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Prof. Hamid Mattiello
Department of Business and Economics, University of Applied Sciences (FHM), Germany

Dr. Deepak Bhaskar Acharya
Department of Computer Science, The University of Alabama in Huntsville, USA

Dr. Ali Golestani Shishvan
Department of Electrical & Computer Engineering, University of Toronto, Canada

Editorial

As global priorities shift toward sustainable energy solutions, digital innovation, and improved healthcare outcomes, contemporary research plays a pivotal role in driving systemic transformation. The selected studies featured in this issue address some of the most pressing technological and societal challenges ranging from hybrid energy optimization in microgrids to the strategic integration of artificial intelligence across industries, and precision-driven diagnostic tools for breast cancer detection. Together, they represent the converging paths of sustainability, intelligence, and human-centered design in modern research.

Designing energy systems that balance efficiency, reliability, and long-term cost-effectiveness is a major challenge in microgrid development. This study evaluates the integration of a Hybrid Energy Storage System (HESS) combining batteries and supercapacitors for a 30kW microgrid. By assigning supercapacitors to manage transient energy fluctuations and reserving batteries for sustained energy delivery, the HESS configuration improves energy management, extends battery lifespan, and enhances overall system resilience. Although HESS entails a higher upfront investment than traditional Battery Energy Storage Systems (BESS), the long-term reduction in replacement costs and performance degradation positions it as a more sustainable and economical solution. The inclusion of a closed-loop control strategy, utilizing a low-pass filter, optimizes power distribution between storage components and reinforces load responsiveness. These findings underscore the critical role of hybrid storage technologies in advancing reliable off-grid and renewable energy systems [1].

Artificial Intelligence continues to revolutionize business operations by reshaping the foundational structures of industries undergoing digital transformation. Through a comprehensive exploration of AI techniques—including machine learning, deep learning, fuzzy logic, genetic algorithms, and generative AI—this study highlights real-world applications that range from supply chain optimization to automated quality assurance in manufacturing. A strategic lens is applied to executive-level decision-making, emphasizing the importance of data governance, ethical considerations, and cross-functional collaboration. Illustrated with practical case studies, the research reinforces AI's capacity to enhance operational efficiency, customer engagement, and innovation readiness. It also points to the urgent need for expanded discourse on evolving regulatory, ethical, and technological considerations in deploying AI responsibly [2].

Early and accurate detection remains a cornerstone of effective breast cancer treatment, and technological advances are expanding diagnostic capabilities at an unprecedented pace. This study introduces a high-performance hybrid model combining Principal Component Analysis (PCA) with a 1D Convolutional Neural Network (CNN) to detect breast cancer using the Wisconsin dataset. PCA is employed not only for dimensionality reduction but also to transform the feature space for enhanced class separability, while the 1D CNN architecture enables deep feature extraction and robust classification. The model achieved remarkable results, including a 99.12% accuracy and 100% precision, outperforming fourteen benchmark models in the literature. With strong validation metrics across multiple folds, the approach demonstrates a compelling fusion of classical and deep learning methods, offering a reliable and scalable solution for medical diagnostics and aiding informed healthcare decisions [3].

Collectively, these contributions reflect the spirit of modern research adaptive, interdisciplinary, and grounded in solving real-world challenges. From resilient energy storage to ethical AI deployment and intelligent healthcare systems, the studies exemplify the transformative power of innovative thinking in shaping a more sustainable and intelligent future.

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Cost & Efficiency analysis of Battery & SC based Hybrid Energy Storage system for Solar OFF Grid applications

Rahul Kotana *

Lead Engineer, Transmission Operation and Maintenance, TATA Power Company Limited, Mumbai, 400066, India

*Corresponding Author: Rahul Kotana, TATA Power Company Limited, Email: kotana.rahul@tatapower.com

E-mail: kotana.rahul@tatapower.com (Rahul Kotana)

ABSTRACT: This study evaluates the feasibility, efficiency, and cost-effectiveness of a Hybrid Energy Storage System (HESS) for a 30KW Microgrid. The research analyses various storage configurations incorporating batteries and supercapacitors, considering factors such as cost, reliability, and performance. While conventional Battery Energy Storage Systems (BESS) offer lower initial costs, they suffer from long-term reliability issues due to frequent replacements. In contrast, a HESS configuration, where supercapacitors handle transient changes and batteries manage low-frequency variations, enhances system stability, extends battery life, and improves overall efficiency. The study reveals that supercapacitors should have a greater share in storage systems where transient disturbances are frequent, while stable environments can rely more on batteries to optimize costs. Despite a higher initial cost, HESS proves to be more cost-effective in the long run by reducing battery degradation and replacement expenses. Additionally, the integration of supercapacitors improves efficiency and system resilience by quickly responding to disturbances, ensuring uninterrupted operation. A closed-loop control strategy, incorporating a low-pass filter, effectively manages power distribution between supercapacitors and batteries, minimizing energy losses and enhancing load response. The findings indicate that HESS presents a sustainable and reliable solution for microgrids, especially in off-grid and renewable energy-based applications.

KEYWORDS: Battery, Microgrid, Super capacitor, Hybrid Energy Storage system.

1. Introduction

Energy plays a crucial role in industrialized societies and economic development. It is an essential factor in daily life, and effective energy management is critical for future economic prosperity. Historically, fossil fuels have been the primary sources of energy generation, as most power infrastructure relies on coal, oil, and gas. However, these sources are not environmentally friendly and are finite. Their depletion will contribute to pollution and global warming. Additionally, energy accessibility remains a challenge in many regions. Approximately 1.2 billion people globally lack access to electricity, including over 635 million in Africa and 237 million in India alone [1]. The high costs of energy production and the distance between power generation and distribution centres are key factors behind this issue. To address these challenges, the transition to renewable energy sources such as solar, wind, hydroelectric, and geothermal power is necessary. Among these, solar energy and hydrogen fuel cells stand out due to their efficiency, reliability, environmental benefits, and high-power density [2]. Solar energy is particularly advantageous as it generates electricity without harmful by-products. Given the need for sustainable energy solutions, microgrid systems are emerging as a viable option. Although AC power transmission is standard, most household appliances—including mobile chargers, laptop adapters, and televisions—internally operate on DC [3]. Studies indicate that many household appliances can function on DC with minimal or no modifications [4–7]. A DC distribution system offers higher efficiency and improved power quality. Devices such as LED lights, laptop chargers, mobile chargers, and domestic fans operate more efficiently on DC than on AC. DC microgrids are gaining popularity in modern electric grids as they facilitate the seamless integration of renewable energy sources (RES), energy storage systems (ESS), and electric loads [8]. Solar power is one of the most cost-effective, sustainable, and environmentally friendly renewable energy sources. Typically, solar power is stored in an energy storage system before being utilized. Among various ESS technologies, batteries are the most common. However, their low power density results in slower charge and discharge cycles [9]. In recent years, supercapacitors (SCs) have emerged as an alternative energy storage solution. SCs provide high power density and respond rapidly to power fluctuations, enhancing system stability [10]. The combination of batteries and supercapacitors, known as a hybrid energy storage system (HESS), enhances overall system performance and extends battery life [11-12]. Several DC microgrid systems have been explored in the literature [13-16]. In [13-17], the authors proposed a DC microgrid system powered solely by solar PV, which connects multiple DC loads through point-on-load converters. However, this system lacks energy storage. [18] developed a solar microgrid with a 24V battery storage system, tested with LED loads. In [19] investigated solar microgrid solutions for Indian homes, proposing different configurations, including a rooftop solar-powered DC microgrid, a solar-AC system with an inverter for AC homes, and a solar-AC system with an inverter-less setup for DC homes. In [20], the authors designed a system incorporating solar PV as a source with battery storage.

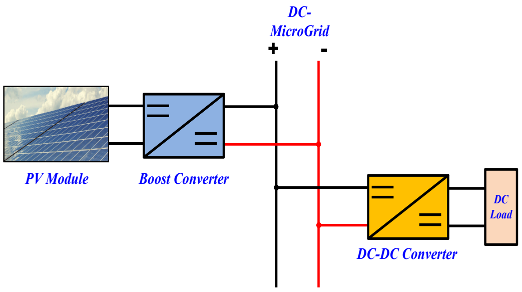

Figure 1: DC Microgrid with solar PV source [17]

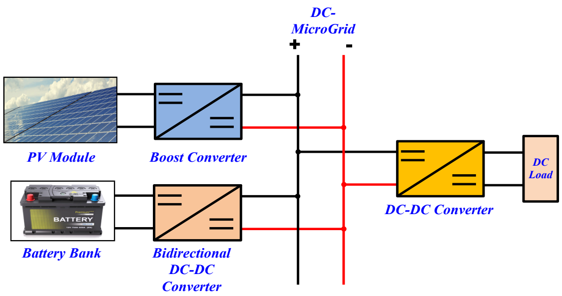

Figure 2: DC Microgrid with solar PV and battery storage [20].

In the Authors suggest [21] analysed the power electronics requirements for operating kitchen appliances on both DC and AC. Their findings suggest that most appliances designed to accept a wide voltage range can function directly on DC. By eliminating the AC-DC conversion step, efficiency can be improved in DC-powered systems. A microgrid system integrating solar PV as a power source with a hybrid storage system consisting of batteries and supercapacitors has been explored in various studies [22-23]. Several works in the literature have discussed microgrids and their storage techniques, with the most conventional and widely used method being the Battery Energy Storage System (BESS). This study aims to conduct a cost analysis and comparison between BESS and the hybrid energy storage system (HESS), which combines batteries and supercapacitors for improved performance and efficiency.

2. Battery & Supercapacitor based Hybrid Storage system configuration.

Hybrid energy storage with a combination of battery and supercapacitor has been gaining a lot of interest lately. There have been developments in the area of research for different applications but mainly concentrating on off-grid solar applications. To develop a hybrid energy storage system (HESS) project, Duke Energy has partnered with Aquion Energy, Maxwell Technologies, and other parties. When solar power is on and the grid varies due to cloud cover or other weather conditions, the hybrid system makes advantage of Maxwell's supercapacitors to help control solar smoothing events in real-time. The solar load is shifted with the help of the Aquion batteries to a period when the utility is more benefitted. It was implemented for a 1MW peak load. The hybrid energy storage system integrates patented energy management algorithms. While the battery bank provides long-duration power, the ultracapacitors handle short, intermittent duties. For example, when a cloud passes in front of the PV array, the ultracapacitors can quickly stabilize the power. When supply exceeds demand briefly, the ultracapacitor will absorb the additional energy [24-25].

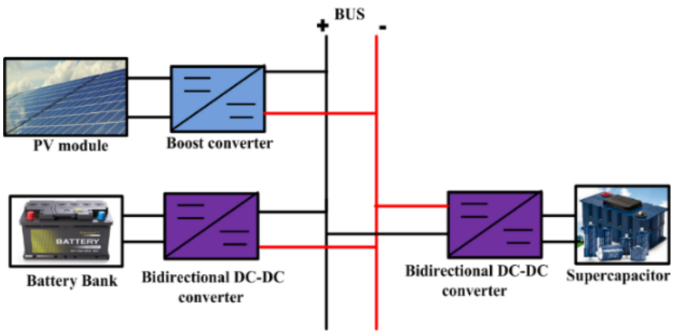

Figure 3: Hybrid Energy storage system (HESS)

Figure 4: Hybrid energy storage system at Duke Energy [24]

Figure 5: (a) Supercapacitor banks [25]

Figure 5: (b) Izu Oshima Island [25]

The development of hybrid battery energy storage technologies has been a focus for Hitachi Ltd. By combining lead-acid batteries, which offer great capacity, safety, and affordability, with lithium-ion capacitors, which have the power to react quickly to fluctuations with fast charge-discharge cycles, the company has created a hybrid battery energy storage system. Together with Shin-Kobe Electric Machinery Co. Ltd., the company has co-developed a 1.5 MW hybrid battery energy storage system. Hitachi has been implementing a hybrid battery energy storage system demonstration project on Izu Oshima Island, south of Tokyo, in collaboration with TEPCO* Power Grid, Inc. Because of its autonomous electrical grid, this island was chosen. The project has been supported by NEDO (The New Energy and Industrial Technology Development Organization).

There have been developments in battery-supercapacitor storage systems for Electric vehicle applications as well. The Tata Hybrid Magic car [26], created by the Automotive Research Association of India (ARAI) and Indian Space Research Organization (ISRO), includes a novel hybrid energy storage system that combines a normal battery pack with supercapacitors provided by ISRO. At Auto Expo 2020, it was on display on the Tata Ace platform. When fully charged, the Tata Magic hybrid prototype can travel between 120 and 150 km. This is because 40% of the vehicle's energy needs are met by the smaller supercapacitor. As a result, there is a decrease in weight and expense and an increase in battery life. IIT Jammu & the Queensland University of Technology have developed a hybrid supercapacitor storage system for Electric vehicles.

3. Cost Analysis

Energy Density: In comparison to supercapacitors, battery storage has a higher energy density, which allows it to store more energy per unit of volume or weight. Supercapacitors and batteries with high energy densities are combined in hybrid storage.

Power Density: Compared to batteries, supercapacitors have a higher power density, which allows them to release and absorb energy more quickly. While batteries provide a steady energy supply, hybrid storage systems make use of the high-power density of supercapacitors to handle peak power demand.

Efficiency: While batteries lose some energy throughout the charging and discharging cycles, supercapacitors are more efficient in these operations. The application and design specifics have an impact on a hybrid system's overall efficiency.

Cost: Although supercapacitors are typically more expensive than batteries, hybrid storage systems can offer cost-effective solutions by fusing the two technologies for maximum efficiency.

Lifespan: Compared to batteries, supercapacitors can withstand more charging cycles and have a longer lifespan. Hybrid storage solutions, on the other hand, can increase the battery life by lowering the quantity of charge-discharge cycles needed.

Considering the 30 KW Micro Grid system (i.e peak load of 30 KW) and considering the backup time to be provided by the storage system to be 14 Hrs.

Therefore, the total energy requirement on the storage system is 420 KWH, considering the worst-case scenario. The production by solar PV heavily depends on the temperature and location of the installation as the level of irradiation varies with location. Fig 6 shows the solar

Irradiation variation throughout a day at one on TATA Power co Ltd's Solar site. Hence design of the hybrid storage system depends on the multiple factors like the application, stability, temperature, and location. Where there are more chances of disturbances/ transient changes to the system, A configuration where supercapacitor contributing to the most of KWH requirement must be chosen since supercapacitor can respond quickly to changes as it releases large amount of energy in a short time. Similarly, the system where there are less chances of transient disturbances, a configuration with less contribution from supercapacitor can be chosen.

However, choosing either only supercapacitor or only battery storage systems have their own disadvantages. i.e., Using only supercapacitor for delivering the complete requirement will be very costly and not ideal. Similarly, using only battery storage implies that the system now cannot respond to any disturbances. It can be observed from the Table.2 that the cost of the storage system is the least when only battery storage is used & the cost is highest if only supercapacitor is used. This implies that both battery & supercapacitors if used alone, have their disadvantages & advantages. To address their disadvantages by merging their advantages, HESS can be a right choice by choosing the correct configuration depending on the application.

Table 1: Characteristics of Li-ion Battery and Supercapacitors [27-33]

Characteristics	Super Capacitors	Li-ion Battery
Specified energy density (Wh/ kg)	1-10	150-200
Specified power density (W/ kg)	<10000	<2000
Charging duration	0.3 to 30s	0.5 to 3h
Discharging Duration	0.3 to 30s	0.5 to 3h
Life cycles	< 50000	5000
Operating Temperature(◦C)	-45 to 85	-30 to 60
Eco-Friendliness	Moderate	Low
Cost per KWH (in Rs)	31000	17000
Efficiency	95%	85-95 %

Table 2: Cost comparison for different configurations of storage systems.

Storage configuration	Cost (Lakhs)	KWH by Battery	KWH by Supercapacitor
Only Battery	71.4	420	0
Only Supercapacitor	130.2	0	420
BAT:80% & SC:20%	83.16	336	84
BAT:70% & SC:30%	89.04	294	126
BAT:60% & SC:40%	94.92	252	168

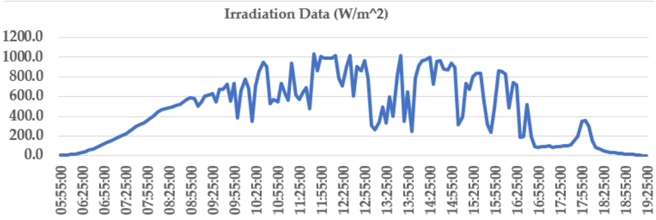

Figure 6: Variation in Solar Irradiation during a day.

The primary source PV in the proposed system is not always reliable because power output is affected by a variety of parameters such as temperature, time, season, and other unknowns. Power management between battery and supercapacitor are controlled through a closed loop control in such a way that the supercapacitor reacts to transient, fast changes while the battery reacts to low frequency changes. The HESS control loop is depicted in Figure 7.

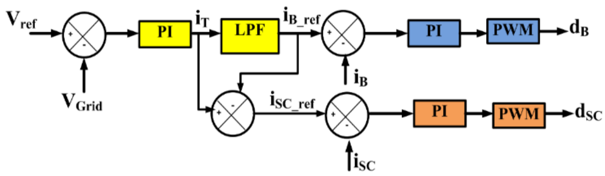

Figure 7: Closed Loop control for power management between battery & supercapacitor [34-35]

As it can be observed, total current is fed into a Low-pass filter and the high frequency part was given to the supercapacitor and the low frequency part to the battery.

The following analysis is done for a 30KW Microgrid for a configuration where battery is contributing to the 60% & supercapacitor is contributing to 40 % of the total energy requirement respectively. The following analysis was done considering the peak load requirement. Whereas, practically, the energy requirement will always be less than 420 KWH. With the help of the Table.1, the cost per KWH of battery and supercapacitor are calculated for different cases.

Figure 8 depicts the initial cost of battery storage & Hybrid storage system. It implies that the hybrid storage system has 32 % more initial cost than the conventional battery systems. However, in a long run, the Hybrid storage system has various advantages over the battery storage system in terms of cost.

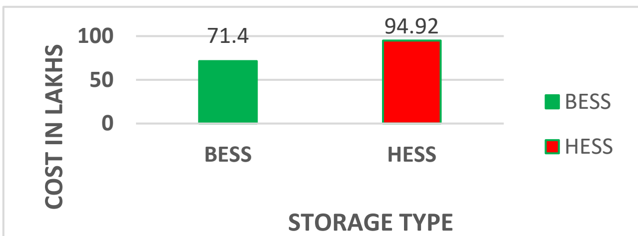

Figure 8: Initial cost for Battery storage & Hybrid storage system

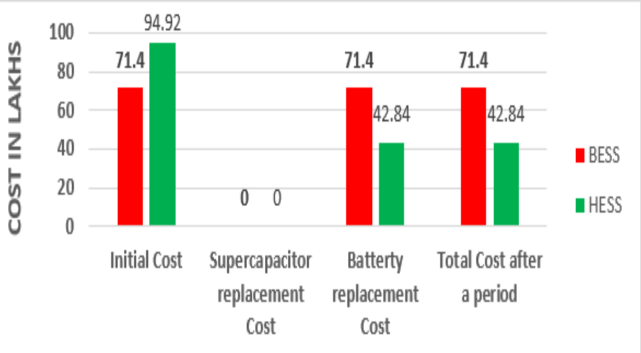

Figure 9: Cost comparison after a period.

It is clear that the initial cost of the battery storage system is less than the hybrid storage system. In the BESS, there is no supercapacitor cost and hence the total cost will be for the battery set/pack. But in HESS, there is inclusion of supercapacitor along with the battery.

Therefore, in hybrid storage, there will be cost towards the supercapacitor as well because now the energy is shared between the battery and supercapacitor. As the batteries have limited life cycles, they need to be replaced after certain period. For a BESS, the whole battery set needs to be replaced after a certain time making the replacement cost same as the initial cost. But in HESS, the replacement cost would be less because the energy contributed by the battery is less as compared to BESS thus resulting in the low replacement cost after a period. It is also important to notice that with the supercapacitor responding to the transient changes in the system, the stress on the battery is reduced thereby reducing the number of cycles, hence increasing the life of the battery i.e., the replacement period in HESS will be slightly more than the conventional BESS.

Figure 10. Summarizes the cost & efficiency analysis between BESS & HESS.

Storage Type	Initial Cost	System Efficiency	Replacement period	Replacement Cost
Battery Storage	Lowest	Lowest	Less	High
Super capacitor Storage	Highest	Highest	NA	NA
Hybrid storage	Slightly higher than BESS	More than the BESS	More	Low

Figure 10: Initial cost for Battery storage & Hybrid storage system

4. Conclusion

This study analysed the feasibility and efficiency of a Hybrid Energy Storage System (HESS) for a 30KW Microgrid with a backup time of 14 hours, requiring a total storage capacity of 420 KWH. The analysis considered various factors such as cost, performance, and reliability of different storage configurations involving batteries and supercapacitors. The study demonstrated that while battery storage alone presents a lower initial cost, it suffers from long-term reliability concerns due to frequent replacements. On the other hand, HESS configuration, where the supercapacitor contributes to transient changes and the battery addresses low-frequency variations, enhances the overall system stability and extends battery life by reducing stress cycles. The findings suggest that in scenarios with high transient disturbances, supercapacitors should have a greater share in the storage mix to enhance system responsiveness. Conversely, in relatively stable environments, the reliance on supercapacitors can be reduced to optimize costs. The cost analysis revealed that although HESS has a 32% higher initial investment than a traditional Battery Energy Storage System (BESS), it offers long-term economic advantages by reducing battery replacement costs and improving overall efficiency. Even though the work has mainly focussed on the cost perspective, the added advantage will be because of higher efficiency as well. Since the supercapacitor is having a higher efficiency than the battery, the efficiency of the combined system will be higher than the battery storage & less than the supercapacitor storage system. Another main added advantage is of the stability. With supercapacitor added in the system, if there are any transients/ disturbances during the day also, the supercapacitor will respond quickly to nullify the effect and will not allow the shutdown of the system thereby increasing the reliability of the complete system. Furthermore, the study highlights that HESS effectively mitigates the limitations of both battery and supercapacitor storage by leveraging their respective strengths. The implementation of a closed-loop control system, which intelligently distributes energy between the supercapacitor and battery using a low-pass filter, ensures optimal power management. This approach minimizes energy losses, enhances response time to load variations, and extends the operational lifespan of the storage components. In conclusion, the adoption of an appropriately configured HESS can provide a cost-effective and sustainable solution for microgrid applications. Future work may focus on optimizing control algorithms and exploring alternative energy storage technologies to further enhance system efficiency and cost-effectiveness. The integration of renewable energy sources with an advanced HESS can significantly improve the reliability and sustainability of microgrids, making them a viable solution for remote and energy-sensitive locations

Conflict of Interest

The authors declare no conflict of interest.

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RAHUL KOTANA has done Bachelor's degree in Electrical & Electronics Engineering from the Institute SRM University AP in 2022. Since 2022, He is working as Lead Engineer at TATA Power Company where he looks over O&M, Equipment Testing, Relay testing activities at Extra High Voltage (EHV) Substation. The main direction of his research is in the area of High Gain DC-DC converters, Micro Grid systems, Renewable energy systems. He has one conference publication & one journal publication. He also holds Indian Patent Grant on "A DC to AC conversion apparatus"

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AI-Driven Digital Transformation: Challenges and Opportunities

Maikel Leon*
Department of Business Technology, Miami Herbert Business School, University of Miami, Miami, Florida, USA
*Corresponding author. Email: mleon@miami.edu

ABSTRACT: This paper explores the crucial role of Artificial Intelligence (AI) in driving digital transformation across industries. It examines machine learning, deep learning, fuzzy logic, genetic algorithms, reinforcement learning, and generative AI techniques, highlighting their development, applications, and examples. Case studies showcase AI's impact in optimizing supply chains, improving financial operations, boosting customer engagement, and revolutionizing quality control in manufacturing, underscoring its strategic importance. The paper also discusses executive-level considerations, including strategic approaches, data governance, ethical frameworks, transparency, and collaboration across departments, all illustrated with examples. While AI offers significant potential for organizational growth, operational excellence, and sustainable innovation, there's an open call for further research into the evolving ethical, regulatory, and technological challenges.

KEYWORDS: AI-Driven Digital Transformation, Machine Learning, Generative AI.

1. Introduction

Digital transformation is the fundamental shift in how businesses operate, brought about by integrating digital technology into every aspect of the organization. It's a significant change in how companies work. This isn't just about upgrading technology; it's about automating tasks people used to do manually, reducing repetitive work and human error. Businesses are increasingly using technology to handle routine tasks, data entry, customer service, and even complex decisions that used to be made solely by human experts [1]. Traditional manual tasks like filing, processing data, and basic customer service are being replaced by automated systems that are more efficient, less prone to errors, and can scale up quickly. For example, robots in manufacturing, online retail platforms that automate sales and inventory, and mobile banking apps that eliminate the need for branch visits are clear examples of how digital tools have transformed long-standing practices. Beyond the rise of the World Wide Web and the all-in-one functionality of smartphones, other examples include the automation of manufacturing with advanced robots, the growth of e-commerce platforms that have disrupted traditional retail, and the development of cloud-based systems that centralize data and enable global teamwork [2].

The fourth industrial revolution is unique because it's fundamentally based on AI, unlike earlier revolutions driven by mechanical production, electricity, or basic computing. Instead of just automating simple tasks, this revolution leverages intelligent systems that can analyze vast amounts of data, learn from complex patterns, and make decisions independently in real time. This move towards cognitive automation and innovative technologies enables real-time decision-making and personalized customer experiences. It also brings a level of operational efficiency and innovation that was previously unimaginable. The deep integration of cyber-physical systems characterizes the Fourth Industrial Revolution, the widespread use of the Internet of Things (IoT), and the adoption of cloud computing. The number of connected IoT devices is projected to be incredibly high in the near future, generating vast amounts of data that power AI algorithms. Cloud computing provides the infrastructure to process this data, while cyber-physical systems, like smart factories with interconnected sensors, allow for real-time optimization and control. This interconnectedness enables automation and responsiveness far beyond what was previously possible. For example, a smart factory might use Machine Learning (ML) to predict equipment failures with 90% accuracy, significantly reducing downtime and maintenance costs. Other examples include smart manufacturing, self-driving cars, and personalized healthcare systems [3].

The rest of this paper is structured as follows. Section 2 provides a detailed look at AI, including definitions, different aspects, and relevant research. Section 3 explores how executives view AI through a survey analysis. Section 4 discusses strategic approaches for deploying AI and compares Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI). Section 5 delves into transparency in AI systems, discussing the historical use of "black box" models, the need for more explainable AI, and efforts to improve transparency in complex neural networks. Section 6 examines how to integrate ethical reasoning and legal compliance in AI, including discussions on reliability, safety, and the roles of different stakeholders. Section 7 focuses on environmentally conscious ML, discussing energy efficiency and model optimization. Section 8 emphasizes the importance of multidisciplinary teams in AI development. Section 9 presents real-world case studies showing how AI is transforming industries. Finally, Section 10 concludes the paper, and Section 11 outlines areas for future research. This roadmap will guide you through the detailed discussions and examples throughout the paper.

2. Understanding Artificial Intelligence: Definitions, Dimensions, and Literature Foundation

Artificial Intelligence (AI) encompasses a range of techniques and systems that learn from data, identify complex patterns, and make decisions based on those patterns. Over decades of research, AI has branched into areas focusing on specific tasks and broader methods of simulating human reasoning. Research in this field goes beyond just designing algorithms; it also considers AI's economic, ethical, and social implications as it fundamentally shapes how people interact with technology and how businesses operate in dynamic environments.

2.1. Machine Learning and Deep Learning

ML aims to extract structured and unstructured data insights to make predictions, classify things, or detect anomalies, enabling better decision-making. Its origins lie in statistical models and pattern recognition, which have evolved significantly with better algorithms and more powerful computers. Today, typical applications include recommendation systems in e-commerce, fraud detection in finance, and predictive analytics for marketing or operations. Early research in ML laid the groundwork for the field, establishing the theoretical foundations and algorithmic approaches that continue to be influential. Further ML applications include personalized medicine, where algorithms predict how patients will respond to treatments based on their genes, and optimizing energy consumption in smart grids by forecasting demand.

Deep learning, a specialized area within ML, uses multiple layers of neural networks to capture complex, high-level features from raw data. Its essential applications include image recognition, speech processing, and natural language understanding. Current developments are addressing challenges like interpretability and computational cost. Techniques like model distillation are being explored to maintain performance using fewer resources. Other examples include self-driving car perception systems and advanced medical image analysis [4].

2.2. Fuzzy Logic

Fuzzy logic moves away from traditional binary true-or-false systems by allowing for degrees of membership, providing a way to handle uncertainty and vagueness in real-world situations. It originated from the need to handle complex decision-making processes with insufficient strict thresholds. This makes it particularly well-suited for adaptive control systems in consumer electronics, automotive engineering, and manufacturing. Modern fuzzy logic applications extend to sophisticated decision-support systems where precise boundaries are hard to define. For instance, in manufacturing quality control, fuzzy logic systems can interpret sensor readings to determine if variations in product specifications are within acceptable limits, enabling a more nuanced control mechanism than a simple pass/fail system. Further examples include climate control systems in smart buildings and adaptive user interfaces that adjust to changing conditions [5].

From an executive's perspective, fuzzy logic provides a flexible framework that improves decision-making by accounting for many business processes' inherent complexities and ambiguities. For example, an executive might use fuzzy logic to fine-tune automated control systems on production lines or optimize customer service response systems that handle various inputs. This technology improves operational efficiency and builds confidence in automated systems that operate under uncertain conditions, supporting a sustainable competitive advantage [6].

2.3. Genetic Algorithms

Genetic algorithms iteratively refine solutions by mimicking principles of biological evolution, such as selection, crossover, and mutation, to efficiently search large solution spaces. Early implementations revolutionized optimization tasks in scheduling, routing, and engineering design by effectively navigating complex problem spaces. In today's business world, genetic algorithms are used to optimize complex investment portfolios, manage supply chain logistics, and even design innovative products by exploring a vast range of potential configurations that would be too computationally expensive to analyze using traditional methods. Further examples include optimizing traffic flow in smart cities and refining marketing campaign strategies [7].

For executives, genetic algorithms are powerful tools for achieving optimal performance in systems where conventional optimization techniques might fail. For example, a financial institution might use genetic algorithms to rebalance investment portfolios continuously in response to volatile market conditions. In contrast, a logistics company could use them to optimize real-time delivery routes, reducing operational costs and improving customer satisfaction. Genetic algorithms' dynamic adaptability makes them a valuable strategic asset in competitive business environments, offering flexible and efficient solutions.

2.4. Reinforcement Learning

Reinforcement learning enables systems (agents) to learn optimal actions through trial and error, guided by a reward system based on feedback from their environment. This leads to continuous improvement over time. Early demonstrations included simple game-playing programs, but advances in computing have allowed reinforcement learning to power breakthroughs in robotics, autonomous driving, and dynamic resource allocation. This approach integrates deep learning techniques to handle high-dimensional inputs, making it applicable to various complex decision-making scenarios. Other examples include personalized content recommendation systems and adaptive energy management in smart grids.

By training reinforcement learning agents on:

- Streaming traffic data from city sensors that provide real-time congestion information,
- GPS feedback from vehicles providing precise location tracking,
- Detailed delivery schedules with varying priorities reflecting customer demands,

The system learned to dynamically recalculate routes in response to traffic jams, accidents, or bad weather, leading to significant operational improvements. For example, a transportation company might use reinforcement learning to adjust real-time routing strategies, reducing delays and fuel consumption. In manufacturing, reinforcement learning can optimize production processes to ensure high efficiency even with varying raw material quality or changing market demands. Executives can leverage these improvements to drive substantial cost savings and operational enhancements across various applications [8].

2.5. Generative AI

Generative AI focuses on creating new digital content, such as text, images, audio, or video, using advanced models that learn the underlying patterns in data to produce outputs that can be remarkably similar to those created by humans. Early work in this area laid the foundation for advanced systems capable of producing realistic images and natural-sounding speech. Today, these systems are used in a wide variety of applications. Generative AI has far-reaching applications in design, advertising, and content creation, enabling the rapid production of personalized marketing materials and innovative prototypes. Further examples include creating virtual environments for training simulations and automated scriptwriting for entertainment [9].

For executives, generative AI offers the potential to revolutionize creative processes by automating aspects of content generation that used to require significant human effort. For instance, a media company might use generative AI to produce tailored promotional campaigns based on detailed consumer behavior data, enhancing personalization and engagement. Furthermore, generative AI can facilitate rapid prototyping in product design, reducing time to market and fostering a culture of innovation within the organization. These capabilities enable companies to respond more quickly to market changes and customer needs [10].

2.6. Summary of AI Approaches

ML and deep learning have become primary approaches for classifying, predicting, and recognizing complex patterns, boosted by large datasets and modern computing power. Fuzzy logic introduced the concept of partial truth values, which is particularly useful in control systems and situations requiring fine-grained distinctions. Inspired by evolutionary processes, genetic algorithms excel at solving complex optimization problems. Reinforcement learning uses reward-based feedback loops to enable systems to adapt through continuous trial and error [11]. At the same time, generative AI extends these capabilities to creative tasks by producing new text, images, and audio content that closely mimic human output. This section provides a comprehensive overview of popular AI methods and includes extra examples to illustrate each approach.

ML is a method that learns from data. It is commonly used in predictive analytics, fraud detection, and recommendation systems. By analyzing past data, ML models can predict future outcomes, recognize patterns, and provide recommendations based on user behavior. Deep Learning utilizes layered neural networks to model complex patterns in data. This approach is widely applied in computer vision, natural language processing, and autonomous vehicles. Deep learning benefits tasks like image recognition and speech processing, and enables self-driving cars.

Fuzzy Logic operates on degrees of truth rather than traditional binary logic. It is employed in control systems, quality control, and adaptive user interfaces. Fuzzy logic helps manage uncertainty and imprecision in decision-making processes, making it ideal for dynamic and unpredictable environments. Genetic Algorithms use evolutionary search techniques, simulating natural selection to find optimal solutions. This approach effectively solves optimization problems, scheduling tasks, and portfolio management. Genetic algorithms excel in situations where other methods may fail to identify the best solution, mainly when dealing with complex or large-scale search spaces.

Reinforcement Learning is based on a system of rewards and penalties, where an agent learns to take actions in an environment to maximize cumulative rewards. This method is used in game AI, robotics, and dynamic resource allocation. Reinforcement learning allows systems to learn from trial and error, making it practical for uncertain or constantly changing environments. Generative AI focuses on creating content, enabling machines to generate new data resembling human-created content. It is used in design, data augmentation, and automated content production. This approach allows for generating images, text, and even music, offering innovative solutions for creative industries.

These varied methods show AI's flexibility in addressing complex business problems, including classification, prediction, control, optimization, autonomous interaction, and creative output. Given this wide range of options, executives must carefully evaluate which AI strategies align with their core objectives and available data. Numerous real-world examples show that a deliberate selection process, guided by strong governance and ethical oversight, is essential for sustainable AI integration [12].

3. Exploring Executives' Perceptions

This study explores how executives perceive AI's role in digitally transforming their companies' services and products, providing valuable insights from various industries. A comprehensive survey analysis assesses how AI technologies contribute to operational efficiency, competitive advantage, and ethical business practices.

We surveyed 500 executives across diverse industries to evaluate the integration and impact of AI in their operations, capturing a wide range of opinions. Respondents rated their agreement with a series of statements on a Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree), allowing for quantitative insights. The survey included questions about AI's role in daily operations, its contribution to competitive advantage, investment levels in AI technologies, concerns about the rapid evolution of AI, and the adequacy of current AI knowledge among company leadership, among other topics.

The following are the questions executives answered:

1. To what extent has AI been integrated into your company's services and products?

2. How significantly has AI impacted the daily operational activities of your company?
3. Do you believe AI technology gives your company a competitive advantage?
4. Is your company currently investing adequately in AI technologies?
5. Are you concerned about your company's ability to keep up with the rapid evolution of AI technology?
6. Do you feel that the current level of AI knowledge within your company's leadership is sufficient?
7. Is there a plan to increase the hiring of AI specialists shortly?
8. Is your company considering appointing a Chief AI Officer (CAIO) to oversee AI strategy?
9. How important are ethical considerations in your company's AI strategy?
10. Does your company have a clear long-term strategy for AI?

3.1. Analysis

We calculated descriptive statistics for each survey question and conducted chi-square tests for goodness of fit to determine if the distribution of responses significantly deviated from a hypothetical uniform distribution, providing statistical validation. We can observe the median, mode, and standard deviation for the 10 survey items, along with further details that illustrate the overall sentiment among the respondents [13].

The survey responses were analyzed for various aspects of AI integration and its impact on operations. The overall mean score for AI integration was 4.1, with a median of 4 and a mode of 4, indicating general agreement among respondents on the importance of AI integration. The standard deviation of 0.8 suggests some variation in the responses. Regarding the impact of AI on operations, the mean score was 4.3, with a median of 4 and a mode of 5, suggesting that most respondents recognized a significant positive impact on operations. The standard deviation of 0.7 indicates relatively consistent opinions, with a slight variation among responses. For competitive advantage, the mean score was 4.2, with a median and mode of 4, indicating that AI was generally seen as a key driver of competitive advantage. However, there was some variation in opinions, as evidenced by the standard deviation of 0.75. Regarding investment in AI, the mean score was 3.8, with a median of 4 and a mode of 4. This suggests that while AI investment is considered necessary, there may be some reluctance or differing opinions. The standard deviation of 0.85 highlights the diversity of responses on this issue.

Concerns about the future of AI received a mean score of 4.5, with a median and mode of 5, reflecting high concern and importance among the respondents. The low standard deviation of 0.6 suggests near consensus on this point. On the adequacy of knowledge about AI, the mean score was 3.5, with a median and mode of 3, indicating that respondents generally felt their understanding of AI was somewhat lacking, with a higher standard deviation of 1.0 indicating variability in individual responses. The issue of hiring AI talent received a mean score of 4.2, with a median and mode of 4, signaling a recognition of the importance of AI talent. The standard deviation of 0.8 shows a slight variation in the responses. The importance of having a Chief AI Officer was rated with a mean of 3.7, a median of 4, and a mode of 4, indicating some support for the role but with a range of opinions. The standard deviation of 1.1 reflects a higher level of disagreement.

Ethical considerations in AI were highly rated, with a mean of 4.0, a median and mode of 4, and a standard deviation of 0.9, showing that most respondents recognized the significance of ethics in AI development and deployment. Finally, the long-term AI strategy received a mean score of 3.9, with a median and mode of 4, suggesting moderate support for a long-term AI strategy within organizations. The standard deviation of 0.95 indicates some variation in opinions on the importance of long-term planning for AI. Chi-square tests confirmed significant deviations from a uniform distribution across all survey questions ($p < 0.05$), indicating that executives hold strong opinions regarding the various statements in the survey.

3.2. Findings

Over 90% of the executives indicated that AI has significantly altered daily operations within their companies, demonstrating its critical role in enhancing business processes and operational efficiency. Many respondents expressed concern about their ability to keep up with the rapid evolution of AI technologies, reflecting widespread anxiety about potential knowledge gaps at the leadership level and the fast pace of technological advancements in this area. The data reveal a proactive stance toward AI integration, with over 80% of executives planning to hire more AI specialists and more than 50% considering appointing a Chief AI Officer to manage AI initiatives much more strategically. Approximately 70% of the participants rated ethical considerations as highly significant in their AI strategies, suggesting a thoughtful approach to AI deployment, despite about 65% reporting the existence of a clear long-term AI strategy. These findings indicate that some companies may need further strategic development to harness AI's transformative potential fully.

4. Strategizing AI Deployment and Methodology

Organizations that embed AI within their broader digital transformation efforts are more likely to create lasting value, especially when adopting a systematic AI integration approach. A good first step is to clarify a high-level vision and specific AI use cases. This ensures that technical investments are closely aligned with measurable improvements in service quality, operational efficiency, or competitive differentiation. It's helpful to begin with a clear statement of purpose and then identify which processes or offerings would benefit most from AI. Establishing pilot projects with measurable objectives can help teams discover the technology's advantages and potential drawbacks before scaling up deployment across the entire organization [14].

Adopting a robust methodological framework is also crucial. Data governance policies must ensure the correct data is collected, validated, and stored securely. A well-planned pilot phase clarifies success metrics and highlights organizational needs related to talent and technology infrastructure [15]. Many companies consult academic papers, industry reports, and real-world case studies when selecting and designing AI projects. Further examples include successful implementations in manufacturing, finance, and healthcare. This comprehensive approach helps set realistic expectations for timelines, budgets, and the potential for scaling up.

4.1. Artificial Narrow Intelligence (ANI) vs. Artificial General Intelligence (AGI)

Artificial Narrow Intelligence (ANI) and Artificial General Intelligence (AGI) represent two fundamentally different paradigms within the field of artificial intelligence. ANI is designed to perform specific tasks with high efficiency and accuracy, such as image recognition, natural language processing, or fraud detection. Today, it is the most common form of AI and has demonstrated considerable practical value. Examples of ANI include IBM Watson in medical diagnostics, voice assistants like Siri and Alexa, recommendation algorithms on streaming platforms, and automated fraud detection systems used by financial institutions. ANI excels at targeted applications but cannot generalize across domains.

In contrast, AGI aspires to replicate human-like cognitive abilities, allowing for flexible reasoning and problem-solving across various tasks without needing task-specific programming. AGI systems would theoretically be capable of understanding and learning from any new situation, much like a human brain. Although AGI remains a theoretical concept, ongoing research aims to bridge the gap between specialized and general intelligence. Achieving AGI would represent a significant breakthrough, potentially transforming industries through unprecedented adaptability and learning capabilities.

The following points highlight key distinctions between the two:

- **Scope and Flexibility:**
  - **ANI:** Performs specific tasks with high precision but cannot generalize across domains.
    - *Example:* Image recognition systems that detect objects but cannot understand context.
  - **AGI:** Emulates human-like cognitive abilities, allowing flexible reasoning and learning across various tasks.
    - *Example:* Hypothetical systems can solve novel problems without prior programming.
- **Current State of Development:**
  - **ANI:** Well-established and widely used in various industries.
    - *Example:* IBM Watson in medical diagnostics, Siri and Alexa as voice assistants.
  - **AGI:** Remains theoretical and under active research, with no practical implementations yet.
    - *Example:* Research projects like OpenAI's efforts toward creating more generalized systems.
- **Practical Applications:**
  - **ANI:** Used for targeted solutions that provide immediate operational benefits.
    - *Example:* Fraud detection in banking and personalized recommendations on streaming platforms.
  - **AGI:** Aims to achieve human-like decision-making, potentially revolutionizing how machines understand and interact with the world.
    - *Example:* Conceptual frameworks that could perform any intellectual task a human can do.
- **Challenges and Risks:**
  - **ANI:** Limited by its task-specific nature and lack of adaptability.
    - *Risk:* Performance drops significantly if input data deviates from training scenarios.
  - **AGI:** Poses ethical and safety challenges due to its potential for autonomous decision-making.
    - *Risk:* Unintended consequences from actions taken without human oversight.

Understanding the distinction between ANI and AGI is essential for decision-makers. While ANI offers immediate and actionable benefits that can enhance operational efficiency and drive innovation, AGI represents a long-term strategic vision requiring careful consideration of ethical, social, and technical implications. Balancing investments between these two paradigms requires a strategic approach, recognizing the practical advantages of ANI alongside the transformative potential of AGI.

4.2. Self-Learning Systems and Adaptive Algorithms

AI that continuously refines its parameters based on real-time data can be highly effective. Still, it also has the potential to drift away from its initially intended performance if not properly monitored. Monitoring these changes requires systematic checks, creative safety measures, and ongoing performance evaluations. Adaptive algorithms pose unique challenges in terms of monitoring and transparency. As these models adjust their outputs with minimal human intervention, organizations may need to implement robust safeguards to prevent unexpected or ethically questionable behaviors [16]. It's also essential to provide clear disclosure to users about how these systems learn and their implications for privacy or important real-life decisions, ensuring accountability and trust.

4.3. AI as a Component of a Larger System

AI rarely operates in isolation in modern business environments. In today's highly interconnected world, AI is embedded into nearly every aspect of business operations, from data pipelines and customer service interfaces to enterprise resource planning and supply chain management systems. This widespread presence means that AI is intricately intertwined with legacy systems, human decision-making processes, and other digital tools, making it difficult to isolate as a separate entity for study or regulation. Instead, AI should be understood as a fundamental part of a larger technological ecosystem, where its performance and overall impact depend on its interactions with other system elements. This complexity requires the development of comprehensive governance frameworks that address both individual components and their interdependencies, as seen in integrated smart city solutions and interconnected healthcare monitoring systems [17].

4.4. Challenges and Mitigation Strategies

While the potential benefits of AI are significant, organizations often face several challenges during deployment. These include:

- Data Quality Issues: AI algorithms depend heavily on the quality of the input data. Inaccurate, incomplete, or biased data can lead to flawed results and poor decisions. Mitigation includes implementing robust data governance policies, including validation, cleaning, and preprocessing. Regularly audit data sources for accuracy and completeness.

- Lack of Skilled Personnel: The demand for AI specialists (data scientists, ML engineers, etc.) often exceeds the supply. Mitigation includes investing in training and upskilling existing employees, partnering with universities and research institutions. Consider outsourcing specific AI tasks to specialized vendors.

- Integration with Legacy Systems: Integrating AI solutions with IT infrastructure can be complex and costly. Mitigation includes adopting a modular, API-driven approach to AI development. Prioritize projects that can be easily integrated with existing systems. Consider a phased implementation, starting with pilot projects.

- Ensuring Scalability: AI solutions that work well in a pilot setting may not scale effectively to handle larger datasets or more complex scenarios. Mitigation includes designing AI systems with scalability in mind from the start. Use cloud-based infrastructure and scalable algorithms. Continuously monitor performance and adjust resources as needed.

- Cost of Implementation: Setting up a good AI infrastructure can be expensive. Mitigation includes trying to use open-source and free software whenever possible. Focus the AI strategy on the company's parts that will benefit the most.

5. Transparency in AI Systems

For decades, no mandatory policies have required companies to be transparent about how their AI systems work, leading to significant differences in disclosure practices. Despite growing calls for accountability, many organizations have operated with minimal regulatory oversight. Several initiatives and declarations have been proposed, including the European Commission's guidelines for trustworthy AI, the OECD AI Principles, and IEEE's Ethically Aligned Design document. These have all sought to establish voluntary standards for transparency. However, without binding regulations, compliance remains inconsistent. This lack of enforced transparency has allowed companies to maintain proprietary control over their algorithms, even as these systems increasingly influence essential societal and economic outcomes. Further examples include voluntary self-reporting frameworks in sectors like finance and healthcare, which, while helpful, don't replace enforceable legal standards [18].

Efforts to promote transparency have also included industry self-regulation and public declarations, but these measures haven't translated into legally enforceable policies. The absence of mandated transparency standards has resulted in a fragmented landscape where companies adhere to varying levels of disclosure. This situation highlights the urgent need for comprehensive policies that require precise, consistent, and accessible explanations of AI systems, especially as their influence continues to expand across multiple sectors and impacts a wide range of stakeholders [19].

5.1. Historical Use of Black Box Models and the Need for Explainable AI

Historically, many AI systems, particularly complex neural networks used in critical applications, have operated as "black boxes," meaning their internal decision-making processes were hidden from users and even their developers. These black box models, like deep convolutional neural networks used for image recognition or recurrent neural networks used in natural language processing, often produced impressive results but lacked transparency. This lack of transparency has led to difficulties in diagnosing errors, ensuring fairness, and understanding biases in the system. Recently, researchers have started re-examining these complex models to make them more transparent. Efforts like developing explainable AI (XAI) frameworks, techniques like Layer-wise Relevance Propagation (LRP), and integrating attention mechanisms in neural networks aim to show how these systems work. These initiatives are increasingly being implemented in sectors like healthcare and finance, where understanding the reasoning behind AI decisions is crucial for compliance and ethical accountability [20].

5.2. AI Biases and Ethical Implications

AI biases have emerged as a significant challenge in developing and deploying artificial intelligence systems, significantly impacting fairness, equity, and trust. Biases can arise from several sources, including biased training data, flawed model design, or unintended consequences from algorithmic optimization. These biases can perpetuate discrimination and reinforce societal inequalities when left unchecked. For instance, facial recognition systems have performed poorly on individuals from underrepresented demographic groups, leading to false identifications and wrongful outcomes in law enforcement contexts. Similarly, automated hiring systems may inadvertently favor candidates based on irrelevant attributes if historical data reflects biased human decision-making.

Biases in AI systems can manifest in various forms, including gender bias, racial bias, and socioeconomic bias, often magnified when data sets are unrepresentative or inherently skewed. For example, natural language processing models trained predominantly on English text from Western sources may struggle to accurately process inputs from other cultures or languages, leading to misinterpretations or biased outputs. Furthermore, predictive policing algorithms may disproportionately target minority communities when historical crime data reflects prior discriminatory practices, resulting in unfair surveillance or policing practices. Researchers are increasingly advocating for more robust bias detection and mitigation techniques to address this. One strategy to address these challenges is data auditing, which involves systematically examining training data for biases and ensuring diversity in data representation. Another approach focuses on algorithmic fairness metrics, incorporating fairness constraints during model training to reduce disparate impacts on specific groups. Human oversight is also essential, as well as integrating human judgment to review AI decisions in high-stakes applications such as healthcare. Bias mitigation algorithms, like reweighting or data augmentation, help balance representation within training data. Additionally, transparent reporting is crucial, clearly communicating the limitations of AI models and the potential biases of AI modeling and end-user interfaces.

Despite ongoing efforts, achieving fully unbiased AI remains a formidable challenge. Addressing bias requires not only solutions but also sociocultural and interdisciplinary collaboration. Policymakers and industry leaders must prioritize ethical considerations during system design and deployment, guided by comprehensive governance frameworks that mandate regular evaluations of bias and discrimination risks. Tackling AI bias is a technical and societal problem requiring a commitment to ethical AI development and transparent practices. As AI systems continue to influence critical decisions in finance, healthcare, law enforcement, and beyond, addressing bias remains central to building trustworthy and responsible AI systems that serve all stakeholders equitably.

6. Embedding Ethical Reasoning and Legal Compliance in AI

Embedding ethical reasoning at every stage of AI design and deployment isn't just about doing the right thing; it protects brands from legal risks and fosters long-term public trust. Organizations can create solutions that meet both moral and legal standards by thoroughly analyzing AI's potential benefits and inherent risks well in advance. Demonstrating responsible AI practices in competitive markets can set a company apart and strengthen its market position. The ethical aspect of AI involves ensuring fairness, accountability, and transparency, while the legal aspect requires strict adherence to data protection laws, regulatory standards, and contractual obligations [21]. For example, a company deploying facial recognition technology must ethically ensure non-discrimination and privacy for its users while legally complying with regulations like the General Data Protection Regulation (GDPR) in Europe or similar frameworks in other regions. Understanding these differences allows executives to balance innovation with rigorous risk management.

6.1. *Reliability, Safety, and Ethical-Legal Application*

An AI system must be dependable, secure, and understandable to be ethically sound and legally compliant. A malfunctioning system can seriously damage stakeholder confidence, while an opaque system might invite legal challenges due to a lack of accountability. Therefore, organizations must ensure that their AI consistently performs well in accuracy, speed, and traceability while providing clear explanations for its decisions. Furthermore, these systems should be designed to avoid posing unnecessary risks—whether cyber or otherwise—and must operate within the well-defined boundaries of ethical principles and legal mandates. For instance, an AI in self-driving cars must adhere to strict safety protocols to prevent accidents and protect human life, ensuring its decision-making processes are auditable in case of legal disputes. Similarly, an AI system used in financial services must maintain high levels of reliability and transparency to comply with stringent regulatory standards and prevent fraud. Combining these elements into a cohesive framework minimizes risk and builds long-term trust with customers, regulators, and the public [22].

6.2. *Role of AI Developers*

Whether they work in-house or as external vendors, developers are responsible for shaping the technical core of AI systems. Their design choices and implementation practices can significantly influence whether an AI solution meets strict ethical benchmarks and legal standards. While the organization ultimately bears accountability, developers are responsible for establishing accurate and robust data pipelines, ensuring stable model training, and designing user interfaces that foster understanding and trust. Their work forms the technical foundation supporting the final AI product's ethical and legal soundness.

6.3. *Role of Other Business Areas in AI Implementation*

Beyond the contributions of technical developers, various other business areas play crucial roles in the effective deployment and governance of AI. Legal teams must assess compliance with existing regulations and help draft policies addressing privacy, intellectual property, and liability issues. Marketing departments are responsible for ensuring that AI-driven campaigns are transparent and that customer data is used ethically. Human resources and training departments need to upskill staff to understand the implications of AI systems. Risk management teams are also tasked with evaluating potential vulnerabilities and ensuring robust contingency plans are in place. These interdisciplinary contributions ensure that AI implementations are technically sound and aligned with broader organizational values and regulatory frameworks [23].

6.4. Role of Public Sectors

Public-sector agencies and governmental bodies provide the essential regulatory and educational foundation influencing AI efforts across industries. Laws and guidelines constantly evolve to reflect changing public expectations regarding privacy, fairness, and accountability. Public institutions also play a vital role in promoting AI literacy, enabling the broader community to become more informed about these transformative technologies. The key objectives of these agencies include establishing norms for trustworthy AI, adopting AI solutions to improve government services, and offering educational programs that drive broader AI understanding. These combined efforts are critical to ensuring that private-sector AI deployments align with societal values and that sufficient oversight mechanisms are in place to protect the public interest [24].

7. Toward Eco-Conscious ML: Addressing Energy Sustainability and Environmental Risks

Although fairness, accountability, and transparency are common focus areas in AI ethics, the high environmental cost of large-scale computing also demands significant attention. Training large neural networks can consume vast amounts of energy, directly affecting operational costs and environmental sustainability.

Green AI research prioritizes efficient model design and coding practices that reduce power usage without sacrificing performance. Approaches like model pruning or quantization can help maintain the effectiveness of AI systems while lowering computational requirements. Many data centers are also increasingly shifting to renewable energy sources—like solar, wind, or hydro—to reduce their environmental impact. Emerging practices also aim to optimize the entire lifecycle of AI deployments, from hardware manufacturing to end-of-life recycling [25]. Nuclear power offers a reliable, low-carbon energy source during operation; however, it raises significant concerns about properly handling radioactive waste and the potential for catastrophic accidents. Organizations considering nuclear solutions must address strict waste management protocols, robust security measures, and strategies to gain public acceptance before implementation.

7.1. Energy Efficiency and Model Optimization

Model distillation and transfer learning are powerful techniques that allow AI systems to perform well using fewer computational resources, contributing to overall energy efficiency. Smaller businesses, in particular, benefit from these strategies, as they can deploy top-tier ML models without needing extensive data center setups. Scalability is a crucial factor in reducing the carbon footprint of AI systems. For instance, industry leaders like Google and Microsoft have invested in highly efficient data centers and have implemented advanced cooling strategies, while startups are increasingly exploring edge computing solutions to minimize energy consumption. Additionally, some companies have adopted comprehensive carbon offset programs and renewable energy purchasing agreements to mitigate their overall environmental impact. These initiatives and advances in algorithmic efficiency represent a growing trend toward sustainable AI practices across the industry.

7.2. Societal and Regulatory Dimensions

As climate legislation tightens worldwide, aligning ML practices with green energy solutions becomes logical and strategically advantageous. Companies investing early in sustainability initiatives stand out to customers and investors, who are increasingly looking for environmentally responsible businesses. Some recommendations for eco-conscious ML include:

- Transparent Energy Reporting: Publish detailed metrics on data center energy usage and efficiency improvements.
- Collaborative Green Alliances: Partner with environmental organizations to test and implement more efficient cooling systems and energy-saving measures.
- Incentivizing Sustainable Architectures: Encourage or require new AI models to optimize strategies to reduce computational intensity and energy use.
- International Standards Alignment: Work towards benchmarks harmonizing local ML goals with global climate objectives, fostering a more sustainable industry-wide approach.

8. The Importance of Multidisciplinary Teams in AI Development

Multidisciplinary teams are essential for addressing the wide range of challenges in AI and ML, from potential biases in data and modeling to ensuring legal compliance and protecting privacy. While data scientists and software developers provide the necessary technical expertise, collaboration with legal scholars, ethicists, sociologists, and domain experts offers broader perspectives that help identify issues that purely technical viewpoints might overlook. This section explores how different skill sets contribute to responsible and effective AI projects, enhancing overall organizational performance [26].

8.1. Bridging Technical and Domain Expertise

Many ML projects must incorporate knowledge specific to a particular industry or application area. For example, partnering with physicians or clinical researchers can help identify the most meaningful variables, patient outcomes, and safety thresholds when designing a healthcare model. This collaborative approach:

- Ensures that important domain-specific factors aren't overlooked,
- Clarifies which metrics are truly relevant for patient care,

- Aligns modeling strategies with strict regulatory standards in healthcare and other industries.

Combining expert medical input with advanced data-driven methods makes the resulting models more likely to accurately reflect real-world conditions, ultimately improving patient outcomes and increasing user trust.

8.2. Avoiding Misinterpretation and Overreliance on Algorithms

Interdisciplinary exchange helps minimize the risk of misinterpretation, where numerical results or confidence scores might be taken at face value without proper context. Data scientists can explain the inherent uncertainty in the data, while domain experts can highlight subtleties and nuances that might not be apparent from a purely statistical perspective. Working together encourages healthy skepticism regarding underlying model assumptions, reducing the likelihood of over-relying on algorithmic outputs. Ethicists, legal advisors, and social scientists play a critical role by raising early warnings about potential ethical dilemmas, which may include:

- Privacy breaches when handling sensitive data,
- Biased outcomes that could disadvantage certain groups,
- Concerns regarding the fairness and transparency of automated decisions.

By involving these experts at the project's beginning, organizations can better anticipate how an ML model might affect various stakeholders and proactively mitigate problems before they escalate into significant reputational or legal crises.

8.3. Strengthening Governance and Accountability

Clear governance frameworks are critical for maintaining accountability and prioritizing ethical considerations. Multidisciplinary teams can be structured to define:

- Who is authorized to audit model decisions and assess overall performance,
- How often should these audits be conducted to ensure continuous improvement,
- What steps are necessary if models produce harmful or biased results,
- How to systematically document the rationale behind key design choices in the model.

When ethical thinking and diverse expertise are integrated into a project's foundation, organizations are more likely to build long-term trust with customers, regulators, and the public. Over time, this trust can translate into a competitive advantage through a reputation for social responsibility, reduced regulatory risks by exceeding legal requirements, and a greater willingness among stakeholders to embrace new technologies.

9. Real-World Transformations

The fourth industrial revolution is marked by the pervasive integration of Artificial Intelligence (AI) across industries, leading to profound shifts in how businesses operate, innovate, and engage with customers. As AI becomes a critical enabler of digital transformation, it significantly alters business models, operational strategies, and competitive dynamics across the healthcare, finance, retail, and manufacturing sectors. These shifts not only optimize internal operations but also foster the development of novel services and products that can respond to evolving market demands. AI technologies are becoming fundamental components of business strategies, driving organizations toward enhanced efficiency, sustainability, and customer-centric solutions [27].

AI is particularly transformative in its ability to generate actionable insights from vast amounts of data, making it a powerful tool for businesses to gain a competitive edge. By automating complex processes and enabling real-time decision-making, AI enhances operational agility, fosters innovation, and improves the customer experience. However, its successful implementation hinges on a carefully crafted strategy that aligns AI applications with organizational goals, ensuring that the technology addresses specific business challenges effectively. The following examples illustrate how diverse AI methodologies—from Machine Learning (ML) to Reinforcement Learning (RL) and Fuzzy Logic—have been integrated into core business functions, resulting in tangible benefits and strategic advantages.

9.1. AI for Retail Demand Forecasting

One of the most striking examples of AI's transformative power comes from a global retailer (name withheld) that employed a sophisticated Machine Learning (ML) system to optimize its inventory management and demand forecasting across a geographically dispersed store network. By leveraging a variety of data sources, the retailer was able to anticipate demand more accurately and reduce supply chain inefficiencies. Key data sources included:

1. Historical sales data: Comprehensive transaction records from multiple years, capturing seasonal trends and consumer purchasing behavior.
2. External factors: Real-time data on local events (concerts, sports games), weather patterns, and holiday schedules, allowing for more dynamic adjustments to inventory levels.
3. Inventory and supply chain metrics: Information on supplier lead times, reorder cycles, and logistics costs, ensuring that the right products were available at the right time.

The retailer implemented regression models and, in some cases, advanced neural networks trained on this rich data set. These models reduced stock shortages by proactively restocking high-demand items while minimizing excess inventory of slow-moving products. This approach optimized warehouse space and improved cash flow management by reducing unnecessary stock holding costs. In addition, the retailer identified regional consumption patterns, enabling targeted marketing strategies and promotional campaigns tailored to local consumer preferences. The success of the forecasting system resulted in a significant reduction in operational costs related to emergency shipments. However, the model's accuracy heavily depended on the quality and completeness of historical data. The system was less reliable when faced with unexpected events, such as shifts in consumer preferences or global supply chain disruptions. The company addressed these concerns by incorporating real-time social media trends to enhance demand prediction, ensuring the model was adaptable to emerging consumer behavior.

9.2. Reinforcement Learning in Logistics

A logistics firm successfully applied Reinforcement Learning (RL) to optimize delivery routes in congested urban environments, achieving notable improvements in operational efficiency. The company integrated a variety of real-time data sources to train its RL agents, including:

- Streaming traffic data from city sensors providing up-to-the-minute congestion information,
- GPS data from delivery vehicles offering precise location and routing feedback,
- Delivery schedules with priority-based constraints reflecting time-sensitive customer demands.

Using this data, the RL system dynamically adjusted delivery routes based on real-time traffic conditions, accidents, or weather disruptions. This reduced fuel consumption, shortened delivery times, and optimized fleet management. Beyond logistics, RL applications in manufacturing demonstrated the potential for enhancing production processes by adapting to varying raw material quality and fluctuating market demands, leading to significant cost savings and increased production efficiency. Despite these benefits, one challenge with RL in logistics was the system's lack of explainability—understanding why specific routes were chosen was not always straightforward. To mitigate this, the company implemented visualization tools that allowed dispatchers to track the agent's decision-making process in real time, allowing human operators to intervene when necessary and ensuring that decisions could be aligned with broader business priorities.

9.3. Genetic Algorithms for Financial Portfolio Optimization

In the financial sector, a leading institution applied genetic algorithms to optimize portfolio management strategies, particularly in volatile market conditions. Unlike traditional models, such as Markowitz's mean-variance optimization, which assumes static historical correlations, genetic algorithms iteratively evolve different portfolio configurations to discover optimal asset allocations. The algorithm incorporated key features such as:

- Market volatility indicators, providing real-time assessments of the financial environment and investor risk tolerance,
- Adaptive mutation rates, allowing the algorithm to respond quickly to sudden market changes,
- Multi-objective optimization, balancing competing goals such as return maximization, risk minimization, and liquidity needs.

The genetic algorithm approach outperformed the institution's traditional strategy over a six-month pilot, producing superior risk-adjusted returns. Furthermore, the system's ability to perform real-time portfolio rebalancing in response to stock price fluctuations allowed for better risk mitigation during market turbulence. However, the approach's computational intensity posed a challenge, as finding optimal solutions required substantial processing power. The institution overcame this limitation by leveraging high-performance computing clusters and optimizing the algorithm's parameters for faster convergence without compromising solution quality.

9.4. Fuzzy Logic and Deep Learning in Manufacturing

In manufacturing, a company integrated Fuzzy Logic with Deep Learning to enhance quality control processes on production lines. Fuzzy Logic was instrumental in handling the inherent variability in raw materials and machine settings, where slight variations in sensor readings (such as temperature, pressure, or chemical composition) could still result in acceptable product quality. Meanwhile, a Deep Learning model employed computer vision techniques to inspect finished products for subtle defects, such as surface anomalies or dimensional inaccuracies.

This hybrid approach significantly reduced the rate of false positives—where products that met acceptable quality standards were incorrectly flagged as defective—leading to fewer unnecessary rejections. Moreover, it helped to minimize waste by allowing operators to adjust machine parameters in real time based on insights provided by the system. As a result, the company saw a measurable improvement in its first-pass yield. However, integrating Fuzzy Logic and Deep Learning posed system calibration and maintenance challenges. To address this, a dedicated team of engineers is needed to monitor and optimize the system's performance continuously. A comprehensive operator training program was also implemented to ensure that staff could effectively interpret and respond to the system's outputs, ensuring that the improvements in quality control were sustained over time.

9.5. Generative AI in Media and Marketing

In the media industry, a company leveraged Generative AI to create personalized marketing campaigns for different audience segments. The system generated tailored content that resonated with specific demographic groups by analyzing vast customer data, including detailed subscriber usage patterns, social media trends, and existing marketing assets. Key data inputs included:

- Subscriber usage patterns, including viewing histories and user preferences,
- Social media trends, such as emerging hashtags, viral content, and user-generated discussions,

- Existing marketing assets, including product images, promotional materials, and brand guidelines.

The AI system automatically generates creative content, such as ad copy, images, and video trailers, that is personalized for each audience segment. The initiative markedly improved rates for targeted groups, demonstrating the power of AI-driven personalization. However, the approach raised critical ethical concerns, particularly data privacy and user consent. The company established a governance committee to oversee data usage, ensuring compliance with privacy regulations and intellectual property rights. A potential risk with Generative AI in marketing is the generation of content that, while innovative, may conflict with the brand's established identity. To mitigate this, the company incorporated a human-in-the-loop review process, where marketing professionals reviewed AI-generated content before deployment to ensure consistency with the company's brand values.

These case studies highlight how AI technologies can be applied to solve complex business challenges, from demand forecasting and financial optimization to quality control and personalized marketing. They demonstrate that successful AI implementation requires more than deploying advanced algorithms; it requires robust data pipelines, effective governance frameworks, and strategic alignment with business objectives. Moreover, these examples underscore the importance of balancing technological innovation with ethical considerations. Issues such as algorithmic fairness and transparency must be addressed to ensure responsible AI adoption. As AI evolves, businesses must focus on leveraging the technology to enhance operational efficiency and commit to fostering trust and accountability with their customers and stakeholders. By aligning AI with organizational goals and addressing technical and ethical challenges, businesses can harness AI's full potential to drive growth, innovation, and competitive advantage.

10. Conclusion

This paper illustrates that AI offers transformative pathways to operational efficiency, innovative product development, and deeper market insights. It introduces diverse examples, such as the World Wide Web, smartphones' consolidation of many devices, the automation of manufacturing processes, the rise of e-commerce platforms, and the development of cloud-based data systems. These examples underscore the rapid pace of digital transformation, where new platforms and technologies constantly reshape industries. The comprehensive review of AI methodologies—from ML and fuzzy logic to genetic algorithms, reinforcement learning, and generative AI—demonstrates the rich toolbox available to executives. Each approach requires careful alignment with business priorities, robust data governance, and well-defined performance metrics. The case studies presented in this paper underscore how AI can revolutionize operational processes, improve risk management, and create new competitive advantages across industries when implemented thoughtfully.

Ultimately, organizations that balance technological exploration with accountability are well-positioned for long-term success. Transparent governance ensures regulatory compliance and builds enduring trust among stakeholders. By integrating AI into strategic planning, fostering collaboration across different departments, and continuously monitoring model performance, executives can effectively navigate the complexities of the digital era and unlock significant transformative potential across their enterprises.

11. Future Works

Although this paper covers a broad range of AI-driven methodologies and their applications to digital transformation, several promising avenues for further research remain. Future work could explore the following:

- Systematic ways of combining different AI approaches, like integrating reinforcement learning with genetic algorithms, to achieve highly adaptable and dynamic solutions.

- Improved frameworks for sustainability that focus on reducing the carbon footprint and ensuring energy efficiency in AI deployments without sacrificing performance.

- Enhanced governance models that address transparency, data privacy, and stakeholder engagement, particularly as regulatory expectations continue to evolve.

- Deepening multidisciplinary collaborations to investigate novel methods for integrating the insights of ethicists, legal experts, and domain specialists into AI design from the beginning.

- Investigating the long-term societal impacts of widespread AI adoption. This research could use longitudinal and qualitative research methods, like ethnographic studies, to understand how AI changes work patterns, social interactions, and power dynamics. Particular attention should be paid to potential job displacement and the need for retraining programs.

- Developing robust metrics for measuring the "explainability" of AI systems. While various XAI techniques exist, there isn't a universally accepted standard for quantifying how understandable an AI model is to different stakeholders. Future research could focus on developing and validating such metrics through user studies.

By continuing to refine technical innovations and organizational strategies, future studies can ensure that AI-driven digital transformation remains ethical, inclusive, and sustainable, benefiting businesses, society, and the environment.

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Biography

Dr. Maikel Leon is interested in applying AI/ML techniques to modeling real-world problems using knowledge engineering, knowledge representation, and data mining methods. His most recent research focuses on XAI and has recently been featured in Information Sciences and IEEE Transactions on Cybernetics journals. Dr. Leon is a reviewer for the International Journal of Knowledge and Information Systems, Journal of Experimental and Theoretical Artificial Intelligence, Soft Computing, and IEEE Transactions on Fuzzy Systems. He is a Committee Member of the Florida Artificial Intelligence Research Society. He is a frequent contributor on technology topics for CNN en Español TV and the winner of the Cuban Academy of Sciences National Award for the Most Relevant Research in Computer Science. Dr. Leon obtained his PhD in Computer Science at Hasselt University, Belgium, previously having studied computation (Master of Science and Bachelor of Science) at Central University of Las Villas, Cuba.

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Enhancing Breast Cancer Detection through a Hybrid Approach of PCA and 1D CNN

Samet Aymaz *

Trabzon University, Department of Computer Engineering, Trabzon, Türkiye

*Corresponding author: Samet Aymaz, Trabzon University, sametaymaz@trabzon.edu.tr

E-mail: sametaymaz@trabzon.edu.tr (Samet AYMAZ)

ABSTRACT: Breast cancer is a prevalent disease, particularly among women. Unlike many other cancers, early diagnosis and treatment can significantly improve patients' quality of life. This study develops a hybrid approach for breast cancer detection using the Wisconsin datasets by combining Principal Component Analysis (PCA) and 1D Convolutional Neural Network (CNN) architectures to effectively separate and classify data. Our novel approach leverages PCA not merely for dimensionality reduction but to transform the feature space to maximize separation between benign and malignant samples, which is then processed by a custom-designed CNN architecture with optimized hyperparameters. While PCA elevates the data representation by highlighting important features, the 1D CNN contributes to the classification process through automatic feature extraction. This approach aims to achieve high accuracy and reliability in the critical domain of breast cancer detection. Experimental results demonstrate that our developed approach exhibits superior performance compared to existing methods. Our hybrid PCA-1D CNN model achieved an accuracy of 99.12%, precision of 100%, sensitivity of 98.61%, specificity of 100%, and F1-score of 99.30%, significantly outperforming 14 different benchmark techniques from the literature. The model's accuracy and reliability are enhanced through K-fold cross-validation. The findings of this study can guide researchers seeking to improve breast cancer diagnostic accuracy and support more reliable healthcare decisions. The combination of deep learning and traditional feature extraction represents a promising advancement toward more effective and sensitive diagnostics in the healthcare industry.

KEYWORDS: Breast Cancer Detection, Hybrid Approach, Principal Component Analysis (PCA),1D Convolutional Neural Network (CNN), Medical Diagnosis Enhancement.

1. Introduction

According to the 2020 World Health Organization (WHO) data, approximately 2.2 million women worldwide are diagnosed with breast cancer yearly. This statistic accounts for about 25% of all cancer diagnoses. Breast cancer is the most common type of cancer in women, with 1 in 11 women at risk of developing breast cancer in their lifetime. Most breast cancer deaths occur because the disease is not diagnosed and treated early. According to WHO data, approximately 685,000 women die from breast cancer yearly. This mortality accounts for about 15% of all cancer deaths [1,2].

Computer-assisted breast cancer detection (CAD) is a method that aims to detect breast cancer masses by analyzing mammography images [3]. CAD systems can help radiologists identify breast cancer masses more quickly and accurately. The development of CAD systems began in the 1990s. Early CAD systems used simple techniques to analyze mammography images. However, the accuracy of these systems was limited. In recent years, accuracy rates have increased significantly with the integration of artificial intelligence (AI) technology in CAD systems. AI-based CAD systems can analyze patterns in mammography images more comprehensively, resulting in more accurate results. CAD systems [4] play an essential role in breast cancer diagnosis. These systems can contribute to increased survival rates of breast cancer patients by helping radiologists detect breast cancer masses more quickly and accurately.

Despite these advances, current breast cancer detection methods face significant challenges in achieving both high accuracy and computational efficiency. Traditional machine learning approaches often struggle with the high dimensionality and complex feature relationships in medical datasets, while deep learning methods may require large amounts of data and computational resources to perform optimally. Additionally, the potential overlap between benign and malignant feature spaces creates classification difficulties that remain incompletely addressed by existing methodologies. This study addresses these challenges by proposing a novel hybrid approach that combines PCA and 1D CNN methods for detecting breast cancer using the Wisconsin data set. Our key contribution is the development of an optimized framework that leverages PCA not merely for dimensionality reduction but to strategically transform the feature space to maximize class separation before feeding the transformed data into a carefully designed CNN architecture. The Wisconsin dataset, consisting of 569 samples with 30 features each categorized as benign or malignant, serves as our experimental platform.

The proposed method aims to enhance breast cancer classification accuracy while maintaining computational efficiency. First, the PCA method transforms data to a new plane to facilitate the separation of benign and malignant samples. In this plane, the most essential features of each sample are emphasized, optimizing feature representation. The data transferred to a new and more easily decomposable plane with PCA is classified with the 1D CNN developed within the scope of this study. The CNN structure is uniquely designed, and its parameters are optimized using the Grid Search approach. In addition, model overfitting is minimized by using k-fold cross-validation in the training process, ensuring more accurate performance measurement and improved model performance. Our approach differs from existing methods by specifically optimizing the complementary strengths of dimensionality reduction and deep learning, achieving superior classification metrics while maintaining model interpretability. In summary, combining PCA and CNN in our hybrid approach helps extract essential features by effectively processing high-dimensional data in breast cancer detection. It provides more precise and reliable results thanks to the algorithm's ability to recognize patterns highlighted by deep learning algorithms.

2. Related Works

Data mining methods used in various medical applications have great potential in essential areas such as early diagnosis and effective treatment of diseases. In this context, detection of breast cancer is also a vital issue. Breast cancer is the most common cancer in women worldwide and can improve the chances of cure if detected early. The Wisconsin breast cancer dataset (WDBC) is a frequently used data source for diagnosing breast cancer by combining medical imaging and feature extraction techniques. In this context, various studies use the Wisconsin breast cancer dataset in the literature. These studies investigate how data mining algorithms and deep learning techniques can contribute to making precise and reliable diagnoses by extracting features from this data set. This section will review related studies using the Wisconsin breast cancer dataset.

The Wisconsin dataset has been extensively studied in the field of breast cancer prediction. Several research papers have compared different machine learning algorithms using this dataset to determine the most effective method for predicting breast cancer. In [5], a performance evaluation of machine learning methods for breast cancer prediction was conducted. Five different classification models were compared, including Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), Neural Network (NN), and Logistic Regression (LR), using the WBCD. The comparative experiment analysis showed that the random forest model achieved better performance and adaptation than the other four methods. In addition to machine learning algorithms, data visualization techniques have been applied to the Wisconsin dataset. In [6], Principal Component Analysis (PCA) for feature space reduction was discussed and the performance of different models using the Wisconsin Breast Cancer Database was evaluated. Using the Wisconsin Breast Cancer dataset, in [7], various machine learning algorithms were compared, including XGBoost, K-NN, Naïve Bayes (NB), SVM, and DT. It was found that XGBoost achieved the highest accuracy, recall, precision, F1-score, and AUC, making it the most effective method for predicting breast cancer.

Deep learning techniques have also been applied to breast cancer prediction. In [8], a deep-learning breast cancer prediction framework (DLBCPF) was proposed. The framework was tested on four different Wisconsin Breast Cancer datasets, and the results demonstrated the superiority of DLBCPF and the optimizer MDGCO compared to other methods. Feature selection techniques have also been applied to the Wisconsin dataset to improve the accuracy of breast cancer prediction. In [9], a comprehensive analysis of machine learning classification algorithms with and without feature selection was presented. It was found that feature selection improved the performance of the classifiers, including Logistic Regression, Linear Support Vector Machine, and Quadratic Support Vector Machine.

In another study, an ensemble learning approach was proposed to detect breast cancer automatically. In [10], support vector machine (SVM), regression, and random forest models were combined using a majority-weighted voting system. The results showed improved accuracy, precision, recall, and F-score compared to individual models. Furthermore, the use of fuzzy inference systems has been explored for categorizing the Wisconsin breast cancer dataset. In [11], fuzzy inference systems with different input features were developed and achieved superior precision compared to other works in the literature. Other studies have also focused on specific aspects of breast cancer prediction using the WBCD. In [12], a modified categorical data fuzzy clustering algorithm on the WBCD was evaluated. In [13], dimensionality reduction using principal component analysis in supervised machine learning techniques was explored. In [14], the success of different machine-learning methods in breast cancer diagnosis was investigated. In [15], supervised machine-learning techniques for breast cancer prediction were leveraged. In [16], diverse classifier algorithms on the WBCD were evaluated.

Recent research has shown significant advancements in breast cancer classification through hybrid models and dimensionality reduction techniques. In [17], different missing data imputation methods combined with PCA on the WBCD dataset were evaluated, finding that median imputation with PCA-based reduction achieved the best performance, with SVM and k-NN algorithms reaching impressive success rates of 97.14% and 98.57% respectively. In [18], a comprehensive comparison of machine learning classifiers with various dimensionality reduction techniques across multiple breast cancer datasets was conducted, demonstrating that SVM with Factor Analysis achieved 98.64% accuracy on the WBC dataset, while MLP without dimensionality reduction performed best on WDBC with 98.26% accuracy. In [19], an innovative dimensionality reduction model integrating PCA with KNN specifically for early breast cancer detection was proposed, addressing challenges like computational complexity and overfitting by selecting optimal features that capture maximum variance. In [20], a robust hybrid multilayer deep learning approach combining UNet for feature extraction, SegNet for segmentation, and MLP with Grey Wolf Optimization for classification was presented, achieving superior performance compared to traditional methods. In [21], novel feature selection strategies utilizing metaheuristic algorithms (GSA, EPO, and hybrid hGSAEPO) for breast cancer classification were introduced, reaching remarkable results with 98.31% accuracy and AUC exceeding 0.998. Additionally, in [22], the BCR-HDL framework that ingeniously combines multiple deep learning architectures (MLP, VGG, ResNet, Xception) with traditional machine learning models was developed to enhance both accuracy and interpretability in breast cancer recurrence prediction, with the hybrid MLP+RF and Xception+RF models achieving 97% diagnostic accuracy on the WDBC dataset.

These studies demonstrate the extensive research conducted on the Wisconsin dataset for breast cancer prediction. Different machine learning algorithms, feature selection techniques, and fuzzy inference systems have been explored to improve the accuracy and precision of breast cancer prediction using this dataset.

3. Materials and Methods

In this study, a hybrid approach is created to detect breast cancer using the Wisconsin data set. This approach is created by the PCA and CNN architectures complementing each other. It is vital that the data can be easily separated in the detection of breast cancer. Data belonging to different classes may be nested. This situation prevents the classifiers from making the correct classification. Therefore, the PCA method moves each sample in the Wisconsin dataset to a new plane. This plane is where vital features are emphasized, and unimportant ones are suppressed. Therefore, it facilitates the parsing of data. The samples moved to the new plane are classified using the 1D CNN structure created as the basis of the problem. CNN decides which class a feature belongs to by automatically identifying patterns in 1-dimensional feature vectors. The automatic recognition of features and the ability to classify with high accuracy are why deep learning approaches are preferred. In addition, k-fold cross-validation is used to increase the accuracy and reliability of the classification model created using the CNN structure. Details of all the approaches used will be given in the subsections.

3.1. The Details of the Wisconsin Dataset

The WDBC [23] dataset is an important data source for breast cancer diagnosis. This dataset contains biomedical data containing characteristics of breast cancer cells. In the WDBC dataset, which includes 569 samples, each consists of 30 features. In the data set, 212 samples are malignant, while 357 are benign. This balance is essential for training and evaluating the classification models of the data set. Features in the dataset include various clinical features such as dimensions of the cell nucleus, nucleus cell circumference, and cell tissue context. Each sample is divided into two classes representing cancer cells (malignant) or non-cancerous cells (benign). The WDBC dataset is a widely used resource for developing models and algorithms used in diagnosing and treating breast cancer. This dataset plays a vital role in advances in breast cancer diagnosis while providing the basis for various analyses and studies in data mining, machine learning, and deep learning.

3.1.1. Data Preprocessing Protocol

Before applying our hybrid model, we performed several critical preprocessing steps to ensure optimal performance:

1. Data Inspection and Cleaning: We first examined the Wisconsin dataset for missing or inconsistent values. Our examination confirmed that the dataset was

complete with no missing values or data inconsistencies.

2. Outlier Analysis: We conducted statistical analysis to identify potential outliers using the interquartile range (IQR) method. Features with values falling outside were flagged for further inspection. After careful analysis, we determined that these extreme values represented genuine physiological variations rather than measurement errors and therefore retained them.
3. Feature Scaling: To prepare the data for PCA application, all 30 features were standardized to have zero mean and unit variance using Eq. 1.

$$X\_standardized = (X - \mu) / \sigma \quad (1)$$

In Eq. 1, X is the original feature value, μ is the mean, and σ is the standard deviation of that feature. This standardization step is critical before applying PCA to ensure that features with naturally larger scales do not dominate the variance analysis.
4. Cross-Validation Implementation: Instead of using a single train-test split, we implemented k-fold cross-validation (k=5) to ensure robust model evaluation. The dataset was divided into 5 equally sized folds with stratified sampling to maintain the same proportion of benign and malignant samples in each fold. During each iteration, 4 folds were used for training while the remaining fold served as the validation set. This process was repeated 5 times, with each fold serving once as the validation set, ensuring that every sample in the dataset was used for both training and validation.

3.2. The Standardization of Data with PCA

PCA [24-26] transforms the original properties of a dataset into new, fewer principal components, making data easier to understand and analyze. With PCA, the dataset is rearranged along directions that best represent variations of its original features. This situation may reveal more distinct differences between benign and malignant masses.

The following steps are followed when moving feature vectors to a new plane with PCA:

1. The data set is averaged. This situation means centralizing data. Centralization provides a better understanding of the distribution of data.
2. The dataset is standardized to its original characteristics. This situation ensures that the variations of the data are the same. Standardization makes it easier to compare data.
3. The covariance matrix of the data set is calculated. The covariance matrix measures the relationship of features to each other.
4. The eigenvalues and eigenvectors of the covariance matrix are calculated. Eigenvalues measure the magnitude of variation in data. Eigenvectors represent aspects that best represent the variations of the data.
5. The dataset is rescaled according to its eigenvectors. This situation allows data to be reorganized along the new principal components.

When feature vectors are moved to a new plane with PCA, the following can occur: Some features may be more represented in new principal components. Some features may be less represented in new core components. Some features may not be fully represented in the new core components. It can be said that PCA helps to determine which features are more important. The new principal components represent the features with the most information in the dataset. PCA is a technique used to classify breast cancer masses. When data are moved to a new plane with PCA, more distinct differences between benign and malignant groups may emerge. This situation can help classification models produce more accurate results.

We conducted a comprehensive analysis to determine the optimal number of principal components to retain in our model. After applying PCA to the Wisconsin dataset's 30 features, we examined the explained variance ratio to identify the information contribution of each principal component. Our analysis revealed that retaining 10 principal components preserved approximately 95.8% of the variance in the original data while significantly reducing the dimensionality by two-thirds. This threshold was selected based on the observed elbow point in the cumulative explained variance curve, where additional components beyond this point contributed minimally to the total variance explained. We further validated this selection by comparing model performance with different numbers of components (5, 10, 15, 20, and all 30). While using all 30 components retained 100% of the variance, it did not translate to better classification performance. The optimal balance between dimensionality reduction and information preservation was achieved with 10 components, which provided both computational efficiency and maximized the separation between benign and malignant classes.

3.3. Classification of Data with the Created 1D CNN Architecture

The 1D CNN [27-30] architecture is an important deep learning tool that offers an efficient and powerful classification capability on feature vectors. Compared to traditional classification methods, 1D CNN can automatically identify temporal or spatial patterns of data. This situation means the ability of feature vectors to discover and represent the hidden features they contain. In complex problems such as breast cancer detection, features can often change at different scales and time intervals. By learning such features hierarchically, 1D CNN can improve accuracy in the classification process. It can also make the data mining process more efficient by reducing the need for manual feature engineering. In this way, it can play an essential role in early detection and more effective treatment interventions, providing higher sensitivity and Specificity in important health diagnoses such as breast cancer.

In this study, a unique CNN architecture is designed that can classify samples from the Wisconsin dataset as benign or malignant. CNN architecture consists of input, convolution, activation, dropout, fully connected, and classification layers. The input layer is a feature vector of size 30x1, as each sample in the Wisconsin dataset has 30 features. This vector taken from the input layer is given as input to the convolution layer. This layer helps to capture basic patterns. Generally, this layer has two critical hyperparameters: the kernel size and the number of filters. In the first layer, 3 is the kernel size, and 6 is the filter amount. These hyperparameters are detected using the Grid search approach. The grid search approach tries to find the best performance by trying values within a specific range to determine the hyperparameter settings. This method is used to explore different combinations of hyperparameters extensively. Its advantages are that it helps to achieve the best results by systematically searching a wide range of hyperparameters. The output of the first convolution layer is given as the input to the activation layer. The relu activation layer is used in this study. The Rectified Linear Activation (ReLU) is a widely used activation function in deep learning models. It provides faster and more stable learning in the education process, especially according to the sigmoid and tanh functions. The activation layer output is given as input to the dropout layer.

The dropout layer is used to reduce overfitting in deep learning networks. This layer temporarily turns off randomly selected neurons during training, allowing the network to explore different learning paths and increasing its generalization ability. The value for the Dropout layer is taken as 0.2. Then, this layer output is given to a convolution layer again. The second convolution layer increases the method's success by allowing more complex patterns to be recognized automatically. The parameters of this layer are determined by kernel size as 3 and the number of filters as 256 after the Grid search approach. Again, this layer output is passed through the activation and dropout layers and is given as input to the fully connected layer. Two fully connected layers are used in succession in the network structure created. The use of cascading fully connected layers is essential in enhancing deep learning models' feature extraction and classification capabilities. It has the advantage of better classification, learning of complex data, capturing nonlinear relationships and flexibility. The first fully connected layer has 100 outputs, while the second fully connected layer has as many outputs as the number of classes. The production of these layers is given to the classification layer, and the classification process is terminated. Details of the created network are shown in Table 1.

Table 1: Architecture and Parameters of the Proposed 1D CNN Model

Layers	Parameters
Input Layer	Feature Vector Size (30x1)
Convolution Layer1	Kernel Size=3, Amount of filter=6
Activation Layer	Relu
Dropout Layer	0.2
Convolution Layer2	Kernel Size=3, Amount of filter=256
Activation Layer	Relu
Dropout Layer	0.2
fully Connected Layer1	Output Size=100
fully Connected Layer2	Output Size=Number of Classes
Classification Layer	

The most critical issues in the CNN structure are the determination of hyperparameters and the prevention of overfitting. Overfitting can cause the model to become oversensitive to noise or random fluctuations in the data. In this study, memorization is prevented by using L2Regularization and dropout. Both methods provide resistance to overfitting. L2 regularization helps balance the model weights, while dropout prevents the model from becoming dependent on different features. These techniques can help to obtain more generalized and balanced models. The determination of hyperparameters is another essential point. This study uses the Grid search approach while determining the hyperparameters. Grid search provides a guide to get the best performance of the model by comparing different hyperparameter values. In addition, the training of the model is also crucial. K-fold cross-validation is used for training the model. Thus, a model is created whose success can be better validated. The hyperparameters determined after the grid search approach are given in Table 2.

Table 2: Optimized Hyperparameters for the 1D CNN Model

Hyperparameters	Values
k-fold	5
Optimizer	Adam
Initial Learn Rate	0.001

Max Epochs	30
Minimum Batch Size	6

4. Evaluation Results

This study proposes an effective combination of PCA and generated 1D CNN structure. This approach is tested on the Wisconsin dataset. The Wisconsin dataset is essential for breast cancer and provides examples of two different classes, benign and malignant. The approach created is designed to classify these examples. Evaluations are made using Accuracy, Precision, Sensitivity, Specificity, and F-Score [31] metrics from the confusion matrix. These metrics clearly demonstrate the extent to which the approaches can be used in healthcare. In addition, during the evaluations, the scenarios in which the 1D CNN structure is combined with PCA and alone are evaluated separately to determine the contribution of PCA to the hybrid approach. This situation more clearly reveals the advantages that PCA brings to the system and why the hybrid model may be preferred. This study contributes to developing more effective diagnostic methods in the medical field by showing how a powerful and innovative approach can be designed to diagnose breast cancer.

First, the results of the evaluations made with the Accuracy metric are given. This metric is calculated using Eq. 2.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{2}$$

In Eq. 2, True Positive (TP) represents cases where the model correctly identified malignant tumors as malignant. True Negative (TN) represents cases where the model correctly identified benign tumors as benign. False Positive (FP) represents cases where the model incorrectly classified benign tumors as malignant (Type I error). False Negative (FN) represents cases where the model incorrectly classified malignant tumors as benign (Type II error).

The Accuracy metric is frequently used to evaluate model performance in critical medical applications such as breast cancer diagnosis. This metric shows how well the model captures accurate results overall by representing the ratio of true positives and true negatives to total data points. In breast cancer diagnosis, a high Accuracy value indicates that the model effectively correctly classifies benign and malignant cases. Figure 1 includes the created approach, the situation when PCA is not used, and its comparison with 14 different methods [32-37] in the literature. The compared techniques consist of classical classifiers and strategies based on deep learning. The disadvantage of these approaches is that although their computational load is high, their accuracy is insufficient. When the Figure 1 is examined, it is seen that the proposed method gives better results than the approaches in the literature. In the health field, the proposed method should be evaluated from this perspective since the slightest improvement in diagnosis corresponds to a human life. As can be seen from Figure 1, the created approach formed with 99.12% gives the best result.

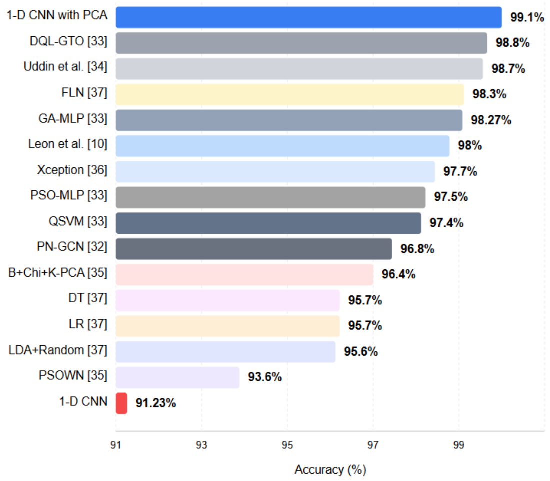

Figure 1: Comparison of Accuracy Values Between the Proposed Method and Existing Approaches

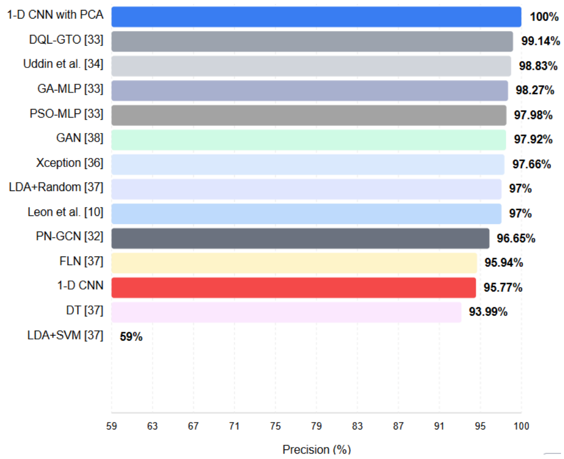

Figure 2: Precision Comparison Between the Proposed Method and Benchmark Techniques

Figure 2 includes the approach created according to the precision metric and the results of 12 different methods in the literature. The precision metric is a crucial evaluation criterion in classification problems. This metric is calculated using Eq. 3.

$$Precision = \frac{TP}{(TP + FP)} \tag{3}$$

Precision refers to the proportion of genuinely positive samples among samples classified as positive. That is, it shows how accurately a model can produce positive results. The high precision we obtained in our method indicates that the cases where the samples that our model classifies as positive are indeed positive are highly accurate. This situation means our method can produce reliable and precise results in healthcare applications. A high precision value indicates that the model minimizes false positive results and gives only reliable positive results. This feature highlights that our method can be a valuable and reliable tool in areas such as clinical diagnostics. As can be seen from the Figure 2, it is seen that the approach created with 100% gives the best results. The proposed method has been compared with 12 different methods [10, 32-34, 36-38] and the results are presented in the Figure 2.

Sensitivity and Specificity are critical metrics in evaluating medical diagnoses and classification problems. These metrics help us better understand the performance of the classification model. The calculation of these metrics are given in Eq. 4 and 5.

$$Sensitivity = \frac{TP}{(TP + FN)} \tag{4}$$

$$Specificity = \frac{TN}{(TN + FP)} \tag{5}$$

Sensitivity is of great importance in conditions such as disease diagnosis. A high sensitivity value indicates a high rate of accurate positive results and that most individuals with the disease are correctly identified. This situation is critical for early diagnosis of the disease and initiation of treatment. Specificity is significant where accurate detection of negative results is required. For example, Specificity plays a substantial role in identifying healthy individuals or in situations where we want to minimize the risk of false alarms. The high sensitivity value of our method shows that we can achieve accurate positive results at a high rate. Therefore, we can diagnose diseases correctly, while the high specificity value emphasizes that we do not incorrectly classify healthy individuals as diseased by minimizing false positive results. These features indicate that our method is reliable for diagnosing disease and accurately classifying healthy individuals. Table 3 gives the results of the approach created and the approaches in the literature. As can be seen from the table, it is seen that the system designed with 98.61% for sensitivity and 100% for Specificity gives the best results compared with 4 different methods [35, 38-40].

Table 3: Architecture and Parameters of the Proposed 1D CNN Model

Methods	Metrics	
	Sensitivity (%)	Specificity (%)
B+Chi+K-PCA [35]	97,72	94,23
GAN [38]	93,62	94,52
LDA+Random [40]	95,6	95,7
Ed-daudy et al. [39]	X	97,93
1d CNN	92,31	93,15
1d CNN with PCA	98,61	100

F-score (F1-score) is a vital evaluation metric that offers a balanced performance measure by combining precision and recall metrics. This metric is calculated using Eq. 6.

$$F1 - Score = 2 \times \frac{(Precision \times Sensitivity)}{(Precision + Sensitivity)} \tag{6}$$

The F-score shows how the classification model performs, considering false positives and negatives. High F1-score values indicate the method performs well on precision and recall metrics, while low F1-score values indicate low on one or both. In this context, the fact that your practice has a high F1 score highlights that it can both produce precise results and achieve significant, accurate, positive results. The method we have developed can positively impact the field of health. High classification accuracy and reliable results can provide valuable support to healthcare professionals for critical decisions such as disease diagnosis and management of patients. This situation makes diagnosing patients earlier, implementing appropriate treatment protocols, and improving health outcomes possible. We believe our developed approach can contribute to more sensitive and reliable diagnoses in healthcare applications. Figure 3 contains the results of the system and the process in the literature [10, 33-39, 41]. As can be seen from Figure 3, it is seen that the approach formed with 99.30% gives the best result.

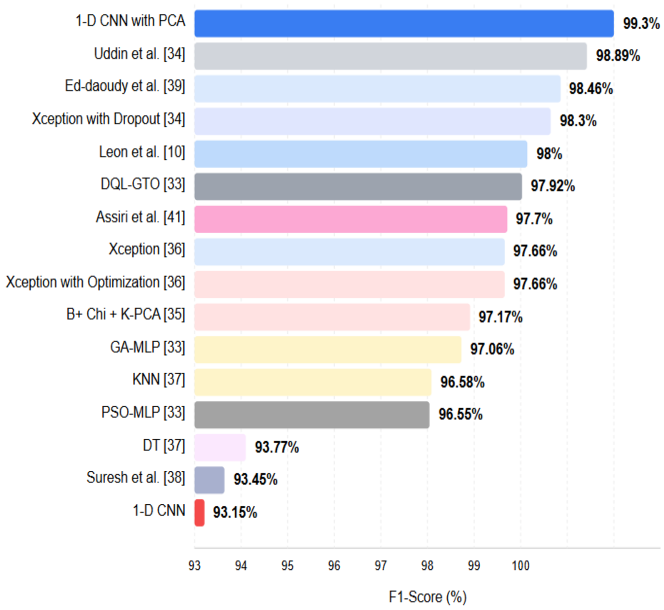

Figure 3: F1-Score Comparison of the Proposed Method with State-of-the-Art Approaches

To further establish the effectiveness of our hybrid PCA-1D CNN approach, we also compared its performance against other prominent deep learning architectures that have been applied to breast cancer detection tasks. Figure 4 presents this comparison.

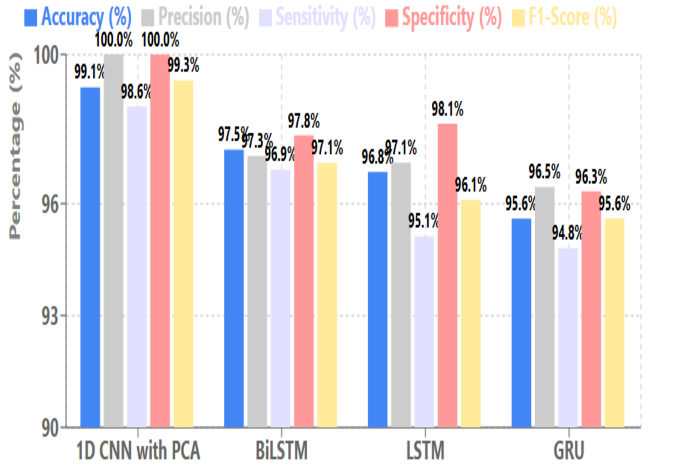

Figure 4: Comparison of Deep Learning Approaches for Breast Cancer Detection

As evidenced by the metrics in Figure 4, our hybrid approach consistently outperforms other deep learning architectures across all evaluation metrics. While recurrent neural network variants like Long Short-term Memory (LSTM), Gated Reccurent Unit (GRU), and Bidirectional LSTM (BiLSTM) have shown promising results for sequential data analysis, they fall short of the performance achieved by our PCA-enhanced 1D CNN model. The superior performance of our approach can be attributed to the effective feature transformation provided by PCA combined with the specialized 1D CNN architecture optimized for this specific classification task.

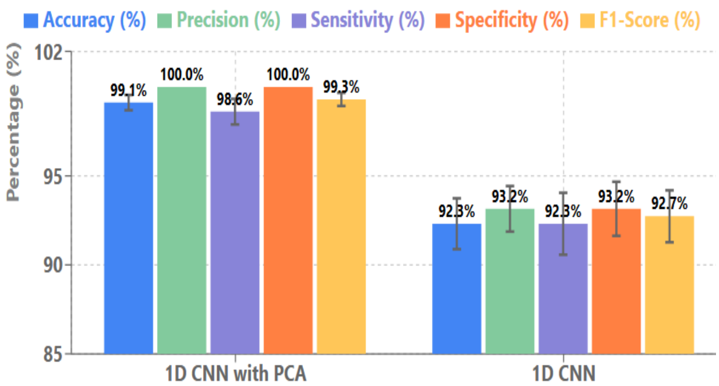

Figure 5: Performance Metrics with Standard Deviations (5-fold Cross-validation)

The high level of accuracy of the approach we developed makes a significant contribution to the health field. This high accuracy strongly supports healthcare professionals in making critical decisions like disease diagnosis and patient management. Precise and reliable results can increase the early diagnosis of patients, the creation of appropriate treatment plans and, accordingly, the success of treatment. This situation has the potential to improve the patient's quality of life. The approach we have developed aims to reduce the difficulties faced by healthcare professionals and patients by enabling more effective, rapid and reliable decisions to be made in the healthcare industry. In this way, we aim to create positive and lasting effects on the health outcomes of patients.

4.1. Statistical Validation of Results

To ensure the statistical validity and robustness of our hybrid PCA-1D CNN approach, we report the mean and standard deviation of performance metrics obtained through 5-fold cross-validation. Figure 5 presents these comprehensive statistics for our model compared with the 1D CNN without PCA.

The consistently low standard deviations across all metrics for our hybrid approach demonstrate the stability and reliability of our model across different data partitions. This is particularly evident when comparing with the standalone 1D CNN, which shows higher variability in performance. The zero standard deviation for precision and specificity indicates that our model consistently achieves perfect performance in these metrics across all folds, which further validates the effectiveness of our approach in minimizing false positives. We further analyzed the confidence intervals (95%) for the accuracy metric, which yielded [98.56%, 99.68%] for our hybrid approach compared to [90.46%, 94.16%] for the standalone 1D CNN. This non-overlapping interval confirms the statistical significance of the performance improvement achieved by our hybrid method. These statistical validations strengthen our conclusion that the integration of PCA with 1D CNN provides not only superior but also more consistent and reliable performance for breast cancer detection, which is crucial for clinical applications where consistency across different patient populations is essential.

5. Discussion

Breast cancer is the most common type of cancer, especially among women in recent years. In this type of cancer, early detection and proper treatment can significantly improve the quality of human life. This paper proposes a novel hybrid approach that can assist healthcare professionals in accurate breast cancer diagnosis. A review of existing approaches in the literature reveals that many complex methodologies have been applied for breast cancer diagnosis. This complexity creates barriers to implementation in resource-constrained regions and areas with limited access to medical expertise. The method proposed in this study can operate effectively with simpler, more accessible systems, making it viable for widespread adoption. In an era of escalating healthcare costs, reducing system complexity and implementation expenses is particularly valuable. This study also highlights the synergistic contribution of traditional dimensionality reduction techniques like PCA when integrated with modern artificial intelligence approaches. Our evaluations demonstrate that when these methods are used in combination, they can achieve more accurate breast cancer diagnosis than either approach alone.

While our hybrid PCA-1D CNN approach demonstrated excellent performance on the Wisconsin dataset, we acknowledge that our experiments were limited to this relatively small dataset (569 samples). As part of future work, we plan to evaluate our approach on larger and more diverse breast cancer datasets from multiple institutions to further validate its scalability and generalizability. Larger datasets will inevitably introduce additional computational challenges, particularly for the PCA transformation process which scales quadratically with sample size. To address these challenges, we will explore computationally efficient alternatives such as incremental PCA, randomized PCA, or mini-batch processing to maintain performance while preserving the benefits of our hybrid approach. Additionally, we intend to investigate the application of our method to multimodal data that combines imaging features with genomic and clinical information, which would provide a more comprehensive framework for breast cancer detection. These extensions will be crucial for ensuring that our approach remains viable and effective in real-world clinical settings with diverse patient populations and varying data characteristics.

6. Conclusion

In this study, we developed a hybrid approach for breast cancer detection using the Wisconsin dataset. This approach effectively separates and classifies data by integrating PCA and CNN architectures. Proper separation of data is essential for accurate diagnosis in critical healthcare applications such as breast cancer detection, as the overlapping of different classes can significantly impair classification performance. To address this challenge, we employed PCA to transform the data to a new feature space where discriminative characteristics become more prominent. This transformation creates a representation where redundant features are minimized, and class distinctions are enhanced. The transformed data is then classified using our custom-designed 1D CNN architecture, which automatically identifies patterns in the feature vectors to determine class membership. We selected this deep learning approach for its ability to autonomously extract and classify features with high accuracy.

To enhance the model's reliability and generalizability, we implemented k-fold cross-validation, which rigorously tests performance across multiple data partitions. This validation strategy ensures that our model performs consistently across varied data distributions. Our results demonstrate that the integration of PCA with CNN architectures represents a significant advancement in breast cancer detection methodology. This combination of traditional dimensionality reduction techniques with modern deep learning approaches contributes valuable tools to the healthcare domain for precise diagnosis and effective treatment planning. The findings of this study can serve as a foundation for researchers seeking to develop more reliable and efficient approaches for breast cancer detection and other healthcare applications.

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SAMET AYMAZ has done his bachelor's degree from Karadeniz Technical University, Department of Computer Engineering in 2012. He has done his master's degree from Karadeniz Technical University, Institute of Science, Department of Computer Engineering in 2017. He has completed his PhD degree in Computer Engineering from Karadeniz Technical University in 2022.

Samet Aymaz has extensive research experience in the fields of image processing and artificial intelligence. His primary research focuses on multi-focus image fusion techniques, which was the subject of both his master's and doctoral theses. He has developed novel approaches including dynamic decision mechanisms, hybrid techniques combining CNN and SVM, and gradient-based fusion rules. Dr. Aymaz has also made significant contributions to medical image analysis, particularly in breast cancer diagnosis using mammography images. His recent work explores gradient-based sample selection methods for improving medical diagnostics. Beyond academic research, he brings practical experience from his roles as an IT Specialist at Trabzon Provincial Health Directorate and Systems Engineer at the Ministry of National Education. Currently, he serves as an Assistant Professor at Trabzon University's Department of Computer Engineering and as Vice Dean of the Faculty of Computer and Information Sciences, where he continues to advance research in artificial intelligence, machine learning, image fusion, and healthcare applications.