Postpartum Depression Identification: Integrating Mutual Learning-based Artificial Bee Colony and Proximal Policy Optimization for Enhanced Diagnostic Precision

Yayuan Tang, Tangsen Huang*, Xiangdong Yin
School of Information Engineering, Hunan University of Science and Engineering, Yongzhou 425199, Hunan, China

***Abstract*—Postpartum depression (PPD) affects approximately 12% of mothers, posing significant challenges for maternal and child health. Despite its prevalence, many affected women lack adequate support. Early identification of those at high risk is cost-effective but remains challenging. This study introduces an innovative model for PPD detection, combining the Mutual Learning-based Artificial Bee Colony (ML-ABC) method with Proximal Policy Optimization (PPO). This model uses a PPO-based algorithm tailored to the imbalanced dataset characteristics, employing an artificial neural network (ANN) for policy formation in categorization tasks. PPO enhances stability by preventing drastic policy shifts during training, treating the training process as a series of interconnected decisions, with each data point considered a state. The network, acting as an agent, improves at recognizing fewer common classes through rewards or penalties. The model incorporates an advanced pre-training strategy using ML-ABC to adjust initial weight configurations to increase classification precision, enhancing early pattern recognition. Evaluated on a Swedish study (2009-2018) dataset comprising 4313 cases, the model demonstrates superior precision and accuracy, with accuracy and F-measure scores of 0.91 and 0.88, respectively, proving highly effective for identifying PPD.**

Keywords—Postpartum depression; imbalanced classification; Proximal Policy Optimization; Artificial Bee Colony; reinforcement learning

I. Introduction

PPD is a prevalent condition, impacting 10 to 15 percent of mothers each year [1]. This disorder presents as a range of depressive symptoms, ranging from moderate to intense, either during gestation or within the inaugural year post-delivery. The precise origins of PPD are yet to be fully understood, but it is believed to stem from a mix of psychological, psychosocial, and biological elements [2-4]. Biological factors such as inflammation, the decrease in allopregnanolone, and genetic predispositions are influential. Psychosocial elements, including continuous stress, previous depression episodes, challenges in relationships, and substantial life alterations, also contribute to the likelihood of developing PPD. The impact of PPD is profound, affecting both the mother and her child. Affected mothers may face difficulties in establishing an emotional connection with their children, question their ability to provide care, and sometimes harbor detrimental thoughts towards the child [5]. Though efforts exist to anticipate PPD in the antenatal phase, a consistent and accurate method for identifying women at heightened risk of post-birth depression remains elusive [6].

Traditional statistical approaches often examine the relationship between two factors while considering additional variables [7, 8]. However, Machine Learning (ML) methods enable the simultaneous evaluation of multiple interconnected variables, facilitating the development of predictive models based on data [9, 10]. These models are then analyzed to identify the most efficient predictors. ML can manage complex non-linear relationships and amalgamate diverse data types from various sources. Over the last decade, ML's utilization has grown in various medical domains, such as cardiology, hematology, oncology, cardiology, intensive care, and psychiatry. In the context of PPD, a condition with a moderate risk of evolving into a severe psychiatric issue and with a reasonably precise predictability of symptom emergence, ML holds significant value, considering the societal effects of PPD. However, monitoring each individual for early symptoms of PPD is not feasible. A more effective approach involves focusing on high-risk groups by health professionals such as nurses or midwives during postnatal examinations rather than targeting the general population. In Sweden, which experiences around 120,000 births annually, with women undergoing numerous adjustments after childbirth and an average PPD incidence of about 12%, this specific strategy is particularly beneficial for providing personalized, cost-effective mental healthcare for mothers and newborns.

ML encounters challenges in feature extraction, which can affect processing duration, generalization, and accuracy [11]. The advent of deep learning, especially the Multi-Layer Perceptron (MLP), has enhanced categorization abilities [12]. Tailored for complex XOR challenges, MLP is versatile across various works [13]. It operates similarly to human neural processing, with each node in an ANN handling input and producing outputs through an activation function. In MLP, these nodes interconnect over multiple strata without linkages within the same stratum.

In medical classification, an imbalance in data is a significant challenge. This problem, marked by a notable discrepancy in sample sizes among different classes, can hinder classification accuracy. Countermeasures at the data and algorithmic levels address this [11, 14-16]. Data-level strategies, such as down-sampling and up-sampling, aim to reduce the adverse effects of uneven data distribution [17]. Algorithmic methods enhance the importance of underrepresented classes to combat imbalance [18]. Deep Reinforcement Learning (DRL) has been acknowledged for its efficiency in handling classification with uneven data [19]. Nonetheless, these techniques face hurdles in maintaining an equilibrium between bias and variance [20]. The susceptibility of DRL to hyperparameter variations adds complexity, leading to variable outcomes across different datasets and tasks. In this scenario, PPO stands out in on-policy reinforcement learning. PPO's distinctive mechanism, the PPO-clip, regulates policy alterations during training, ensuring the learning agent remains aligned with its existing policy, balancing exploration with exploitation. This stability is vital to prevent erratic behavior and promote consistent learning. PPO's computational efficiency makes it suitable for complex tasks and ideal for large state spaces, continuous action environments, or scalable and reliable real-world applications. PPO's foundational principles allow it to manage increasing data complexities adeptly, rendering it a valuable tool in various reinforcement learning scenarios [21].

Deep learning models frequently use training algorithms like backpropagation [22-24], which adjusts model weights to reduce errors. However, backpropagation faces challenges, such as susceptibility to initial weight configurations and the hazard of entrapment in local minima, especially in categorization tasks [25]. To overcome these, there is growing interest in meta-heuristic algorithms like PO (Puma optimizer) [26], AOA (Arithmetic Optimization Algorithm) [27], Chaotic Sand Cat Swarm Optimization (CSCSO) [28], SSA (Sparrow Search Algorithm) [29], WOA (Whale Optimization Algorithm) [30], PSCSO (Political Sand Cat Swarm Optimization) [31], known for its thorough exploration of solution spaces, reducing the likelihood of local minima entrapment. Among meta-heuristic algorithms, the ABC algorithm was specifically chosen for this study due to its unique search mechanisms that simulate honey bees' food-foraging behavior. This natural heuristic approach allows for an efficient balance between exploration and exploitation of the search space, which is crucial in finding global optima in complex optimization problems like those often encountered in deep learning. Furthermore, the ABC algorithm is particularly effective in scenarios with high-dimensional data and multiple local optima, making it highly suitable for our deep learning model's training process. It also avoids premature convergence—a common problem in traditional optimization techniques—thus enhancing our model's robustness and generalization ability. An advanced version of ABC, the ML-ABC, introduces a mutual learning approach among its algorithmic elements, enhancing adaptability and addressing issues related to weight initialization in gradient-based methods. ML-ABC improves optimization by facilitating information sharing, aiming to bypass local minima for more effective solutions [32, 33].

This study introduces a training algorithm based on PPO for PPD, utilizing data from the population-centric BASIC research conducted in Uppsala, Sweden. This algorithm specifically addresses the issue of data imbalance. The employed PPO strategy allows an agent to progressively learn through interactions, gaining rewards for accurate predictions and incurring penalties for errors. Importantly, higher rewards are given for correctly identifying instances from the underrepresented class. This approach aims to enhance classification accuracy and maximize overall rewards. The inquiry further addresses the frailties of gradient-based education methods, notably their sensitivity to initial weight configurations. It integrates the groundbreaking ML-ABC approach, which dynamically refines the optimization procedure through mutual learning influenced by initial weights, thereby elevating the model's efficiency. The method demonstrates outstanding performance in PPD prediction, attaining a precision rate exceeding 90%. This paper underscores the efficiency of integrating deep learning with PPO and the novel ML-ABC technique in addressing the issues of data imbalance and sensitivity to initial weights in classification models. The significant contributions of this paper include:

- This research introduces an algorithm based on PPO specifically developed for PPD. Its significance lies in applying sophisticated reinforcement learning methods to address a crucial challenge in medical diagnosis.
- The proposed model employs a PPO strategy to rectify data imbalance, a frequent issue in medical data sets. This approach, which rewards accurate identification of the underrepresented class, innovatively resolves this issue, thus enhancing the model's dependability and equity.
- The study tackles the prevalent problem of initial weight sensitivity in gradient-based training methods. The model dynamically enhances optimization by implementing the ML-ABC methodology, capitalizing on mutual learning informed by initial weights.

The structure of this study is as follows: Section II reviews related literature, while Section III outlines our proposed methodology for diagnosing PPD. Section IV displays the outcomes of our experiments. Section V concludes the paper with a summary of our findings.

II. Related Work

The recent surge in the application of ML within medical science, especially in predicting and classifying health conditions like PPD, marks a significant advancement in the field [34]. A comprehensive review of various groundbreaking studies sheds light on the evolution, methodologies, and accuracy levels achieved in classifying PPD using these techniques. These studies have utilized various ML approaches, each with unique strengths and implications for PPD prediction. The increasing sophistication of these models has opened new frontiers in understanding and managing PPD, offering more accurate and timely diagnoses. The integration of ML in medical diagnosis, particularly in PPD, signifies a shift towards more data-driven, personalized healthcare.

The research conducted by Zhang et al. [35] utilized a Support Vector Machine (SVM) and Feature Selection using Random Forest (FFS-RF) to predict PPD. Their extensive longitudinal study involved 508 women, with the Edinburgh Postnatal Depression Scale (EPDS) serving as the primary tool for assessing PPD risk. Building on this, Zhang et al. [36] further leveraged Electronic Health Records (EHR) datasets to study

PPD risk. The outcomes highlighted that logistic regression with L2 regularization was the most effective approach before childbirth, while the MLP technique proved more successful following childbirth. Jasiya et al. [37] significantly contributed by developing an ML system to identify the risk factors and prevalence of PPD in Bangladesh. This study analyzed data from 150 women, employing modified EPDS and PHQ-2 scales and socio-demographic queries. The Random Forest algorithm was identified as the most effective in this context. Park et al. [38] explored approaches to diminish bias in ML methods in a different study. They utilized health information from the IBM dataset. Their evaluation encompassed random forest, logistic regression, and extreme gradient boosting methods for PPD, investigating bias reduction techniques like reweighing.

The scope of PPD research was further broadened by Shin et al. [39], who employed the PRAMS 2012-2013 dataset and the PHQ-2 questionnaire to test various ML algorithms for determining PPD prevalence. Their analysis found that the Random Forest algorithm was the most effective. Similarly, Andersson et al. [40] experimented with multiple ML models using data from Swedish hospitals, concluding that the Extremely Randomized Trees model provided the best performance. In a hospital-based study, Nataranjan et al. [41] compared various methods, including Naive Bayes, decision trees, Functional-gradient boosting, SVM, and Naive Bayes. Their study, based on a longitudinally curated dataset, determined that Naive Bayes was the most efficient approach.

However, the path of integrating ML in medical diagnostics, while promising, could be more challenging. The diverse array of algorithms available presents a significant hurdle, as selecting the most suitable model for a specific application often requires extensive testing and a considerable allocation of resources [42]. This procedure can be both protracted and resource-intensive, demanding a careful balance between accuracy and practicality. Furthermore, the variation in datasets used in different studies introduces another layer of complexity. Different studies may use varying methodologies, sample sizes, demographic profiles, and data collection techniques, leading to inconsistent and sometimes conflicting results. This diversity underscores the need for standardized data collection and analysis methods to ensure comparability and reliability of results across different research initiatives.

III. The Proposed Method

Fig. 1 illustrates the structure of our novel model, meticulously designed to improve PPD detection and tackle issues, including class imbalance initial weight. This model harmoniously integrates the ML-ABC with PPO, effectively overcoming challenges commonly encountered in traditional models. Conventional algorithms often need a systematic method for setting initial weights, leading to slower learning rates and a tendency to converge on suboptimal solutions. This is especially problematic in medical fields where swift and precise diagnostics are crucial. The model addresses the prevalent challenge of class imbalance in classification tasks, favoring majority classes and neglecting vital minority classes essential for precise PPD detection. Our strategy employs ML-ABC to supply various initial weights, empowering the construct to circumvent local minima and amalgamate more adeptly towards holistic resolutions.

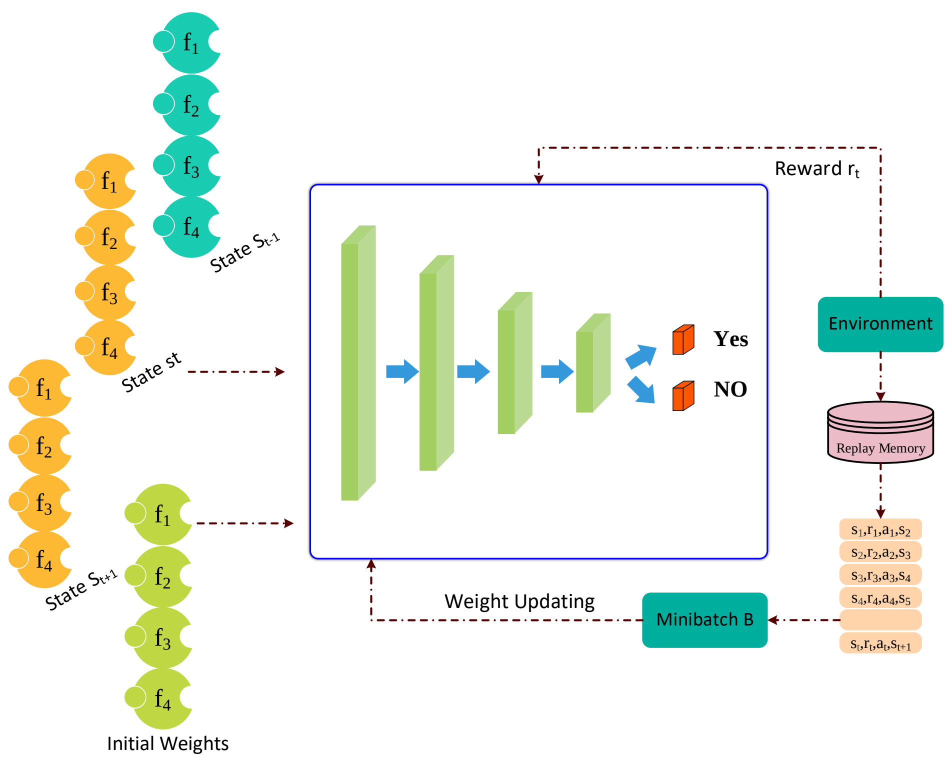

Fig. 1. A novel model blending ML-ABC and PPO for enhanced accuracy and class balance in PDD.

Moreover, the PPO facet of our construct is meticulously engineered to substantially incentivize more exact categorization of the less represented group, redirecting attention to these pivotal forecasts. This marks a significant advancement beyond conventional tutored learning approaches, which frequently need more comprehensive training data spanning diverse groups. PPO's adaptable schooling strategy facilitates a more equitable investigation of choices, culminating in approaches that more precisely identify minority categories. The flexibility of PPO within our framework sets it apart from traditional schemes, arming it to overcome the innate hurdles of standard classification techniques in PPD identification.

A. Initial Weight

The accurate setting of initial network weights is necessary for deep methods. Inaccuracies in these initial configurations can complicate the model's training phase, particularly regarding convergence. Acknowledging the critical role of weight initialization, our research initially focuses on identifying the most optimal configurations for ANN. To tackle challenges in initial network weights, we use the ML-ABC technique. ML-ABC demonstrates exceptional performance in optimization problems. It effectively explores the solution space, identifying promising regions and refining them iteratively. By utilizing ML-ABC, we aim to discover initial weight configurations that lead to faster and more stable ANN training, ultimately enhancing the overall predictive performance of the models.

1) The ML-ABC algorithm: Influenced by the complex foraging behaviors of honeybees, the ABC algorithm emulates nature's collective intelligence and sophisticated mechanisms, providing a systematic and instinctive method for addressing optimization challenges. The ABC algorithm is composed of four critical elements:

- Worker Bees: These bees initially explore, seeking potential food sources informed by their prior knowledge, focusing on the quality and quantity of nectar. After exploring, they return to the hive to share their findings.
- Observer Bees: Located within the hive, these bees assess the information provided by the worker bees, making decisions based on the reported nectar quality and quantity. They follow leads from worker bees' dances that indicate abundant food sources, efficiently exploiting these promising locations.
- Scout Bees: Tasked with discovering new food sources as current ones are exhausted, their search is more random than worker bees, allowing for adaptation to environmental changes.
- Food Sources: Symbolizing potential optimization solutions, the nectar amount at each food source signifies the solution's quality or effectiveness. The collective goal is to optimize nectar collection, paralleling the pursuit of optimal solutions in computational settings.

The ABC algorithm's adaptability is significant, balancing exploring new solutions and capitalizing on known ones. This balance, inspired by natural processes, makes the ABC algorithm a robust tool for optimization [43]. Eq. (1) demonstrates the method of creating new positions based on the spatial information from a worker bee. If a new position offers improved nectar quality, the bee moves there; otherwise, it retains its previous position.

$$v_i^j = s_i^j + \varphi_i^j (s_i^j - s_k^j) \tag{1}$$

In the given formula, the j-th index represents the position of the i-th solution s_i, which encompasses D variables, signifying the total number of parameters. The variable k corresponds to a distinct random solution. The component φ_i^j is a random number chosen from the interval [0, 1], modifies a single parameter of s_i , resulting in a new solution v_i . In a D-dimensional optimization scenario, one dimension is altered randomly. The decision regarding the most favorable solution is based on comparing fitness values. The diversity and innovation in the newly derived food source v_i are depend on s_i^j and s_k^j. When evaluating food sources, those with higher fitness leverage insights from both adjacent and current sources. This approach is fundamental in the ABC algorithm, which aims to discover food sources demonstrating superior fitness [44].

$$v_i^j = \begin{cases} s_i^j + \varphi_i^j \left(s_k^j - s_i^j\right), & Fit_i < Fit_k \\ s_k^j + \varphi_i^j \left(s_i^j - s_k^j\right), & Fit_i \geq Fit_k \end{cases} \tag{2}$$

In this expression, Fit_i and Fit_k denote the fitness values of adjacent and current food sources. The term φ_i^j is a random element ranging from 0 to F, the mutual learning factor, which is positive. Solutions are refined by assessing and favoring sources with higher fitness. The value of F, a non-negative quantity, affects the stability and enhancement of the solution. An increase in F reduces disturbances, indicating convergence towards a higher fitness level for the alternative food source. However, an overly high value of F may disrupt the balance between exploration and exploitation.

Our study incorporates a sophisticated encoding strategy in the ML-ABC algorithm, encompassing feed-forward weights despite the inherent precision-related complexities. Fig. 2 depicts the encoding process of a feed-forward network comprising four hidden layers. In this illustration, the weight matrices of the network are methodically laid out as sequential rows within an array structure.

The effectiveness of the ML-ABC algorithm is quantified through a fitness factor, formulated as follows:

$$Fitness = \frac{1}{1 + \sum_{i=0}^{N} (y_i - \tilde{y}_i)^2} \tag{3}$$

Within this formulation, y_i represents the actual label, and $\tilde{y}_i$ denotes the predicted label for each instance in the i-th dataset. The symbol N refers to the aggregate count of instances in the dataset.

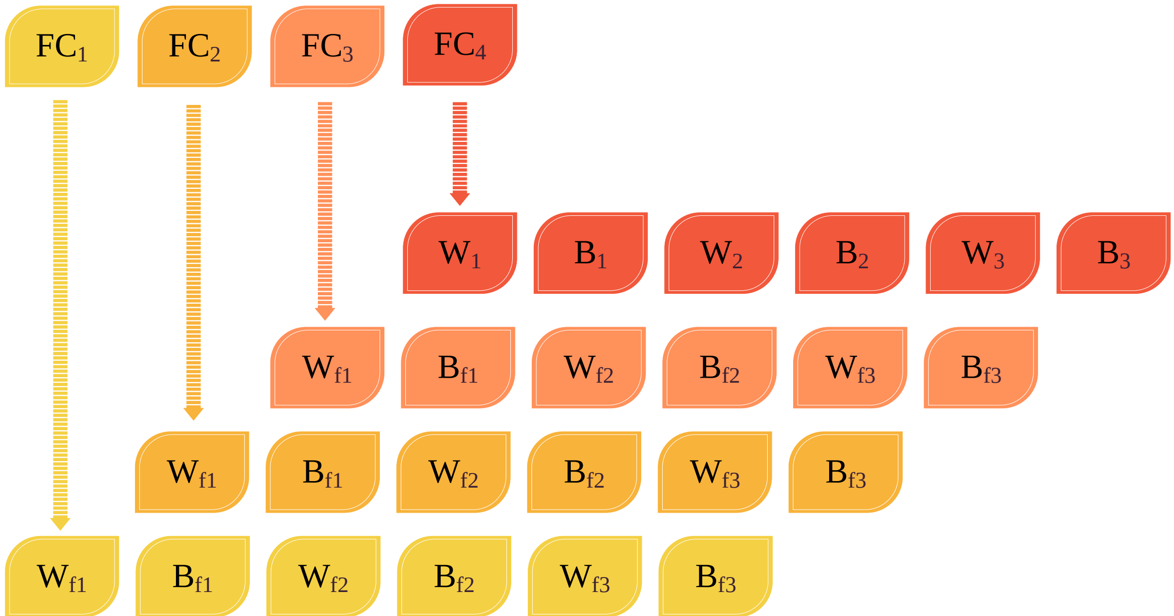

Fig. 2. Illustration of the encoding strategy used in the proposed algorithm.

B. Classification

1) Deep reinforcement learning: DRL is an advanced method in deep learning characterized by an agent's dynamic interaction with its environment to enhance a reward function. Such learning empowers the agent to formulate decisions in uncertain scenarios, proving invaluable across various domains, including robotics, healthcare, and finance. Notably adept at sequential decision-making tasks, DRL effectively adjusts to unpredictable settings, highlighting its broad range of practical uses. A notable challenge in categorization tasks is the presence of datasets with uneven distribution, often dominated by a particular category. This scenario can result in skewed learning, as traditional categorization techniques favor the more prevalent category, thereby diminishing the recognition of less dominant categories. DRL offers an advanced solution for training neural networks in such contexts, tackling imbalanced classification by incorporating a reward-based mechanism. Through strategically allocating rewards, DRL shifts the agent's focus to instances from less prevalent categories, thus enhancing their recognition. This approach ensures thorough decision-making, prioritizing identifying and classifying infrequent occurrences or minority categories [45, 46].

The agent's chief aim within Q-learning is to elect actions that amplify forthcoming incentives. These future rewards, diminished over time by a discount factor γ, are captured in Eq. (4) [11]. In this formula, R_t shows the return from time t, the sum of the discounted rewards from time t to time T. T signifies the concluding step of a given episode, and $r_{t'}$ is the reward received at time step t'.

$$R_t = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'} \tag{4}$$

Q-values, which are crucial in reinforcement learning, represent the expected outcome of a chosen policy π after executing action a in state s. This is illustrated in Eq. (5), providing a clear understanding of their importance. In this equation, $Q^{\pi}(s,a)$ is the expected return for selecting action a in state s under policy π, and E is mathematical expectation.

$$Q^{\pi}(s,a) = E[R_t | s_t = s, a_t = a, \pi] \tag{5}$$

Eq. (6) computes the quintessential action-value function, $Q^*(s,a)$, representing the apex of expected rewards for all possible strategies after observing state s and taking action a.

$$Q^*(s,a) = max_{\pi}\, E[R_t | s_t = s, a_t = a, \pi] \tag{6}$$

This function employs the Bellman equation [47], positing that the optimal forecasted outcome for any action is the aggregate of the immediate reward and the optimal expected return from subsequent actions, as elucidated in Eq. (7).

$$Q^*(s,a) = E[r + \gamma\, max_{a'} Q^*(s',a') | s_t = s, a_t = a] \tag{7}$$

The optimal action-value function progressively evolves by employing the Bellman equation, as exhibited in Eq. (8). In this equation, i means iteration.

$$Q_{i+1}(s,a) = E[r + \gamma\, max_{a'} Q_i(s',a') | s_t = s, a_t = a] \tag{8}$$

During the training phase, the network encounters state s and generates a corresponding action a. The environment then offers a reward r and transitions to the subsequent state s'. These components, forming a tuple (s,a,r,s'), are stored in memory M. Batches B of these tuples contribute to gradient descent, a practical application of mathematical concepts, with the loss function determined as per Eq. (9).

$$L_i(\theta_i) = \sum_{(s,a,r,s') \in B} (y - Q(s,a;\theta_i))^2 \tag{9}$$

In this context, θ symbolizes the model's parameters, and y is the projected target for the Q function, computed as the sum of the reward for the state-action pair and the discounted maximum future Q value, as illustrated in Eq. (10).

$$y = r + \gamma \; max_{a'} Q(s', a'; \; \theta_{k-1}) \tag{10}$$

The gradient intensity at cycle i is deduced via Eq. (11).

$$\nabla_{\theta_i} L(\theta_i) = -2 \sum_{(s,a,r,s') \in B} (y - Q(s, a; \theta_i)) \nabla_{\theta_i} Q(s, a; \theta_i) \tag{11}$$

Adjustments to the model weights are made through gradient descent on the loss function, as shown in Eq. (12), where α denotes the learning rate dictating the optimization pace.

$$\theta_{i+1} = \theta_i + \alpha \nabla_{\theta_i} Q(s, a; \theta_i) \tag{12}$$

2) Proximal policy optimization: PPO [48], an on-policy reinforcement learning technique, is renowned for its efficiency and effectiveness in refining policies within discrete and continuous action spaces. PPO, devised to surmount the limitations of preceding Policy Gradient methods, tackles issues such as excessive sample requirements and instability. Its fundamental principle involves updating policies incrementally, thereby minimizing the risk of detrimental alterations that could degrade policy quality. PPO establishes a trust region around the current policy to ensure updates remain proximate to the original policy. This is achieved through a surrogate objective function encouraging modest policy alterations while enhancing rewards. The surrogate objective function of PPO varies with the action space and typically employs a clipped surrogate objective method. This approach constructs the objective by opting for the lower of two probability ratios. Based on gathered data, the first ratio assesses the probability of actions under the new policy relative to the old one. The second ratio remains confined within a predefined limit, curbing the magnitude of policy updates [49]. PPO's efficacy is partly attributable to its adept use of parallelization. Being an on-policy algorithm, it utilizes multiple parallel environments for data acquisition, expediting convergence and augmenting sample efficiency. PPO also permits the reuse of previously collected data, stabilizing the learning process and optimizing data utilization.

PPO commences with the current policy parameter θ_i, endeavoring to identify the subsequent policy parameter θ_{i+1} that optimizes the expected value of the surrogate objective function $L(s, a, \theta_i, \theta)$ for state-action pairs (s, a) sampled from the active policy $\pi(\theta_i)$. The surrogate objective function $L(s, a, \theta_i, \theta)$, delineated in Eq. (13), is the minimum of two elements: the ratio of the probability of action a in state s under the new versus old policies and a clipped variant of this ratio. In Eq. (13), ϵ (epsilon) is a hyperparameter that controls the amount of clipping in the objective function.

$$L_{PPO}^{CLIP} = E_{s \sim \rho_{\pi_{\theta_i}}, a \sim \pi_\theta} [\min(\frac{\pi_\theta(a|s)}{\pi_{\theta_i}(a|s)} A_{\pi_{\theta_i}}(s, a), clip(\frac{\pi_\theta(a|s)}{\pi_{\theta_i}(a|s)}, 1- \; , 1+\epsilon) A_{\pi_{\theta_i}}(s, a))] \tag{13}$$

The clip function restricts policy alterations, averting radical departures from the initial policy:

$$clip(x, a, b) \; = \; max(a, min(b, x)) \tag{14}$$

where, x is the value to be clipped. a and b are the lower and upper bound of the clipping, respectively. In PPO-clip, the clip function constrains the product of the probability ratio and the advantage estimator $A_{\pi_{\theta_i}}(s, a)$, which evaluates the relative merit of action a in state s under policy π_{θ_i}. By limiting policy updates, the PPO-clip ensures the new policy stays within a confined spectrum around the old policy, circumventing extensive modifications that could lead to instability. This characteristic is vital for the stability and efficacy of the PPO-clip, facilitating gradual likely to bolster the policy [50].

3) Problem formulation: In this research, we apply the PPO algorithm to the detection of PPD. The methodology and interpretation of each component are outlined as follows:

- State $\boldsymbol{s_t}$ denotes the sample extracted from the dataset at time step t.
- Action $\boldsymbol{a_t}$ represents the classification executed on the sample.
- Reward $\boldsymbol{r_t}$ is assigned for each classification, formulated as:

$$r_t(s_t, a_t, y_t) = \begin{cases} +1 \, , a_t = y_t \; and \; s_t \in D_O \\ -1 \, , a_t \neq y_t \; and \; s_t \in D_O \\ \lambda \, , a_t = y_t \; and \; s_t \in D_N \\ -\lambda \, , a_t \neq y_t \; and \; s_t \in D_N \end{cases} \tag{15}$$

where, D_N and D_O symbolize the minority and majority classes, respectively. Correct or incorrect categorization of a sample from the dominant class results in a reward or penalty of +λ or -λ, respectively. This strategy aims to direct the network's focus on accurately categorizing the less prevalent class by assigning a greater magnitude of reward. Additionally, the inclusion of the Normal class and the adaptable reward parameter λ (0 < λ < 1) introduces complexity to the reward structure, allowing for nuanced tuning of the network's attention between common and rare classes.

IV. Experimental Results

The source of our predictive model development dataset was the "Biology, Affect, Stress, Imaging, and Cognition during Pregnancy and the Puerperium" project [51]. It was a population-based prospective cohort study in Uppsala, Sweden. The study collected data from 500 women from 2009 to 2018, following them through pregnancy and the first year postpartum. The dataset includes information on demographics, medical history, pregnancy-related factors, psychometric questionnaires, and neuroimaging data.

The study was conducted on a 64-bit Windows operating system computer. This machine featured 64 gigabytes (GB) of random-access memory (RAM), enhancing its ability to manage large datasets and perform intensive computations without any drop in performance. Additionally, it was outfitted with a 64 GB graphics processing unit (GPU), likely produced by a leading manufacturer such as NVIDIA (NVidia corporation) or advanced micro devices (AMD), which significantly improved computational speed, especially for parallel processing tasks prevalent in deep learning and other demanding algorithms. The system also utilized an Intel Core i9 processor or its equivalent, which boasts multiple cores to deliver substantial computational power for efficiently handling complex operations. Storage was provided by a 1 terabyte (TB) solid-state drive (SSD), facilitating rapid data access and robust storage capacity, crucial for swiftly and effectively managing large data volumes. This setup ensured the seamless operation of multiple applications and services concurrently and guaranteed that our research's computational demands were met with high efficiency and reliability.

Hyperparameters utilized in the proposed model are detailed in Table I. For evaluation, our model was rigorously benchmarked against six well-known models: Naïve Bayes [52], K-nearest Neighbors (KNN) [53], Support vector machine (SVM) [54], Random forests [55], Logistic Regression [56], and Decision tree [57]. Table II outlines the parameters applied to these models. Additionally, two derivative versions of our proposed model were analyzed. The first, titled Proposed+random weights, used random initial weights to examine the impact of weight initialization on performance. The second, Proposed+random weights+PPO, incorporated PPO to enhance classification accuracy and overall robustness potentially. We employed standard performance metrics such as Accuracy, F-measure, and G-means, which are particularly important for evaluating imbalanced datasets. As illustrated in Fig. 3, while all models performed comparably, our proposed model and its variants demonstrated superior capability. Specifically, the proposed model was particularly effective, achieving the highest scores across all metrics. It showed an 18% improvement in F-measure and a 54% increase in G-means compared to the baseline models, illustrating significant advancements over traditional methods like Decision Tree, previously considered optimal. This enhancement indicates our model's superior handling of skewed data distributions and its predictive accuracy. Further, the comparative analysis between our proposed model and its derivatives—Proposed+random weights and Proposed+random weights+PPO—highlighted the critical impact of sophisticated weight initialization and PPO integration. The Proposed model significantly outperformed these variants, showcasing a 53% reduction in error rates, affirming its efficacy and suitability for the chosen problem domain. This clear empirical evidence supports the proposed model as the best fit for addressing the complexities inherent in our targeted application area.

To ascertain the robustness of our developed model and mitigate overfitting while ensuring peak performance across training and test datasets, we have thoroughly depicted its efficiency in Fig. 4. This illustration offers a detailed analysis of the Root Mean Square Error (RMSE) loss curves for both datasets throughout the training period. The loss computation occurs after each forward operation during training, followed by backward propagation to adjust weights at the end of every epoch. In parallel, validation loss is evaluated after each epoch through a forward operation on the validation dataset without modifying the model's weights. Training and validation losses should decrease simultaneously and stabilize at a minimal level, signifying the model's adeptness in learning and generalizing. In contrast, a divergence, characterized by decreasing training loss but increasing validation loss, indicates overfitting, implying that the model is excessively fine-tuned to the nuances of the training data, which could detrimentally affect its predictive accuracy on new data.

TABLE I. SETTINGS OF HYPERPARAMETERS FOR THE PROPOSED MODEL

Configuration parameter	Setting
Training cycles	128
Size of batch	32
Rate of learning	0.01
Rate of dropout	0.40
Factor of discount	0.40

TABLE II. CONFIGURATION OF HYPERPARAMETERS FOR VARIOUS MACHINE LEARNING APPROACHES

Method	Parameter	Specification
Naïve Bayes	α (Smoothing factor for lidstone)	0.6
KNN	k (Count of nearest neighbors)	7
	Metric for distance	Manhattan (p=2), Euclidean (p=3)
SVM	Type of kernel	Polynomial
	γ (Coefficient for kernel)	0.7
Random Forests	Trees in forest	25
	Maximum tree depth	15
Logistic Regression	C (Strength of regularization)	0.4
	Algorithm for optimization	liblinear
Decision Tree	Splitting criterion	entropy
	Maximum depth	12

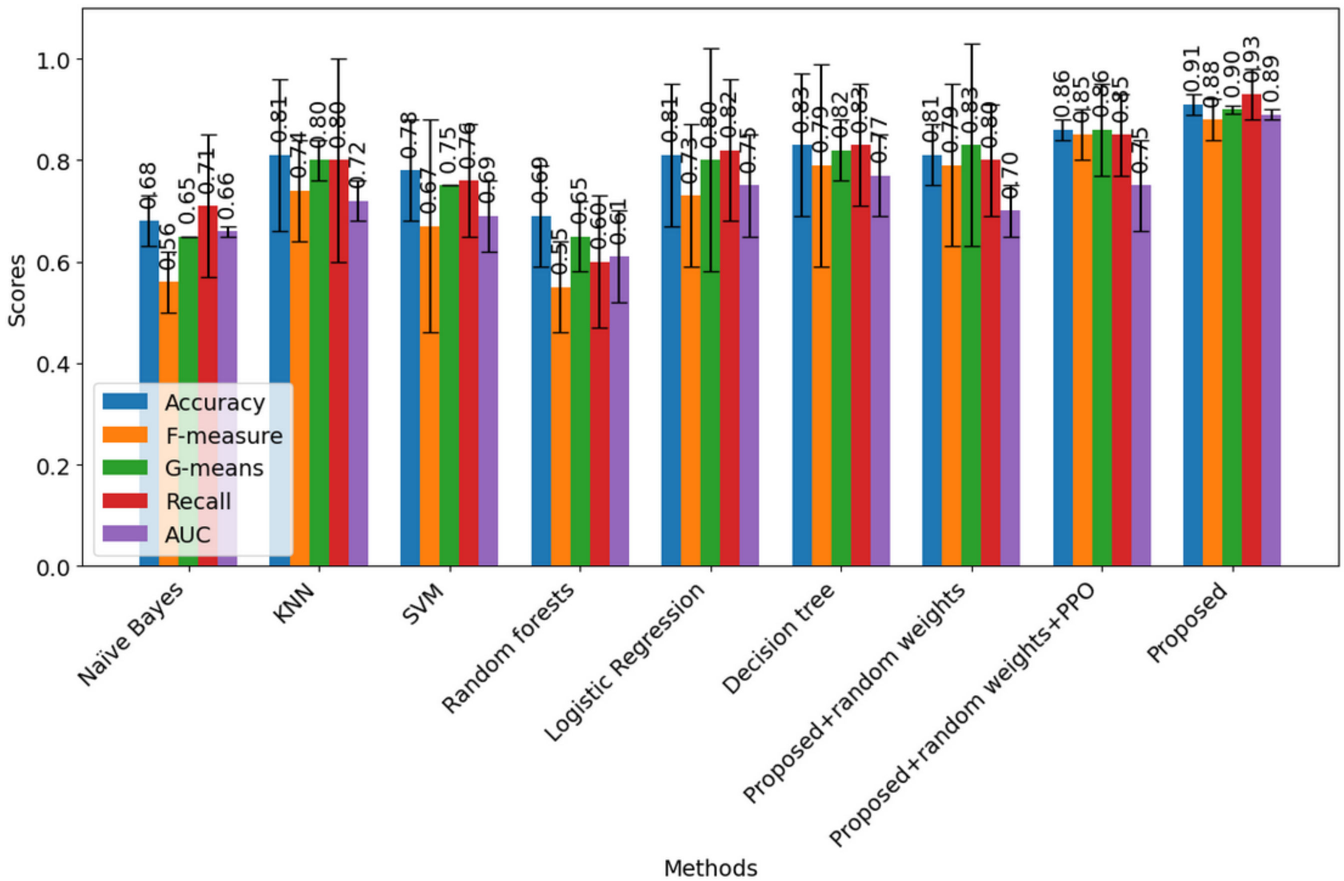

Fig. 3. Performance results of different classification techniques.

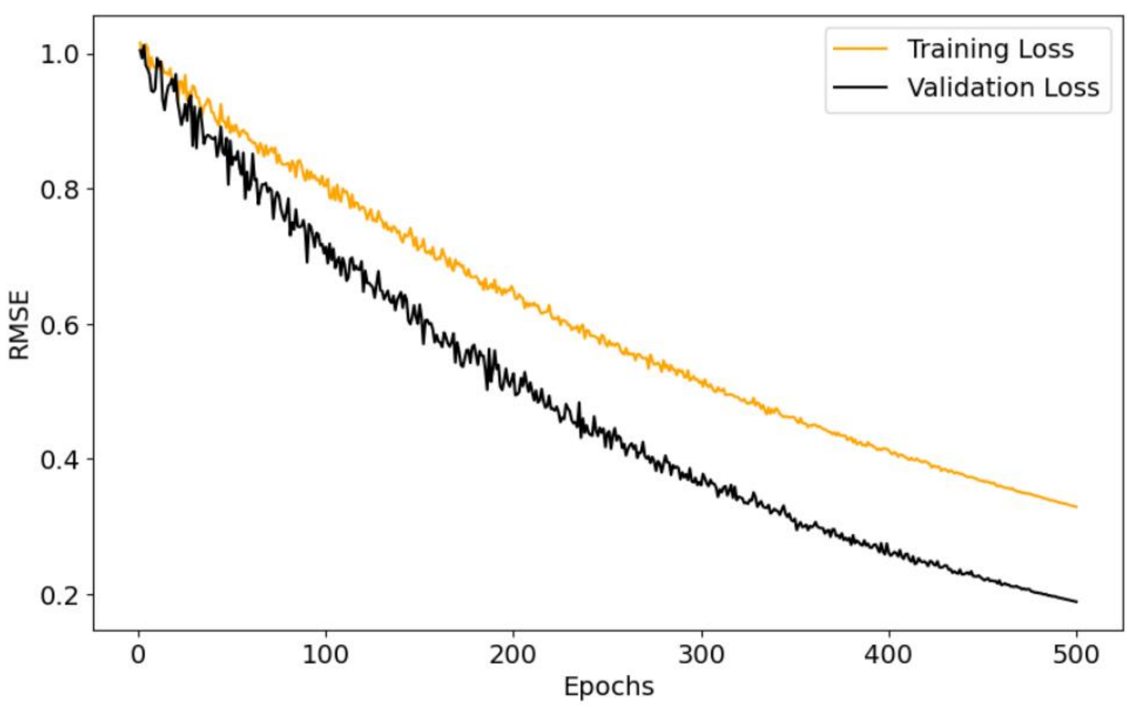

Fig. 4. Training and validation dataset loss trends in the developed model.

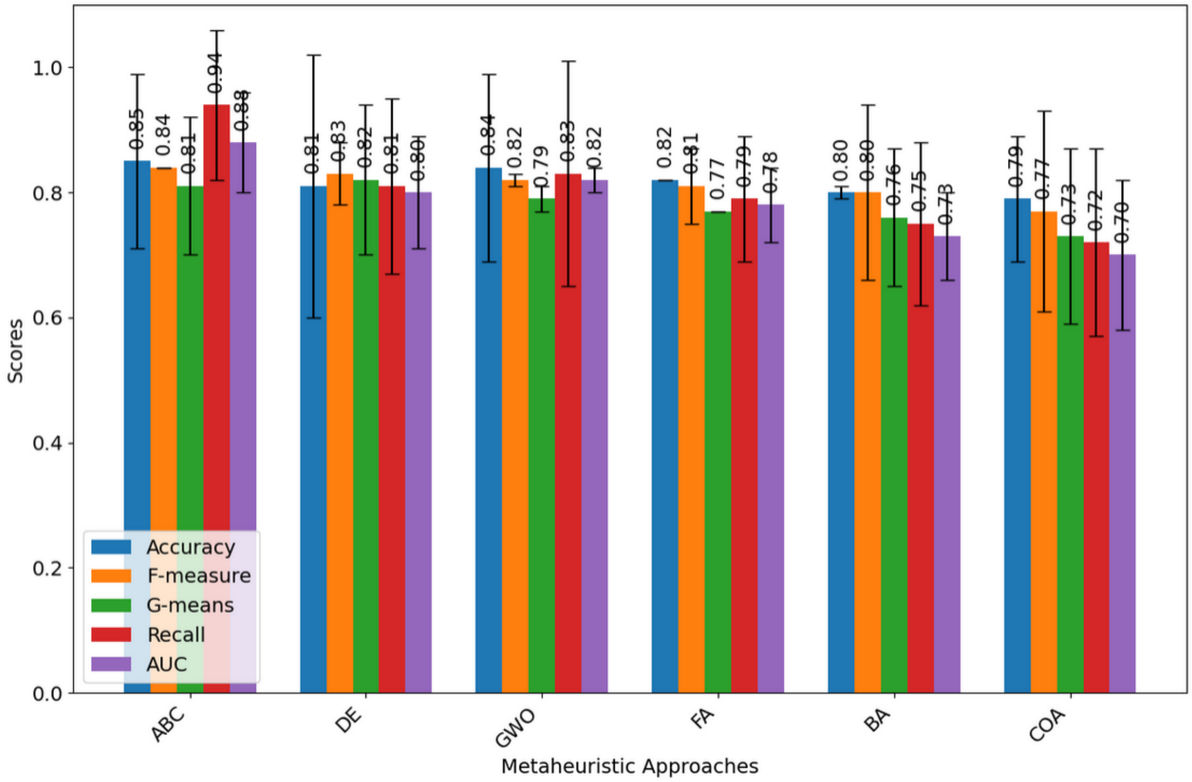

Fig. 5. Comparative performance of various metaheuristic approaches.

A. Analyzing the ML-ABC Algorithm

A comprehensive study juxtaposed the ML-ABC technique with other metaheuristic techniques. For a balanced comparison, diverse metaheuristics were utilized to obtain initial weights while maintaining consistency in other model components. The assessment included six techniques: ABC [58], Grey Wolf Optimizer (GWO) [59], Firefly Algorithm (FA) [60], Bat Algorithm (BA) [61], and Cuckoo Optimization Algorithm (COA) [62]. Each technique was set with a population size of 200 and function evaluations capped at 4,000. The standard configurations are outlined in Table III. The outcomes of the extensive experiment are methodically displayed in Fig. 5, yielding crucial insights into each algorithm's efficacy. Remarkably, the results underscored the superior performance of the ML-ABC algorithm, which exhibited a noteworthy 30% reduction in error relative to ABC. Moreover, the ML-ABC technique surpassed other renowned algorithms, such as BA and GWO, consolidating its status as a preeminent choice among the evaluated metaheuristic optimization techniques.

Fig. 6 graphically delineates the evolution of the objective function throughout various iterations employing the ML-ABC algorithm. The x-axis represents the number of iterations or generations, and the y-axis shows the values of the objective function. This visual portrayal provides an explicit understanding of the algorithm's operational mechanisms. An in-depth examination of Fig. 6 reveals distinct trends: initial iterations experience significant variability in the objective function values, reflecting the exploration stage of the ML-ABC algorithm. During this phase, the algorithm extensively scans the solution space to evade premature convergence to local optima and to pinpoint promising areas. As the iterations advance, signs of convergence emerge. The fluctuations in the objective function values lessen, indicating a refinement in the algorithm's strategy as it zeroes in on and perfects the most viable solutions. It is crucial to monitor for instances of minimal or no changes in the objective function values, as this might indicate the algorithm reaching a standstill at the local optimum, necessitating parameter adjustments or introducing additional methods to boost exploration capabilities.

TABLE III. CONFIGURATION DETAILS OF HYPERPARAMETERS FOR METAHEURISTIC ALGORITHMS

Technique	Configuration	Adjustment
DE	Factor of Scaling	0.7
	Probability of crossover	0.82
ABC	Boundary for scouts	n_e × dimensions
	Employed bees	50% of of total bees
	Onlooker bees	50% of total bees
	Scout bees	1
FA	Light absorption coefficient	.0.8
	Attractiveness at Base	0.4
	Scaling factor	0.35
BA	Loudness update rate	0.6
	Pulse emission rate	0.7
	Pulse frequency initial value	0.003
COA	Lévy flight parameter	1.5

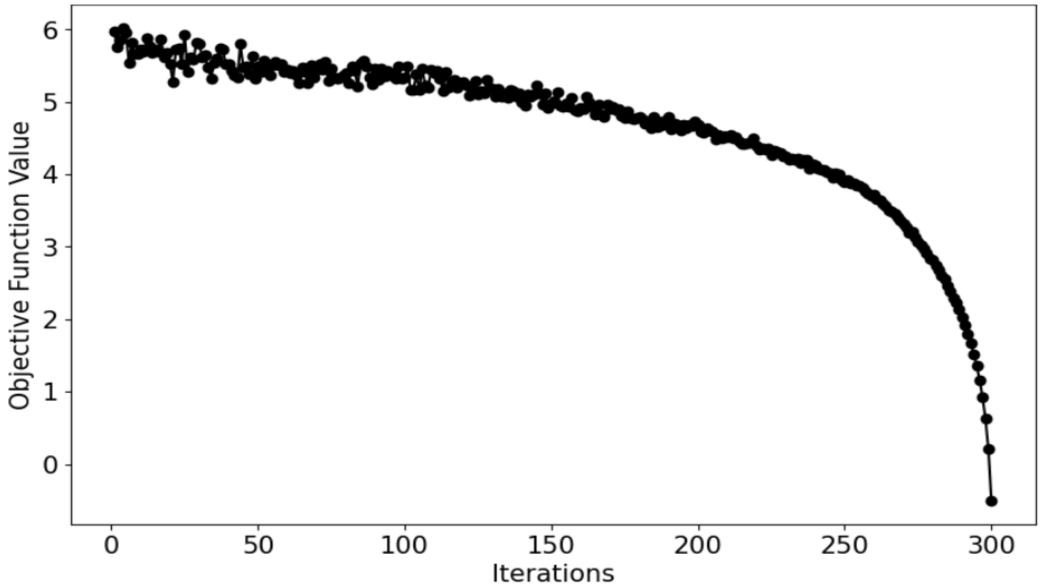

Fig. 6. Evolution of the objective function in various iterations with the ML-ABC algorithm.

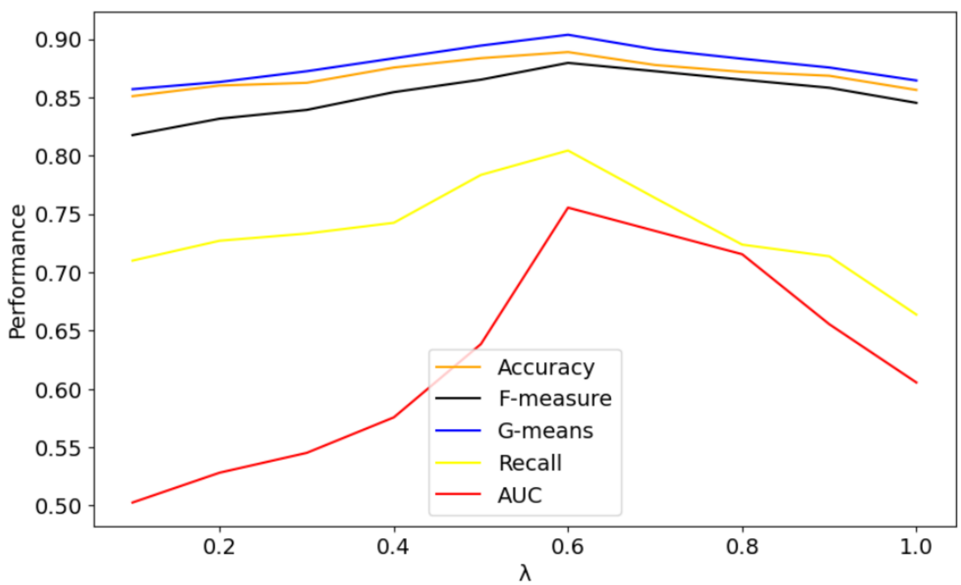

Fig. 7. Performance metrics variation of the model corresponding to various λ values in the reward function.

B. *Impact of Reward Operation*

Incentives allotted to predominant and less represented groups for correct and mistaken identifications are +1 and ±λ, respectively. The magnitude of λ hinges on the proportion of larger to smaller groups, with expectations that the ideal λ magnitude dwindles as this proportion escalates. To probe λ's effect, we assessed the method's proficiency across varied λ values spanning zero to one. The assessments are illustrated in Fig. 7. At λ equating to 0, the dominance of the larger group becomes trivial, whereas at λ = 1, both groups impose equivalent impacts. The outcomes insinuate that the method reaches its pinnacle performance at λ set to 0.6 for all scrutinized measures, signifying that the most fitting λ magnitude resides within the 0 to 1 spectrum. Acknowledging that diminishing the larger group's influence by reducing λ might detrimentally impact the method's comprehensive proficiency is pivotal. The insights emphasize that the selection of λ profoundly affects the method's functionality, with the prime λ contingent on the comparative sizes of larger to smaller samples, accentuating the necessity of meticulous choice for attaining excellent outcomes.

C. *Impact of MLP*

The research further underscores that augmenting the layers in an MLP potentially heightens overfitting risks. Conversely, a limited number of layers might restrict the method's capacity to discern salient features. Here, we experimented with varying the number of MLP layers (1, 2, 4, 8, 10, 12) to determine their effect on model performance. The outcomes, showcased in Fig. 8, reveal a diminishing trend in model efficacy when layer counts range from 8 to 12, followed by an ascending trend for layer counts from 1 to 8. This pattern indicates that an optimal MLP with four layers balances complexity and performance.

D. Impact of the Loss Function

Different strategies exist to address data imbalances in machine learning, notably in choosing a loss function. Selecting a loss function is pivotal in helping effective learning from minority classes. We scrutinized functions such as Weighted Cross-Entropy (WCE) [63], Binary Cross-Entropy [64], Dice Loss (DL) [65], Tversky Loss (TL) [66], and Combo Loss (CL) [67]. WCE and BCE treat positive and negative instances equally, which may be better for imbalanced datasets. DL and TL are more suited for such datasets, enhancing minority class performance. CL, advantageous in unbalanced data scenarios, adjusts loss function weights to prioritize complex samples over simpler ones. Our experiments in Fig. 9 demonstrate that CL outperforms TL, reducing error rates by 21% in accuracy and 32% in F-measure. However, it underperforms FL by 18%, a function tailored for binary classification tasks. These outcomes necessitate considering the specific dataset and problem context. While CL surpasses TL, it is less effective than FL.

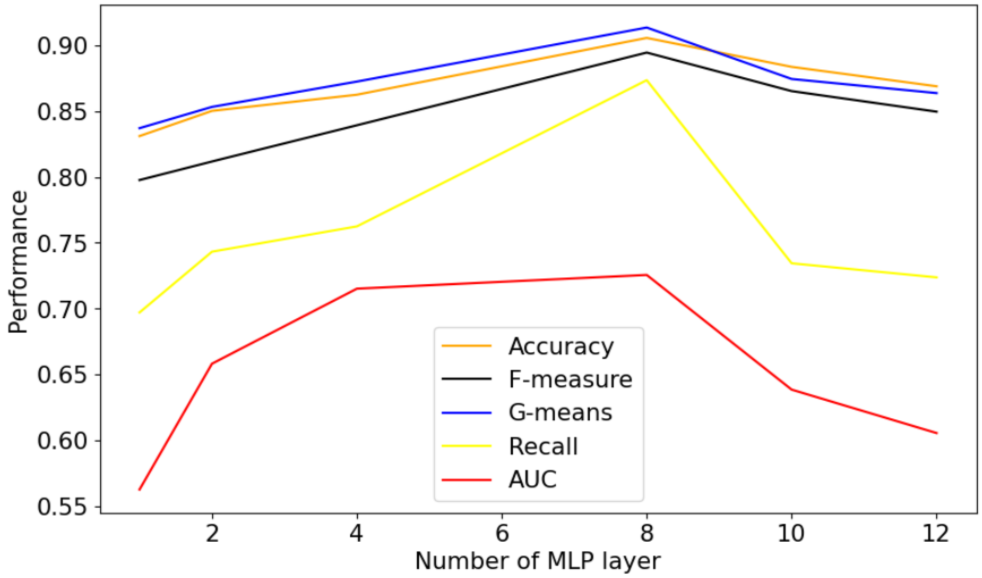

Fig. 8. Graphical representation of performance metrics against different numbers of MLP layers in the model.

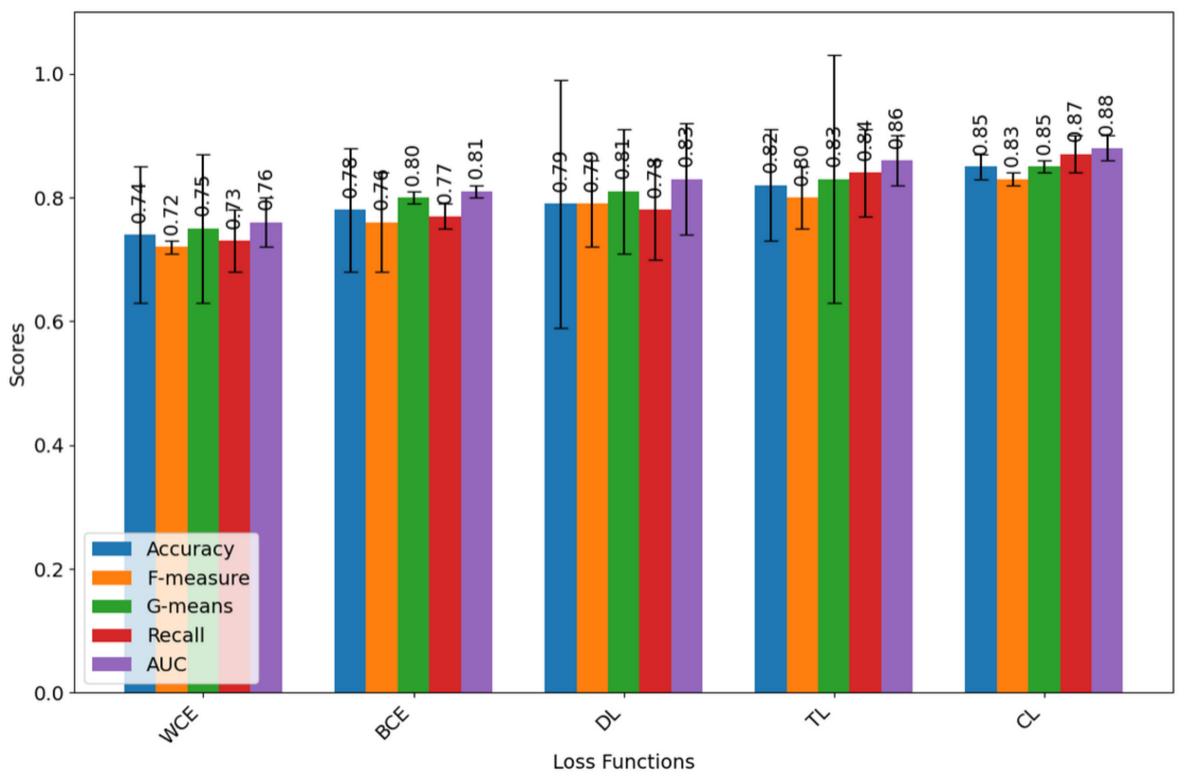

Fig. 9. Comparative analysis of loss function results.

E. Discussion

This study unveils an innovative model combining the ML-ABC with PPO to tackle PPD, addressing dataset imbalance with a PPO-driven approach. Anchored in an ANN, it views categorization through a policy-based lens, enhancing stability with PPO's gradual policy shifts. The model, empowered by ML-ABC, refines initial weights through mutual learning, elevating understanding of intricate patterns for improved classification accuracy.

PPO is chosen for its effectiveness in handling policy-based decision-making processes, which is crucial for managing imbalanced datasets like those found in PPD detection. PPO operates by optimizing a particular objective function that minimizes the deviation from an old policy while ensuring that the new policy improves upon it, thus maintaining a balance between exploration and exploitation [68]. This characteristic is particularly beneficial in healthcare applications where each decision or classification can have significant repercussions. By implementing PPO, the model ensures that updates to the policy are manageable, which could lead to unstable training cycles. Instead, PPO facilitates smoother updates and enhances the stability of the learning process. This leads to more reliable and consistent recognition of patterns in data, which is vital when the data is skewed or when specific categories are underrepresented, as often seen in clinical datasets [69].

The ABC algorithm is selected for its robust search capabilities in complex optimization problems, essential for setting up the initial configurations of neural network weights. ABC algorithm mimics the food-foraging behavior of honey bees, making it excellent for exploring diverse solution spaces efficiently [70]. In detecting PPD, where the dataset characteristics include high dimensionality and potential multimodality, ABC helps navigate potential local optima to find the best global solutions. This capability is crucial for the initial phase of model training, where starting points (i.e., weights) significantly influence the learning trajectory and, ultimately, the model's performance. Using ABC, the model benefits from an optimized exploration of the weight space, leading to a more effective learning process and better generalization capabilities on unseen data. This setup is particularly effective in healthcare settings, where precision in initial model configurations can substantially improve diagnostic accuracy.

ML-ABC is employed to leverage the collective intelligence of multiple agents (i.e., artificial bees) that share information and learn collaboratively, enhancing the ABC algorithm's convergence speed and solution quality. In the PPD detection model, ML-ABC is instrumental in fine-tuning the weights and parameters of the neural network, ensuring that the model adapts more effectively to the complexities of imbalanced clinical data [44]. By integrating mutual learning principles, ML-ABC allows individual solutions to benefit from the discoveries and successes of others in the swarm, thus promoting a more diversified search of the solution space and preventing premature convergence on suboptimal solutions. This approach is especially beneficial in medical applications where the dataset may contain subtle patterns that are difficult to recognize but critical for accurate diagnosis [20]. The enhanced learning mechanism of ML-ABC ensures that the model is not only effective in recognizing common patterns but also adept at identifying less frequent, yet clinically significant, indicators of PPD.

The theoretical implications of our research are significant, offering substantial contributions to both the fields of artificial intelligence and healthcare. The integration of PPO and ML-ABC into a cohesive model for PPD detection represents a pioneering approach to applying hybrid meta-heuristic algorithms to medical diagnostics. This model demonstrates the potential of combining robust optimization and policy-based learning to address the inherent challenges of imbalanced datasets, which are prevalent in many medical conditions beyond PPD. Theoretically, this approach highlights the adaptability of meta-heuristic methods to complex, real-world problems where traditional algorithms might fail to deliver optimal results due to constraints in exploration capabilities and sensitivity to initial conditions. Additionally, a policy optimization method that treats the training process as a series of decision-making steps reflects an innovative shift towards more dynamic, context-aware systems in healthcare applications. This model advances the understanding of algorithmic design and sets a precedent for future research where machine learning can be intricately tailored to meet specific clinical needs, enhancing diagnostic precision and improving patient outcomes.

The reliance of the proposed model on the ML-ABC and PPO techniques presents a nuanced challenge in accurately diagnosing PPD. These advanced computational methods, though groundbreaking, may fall short of embracing the intricate and evolving landscape of PPD, which is deeply rooted in a confluence of biological, psychological, and sociocultural determinants [71]. The inherent complexity of PPD, characterized by its varying symptoms and severity, demands a diagnostic approach that can adapt to the broad spectrum of influences affecting maternal mental health. Biological factors, such as hormonal fluctuations post-delivery, genetic predispositions, and changes in brain chemistry, play a pivotal role in the onset of PPD [72]. The model's current algorithmic structure may not have the capacity to fully interpret the subtle biological signals that indicate a predisposition to or the presence of PPD. Similarly, psychological components, including a history of mental health issues, the psychological response to motherhood, and the presence of stressors like sleep deprivation, are critical in assessing the risk and presence of PPD. The model may not be designed to parse these nuanced psychological variables, which can vary significantly from one individual to another [73]. Furthermore, the social environment, encompassing support systems, cultural expectations of motherhood, and socioeconomic status, substantially influences the mental health of new mothers. The model might lack the ability to integrate these social determinants, which can mitigate or exacerbate the risk and severity of PPD. For example, the absence of a supportive partner or family, the societal stigma surrounding mental health, or the pressures of motherhood can profoundly impact the development and diagnosis of PPD [74]. To address these limitations, future iterations of the model could incorporate a more holistic approach that includes multidimensional data inputs reflecting the biological, psychological, and social factors relevant to PPD. Integrating qualitative data through natural language processing or enhancing the model's learning algorithms to recognize complex patterns associated with these factors might improve its diagnostic accuracy. Collaboration with interdisciplinary experts in psychiatry, obstetrics, and social sciences could provide deeper insights into the multifaceted nature of PPD, guiding the refinement of the model to ensure it captures the full spectrum of influences on maternal mental health [75].

The dataset's scope and representativeness considerably challenge the model's applicability and reliability [76]. Given that the model's evaluation was anchored to data derived from a Swedish study, its predictions and effectiveness could be inherently biased toward the Swedish population's demographic, cultural, and healthcare nuances. This limitation raises concerns about the model's performance across diverse global populations, where factors such as genetic diversity, cultural norms surrounding motherhood, and access to healthcare can significantly influence the incidence and manifestation of PPD [77]. Cultural diversity, in particular, plays a critical role in the perception, reporting, and management of PPD symptoms [78]. In some cultures, mental health issues may be stigmatized or underreported due to societal norms, potentially leading to underrepresentation in the dataset and, by extension, the model's training process. This could skew the model's predictive accuracy, making it less effective in identifying PPD in populations with different cultural backgrounds from the dataset on which it was trained. Furthermore, healthcare practices and accessibility vary widely across regions. In countries with limited access to mental health services, PPD may go undiagnosed or be treated differently than in countries with more robust healthcare systems [79]. This variance in healthcare infrastructure and practices can influence the type and amount of data available for training models like the one proposed, potentially limiting its effectiveness in regions with disparate healthcare systems. To enhance the model's generalizability and accuracy across varied populations, it may be necessary to incorporate data from a more diverse range of sources. This could involve aggregating datasets from multiple countries, cultures, and healthcare systems to create a more comprehensive and representative training dataset. Additionally, employing techniques such as transfer learning could enable the model to adapt to new populations by fine-tuning pre-trained models with localized data. Such approaches would bolster certitude that the method stays perceptive and pliant to the multifarious manifestations of PPD, ultimately improving its utility and impact in global maternal health care [2].

The practical deployment of the proposed model within clinical environments entails navigating the intricacies of healthcare operations, technology integration, and professional training. The transition from theoretical machine learning models to tools that healthcare professionals can rely on daily involves overcoming barriers related to system compatibility, data privacy, and user-friendliness [5]. The advanced nature of the model, while a strength in analytical capabilities, may present a steep learning curve for clinicians who need to be versed in data science or machine learning. This gap between technological innovation and practical application could slow the adoption rate and reduce the model's effectiveness in real-world settings. Moreover, integrating such models into existing healthcare information technology (IT) systems poses significant logistical challenges. Healthcare systems often operate on diverse platforms with varying degrees of digital sophistication. Ensuring that the model is compatible with these systems while maintaining the integrity and confidentiality of sensitive patient data is paramount [80]. This requires a robust framework for data handling, adherence to healthcare regulations like Health Insurance Portability and Accountability Act (HIPAA) in the United States and United States and the General Data Protection Regulation (GDPR) in Europe, and a secure interface for data input and output [81]. Furthermore, the model's adoption depends healthcare providers' trust and confidence in its predictions. To build this trust, it is essential to demonstrate the model's accuracy, reliability, and clinical relevance through rigorous validation studies. Additionally, transparency in how the model processes data and arrives at its predictions can help demystify its operations for healthcare professionals, making them more likely to embrace its use. To address these challenges, a multifaceted approach is needed. Simplifying the model's interface to make it more intuitive for clinical use without compromising its analytical depth can enhance user-friendliness. Developing comprehensive guidelines and protocols for the model's clinical application can provide healthcare professionals with a clear framework. Furthermore, implementing targeted training programs that educate healthcare providers about the model's functionality, interpretation of its outputs, and integration into patient care can bridge the gap between technological innovation and clinical practice. These initiatives can collectively ensure that the model serves as a cutting-edge PPD detection tool and becomes an integral and user-friendly component of maternal healthcare services [82].

V. Conclusion

This study introduced a novel model integrating the ML-ABC approach with PPO to tackle PPD detection, achieving notable accuracy and F-measure scores of 0.91 and 0.88, respectively. The model's use of PPO addressed the imbalanced dataset effectively, stabilizing the learning process by mitigating sudden policy shifts. It employed an ANN as its core, using a continuous decision-making framework to enhance the identification of underrepresented classes. Implementing ML-ABC in pre-training significantly refined the initial weight configurations, boosting the model's ability to discern complex patterns from the outset.

Looking forward, there is significant potential to broaden the model's utility across different populations by testing its effectiveness on diverse datasets from varied geographic and cultural contexts. This would provide insights into its adaptability and generalizability. Further, incorporating additional variables like genetic, hormonal, and environmental factors could substantially improve its predictive capabilities. Practical applications in clinical settings, such as hospitals and maternal health clinics, are also envisioned. Deploying the model in real-world conditions will allow for a dynamic assessment of its performance, offering a valuable tool for integrating advanced analytics into routine healthcare practice, thus enhancing early detection and intervention strategies for PPD.

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