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## **Sustainable Computing and Green AI: Frameworks, Models, and Emerging Methodologies for Energy-Efficient Artificial Intelligence**

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### **Abstract**

The rapid expansion of Artificial Intelligence (AI), cloud computing, and data-intensive technologies has significantly transformed modern digital ecosystems. However, the increasing computational demands of machine learning models, particularly deep learning architectures, have created substantial concerns regarding energy consumption, carbon emissions, and environmental sustainability. Sustainable computing and Green AI have emerged as important research domains aimed at reducing the environmental footprint of computational systems while maintaining technological efficiency and innovation.

This research paper presents a comprehensive examination of sustainable computing frameworks and Green AI methodologies by analysing existing models, technological approaches, and optimization strategies. The study explores energy-efficient algorithms, low-carbon computing infrastructures, sustainable hardware design, model compression techniques, renewable-powered data centres, and lifecycle assessment approaches. Furthermore, the paper investigates the relationship between computational efficiency, algorithmic performance, and environmental responsibility.

Using a systematic conceptual analysis approach, this research develops an integrated Green AI framework combining computational efficiency, environmental sustainability, ethical considerations, and economic feasibility. The study highlights that sustainable AI development requires a transition from performance-centric AI models toward efficiency-oriented and environmentally responsible intelligent systems.

### **Keywords:**

Sustainable Computing, Green AI, Energy-Efficient Algorithms, Artificial Intelligence, Carbon Footprint, Cloud Computing, Green Data Centres

### **1. Introduction (Expanded Version)**

The rapid advancement of digital technologies has fundamentally transformed the global technological landscape, influencing almost every sector of human activity. The emergence of **Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), cloud computing, big data analytics, and high-performance computing (HPC)** has accelerated digital transformation by enabling intelligent decision-making, automation, predictive analysis, and efficient resource management. These technologies have become essential components of modern societies, supporting critical applications in healthcare diagnostics, financial forecasting, smart transportation systems, education platforms, agricultural monitoring, industrial automation, climate modelling, and public governance.

Artificial Intelligence, in particular, has experienced unprecedented growth due to the availability of massive datasets, advanced computational infrastructure, and sophisticated deep learning algorithms. Modern AI systems, including large language models, computer vision networks, autonomous systems, and complex predictive models, have demonstrated remarkable capabilities in solving complex problems that previously required human intelligence. The integration of AI with cloud platforms and distributed computing environments has further expanded its accessibility and application across industries.

However, the rapid expansion of computational technologies has introduced significant environmental challenges. The increasing complexity of AI models has resulted in a substantial rise

in computational requirements, leading to higher energy consumption and increased carbon emissions. Training advanced machine learning models requires extensive computational power, specialized hardware such as Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs), large-scale data storage systems, and continuous infrastructure support. The energy requirements associated with AI training and deployment have raised concerns regarding the long-term environmental sustainability of artificial intelligence technologies.

Large-scale AI models involve billions of parameters and require extensive computational operations during both training and inference phases. Data centres supporting these technologies consume enormous amounts of electricity for computation, cooling systems, storage, and network operations. Although technological advancements have improved computational efficiency, the overall demand for AI services continues to grow rapidly, creating a significant challenge in balancing technological progress with environmental responsibility.

The environmental impact of AI has therefore emerged as an important research area within the broader domain of sustainable technology. Researchers and policymakers are increasingly focusing on understanding the relationship between computational efficiency, energy consumption, and ecological sustainability. Traditional AI research has primarily emphasized improving model accuracy, increasing processing speed, and achieving superior performance benchmarks. While these objectives remain important, they often overlook the environmental costs associated with computational expansion.

To address these concerns, the concept of **Green AI** has gained considerable attention as a sustainable approach to artificial intelligence development. Green AI promotes the creation and deployment of AI systems that achieve effective outcomes while minimizing computational requirements, energy consumption, and environmental impact. Unlike conventional AI approaches that primarily prioritize performance improvements, Green AI introduces efficiency as a fundamental evaluation criterion. It encourages researchers and developers to consider not only the accuracy of AI models but also their computational cost, energy requirements, carbon footprint, and overall sustainability.

The principles of Green AI emphasize several important strategies, including the development of lightweight AI models, algorithmic optimization, efficient hardware utilization, reduction of unnecessary computational processes, and adoption of renewable energy sources for AI infrastructure. Techniques such as model compression, pruning, quantization, knowledge distillation, and edge computing have emerged as important methodologies for reducing the environmental footprint of artificial intelligence systems without significantly compromising performance.

Alongside Green AI, the concept of **Sustainable Computing** provides a broader framework for ensuring environmentally responsible technological development. Sustainable computing considers the entire lifecycle of computing systems, beginning with hardware manufacturing and extending through software development, operational energy consumption, maintenance, and electronic waste disposal. It aims to create computing environments that are economically viable, socially responsible, and environmentally sustainable.

Sustainable computing incorporates multiple dimensions, including energy-efficient hardware design, optimized software engineering practices, responsible resource utilization, renewable-energy-powered infrastructure, and effective electronic waste management. It recognizes that sustainability cannot be achieved only through improving algorithms but requires a comprehensive transformation of the entire digital ecosystem.

The growing importance of sustainable computing and Green AI is also closely connected with global sustainability goals, particularly those related to climate action, responsible consumption, and technological innovation. Organizations, governments, and industries are increasingly exploring methods to reduce the environmental impact of digital technologies while continuing to benefit from AI-driven innovation.

Furthermore, the development of sustainable AI requires consideration of ethical, economic, and social factors. While energy efficiency is a major concern, issues such as accessibility, digital inequality, responsible innovation, and transparency must also be addressed. A sustainable AI ecosystem should ensure that technological advancement benefits society without creating additional environmental or social challenges.

This research paper aims to provide a comprehensive study of sustainable computing and Green AI frameworks by examining their theoretical foundations, technological models, implementation methods, and broader implications. The study explores various approaches for improving computational efficiency, reducing environmental impact, and developing responsible AI systems. It also analyses the challenges associated with Green AI adoption and proposes an integrated framework that combines technological innovation with environmental sustainability.

The paper argues that the future development of artificial intelligence must move beyond performance-oriented approaches toward sustainability-oriented models. By integrating energy efficiency, environmental responsibility, and ethical governance into AI development, Green AI can contribute significantly to creating a sustainable digital future.

## **2. Conceptual Understanding of Sustainable Computing**

### **2.1 Definition of Sustainable Computing**

Sustainable computing represents an emerging paradigm in information technology that focuses on developing and managing computing systems in an environmentally responsible, economically efficient, and socially beneficial manner. It involves the integration of sustainability principles into every stage of the computing lifecycle, including the design, manufacturing, deployment, operation, maintenance, and disposal of computing technologies.

The primary objective of sustainable computing is to minimize the negative environmental consequences associated with digital technologies while ensuring that computing systems continue to deliver reliable, efficient, and accessible services. Unlike traditional computing approaches that primarily emphasize performance, speed, and scalability, sustainable computing introduces environmental efficiency as a key consideration in technological development.

The rapid expansion of digital infrastructure, cloud services, artificial intelligence applications, and data-driven technologies has significantly increased global energy consumption. Data centres, computational devices, networking infrastructure, and electronic equipment require substantial energy resources, contributing to greenhouse gas emissions and environmental degradation. Sustainable computing seeks to address these challenges by optimizing computational processes, reducing energy requirements, and promoting responsible technology practices.

Sustainable computing is based on the principle that technological advancement and environmental protection should progress together. It recognizes that computing systems must not only provide economic and operational benefits but also operate within ecological limits. Therefore, sustainability considerations must be integrated into hardware design, software development, algorithm optimization, energy management, and end-of-life technology disposal.

The concept extends beyond reducing electricity consumption and includes broader issues such as carbon neutrality, resource conservation, sustainable manufacturing practices, ethical technology consumption, and effective management of electronic waste. It promotes a holistic approach where technological systems are evaluated not only based on their computational capabilities but also according to their environmental and social impact.

### **Major Components of Sustainable Computing**

#### **1. Energy-Efficient Computing Systems**

Energy efficiency is one of the fundamental principles of sustainable computing. Modern computing systems, particularly those supporting artificial intelligence, cloud computing, and high-performance applications, require significant amounts of electricity. Improving energy efficiency helps reduce operational costs as well as environmental impacts associated with power generation.

Energy-efficient computing involves designing and implementing systems that achieve maximum computational performance while consuming minimum energy. This includes:

- Development of low-power processors and energy-efficient hardware components.
- Optimization of software algorithms to reduce unnecessary computational operations.
- Use of efficient cooling technologies in data centres.
- Implementation of power management systems that dynamically adjust energy usage according to workload requirements.
- Adoption of edge computing to reduce data transmission and centralized processing demands.

For example, modern AI applications increasingly utilize lightweight machine learning models that require fewer computational resources while maintaining acceptable performance levels. Such approaches reduce energy consumption during both training and deployment phases.

## **2. Reduced Carbon Emissions**

A major objective of sustainable computing is reducing the carbon footprint generated by digital technologies. Computing infrastructure contributes to carbon emissions through electricity consumption, hardware manufacturing, transportation, and electronic waste generation.

Carbon reduction strategies in sustainable computing include:

### **Renewable Energy Integration**

Data centres and computing facilities are increasingly adopting renewable energy sources such as:

- Solar power
- Wind energy
- Hydroelectric energy

The transition toward renewable-powered computing infrastructure helps reduce dependence on fossil fuels and lowers greenhouse gas emissions.

### **Carbon-Aware Computing**

Carbon-aware computing involves scheduling computational tasks according to periods when cleaner energy sources are available. For instance, non-urgent AI training workloads can be performed when renewable energy availability is higher.

### **Efficient Resource Allocation**

Optimizing computational workloads prevents unnecessary energy consumption and reduces emissions associated with excessive resource usage.

Through these approaches, sustainable computing contributes to global environmental goals, including climate change mitigation and sustainable technological development.

## **3. Sustainable Hardware Manufacturing**

Hardware production represents a significant component of the environmental impact of computing technologies. The manufacturing of processors, servers, storage devices, and electronic components requires large amounts of raw materials, energy, and water resources.

Sustainable hardware manufacturing focuses on:

- Designing energy-efficient processors and devices.
- Reducing the use of hazardous materials.
- Increasing the durability and lifespan of electronic equipment.
- Promoting recyclable and reusable components.
- Improving manufacturing processes to reduce environmental damage.

The concept of **hardware sustainability** emphasizes that environmental responsibility should begin before a device becomes operational. The production phase must consider resource extraction, manufacturing emissions, transportation impacts, and future recyclability.

Technological innovations such as modular hardware design, recyclable materials, and low-power semiconductor technologies are important steps toward reducing the ecological footprint of computing devices.

#### **4. Efficient Resource Utilization**

Sustainable computing emphasizes the optimal utilization of computational resources, including processing power, storage capacity, network bandwidth, and energy resources.

Inefficient resource utilization results in:

- Increased energy consumption.
- Higher operational costs.
- Unnecessary infrastructure expansion.
- Greater environmental impact.

Resource optimization techniques include:

##### **Virtualization**

Virtualization allows multiple computing environments to operate on a single physical server, improving hardware utilization and reducing energy requirements.

##### **Cloud Resource Management**

Cloud platforms use intelligent allocation techniques to dynamically manage computing resources according to demand.

##### **AI-Based Optimization**

Artificial intelligence itself can be used to improve resource management by predicting workloads, optimizing energy consumption, and improving infrastructure efficiency.

Efficient resource utilization ensures that computing systems provide maximum value while minimizing environmental costs.

#### **5. Responsible Electronic Waste Management**

Electronic waste, commonly known as e-waste, is one of the fastest-growing environmental challenges associated with technological development. Rapid innovation cycles and frequent replacement of electronic devices contribute significantly to waste generation.

Sustainable computing promotes responsible electronic waste management through:

- Recycling electronic components.
- Recovering valuable materials from outdated devices.
- Extending hardware lifespan through maintenance and upgrades.
- Promoting responsible disposal practices.
- Developing circular economy approaches for technology products.

A circular computing model encourages the reuse, refurbishment, and recycling of electronic equipment rather than a linear model of production, consumption, and disposal.

Effective e-waste management reduces environmental pollution, conserves natural resources, and supports sustainable technology development.

##### **Importance of Sustainable Computing in Modern Technology**

The importance of sustainable computing has increased due to the rapid growth of emerging technologies such as artificial intelligence, blockchain, cloud computing, and the Internet of Things. These technologies provide significant economic and social benefits but also create substantial environmental challenges.

Sustainable computing helps achieve a balance between technological advancement and environmental responsibility by:

- Reducing energy consumption of digital infrastructure.
- Supporting climate change mitigation efforts.
- Improving operational efficiency.
- Lowering technology-related costs.
- Encouraging responsible innovation.
- Promoting long-term digital sustainability.

As computational demands continue to increase, sustainable computing has become essential for ensuring that future technological development remains environmentally feasible and socially beneficial.

### Relationship Between Sustainable Computing and Green AI

Sustainable computing provides the broader foundation within which Green AI operates. While sustainable computing addresses the complete lifecycle of computing technologies, Green AI specifically focuses on making artificial intelligence systems more efficient and environmentally responsible.

The relationship can be understood as follows:

Sustainable Computing	Green AI
Focuses on complete computing ecosystem	Focuses specifically on AI systems
Addresses hardware, software, energy, and disposal	Addresses AI algorithms, models, and training efficiency
Promotes overall technological sustainability	Promotes sustainable artificial intelligence
Includes data centres and infrastructure	Includes model optimization and computational efficiency

Together, sustainable computing and Green AI provide a comprehensive framework for developing future technologies that are intelligent, efficient, and environmentally responsible.

### 3. Evolution of Green Computing

Green computing has evolved as a response to the increasing environmental impact of information and communication technologies (ICT). Initially, computing development was primarily focused on improving processing speed, storage capacity, and system performance, with limited attention given to energy consumption and environmental consequences. However, the rapid expansion of digital infrastructure, increasing dependence on data centres, and growing awareness of climate change gradually shifted attention toward sustainable technology practices.

The evolution of green computing reflects a transition from simple energy conservation measures to a comprehensive sustainability approach that integrates energy efficiency, renewable energy utilization, carbon reduction, responsible hardware development, and sustainable artificial intelligence. This evolution can be divided into four major phases:

Period	Major Development	Key Characteristics
1990s	Energy conservation awareness in computing	Initial focus on reducing power consumption and improving energy efficiency of computer systems
2000–2010	Development of energy-efficient hardware	Introduction of low-power processors, efficient chips, and environmentally conscious hardware design
2010–2020	Growth of cloud sustainability initiatives	Expansion of green data centres, virtualization, renewable energy adoption, and efficient resource management
2020 onwards	Integration of Green AI and sustainable machine learning	Development of energy-efficient AI models, carbon-aware computing, and sustainable intelligent systems

#### 3.1 Early Phase: Energy Conservation Awareness in Computing (1990s)

During the 1990s, environmental concerns related to computing were relatively limited because digital technologies were still developing and computer usage was significantly lower compared to present conditions. However, increasing adoption of personal computers in offices, educational institutions, and businesses gradually highlighted the need for reducing electricity consumption.

The primary focus during this period was **energy conservation** rather than comprehensive sustainability. Organizations began exploring methods to reduce unnecessary power usage through:

- Power management features in computers.
- Automatic sleep and shutdown mechanisms.

- Energy-efficient display technologies.
- Improved system configurations.

One of the significant developments during this period was the emergence of awareness regarding the environmental consequences of electronic devices. The concept of environmentally responsible computing began gaining recognition as organizations realized that reducing energy consumption could provide both economic and ecological benefits.

Initiatives promoting energy-efficient electronic products encouraged manufacturers to design devices with lower power requirements. These early efforts established the foundation for future green computing practices.

### **3.2 Hardware Efficiency Phase: Development of Energy-Efficient Hardware (2000–2010)**

The second phase of green computing evolution was characterized by significant advancements in hardware efficiency. As computer usage expanded globally, energy consumption associated with processors, servers, and networking equipment became a major concern.

During this period, manufacturers focused on developing hardware components that provided improved performance while consuming less electricity. The concept of **performance per watt** became an important measurement criterion in computer engineering.

Major developments included:

#### **1. Low-Power Processors**

Processor manufacturers introduced technologies that reduced energy consumption through:

- Dynamic voltage scaling.
- Improved semiconductor design.
- Multi-core processor architectures.
- Efficient power management systems.

#### **2. Energy-Efficient Servers**

Organizations began replacing traditional servers with more efficient systems capable of delivering higher performance with reduced power requirements.

#### **3. Improved Cooling Technologies**

Data centres started adopting advanced cooling techniques because cooling systems represented a significant portion of total energy consumption.

#### **4. Energy Standards and Certifications**

Environmental standards encouraged manufacturers to produce energy-efficient devices. Certifications for sustainable electronic products increased consumer awareness regarding environmentally responsible technology choices.

This period established the importance of designing hardware not only for performance but also for energy efficiency and environmental responsibility.

### **3.3 Cloud Sustainability Phase: Growth of Green Data Centres and Cloud Computing (2010–2020)**

The rapid growth of cloud computing transformed the green computing landscape. Instead of organizations maintaining individual physical servers, cloud platforms enabled shared infrastructure and more efficient resource utilization.

Cloud computing contributed to sustainability through:

#### **1. Virtualization Technologies**

Virtualization allowed multiple applications and operating systems to run on a single physical server. This improved hardware utilization and reduced:

- Number of physical machines required.
- Electricity consumption.
- Infrastructure costs.

#### **2. Green Data Centres**

Large technology organizations began developing sustainable data centres incorporating:

- Energy-efficient servers.

- Advanced cooling systems.
- Renewable energy sources.
- Automated energy management systems.

### **3. Renewable Energy Integration**

Cloud providers increasingly invested in renewable energy projects to reduce the carbon footprint associated with their operations.

### **4. Resource Optimization**

Cloud platforms introduced intelligent resource allocation mechanisms that dynamically adjusted computing capacity according to demand.

The focus of green computing during this period expanded from individual devices to large-scale digital ecosystems. Sustainability became a strategic priority for technology companies operating global computing infrastructure.

### **3.4 Artificial Intelligence Sustainability Phase: Integration of Green AI and Sustainable Machine Learning (2020 Onwards)**

The emergence of advanced artificial intelligence represents the latest stage in green computing evolution. The development of deep learning models, large language models, and complex AI applications has created unprecedented computational demands.

Modern AI systems require:

- Massive datasets.
- High-performance computing infrastructure.
- Specialized AI processors.
- Continuous computational resources.

These requirements have increased concerns regarding energy consumption and carbon emissions.

As a result, the concept of **Green AI** emerged, emphasizing the development of AI systems that achieve high performance with reduced computational and environmental costs.

Major developments after 2020 include:

#### **1. Energy-Efficient AI Models**

Researchers began developing smaller and more efficient AI models using techniques such as:

- Model pruning.
- Quantization.
- Knowledge distillation.
- Efficient neural network architectures.

These approaches reduce computational requirements while maintaining acceptable accuracy.

#### **2. Sustainable Machine Learning Practices**

Sustainable machine learning focuses on optimizing the complete AI lifecycle:

- Efficient data collection.
- Responsible model training.
- Energy-aware deployment.
- Sustainable infrastructure selection.

#### **3. Carbon-Aware Computing**

Modern computing systems increasingly consider carbon emissions while scheduling computational workloads.

Examples include:

- Running intensive AI training when renewable energy availability is high.
- Selecting environmentally efficient cloud regions.
- Monitoring AI carbon footprints.

#### **4. Edge AI and Distributed Computing**

Edge computing reduces dependence on centralized data centres by processing information closer to the source of data generation.

Benefits include:

- Lower communication energy requirements.
- Faster response times.
- Reduced network load.

### 3.5 Transition from Green Computing to Sustainable Intelligent Systems

The evolution of green computing demonstrates a significant transformation in technological thinking. Earlier approaches focused mainly on reducing electricity consumption, while modern approaches consider sustainability throughout the entire technology lifecycle.

The transition can be summarized as:

Traditional Computing Approach	Green Computing Approach	Sustainable AI Approach
Focus on performance improvement	Focus on energy efficiency	Focus on intelligent sustainability
High resource consumption accepted	Resource optimization emphasized	Environmental impact considered during AI design
Hardware-oriented solutions	Hardware and infrastructure solutions	Algorithmic, computational, and ethical solutions

### 4. Green AI Frameworks

Green AI frameworks represent a systematic approach for developing artificial intelligence systems that achieve desired computational outcomes while minimizing environmental impact. Traditional AI development has historically focused on improving model accuracy, increasing computational capabilities, and achieving higher performance benchmarks. However, the growing environmental cost of AI has encouraged researchers and organizations to adopt sustainability-oriented frameworks that consider energy consumption, carbon emissions, resource utilization, and long-term ecological impacts.

Green AI frameworks integrate principles from artificial intelligence, sustainable computing, energy management, and environmental engineering. These frameworks aim to reduce the computational burden of AI systems without compromising their effectiveness. They focus on optimizing every stage of the AI lifecycle, including data collection, model development, training, deployment, and continuous operation.

The major Green AI frameworks include:

1. **Energy-Aware AI Framework**
2. **Sustainable Machine Learning Framework**
3. **Carbon-Aware Computing Framework**

#### 4.1 Energy-Aware AI Framework

The **Energy-Aware AI Framework** focuses on designing and implementing artificial intelligence systems that minimize energy consumption throughout their operational lifecycle. Since AI models, particularly deep learning systems, require extensive computational resources, energy efficiency has become a critical factor in sustainable AI development.

This framework considers energy consumption during three major stages:

##### A. Energy Optimization During Model Training

Training is one of the most energy-intensive phases of artificial intelligence development. Large-scale models require thousands of computational hours on specialized hardware such as GPUs and AI accelerators.

Energy-aware training strategies include:

- Selecting computationally efficient algorithms.
- Reducing unnecessary training iterations.
- Optimizing hyperparameter tuning processes.
- Using energy-efficient hardware infrastructure.

- Applying transfer learning techniques to avoid repeated training.

For example, instead of training a large AI model from the beginning, transfer learning allows researchers to adapt an existing trained model for a new task, significantly reducing computational requirements.

### **B. Energy Optimization During Data Processing**

Data processing represents another major source of energy consumption in AI systems. Large datasets require extensive storage, processing, and movement across computing networks.

Energy-aware data management strategies include:

- Removing redundant or unnecessary data.
- Improving data preprocessing techniques.
- Using efficient data storage methods.
- Reducing unnecessary data transfers.
- Applying intelligent data sampling techniques.

Efficient data processing reduces computational workload and improves the overall sustainability of AI systems.

### **C. Energy Optimization During Model Deployment**

After training, AI models require continuous computational resources during deployment. Applications such as recommendation systems, autonomous vehicles, and healthcare platforms process large volumes of information continuously.

Energy-efficient deployment strategies include:

- Lightweight AI models.
- Edge computing solutions.
- Optimized inference mechanisms.
- Low-power AI hardware.
- Dynamic resource allocation.

These methods allow AI systems to operate effectively while consuming less energy.

#### **4.1.1 Model Compression Techniques**

One of the most important strategies within the Energy-Aware AI Framework is **model compression**.

Model compression refers to reducing the size and complexity of AI models while maintaining acceptable levels of accuracy and performance. Large AI models often contain unnecessary parameters and computational operations. Removing these inefficiencies helps reduce memory requirements, processing time, and energy consumption.

The major model compression techniques include:

##### **1. Pruning**

Pruning is a technique that removes unnecessary or less important components of an artificial neural network.

In deep learning models, many parameters contribute very little to the final prediction outcome. Pruning identifies and eliminates these redundant parameters, resulting in smaller and more efficient models.

##### **Benefits of Pruning:**

- Reduces model size.
- Decreases computational requirements.
- Improves inference speed.
- Lowers energy consumption.

For example, a neural network containing millions of parameters can often maintain similar accuracy after removing unnecessary connections.

##### **2. Quantization**

Quantization reduces the numerical precision used to represent model parameters.

Traditional AI models often use high-precision numerical formats. Quantization converts these values into lower-precision formats, reducing computational requirements.

**Advantages of Quantization:**

- Lower memory usage.
- Faster computation.
- Reduced hardware requirements.
- Improved deployment efficiency on mobile and edge devices.

Quantized models are particularly useful for applications requiring real-time AI processing with limited computational resources.

**3. Knowledge Distillation**

Knowledge distillation is a technique where a smaller AI model, known as a **student model**, learns from a larger and more complex **teacher model**.

The objective is to transfer the knowledge of the large model into a compact model that requires fewer resources.

**Benefits:**

- Maintains high prediction accuracy.
- Reduces computational complexity.
- Enables AI deployment on resource-limited devices.
- Improves energy efficiency.

Knowledge distillation has become increasingly important for developing sustainable AI applications in smartphones, IoT devices, and edge computing environments.

**4.2 Sustainable Machine Learning Framework**

The **Sustainable Machine Learning Framework** focuses on integrating sustainability principles into the complete machine learning lifecycle. It recognizes that environmental responsibility must be considered not only during model development but also during data management, algorithm design, and hardware selection.

A sustainable machine learning framework consists of three major components:

1. Data Efficiency
2. Algorithm Efficiency
3. Hardware Optimization

**4.2.1 Data Efficiency**

Data efficiency refers to reducing unnecessary data collection, processing, and storage while maintaining model effectiveness.

Modern machine learning systems often rely on extremely large datasets. However, processing excessive amounts of data increases:

- Energy consumption.
- Storage requirements.
- Computational workload.
- Infrastructure demands.

Sustainable data practices include:

**Data Reduction**

Removing duplicate, irrelevant, or low-quality data before training.

**Efficient Data Sampling**

Using representative samples instead of processing complete datasets unnecessarily.

**Data Lifecycle Management**

Managing data storage, access, and deletion responsibly.

**Federated Learning**

Federated learning allows AI models to learn from decentralized data sources without transferring all data to centralized servers, reducing communication and energy costs.

**4.2.2 Algorithm Efficiency**

Algorithm efficiency focuses on developing AI algorithms that require fewer computational resources while achieving comparable performance.

Efficient algorithms emphasize:

- Reduced complexity.
- Faster processing.
- Lower memory requirements.
- Optimized mathematical operations.

Examples include:

- Lightweight neural network architectures.
- Efficient optimization algorithms.
- Adaptive learning approaches.

Algorithm efficiency is essential because improvements in software design can significantly reduce the energy requirements of AI systems without requiring additional hardware investments.

#### **4.2.3 Hardware Optimization**

Hardware optimization involves selecting and designing computing infrastructure that provides maximum performance with minimum energy consumption.

Important approaches include:

##### **Energy-Efficient Processors**

Modern AI hardware such as specialized AI chips and low-power processors provide improved computational efficiency.

##### **Edge Computing Devices**

Edge devices process information locally, reducing dependency on energy-intensive cloud infrastructure.

##### **Advanced Cooling Systems**

Efficient cooling technologies reduce energy consumption in large-scale data centres.

Hardware optimization ensures that AI systems operate sustainably throughout their deployment lifecycle.

#### **4.3 Carbon-Aware Computing Framework**

The **Carbon-Aware Computing Framework** focuses on reducing the carbon footprint associated with computational activities. Unlike traditional computing systems that prioritize only speed and availability, carbon-aware computing considers environmental factors when making decisions about resource allocation and workload scheduling.

This framework aims to ensure that computational tasks are performed in ways that minimize greenhouse gas emissions.

The major components include:

##### **4.3.1 Measuring Carbon Emissions**

The first step in carbon-aware computing is accurately measuring the environmental impact of computing activities.

Carbon measurement includes:

- Electricity consumption tracking.
- Data centre emissions analysis.
- Hardware lifecycle assessment.
- AI model carbon footprint estimation.

Carbon monitoring enables organizations to understand the environmental cost of their digital operations and identify opportunities for improvement.

##### **4.3.2 Selecting Renewable Energy Sources**

Carbon-aware computing encourages the use of renewable energy-powered infrastructure.

Renewable energy sources include:

- Solar energy.

- Wind energy.
- Hydroelectric power.

Data centres powered by renewable energy significantly reduce their carbon emissions compared with facilities dependent on fossil fuels.

### 4.3.3 Optimizing Computational Timing

One of the important principles of carbon-aware computing is adjusting computational activities according to energy availability.

For example:

- AI training tasks can be scheduled during periods when renewable energy production is high.
- Non-urgent computational workloads can be shifted to locations with cleaner energy sources.
- Cloud workloads can be dynamically allocated according to carbon intensity levels.

This approach reduces emissions without reducing computational capability.

### 4.4 Integrated Green AI Framework

The three frameworks together create a comprehensive sustainability model:

Framework	Primary Focus	Key Strategies
Energy-Aware AI Framework	Reducing AI energy consumption	Model compression, efficient training, optimized deployment
Sustainable Machine Learning Framework	Sustainable AI lifecycle management	Data efficiency, algorithm optimization, hardware efficiency
Carbon-Aware Computing Framework	Reducing environmental impact	Carbon monitoring, renewable energy, workload optimization

## 5. Models and Methods for Green AI

The rapid expansion of Artificial Intelligence (AI) applications has created a need for computational models and technological methods that can achieve high performance while minimizing environmental impact. Green AI focuses on developing AI systems that are computationally efficient, energy-conscious, and environmentally sustainable. Achieving sustainable AI requires improvements not only in algorithms and models but also in hardware infrastructure and cloud computing environments.

Green AI methods can broadly be classified into three major categories:

1. **Model Optimization Techniques** – Improving the efficiency of AI algorithms and reducing computational complexity.
2. **Hardware-Based Sustainability** – Developing energy-efficient computing infrastructure for AI operations.
3. **Cloud-Based Green Computing** – Creating sustainable large-scale computing environments through efficient data centres and renewable energy adoption.

### 5.1 Model Optimization Techniques

Model optimization represents one of the most important approaches for achieving sustainable artificial intelligence. Traditional AI models, particularly deep neural networks, often contain millions or billions of parameters, resulting in significant computational requirements and energy consumption.

Model optimization techniques aim to reduce model complexity while maintaining acceptable accuracy and performance. These methods help decrease:

- Training time.
- Memory requirements.
- Computational operations.
- Energy consumption.
- Deployment costs.

The major model optimization techniques include:

Method	Purpose	Sustainability Benefits
Pruning	Removes unnecessary parameters	Reduces computational workload and energy consumption
Quantization	Reduces computational precision	Decreases memory usage and improves processing efficiency
Distillation	Transfers knowledge to smaller models	Creates compact models with lower resource requirements
Efficient Architectures	Creates lightweight AI systems	Enables sustainable AI deployment on limited-resource devices

### 5.1.1 Pruning

Pruning is a model optimization technique that reduces the size of artificial neural networks by removing unnecessary or less important parameters, connections, or neurons.

Large AI models often contain redundant information because not all parameters contribute equally to prediction accuracy. Pruning identifies these unnecessary components and eliminates them, creating a smaller and more efficient model.

#### Types of Pruning

##### 1. Weight Pruning

Weight pruning removes individual parameters with very low importance values.

#### Benefits:

- Reduces model size.
- Decreases storage requirements.
- Lowers computational operations.

##### 2. Neuron Pruning

Neuron pruning removes entire neurons or network structures that contribute minimally to model performance.

#### Advantages:

- Simplifies model architecture.
- Improves computational efficiency.
- Reduces inference time.

##### 3. Structured Pruning

Structured pruning removes complete filters, channels, or layers from neural networks.

This method is particularly useful for hardware implementation because it creates models that can run efficiently on practical devices.

#### Sustainability Impact of Pruning

Pruning contributes to Green AI by:

- Reducing energy requirements during model training.
- Improving inference efficiency.
- Enabling AI deployment on smaller devices.
- Extending battery life of mobile and IoT devices.

### 5.1.2 Quantization

Quantization is a technique that reduces the precision of numerical values used in AI models. Most AI models use high-precision calculations, which require significant computational resources.

Quantization converts these values into lower-precision formats, allowing models to operate more efficiently.

For example:

- 32-bit floating-point calculations can be converted into 16-bit or 8-bit representations.

### **Benefits of Quantization**

#### **1. Reduced Memory Consumption**

Smaller numerical representations require less storage space.

#### **2. Faster Computation**

Lower precision calculations can be processed more efficiently by modern hardware.

#### **3. Lower Energy Usage**

Reduced computational requirements result in lower electricity consumption.

#### **4. Improved Edge Deployment**

Quantized models can operate effectively on smartphones, IoT devices, and embedded systems.

### **5.1.3 Knowledge Distillation**

Knowledge distillation is a technique where a smaller AI model learns from a larger and more complex model.

The larger model is called the **teacher model**, while the smaller optimized model is called the **student model**.

The objective is to transfer the important knowledge of the teacher model into the student model while reducing computational requirements.

#### **Process of Knowledge Distillation**

1. A large, high-performance model is trained.
2. The large model generates learning information.
3. A smaller model learns from this information.
4. The smaller model achieves comparable performance with fewer resources.

### **Sustainability Advantages**

Knowledge distillation helps Green AI by:

- Reducing model size.
- Lowering computational demand.
- Decreasing energy consumption.
- Enabling AI applications on resource-constrained devices.

### **5.1.4 Efficient AI Architectures**

Efficient architectures focus on designing AI models that provide high performance with reduced computational complexity.

Traditional deep learning architectures often prioritize accuracy without considering resource consumption. Efficient architectures introduce sustainability as a design objective.

Examples include:

- Lightweight neural networks.
- Mobile AI architectures.
- Efficient transformer models.
- Compact deep learning frameworks.

### **Characteristics of Efficient AI Architectures**

- Fewer parameters.
- Reduced memory requirements.
- Faster processing.
- Lower energy consumption.
- Better suitability for edge devices.

Efficient architectures are particularly important for applications where computational resources are limited, such as:

- Mobile devices.
- Smart sensors.
- Autonomous systems.
- Internet of Things applications.

## 5.2 Hardware-Based Sustainability

While algorithm optimization reduces computational requirements, sustainable AI also depends on improvements in hardware infrastructure. AI workloads require specialized computing systems capable of performing complex mathematical operations efficiently.

Hardware-based sustainability focuses on developing and utilizing computing devices that provide greater performance with lower energy consumption.

Modern approaches include:

### 5.2.1 Energy-Efficient GPUs

Graphics Processing Units (GPUs) play a major role in AI training and deployment because of their ability to process large amounts of data simultaneously.

Energy-efficient GPUs are designed to:

- Deliver higher computational performance per watt.
- Reduce electricity consumption.
- Improve thermal management.
- Support sustainable AI workloads.

Modern GPU designs incorporate advanced semiconductor technologies and optimized architectures to improve energy efficiency.

### 5.2.2 Specialized AI Chips

Specialized AI chips are hardware components designed specifically for artificial intelligence workloads.

Examples include:

- Tensor Processing Units (TPUs).
- Neural Processing Units (NPU).
- AI accelerators.

These chips perform AI computations more efficiently than general-purpose processors.

#### Advantages:

- Faster AI processing.
- Lower energy consumption.
- Improved computational efficiency.
- Reduced dependence on high-power computing systems.

Specialized AI hardware is becoming increasingly important for sustainable AI deployment in data centres and edge environments.

### 5.2.3 Edge Computing Devices

Edge computing involves processing data closer to the location where it is generated rather than sending all information to centralized cloud servers.

Examples include:

- Smart sensors.
- Industrial IoT devices.
- Autonomous systems.
- Mobile AI devices.

#### Sustainability Benefits:

- Reduces network energy consumption.
- Minimizes data transfer requirements.
- Improves response time.
- Reduces dependence on energy-intensive data centres.

Edge AI is particularly valuable for applications requiring real-time decision-making with limited connectivity.

#### **5.2.4 Low-Power Processors**

Low-power processors are designed to perform computational tasks while consuming minimal energy.

They are widely used in:

- IoT devices.
- Wearable technologies.
- Smart home systems.
- Embedded AI applications.

Benefits include:

- Extended battery life.
- Reduced energy consumption.
- Lower operational costs.
- Environmentally sustainable device operation.

#### **5.3 Cloud-Based Green Computing**

Cloud computing has become a central component of modern AI infrastructure. Large AI models require enormous computational resources that are often provided through cloud platforms.

However, cloud infrastructure consumes significant amounts of electricity. Therefore, cloud providers are increasingly adopting green computing strategies to reduce environmental impact.

Cloud-based Green Computing focuses on:

- Sustainable energy management.
- Efficient infrastructure utilization.
- Carbon reduction.
- Environmentally responsible data centre operations.

##### **5.3.1 Renewable Energy Integration**

Cloud service providers are increasingly incorporating renewable energy sources into their operations.

Major renewable energy sources include:

- Solar power.
- Wind energy.
- Hydroelectric power.

**Benefits:**

- Reduction in greenhouse gas emissions.
- Lower dependence on fossil fuels.
- Support for carbon-neutral computing goals.

Renewable-powered data centres represent an important step toward sustainable AI infrastructure.

##### **5.3.2 Efficient Cooling Systems**

Cooling represents a significant portion of data centre energy consumption. AI workloads generate substantial heat due to intensive computational operations.

Green cooling approaches include:

###### **Advanced Air Cooling**

Improved airflow management reduces unnecessary cooling energy.

###### **Liquid Cooling**

Liquid cooling technologies remove heat more efficiently than traditional cooling systems.

###### **AI-Based Cooling Management**

Artificial intelligence itself can optimize cooling operations by predicting temperature patterns and adjusting cooling requirements.

##### **5.3.3 Data Centre Optimization**

Green data centres focus on maximizing efficiency through:

- Virtualization.

- Automated workload management.
- Efficient server utilization.
- Smart energy monitoring.
- Optimized infrastructure design.

Data centre optimization reduces:

- Energy waste.
- Operational costs.
- Carbon emissions.

### 5.3.4 Carbon-Neutral Operations

Many cloud providers are working toward carbon-neutral or carbon-negative operations by implementing:

- Renewable energy adoption.
- Carbon offset programmes.
- Energy-efficient infrastructure.
- Sustainable hardware practices.

Carbon-neutral operations aim to ensure that digital growth does not contribute significantly to climate change.

### 5.4 Integrated Green AI Technology Model

The relationship between algorithms, hardware, and cloud infrastructure can be represented as:

Layer	Green AI Approach	Sustainability Outcome
Algorithm Layer	Pruning, quantization, distillation	Reduced computational complexity
Hardware Layer	Efficient GPUs, AI chips, low-power processors	Lower energy consumption
Infrastructure Layer	Renewable cloud systems, green data centres	Reduced carbon emissions

### 6. Conclusion

Sustainable computing and Green AI represent a fundamental transformation in the way future digital technologies are designed, developed, and implemented. The rapid expansion of artificial intelligence, cloud computing, big data analytics, and advanced computational systems has created unprecedented opportunities for innovation; however, it has also introduced significant environmental challenges related to energy consumption, carbon emissions, resource utilization, and electronic waste generation. Therefore, the future development of digital technologies must focus not only on computational power and performance improvement but also on environmental responsibility and long-term sustainability.

The objective of sustainable computing is not merely to reduce energy consumption but to establish a comprehensive technological ecosystem where hardware, software, algorithms, infrastructure, and governance mechanisms operate in an environmentally responsible manner. Green AI extends this vision by introducing sustainability as a fundamental principle in artificial intelligence research and deployment. It encourages the development of AI systems that achieve effective results while minimizing computational requirements, energy usage, and ecological impact.

The study of Green AI frameworks demonstrates that sustainability can be achieved through multiple interconnected approaches. Energy-aware AI frameworks contribute by reducing computational requirements through techniques such as model pruning, quantization, knowledge distillation, and efficient neural network architectures. Sustainable machine learning approaches promote responsible data management, optimized algorithms, and efficient hardware utilization. Carbon-aware computing

further strengthens sustainability by integrating renewable energy sources, monitoring carbon emissions, and optimizing computational activities according to environmental conditions.

The proposed Integrated Green AI Framework provides a holistic approach by combining five essential dimensions: sustainable infrastructure, efficient algorithms, responsible data management, environmental measurement, and ethical AI governance. This framework recognizes that sustainable artificial intelligence cannot be achieved through isolated technological improvements but requires coordinated efforts across the entire AI lifecycle.

However, the transition toward sustainable AI is accompanied by several challenges. The balance between accuracy and sustainability remains a major concern because high-performance AI models often require extensive computational resources. Additionally, the absence of universally accepted sustainability measurement standards creates difficulties in evaluating and comparing the environmental impact of AI systems. Dependence on resource-intensive hardware and increasing electronic waste further highlight the need for sustainable manufacturing, recycling practices, and circular economy approaches.

Despite these challenges, Green AI provides significant opportunities for creating a more responsible digital future. By prioritizing computational efficiency, renewable energy adoption, ethical governance, and environmental awareness, AI technologies can contribute positively to sustainable development goals while continuing to drive innovation across industries.

The future of artificial intelligence should therefore move beyond a performance-centered approach toward a sustainability-oriented model. The success of AI will not only depend on how intelligent systems become but also on how responsibly they are developed and operated. Green AI frameworks provide a pathway for achieving a balance between technological advancement and ecological preservation, ensuring that future digital transformation remains efficient, ethical, and environmentally sustainable.

In conclusion, sustainable computing and Green AI are not merely technological trends but essential components of responsible innovation. As computational demands continue to grow, integrating sustainability principles into AI development will be crucial for creating intelligent systems that benefit society while protecting the environment for future generations.

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