International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 15s, 2025
https://theaspd.com/index.php

Green Computing of Machine Learning In Business Intelligence

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ABSTRACT
The purpose of this research study was threefold: firstly, to address real-world problems of electronic businesses by utilizing business intelligence, machine learning and green computing techniques to minimize carbon footprint emissions from computational resources. Secondly, we conducted an in-depth study of Green Computing (GC), Business Intelligence (BI), and Machine Learning (ML) technologies to provide an overview of their state-of-art, scopes, and associated challenges, highlighting directions for further research. Green computing is a new revolution to minimize carbon footprint from computational resources used for computations while addressing real-world electronic businesses problems through algorithmic efficiency and machine learning models. Business Intelligence is critical in enhancing decision-making processes, operational efficiency, and positive outcomes such as improved customer service, stronger customer relationships, increased profitability, and lower failure rates. Machine learning is the subset of artificial intelligence (AI) that trains computers to learn from experience by the use of data without explicitly programmed to make desirable decision. Adaptive Business Intelligence (ABI) model is a business model that integrates business intelligence, machine learning, and green computing to enhance the adaptability of decision-making processes into a cohesive system in dynamic business environments. ABI model can be considered a type of sustainable Artificial Intelligence (AI) model. The objective of ABI model was to solve the problems of businesses by utilizing business intelligence, machine learning and green computing to reduce energy consumption and carbon footprint emission from computational resources. Thirdly, we have developed two ABI models— Adaptive Multiple Linear Regression (AMLR) and Adaptive Decision Tree Regression (ADTR). The developed Adaptive Business Intelligence model can be deploying in businesses to take right decision-making at an optimal level. For a specific dataset, the ADTR model outperformed the AMLR model in terms of training time, Central Processing Unit (CPU) computational efficiency, and carbon footprint, making it more suitable for lightweight, energy-efficient modelling. We also observed that certain features are outperformed by AMLR over ADTR in terms of MSE and R^2.

Keywords: *Green Computing (GC), Machine Learning (ML), Business Intelligence (BI), Adaptive Business Intelligence (ABI) model.*

INTRODUCTION

In this modern era, global warming is a major issue that affects our planet and all living creatures that depend on it, and it must be addressed with deliberate and urgent attention. One of the key factors contributing to global warming is the rapid and excessive use of computer computational resources. These resources include hardware components such as the CPU, main memory, and other hardware components as well as software systems like operating systems, application software and other software systems. Business Intelligence (BI) utilizes computer computational resources in its day-to-day operations to analyze data and solve business-related problems. Adaptive Business Intelligence is at the heart of every successful modern business. A solution to the global warming impact caused by computer resource usage in business intelligence is the adoption of machine learning techniques integrated with green computing. We must not overlook the importance of integrating machine learning with green computing techniques in the computer resources used by business intelligence, as this helps minimize the carbon footprint. Some machine learning models are designed to solve real-world business problems efficiently, consuming less time and energy, and consequently producing lower CO_2 emissions. To solve business problems and to take optimal right decision at the given time is possible by adaptive business intelligence model which utilizes algorithmic efficiency, business intelligence, machine learning, and green computing techniques. Algorithmic efficiency is the heart and soul of green computing. In machine learning, algorithmic efficiency determines the effectiveness and efficiency of computer algorithm's to solve business problem that utilizes computational resources such as CPU, graphics processing unit (GPU), random access memory (RAM), energy or power consumption, storage hard disk drive (HDD) and others. Adaptive Business Intelligence model was developed to solve the problems of businesses by utilizing business intelligence, machine learning and green computing techniques to reduce energy consumption and carbon footprint emission from computational resources.

1.1 Chronicle and Evolution of Green Computing

Green Computing is an evolving discipline, continuously adapting to advancements in technology and responding to environmental, spatial, and temporal dynamics. According to (Ben Fox., 2023), the origins of green computing can be traced back to the late 1960s and early 1970s, marking the initial awareness of the environmental implications of computing technologies [37], [38]. (Robert R. Harmon[1] and Nora Auseklis[2]., 2009) highlight that a pivotal moment in the evolution of green computing occurred in 1991, when the U.S. The agency that introduced the important and shapes the green lights program was the Environmental Protection Agency (EPA) to adopt green lighting system. After this vital green lights program was then Energy Star program to have healthy environment reducing global warming produce by information and communications technologies (ICT) includes all related electronics and computing equipments in the year 1992 [21].According to the (IBM Cloud Education Team., 2025), prior to the emergence of green computing, the IT industry's primary focus was on developing smaller and faster devices, often without consideration for sustainability or the environmental impact of emissions. Traditional computing, characterized by on-premises physical servers and hardware, contrasts sharply with the eco-friendly orientation of modern cloud computing, which emphasizes energy efficiency and resource optimization. IBM has demonstrated a long-standing commitment to sustainable green IT practices throughout its business ecosystem—including green design, efficient operations, and environmentally conscious technology usage. Notably, IBM issued its first corporate policy on environmental affairs as early as 1971, underscore the company's enduring commitment to environmental stewardship across its global operations [25]. According to (Vandana Sehgal[1] and Sonia Choudhary[2]., 2015), the U.S. Environmental Protection Agency launched the Energy Star program in 1992 as a voluntary labeling initiative aimed at promoting and recognizing energy-efficient technologies, including computer monitors, climate control systems, and other electronic equipment. This program played a pivotal role in raising awareness about sustainable technology practices. It is widely believed that the term "green computing" emerged shortly after the introduction of the Energy Star program, marking the beginning of a formalized effort toward environmentally responsible computing practices [4], [6], [7], [11], [13], [16], [65]. According to (Shaik Khaja Mohiddin[1] and Yashashwini Suresh Babu[2]., 2015), the most important and decisive of implementation of green computing toward green environment was virtualization of computer. It is the process of creating and running virtual computer environments/systems on a single physical machine that can switch to different operating systems on the same server which improve computer resources like CPU, GPU, memory, storage, server, network devices etc., utilization and reduce power consumption. While the concept of virtualization originated with IBM mainframe operating systems in the 1960s, its commercial implementation for x86 compatible systems began only in the 1990s [6], [11], [36]. According to (Shalabh Agarwal[1] and Asoke Nath[2]., 2011), Green IT encompasses all information technology solutions that contribute to energy conservation across multiple levels of usage. These include energy-efficient strategies in (i) hardware, (ii) software, and (iii) IT services [12].

1.2 Definitions of Green computing

According to (L.Dhanam et al., 2014; Vandana Sehgal[1] and Sonia Choudhary[2]., 2015; Parichay Chakraborty et al., 2009), defined Green Computing or Green IT as the study and practice of using computing resources efficiently [34], [65], [8], [30]. According to (Sr. Jainy Jacob M.,2015; Qilin Li[1] and Mingtian Zhou[2]., 2011), Green computing, also referred to as green IT, involves practices that promote environmentally sustainable computing by optimizing the use of energy and resources throughout the technology lifecycle [1], [4], [16], [26], [48], [52]. According to (Showmick Guha Paul et al., 2023), green computing—also referred to as sustainable computing which involves the design and enhancement of computer hardware and software systems which reduce computational cost and result in less harm to environment [2]. (Jagadeesh U[1] and Anwar Abdullah[2]., 2017), defined Green Computing as the study to develop of electronics/computer hardware and software that will have minimum negative impact to environment. It has gained the attention not only of environmental organizations but also of businesses across various industries [5], [6], [7], [9], [7],[10],[11]. According to (Biswajit Saha., 2014), green computing—also known as Green ICT, Green IT, Sustainable IT, ICT sustainability—is the discipline focused on developing and applying environmentally sustainable computing, in line with standards such as the environmental protection agency, international federation of green (IFG) ICT [14], [15].According to (A G Andurkar[1] and Ritupriya Ganesh Andurkar[2]., 2017), the objectives of green computing parallel those of green chemistry, focusing on minimizing hazardous substances, enhancing energy efficiency across a product's lifecycle, and encouraging the reuse or biodegradation of outdated devices and industrial waste. This concept is relevant to systems ranging from mobile devices to extensive data centers [47]. According to (Qilin Li[1] and Mingtian Zhou[2]., 2011), green computing refers to the areas of computing equipment/devices to design, produce, operate, and dispose of electronics/computer equipments and their parts such as CPU, GPU, memory, servers, monitors, printers, storage devices, and communication devices in way that produce less harmful to environment [16], [18]. (You Zhou et al., 2023), referred to Green Computing as an approach that seeks to balance the performance of Artificial Intelligence (AI) solutions with the cost of computational resources and environmental impacts [17]. According to (Sunil Kumar Mohapatra et al., 2019), green computing can be elaborated as electronics environment and sustainable development of electronics that meet the present needs of the society without hamper the future generation without affecting the environment. [19].According to (Patrick Kurp., 2008), the central objective of green computing is to create an efficient digital infrastructure by minimizing energy usage and enhancing energy efficiency throughout the lifecycle of computing devices—from production and operation to disposal [20]. According to (Dhaini et al., 2019), Green software implementation emphasizes minimizing CPU usage, optimizing the number of parameters, and addressing various other factors that contribute to total energy consumption [22]. According to (Girish Bekaroo et al., 2009), the energy consumption of an IT organization is shaped by multiple elements such as software practices, hardware utilization, architectural design of buildings, and operational business processes [27]. According to (Appasami G[1] and Suresh Joseph K[2]., 2011), green computing refers to the efficient and environmentally responsible use of computing resources, with particular emphasis on conserving electrical energy [28]. According to (San Murugesan[1] and G R Gangadharan2., 2012), green IT— or green computing—is the discipline concerned with designing, producing, and utilizing computing systems and peripheral devices in a way that ensures high efficiency while minimizing or eliminating environmental impact [29]. According to (Jamshed Siddiqui., 2013), IT sustainability is framed through the principles of green computing—also known as Green IT or Green ICT—which involves the study and application of environmentally responsible practices in computing and information technology [32], [33]. According to (Khan et al., 2015), the successful implementation of Green IT or Green Computing depends on six key parameters: energy efficiency; development and use of environmentally friendly software; reduction of overall business costs; promotion of reusability and sustainability in hardware and software; enhancement of service quality; and the deployment of virtualization strategies across hardware, software, and processes. These parameters emphasize the multidimensional approach necessary to realize environmentally sustainable computing practices in modern IT infrastructures [39]. According to (Srikanth Subburaj et al., 2013), Green IT refers to the strategic application of Information and Communication Technology to enhance the environmental sustainability of enterprise operations throughout their entire lifecycle [40]. According to (Purushottam kewat et al., 2015; P Visalakshi et al., 2013), Green Computing, also known as Green IT or ICT Sustainability, refers to environmentally sustainable computing or information technology, which emphasizes minimizing the negative impact of IT systems on the environment [45], [50], [51]. According to the (IBM Cloud Education Team., 2025), Green Computing— also referred to as Green IT or Sustainable IT—encompasses the design, manufacture, utilization, and disposal of computers, chips, peripherals, and other technology components in ways that reduce harmful environmental impact [25]. According to (Andrea Pazienza et al., 2024), the Environmentally Sustainable Computing (ESC) paradigm—also known as Sustainable IT or Green IT—offers a contemporary framework for reducing the environmental impact of information technology. The Green Software Foundation (GSF) characterizes Sustainable IT as a multidisciplinary field that integrates climate science, software design, electricity markets, hardware, and data center architecture. This paradigm prioritizes the development and operation of computing technologies in a manner that aligns with broader environmental sustainability objectives [49]. According to (Jagwinder Singh., 2016), a reduction in power consumption can indirectly result in lower carbon emissions, thereby contributing to a greener computing environment. The carbon emissions associated with software can be modeled such that if an application consumes y watts of power and generates x units of carbon emissions, reducing power usage by 50% would correspondingly decrease emissions to x/2. This highlights the impact of energy efficient design choices in sustainable computing. (Singh., 2016), Green Computing is the process of sustainable computing the tasks with computer resources that optimize energy efficiency throughout their entire lifecycle while minimizing carbon dioxide (CO_2) emissions [41].

2. Related work

In this section of related work, we first discussed Green Computing, Business Intelligence, and Machine Learning, focusing on their respective approaches, definitions, techniques, and technologies.

2.1 Green computing

In this session, we discussed Green Computing approaches and its limitations. Approaches to green computing are:

(a) Algorithmic Efficiency

(Shivam Singh., 2015), highlights that the efficiency of algorithms significantly impacts the amount of computing resources required to perform specific functions. In practice, there are numerous efficiency tradeoffs when writing programs. For instance, modifying an algorithm—such as transitioning from a slower linear search to a more efficient hashed or indexed search—can dramatically reduce the computational resources needed for a task, sometimes bringing them from substantial levels down to nearly negligible [24], [12], [28], [35]. (Wikipedia., 2025), defines algorithmic efficiency as a property of an algorithm that concerns the amount of computational resources it utilizes. Achieving maximum efficiency involves minimizing the use of these resources, which commonly include time, power and memory [53]. (Oyile Paul Oduor[1] and Wabwoba Franklin[2]., 2024), explain that algorithmic efficiency entails designing and implementing algorithms that minimize computational complexity and overall resource consumption. By reducing the number of operations required to perform a specific task, efficient algorithms not only improve system performance but also contribute significantly to lowering the energy consumption of both software applications and the hardware systems that run them [1]. (Bhavana Narain[1] and Sanjay Kumar[2] ., 2013), emphasized that improving algorithmic efficiency by decreasing the number of computational steps and storage requirements can significantly reduce electrical power consumption, thereby contributing to the goals of green computing. The efficiency of algorithms directly influences the demand on computer resources for executing a task. There are often trade-offs in writing programs to balance performance and resource use. For example, switching from a slow, linear search algorithm to a more efficient hashed or indexed search algorithm can dramatically reduce resource usage—sometimes from substantial to nearly zero. A notable instance is the reduction of computational complexity from $N \times N$ to $N \times \log(N)$, which has a profound impact on computing resources, especially at large scales such as $N = 30$ billion [44]. (Oyile Paul Oduor[1] and Wabwoba Franklin[2]., 2024), highlight that the integration of Artificial Intelligence and Machine Learning techniques is poised to significantly advance the domain of energy-efficient computing. AI-based optimization algorithms possess the capability to learn dynamically and adapt to system usage patterns and workload characteristics, thus enabling more precise and context-sensitive power management. Moreover, ML techniques can be effectively applied to predict the energy consumption of software applications and uncover optimization opportunities. As these technologies continue to evolve and gain broader adoption, they are expected to play a critical role in fostering sustainable computing practices and minimizing the environmental impact of IT systems [1].

(b) Energy Efficient Coding

(Shivam Singh., 2015), emphasizes that the core principle of energy-efficient coding is to conserve power by designing software that reduces hardware utilization, rather than merely relying on executing existing code on more energy-efficient hardware. Moreover, Singh notes that combining this software-centric strategy with the deployment of low-power hardware solutions can result in even greater energy savings, reinforcing the importance of integrated approaches in achieving green computing objectives [24]. (Oyile Paul Oduor[1] and Wabwoba Franklin[2]., 2024), highlight that green coding practices are essential in reducing the energy footprint of software applications. This can be done by minimize memory usage, reusable code/ code modular and optimize computation/algorithm. By adopting these techniques, developers can significantly lower the energy demands of software, contributing to the broader goals of green computing and sustainable IT. These optimizations not only improve performance but also support environmentally responsible technology development by lowering power consumption during software execution [1]. (Shubhangi Gadhwe., 2016), emphasizes that the efficiency of an algorithm is primarily determined by two key complexities: time and memory space required for its execution. The author further identifies four critical aspects of main memory (often RAM) usage to be considered: the memory required to store the algorithm's code, the memory needed for the input data, the memory needed for any output data, and the working memory necessary during the computational process. Understanding and optimizing these memory components are essential for enhancing algorithmic efficiency, which directly contributes to reduced energy consumption and supports green computing practices [46].

(c) Vectorization

(San Murugesan[1] and G R Gangadharan[2]., 2012), highlight as an effective technique to attain better computational efficiency than scalar C-code by using advanced instructions such as single-instruction multiple data (SIMD) for instruction-level data parallelism. Vectorized code executes faster and results in significant power savings, contributing to energy-efficient computing. In the context of machine learning, vectorization plays a crucial role, as many algorithms depend on vectorized data to train models effectively. Features extracted from raw datasets are transformed into vectors, which are then processed to identify patterns and generate predictions. Moreover, in numerical computations, vectorization is widely applied to operations involving arrays and matrices—such as dot products or matrix multiplications—allowing for faster and more efficient execution compared to traditional loop-based methods. [29].

(d) Approximate Computing

(Hrishav Bakul Barua et al., 2022), describe Approximate Computing (AC) as a computational paradigm that reduces energy consumption and execution time by allowing a tolerable level of inaccuracy in the system. This concept can be applied across various components, including software code, algorithms, hardware architectures, arithmetic or logic circuits, storage systems, and data communication system. For example, consider the equations: $Y = 1/X$ and $Y = 2.823 - 1.882 \times X$ where, Y in the first equation gives an approximate (in-exact) result very close to the second equation for a range of X = [0.5, 1]. But, the catch here is that, the second equation takes much lesser time (almost 2 times faster) to execute compared to the first equation because division operation requires much higher machine cycles to execute than mere addition and subtraction or even multiplication. This also guarantees energy savings by reducing the machine cycles in the CPU and workload and power usage [43]. (Gaurav Buddhawar et al., 2014), highlight several programming and compiler level strategies aimed at enhancing energy efficiency in computing systems. One such technique is instruction clustering, where specially designed compiler architecture can execute a cluster of instructions in one cycle. This technique has demonstrated energy savings ranging from 26% to 47%, significantly reducing program runtime. Another approach is loop optimization, which analyzes nested loops through dependency graphs; if no cycles are found, the compiler parallelizes loop execution via interleaved processing, further improving efficiency. Additionally, the authors advocate for iteration over recursion, as recursion generally consumes more energy due to longer execution times and deeper stack usage. Lastly, data structures and algorithms with lower time complexity and energy efficient data structures can greatly contribute to reducing power consumption in software applications [31].

(e) Virtualization

According to **(**Shivam Singh., 2015)**,** virtualization refers to the abstraction of computer resources, wherein multiple computer systems can operate simultaneously on a single physical hardware setup. This technological approach allows system administrators to consolidate several physical machines into virtual machines (VMs) hosted on a single, high performance system. As a result, unplugging the original hardware and reducing power and cooling consumption, thereby contributing to environmentally sustainable computing practices [24]. According to (Sonu Choudhary., 2014), in nonvirtualized systems, a single operating system has complete ownership and control over all hardware resources. In contrast, virtualized systems enable multiple operating systems share hardware resources. The virtualization layer lies between the hardware and operating system (OS). This layer is managed by a virtual machine monitor (VMM), which assumes control over resource allocation and plays a crucial role in system power management to ensure efficient operation. This structure allows for better utilization of hardware and supports energyefficient computing practices [42]. (Shubhangi Gadhwel., 2016), with virtualization, a system administrator could combine several physical systems into virtual machines on one single, powerful system, thereby unplugging the original hardware and reducing power and cooling consumption. Virtualization allows a system administrator to consolidate multiple physical systems into virtual machines hosted on a single, powerful physical system. Virtualization contributes to environmentally sustainable computing by minimizing energy consumption and hardware waste [46], [12]. Through virtualization, multiple operating systems and applications can run concurrently on a single physical machine, thereby maximizing hardware utilization and reducing the need for additional infrastructure. This leads to significant savings in power consumption and cooling requirements, making virtualization a key enabler of green computing practices.

(f) Computer Multitasking

(Appasami G[1] and Suresh Joseph K[2]., 2011), explain that in computing, multitasking in operating allows multiple tasks (or processes) to run in a concurrent or quick interleaved between the tasks, which utilize CPU to optimal level. In multitasking, only one task of instructions at a time in a single CPU. Multitasking addresses this limitation by scheduling tasks in such a way that each gets a share of CPU time. The CPU is reassigned from one task to another through a process called context switching. When these context switches happen rapidly, the system creates an illusion of parallelism**,** allowing users and applications to perceive that multiple tasks are running simultaneously [28].

(g) Multithreading

(Abhinav Chunchu., 2024)**,** Multithreading is a specific form of parallelism, allows multiple threads of execution to run concurrently within a single process. This can significantly improve performance and resource utilization. In high performance computing (HPC) applications, multithreading helps utilize available cores efficiently and minimizes idle time. Multithreading can increases performance up to 45% in high-performance computing applications [55]. Multithreading, as described by (Bhutani[1] and Shinde[2]., 2024), is a method of parallel execution wherein a single program process is divided into multiple threads, each capable of executing independently. This form of thread-level parallelism allows multiple activities to be performed concurrently, significantly reducing the total execution time of a program. The technique is particularly beneficial in scenarios involving I/O-bound tasks or frequent context switches, as it enhances system responsiveness and overall throughput. Additionally, multithreading can contribute to optimized memory utilization through the sharing of resources among threads within the same process. However, this approach is not without its limitations. One of the primary challenges associated with multithreading is the increased energy consumption resulting from the continuous activity of numerous threads. The constant context switching between threads incurs overhead, which, while improving performance can undermine energy efficiency—an important consideration in sustainable computing practices [54]. According to (San Murugesan[1] and G R Gangadharan[2]., 2012), balanced multithreading—where thread provisioning is carefully managed to avoid over-provisioned —can significantly enhance both performance and energy efficiency in computing systems. When compared to single-threaded execution, multithreaded processing can complete workloads in a shorter time frame while consuming less energy. The study emphasizes that executing a task using a single thread typically results in longer processing times and higher energy consumption, whereas appropriately balanced multithreading optimizes resource utilization and reduces overall power usage. Proper utilization the scheme of multithreading can enhance computation capacity and reduce power consumption and as a result reduce harmful impact to environment. [29].

(h) Data Efficiency

(San Murugesan[1] and G R Gangadharan[2]., 2012), Data efficiency and minimize unnecessary data movement can improve system computation. Data efficiency can be attained through the development of software algorithms specifically designed to reduce data transfer, the implementation of optimized memory hierarchies that retain data in proximity to processing units, and application software that makes effective use of cache memory. Several practical strategies contribute to data efficiency, including efficient management of disk input–output (I/O), employing block reads, utilizing native command queuing, minimizing file fragmentation, leveraging multithreaded code for disk operations, and incorporating techniques such as pre-fetching and caching. Collectively, these approaches lead to both improved computational throughput and energy conservation [29].

(i) Product Longevity

According to (Sonu Choudhary., 2014), Gartner research indicates that approximately 70% of the natural resources consumed over a personal computer's (PC) life cycle are expended during the manufacturing phase. Consequently, one of the most effective strategies for advancing green computing is to extend the operational lifespan of computing equipment. In alignment with this perspective, Gartner further recommends prioritizing product longevity, particularly by emphasizing upgradability and modularity. For example, upgrading components such as RAM modules has a significantly lower environmental impact compared to manufacturing an entirely new PC. This approach supports sustainable computing practices by reducing electronic waste and minimizing the ecological footprint associated with hardware production [42]. **(j) Data Center Design**

According to (Sonu Choudhary., 2014), Data center facilities are among the most energy-intensive infrastructures, consuming approximately 100 to 200 times more energy than conventional office buildings, as estimated by the U.S. Department of Energy. This significant energy demand underscores the critical need for energy-efficient data center design. The Department of Energy identifies several key focus areas for optimizing energy use within data centers: information technology (IT) systems, environmental conditions, air management, cooling systems, and electrical infrastructure. Implementing best practices in these domains can lead to substantial improvements in energy efficiency, cost savings, and environmental sustainability [42].

(k) Power Management

(Sonu Choudhary., 2014), highlights the importance of the Advanced Configuration and Power Interface (ACPI), an open industry standard that enables the operating system to manage power-saving functionalities of hardware components directly. Through ACPI, systems can automatically power down peripherals such as monitors and hard drives after designated periods of inactivity. Furthermore, a system may hibernate, when most components (including the CPU and the system RAM) are turned off —are powered down to conserve energy [42].

(l) Telecommunication Network Devices Energy Indices

(Sonu Choudhary., 2014), emphasizes that the energy consumption associated with Information and Communication Technologies (ICTs) has become notably significant, rivalling that of many traditional industries. Recent studies have attempted to identify key energy indices that facilitate meaningful comparisons between various ICT devices, particularly network elements. These analyses primarily focus on optimizing the energy consumption of individual devices and entire telecommunication networks, particularly within carrier-grade infrastructure. The overarching aim is to foster a clearer understanding of the correlation between network technology choices and their corresponding environmental impacts [42].

(m) Resource Allocation

According to (Shubhangi Gadhwe., 2016), effective resource allocation techniques are essential in cloud computing environments to minimize issues such as resource contention, fragmentation, and overprovisioning. These problems commonly arise when multiple applications attempt to access the same resources simultaneously or when demand exceeds the availability of computing resources. Optimized resource allocation strategies must be designed to ensure fair and efficient distribution of heterogeneous resources—including operating systems, CPUs, memory, and I/O devices—across multiple applications with varying requirements [46].

(n) Terminal Servers

According to (Shubhangi Gadhwe., 2016), in cloud computing environments, all computing operations are handled at the server level, while the end user interacts primarily with the operating system interface. Effective resource allocation techniques are crucial to optimizing system performance and ensuring efficient utilization of infrastructure. Poorly managed resource allocation can result in issues such as resource contention, fragmentation, and over-provisioning. These challenges typically arise in scenarios where multiple applications simultaneously compete for limited resources, such as CPU, memory, I/O devices, and operating systems. To address this, resource allocation strategies must be designed to accommodate diverse application requirements, ensuring balanced and fair distribution across shared cloud infrastructure [46].

(o) Using Solid State Storage Device

According to (Shalabh Agarwal[1] and Asoke Nath[2]., 2011), hard disk drives (HDDs) with smaller form factors generally consume less power per gigabyte compared to larger physical drives. In contrast to HDDs, solid-state drives (SSDs) utilize flash memory or DRAM for data storage. Due to the absence of moving parts, low-capacity flash-based SSDs can offer reduced power consumption. However, it is important to note that DRAM-based SSDs, even at moderate storage capacities, may consume more energy than traditional hard disks. Furthermore, despite their advantages in terms of durability and energy efficiency, many flash-based SSDs tend to exhibit slower write speeds compared to conventional hard drives [12].

(p) Using LED Display
According to (Shalabh Agarwal[1] and Asoke Nath[2]., 2011), traditional liquid-crystal display (LCD) monitors typically rely on cold-cathode fluorescent lamps (CCFLs) for backlighting. However, advancements in display technology have led to the adoption of light-emitting diode (LED) arrays as an alternative backlight source. LED displays are energy-efficient as compared to other displays technology, which consumpt less power in display visual output. [12].

(q) Operating System Issues

(Shalabh Agarwa[l] and Asoke Nath[2]., 2011), note that Microsoft has faced significant criticism for releasing operating systems that, by default, are not optimized for energy efficiency. In response to these concerns, Microsoft has begun incorporating power-saving features into its operating systems to reduce overall energy consumption [12].

(r) Materials Recycling

According to (Shalabh Agarwa[l] and Asoke Nath[2]., 2011), computer systems like CPU, memory, monitor, printer, keyboard, hard disk, mouse, sound system and others that are no more useable as per the specification of the products can be send to electronic waste management system - recycling centers for recycling them. Proper treatment or recycling of electronics waste is very important for the healthy environment. Hazardous substances includes lead, zinc, mercury, cadmium, zinc, chromium, nickel, and others are harmful to environmental. The result of recycling of electronics waste, it can extract gold, copper and others useful element. This can also reduce producing harmful substances to the environment [12].

Limitations of Green Computing

(Mahdi Dhaini et al., 2019), explained the important of software sustainability and showed that achieving a better performance does not guarantee better energy efficiency [22]. (Capra et al., 2010) emphasized that energy consumption in Information Technology (IT) systems is influenced not only by infrastructural layers such as hardware and networking components but also significantly by the Management Information Systems (MIS) application layer. Their study highlighted three key findings: (i) the MIS application layer plays a crucial role in overall energy usage; (ii) different MIS applications that fulfil the same functional requirements can vary significantly in their energy consumption; and (iii) enhancing time performance alone does not necessarily lead to improved energy efficiency in all scenarios [23].

2.2 Business Intelligence

In this session, we discussed the terminology, issues and challenges of business intelligence. According to (Kopelo Letou[1] and S.Thiyagarajan[2]., 2023), Business Intelligence (BI) is the process of transforming various types of business data into meaningful information and finally intelligence that can help in decision making at all levels and improve business performance to optimal desire goals. In the context of Machine Learning, the term Business Intelligence can be defined as a adaptive business intelligence model encompass of processes, components, products and machine learning technology which extract business data from large datasets and transformed it into intelligence in problem-solving, decision-making, achieve desire's optimum goal in business and control its actions [56]. (Davis Gary Alan[1] & Woratschek Charles R[2].,2015), the term Business Intelligence (BI) was originally coined by Richard Millar Devens in 1865 to describe how banker Sir Henry Furnese gained in his business over his competitors as he collected, analyzed and utilized factual data/information in the environment of business competition. He took decision on business based on this factual information rather than intuitive information. From here, the term business intelligence concepts was born. This concept—where timely and actionable information forms the core of decision-making—remains central to modern definitions of BI [57]. According to (Elena Cebotarean., 2011), the concept of Business Intelligence (BI) was formalized in 1989 when Howard Dresner, who later became a Gartner Group analyst, introduced it as an umbrella term to encompass a wide range of concepts and methods for improving decision-making through the use of fact-based support systems. And according to Forrester Research, business intelligence comprises of methodologies, processes, architectures, and technologies that convert raw information into intelligence information decisive optimal decision-making. This transformation empowers organizations to enhance their strategic, tactical, and operational decisionmaking capabilities, providing a competitive advantage in anticipating and responding to business challenges [58]. (Rouhani et al., 2012), defined Business Intelligence as a combination of capabilities, tools, and techniques that assist managers in comprehending business situations. Prior to BI system they were many names such as data-driven decision support system (DSS), executive information system (EIS), online analytical processing (OLAP) that were used to collect business information from business database, analyzed it, produced summary of the business reports and then take decision[59]. (Shatat Abdalla et al., 2024), emphasized that Business Intelligence plays a vital role in improving decision-making processes and operational efficiency. It contributes to beneficial outcomes including enhanced customer service, stronger customer relationships, increased profitability, and reduced failure rates [60]. (Kawtar Moussas et al., 2024), defined Business Intelligence as both a process—that involves the collection, integration, analysis, and presentation of business information—and a product—the information and insights that support decisionmaking processes [3].

Issues and Challenges of Business Intelligence

In traditional Business Intelligence systems, both data flow and control flow are typically unidirectional—data was collected, processed, and then presented in a linear manner, often limiting the system's responsiveness and flexibility. These conventional systems primarily support retrospective analysis through historical data, offering limited adaptability to dynamic business environments. However, modern Business Intelligence systems have evolved to support multidirectional flows of data and control communication, allowing for more interactive and real-time right decision making at the optimal level. These systems enable feedback loops, collaborative decision-making, and seamless integration across various functional units. Such advancements facilitate not only descriptive but also predictive and prescriptive analytics, thus enhancing organizational agility and responsiveness. Despite these benefits, modern BI systems also face several challenges and issues, including: Data integration complexities due to heterogeneous data sources, real-time processing requirements, which demand high computational resources, security and privacy concerns related to data sharing across systems, scalability issues in managing large volumes of structured and unstructured data, user adoption challenges, especially when shifting from static to interactive analytics interfaces.

2.3 Machine Learning

In this session, we discussed the terminology and techniques of machine learning.

Terminology of Machine Learning

According to (Kopelo Letou[1] and S.Thiyagarajan[2]., 2023) defined Machine Learning (ML) as the scientific study of techniques and algorithms to develop adaptive machine learning models that can learn from large dataset and improve performance tasks automatically overtime with more dataset without explicit instructions [56]. According to (Mitchell Tom M., 1997), machine learning is defined as the study of algorithms that enable computer programs to automatically improve through experience [61].According to (Janiesch Christian et al., 2021), machine learning is a computer program's performance that improves with experience with respect to some class of tasks and performance measures [62]. According to (Sah Shagan., 2020), machine learning is the study of computer algorithms that enable systems to automatically learn and improve from experience [63].

Techniques of Machine Learning

There are various techniques of machine learning. According to (Kopelo Letou[1] and S.Thiyagarajan[2]., 2023; Sarker Iqbal H., 2021), in supervised machine learning, there are mainly two techniques to train a model that is regression technique and classification technique. In unsupervised machine learning, there are mainly two techniques to train a model that is clustering technique and association technique. In semi-supervised machine learning techniques to train a machine learning model are semi supervised clustering technique, semi supervised regression technique and semi-supervised classification technique. In reinforcement machine learning, there are mainly three techniques to train a model that is Model-based RL technique, Model-free RL technique and Hybrid RL technique. In reinforcement machine learning, there are mainly three techniques to train a model that is supervised deep learning technique, unsupervised deep learning technique and hybrid deep learning technique [56], [64]. Here we discussed Multiple Linear Regression Model and Decision Tree Regression Model which used regression technique. Multiple Linear Regression is a supervised learning technique used for regression tasks. The aim of multiple linear regression model is to model the linear relationship between two or more input independent features/variables and output dependent target/variable. The equation for simple linear regression is: $Y=\beta_0+\beta_1X+\varepsilon$, Y is the predicted output value (dependent/ response variable), X is the input features (independent/predictor variable), β_0 is the intercept and β_1 is the coefficients or slope (weights) for the input features, ε (Epsilon) is the random error term or random deviation. Input: Multiple continuous or categorical variables, Output: Single continuous variable, Assumption: Linear relationship between dependent and independent variables, Algorithm Goal: Minimize the Sum of Squared Errors (SSE) to find the best-fit line. Decision Tree Regression is a supervised machine learning algorithm that uses a tree-like structured model to make predictions for continuous numerical values (i.e., it performs regression, not classification). In other words, Decision Tree Regression is a supervised learning algorithm used when the target variable is continuous (i.e., real-valued numbers like price of house/retail, salary, temperature, etc.,) for a given set of features. It builds a model in the form of a tree structure where data is continuously split according to certain parameters. Decision Tree Regression is the regression version of a classification trees/ decision tree classifier and aims to predict a numerical value/quantity rather than a categorical label.

3. RESEARCH METHODOLOGY

A systematic review was done on Green Computing, Business Intelligence and Machine Learning along with their chronological and evolution of terminologies, technologies, techniques and applications. There are several approaches to addressing the challenges of global warming and promoting sustainable development within the domain of electronic business. Some of the approaches are business intelligence, machine learning and green computing techniques which focus on optimizing computational processes to reduce energy consumption and carbon footprint emission when performing business tasks. Adaptive Business Intelligence (ABI) model is a business model that integrates business intelligence, machine learning and green computing to enhance the adaptability of decision-making processes into a cohesive system in dynamic business environments. ABI model can be one of the types of sustainable Artificial Intelligence (AI) model. In other words, Adaptive Business Intelligence (ABI) is a Green Artificial Intelligence in the context of business. To contribute to environmental sustainability, our methodology emphasizes an efficient, effective, and adaptable model approach, aiming to minimize the carbon footprint associated with data processing, data computation and training models. We have designed Adaptive Business Intelligence models to solve the problems of businesses by utilizing business intelligence, machine learning and green computing to reduce energy consumption and carbon footprint emission from computational resources. In this, we developed and evaluated two Adaptive Business Intelligence models using a specific dataset: Adaptive Multiple Linear Regression model and Adaptive Decision Tree Regression model. An Adaptive Multiple Linear Regression (AMLR) model is a linear regression of supervised machine learning model that incrementally learns from inputs data streams or real-time data to predict the value of a dependent variable based on multiple independent variables. An Adaptive Decision Tree Regression (ADTR) model is a regression decision tree of supervised machine learning model that incrementally learns from inputs data streams or real-time data to predict a numerical (continuous) value for a given set of features.

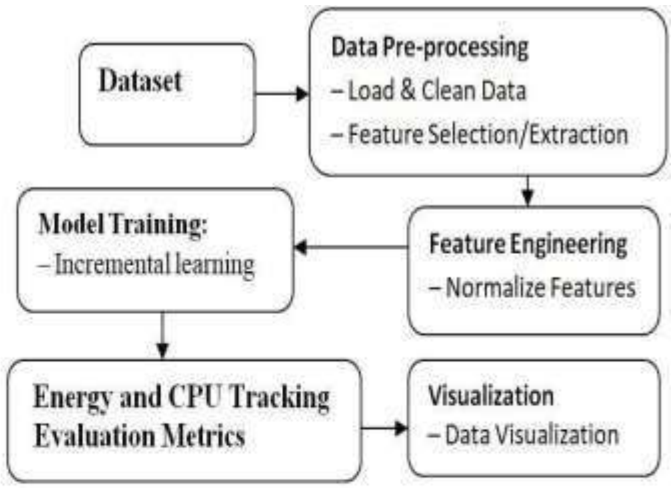

Fig 1. Adaptive Business Intelligence (ABI) Model

This Adaptive Business Intelligence model was designed to reduce computational cost, that is the amount of resources (such as time, memory, CPU/GPU power, or energy) required executing a task, such as training or running a machine learning model. We have used a structured data set in this model. In this model Fig 1. Adaptive Business Intelligence Model there is mainly seven sections: developed these models we first collected the data set, data pre-processing, feature engineering, model training using the right algorithm, CPU and energy tracking, evaluation metrics and model visualization. 1. Data Collection: It is very critical and crucial as it identify the problems to build adaptive business intelligence model which is a kind of machine learning model. Types of data such as unstructured data, semi-structured data and structured data that can be use in machine learning models. The data type that we used was structured data in adaptive business intelligence model to extract patterns, find trends for insightful informed decision making in businesses. Structured data have strict format and well organized in the database. 2. Data Pre-processing: It is very crucial as it involves preparing raw data and cleaning data to make it suitable for adaptive business intelligence model. Data cleaning is the process of identifying missing values, inconsistencies format, inaccuracies duplicates, errors, Outliers and correcting missing values, inconsistencies formatting, inaccuracies duplicates, errors, normalizing or scaling data, remove outliers in datasets to improve their quality, accuracy, and reliability for better adaptive business intelligence model performance. 3. Feature Engineering: It is the process of transforming selected existing relevant features into new useful features to enhance better performance of adaptive business intelligence model. feature engineering techniques are handling missing values include imputation and deletion, discretization, handling outliers include replace, transformations and delete, encoding categorical variables include label encoding, ordinal encoding and one-hot encoding, feature splitting, feature scaling include min-max scaling (normalization scaling) and zscore scaling (standardization/ variance scaling), feature selection include filter methods and wrapper methods, creating new features, and dimensionality reduction include PCA. Types of feature engineering are numerical features, categorical features, time-series features, and text features. Important of feature engineering are improves model accuracy, reduces overfitting and underfitting, enhances model interpretability, boosts training efficiency, and handles noisy and missing data. 4. Model Training: To effectively and efficiently train adaptive business intelligence model, it is very crucial and critical to choose the right machine learning algorithm. The given data set was divided into three portions that is train data set, validation data set and test data set. The model was trained on the training data set. The two adaptive business intelligence models using a specific dataset are adaptive multiple linear regression model and adaptive decision tree regression model. Adaptive Multiple Linear Regression model in machine learning used Multiple Linear Regression algorithm which is supervised learning algorithm that incrementally learns from inputs data streams. Various Regression algorithms are ElasticNet regression, Linear Regression, Polynomial Regression, Ridge regression, and Lasso Regression. Linear regression models are parametric in nature. The prediction of linear regression model is continuous in nature. This essentially means that each input will result in different output. In machine learning, multiple linear regression algorithm is a supervised algorithm that model the relationship between one dependent variable and more than two independent features (variables). Decision tree regression is a decision tree structured that selects input features and then split the features data starting the root node and branching out to child nodes and then leaf nodes to get the final result predictions. In decision tree regression, there can be one dependent variable output from different independent variables inputs. The predictor variables are non-linear. Decision tree regression models are non-parametric in nature. A decision tree where the target variable can be continuous/ numerical/discrete for a given input features. Adaptive Decision Tree Regression model in machine learning used Decision Tree Regression algorithm which is supervised learning algorithm that incrementally learns from inputs data streams. In machine learning, Decision Tree Regression algorithm is a supervised algorithm that model the relationship between one dependent variable and more than two independent features (variables). Hyperparameters may be tuned using the validation data set, and the objective was to train a model that can generalize well to unseen data. 5. CPU and Energy Tracking: Tracks the computational resources consumed (e.g., CPU/GPU usage, memory, training time), estimates the energy cost of training and running the model, objective was to build energy-efficient ML models with low carbon footprint. 6. Model Evaluation: After the model was trained, the model's performance and accuracy were evaluated on the test data set by using metrics of Mean Squared Error (MSE) and R^2 score. And cross validation was done on trained model using cross-validation data set to ensure that the model generalizes well to unseen data. Some of the metrics used in regression include root mean squared error (RMSE), Rsquared (R^2 score), mean squared error (MSE), mean absolute error (MAE), and others. Tuning and optimizing facilitate trained model to optimize its generalization and performance. 7. Model Visualization: Model Visualization was used to visualized how good the trained model for predictions the trends and performance that can be seen through the graph (Time Series Line Graph). Time series line graphs visualize dynamically the data points changes with respect to time connecting these data points with a line showing the trends and patterns. We have not only visualized the data but also visualized how

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 15s, 2025
https://theaspd.com/index.php

good the trained model performed on the data. The trained model's performance was evaluated depends on how far or close prediction to the actual values. The final version of the trained Adaptive Business Intelligence model was ready for deployment trends prediction for real-time decision-making to optimal level.

4. Findings Adaptive Multiple Linear Regression Model for Revenue Prediction

A line graph in Fig. 2 displayed revenue that changes continuously overtime. A line graph on the x-axis showed month- year that is monthly time periods and on the y-axis showed revenue that is total sold per month. In this graph, there were two lines. The actual revenue line was the true revenue values from the given dataset were represented by solid line with circles. And the predicted revenue line which showed the trends of revenue values generated by the Adaptive Linear Regression model was represented by dashed line. These two lines on the graph are on the x-axis showed time and on the y-axis showed revenue evidently illustrated the Adaptive Linear Regression model's capability to keep track of revenue trends.

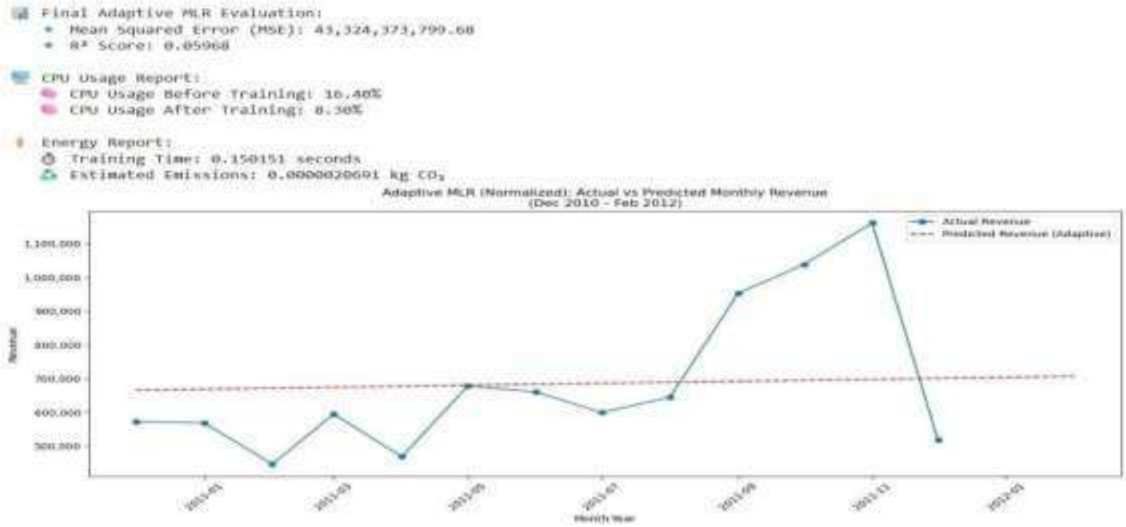

Fig. 2 Adaptive Multiple Linear Regression model for revenue prediction

Adaptive Decision Tree Regression Model for Revenue Prediction

A line graph in Fig. 3 displayed revenue that changes continuously overtime. A line graph on the x-axis showed month- year that is monthly time periods and on the y-axis showed revenue that is total sold per month. In this graph, there were two lines. The actual revenue line was the true revenue values from the given dataset were represented by solid line with circles. And the predicted revenue line which showed the trends of revenue values generated by the Adaptive Decision Tree Regression model was represented by dashed line. These two lines on the graph are on the x-axis showed time and on the y-axis showed revenue evidently illustrated the Adaptive Decision Tree Regression model's capability to keep track of revenue trends.

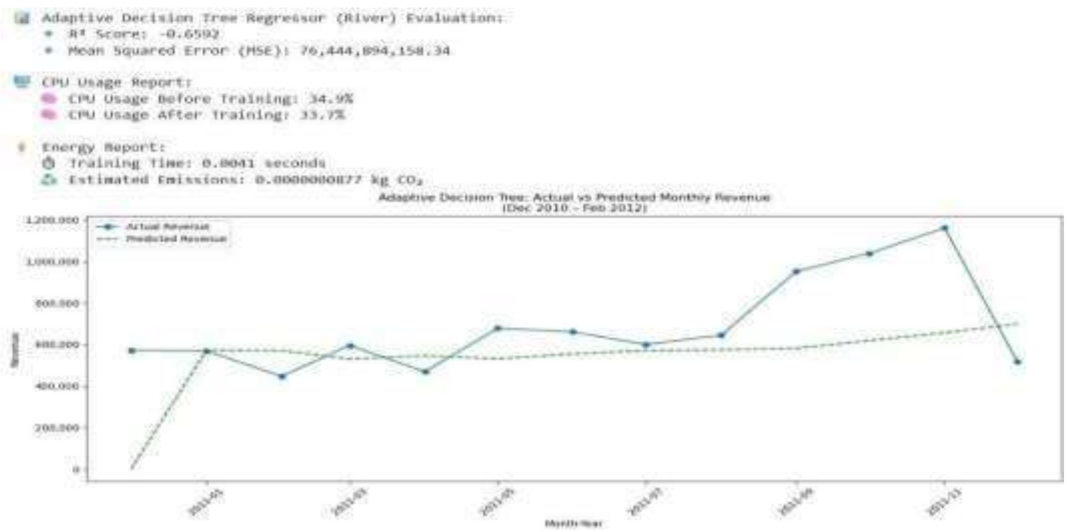

Fig. 3 Adaptive Decision Tree Regression model for revenue prediction

Result in Table 1 from Adaptive Multiple Linear Regression (AMLR) Model and Adaptive Decision Tree Regression (ADTR) Model for Revenue Prediction.

Table 1. Result from AMLR model in Fig. 2 and ADTR model in Fig. 3.

Metrics	**Adaptive Multiple Linear Regression Model**	**Adaptive Decision Tree Regression Model**
Mean Squared Error (MSE)	43,324,373,799.68 Or 4.33×10^{10}	76,444,894,158.34 Or 7.64×10^{10}
R^2 Score	0.05968	-0.6592
CPU Usage Before Training	16.40%	34.9%
CPU Usage After Training	8.30%	33.7%
Estimated CPU Usage During Training	16.40% - 8.30%= 8.10%	34.9% - 33.7% = 1.20%
Training Time (second)	0.150151 seconds Or 1.50×10^{-1} seconds	0.0041 seconds Or $4.10 \times 10^{-*}$ seconds
Estimated Emissions of CO_2	0.0000020691 kg CO_2 Or 2.07×10^{-6} kg CO_2	0.0000000877 kg CO_2 8.77×10^{-8} kg CO_2

We have used various evaluation metrics - mean squared error (MSE), R2 score, CPU usage, training time and emissions of CO_2 in both the Adaptive Multiple Linear Regression (AMLR) model and the Adaptive Decision Tree Regression (ADTR) model to determine their performance. We have found that:-

(i). The Mean Squared Error (MSE) values for Adaptive Multiple Linear Regression (AMLR) was 4.33×10^{10} and Adaptive Decision Tree Regression was 7.64×10^{10}. The Mean Squared Error (MSE) measures the average of the squared differences between the actual revenue values and the predicted revenue values. The mean squared error for the AMLR model was significantly lower than that of the Adaptive Decision Tree Regression model. This indicates that the AMLR model performed better in predictive accuracy for the given specific dataset. In contrast, the Adaptive Decision Tree Regression model made larger errors on average, as reflected by its higher MSE value. A lower MSE value suggests a model that fits the data more closely, making AMLR a more effective algorithmic approach in this scenario.

(ii). The R2 Score values for Adaptive Multiple Linear Regression (AMLR) was 0.05968 and Adaptive Decision Tree Regression (ADTR) was-0.6592. The R2 Score of the AMLR model (0.05968) was significantly closer to 1 compared to the ADTR's score of -0.6592. This demonstrates that the AMLR model provides a better fit to the data and captures the underlying trend more effectively. In contrast, the ADTR model performs poorly, with a negative R2 score suggested that it fails to generalize the data well. This may indicate overfitting or underfitting, where the model either memorizes the training data without capturing the pattern, or lacks complexity to model the trend, respectively. The ADTR thus fails to capture the trends in this particular dataset. Hence, the AMLR model (R2 = 0.3708) was clearly the better-performing model in terms of goodness-of-fit and predictive accuracy for this scenario.

(iii) CPU Usage refers to the percentage of total processing power used by the computer's CPU at a given time. In the context of training machine learning models, it reflects the computational load required to train a model. During training, the Adaptive Multiple Linear Regression (AMLR) model had an estimated CPU usage of 8.10% and the Adaptive Decision Tree Regression (ADTR) model had a lower estimated CPU usage of 1.20%. This indicates that the ADTR model was more CPU computationally efficient, utilizing significantly less processing power compared to the AMLR model. Therefore, the ADTR model is more lightweight and resource-friendly, making it better suited for scenarios where computational efficiency is a priority. (iv). The training time for Adaptive Multiple Linear Regression (AMLR) model was 1.50×10^{-1} seconds, whereas for the Adaptive Decision Tree Regression (ADTR) model, it was $4.10 \times 10^{-*}$ seconds. This indicates that the ADTR model required less time to train compared to the AMLR for the given specific dataset. Hence, the ADTR model showed better computational efficiency when consider for model training time period is a priority.

(v). The estimated emissions for the Adaptive Multiple Linear Regression (AMLR) model was 2.07×10^{-6} kg CO_2, whereas for the Adaptive Decision Tree Regression (ADTR), the emissions was 8.77×10^{-8} kg CO_2. This demonstrates that the ADTR model produced significantly lower carbon emissions compared to the AMLR for the given specific dataset. Therefore, from an environmental sustainability perspective, ADTR is a more eco-efficient algorithm, contributing less to carbon footprint during model training for a

given specific dataset. Carbon footprint refers to the CO_2 emissions generated during the model's training and execution. Here, we have observed that ADTR released less CO_2 emissions than AMLR.

5. DISCUSSION

(i) If the priority is minimizing model error (mean squared error - MSE), then adaptive multiple linear regression is preferred due to its lower average prediction error.

(ii) If the priority is predictive accuracy and generalization performance (R2 score), then adaptive multiple linear regression may be considered as it indicates better generalization and prediction performance. (iii) If the priority is reducing training time (lower computational cost), then adaptive decision tree regression model due to its efficiency and faster training.

(iv) If the priority is low CPU usage, then adaptive multiple linear regressions may be considered due to its lower energy consumption.

(v) If the priority is lower estimated CO_2 emissions (environmental sustainability), then adaptive decision tree regression should be considered due to its low emission of carbon footprint.

(vi) In most real-world forecasting scenarios, the selection of a adaptive machine learning model should depend on multiple factors including like dataset size and its complexity, accuracy requirements, training time, CPU and memory usage, energy consumption, carbon release and availability of computational resources.

6. CONCLUSION

In this research paper, we have rigorously presented various definitions, approaches and techniques of green computing, machine learning, and business intelligence. In this research, we have first identified the business problems and next we have came up with the solution of business intelligence, machine learning and green computing to solved those business problems without or with minimum negative impact to environment. Green computing approaches are behind implementation of green environment that is without or with minimum negative impact to environment. The developed Adaptive Business Intelligence (ABI) model can be deploying for real-time decision-making to optimal level. We have developed two Adaptive Business Intelligence (ABI) models were Adaptive Multiple Linear Regression (AMLR) model and Adaptive Decision Tree Regression (ADTR) model for a specific dataset. Developed these models, we first collected the data set, data pre-processing, feature engineering, model training using the right algorithm, CPU and energy tracking, evaluation metrics and model visualization. ABI models were used to determine how far off our predicted values are from the actual values along with the usage of computer resources and emission of carbon footprint. For a small dataset, ADTR model outperforms AMLR model in respect of CUP usage, training time and emission of carbon footprint. An AMLR model outperforms ADTR model in respect of Mean Squared Error (MSE) and R2 Score. We have observed that Lower CPU usage generally results in lower CO_2 emissions during computations. To choose the model depend on priority criteria over accuracy, usage of CPU, memory, energy, training time, and emission of carbon footprint. Future research directions, there are various business intelligence models that can be integrated with various advanced approaches of business intelligence, green computing and machine learning techniques to solve real world problems which have high positive impact on the green environment. There may be chances that low CPU usage doesn't always guarantee low CO_2 emissions. Priority matters over which criteria are considered like energy consumption, CPU and memory usage, accuracy, training time, release carbon footprint.

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