Green Artificial Intelligence and Digitalization Facilitate

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Green AI (Artificial Intelligence) and digitalization facilitate the “Dual-Carbon” goal of low-carbon, high-quality economic development. Green AI is moving from “cloud” to “edge” devices like TinyML, which supports devices from cameras to wearables, offering low-power IoT computing.

climate governance | environmental sustainability | green AI | TinyML

1. Introduction

Major economies are regaining growth while facing challenges of carbon reduction and environmental protection [1]. Digital wave offers opportunities to achieve the goal of “Dual Carbon” [2], and green AI (Artificial Intelligence) is a tool designed to achieve quality development in a low-carbon economy [3]. As basic research on AI continues to progress [4][5][6][7], AI is accelerating from the “cloud” to the “edge” in the fields of smart manufacturing and smart cities [8], into smaller IoT devices for low-carbon energy-efficient computing and public information monitoring [9].

Negative impacts of AI on climate policy include increased electricity consumption and carbon emissions [10], i.e., threats such as cryptocurrencies. A shift to sustainable AI is imperative [3][11][12]. Inclusive, credible, explainable, ethical, and responsible technological approaches are required to drive smart city transformation [13] to mitigate planetary issues in a sustainable manner [13][14].

TinyML (Tiny Machine Learning) supports smart cameras, remote monitoring devices, wearable devices, audio capture hardware, and various sensors [15]. The power consumption and carbon footprint of TinyML devices are much lower than those of cloud computing and ordinary mobile devices, i.e., TinyML devices operate at a MHz level and consume power at a mW level, which is 1000 orders of magnitude lower than cloud computing and mobile devices; CO_2 emission levels are at a kg level, which is one order of magnitude lower.

Undoubtedly, an ecosystem of at least tens of billions of IoT devices will gain machine learning capabilities [16]. Low-carbon and green TinyML can create a healthier and more sustainable environment [17].

2. Green Artificial Intelligence

Due to the rapid development of the digital era, smart technologies are seen as an effective tool for solving challenging issues facing the world today and mitigating environmental, social, and economic crises on a global scale [18]. The EU's "Green New Deal" sets out the strategic goal of decoupling economic growth from resource use [19][20]. Industry 4.0 has given rise to the new concept of Cities 4.0 [21], which aims to improve quality of life, productivity, and sustainability of cities with AI [22]. Sustainability profoundly influences the direction of energy, transportation, housing, and agriculture [23]. Green AI advocates a "circular economy" that aims to reduce, reuse, and recycle across sectors and geographies [24]. Thus, the research value of green AI is highlighted. Human capital, financing power, technological innovation, and government policies play critical roles in the green transformation of AI [25]. Patent and open source provide the technical knowledge required to integrate intelligence and greenness [26].

The essence of AI innovation lies in fulfilling efficient and accurate intelligent algorithms [27] to promote humanistic and responsible technological development [28] and social progress [29][30]. Through continuous exploration and improvement of green AI technologies to reduce dependence on natural resources, and multi-disciplinary cooperation and application, people are forging a sustainable [14] intelligent path for the future of human beings and the planet [31]. TinyML [32] implements efficient machine learning models on edge devices with low power consumption and low resource consumption [33], reduces energy dependence, lowers the burden on the environment, which drives green AI technologies, and redefines smart cities [13].

The application and promotion of TinyML is increasing [34]. In recent years, TinyML as a typical technology for green AI is continuously progressing in climate governance, environmental protection, precision agriculture, and smart cities, as demonstrated below.

2.1. In Environmental and Climate Governance

Reducing carbon footprint is crucial. TinyML as green AI is an important tool for realizing climate and environmental policies [35], e.g., overcoming limitations of traditional sensors and monitoring systems [36], superior efficiency and energy saving advantages over traditional machine learning algorithms when running on small devices [37], low power consumption, high efficiency and energy saving capabilities, and low storage costs in environmental radiation-monitoring systems [38][39]. It also offers adaptive unsupervised anomaly detection for extreme environments [40], thus facilitating provision of accurate data for weather forecasting and disaster warnings [41]. The combination of TinyML and CloudML (cloud machine learning) even enhances environmental monitoring and climate prediction [42].

2.2. In Precision Agriculture

TinyML-based green AI addresses key challenges in precision agriculture by providing better tuning of environmental parameters [43], reducing resource consumption [44], improving crop yield and quality [45], and promoting sustainable development. As an example, the TinyML intelligent control system outperforms traditional models in maintaining temperature and humidity balance [46], reducing system response time and resource consumption [47], achieving smarter and more efficient food production [48], reducing energy waste and environmental pollution [49], and thus protecting the environment and mitigating climate change [17].

2.3. In Smart Cities

Industry 4.0 has spawned the new concept of Cities 4.0 [21]. TinyML better realizes the collection and management of urban data. The Intelligent Transportation System (ITS), based on TinyML IoT, can reduce traffic congestion and pollution [44], and promote the green and low-carbon development of smart cities [18][22][50].

2.4. Technological Innovation

TinyML promotes technological innovation through algorithmic optimization. The TinyML algorithm improves energy output efficiency by implementing a Square Cross-section Two-phase Closed heat pump (SCTC) in a photovoltaic (PV) system [51]. TinyReptile, a decentralized edge machine learning model, combines TinyML and coalitional meta-learning to improve computational efficiency and performance [52]. Generalized TinyML benchmarking framework based on different operating system platforms lays the foundation for evaluation [53]. The TinyML compression algorithm reduces memory usage and computational complexity [54], enabling energy-efficient reasoning on Unmanned Aerial Vehicles (UAVs) [55]. The efficiency of the C4.5 decision tree algorithm is improved by determining economic granularity interval in TinyML algorithm optimization [56].

2.5. Competition and Synergy between Proprietary and Open Source

Differences between open source and proprietary have different impacts on the software industry [57] and can be strategically complementary [58] and balanced [59]. Open source and patents have strong synergies [60]. Patents often have a technological lead over open source, but open source can also compete effectively [61]. Patents use a lock-in strategy, while open source offers greater flexibility and freedom [62][63]. Open source is more reliable and secure due to open management and auditing of source code [64][65]. RIVICE (Open Source River Ice Model) demonstrates the benefits of open source in environmental research collaboration and problem solving [66]. Migration timing framework from patents to open source provides strategic guidance [24], and the governance model and platform ecosystem will change [67].

The literature referred to above shows that TinyML's patent and open-source technologies provide additional opportunities for climate governance and environmental protection in multiple areas. Synergy needs to be further investigated.

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