

Review Article

Advancements, Applications, and Emerging Trends in Computational Intelligence

P Geetha

Student, Department of Civil Engineering, Rajalakshmi Engineering College, Rajalakshmi Nagar Thandalam, Chennai, India

I N F O

E-mail Id:

geethap22@gmail.com

Orcid Id:

<https://orcid.org/0009-0004-4821-083X>

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A B S T R A C T

Computational Intelligence (CI) encompasses a broad range of techniques and methodologies designed to solve complex, real-world problems by mimicking natural processes and human cognition. This review article provides an in-depth exploration of key areas within CI, including Artificial Neural Networks (ANNs), Fuzzy Logic, Evolutionary Algorithms, Swarm Intelligence, and Machine Learning. It highlights the recent advancements in these fields and discusses their applications in various industries such as healthcare, finance, robotics, and industrial automation. Despite the significant progress made, several challenges persist, including issues related to scalability, explainability, generalization, and ethical considerations. This article concludes by discussing the future directions of CI research, emphasizing the importance of scalability, transparency, and fairness in the development of intelligent systems. The continued evolution of CI has the potential to further transform a wide range of sectors, driving innovations that could shape the future of technology and society.

Keywords: Computational Intelligence, Machine Learning, Neural Networks, Fuzzy Logic, Evolutionary Algorithms

Introduction

Computational Intelligence (CI) is a rapidly evolving field that focuses on creating intelligent systems capable of solving complex and dynamic problems by leveraging computational techniques inspired by natural processes. Unlike traditional methods that rely on explicit programming, CI emphasizes adaptive systems that can learn, reason, and make decisions in uncertain and dynamic environments. CI integrates various approaches, including artificial neural networks (ANNs), fuzzy logic, evolutionary algorithms, and swarm intelligence, to build systems that exhibit flexibility, robustness, and efficiency.¹

Over the past few decades, CI has gained prominence due to its ability to address real-world problems across a wide range of domains, from healthcare and finance to robotics and industrial automation. The fusion of techniques

like machine learning, deep learning, and optimization algorithms has led to significant breakthroughs, enabling systems to solve problems that were previously too complex or computationally expensive. This interdisciplinary field combines elements of artificial intelligence, machine learning, computational biology, and evolutionary theory, making it one of the most exciting areas of research in both academia and industry.²

Key Areas of Computational Intelligence

Computational Intelligence (CI) encompasses a variety of methodologies that allow systems to adapt, learn, and make intelligent decisions in uncertain and complex environments. The main techniques used in CI are inspired by natural processes such as the human brain, evolutionary biology, and collective animal behavior. Below, we discuss the key areas of CI, highlighting their principles, advancements, and applications.

Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of the human brain. They consist of layers of interconnected nodes, or neurons, that process information in parallel. ANNs can learn from data, make predictions, and recognize patterns, making them essential tools in fields such as image recognition, speech processing, and natural language processing.

Recent Advancements

- **Deep Learning:** A subset of ANNs, deep learning has gained significant attention with its ability to process vast amounts of unstructured data (e.g., images, audio, and text). Deep neural networks (DNNs), particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have achieved breakthroughs in fields like computer vision, speech recognition, and natural language understanding.
- **Transformer Models:** The rise of Transformer models such as BERT, GPT, and T5 has revolutionized natural language processing by significantly improving machine translation, text generation, and question-answering tasks.
- **Explainability in Neural Networks:** With deep learning models becoming more complex, the need for model interpretability has surged. New research focuses on creating methods to explain how deep neural networks make decisions, improving trust and transparency in AI systems.

Applications:

- **Healthcare:** ANNs are used for medical image analysis (e.g., detecting tumors in radiographs), disease prediction, and patient monitoring.
- **Autonomous Systems:** Deep learning algorithms power self-driving cars, enabling them to interpret and respond to the surrounding environment.

Fuzzy Logic Systems

Fuzzy Logic, introduced by Lotfi Zadeh in the 1960s, deals with reasoning that is approximate rather than fixed and exact. In contrast to classical binary logic, where all propositions are either true or false, fuzzy logic allows for values between true and false, reflecting real-world uncertainty. This approach is especially useful when dealing with vague or imprecise information.³

Recent Advancements:

Fuzzy Clustering and Decision-Making: Fuzzy logic is widely used in clustering techniques, allowing systems to classify data with ambiguity. It is also applied in decision-making processes where precision is not achievable, such as in medical diagnostics or control systems.

Integration with Machine Learning: Fuzzy systems are increasingly being hybridized with machine learning techniques to handle noisy data, improving the adaptability of intelligent systems.

Applications:

- **Control Systems:** Fuzzy logic is employed in many industrial applications, such as controlling temperature in ovens, regulating speed in motors, and adjusting lighting in buildings based on ambient conditions.
- **Healthcare:** Fuzzy systems help in medical decision support, particularly in environments with incomplete or uncertain patient data, such as predicting disease progression or recommending treatment plans.

Evolutionary Algorithms (EAs)

Evolutionary Algorithms (EAs) are optimization techniques inspired by the process of natural selection. These algorithms iteratively evolve a population of potential solutions to a problem through mechanisms like selection, mutation, and crossover. The most common evolutionary algorithms include Genetic Algorithms (GAs), Genetic Programming (GP), and Evolution Strategies (ES).⁴

Recent Advancements:

- **Multi-Objective Optimization:** Traditional evolutionary algorithms are being adapted to solve problems with multiple, often conflicting objectives. This approach has been crucial in engineering design, resource allocation, and portfolio optimization.
- **Hybrid Models:** Researchers are combining evolutionary algorithms with other optimization techniques, such as gradient-based methods and machine learning, to improve convergence speed and solution quality in real-time applications.

Applications:

- **Engineering and Design:** EAs are used to optimize complex designs in aerospace, automotive, and manufacturing industries, where traditional methods may fail due to the complexity and non-linearity of the problems.
- **Finance and Portfolio Management:** In finance, EAs are employed to optimize investment portfolios by considering multiple objectives, such as maximizing returns while minimizing risks.

Swarm Intelligence

Swarm Intelligence (SI) refers to the collective behavior of decentralized, self-organized systems, typically seen in natural systems like bird flocks, fish schools, or ant colonies. SI algorithms, such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), are inspired by these behaviors and are used to solve optimization and search problems.

Recent Advancements:

- **Hybrid Swarm Intelligence:** Modern research often combines swarm intelligence with machine learning and other optimization techniques to enhance performance, especially in dynamic and complex environments.
- **Applications in Robotics:** Swarm robotics, which uses swarm intelligence algorithms, is a growing field that enables a group of robots to collaboratively perform tasks such as search and rescue, exploration, and monitoring.

Applications:

- **Optimization:** Swarm intelligence algorithms are applied to solve complex optimization problems in logistics, network design, and path planning.
- **Robotics:** Swarm robots, guided by principles of swarm intelligence, are used in applications where autonomous systems need to coordinate their actions in real-time, such as in environmental monitoring or search-and-rescue operations.

Machine Learning (ML) and Deep Learning

Machine Learning, a core area of computational intelligence, focuses on enabling systems to learn from data and improve their performance without being explicitly programmed. Deep learning, a subset of machine learning, involves neural networks with many layers and has significantly advanced the field, allowing for the automation of complex decision-making processes.^{5,6}

Recent Advancements:

- **Transfer Learning:** Transfer learning allows models to leverage knowledge gained from one task to improve performance on a different but related task, reducing the need for large datasets in every new application.
- **Reinforcement Learning (RL):** RL has gained attention in recent years for its ability to enable autonomous agents to learn by interacting with their environments and receiving feedback in the form of rewards or penalties.
- **Federated Learning:** This emerging approach allows machine learning models to be trained across multiple decentralized devices or servers while keeping data localized, enhancing privacy and efficiency.

Applications:

- **Healthcare:** Machine learning models are increasingly being applied to medical image analysis, drug discovery, and personalized medicine, making predictions about disease progression or patient outcomes based on historical data.
- **Autonomous Vehicles:** Deep learning plays a critical role in the development of self-driving cars, enabling

them to process sensor data and make decisions in real-time.

- **Natural Language Processing (NLP):** Advanced ML techniques, such as transformers, are being used for tasks like text generation, sentiment analysis, and automatic translation.

Applications of Computational Intelligence

Computational Intelligence (CI) has proven to be a transformative force across various industries, providing robust solutions to complex, real-world problems. By leveraging techniques such as Artificial Neural Networks (ANNs), Fuzzy Logic, Evolutionary Algorithms, Swarm Intelligence, and Machine Learning, CI can tackle challenges that traditional approaches may struggle with. Below are key sectors where CI has made significant impacts, along with some of its notable applications:

Healthcare

In the healthcare sector, CI has brought about advancements in diagnostics, treatment planning, personalized medicine, and patient care. By using algorithms that can learn from data, healthcare systems are becoming more intelligent, capable of providing quicker, more accurate predictions and recommendations.

Key Applications:

- **Medical Imaging and Diagnosis:** CI models, especially deep learning techniques like Convolutional Neural Networks (CNNs), are widely used in medical imaging to detect abnormalities such as tumors, fractures, and other conditions from X-rays, MRIs, and CT scans. These models can recognize patterns and anomalies that may be difficult for human clinicians to detect.
- **Predictive Healthcare Models:** Machine learning algorithms are used to predict disease outbreaks, patient deterioration, and the progression of chronic conditions. Predictive models help in early detection, enabling timely intervention and reducing the burden on healthcare systems.
- **Personalized Medicine:** By analyzing patient data, CI techniques such as fuzzy logic and evolutionary algorithms can assist in creating personalized treatment plans based on an individual's genetic makeup, lifestyle, and medical history.
- **Robotics and Surgery:** CI plays a role in enhancing robotic surgery systems, where precision and adaptability are critical. Robots equipped with CI algorithms can adapt to changing surgical environments and improve outcomes.^{7,8}

Finance

Computational Intelligence has become a cornerstone of the financial industry, helping optimize trading strategies,

manage risks, and automate decision-making processes. CI-based solutions are used for fraud detection, credit scoring, and optimizing investment portfolios.

Key Applications:

- **Algorithmic Trading:** Evolutionary algorithms and machine learning are commonly used to design trading strategies that can analyze vast amounts of financial data, identify trends, and execute trades at high speeds. These algorithms can adapt to market changes and optimize returns over time.
- **Credit Scoring and Risk Assessment:** Machine learning models, particularly decision trees and neural networks, are employed by banks and financial institutions to evaluate loan applicants, assess creditworthiness, and predict potential risks based on historical data.
- **Fraud Detection:** CI systems are used to detect fraudulent activity in banking and e-commerce by identifying unusual patterns in transaction data. Neural networks and anomaly detection algorithms are able to spot suspicious behavior and prevent fraud in real-time.
- **Portfolio Optimization:** Evolutionary algorithms such as Genetic Algorithms (GAs) are used to optimize investment portfolios, balancing risks and returns by adjusting asset allocations dynamically.

Robotics and Autonomous Systems

CI has significantly advanced the field of robotics, particularly in the development of autonomous systems capable of making real-time decisions and adapting to dynamic environments. This includes applications in industrial automation, drones, and autonomous vehicles.

Key Applications:

- **Autonomous Vehicles:** Machine learning and swarm intelligence algorithms are at the heart of autonomous vehicle systems. They enable self-driving cars to navigate traffic, avoid obstacles, and make decisions in real time using sensor data such as LIDAR, cameras, and GPS.
- **Swarm Robotics:** Swarm intelligence algorithms like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) are applied in multi-robot systems where individual robots collaborate to complete tasks such as exploration, surveillance, and search-and-rescue operations.
- **Industrial Automation:** CI techniques are used in robotics for automating manufacturing processes. Robots powered by machine learning can adjust their behavior based on sensory input, optimizing assembly lines and minimizing errors.

Manufacturing and Industrial Systems

CI plays a critical role in optimizing manufacturing processes, predictive maintenance, and quality control.

From enhancing production efficiency to predicting failures before they occur, CI-based solutions are transforming how industries operate.

Key Applications:

- **Predictive Maintenance:** Machine learning models analyze historical equipment data to predict when machines are likely to fail, enabling proactive maintenance scheduling. This reduces downtime and extends the lifespan of equipment.
- **Supply Chain Optimization:** Evolutionary algorithms and swarm intelligence are used to optimize the flow of materials, scheduling, and logistics within manufacturing and distribution systems. This enhances efficiency and reduces costs in supply chains.
- **Quality Control:** Fuzzy logic systems are applied to monitor product quality, particularly in cases where exact measurements are difficult or subjective. These systems can ensure that products meet quality standards by adjusting manufacturing parameters based on real-time feedback.

Energy and Environment

CI techniques are being applied to optimize energy production, distribution, and consumption, as well as to address environmental challenges such as climate change, pollution, and resource management.

Key Applications:

- **Smart Grids:** Evolutionary algorithms and machine learning techniques are used in smart grids to optimize electricity distribution, predict demand patterns, and manage energy storage more effectively, ensuring that energy is used efficiently and sustainably.
- **Energy Management Systems:** CI helps optimize the usage of energy in industries, buildings, and homes by predicting consumption patterns and adjusting systems like heating, ventilation, and air conditioning (HVAC) to reduce waste and costs.
- **Environmental Monitoring:** Swarm intelligence is used for environmental monitoring, such as tracking pollution levels, monitoring air and water quality, and tracking wildlife. Sensor networks powered by swarm algorithms can autonomously collect and transmit data, improving real-time environmental surveillance.^{9,10}

Telecommunications and Networking

In telecommunications and networking, CI is used to optimize network routing, enhance signal processing, and improve the overall performance and reliability of communication systems.

Key Applications:

- **Network Optimization:** Evolutionary algorithms and swarm intelligence are applied to optimize network

routing, reducing latency and congestion while ensuring efficient data flow across the network. CI also helps improve load balancing and fault detection.

- **Wireless Sensor Networks (WSNs):** In WSNs, swarm intelligence algorithms coordinate the activities of sensor nodes to collect data efficiently, minimize energy consumption, and ensure reliable communication in large-scale networks.
- **Signal Processing:** Machine learning techniques, particularly deep learning, are employed to enhance signal processing in telecommunications. This includes tasks like noise reduction, error correction, and modulation/demodulation in communication systems.

Education and E-Learning

Computational Intelligence is being utilized to personalize learning experiences, optimize student assessments, and provide adaptive learning platforms that cater to individual needs and learning styles.

Key Applications:

- **Adaptive Learning Systems:** Machine learning algorithms power adaptive learning platforms that tailor educational content to the needs, abilities, and progress of individual students. These systems adjust the difficulty of tasks in real time to provide personalized learning experiences.
- **Automated Grading and Feedback:** CI-based systems can automatically grade assignments, quizzes, and exams, providing instant feedback to students. Natural language processing (NLP) is used to assess written responses and provide constructive feedback.
- **Intelligent Tutoring Systems:** AI-driven tutoring systems powered by neural networks or fuzzy logic can offer personalized assistance to students, providing explanations, answering questions, and guiding them through problems.

Natural Language Processing (NLP)

NLP, a subfield of AI, has benefited greatly from CI techniques. Machine learning and deep learning have revolutionized language processing, enabling machines to understand, generate, and translate human language with remarkable accuracy.

Key Applications:

- **Machine Translation:** Neural networks, particularly transformer models like Google's BERT and OpenAI's GPT, have greatly improved machine translation systems, enabling more accurate and fluent translations between languages.
- **Sentiment Analysis:** Machine learning algorithms are widely used in sentiment analysis, where they analyze text data from social media, reviews, and customer

feedback to gauge public opinion and sentiment toward brands, products, or services.

- **Chatbots and Virtual Assistants:** CI-based systems like natural language processing and machine learning enable chatbots and virtual assistants to understand and respond to user queries in a conversational manner, enhancing user experience and customer support.¹¹⁻¹³

Challenges and Future Directions

While Computational Intelligence (CI) has made tremendous strides in addressing complex, real-world problems, it is not without its challenges. These challenges range from issues of scalability and interpretability to the ethical implications of AI systems. As CI continues to evolve, it must overcome these barriers to achieve its full potential. This section outlines the key challenges facing CI and explores the promising future directions that could guide its growth.

Scalability

One of the primary challenges faced by CI methods is scalability. Many computational intelligence algorithms, particularly those in machine learning and deep learning, require enormous amounts of data and computational power to perform effectively. As the size and complexity of datasets continue to grow, CI systems must evolve to handle increasingly large-scale problems efficiently.

Key Issues:

- **Data Volume and Processing Power:** As the availability of big data increases, CI systems must be capable of processing massive datasets in real time. Algorithms like deep learning models require significant computational resources, often necessitating powerful hardware (such as GPUs and TPUs), which may not always be accessible or cost-effective.
- **Distributed and Parallel Processing:** CI systems often rely on distributed computing techniques to handle large datasets. However, ensuring that algorithms perform efficiently across multiple machines or in parallel processing environments remains a complex challenge.

Future Directions:

- **Quantum Computing:** As quantum computing evolves, it holds the potential to revolutionize CI by providing exponential speedups in solving computationally intensive problems. Quantum machine learning algorithms are already being explored to overcome scalability issues.
- **Edge Computing:** Edge computing, which involves processing data closer to where it is generated (e.g., on sensors or mobile devices), can alleviate the strain on centralized cloud systems and enable more scalable and real-time CI applications.

Interpretability and Explainability

One of the most pressing concerns in modern CI, particularly with deep learning models, is the “black-box” nature of many algorithms. While models like neural networks achieve high performance, their decision-making processes are often not easily interpretable by humans. This lack of transparency can hinder their adoption, especially in critical fields like healthcare, finance, and law enforcement.

Key Issues:

- **Model Complexity:** Deep learning and other CI methods are often characterized by their complexity, involving millions of parameters and intricate architectures. As a result, understanding how these models arrive at specific decisions is challenging.
- **Accountability:** The inability to explain how a model works makes it difficult to trust and verify the results, which is a critical issue in domains like medicine or criminal justice, where mistakes can have serious consequences.

Future Directions:

- **Explainable AI (XAI):** Research into explainable AI aims to make machine learning models more transparent and interpretable. Techniques like attention mechanisms, saliency maps, and surrogate models are being developed to provide more insight into how CI models make decisions.
- **Hybrid Models:** Combining CI approaches with traditional rule-based or symbolic reasoning systems may help improve the explainability of intelligent systems, while maintaining their flexibility and adaptability.

Ethical and Bias Concerns

The deployment of CI technologies raises significant ethical concerns, particularly around fairness, transparency, and privacy. Algorithms, particularly those used in machine learning and AI, are susceptible to biases in the data they are trained on. This can lead to discriminatory outcomes, especially when applied in sensitive areas like hiring, criminal justice, or lending.

Key Issues:

- **Bias in Training Data:** If training data reflects historical biases or societal inequalities, CI systems may inadvertently perpetuate or amplify these biases, leading to unfair or unethical outcomes.
- **Privacy:** With the increasing use of personal data in CI models, safeguarding privacy and ensuring that individuals’ data is used responsibly remains a key challenge. The use of data without adequate consent or protection can lead to privacy violations and public distrust.

- **Ethical Decision-Making:** As CI technologies become more autonomous, ensuring that these systems make ethical decisions in complex, high-stakes scenarios will be crucial.

Future Directions:

- **Fairness and Bias Mitigation:** There is growing research on methods to detect and mitigate bias in CI algorithms. Techniques like fairness-aware machine learning, adversarial debiasing, and re-sampling methods are being explored to reduce bias in training data.
- **Privacy-Preserving AI:** Techniques such as federated learning and differential privacy aim to allow machine learning models to train on data while preserving individual privacy. These methods can enable secure and ethical use of sensitive data without compromising personal information.
- **Ethical AI Frameworks:** The development of ethical guidelines, standards, and regulatory frameworks is essential to ensure the responsible deployment of CI technologies. These frameworks should prioritize fairness, transparency, and accountability in AI systems.

Generalization and Robustness

While CI models, particularly deep learning, have demonstrated impressive performance on specific tasks, they often struggle to generalize well to new or unseen data. Many models perform exceptionally well under controlled conditions but can fail when exposed to real-world scenarios with variability or noise. This lack of robustness is a significant barrier to deploying CI systems in dynamic environments.¹⁰

Key Issues:

- **Overfitting:** Deep learning models can overfit to the training data, meaning they perform well on known data but fail to generalize to new, unseen examples. This issue is particularly pronounced when there is a limited amount of labeled data for training.
- **Adversarial Attacks:** CI systems, especially deep learning models, are vulnerable to adversarial attacks—small, carefully crafted changes to input data that can drastically alter model behavior. This raises concerns about the security and trustworthiness of CI systems in critical applications.

Future Directions:

- **Robust Learning Techniques:** Research into methods that improve the robustness of CI systems, such as adversarial training, transfer learning, and data augmentation, is ongoing. These techniques can help models generalize better to new situations and reduce vulnerability to adversarial manipulation.
- **Few-Shot Learning and Meta-Learning:** Few-shot learning allows models to learn effectively from very

limited data, which is crucial for generalizing to unseen situations. Meta-learning, or “learning to learn,” could also improve a model’s ability to adapt to new environments or tasks with minimal retraining.^{11,12}

Real-Time Decision Making

Many CI applications, particularly in robotics, autonomous vehicles, and smart cities, require real-time decision-making and responsiveness to dynamic environments. Ensuring that CI systems can make decisions quickly and accurately, without compromising safety or reliability, is a challenge.

Key Issues:

- **Real-Time Data Processing:** CI systems often need to process large amounts of real-time data from various sensors and sources. Ensuring low-latency processing and decision-making in such scenarios is a significant challenge.
- **Safety and Reliability:** In safety-critical applications such as autonomous driving or industrial automation, the reliability of CI systems is crucial. Failure to make correct decisions in a timely manner can have disastrous consequences.

Future Directions:

- **Edge AI:** Edge AI involves running CI algorithms on local devices rather than relying on cloud-based processing. This reduces latency and enables faster decision-making, which is critical for real-time applications like autonomous driving and industrial robotics.
- **Reinforcement Learning (RL):** RL algorithms, which allow agents to learn from their interactions with the environment, are becoming increasingly effective in real-time decision-making tasks. Continued advancements in RL will enable more adaptive and autonomous systems in dynamic environments.^{13,15}

Conclusion

The future of Computational Intelligence (CI) is filled with immense potential, yet it also faces a set of formidable challenges. While CI techniques have already demonstrated transformative impacts across a variety of industries, addressing key issues such as scalability, interpretability, ethical concerns, generalization, and real-time decision-making will be essential for maximizing their widespread adoption and effectiveness. In particular, the need for more efficient algorithms capable of processing vast datasets in real time remains a critical hurdle. As computational power continues to evolve, innovations in quantum computing and edge AI could provide the necessary advancements to handle increasingly complex problems, opening the door to real-time, high-performance CI applications.

Furthermore, the call for greater transparency and interpretability in machine learning models is a crucial

step toward ensuring that CI systems are trustworthy and ethically aligned with human values. As we integrate CI systems into sensitive domains like healthcare, finance, and criminal justice, ensuring fairness, transparency, and accountability will not only build trust but also foster wider acceptance and adoption of these technologies. The development of explainable AI (XAI) and techniques for mitigating bias will play a pivotal role in making these systems more accessible and reliable.

Generalization remains a significant challenge for CI systems, particularly in ensuring they can perform effectively in diverse, real-world settings that differ from their training environments. Advances in few-shot learning, meta-learning, and robust learning techniques could help overcome these limitations, allowing CI systems to adapt more seamlessly to new, unforeseen situations.

Additionally, the growing need for real-time decision-making in autonomous systems, robotics, and smart environments will require CI methods that can operate with minimal latency while maintaining high reliability and safety. Edge computing and reinforcement learning are promising solutions that can support real-time data processing and enable systems to adapt quickly to changing conditions.

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