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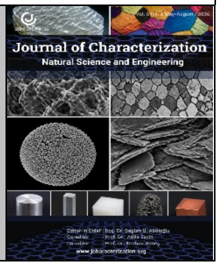

Artificial Intelligence–Driven Innovations in the Glass Industry

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Abstract

This review article examines the technological transformation driven by artificial intelligence (AI) and advanced manufacturing techniques in the glass industry. The objective of this study is to analyze the role of AI tools across the entire glass manufacturing pipeline—from raw material processing to automated quality control—within the framework of Industry 4.0. Following a systematic review methodology, relevant peer-reviewed literature was synthesized across key thematic domains: real-time defect detection using computer vision, predictive furnace maintenance via digital twins, additive manufacturing (3D printing) of glass, and smart glass innovations. The findings indicate that AI-driven vision systems significantly improve defect identification speeds over manual inspection, while predictive modeling optimizes thermal distribution and reduces energy consumption. However, technical limitations such as class imbalance, sensor reliability, and high deployment costs necessitate human-in-the-loop systems for adaptive, low-volume production scenarios. Overall, this study synthesizes current advancements and provides a strategic roadmap for integrating sustainable, data-driven solutions into glass production systems.

Keywords: Artificial Intelligence, Smart Glass Technologies, Quality Control, Sustainable Manufacturing, Machine Learning, Digital Twin, Glass Technologies.

Cam Endüstrisinde Yapay Zeka Destekli Yenilikler

Öz

Bu derleme makalesi, yapay zekâ (YZ) ve ileri üretim tekniklerinin cam endüstrisinde yarattığı teknolojik dönüşümü bütüncül bir yaklaşımla incelemektedir. Çalışmanın amacı, YZ teknolojilerinin hammadde işlemesinden otomatik kalite kontrolüne kadar tüm cam üretim süreçlerindeki rolünü Endüstri 4.0 hedefleri doğrultusunda analiz etmektir. Sistematik derleme metodolojisi izlenerek; bilgisayarlı görü ile gerçek zamanlı kusur tespiti, dijital ikizler aracılığıyla öngörücü fırın bakımı, camın 3 boyutlu baskısı ve akıllı cam teknolojileri odaklı nitelikli literatür sentezlenmiştir. Elde edilen bulgular, YZ destekli görüntü işleme sistemlerinin manuel muayeneye kıyasla kusur algılama hızını artırdığını, öngörücü modellerin ise termal dalgalanmaları optimize ederek enerji tüketimini ve atık oranını azalttığını göstermektedir. Buna karşın, veri kısıtları ve yüksek kurulum maliyetleri gibi sınırlılıklar nedeniyle esnek üretim senaryolarında insan uzmanlığının varlığı halen kritik önem taşımaktadır. Bu çalışma, mevcut teknolojik gelişmeleri sentezleyerek cam sektöründe sürdürülebilir ve veri odaklı sistemlerin entegrasyonuna yönelik akademik bir yol haritası sunmaktadır.

Anahtar Kelimeler: Yapay Zeka, Akıllı Cam Teknolojileri, Kalite Kontrol, Sürdürülebilir Üretim, Makine Öğrenimi, Dijital İkiz, Cam Teknolojileri.

1. Introduction

Artificial intelligence (AI) is a term given to the hardware and software capabilities that allow digital machines or computers to fulfil the vast majority of tasks with no involvement by human minds. AI is now being employed in diverse fields and throughout many industries. [1-3].

Innovative developments in glass design have significantly broadened the scope of its applications, combining functionality, aesthetics, and sustainability. Smart glass technologies—such as electrochromic, thermochromic, and photochromic glass—enable dynamic control over light, heat, and transparency, leading to energy-efficient buildings and adaptive vehicle windows. The emergence of additive manufacturing (3D printing) in glass design, though technically challenging due to high melting points and material brittleness, allows for highly customized and complex geometries, opening new possibilities in optics, biomedical devices, and decorative art. In parallel, AI and machine learning are increasingly integrated into glass manufacturing processes, enabling predictive maintenance, real-time process control, and enhanced quality assurance through automated defect detection. The use of digital twins offers virtual replicas of production lines, improving simulation accuracy and operational efficiency. Furthermore, innovations in surface engineering have led to the development of multifunctional coatings—such as hydrophobic, self-cleaning, anti-reflective, and antibacterial layers—enhancing both performance and durability. These advancements make glass not just a structural or aesthetic element but a high-performance, intelligent material with a central role in Industry 4.0 and sustainable design strategies [4]. Within this framework of Industry 4.0, AI-driven computer vision systems are also utilized in structural safety inspections, such as automating the fragment counting and segmentation process in the standardized EN 12150-1 tempered glass test (Figure 1).

The glass industry continues to grow steadily. Recent market analyses indicate that the global glass packaging and container market was valued at approximately USD 70 billion in 2025 and is projected to surpass USD 100 billion by the early 2030s, driven largely by the rise of craft producers and premium brands. In response to emerging trends in packaging, urbanization, and consumer preferences, the glass industry faces both new challenges and opportunities. Glass remains widely renowned as a sustainable, green product that positively influences environmental conservation [6]. However, the vision of tomorrow's green product design necessitates meeting the changing functional glass demands of end-users, recycling glass waste within the framework of circular economy models, and integrating these materials into new industrial revolutions. Accordingly, modern nanotechnology, bioengineering, and polymer surface modification methods are being utilized to improve existing technical properties such as material transparency, mechanical strength, fire resistance, and electromagnetic interference (EMI) shielding; thus, new, advanced glass composites and hybrid materials are being developed.

Three growth opportunities of interest for novel glass development are reviewed in the fields of smart materials, opto-electronics, and vehicle applications [5]. The transparent economy sector predominantly focuses on the following three production processes. The first is the manufacture of the raw glass, composed of silicate-borate-alumina that melts at a high temperature (1000–1700 °C) in melting furnaces. White glass masses having different compositions are manufactured for packaging pot, flat, and optical glasses. The second is glass shaping, which encompasses the formation of the glass, such as forming containers. Here, there are six manufacturing technologies: press, blow, draw, cast, mold, and extrusion. The products of this sector include panels, hollow glass, goblets, and lab tubes. The third involves glass post-processing (coating), in which glass surfaces are transferred into value-added finished glass products by using various coating methods [7-8].

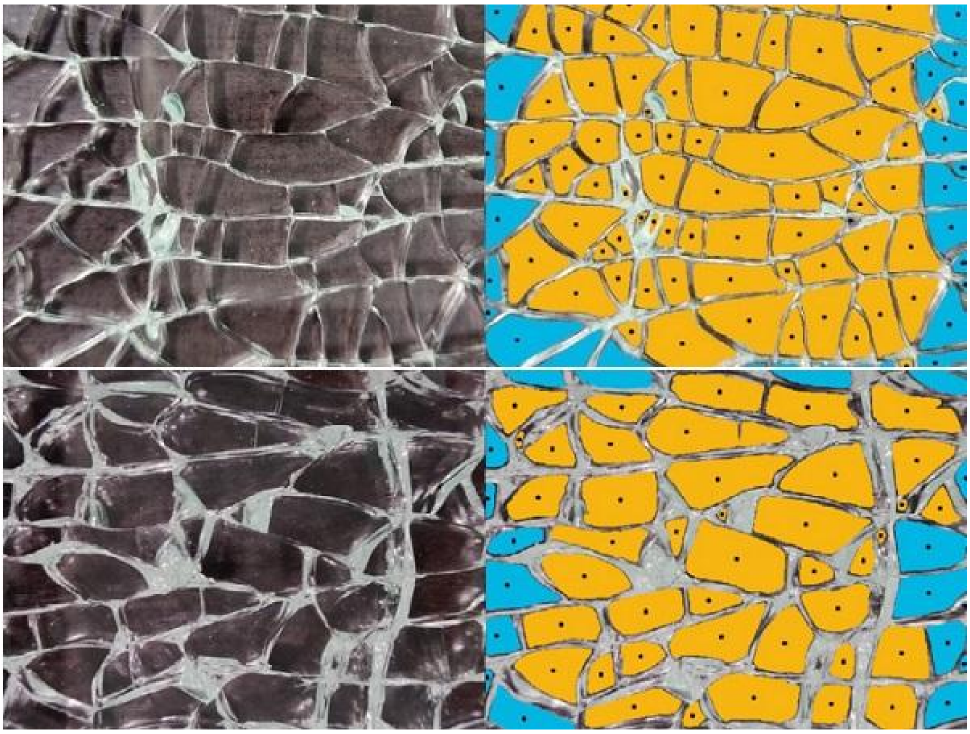

Figure 1. AI-based fragment segmentation and automated counting in the EN 12150-1 tempered glass safety test (Adapted from [5])

2. Review Methodology

In this review study, artificial intelligence applications, innovative production techniques, and sustainability-focused transformations in the glass industry are examined using a holistic approach. The literature review process was structured in accordance with the principles of transparency, reproducibility, and scientific reliability. Within this framework, a comprehensive search was conducted using internationally recognized databases such as Web of Science, Scopus, IEEE Xplore, ScienceDirect, Google Scholar, and ResearchGate. The search utilized key keyword combinations such as "Artificial intelligence in glass manufacturing," "Computer vision quality control in glass," "EN 12150-1 fragmentation test AI," "3D printing of glass for biomedical applications," "Smart electrochromic glass for energy savings," and "Digital twin predictive maintenance for furnaces." To reflect the current state of the field and future projections, the study focused primarily on high-quality publications released between 2016 and 2026; however, pioneering sources that shaped the field's historical development and fundamental theoretical framework, as well as international standards, were exempt from this time constraint.

3. Historical Context of AI in Manufacturing

Although artificial intelligence (AI) has been in development for decades, research on its industrial use remains limited—particularly regarding comparative studies across different industries. The global industrial AI market is still in its early stages and is largely concentrated in large multinational corporations. However, AI has profound and widespread impacts on society, reshaping how people live, think, and work. The manufacturing sector, in particular, has lagged behind other industries in the integration of information and communication technologies (ICT), prompting apprehensions regarding industrial competitiveness and labor market displacement within advanced economies. AI has the potential to drastically transform manufacturing by enhancing efficiency, quality, and flexibility, and by enabling tasks that were previously unattainable with conventional technologies. Developed throughout the computer science revolution, AI and machine learning have regained significance alongside traditional automation. Recent progress in neural networks—especially in image recognition, speech processing, recommendation systems, and industrial engineering—demonstrates the maturity and effectiveness of AI approaches in modern applications [9-12].

The development of artificial intelligence (AI) in manufacturing has followed a path parallel to the evolution of industrial revolutions. This process can be examined in four key periods representing the transition from simple automation to complex cognitive systems.

The roots of AI in manufacturing go back to Unimate, the first industrial robot patented by George Devol in the early 1950s and used on a General Motors assembly line in 1961 [13]. During this period, AI did not yet exist as a "learning" structure, but only as a deterministic mechanism performing pre-programmed tasks. However, this development became the first concrete example of the idea that mechanical intelligence could replace human labor.

In the 1980s, "Expert Systems" gained popularity in the manufacturing sector. These systems relied on transferring human expertise in a specific area to computer memory using "If-Then" rules. Rule-based systems have been used in furnace management and quality control processes, particularly in industries requiring precise temperature control, such as glass and ceramics [14]. However, the lack of data learning capabilities and inadequacy in complex scenarios have limited their development. With the widespread adoption of the internet and the decrease in data storage costs, AI has become an integral part of manufacturing. During this period, the focus shifted from rule-based systems to Machine Learning (ML) algorithms. Support Vector Machines (SVM) and artificial neural networks have paved the way for "Predictive Maintenance" applications using data from sensors on production lines [15]. This has been a revolutionary step in minimizing downtime in processes requiring continuous flow, such as glass production.

With the introduction of the "Industry 4.0" concept at the Hannover Fair in 2011, AI has become the central nervous system of manufacturing [16]. Today, Big Data, Internet of Things (IoT), and Deep Learning technologies are used in fault detection, energy optimization, and supply chain management. In particular, computer vision systems can detect microscopic cracks on glass surfaces much faster and more accurately than the human eye [17].

4. Current Trends in Glass Manufacturing

Glass is a vital material across industries due to its transparency, aesthetic appeal, chemical stability, biocompatibility, thermal and electrical properties. It is commonly used in displays, sensors, containers, and solar cells. Traditional manufacturing involves float processes for flat glass and molding for curved shapes, with subtractive techniques like grinding and etching used for shaping.

Despite advancements in artificial intelligence, glass remains one of the most challenging materials to adopt additive manufacturing (AM) methods such as 3D printing (Figure 2), due to its high melting point and brittleness. While AM has advanced significantly for polymers and metals—offering rapid, precision fabrication that eliminates the need for molding—glass 3D printing still faces obstacles such as high processing complexity, time-consuming customization, low dimensional accuracy, and poor surface finish. Nevertheless, due to glass' exceptional optical and physical properties, improving AM techniques for glass remains a promising and ongoing research area [18-21].

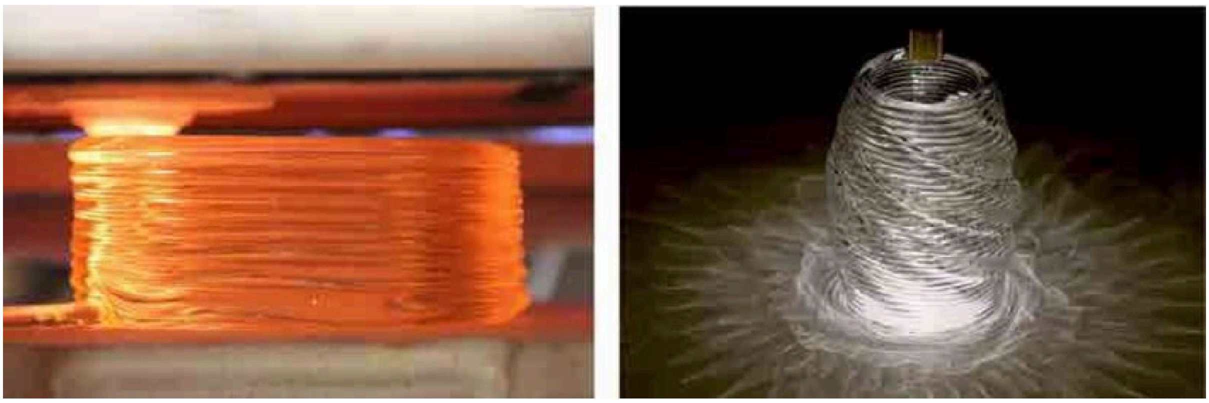

Figure 2. Glass 3D printing process (Adapted from [18])

4.1. AI in Quality Control and Defect Detection

Glass production is a highly complex process requiring precise temperature control and consistent material quality. While partial automation exists, large volumes of industrial data—especially spectra and time series—remain underutilized. To use this data effectively, AI-based analytics are needed. Recent innovations integrate AI tools with physicochemical understanding to develop intelligent soft-sensors and autonomous controllers for glass manufacturing. Modern automated glass inspection systems utilize real-time deep learning pipelines operating at the edge of the production line. In practical applications—such as the inspection of industrial float glass or container glass—high-speed line-scan cameras capture synchronized frames under controlled multi-angle LED illumination. The integrated AI vision system performs object detection and instance segmentation tasks simultaneously. It successfully isolates structural defects by drawing precise bounding boxes and masks around the anomalies, thereby differentiating true defects from harmless environmental reflections or surface dust [22-23].

Quality control is vital for maintaining product standards and brand reputation. With increasing demands for higher quality in smaller batches and under evolving standards, more accurate and robust quality control methods are needed. The digitalization of manufacturing—fueled by cheaper sensors and connectivity—enables the use of digital twins, enhancing design and optimization capabilities. Labor shortages further drive the need for automation.

However, technological bottlenecks must be addressed, including challenges in data storage, analysis, knowledge integration, and real-time modeling of complex processes. AI offers powerful tools for automation, modeling, and optimization, significantly improving performance and cost-efficiency. One major AI application is automated visual inspection, which has shown superior performance over traditional methods in many contexts. Still, AI struggles in scenarios involving adaptive production, custom products, and low-volume outputs, where human involvement remains essential. These limitations highlight the need for hybrid, human-in-the-loop systems in certain quality control settings [24-25].

4.2. Process Optimization, Energy Efficiency, and Waste Reduction

Process optimization is a core element of Industry 4.0 and plays a central role in Manufacturing Intelligence systems. While process intelligence applications are well-established in sectors requiring precise technological operations, several fundamental challenges remain unresolved. This analysis explores those challenges and proposes future research directions.

Figure 3. Industrial glass furnace control room operator monitoring scada system screen predictive optimization software (Adapted from [26])

As demonstrated in Figure 3, advanced process optimization in modern glass manufacturing facilities transitions from traditional manual operations to AI-powered Model Predictive Control (MPC) frameworks monitored via industrial control interfaces. The real-world application layer continuously ingests multi-variable process parameters—such as oxygen trim, fuel-to-air ratios, glass level, and crown temperatures. By utilizing deep regression trees or recurrent neural networks (RNNs), predictive software models aim to project thermal trends within short-term operational timeframes, enabling proactive adjustments to furnace behavior. This allows the system to autonomously execute proactive micro-adjustments on the combustion loops, smoothing out thermal fluctuations that would otherwise cause defects in the glass matrix [26].

Artificial Intelligence (AI) is increasingly being adopted in the glass industry to enhance efficiency, precision, and multi-variable process control across the entire manufacturing chain. By leveraging real-time data streaming from distributed sensors, thermodynamic furnaces, and post-forming inspection systems, AI algorithms can continually monitor temperature consistency, detect subtle structural defects, and predict mechanical equipment failures well before they manifest—significantly mitigating unplanned downtime and material waste. Specifically, AI-driven predictive analytics optimize raw material batch formulations and dynamic fuel gas distribution, directly addressing the intensive energy demands and carbon footprints inherent to glass melting processes [27-28].

In the domain of quality assurance, automated visual inspection systems powered by advanced machine learning architectures (such as Convolutional Neural Networks) substantially surpass traditional threshold-based imaging in both inspection speed and classification accuracy. This enables the automated identification of critical micro-defects, stones, cords, and surface anomalies that frequently elude manual operators. Furthermore, the integration of AI with cyber-physical digital twin technologies allows for the virtual simulation, stress testing, and real-time fine-tuning of complex production parameters. This virtual prototyping drastically minimizes empirical trial-and-error cycles, optimizes mold design, and accelerates time-to-market. Ultimately, this holistic AI deployment transmutes conventional, reactive glass manufacturing into an autonomous, data-driven ecosystem, seamlessly aligning with Industry 4.0 paradigms of high-tier automation, environmental sustainability, and continuous operational optimization [23].

AI technologies are playing a pivotal role in reducing waste in the glass industry by enabling smarter, data-driven decision-making throughout the production process. Machine learning models analyze real-time sensor data to optimize furnace temperatures, batch compositions, and forming processes, minimizing material defects and energy overuse. AI-based predictive maintenance systems detect early signs of equipment wear or failure, preventing unplanned downtime and reducing the waste generated by interrupted or faulty production runs. In quality inspection, AI-powered visual systems can identify micro-cracks, bubbles, and shape irregularities at high speed and accuracy, allowing defective products to be detected and corrected early—before costly downstream processing. Furthermore, AI supports process optimization by modeling and simulating various production scenarios, enabling manufacturers to fine-tune operations with minimal trial-and-error and material loss [29].

In the energy-intensive glass sector, waste mitigation represents a critical vector for enhancing both economic viability and environmental sustainability. Artificial Intelligence (AI) serves as a primary driver in minimizing raw material and product losses by shifting operations from reactive adjustments to proactive prevention. For instance, high-temperature glass melting and forming processes are highly susceptible to defects due to multivariate instabilities; here, machine learning and deep learning models are deployed to optimize process parameters, thereby directly lowering the generation of structural process waste at the source [30].

Furthermore, data-driven frameworks and computer vision architectures integrated into inspection lines drastically reduce mechanical defects and optimize sorting mechanisms. Advanced classification algorithms allow systems to precisely differentiate between critical structural anomalies that necessitate rejection and harmless superficial variations [31]. This high-precision classification prevents the unnecessary discarding of commercially viable products into the cullet stream. In addition to defect sorting, the integration of deep reinforcement learning and predictive intelligence across the production line enables dynamic process control, preventing systemic errors before they propagate and reducing overall factory scrap rates [30]. These verified digital control loops establish a resource-efficient manufacturing paradigm that aligns with modern circular economy and smart factory standards.

4.3. Future Prospects of AI in the Glass Industry

The future of artificial intelligence (AI) in the glass industry presents numerous opportunities, particularly in glass recycling. Currently, the recycling process is costly, labor-intensive, and prone to errors due to manual sorting. Broken glass often damages equipment, causing downtime and financial losses. To address this, the industry is developing AI-based monitoring and sorting systems. By equipping existing machines with cameras, large datasets can be collected and used by deep learning models to enable real-time, automated sorting. This approach is also compatible with older machinery, making AI integration more feasible.

Beyond recycling, the glass industry is expected to expand into high-value functional and structural lifestyle products. Instead of conventional consumer containers, this expansion focuses on advanced fields such as smart architectural glass with electrochromic properties, chemically strengthened cover glass for consumer electronics, precision optical components, and health-related items like eye care cups and bioactive glasses. Bioactive glass, particularly advanced in Europe, holds potential in medical applications like bone repair. Companies may pursue partnerships or acquisitions to accelerate innovation in these areas [25-30].

5. Discussion and Limitations

Although artificial intelligence and machine learning architectures offer unprecedented capabilities in optimizing glass manufacturing lines, several technological, economic, and operational bottlenecks hinder their seamless deployment. A primary technical barrier is data quality and severe class imbalance in real-time defect detection datasets. Since high-standard manufacturing lines inherently produce low defect rates, positive anomaly samples remain extremely scarce compared to normal surface data, leading to model bias and reduced detection sensitivity [32]. Furthermore, the generalisability of deep learning models is frequently constrained when deployed across different production facilities due to operational variations in line speeds, ambient lighting, and raw material batch compositions [33].

From an instrumentation perspective, the performance of predictive control systems and digital twins relies heavily on continuous data streams from high-temperature sensors and thermal cameras embedded in harsh furnace environments. Sensor drift, degradation, and environmental interference can contaminate real-time data pipelines, risking erroneous model predictions that lead to catastrophic thermal instabilities or severe financial losses from misclassification costs. Additionally, the non-transparent decision-making nature of advanced deep learning architectures limits their operational adoption. The lack of explainable artificial intelligence mechanisms prevents domain engineers and furnace operators from validating the underlying decision-making logic of autonomous models before executing high-risk parameter adjustments [34].

Finally, organizational and financial constraints pose significant barriers to wide-scale adoption. The implementation of edge computing infrastructures and automated optical inspection systems requires substantial initial capital expenditures, high-performance computing hardware, and specialized technical expertise, which can be prohibitive for small and medium-sized enterprises. Furthermore, integrating interconnected Industrial Internet of Things sensors introduces critical data security and cybersecurity vulnerabilities, exposing proprietary manufacturing algorithms and process parameters to potential industrial espionage or cyberattacks [35]. Consequently, successful artificial intelligence integration in the glass industry requires a balanced, human-in-the-loop paradigm that couples algorithmic intelligence with rigorous sensor calibration and robust cyber-physical security measures.

6. Conclusions

Artificial intelligence (AI) and machine learning (ML) technologies are gaining greater acceptance in the glass industry and are beginning to be used for quality control (QC) and process monitoring (PM) in an increasing number of applications. Prominent glass manufacturers are employing AI, creating collaborative research alliances with universities, and developing innovative platforms and tools. There is a demand for expert QC teams to evaluate operational anomalies, and there is a concern that with an escalating frequency of structural glass defects, managing these specialized human assets will become increasingly unsustainable. Without an organized architecture to process these material anomalies, a substantial accumulation of unverified inspection data would build, making it increasingly difficult to produce defect-free glass.

In addition to investment in AI and ML technologies to modernize quality control (QC) and process monitoring (PM) systems, the glass industry is shifting toward more proactive approaches to make manufacturing increasingly autonomous and less dependent on manual intervention. In this regard, AI-driven closed-loop optimization frameworks and cognitive control systems are being developed. By embedding these intelligent architectures directly into the manufacturing line, proactive process improvement pathways can be generated during real-time production, potentially allowing QC experts to reallocate their cognitive bandwidth toward long-term operational strategies. The AI framework can highlight positive operational developments at the facilities, transforming them into institutional learning opportunities. Conversely, it flags subtle parameter drifts that might otherwise be overlooked, preventing process deterioration and subsequent defect propagation in the production chain.

Synthesis of findings across the literature demonstrates that while computer vision and deep learning pipelines achieve superior speed and accuracy in automated surface inspection compared to traditional optical methods, predictive control models significantly mitigate thermal fluctuations in melting furnaces. However, as highlighted in this review, current deployments remain constrained by data class imbalance, sensor degradation in harsh thermal environments, non-transparent model decisions, and substantial initial capital investments.

Manufacturing high-quality glass is a highly non-linear, multifaceted process. Each equipment component, each process step, and each defect mechanism possesses specific operational and engineering requirements that must be fully elucidated for optimal solutions to be developed. Therefore, future implementations must adopt a balanced, human-in-the-loop framework where algorithmic intelligence complements domain expertise rather than completely replacing it. Industry 4.0 will trigger new solutions not considered before. In this regard, an emphasis is initially placed on developments through rigorous empirical methodologies leading to a robust academic proof of concept.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in their studies do not require ethical committee approval and/or legal-specific permission.

Authors' Contributions

O. Evcin: Selection and conceptualization of the review topic, coordination of the manuscript preparation, literature synthesis, and drafting of the main text.

U. Durdu: Conducted literature research on AI applications and process optimization in manufacturing, analyzed gathered data, and participated in critical revisions.

M. M. Ergenç: Investigated AI-driven efficiency enhancement and waste reduction mechanisms, and drafted the corresponding sections.

N. Çoban Gür: Reviewed future trends and advanced glass technologies, validated literature data, and carried out comprehensive proofreading and editing of the final manuscript. All authors read and approved the final version.

Conflict of Interest

There is no conflict of interest in this study.

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