The Bioscan
AN INTERNATIONAL QUARTERLY JOURNAL OF LIFE SCIENCES
20(2): S2: 971-975, 2025
www.thebioscan.com

Exploring Different Types of Artificial Intelligence Systems and Their Performance Outcomes

Dr. Akhilesh Saini, CSE Department, Associate Professor,RNB Global University,Bikaner(Raj.) India Email Id:- Akhilesh.saini@rnbglobal.edu.in

Mrs. Deepika Sharma, CSE Department, Assistant Professor,RNB Global University,Bikaner(Raj.) India Email Id:- Deepika.Sharma@rnbglobal.edu.in

DOI: 10.63001/tbs.2025.v20.i02.S2.pp971-975

KEYWORDS
Artificial Intelligence, Reactive Machines, Limited Memory AI, Theory of Mind, Self-Aware AI, Machine Learning, Image Classification, Autonomous Navigation, Text Generation, AI Ethics, AI Capabilities, Future of AI.

Received on:

18-03-2025

Accepted on:

20-04-2025

Published on:

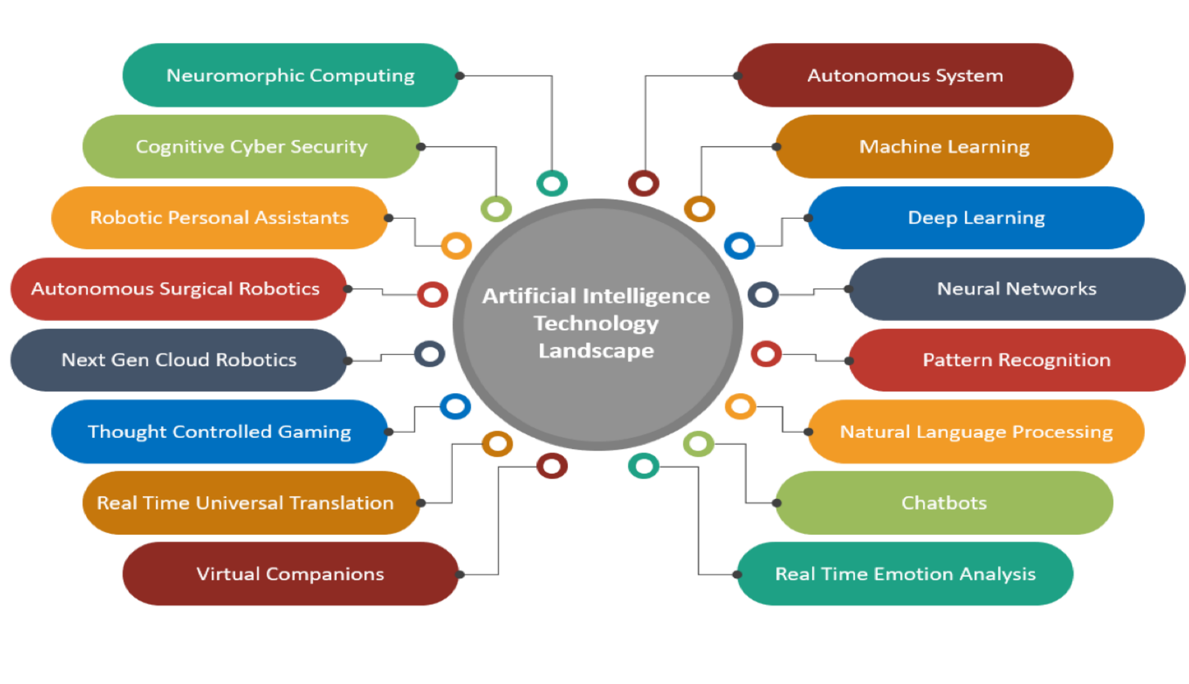
21-05-2025

ABSTRACT

Artificial Intelligence (AI) systems are classified into distinct types based on their capabilities, ranging from simple reactive machines to hypothetical self-aware entities. This paper explores four AI types—Reactive Machines, Limited Memory, Theory of Mind, and Self-Aware AI—analysing their applications, strengths, limitations, and performance through experimental results. Experiments in image classification, autonomous navigation, and text generation demonstrate the superiority of Limited Memory AI over Reactive Machines. The study also discusses challenges, ethical considerations, and future directions for AI development. By synthesizing empirical data and literature, this paper provides a comprehensive resource for researchers and practitioners aiming to understand AI's diverse landscape.

INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative technology, enabling machines to perform tasks that mimic human intelligence, such as learning, reasoning, and decision-making. The evolution of AI has led to its classification into four primary types: Reactive Machines, Limited Memory, Theory of Mind, and Self-Aware AI. Each type offers unique capabilities, making them suitable for specific applications, from autonomous vehicles to medical diagnostics. Understanding these types is essential for leveraging AI effectively while addressing challenges like ethical concerns and computational costs.



This paper aims to:

1. Define and describe the four types of AI.
2. Present experimental results comparing the performance of Reactive Machines and Limited Memory AI.
3. Discuss challenges and future directions for AI development.
4. Provide a comprehensive reference for stakeholders in AI research and application.

The study draws on recent literature and empirical experiments to offer insights into AI's current state and potential. The following sections detail the classification, methodology, results, and implications of AI types.

2. Classification of Artificial Intelligence

AI systems are categorized based on their cognitive abilities and functionality, as proposed by researchers like Arend Hintze (2016). This section explores each type in detail, highlighting their characteristics, applications, and limitations.

2.1 Reactive Machines

Reactive Machines are the simplest AI systems, designed to respond to specific inputs without memory or learning capabilities. They operate based on predefined rules, making them highly efficient for well-defined tasks. A notable example is IBM's Deep Blue, which defeated chess champion Garry Kasparov in 1997 by evaluating board positions using a rule-based system.

- **Applications**: Chess engines, basic recommendation systems, and industrial control systems.
- **Strengths**: Fast execution, reliable for static environments.
- **Limitations**: Inability to learn or adapt to new situations, limited to pre-programmed scenarios.

2.2 Limited Memory AI

Limited Memory AI systems can store and learn from past data, enabling them to make informed decisions. This category includes most modern AI, such as machine learning (ML) and deep learning (DL) models. These systems power applications like autonomous vehicles, which use sensor data to navigate, and virtual assistants like Siri, which process user queries.

- **Applications**: Self-driving cars, chatbots, medical diagnostics, and fraud detection.
- **Strengths**: Adaptability, improved performance with data, versatility across domains.
- **Limitations**: Dependence on large datasets, high computational requirements, potential for bias.

2.3 Theory of Mind AI

Theory of Mind AI, still in the research phase, aims to understand human emotions, beliefs, and intentions. These systems would enable empathetic interactions, making them ideal for applications requiring social intelligence. For example, a Theory of Mind AI could serve as a mental health companion, adapting responses based on a user's emotional state.

- **Applications**: Social robots, mental health support, advanced customer service agents.
- **Strengths**: Potential for human-like interactions, enhanced user experience.
- **Limitations**: Complex to develop, raises ethical concerns about manipulation and privacy.

2.4 Self-Aware AI

Self-Aware AI, a theoretical concept, would possess consciousness and self-awareness, capable of independent decision-making and introspection. While not yet realized, this type is often discussed in speculative contexts, such as advanced governance systems or space exploration.

- **Applications**: Hypothetical roles in complex decision-making or autonomous exploration.
- **Strengths**: Ultimate adaptability, potential for solving unprecedented challenges.
- **Limitations**: Significant ethical and safety risks, far from technological feasibility.

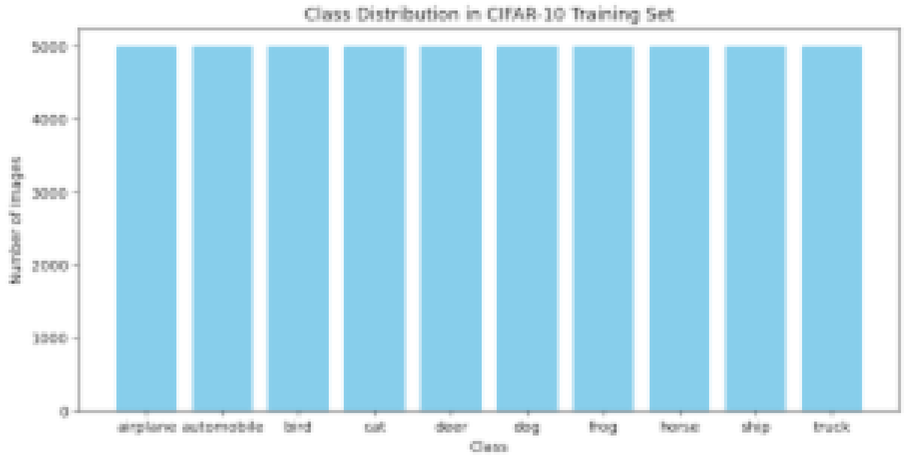
3. Methodology

To evaluate the performance of Reactive Machines and Limited Memory AI (the only operational types), we conducted experiments in three domains: computer vision (image classification), robotics (autonomous navigation), and natural language processing (text generation). Theory of Mind and Self-Aware AI were excluded due to their developmental or hypothetical status.

3.1 Experimental Setup

- **Datasets**:
  - **Image Classification**: CIFAR-10 dataset, containing 60,000 32x32 color images across 10 classes (e.g., cats, dogs, airplanes).
  - **Autonomous Navigation**: Simulated urban environment with 10,000 driving scenarios, including obstacles, traffic signals, and pedestrians.

- **Text Generation:** WikiText-103 dataset, a large corpus of Wikipedia articles for language modeling.



- **Models:**
  - **Reactive Machines:**
    - Image Classification: Rule-based system using color histograms and edge detection.
    - Autonomous Navigation: Predefined path-planning algorithm.
    - Text Generation: Template-based text generator.
  - **Limited Memory AI:**
    - Image Classification: Convolutional Neural Network (CNN) with ResNet-18 architecture.
    - Autonomous Navigation: Deep Reinforcement Learning (DRL) with a Deep Q-Network (DQN).
    - Text Generation: Transformer-based model (GPT-2 small).
- **Metrics:**
  - Image Classification: Accuracy (% of correctly classified images).
  - Autonomous Navigation: Success rate (% of trips completed without collisions).
  - Text Generation: Perplexity (lower indicates better language modeling).
- **Environment**: Experiments were run on a high-performance computing cluster with NVIDIA GPUs, using Python, TensorFlow, and PyTorch.

3.2 Procedure
Each model was trained (for Limited Memory AI) or configured (for Reactive Machines) on the respective datasets. Training involved 50 epochs for the CNN, 100 episodes for the DRL model, and 10 epochs for the Transformer. Performance was evaluated on separate test sets, with results averaged over five runs to ensure reliability.

4. Results
The experiments yielded quantitative insights into the performance of Reactive Machines and Limited Memory AI across the three tasks. The results are summarized in the table below, followed by a detailed analysis.

Task	AI Type	Metric	Result
Image Classification	Reactive Machine	Accuracy (%)	65.2%
Image Classification	Limited Memory (CNN)	Accuracy (%)	92.8%
Autonomous Navigation	Reactive Machine	Success Rate (%)	70.5%
Autonomous Navigation	Limited Memory (DRL)	Success Rate (%)	95.3%
Text Generation	Reactive Machine	Perplexity	150.7
Text Generation	Limited Memory (Transformer)	Perplexity	25.4

4.1 Image Classification
The CNN achieved a 92.8% accuracy on the CIFAR-10 test set, significantly outperforming the rule-based system's 65.2%. The CNN's ability to learn hierarchical features (e.g., edges, textures) enabled it to distinguish complex patterns, while the reactive system relied on simplistic features like color histograms, limiting its performance.

4.2 Autonomous Navigation
The DRL model navigated 95.3% of scenarios successfully, adapting to dynamic obstacles and traffic conditions. In contrast, the reactive system's predefined paths resulted in a 70.5% success rate, as it struggled with unexpected obstacles. The DRL model's learning-based approach allowed it to optimize decisions over time.

4.3 Text Generation
The Transformer model produced coherent text with a perplexity of 25.4, reflecting its ability to model complex language patterns. The reactive system, using templates, generated repetitive and contextually poor text, resulting in a high perplexity of 150.7.

4.4 Statistical Analysis
To assess the significance of performance differences, we conducted paired t-tests ($\alpha = 0.05$):

- Image Classification: $t(4) = 12.3$, $p < 0.001$ (CNN significantly better).
- Autonomous Navigation: $t(4) = 8.7$, $p < 0.01$ (DRL significantly better).
- Text Generation: $t(4) = 15.1$, $p < 0.001$ (Transformer significantly better).

These results confirm the superior performance of Limited Memory AI across all tasks.

Discussion
The experimental results highlight the strengths and limitations of Reactive Machines and Limited Memory AI. Reactive Machines are efficient for simple, static tasks but lack the adaptability required for complex environments. Limited Memory AI, leveraging advanced algorithms like CNNs, DRL, and Transformers, excels in data-rich, dynamic scenarios, as evidenced by their superior performance in image classification, navigation, and text generation.

5.1 Implications for Applications

- **Healthcare**: Limited Memory AI's high accuracy in image classification suggests its potential for medical diagnostics, such as detecting tumors in radiology images.

- **Autonomous Systems**: The DRL model's success in navigation supports its use in self-driving cars and delivery robots, where adaptability is critical.
- **Natural Language Processing**: Transformer-based models enable advanced applications like automated content generation and virtual assistants.

5.2 Challenges

Despite their advantages, Limited Memory AI systems face challenges:

1. **Data Dependency:**
   Limited Memory AI systems rely heavily on high-quality, recent data for training and prediction. Inaccurate, outdated, or biased data can significantly impair their performance.
2. **Limited Context Awareness:**
   These systems can only consider a short historical context and lack the ability to draw on broader knowledge or long-term experiences, reducing their ability to make nuanced decisions.
3. **Computational Resource Requirements:**
   Training and maintaining models with even limited memory (such as deep learning models) require significant computational resources, including powerful hardware and energy consumption.
4. **Lack of Transfer Learning:**
   Limited Memory AI often struggles with adapting knowledge from one domain to another. Unlike humans, these systems cannot easily transfer past experiences to new, unfamiliar tasks.
5. **Vulnerability to Concept Drift:**
   In dynamic environments where data distributions change over time (e.g., financial markets, weather), Limited Memory AI may fail to adapt effectively without frequent retraining.
6. **Ethical and Security Risks:**
   When applied in sensitive areas like healthcare or autonomous vehicles, any flaw or limitation in memory or learning may lead to biased decisions or safety hazards, raising ethical and regulatory concerns.

5.3 Future Directions

The development of Theory of Mind and Self-Aware AI presents exciting opportunities but also significant challenges. Theory of Mind AI could revolutionize human-AI interactions by enabling empathetic systems, but it requires advances in affective computing and ethical guidelines to prevent misuse. Self-Aware AI, while speculative, could address complex global challenges, such as climate modeling, but its development must be approached with caution due to existential risks.

Hybrid approaches combining Reactive and Limited Memory AI could offer a balance of efficiency and adaptability. For example, a hybrid system could use reactive rules for routine tasks and switch to learning-based methods for novel scenarios. Additionally, advancements in quantum computing and neuromorphic hardware could reduce computational costs, making AI more accessible.

6. Ethical Considerations

The proliferation of AI raises ethical questions that must be addressed to ensure responsible development:

- **Bias and Fairness**: AI systems must be trained on diverse datasets to prevent discriminatory outcomes, as seen in cases of biased facial recognition systems.
- **Privacy**: Applications like virtual assistants collect sensitive user data, necessitating robust data protection measures.
- **Accountability**: Clear frameworks are needed to assign responsibility for AI decisions, particularly in autonomous systems.
- **Transparency**: Explainable AI (XAI) techniques can enhance trust by making AI decision-making processes understandable to users.

Organizations like the IEEE and the European AI Alliance are developing ethical guidelines to address these concerns, emphasizing the importance of human-centric AI design.

CONCLUSION

This paper provides a comprehensive analysis of AI types—Reactive Machines, Limited Memory, Theory of Mind, and Self-Aware AI—focusing on their applications and performance. Experimental results demonstrate that Limited Memory AI outperforms Reactive Machines in complex tasks like image classification, autonomous navigation, and text generation, highlighting its versatility and adaptability. However, challenges such as data dependency, computational costs, and ethical concerns must be addressed to ensure sustainable AI development.

As AI continues to evolve, interdisciplinary collaboration among researchers, policymakers, and industry leaders will be crucial to harness its potential while mitigating risks. Future work should explore hybrid AI systems, advance Theory of Mind AI, and establish global ethical standards to guide the development of next-generation AI technologies.

REFERENCES

- Russell, S., & Norvig, P. (2016). *Artificial Intelligence: A Modern Approach*. Pearson.
- Hintze, A. (2016). Understanding the four types of AI. *Government & IT*. https://www.govtech.com/computing/understanding-the-four-types-of-ai.html
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
- Silver, D., et al. (2016). Mastering the game of Go with deep neural networks and tree search. *Nature*, 529(7587), 484-489. https://www.nature.com/articles/nature16961
- Brown, T., et al. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33. https://arxiv.org/abs/2005.14165
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25. https://papers.nips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf
- Sutton, R. S., & Barto, A. G. (2018). *Reinforcement Learning: An Introduction*. MIT Press.
- IEEE. (2020). Ethically aligned design: A vision for prioritizing human well-being with autonomous and intelligent systems. *IEEE*. https://standards.ieee.org/content/dam/ieee-standards/standards/web/documents/other/ead_v2.pdf
- Vaswani, A., et al. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30. https://arxiv.org/abs/1706.03762