

| RESEARCH ARTICLE

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GREEN ARTIFICIAL INTELLIGENCE: DESIGNING ENERGY-EFFICIENT MACHINE LEARNING MODELS FOR SUSTAINABLE COMPUTING

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| ABSTRACT

The rapid expansion of Artificial Intelligence (AI) has significantly improved automation, data analytics, and intelligent decision-making across numerous sectors. However, the increasing complexity of modern AI models has resulted in substantial computational requirements and energy consumption, raising concerns regarding environmental sustainability. Green Artificial Intelligence (Green AI) has emerged as an important research field that emphasizes the development of energy-efficient algorithms, resource-aware computing, and environmentally responsible AI systems. This paper presents a comprehensive review of Green AI, examining its principles, enabling technologies, applications, challenges, and future research directions. The study explores optimization techniques including model compression, pruning, quantization, knowledge distillation, and efficient neural network architectures.

| KEYWORDS

Green Artificial Intelligence, Sustainable Computing, Energy-Efficient Machine Learning, Model Compression, Carbon-Aware Computing, Edge AI, Deep Learning.

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Abstract:-

The rapid expansion of Artificial Intelligence (AI) has significantly improved automation, data analytics, and intelligent decision-making across numerous sectors. However, the increasing complexity of modern AI models has resulted in substantial computational requirements and energy consumption, raising concerns regarding environmental sustainability. Green Artificial Intelligence (Green AI) has emerged as an important research field that emphasizes the development of energy-efficient algorithms, resource-aware computing, and environmentally responsible AI systems. This paper presents a comprehensive review of Green AI, examining its principles, enabling technologies, applications, challenges, and future research directions. The study explores optimization techniques including model compression, pruning, quantization, knowledge distillation, and efficient neural network architectures. Additionally, it discusses the integration of renewable energy resources, cloud optimization, edge intelligence, and carbon-aware computing for sustainable AI deployment. The findings demonstrate that Green AI can substantially reduce computational costs and carbon emissions while maintaining acceptable predictive performance, thereby contributing to environmentally sustainable digital transformation.

Introduction:-

Artificial Intelligence has become a fundamental technology in modern computing, supporting applications ranging from healthcare and finance to education and autonomous systems. Recent advances in deep learning have led to increasingly large and complex models requiring massive computational resources for training and inference. These computational demands contribute to higher electricity consumption, increased operational costs, and greater environmental impact. Green Artificial

Intelligence addresses these concerns by focusing on reducing the energy requirements of AI systems while maintaining their effectiveness. The objective is to design intelligent algorithms that consume fewer computational resources, reduce greenhouse gas emissions, and promote sustainable digital infrastructure. This paper reviews Green AI technologies, discusses current optimization strategies, highlights practical applications, and identifies future research opportunities in sustainable artificial intelligence.

Background:-

Artificial Intelligence:-

Artificial Intelligence enables computer systems to perform tasks that typically require human intelligence, including learning, reasoning, prediction, and decision-making.

Major AI domains include:-

- Machine Learning
- Deep Learning
- Computer Vision
- Natural Language Processing
- Reinforcement Learning

Sustainable Computing:-

Sustainable computing focuses on reducing the environmental impact of computing systems through energy-efficient hardware, optimized software, renewable energy integration, and responsible resource management.

Principles of Green Artificial Intelligence:-

Green AI promotes efficient use of computational resources throughout the AI lifecycle.

Key principles include:-

- Energy-efficient algorithm design
- Reduced computational complexity
- Hardware optimization
- Carbon-aware scheduling
- Efficient resource utilization
- Sustainable model deployment

Techniques for Energy-Efficient AI:-

Model Compression:-

Removes redundant parameters while maintaining prediction accuracy.

Network Pruning:-

Eliminates unnecessary neural network connections to reduce computational load.

Quantization:-

Reduces numerical precision to decrease memory usage and accelerate computation.

Knowledge Distillation:-

Transfers knowledge from a large model (teacher) to a smaller model (student).

Efficient Neural Network Architectures:-

Designs lightweight architectures suitable for mobile and edge devices.

Applications:-

Smart Healthcare:-

- Energy-efficient medical diagnosis
- Wearable health monitoring
- Portable AI-assisted devices

Smart Agriculture:-

- Crop monitoring
- Precision irrigation

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- Disease detection

Environmental Monitoring:-

- Climate prediction
- Air quality assessment
- Wildlife conservation

Smart Transportation:-

- Traffic optimization
- Electric vehicle management
- Intelligent routing

Edge Computing:-

- Mobile AI applications
- Industrial automation
- Internet of Things (IoT)

Benefits of Green AI:-

The implementation of Green AI provides several advantages.

Reduced Energy Consumption:-

Efficient algorithms decrease electricity usage during model training and deployment.

Lower Operational Costs:-

Reduced computational requirements minimize infrastructure expenses.

Environmental Sustainability:-

Lower carbon emissions contribute to climate-friendly computing.

Scalable Deployment:-

Lightweight models operate effectively on resource-constrained devices.

Improved Accessibility:-

Energy-efficient AI enables deployment in developing regions with limited computational resources.

Comparative Analysis:-

Feature	Conventional AI	Green AI
Energy Consumption	High	Low
Computational Cost	High	Optimized
Carbon Emissions	Higher	Lower
Hardware Requirements	Powerful GPUs	Resource-Efficient Devices
Environmental Impact	Significant	Reduced
Deployment Flexibility	Moderate	High

Challenges:-

Although Green AI offers substantial benefits, several challenges remain.

Accuracy Trade-offs:-

Reducing model size may affect predictive performance.

Hardware Diversity:-

Different hardware platforms require customized optimization techniques.

Standardized Evaluation:-

There is a need for universal metrics to measure AI energy efficiency.

Infrastructure Limitations:-

Renewable-energy-powered data centers are not yet widely available.

Carbon Accounting:-

Measuring the environmental impact of AI training remains difficult.

Emerging Trends:-**Current research focuses on:-**

- Carbon-aware machine learning
- TinyML for ultra-low-power devices
- Green cloud computing
- Sustainable data centers
- Neuromorphic computing
- AI accelerator hardware
- Renewable-energy-driven AI infrastructure

Future Research Directions:-**Future studies should investigate:-**

- Self-optimizing AI models
- Carbon-neutral AI systems
- Energy-aware neural architecture search
- Sustainable federated learning
- Green large language models
- Low-power AI processors
- Lifecycle assessment of AI systems

Conclusion:-

Green Artificial Intelligence represents an important evolution in the development of sustainable computing technologies. By emphasizing energy efficiency, optimized resource utilization, and environmentally responsible AI deployment, Green AI addresses the growing ecological challenges associated with modern machine learning. Techniques such as model compression, pruning, quantization, and knowledge distillation enable significant reductions in computational requirements while preserving acceptable predictive performance. Although challenges related to evaluation standards, hardware diversity, and infrastructure remain, continuous research and innovation are expected to make Green AI a fundamental component of future intelligent systems. As governments and industries increasingly prioritize sustainability, Green AI will play a vital role in achieving environmentally responsible digital transformation.

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