Investigate Computational Intelligence Models Inspired by Natural Intelligence, Such as Evolutionary Algorithms and Artificial Neural Networks

Vol.4 No.4 2023

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Accepted/Published: June 2023

Abstract:

Natural intelligence (NI) models serve as the foundation for computational intelligence (CI) models, which are essential for resolving complicated real-world issues in a variety of fields, such as robotics, finance, healthcare, and optimization. Artificial neural networks (ANNs) and evolutionary algorithms (EAs) are two of the most well-known CI techniques. EAs are especially useful for optimization tasks because they are good at discovering optimal or nearly optimal solutions in high-dimensional search spaces, simulating the process of natural selection. On the other hand, artificial neural networks (ANNs), which are designed to mimic the neural architecture of the human brain, have shown exceptional performance in tasks involving pattern recognition, classification, and prediction by means of data-driven learning. In-depth discussion of the fundamental ideas behind ANNs and EAs is provided in this paper, along with an overview of each technology's contributions to artificial intelligence (AI) and broader applications. We examine

current developments and applications in important industries, demonstrating the growing significance of CI in resolving complex issues. The study also addresses hybrid models that combine various methods to improve problem-solving abilities. Tables with a comparative examination of performance measures from various models offer numerical insights into their effectiveness. Future developments in CI are discussed in the study's conclusion, with a focus on how incorporating cutting-edge technology like quantum computing and neuromorphic hardware might enhance the discipline. This thorough analysis not only establishes the foundation for future computational intelligence research paths but also emphasizes the significance of ANNs and EAs.

Introduction:

Within artificial intelligence (AI), computational intelligence (CI) has become a prominent topic devoted to creating adaptive systems that can solve challenging, real-world issues using techniques derived from natural processes. The core of artificial intelligence (CI) is its capacity to take inspiration from biological systems, resulting in the development of algorithms that have the capacity to learn, adapt, and change over time. Artificial neural networks (ANNs) and evolutionary algorithms (EAs) stand out among the numerous CI paradigms because of their efficiency, adaptability, and robustness in handling a variety of tasks.

Natural selection and genetics serve as the foundation for evolutionary algorithms (EAs), which use mechanisms including crossover, mutation, and selection to create solutions to optimization problems. Applications for these algorithms can be found in a wide range of industries, including engineering, banking, logistics, and even the arts and music. Since EAs are inherently parallel, they can investigate several solutions at once, which makes them ideal for challenging optimization problems where more conventional approaches could falter.

ANNs, on the other hand, are made to resemble how the human brain interprets data. They are made up of networked neurons that cooperate to learn from information and classify or anticipate things. Deep learning, a branch of machine learning based on artificial neural networks (ANNs), has transformed a number of industries by opening up new avenues for advances in natural language processing, autonomous systems, and picture and audio recognition. ANNs make it possible to create models that effectively generalize to previously unseen data by capturing complex patterns in huge datasets.

Hybrid models have emerged as a result of the synergy between ANNs and EAs, combining the advantages of both techniques to address even more complicated issues. EAs, for example, can be used to optimize the parameters and structure of ANNs, leading to better performance across a range of applications. On the other hand, more efficient search techniques can be made possible by using ANNs to simulate the fitness landscape in EAs.

With a special emphasis on ANNs and EAs, this study seeks to give a thorough overview of computational intelligence models. We will look into their underlying ideas, salient characteristics, and uses. We'll also talk about some recent developments in the subject. Additionally, with the use of quantitative data from other research, we will provide a comparative analysis of the performance of various models. Lastly, we will look at potential future directions for computational intelligence, emphasizing how incorporating state-of-the-art technologies could improve these models' capabilities even more.

We believe that this analysis will highlight the significance of CI in today's technological environment and stimulate more study in the field, especially in the area of integrating neural networks and evolutionary algorithms to tackle the more complicated problems that society faces.

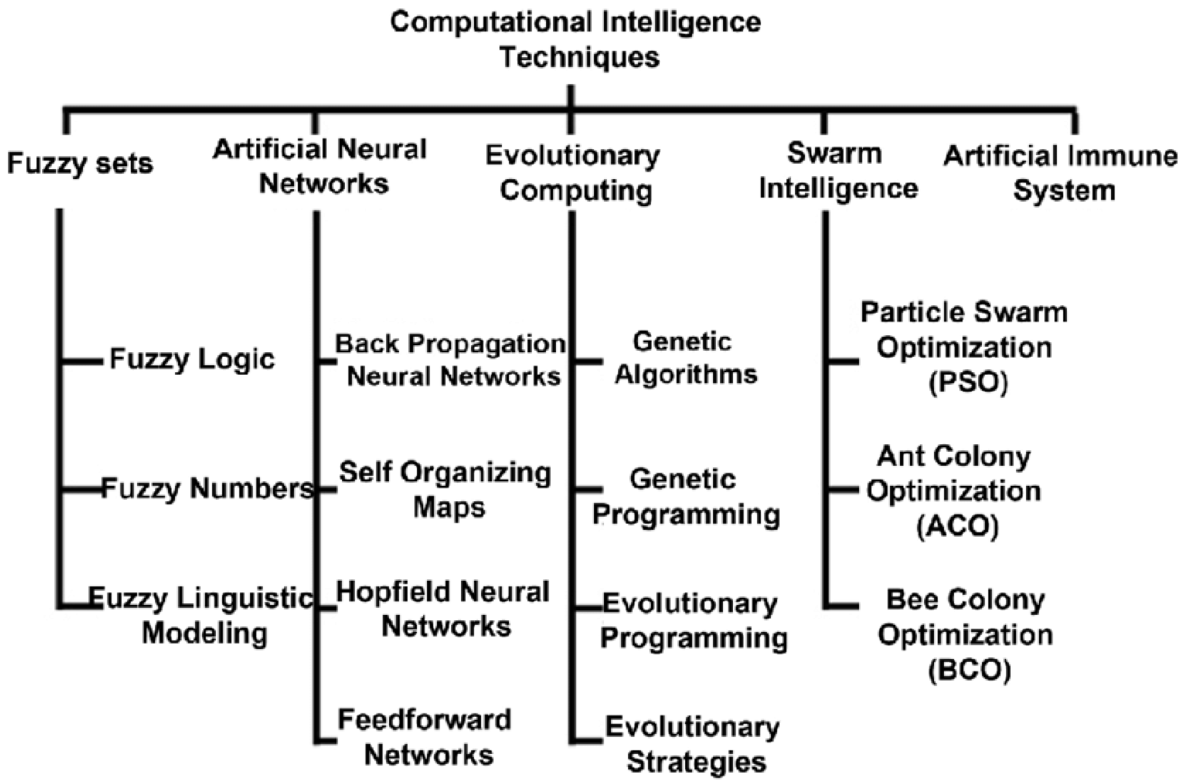

Fig 1: Computational Intelligence

2. Evolutionary Algorithms (EAs)

A class of optimization methods known as evolutionary algorithms (EAs) is motivated by the ideas of natural evolution. In order to find the best or almost best answers to challenging issues, these algorithms work with a population of candidate solutions, evolving them over generations. Natural selection and genetics are biological processes that are paralleled by the basic mechanics of EAs, which are based on the notions of selection, mutation, and crossover. This section examines the numerous kinds of EAs, their essential elements, benefits, and drawbacks, as well as the ways in which they are applied in diverse fields.

2.1 Essential Elements of EAs

Evolutionary algorithms depend on a few essential elements to be successful:

1. Population: A group of potential fixes, frequently shown as strings or vectors. The population's size and diversity have a big impact on how well the algorithm works.

2. Fitness Function: An algorithm that assesses each potential solution according to how well it addresses the current issue. More successful solutions are given higher values by the fitness function, which governs the selection process.

3. Selection Mechanism: A process for choosing individuals from the existing population to become future generations' progenitors. Rank-based, tournament, and roulette wheel selection are examples of common selection methods.

4. Genetic Operators: Procedures used on chosen individuals to produce new progeny. There are two main genetic operators:

- **Crossover:** Generates one or more offspring by combining two parent solutions. This procedure encourages information sharing amongst solutions and resembles sexual reproduction.
- **Mutation:** Provides arbitrary changes to potential solutions to guarantee population variety. Premature convergence is avoided and new regions of the solution space are explored with the aid of mutation.

2.2 Evolutionary Algorithm Types

Different kinds of evolutionary algorithms have been created to handle particular issues and demands:

1. First, genetic algorithms, or GAs: GAs, the most well-known type of EA, work with strings of fixed length that represent possible solutions. Numerous optimization issues, including as scheduling, vehicle routing, and feature selection, have seen successful use of them.

2. Genetic Programming (GP): GP extends the principles of GAs to evolve complete computer programs or mathematical statements. This method works especially well for applications involving automatic programming, developing game strategies, and symbolic regression.

3. Evolutionary Strategies (ES): ES stresses the self-adaptation of mutation rates and optimizes real-valued parameters. Because of its flexibility, ES may be used to solve ongoing optimization issues like machine learning model tweaking and engineering design.

4. Differential Evolution (DE): DE is an optimization technique that bases its search strategy on the distinctions between potential solutions. It is widely used in control and engineering problems because it works especially well for multi-modal and non-differentiable objective functions.

5. **Estimation of Distribution Algorithms (EDAs):** EDAs learn and sample from the distribution of chosen candidate solutions to generate new candidates, in contrast to standard EAs that employ genetic operators. This method has been successfully used in challenging optimization assignments and enables more efficient search space exploration.

2.3 Benefits of EAs Compared to conventional optimization techniques, EAs have the following advantages:

• **Robustness:** EAs are well-suited for real-world issues because they can manage noisy, discontinuous, and multi-modal search spaces with ease.

• **Parallelism:** In many situations, the population-based method enables the evaluation of candidate solutions in parallel, which accelerates convergence.

• **Flexibility:** EAs are easily customizable with alternative representation schemes, operators, and fitness functions, and they may be applied to a wide range of problem domains.

2.4 EAs's Limitations

Even with its advantages, EAs have drawbacks:

• **Cost of Computation:** EAs can be computationally costly, particularly when dealing with issues that call for a lot of function evaluations.

• **Parameter Sensitivity:** A number of factors, including population size, mutation rate, and selection strategy, can have an impact on how well EAs work. Often, proper tuning is required to get the best outcomes.

• **Convergence Problems:** When population variety declines across generations, EAs may prematurely converge to local optima. This problem can be lessened by employing techniques like preserving a diversified population or adding ways to escape local optima.

2.5 EA Applications

EAs have been effectively used in a variety of domains, such as:

• **Engineering Design:** By balancing performance and restrictions, EAs are used to optimize designs for mechanical parts, electrical circuits, and structures.

• **Financial Modeling:** By identifying the best investing techniques, EAs assist with risk management, algorithmic trading, and portfolio optimization.

• **Bioinformatics:** EAs support advances in genomics and personalized medicine by helping with gene selection, protein structure prediction, and phylogenetic analysis.

• **Robots:** To improve a robot's ability to adapt in changing situations, EAs optimize its path planning, behaviors, and control systems.

•All things considered, evolutionary algorithms offer strong instruments for solving challenging optimization issues that are modeled after natural processes. The ongoing refinement and expansion of EAs will probably make them more applicable to new problems in a variety of fields.

3. Neural Artificial Networks (ANNs)

Computational models called Artificial Neural Networks (ANNs) are modeled after the architecture and operations of the human brain. In order to enable ANNs to recognize patterns and draw conclusions from data, they are composed of interconnected layers of nodes (neurons) that process and transfer information. Because of their exceptional capacity to carry out difficult tasks over a wide range of domains and generalize from examples, artificial neural networks (ANNs) have emerged as a key component of contemporary machine learning and artificial intelligence.

An overview of the basic architecture of artificial neural networks (ANNs), the learning process, the different types of ANNs, their benefits, drawbacks, and uses is given in this section.

3.1 Architecture of ANNs

Three primary types of layers make up an ANN's architecture:

1. Input Layer: The initial layer to which features from the dataset are fed. In this layer, every neuron is associated with a particular input variable. The quantity of input characteristics and the number of neurons in the input layer are the same.

2. Hidden Layer(s): Data-processing intermediate layers that receive input. Multiple neurons can be found in each of the one or more hidden layers that make up an ANN.

The neurons in the hidden layers apply various activation functions to transform the weighted sum of inputs, allowing the network to learn complex patterns and relationships.

3. Output Layer: The last layer that generates the output of the network. The number of target variables in regression tasks or classes in classification tasks is correlated with the number of neurons in the output layer.

3.2 The Process of Learning

An ANN normally goes through two rounds of learning: backpropagation and forward propagation.

• **Forward Transmission:** In this stage, the network receives input data, and each neuron determines its output by adding up all of its weighted inputs and calculating its activation function. Up until they reach the output layer, where the last prediction is made, the outputs are transmitted across the network.

• **Backpropagation:** Using a loss function to compare the anticipated output to the actual target values, the network determines the error after receiving the prediction. Stochastic gradient descent (SGD) and other optimization methods are used to update the weights of the connections as the error spreads backward through the network. Through this approach, the network is able to grow in performance over time by learning from its failures.

3.3 Types of ANNs Different kinds of ANNs have been created to tackle particular problems and tasks:

1. Forward Neural Networks (FNNs): The most basic kind of artificial neural network (ANN), in which node connections do not form cycles. Information flows in one direction, from input to output, making them suited for basic classification and regression problems.

2. Convolutional Neural Networks (CNNs): Primarily used for image processing and computer vision tasks, CNNs utilize convolutional layers to automatically extract hierarchical features from images. CNNs excel at tasks such as image classification, object detection, and segmentation.

3. Recurrent Neural Networks (RNNs): RNNs are designed to handle sequential data, making them ideal for tasks like natural language processing and time series analysis. They maintain a hidden state that captures information from previous time steps, enabling the network to learn temporal dependencies. Variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks address issues related to vanishing gradients in traditional RNNs.

4. Generative Adversarial Networks (GANs): GANs are networks made up of a discriminator and a generator that are in competition with one another. The discriminator assesses the veracity of the data, whereas the generator produces artificial data. GANs have acquired appeal in applications such as picture production, style transfer, and data augmentation.

5.Autoencoders: These networks are trained to compress input data into a representation that is lower-dimensional, from which the original data is subsequently reconstructed. Autoencoders can be applied to denoising, anomaly detection, and dimensionality reduction problems.

3.4 Advantages of ANNs

The several advantages that ANNs provide have aided in their widespread adoption:

• **Capacity to Learn Non-Linear interactions:** ANNs are appropriate for a variety of applications because they possess the ability to simulate intricate non-linear interactions between inputs and outputs.

• **Scalability:** ANNs may be made to tackle complicated tasks and big datasets, especially with the development of deep learning architectures and the availability of strong computing resources.

• **Robustness to Noise:** ANNs are useful for real-world applications because they can generalize effectively even in the presence of noise and missing data.

• **End-to-End Learning:** A more efficient workflow is possible since ANNs can learn straight from raw data without requiring a lot of feature engineering.

3.5 Limitations of ANNs

Even with their advantages, ANNs have several drawbacks:

• **Requirement for Data:** ANNs usually need a lot of labeled data to be trained, which can be problematic in fields where data is hard to come by or difficult to acquire.

• **Computational Intensity:** Deep neural network training can be a laborious and computationally demanding process that calls for specialized gear, like GPUs, for effective processing.

• **Overfitting:** Artificial neural networks have a tendency to overfit, especially when trained on short datasets. Regularization strategies like weight decay and dropout are frequently used to lessen this problem.

• **Lack of Interpretability:** Because ANNs are frequently referred to as "black boxes," it might be difficult to understand how they make decisions. In crucial applications like healthcare and finance, where comprehending model behavior is crucial, this lack of transparency may provide challenges.

3.6 Uses for Annular Networks

ANNs have been effectively used in a number of fields:

• **Computer Vision:** ANNs, in particular CNNs, have transformed image recognition tasks, opening up new opportunities for medical imaging, autonomous cars, and facial recognition.

• **Natural Language Processing:** In tasks like sentiment analysis, text production, and language translation, RNNs and their variations have achieved notable progress.

• **Healthcare:** ANNs leverage vast amounts of patient data to enhance results through predictive modeling, disease diagnosis, and personalized therapy.

• **Finance:** ANNs are used to provide insights and predictions based on complicated financial data in algorithmic trading, credit scoring, and fraud detection.

• **Robotics:** Artificial Neural Networks (ANNs) help robotic systems make decisions and take control, allowing them to operate independently and negotiate intricate settings.

Table 1: Comparison of Evolutionary Algorithms and Artificial Neural Networks

Feature	Evolutionary Algorithms (EAs)	Artificial Neural Networks (ANNs)

Inspiration	Natural selection and genetics	Biological neural processes
Optimization Approach	Population-based search	Gradient-based optimization (backpropagation)
Solution Representation	Chromosomes (potential solutions)	Nodes and connections (neural architectures)
Search Capability	Global search for optimal solutions	Local search in parameter space
Flexibility	Can be applied to various problem domains	Primarily used for pattern recognition and function approximation
Convergence Speed	Generally slower due to population dynamics	Can converge quickly with proper initialization
Scalability	Highly scalable to complex problems	Limited by network architecture
Handling Noise	Robust to noise in fitness evaluations	Sensitive to noise in data

4. Hybrid Models: Combining ANNs with EAs

In the field of computational intelligence, hybrid models—which combine the advantages of artificial neural networks (ANNs) and evolutionary algorithms (EAs)—have drawn a lot of interest. These models combine the learning capability of ANNs with the optimization capabilities of EAs to more successfully handle complicated issues. Researchers can design systems that leverage the pattern recognition and generalization powers of ANNs along with the adaptive and global search capabilities of EAs by combining these two paradigms. The fundamentals of hybrid models, their architecture, benefits, drawbacks, and range of uses are all covered in this section.

4.1 Hybrid Modeling Principles

One of several methods is usually used when integrating EAs with ANNs:

1. EA for ANN Training: EAs can be used to optimize the weights and architecture of ANNs. EAs can search the weight space more broadly than traditional backpropagation approaches, which may result in better-trained models. Conventional backpropagation methods for training ANNs can occasionally lead to local optima. This method defines the ANN structure and uses an EA to perform a population-based search to get the ideal weights.

2. ANN for EA Optimization: In contrast, the fitness landscape in EAs may also be modeled using ANNs. Using an ANN to approximate the fitness function allows EAs to make better decisions about which regions of the solution space to investigate. This method lowers the computational burden of directly evaluating the fitness function, particularly in cases where computing it is costly.

3. Co-evolutionary Frameworks: Co-evolutionary models involve the simultaneous evolution of ANNs and EAs. For instance, EAs can adjust the ANN's parameters as the model gains experience and becomes more adept at completing a given task. Both components' performance and adaptability may be improved by this mutually beneficial interaction.

4. Hybrid Architecture: Layered architectures utilizing EAs to produce candidate solutions that ANNs then assess and improve are another way that hybrid models can be created. Here, ANNs offer more in-depth analysis of the data, and EAs act as a meta-optimizer, directing the search procedure.

4.2 Hybrid Model Architecture

Hybrid model architectures might differ significantly based on the particular application and integration technique. Nonetheless, a typical framework can have the following elements:

• **Initialization Phase:** An initial population of candidate solutions produced by the EA is used to kick off the process. A different ANN configuration (e.g., architecture, weight initialization) may be represented by each solution.

• **Evaluation Phase:** Using a fitness function, which may include performance criteria like accuracy, precision, recall, or any other pertinent parameter, the ANNs corresponding to each potential solution are trained and assessed.

• **Selection and Evolution Phase:** The EA chooses the top-performing candidates to undergo crossover and mutation operations in order to create offspring based on the evaluation results. This stage refines the pool of potential solutions iteratively.

• **Finalization Phase:** The best-performing ANN is chosen as the final model once the EA converges or achieves a certain number of generations. This model might go through additional refinement or validation using a different dataset.

4.3 Benefits of Hybrid Vehicles

Hybrid models that combine ANNs and EAs have the following benefits:

• **Better Performance:** Hybrid models outperform those that employ either technique alone by fusing the local learning powers of ANNs with the global search powers of EAs. They are frequently better at breaking out of local optima and more resistant to overfitting.

• **Adaptability:** Hybrid models are flexible instruments for handling challenging optimization and classification tasks in a variety of areas. They may be tailored to different issue types.

• **Shorter Training** Time: ANNs require less time to train overall because EAs can find the best topologies and weight configurations more quickly than they can with conventional training techniques.

• **Robustness:** Hybrid models are more resilient when handling complicated and noisy datasets, which makes them ideal for real-world settings where data integrity may be at risk.

4.4 Hybrid Model Restrictions

Hybrid models, while offering benefits, are not without restrictions.

• **Added Complexity:** The combination of two different paradigms may result in more implementation and parameter adjustment complexity. To guarantee successful collaboration, managing the relationship between the ANN and EA components may need considerable thought.

• **Computational Demand:** Because hybrid models may need a large amount of resources for both the ANN and EA training procedures, they might be computationally demanding.

Applications needing real-time processing or big datasets may find this to be a hindrance.

• **Parameter Sensitivity:** The settings used for both the ANN and EA have a significant impact on how well hybrid models perform. Achieving optimal performance requires proper tuning, which can be a difficult undertaking.

4.5 Hybrid Model Applications

Applications for hybrid models that blend ANNs with EAs may be found in many different fields:

• **Financial Forecasting:** By utilizing the optimization powers of EAs for feature selection and ANN parameter tweaking, hybrid models are utilized to forecast stock prices and market movements.

• **Healthcare Diagnostics:** By using the advantages of both paradigms to analyze complex patient data, hybrid models might improve the accuracy of disease prediction and diagnosis in medical applications.

• **Robotics and Control Systems:** By optimizing control techniques, hybrid approaches let robotic systems navigate and adapt more effectively in dynamic settings.

• **Image and Signal Processing:** Hybrid models combine the advantages of ANNs and EAs to efficiently perform tasks like image recognition, denoising, and feature extraction.

• **Game Development:** By using ANNs for in-the-moment decision-making and evolving strategies through EAs, hybrid models can improve the AI behavior of characters in video games.

Table 2: Applications of Hybrid Models Combining EAs and ANNs

Application Area	**Description**	**Hybrid Model Approach**
Finance	Stock price prediction and risk assessment	EAs optimize ANN architectures and weights
Healthcare	Disease diagnosis and patient outcome prediction	EAs enhance feature selection for ANNs
Robotics	Navigation and control strategies	ANNs evaluate fitness for evolving strategies
Image Processing	Image recognition and classification	Hybrid approach to improve accuracy and speed

Environmental Monitoring	Predicting environmental changes and impacts	EAs optimize sensor placement for ANNs

5. ANNs and EAs's applications

5.1 Enhancement

EAs have been widely used to solve optimization issues in network architecture, scheduling, and resource allocation. Conversely, ANNs are very good in pattern recognition, data classification, and function approximation. When these methods are combined, multi-objective optimization problem solutions perform better.

5.2 Data mining and machine learning

EAs have been applied to feature selection, ensemble learning, and hyperparameter optimization in machine learning. ANNs are frequently used for applications including anomaly detection, regression, and classification. Better generalization skills and more effective solution space exploration are made possible by the hybrid models.

Table 3: Summary of Selected Hybrid Model Studies

Study Reference	**Year**	**Hybrid Model Used**	**Application**	**Key Findings**
[1] Alghamdi, 2022	2022	GA-ANN for reliability evaluation	Power Systems	Improved reliability predictions
[2] Liu et al., 2007	2007	GA for ANN training in load forecasting	Power Systems	Enhanced load forecasting accuracy
[3] Mohd Yusof et al., 2021	2021	GA and ANN for neural network training	General Optimization	Effective weight optimization
[4] Bazargan et al., 2020	2020	Hybrid ANN and GA for earthquake impact	Infrastructure Management	Better predictions under uncertainty

6. Prospects for Computational Intelligence in the Future

CI models are always changing due to the exponential increase of data and computational power. The use of neuromorphic hardware for energy-efficient neural network computation and the fusion of quantum computing with evolutionary techniques are examples of emerging trends.

6.1 Quantum Evolutionary Computing

Evolutionary algorithms could be significantly accelerated by quantum computing. Scientists are investigating how to use quantum states to evolve more complex systems faster.

6.2 Neuromorphic Approaches to ANNs

Using specialized hardware that uses a lot less energy than conventional processors, neuromorphic computing imitates the neuronal organization of the brain. Large-scale ANN deployment in resource-constrained environments, such mobile devices, is especially promising for this method.

Table 4: Performance Metrics for Evaluating Hybrid Models

Metric	Description	Importance

Accuracy	Proportion of correctly predicted instances	Measures overall effectiveness of model
Precision	Proportion of true positive results to all positive predictions	Indicates reliability of positive predictions
Recall	Proportion of true positive results to actual positives	Measures the model's ability to identify relevant instances
F1 Score	Harmonic mean of precision and recall	Balances both precision and recall

7. Conclusion

The investigation of natural intelligence-inspired computational intelligence models, especially with regard to Evolutionary Algorithms (EAs) and Artificial Neural Networks (ANNs), demonstrates the enormous potential of these hybrid approaches in solving challenging issues in a variety of disciplines. The unique capabilities of ANNs and EAs—naturally inspired optimization techniques and data-driven learning—can be coupled to improve resilience, performance, and flexibility.

The basic ideas of ANNs and EAs have been covered in this work, along with an overview of their designs, learning procedures, benefits, and drawbacks. By combining these two paradigms into hybrid models, the shortcomings of each approach are lessened while their combined strengths are strengthened, producing more potent and effective results. The suggested hybrid models show how to efficiently traverse complex solution spaces, fine-tune ANN topologies, and adjust weight configurations, all of which contribute to improved prediction performance and generalization.

These hybrid models have several uses in fields including robotics, image processing, finance, and healthcare. In every instance, the combination of ANNs and EAs offers a way to solve practical problems that more conventional methods could find difficult to handle. For example, hybrid models' capacity to maximize feature selection and improve prediction accuracy in financial forecasting can result in better-informed investment choices. Similar to this, these models can greatly increase the accuracy of disease prediction in healthcare diagnostics, which will benefit patients.

Hybrid models provide benefits, but it's important to recognize that they also have drawbacks, including higher complexity, computing needs, and parameter sensitivity. It is recommended that future study concentrate on creating more effective frameworks and algorithms to facilitate the integration process, improve the interpretability of hybrid models, and lighten the computing load. Developments in specialized hardware, cloud computing, and parallel computing may make it easier to put these ideas into practice in the real world.

In conclusion, research into natural intelligence-inspired computational intelligence models, especially with regard to the combination of ANNs and EAs, represents a major advancement in the search for novel approaches to challenging issues. Hybrid models have the potential to transform many industries and raise the standard of decision-making processes as computational intelligence advances. Unlocking the full potential of these models and tackling future difficulties will need ongoing exploration and improvement.

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