improvement are covered in this section.

3.1 *MCTS and Dilated ResNeXt-based go game algorithm*

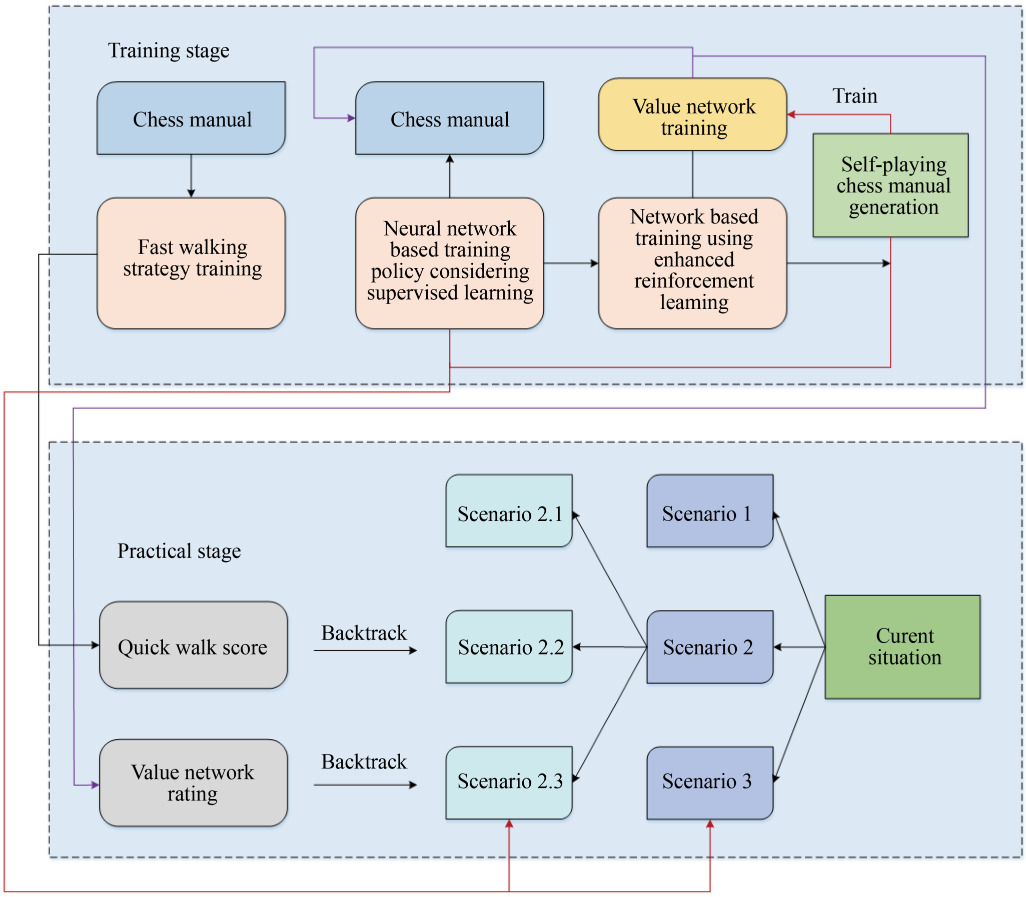

Figure 1. General framework of the proposed AlphaGo-based training and practical strategy model

As everyone is aware, there are up to 10^{170} different legal scenarios in Go. Compared to other games, the branching factor is significantly higher. Computers find it extremely challenging to reach a high level in Go. Several search algorithms that perform well in other chess sets are not readily effective in Go because of the challenge of establishing evaluation functions. A novel RL technique is used after an analysis of the AlphaGo series algorithms. The search algorithm in the Go game has a lot of difficulties because there are so many possible outcomes. The method of priority sampling involves assessing each circumstance and giving it a priority. The algorithm speeds up and improves the quality of the search by giving precedence to the circumstance with the highest priority during the search process. Accurately determining each situation's priorities is crucial to this technique. In order to achieve this, the method uses Dil-ResNeXt to assess the scenario and trains the network to understand its features in order to give it a fair priority. A PUCT approach is employed in order to fully use the training phase's outcomes. AlphaGo is primarily composed of a value network assisted RL, a policy network assisted supervised learning, a rapid walking approach, and an enhanced Monte Carlo Tree Search (MCTS). Figure 1 illustrates the two phases of the suggested AlphaGo system. During the training phase, the model is trained in fast walking strategy learning, value network learning, supervised learning, and self-play. The learned model analyzes situations in the Practical stage to decide the best action through value network outputs and rapid walk scores. Arrows represent information flow among components.

The Dil-ResNeXt-based strategy network takes as input manually collected features from the present scenario. The result is the probability distribution of the actions taken in the present scenario. Human chess players using the KGS platform provide the training data. A classification problem is similar to the training procedure. The input is the preprocessed chess scores, and the output is the resultant actions. The human-selected action in the chess data is the proper action label. The Pufferfish Optimization Algorithm (PufOA) [29] is used in the optimization procedure that tunes the parameter of the model. The technique performs better when Equation (1) is used in PufOA design. In particular, after a new position for PufOA member is created, its superiority as a solution to the problem is evaluated by comparing the values of the objective function. The new location is adopted for the relevant PufOA member if it yields a superior objective function value. On the contrary, the member remains in their previous position and the new position is disqualified if it does not offer a better alternative. Equation (1) illustrates this point by showing that an update for every PufOA member depends upon achieving an improvement in the objective function's value.

$$J_{x,\,y}^{g1} = J_{x,\,y} + (1 - 2t_{x,\,y})\,\frac{ub_y - lb_y}{v} \tag{1}$$

$$i_x = \begin{cases} i_x^{R1},\ H_x^{R1} \leq H_x \\ \\ i_x,\ \text{else,} \end{cases} \tag{2}$$

where, i_x^{R1} indicates the new position resolute for the x^{th} predator in the second phase of PufOA, and $J_{x,\,y}^{Q1}$ indicates its y^{th} component. The expression H_x^{Rl} specifies related objective function value, v denotes iteration index and $t_{x,\,y}$ resembles the random numbers from the range [0, 1].

The ERL-based strategy network and the supervised learning-based network strategy must initially be initialized for the training phase. Then, the final result and the chess score are noted. Simultaneously, the metaheuristic optimization algorithm is employed to raise the likelihood of the ultimate winning move [30]. The supervised learning-based strategy network's chosen course of action is implemented. Then, to improve exploration, a valid action is chosen at random. Lastly, actions are chosen using a novel ERL-based strategy network and the outcome is noted. In the practical stage, the MCTS benefits from the fast-moving sub approach. The quick move strategy makes advantage of a multi-game mode that was manually created. MCTS primarily supplies data for value network (Dil-ResNeXt) training. Given that there are many low-quality sub-trees in the entire game tree, the game tree is constructed using Monte Carlo search. In order to provide more accurate estimations, MCTS needs a large-scale sampling of every scenario. The PUCB algorithm and Monte Carlo tree are combined to create the PUCT, which effectively shrinks MCTS's search space and increases search efficacy.

3.2 *Employing ensemble learning and the PUCT algorithm as an optimization technique for the go game algorithm*

There is randomness in MCTS. As a support, this method frequently necessitates a large amount of experience. Before making a choice in the self-game, the agent must execute 1,600 forward propagations. Every self-playing chess game takes an average of roughly 560,000 forward propagation attempts to finish. Accuracy can be increased by incorporating Dil-ResNeXt into MCTS for strategy iteration. Furthermore, the training data usage rate is low to prevent over-fitting problems, indicating that the acquired training data has not been thoroughly and successfully mined. To further boost the performance, novel RL based method has used. Neural network-based RL techniques are inherently unstable and challenging to train, making initialization crucial to the training process. Based on the Bagging and PUCT algorithms, an ERL board game technique is used to address training constrained by single neural network bias, and parameter tuning burden in the training architecture. To enhance overall prediction performance, this work builds numerous independent models using the bagging technique and aggregates their prediction results.

3.3 *ERLA*

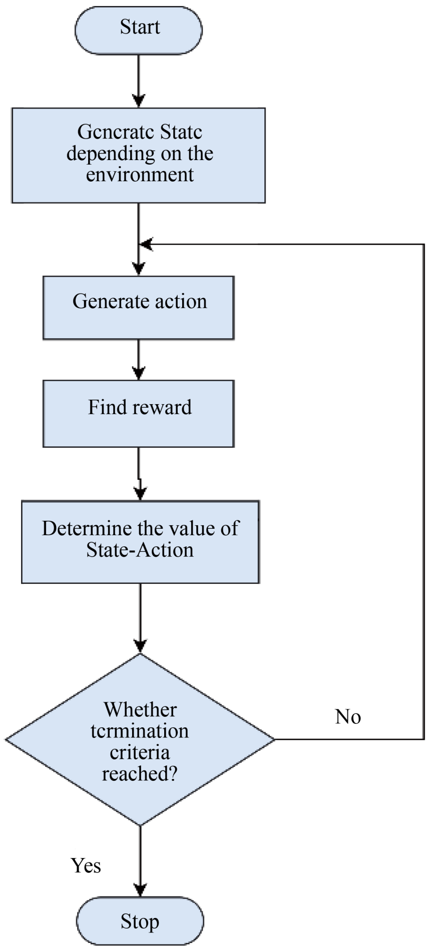

Figure 2. Flowchart of the Reinforcement Learning Automaton (RLA) process

In the proposed method, an Enhanced Reinforcement Learning Algorithm (ERLA) has employed to evaluate the potential success of various game states. The ERLA incorporates BInfLA to enhance the performance. The algorithm learns to predict the loss or win outcome of the game from a board state. The value network training takes the sequences of simulated gameplay between AI agents, current board states and final game outcomes as input [31]. In RLA, the learner, also known as the agent, interacts with its environment as well as chooses which actions to apply based on its present state and the reinforcement it receives from them. The basis of RLA can be the reward functions. The reward, which is given back to the agent by the environment, serves to inform the learning algorithm regarding the influence of most recent action. A value function shows what is good (or bad) over the long run, as opposed to a reward function, which shows in the long term. Figure 2 illustrates the step-by-step workflow of the proposed RLA framework, including action selection, environment feedback, probability updating, and convergence criteria.

Usually, the problem of RLA is shaped by 4-tuple $(U,\ C,\ R,\ T)$, where C characterizes the set of actions, T states the reward function, U designates the set of states, and R designates the state transition matrix probabilities [32]. The environment model is designated by R and T. There are two approaches to RLA problems: model-free and model-based approaches. The agent can learn the environment and improve its policies to achieve optimality in the model-based method. On the other hand, the transition probability matrix calculation is the focus of the learning environment model. As for their higher storage costs and reliance on accuracy, model-based approaches are not very common. In contrast, model-free approaches do not require a transition probability matrix R because the agents can improve the policy without any environment model's prior knowledge.

The policy ϑ_v outlines the learning agent's performance over time v. $\vartheta_v\left(c \mid u\right)$ is comparable to the probability that $c_v = c$ when $u_v = u$. c_v and u_v specifies the action and state at time v. The likelihood of moving from one state u to u' at a given time u by action C is as follows:

$$R\left(u,\ c,\ u'\right) = Rt\left(u' \mid u,\ c\right) = Rt\left\{u_{v+1} = u' \mid u_v = u,\ c_v = c\right\} \mid \sum_{i \in U} R\left(u^i \mid \ldots,\ c\right) = 1. \tag{3}$$

The reward that was received at that time v is regarded as a real number, denoted by T_v. $T(u,\ c)$ shows the reward of both being in the state u and action C. The agent chooses an action at each learning phase of its existence. The agent's goal is to take action in order to raise the global discounted reward, which is denoted by I_v. Therefore, the agent should be able to determine which course of action is required based on the reward obtained thus far in the future. Additionally, an average reward pattern has been taken into consideration in order to define I_v and address optimality. The agent must act in a way that increases the long-term average reward under the average reward scheme.

$$I_v = \lim_{j \to \infty} \frac{1}{j} \sum_{m-0}^{j} T_{v+m+1}. \tag{4}$$

If the agent of environment has the Markov property, which means that just the present state and the actions to be taken will affect the next state, it has:

$$Rt\left\{T_{t+1} = t,\ u_{v+1} = u' \mid \left(u_0,\ c_0,\ T_0\right),\ \ldots\left(u_v,\ c_v,\ T_v\right)\right\} = Rt\left\{T_{v+1} = t,\ u_{v+1} = u' \mid u_v,\ c_v\right\}. \tag{5}$$

The predicted value of the subsequent reward in the Markov property is independent of the preceding rewards. Furthermore, finding a policy to achieve an excessive reward over an extended period of time is necessary to solve the issues with RLA. The ideal policy ϑ_0, which has the action-value function $R^*(.)$ and state-value function $X^*(.)$ described in below equation. ϑ is represented by the policy when the return for each state is equal to or greater than one of the policies ϑ' i.e. $X_g(u) \geq X_g(u)$, $\forall \in T$.

$$X_{g+}(u) = X^*(u) = Max_g X_g(u),\ \forall_n \in T \tag{6}$$

$$T_{g*}(u,\ c) = S^*(u,\ c) = Maxi_g i S_g(u,\ c),\ \forall_u \in T \tag{7}$$

$$T_{g*}(u,\ c) = S^*(u,\ c) = Maxi_g i S_g(u,\ c),\ \forall_u \in T, \tag{8}$$

where, $S_{g^*}(u,\ c)$ designates the action-value of compelling action c in state u under policy ϑ.

The final formula, referred to as a self-consistency requirement, states that the predicted return for the best course of action should match the state value under best policy. The solution to the subsequent system of equations is the function of optimal value ϑ.

$$X^*(u) = \underset{c \in B}{Maxi} \left(S(u,\ c) + \kappa \sum_{u' \in U} \left(R\left(u,\ c,\ u'\right)^* X^*\left(u'\right)\right)\right),\ \forall u \in T \tag{9}$$

To learn the best course of action, search agents in RLA can be placed in complex environments. Given the model-free RLA, the reinforcement agents are only able to learn to make decisions based on their actions and experience, not on any prior knowledge about the environment. Only the tasks assigned to them are visible to the agents in this situation. As a result, the agents can use strategy, including reward and penalty, to learn from their experiences in the environment. One of popular algorithms in RLA is the Q-Learning (QL) method. Using a value-based process, the agents in QL can try to decide the best course of action. Its states and actions can teach the agents. Furthermore, a preset policy is not required in this method since the RLA agent acts randomly, receives a reward or a penalty, and gradually builds an experience based on the action that likely to result in rewards. Additionally, in the QL algorithm, a table called Q-Table is supplied, and the agents try to update their state in order to select the optimal action depending on Q-Table's value, considering all possible action. Henceforth, every agent in action selects to either explore or exploit the environment.

3.3.1 *BInfLA*

Learning automata are particularly well suited to finite-action, stochastic-feedback environments because they operate directly on an action probability vector and update it incrementally based on environmental responses. In such settings, each action initially has equal probability, and one action is randomly selected and evaluated according to the environment's response, which may be favorable or not. Over repeated trials, the automaton updates these probabilities, gradually favoring actions that yield positive outcomes. This makes learning automata sample-efficient and robust to noisy or reward-sparse signals, as typically encountered in board games where rewards are only observed at the end of an episode.

The Bayesian variant BInfLA enhances this mechanism by placing probabilistic priors on action success rates and updating posterior beliefs after each interaction. This provides principled uncertainty estimates, improves exploration-exploitation balance, and enables incorporation of prior knowledge. Bayesian Reinforcement Learning approaches have been shown to reduce regret and yield more stable policies under model uncertainty. BInfLA complements our ensemble/PUCT approach by offering low-variance, uncertainty-aware policy updates that integrate naturally into MCTS sampling and stabilize learning in the presence of noisy human training data. The tuple in BInfLA represents the variable structure of LA; the set of values for an input action is represented as D, the internal state set is designated as φ, and the response set from environment is inferred as ψ. The output mapping is shown as I, the learning algorithm is described as V, and the probability vector that guides the state selection in each phase is shown as R. The learning algorithm is regarded as one of the most important components in LA. The linear reward-penalty method is extensively utilized learning algorithms.

It is a unique type of linear reinforcement model that uses two learning parameters c and d for updating the probability of selecting internal states. In this case, the penalty step is described as d, while the reward step length is quantified as c.

Assume the action chosen at that time v as a sample realization from the probability distribution $r(v)$, and the response δ by environment. Then, the following equation can be used to specify the linear reward-penalty model with T actions for an environment with $\delta \in \{0,\ 1\}$ (for satisfactory response i.e., $\delta \in 0$).

$$r_l(v+1) = \begin{cases} r_l(v) + c(1 - r_l(v)) & \text{if } k = l \\ \\ r_l(v)(1-c) & \text{if } l \neq l. \end{cases} \tag{10}$$

For non-satisfactory response (i.e., when $\delta = 1$),

$$r_l(v+1) = \begin{cases} r_l(v)(1-d) & \text{if } k = l \\ \\ \dfrac{d}{t-1} + (1-d)r_l(v) & \text{if } k \neq l. \end{cases} \tag{11}$$

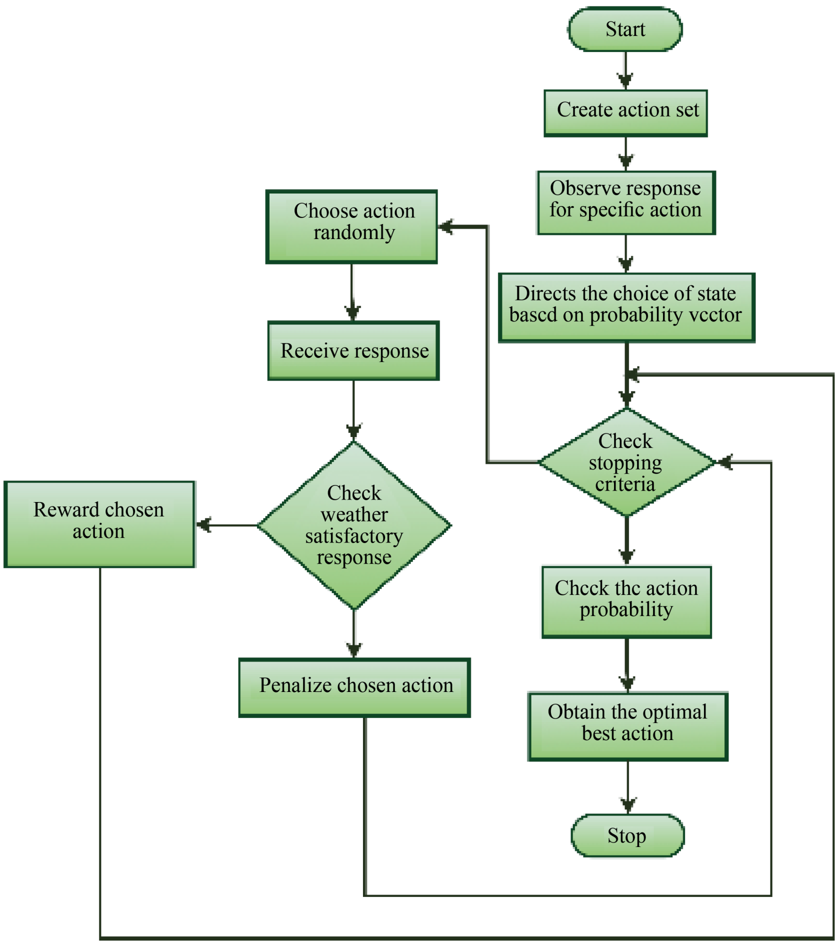

Figure 3. Flowchart of BInfLA

Where, k denotes the automaton state in earlier step and l suggests the automaton state following the automation scheme update. The condition $k = l$ designates that the previous step is retained, while another condition $k \neq l$ indicates that the state has changed in the subsequent step. The flowchart of BInfLA is specified in Figure 3.

Furthermore, BnfLA is distinctly Bayesian in nature, relying on random sampling of beta distribution and the assessment of rewards or penalties. Thus, Bayesian Learning (BL) is referred to as a probabilistic inference model that assigns weights to the data supporting the hypotheses. Finding the best solution to the problems is BL's primary goal. Two positive parameters, ε and β are employed in the beta distribution formula in BInfLA. Therefore, the probability density function has been calculated in the way described below.

$$h(z;\ \beta,\ \varepsilon) = \frac{z^{\beta-1}(1-z)^{z-1}}{\int_0^1 z^{\beta-1}(1-w)^{z-1}dw},\ z \in [0,\ 1], \tag{12}$$

where, β_k and ε_k are set to 1.

3.4 *Dilated ResNeXt*

In the proposed approach, we adopt a Dilated ResNeXt (Dil-ResNeXt) backbone to generate accurate policy and value estimates for the MCTS and PUCT algorithms. This choice is motivated by two complementary architectural advantages. Dilated convolutions systematically expand the receptive field without down sampling or adding parameters, enabling the network to capture long-range spatial dependencies while preserving full board resolution. This is crucial in Go, where board positions are interdependent and strategic patterns often extend over large areas. Such dilation has also been shown to improve dense spatial prediction tasks by providing exponential receptive-field growth without resolution loss. ResNeXt's aggregated convolutions enhance representational capacity through the cardinality dimension, with many parallel low-dimensional transformations aggregated by summation. This provides more expressive power at a given computational cost compared to simply deepening or widening the network. By combining dilated convolutions for global context with ResNeXt's efficient capacity scaling, Dil-ResNeXt yields a compact architecture capable of extracting both local tactical motifs and global positional patterns [33]. The encoded board state, represented as a multi-channel tensor with features such as player stones, opponent stones, and move history, is processed through residual blocks with dilations. This allows the network to learn spatial features at multiple scales, thereby producing robust policy and value estimates that guide search-based decision-making.

To improve network depth and performance, pooling layers and cascading convolutional layers are combined to create classic Convolutional Neural Network (CNN). Pooling layers progressively diminish the input's spatial dimension as the network's depth increases, which may lead to the loss of important information and a decrease in the final output. A dilated convolution method is incorporated to address this issue. Self-attention layers provide real global context, but they do alter the model's inductive biases and typically need a huge amount of data and computation to work effectively. Current research has demonstrated that transformers can enhance performance in some board game situations, but they have larger sample and computer expense, and special optimization needs. In our work, dilated residual CNNs offer a useful trade-off between computationally efficient inference within MCTS/PUCT loops, maintaining required preserved spatial equivariance, and limited training data. They are stable and efficiently computable to train, with large receptive fields and strong locality priors. If ample processing power and very much larger self-play corpora are within reach, attention-augmented architectures hold promise as an alternative to investigate.

Actually, dilated convolution can expand the receptive field without the need for stride, maintaining feature map resolution and avoiding additional computational expenses during network training. The result is a dilated convolution with a $Y \times Y$ size filter J.

$$R_d = \sum_{y_1}^{Y}\sum_{y_2}^{Y} J_{f\times y_1 + f\times y_2,\, d} \times B_{y_1,\, y_2}, \tag{13}$$

where, the locations in the filter B are represented by y_1 and y_2, a feature map is given by J_d, and the relevant output is specified as R_d. In conventional convolutional layers, the stride and the dilation rate have the same function. The network can detect a wider context of the input data while preserving spatial precision in the feature maps by adjusting the dilation rate, which expands the filters' effective receptive field. The ResNeXt block uses the component $\widehat{p} \in \mathbf{R}^{S\times U\times E}$ from which it extracts features as an input. With ResNeXt, residual learning is extended to multi-path group convolution in addition to one-path convolution. Figure 4 depicts the Dil-ResNeXt model for the proposed work.

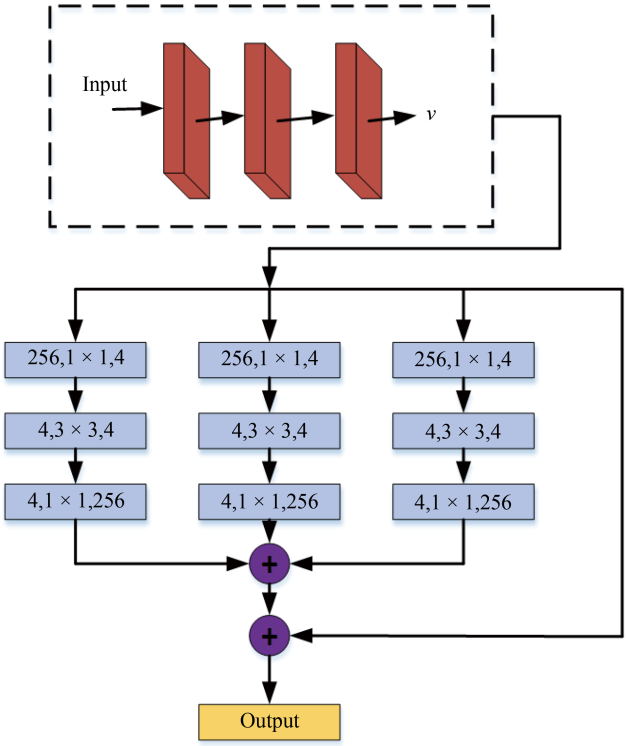

Figure 4. The architecture of Dil-ResNeXt model

A fixed branch base disperses the data $\widehat{p}$ along many paths, and each path independently performs the convolutional process. The results of these computations are concatenated along the channel dimension. This yields the output of the ResNeXt block.

$$Y = H_{\sup}(\widehat{p}) + W \tag{14}$$

$$W = \sum_{y=1}^{J} U_x(\widehat{p}). \tag{15}$$

The 1×1 convolution, a dilated convolutional layer, and a 1×1 second convolution layer create the subblock U_x, which denotes a bottleneck element. The components included in the residual block are indicated by the variable I. The mapping $H_{\text{slap}}(\cdot)$ shows the ResNeXt block's output Y while symbolizing the 1×1 convolution process.

4. Results and discussion

This portion initially examines the algorithm's improvement effect. The system performance is assessed in the second section. Lastly, a methodical application effect test is carried out to confirm the board game's regulatory impact on emotions related to mental health.

For transparency and reproducibility, all important hyperparameters in training were carefully recorded and checked. The model was empirically trained on a batch size of 128 between convergence stability and the limited GPU memory. For avoidance of overfitting, an initial learning rate of 0.01 with exponential decay (rate 0.9 by epoch) after grid search over $\{0.1, 0.01, 0.001\}$. SGD with momentum (0.9) and weight decay $1e^4$ was employed for optimization according to standard practices in ResNeXt-based architectures. Since it yielded the optimal trade-off between exploration and exploitation, the MCTS/PUCT exploration constant was chosen to be 1.5 using constrained grid search. The replay buffer was allowed to hold a maximum of 100k states, allowing for adequate variation without using too much memory, and policy temperature was annealed from 1.0 to 0.1 to promote exploration in the early stages and exploitation later. Performance was between 2 and 3% when key hyperparameters (± 20% learning rate, ± 50% batch size) were modified for robustness testing, which demonstrates that the introduced framework is stable and not very sensitive to tuning decisions.

4.1 *Analysis on the effect of enhancement*

The improvement effect of proposed and existing algorithms is tested by monitoring changes in the neural network output's learning rate, information entropy, total loss, value side loss, and strategy side loss throughout the training process. Total loss among them is equal to strategy loss plus value loss. The enhanced algorithm (Ensemble Deep Reinforcement Learning with Bagging (EDRL-B) and the conventional AlphaGo algorithm (Upper Confidence Bounds for Trees (UCT Algorithm)) are compared. Figure 5 illustrates how different performance indicators changes over training iterations.

The two curves' trends in Figure 5 are largely comparable. However, there are still some distinctions. In vast majority of cases, the proposed method produced comparatively low values for policy loss, information entropy, and total loss. The accuracy of the combined method is verified to a certain degree. The agent's strategy evolved along with the neural network's output behaviors. Later, under the identical circumstance, the winning rate also changed. As a result, there is always some lag in the value-side prediction. Throughout the training quarter, the existing methods displayed a consistent rebound tendency, implying that their stability is insufficient. The neural network has trained by maximizing the sample rate without using ensemble learning techniques in order to examine the effects of raising the sampling rate on game algorithms. Figure 6 illustrates the changes in different neural network losses after maximizing data utilization.

The value side loss in Figure 6 initially changed quickly, indicating that the agent failed to point out useful strategy before settling into local optima. According to Figure 6, training cannot be facilitated by rapidly raising the data rate. Conversely, there are adverse effects. Before the game is placed, 1,000 and 3,000 simulations for Go and Goku are run to evaluate the efficacy of proposed approach during the training phase. Every winning rate is fixed to a winning rate of 20 games due to computational resource constraints. Figure 7 displays the specific outcomes.

After 2,000 training cycles, the model is able to significantly outperform the existing algorithm. However, the winning rate fluctuated differently during the training phase. The winning rate of proposed method has dropped only once. Considering the existing methods, the winning rate of existing conventional AlphaGo algorithm dropped seven times, and the winning rate of EDRL-B dropped only twice. This suggests that proposed method is more stable and has greater chess strength.

K-fold cross-validation, is employed to estimate the generalization ability of the developed model. Each fold is a different training/testing split, and metrics such as average reward, strategic loss, value loss and total loss reported are averaged over folds. The Standard Deviation (SD) estimates offer resistance against data partition bias and reflect variability in performance. The low and relatively constant variance throughout the folds illustrates that the model is stable and dependable under varying training and testing conditions.

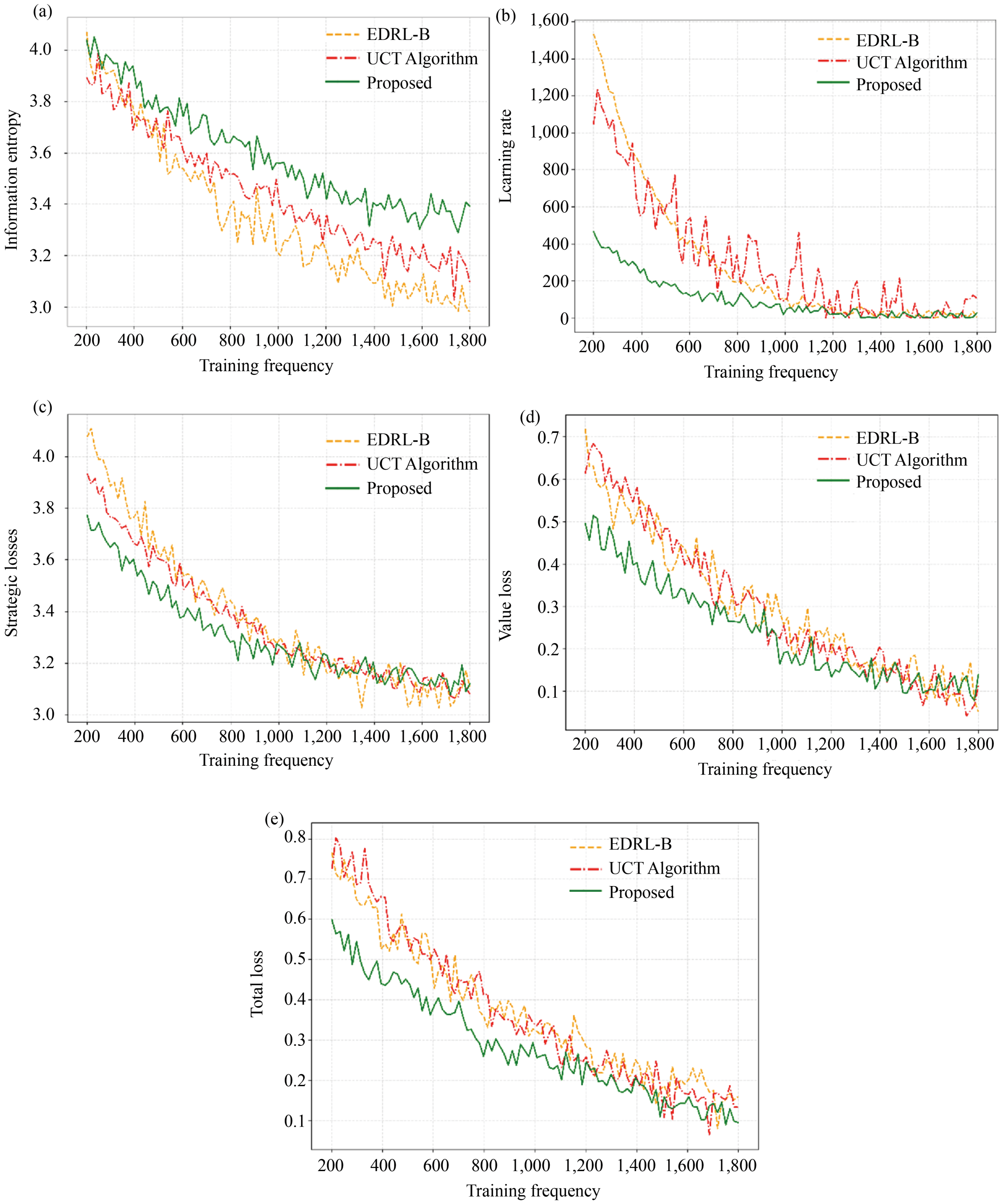

Figure 5. Comparison of variations in different training metrics for proposed and existing methods. (a) Information entropy; (b) Learning rate; (c) Strategic loss; (d) Value loss; (e) Total loss

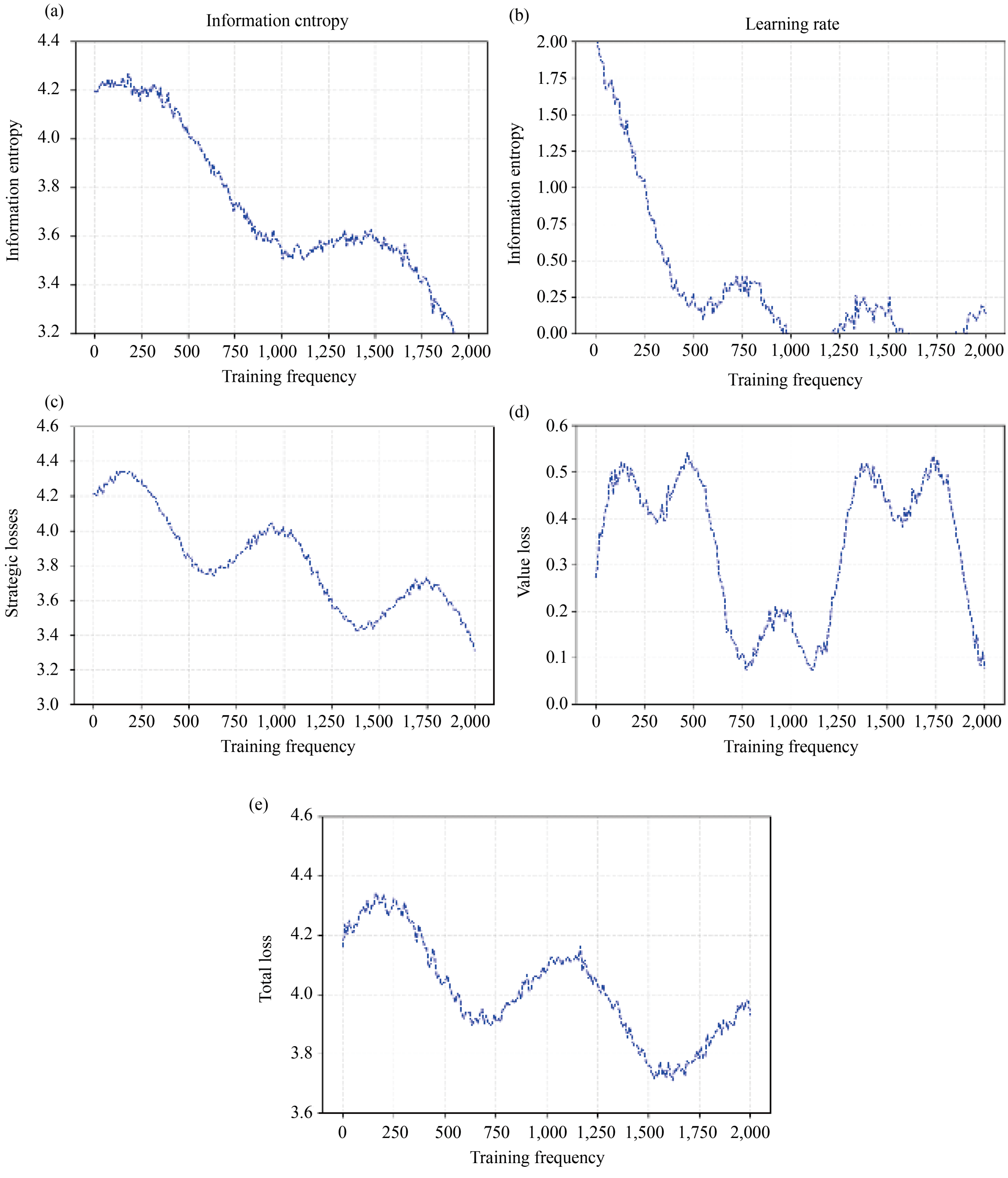

Figure 6. Analysis of game algorithm training process while increasing sampling rate. (a) Information entropy; (b) Learning rate; (c) Strategic loss; (d) Value loss; (e) Total loss

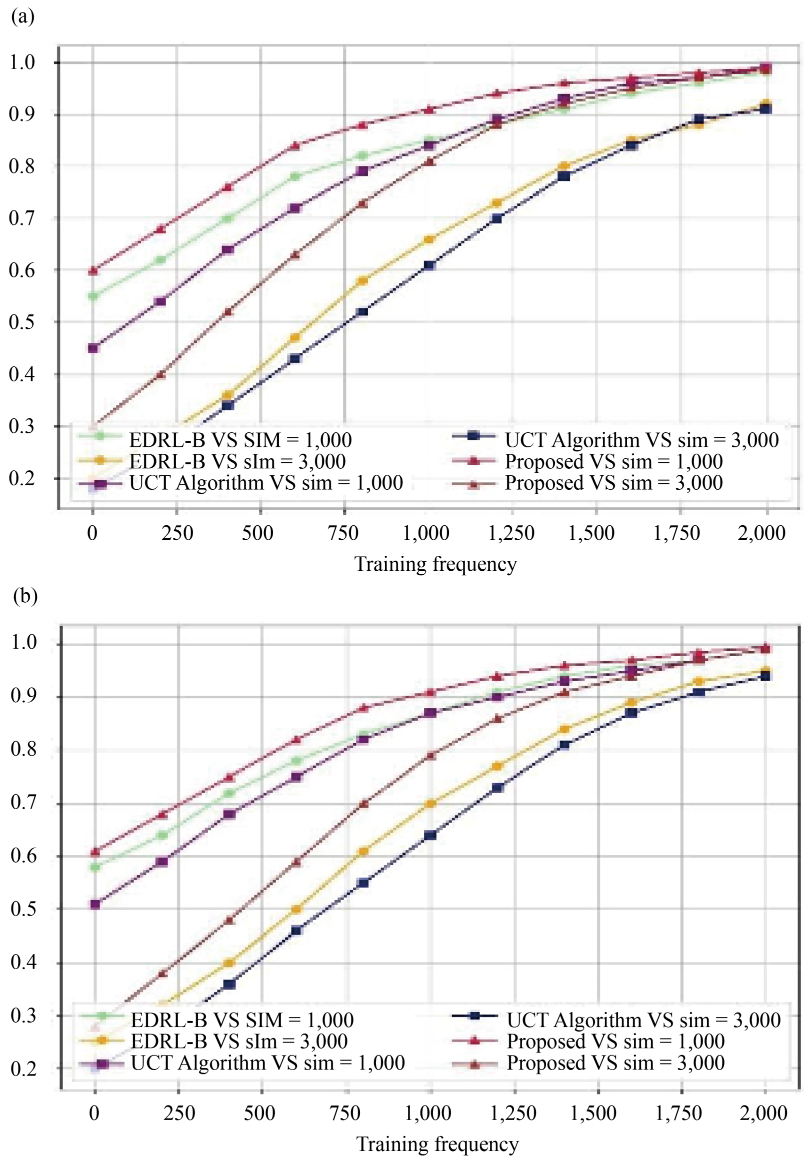

Figure 7. Comparison of the game wining rate for proposed and existing algorithm before improvement and after improvement. (a) Five-piece chess gamey; (b) Go game

Table 1. K-fold cross-validation table

Fold	Average reward	Strategic loss	Value loss	Total loss
Fold 1	0.87	0.12	0.15	0.27
Fold 2	0.88	0.11	0.16	0.27
Fold 3	0.86	0.13	0.15	0.28
Fold 4	0.87	0.12	0.14	0.26
Fold 5	0.88	0.11	0.15	0.26
Mean ± SD	0.87 ± 0.01	0.12 ± 0.01	0.15 ± 0.01	0.27 ± 0.01

Table 1 shows the cross-validation results of each of the five folds. The average reward was stable with a mean of 0.87 ± 0.01 and a range of 0.86 to 0.88, reflecting stable model performance. The value loss was between 0.14 to 0.16 (mean 0.15 ± 0.01), while the strategic loss was between 0.11 to 0.13 (mean 0.12 ± 0.01). The model as suggested proved to be robust and consistently convergent with a mean of 0.27 ± 0.01 and with a total loss varying between 0.26 and 0.28.

Table 2 summarizes the aggregate performance metrics of the suggested model across the five folds. The average reward demonstrated stable performance with a mean of 0.872 ± 0.0084 and a 95% CI of [0.862, 0.882]. The strategic loss also had a mean of 0.118 ± 0.0084 (95% CI: [0.108, 0.128]), whereas the value loss was slightly lower at 0.150 ± 0.0071 (95% CI: [0.141, 0.159]). The net loss remained negligible, with a mean of 0.268 ± 0.0084 and a 95% CI of [0.258, 0.278], reflecting the robustness of the model and the stable convergence.

Table 2. Model performance metrics with mean, SD, and 95% CI across five folds

Metric	Mean	Sample SD	95% CI
Average reward	0.872	0.0084	[0.862, 0.882]
Strategic loss	0.118	0.0084	[0.108, 0.128]
Value loss	0.15	0.0071	[0.141, 0.159]
Total loss	0.268	0.0084	[0.258, 0.278]

4.2 *Evaluation of the board game system's performance*

Following training, ten Go professionals are asked to assess the intelligent game to understand if the neural network can produce action distributions adhering to chess principles. Technical balance, strategy, assessment of shifts in Go thought, and practical shifts in Go are the evaluation indications. Each indicator has a score between 1 and 100 points. The evaluation findings are shown in Table 3.

Table 3. Game outcomes of multiple neural networks and PUCT for single neural network

No. of experiments	Win rates (%)					
	1	2	3	4	5	6
1	96.45	93.67	94.54	90.44	92.35	90.41
2	97.56	94.56	90.34	93.78	96.24	95.73
3	95.45	95.23	93.76	94.35	90.61	93.66
4	92.47	97.24	91.56	91.75	91.25	91.63
5	97.34	94.64	90.51	92.67	92.68	97.32

Table 4 shows the board distribution in the designed board game is reasonable. All four indicators' average scores in Table 1 are higher than 80 points. The game's average technical balance score is 93.13 points. A board game's average strategic score is 91.05 points. The change indicator in chess thinking has an average score of 92.56 points. The truly usable change indicators under the regulations had an average score of 86.87 points.

Table 4. Game outcomes of multiple neural networks and PUCT for single neural network

Go expert ID	Rates of scoring			
	Technical balance	Strategic	Change in Go thinking	Actual available variation
1	91.54	89.67	92.33	85.54
2	93.50	89.24	93.27	88.76
3	94.28	88.84	92.59	86.27
4	90.49	90.53	90.47	89.35
5	95.56	91.27	92.38	87.38
6	93.35	92.42	92.44	85.23
7	91.97	93.35	93.28	87.65
8	92.22	91.39	92.73	86.29
9	95.28	91.31	91.46	88.27
10	93.13	92.49	94.63	83.98
Average	93.13	91.05	92.56	86.87

Comparative tests are carried out with more advanced existing game systems in order to thoroughly validate the functionality of the board game system created in the proposed work. The variation in the algorithm's winning rate as the number of games rises is the experimental content. The chessboard game based PUCT and integrated learning (System 1), an upgraded ant colony algorithm-based human-machine board game system (System 2), an MCTS-based game system (System 3), a UCT-based game system (System 4), and a machine vision and Fourier transform-based game system (System 5) are all included in the comparison system. Figure 8 displays the findings.

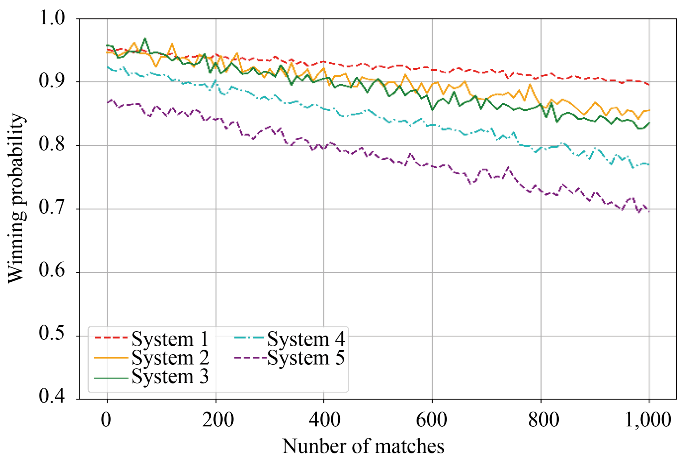

Figure 8. Difference in the game winning rate

In Figure 8, each system's winning rate progressively dropped as the number of matches maximized. Among them, System 1's winning rate fluctuated the least and altered the least. System 1 had a 95.25% victory rate when there were 100 board games. The winning percentage of System 1 was 92.45% when there were 1,000 board games. All four of the other systems' winning rates dropped by more than 15%. According to the information in Figure 8, System 1 possessed greater chess strength and stability.

The experimental results indicate that the digital Go game framework proposed in this work performs better than current algorithms in stability as well as in overall winning rates. The suggested strategy significantly decreased the volatility of winning rates seen within the baseline models, which means there was a more stable and consistent performance throughout sessions.

There are several key real-world applications for this enhanced stability. For players, particularly those who are highly anxious or otherwise emotionally vulnerable, a consistent model that generates predictable outcomes might heighten interest and minimize potential frustration or discouragement. A consistent model encourages continued play and positive emotional experience through predictable feedback and a sense of achievement, while unstable performance in computerized therapeutic games has the potential to demotivate and impair emotional control.

The technological advancements that enable this stability, like enhanced decision-making techniques and adaptive weighing mechanisms prove that the system is stronger against changes in user behavior and external conditions. It is such robustness that is important in real-world systems where user responses and interaction situations are in a state of continuous change. Against the backdrop of digital mental health treatment in general, these results indicate that not only does the suggested model perform better computationally, but it offers real-world advantages for therapy uptake and emotional regulation as well.

4.3 *User study and dataset collection*

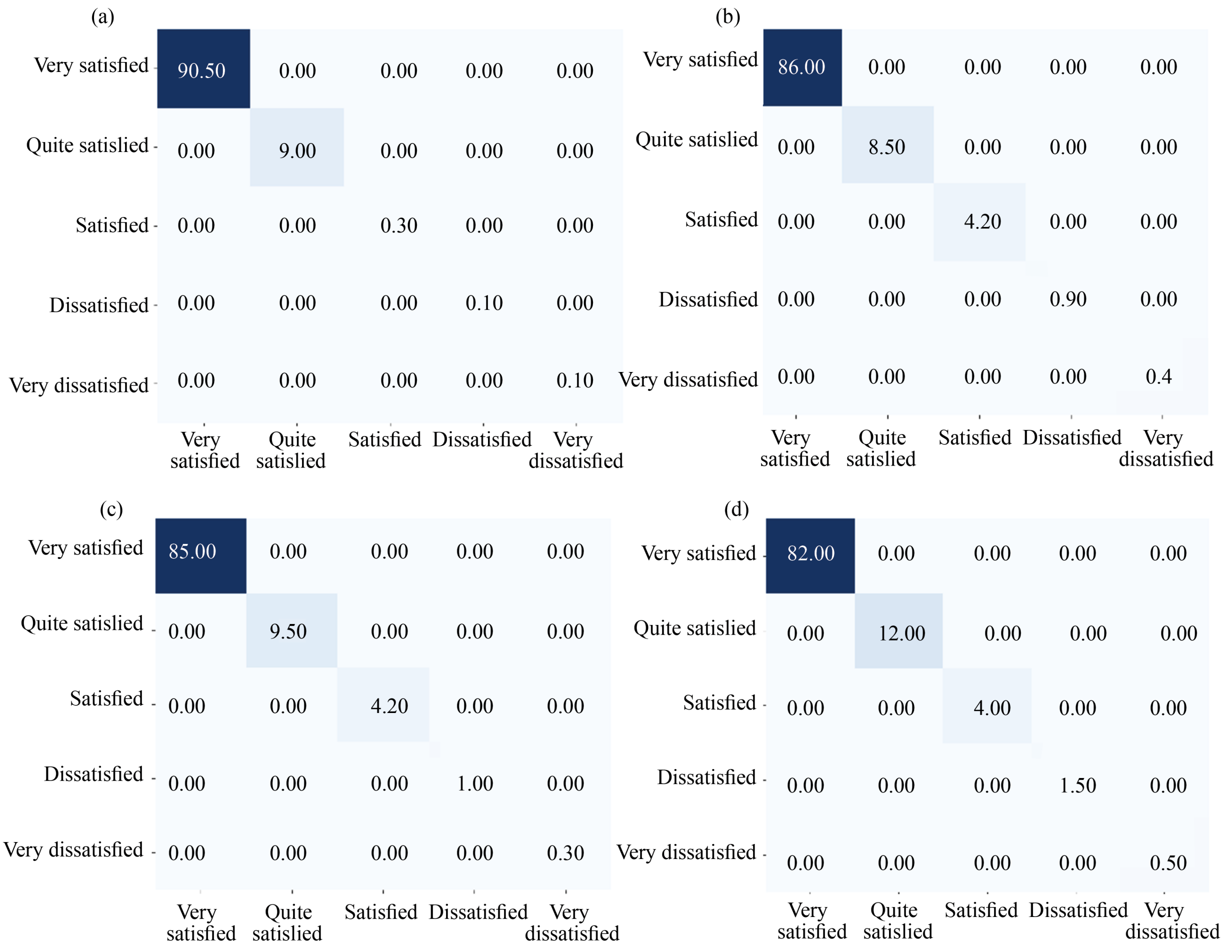

Figure 9. Outcomes of user experience. (a) Game interface experience; (b) Game operation experience; (c) Game experience; (d) Model relief

A pilot study was conducted involving 128 undergraduates with self-reported anxious symptoms, who participated in a controlled digital Go game intervention for one week to explore preliminary therapeutic effects and assess user experience. Following the intervention, a comprehensive questionnaire survey was administered to evaluate four key aspects: quality of gameplay, mood improvement, usability of the interface, and overall operational experience. In social science and psychology research, a minimum of 30 participants or 5-10% of the target population is typically considered sufficient for statistical stability. With 128 participants, this study provides a robust and representative sample for this specific population. To reduce bias and improve the reproducibility of the findings, the participant group was deliberately varied in terms of age, gender, academic background, and level of anxiety. Survey questions were designed to be clear, concise, and specific to ensure accurate data collection. To maintain consistency, all participants completed the survey under identical conditions and instructions. A subset of responses underwent feedback verification to ensure that participant interpretation aligned with the recorded data, further strengthening the dataset's validity. Figure 9 displays the survey results.

The proposed digital intervention may also contribute to sustainability by reducing the need for in-person visits, thereby potentially lowering the associated carbon footprint.

4.4 *Limitations and implications*

A total of 128 undergraduates with self-reported anxiety symptoms participated in a one-week controlled digital Go game intervention to evaluate user experience and preliminary therapeutic effects. While the pilot study provides valuable initial insights, its findings are limited by the controlled laboratory setting and a homogeneous participant sample, which restricts generalizability across different age groups, emotional states, and cultural contexts. Future research will involve larger-scale clinical trials with more diverse populations to assess the system's effectiveness, scalability, and long-term therapeutic impact in real-world settings. Benchmarking against established digital mental health tools, such as Mind Logger and Super Better, will further ensure the framework's practical relevance and competitive performance.

5. Conclusion

This research presents a modified framework for emotion regulation using board games, as well as deep feature extraction via Dilated ResNeXt and BInfLA, which is used to guide Reinforcement Learning. The enhancements to the architecture addressed the limitations of conventional neural networks and RL models regarding decision stability, emotional sensitivity, and differential control of changing user behaviors in play. Empirical evaluations of the prototype support the claim that the system enhances satisfaction, improves performance in board games, and creates measurable improvements in emotional well-being. By utilizing a combination of ensemble learning, probabilistic reasoning, and an exploration method employing scalable tree search, a composite framework is created to address socio-emotional computing and therapeutic interaction. The findings show that the proposed method achieved an average technical balance score of 93.13 points. Future work will extend this methodology to a wider range of psychological conditions and game types, as well as examine hybridization with deep generative models or optimization of Dilated ResNeXt through neural architecture search. Future work will extend this methodology to a wider range of psychological conditions and game types, as well as examine hybridization with deep generative models or optimization of Dilated ResNeXt through neural architecture search. Clinical validation across diverse populations is essential to establish legitimacy within digital mental health interventions. In addition, future research will prioritize therapist integration into the intervention process and pursue regulatory approvals such as FDA and CE certification, ensuring that the framework can evolve into a clinically usable and scalable digital mental health tool.

Author contributions

All authors contributed to the study conception and design, material preparation, data collection and analysis manuscript preparation. All authors read and approved of the final manuscript.

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Conflicts of interest

The authors declare they have no conflicts of interest to report regarding the present study.

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