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Research Article

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Advancements in AI-Driven Optimization for Enhancing Semiconductor Manufacturing Processes: An Exploratory Study

Rajat Suvra Das

Senior Director, Business Development, L&T Technology Services
Email: rajat.tel@gmail.com

Abstract The semiconductor industry plays a vital role in driving technological advancements, and the incorporation of AI (Artificial Intelligence) can greatly enhance its efficiency and productivity. Through optimizing material usage and reducing defects, AI can significantly reduce costs and enhance production efficiency and product quality. However, despite the increasing interest in AI applications in the semiconductor industry, comprehensive reviews are lacking to systematically analyze existing research and identify the challenges and opportunities in this field. This review aims to bridge this gap by providing a thorough overview of AI-driven techniques in optimizing semiconductor manufacturing and offering valuable insights for future research directions. Initially, the review intends to explore and analyze the diverse applications of AI in optimizing semiconductor manufacturing processes. By examining existing research and real-world case studies, this review will provide insights into the specific AI techniques utilized and their impact on different stages of semiconductor manufacturing. By pinpointing these challenges, the review will contribute to a better understanding of the current limitations and areas that require improvement. Additionally, suitable suggestions and recommendations will be provided to address these challenges, ultimately assisting future researchers in advancing the field. Overall, this review paper will contribute to the existing body of knowledge by comprehensively evaluating how AI-driven techniques can revolutionize semiconductor manufacturing. By uncovering the various applications of AI, identifying existing drawbacks, and providing appropriate suggestions, this review aims to guide future researchers and shed light on research conducted in this area. Ultimately, these efforts will foster advancements in semiconductor manufacturing processes.

Keywords Artificial Intelligence, Deep Learning, Machine Learning, Optimization, Semiconductor Manufacturing

1. Introduction

Semiconductors have brought about a tremendous transformation in the realm of electronics, leading to the creation of compact, swifter, and more effective devices. A typical semiconductor is shown in Fig 1. They find application in a diverse array of fields, such as computing, mobile phones, televisions, solar panels, and numerous other electronic systems that have become indispensable in our day-to-day existence. Manufacturing semiconductor is a multi-phase method that includes multifaceted electronic component development on the silicon wafers. The competitiveness of the industry highly depends upon the accuracy and efficacy of manufacturing processes. Concurrently, with the prompt progress of digital computing abilities, the evolvement of IoT (Internet of Things), BDA (Big Data Analytics), and AI (Artificial Intelligence) has turned out to be a significant tool for digitization and technological elevation of universal manufacturing. With the evolution of AI as a robust tool for improvising these processes by evaluating data, optimization parameters, and undertaking adjustments in real-time, the study [1] has used the dynamic CGE (Computable General Equilibrium) model of Taiwan's input/output tables for capturing resource constraints and supply chain interdependencies. Economywise analysis of government schemes and investment of private companies have been undertaken in smart manufacturing, and its influence on the results and application of the ICT industry and Taiwan semiconductors have been assessed. Simulation outcomes have revealed that, under the augmenting investment of AI, semiconductor results will get 10.34% higher in comparison to the baseline.

Further, demand for employment will be 24.61% lower than the baseline in 2025. The outcome has been identical in the ICT industry. Simultaneously, uneven income dissemination and unemployment might remain side impacts while progressing AI upon manufacturing [2]. Furthermore, Deep Q Network has been employed for resolving large-scale scheduling issues in semiconductor manufacturing. Novel RL (Reinforcement Learning) approaches like DQN have better scalability and efficacy. The suggested methods have probably assisted in practical and sophisticated production scheduling issues in the future [3]. In the semiconductor sector [4], automated VI (Visual Inspection) is intended to enhance the recognition and detection of manufacturing defects by leveraging computer vision and AI systems, permitting manufacturers to profit from enhanced yield and minimized costs for manufacturing.

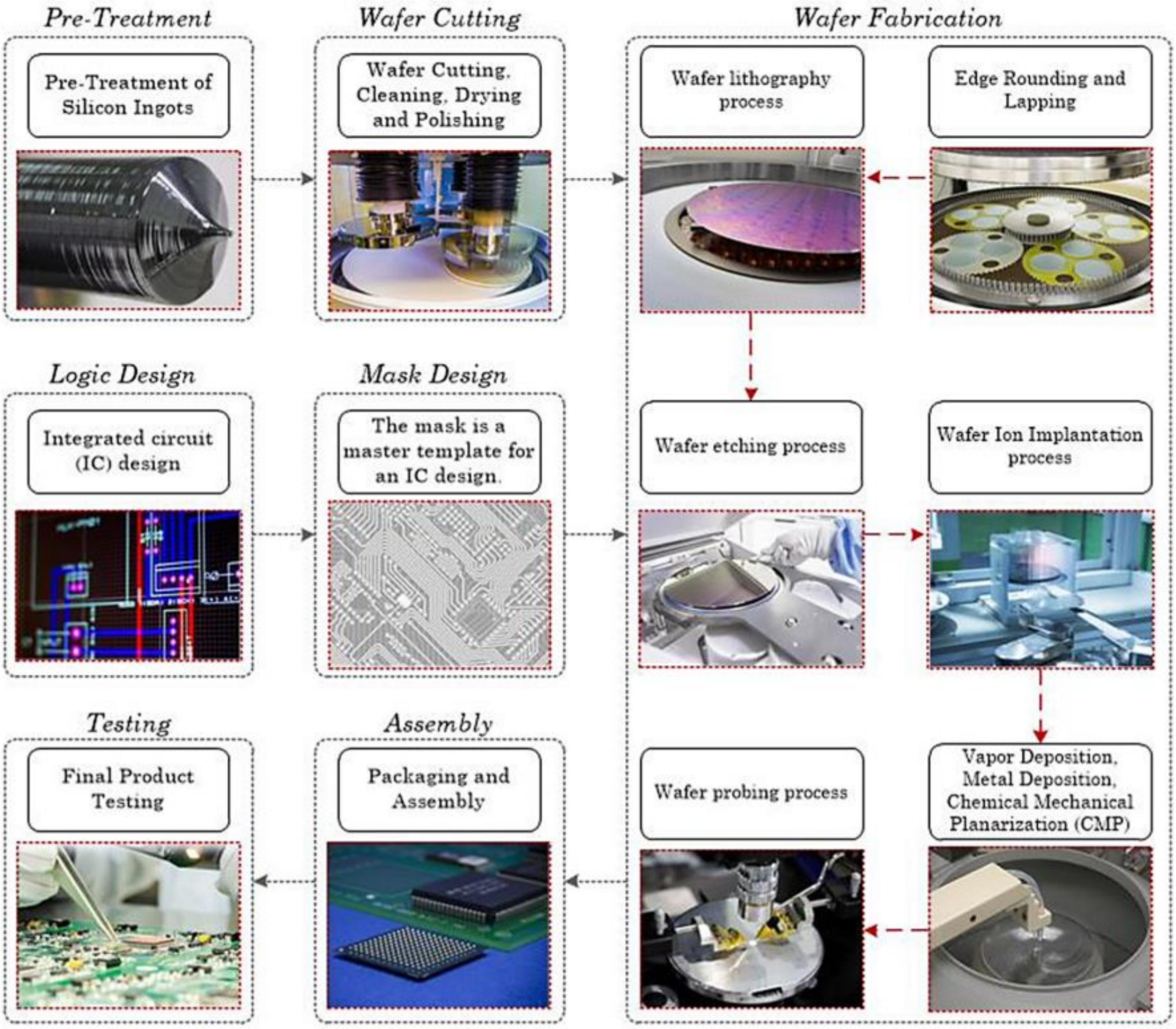

Figure 1: Semiconductor Manufacturing Processes

The production of microelectronic components such as ICs, microprocessors, and memory chips rely heavily on the use of highly pure silicon. The crucial step in the manufacturing process (As shown in Fig 2) involves acquiring semiconductor materials with minimal impurities. Even the slightest traces of contamination can have a detrimental impact on the performance of semiconductors. It is essential to handle the aggressive liquids used in the manufacturing process with great care to ensure safety

Once the semiconductor materials are obtained, the next phase involves the progressing monocrystalline and multicrystalline silicon. These materials are then cut into thin slices known as wafers, which are prepared for further processing. In order to proceed with suitable manufacturing steps, it is necessary to employ design processes and mask design, particularly for photolithographic processes.

In the field of semiconductor manufacturing, the technique of CVD (Chemical Vapor Deposition) holds great significance for the application of thin material films in semiconductor substrates. This paper [5] presents a novel approach to equipment condition modelling, utilizing clustering techniques to identify key sensors that are linked to maintenance requirements. By employing five varied clustering algorithms including hierarchical clustering, K-medoids, K-means, OPTICS and DBSCAN, it has been probable to cluster sensors with similar characteristics and spot those that possess high correlation with equipment's health condition.

Moreover, various other factors have been involved namely, the creation of bSi patterns with varying dimensions having its range from milli-metres to micrometres, with the use of three extensively utilized bSi fabrication methods, MACE (Metal Assisted Chemical Etching) plasma etching and femto-second laser etching. The resulting fabrication features and material properties have been obtained through each method. The results have represented that plasma etching is an appropriate method for devices on the micrometer-scale, whereas, MACE have achieved nearly optimal performance in this regard [6]. The system has attained a remarkable performance with an F1 score of up to 99.5%, indicating an 8.6-fold improvement in fault detection capabilities compared to the current system [7]. Additionally, by tailoring suggested models to specific manufacturing chain, it has been probable to meet runtime constraints while enhancing the detection abilities of the currently employed approaches [8].

Employing AI within the semiconductor manufacturing industry heralds a new transformative era. It revolutionizes various aspects, including circuit design, inline monitoring, wafer testing, fabrication processes, and contemporary packaging. AI's impact is particularly pronounced in circuit design. Predictive modelling and optimization algorithms accelerate iterations, enhance creativity, and minimize errors. In fabrication processes, AI plays a vital role in the efficiency, precision, and lifespan of components. Although challenges persist, ongoing research ensures that greater potential will be unlocked, propelling the industry towards exceptional possibilities [9]. Taking this into consideration, the present article explores how AI-driven methodologies can transfigure semiconductor manufacturing through different aspects of optimization, like defect reduction and material usage

The major contributions of the review are

- To undertake an exploratory analysis of how AI-driven algorithms could revolutionize the optimization of semiconductor manufacturing.
- To uncover the applications of AI in different areas of optimizing semiconductor manufacturing.
- To enlist the issues and provide appropriate suggestions to support future researchers for enlightening the study in this regard

2. Exploratory Survey Analysis

The current exploratory review intends to provide a comprehensive investigation of the literature by examining how AI is utilized to enhance semiconductor manufacturing processes. To achieve this, the process is initiated by categorizing the research papers based on year of publication and the journals in which they were published. Following this, a refined list of relevant keywords is presented and concluded with a detailed analysis of the primary research objective, employing an exploratory survey methodology as depicted in Fig 3.

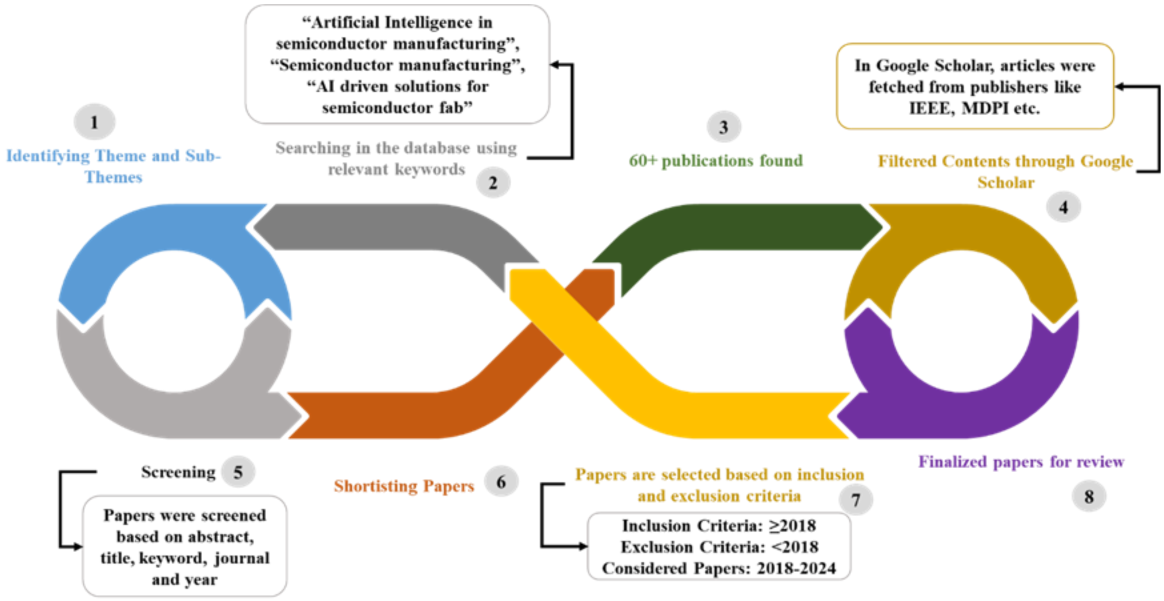

Figure 2: Survey Approach

As explored in Fig 3, initially, themes and sub-themes corresponding to AI in semiconductor manufacturing were identified. Following this, relevant keywords were searched in database. The keywords encompassed "Artificial Intelligence in semiconductor manufacturing," "semiconductor manufacturing," and "AI-driven solutions for semiconductor fab." After searching with suitable keywords, 60+ publications were found. Then, the contents were filtered through Google Scholar, wherein articles were attained from publishers like MDPI, IEEE, etc. Subsequently, papers were screened in accordance with the abstract, title, year, journal, keyword, and year. In accordance with the screening process, the papers were shortlisted. Then, the papers were chosen based on inclusion (≥2018) and exclusion criteria (<2018). Based on this process, the papers were finalized for review.

3. AI in Semiconductor Manufacturing

AI adoption is widespread in the semiconductor industry, as many executives are said to be incorporating or testing this technology in their commercial activities. In addition to opening up new market possibilities, AI enhances predictive maintenance and manufacturing processes, resulting in quality output and improved yields. Moreover, AI possess significant impact on semiconductor manufacturing with regard to quality, cost and speed that eventually leads to optimal outcomes (as shown in Fig 4).

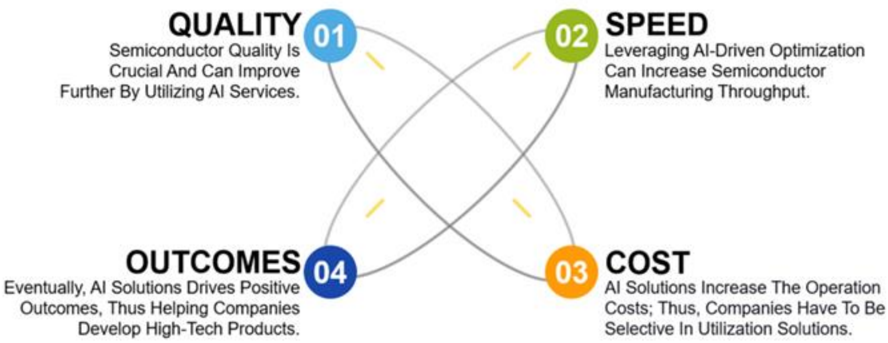

Figure 3: AI's Impact on the Semiconductor Manufacturing Process

In light of such AI advancements, various studies have tried to apply diverse AI-driven solutions to enhance semiconductor manufacturing in different areas. The essence of the efforts is presented in this section.

- Process Quality

In the realm of semiconductor manufacturing, process quality symbolizes the degree of dependability, uniformity, and adherence to precise specifications throughout the fabrication of semiconductor devices. One of the main challenges entangled by traditional quality management methods is dealing with non-linear complex manufacturing data. To tackle this issue, explainable AI has been integrated into quality management. Subsequently, a field experiment has been undertaken to assess the effectiveness of these Compared to the average yield in the considered sample, the experiment resulted in a significant reduction in yield loss at a rate of 21.7%. Additionally, a post-experimental rollout has been executed for the suggested decision model and observed significant improvements in yield. This has exposed the practical value of explainable AI, as it can uncover critical factors influencing process quality that may remain unnoticed when using traditional approaches [10]

- Yield Prediction

In semiconductor manufacturing, maintaining a high yield and accurately forecast yield for satisfying customers, enhancing productivity, and improvising profitability is paramount. However, achieving reliable and precise wafer yield forecasts poses considerable challenges. Owing to this, the study [11] has presented an approach for predicting wafer edge yield by employing a combined model that encompasses both FFNN (Feed-Forward Neural Network) and LSTM (Long Short-Term Memory). Owing to this, the article [12] has introduced an innovative and scalable framework for the prediction of overall test yield in semiconductor manufacturing. Methods such as One Hot Encoder, GMMs (Gaussian Mixture Models), and Label Encoder have been employed to pre-process the data.

- Analyzing the Production Flow

In the semiconductor manufacturing, production flow analysis thoroughly examines and enhances the movement of materials, equipment, and information across the entire production line. Considering this, the aim of the research [13] has been to recognize key production factors that significantly impact the system's throughput and develop the most effective prediction model. The study has employed ML techniques to ascertain critical real-time factors influencing the throughput of a semiconductor manufacturing facility. As a result, four models (Decision Tree, Adaptive Boosting, Random Forest, and Gradient Boosting) with the highest accuracies have been selected, and a scheme to reduce the number of input data types considered in these models has also been recommended.

- Quality Control Framework

The semiconductor manufacturing industry relies on a comprehensive Quality Control Framework comprising a series of meticulous procedures, processes, and benchmarks. This framework is implemented to guarantee the creation of top-notch semiconductor devices. It encompasses every stage of the manufacturing process, commencing from the examination of raw materials to the evaluation of the final product. Correspondingly, the study [14] has endorsed a sophisticated framework for ensuring high quality precision forming. The framework has integrated an experimental design, genetic algorithms, and ML to cater to multiple quality features that are interconnected, considering the variable production settings.

- FDC (Fault Detection and Classification)

FDC plays a vital role in semiconductor manufacturing, enabling engineers to monitor equipment conditions and identify the potential causes of faults. In this process, each piece of equipment is escorted by a large number of sensor readings, termed SVID (Status Variable Identification). Accurate identification of the key SVIDs is crucial for engineers to effectively monitor the manufacturing process and maintain stability while maximizing wafer productivity. To address this challenge, the study [15] has recommended the utilization of random forests to evaluate the significance of SVIDs from the apparatus sensors. For the classification of wafers as abnormal or normal, ensemble models constructed on NB (Naïve Bayes) and KNN (K-Nearest Neighbour) have been presented.

- Anomaly Detection

Detecting anomalies is crucial in monitoring and enhancing the quality of products in manufacturing processes. Particularly in semiconductor manufacturing, where a huge amount of time series data is rapidly gathered from equipment sensors, spotting the abnormal signals within this data poses a notable challenge. The data in question comprises multiple and varying lengths of variables, with a frequently skewed ratio between abnormal and normal signals. Given the characteristics of this data, conventional data-driven methodologies may not be suitable for its analysis. The study [16] has included a novel approach for unsupervised anomaly detection in evaluating multivariate time series data. The suggested model has included a distinctive RNN (Recurrent Neural Network) model and specialized objective function to identify anomalies.

- Predictive Maintenance

Predictive maintenance has emerged as an effective and cost-efficient strategy for managing critical equipment across various industries. The semiconductor industry can also benefit from this approach. Most semiconductor fab plants are fortified with extensive diagnostic and quality control sensors. This can be used for monitoring the condition of assets. Furthermore, ML approaches can gather information regarding a situation through sensors or human input. Then, it is compared to stored data, enabling the algorithm to make informed interpretations. This study [17] presents the outcomes of applying ML to a predictive maintenance dataset, specifically aiming to identify future vibration-associated failures.

- Annealing

Annealing in the realm of semiconductor manufacturing refers to the procedure of subjecting a semiconductor material to the cycles of heating and cooling to alter its properties. This practice is typically carried out after particular manufacturing stages, like ion implantation or deposition, to optimize the arrangement of crystals and eliminate flaws in the material. Semiconductor manufacturing employs various annealing methods, such as furnace annealing and RTA (Rapid Thermal Annealing). Rather than relying upon commonly used unsupervised and supervised learning techniques, RL (Reinforcement Learning) has been employed in the study [18] to determine the optimal process parameters for curtailing the sheet resistance of a device. It has incorporated seven independent variables in fabricating these devices, inclusive of D-Dose, E-Energy, Rep-Repetition rate, W-Wavelength, I-Dopant Ions, P-Power, and T-Temperature. Optimizing the Lithography Process In research [19], an innovative AI system has been used that utilizes this extensive logging data. The purpose of the system has been to enhance exposure tool uptime, productivity, and performance related to yield.

Table 1: Significant Applications

Applications	Description
Defect Detection & Fault Diagnosis	AI algorithms can analyze images or sensor data to identify defects in semiconductor wafers or chips, improving quality control and reducing manufacturing defects.AI can analyze sensor data and historical records to diagnose equipment faults or process deviations, enabling quick identification and resolution of issues.
Predictive Maintenance	AI can monitor equipment and predict maintenance needs by analyzing sensor data, reducing downtime and improving overall equipment effectiveness.
Supply Chain Optimization	AI can optimize the supply chain by analyzing demand forecasts, inventory levels, and production schedules, helping manufacturers reduce costs and improve efficiency.
Equipment Health Monitoring	AI algorithms can monitor equipment health by analyzing sensor data, detecting anomalies, and predicting failures, enabling proactive maintenance and minimizing downtime.
Process Optimization	AI can optimize various manufacturing processes, such as etching, deposition, and lithography, by analyzing data and adjusting parameters in real-time to improve efficiency and yield.

4. Challenges and Future Directions

The overview of the existing studies are mentioned in the Table 2 with different algorithm and different methods in AI model.

Table 2: Overall pre-existing studies for the semi-conductor manufacturing

References	Model	Algorithm	Outcome
[10]	ML	Decision tree Random Forest	Co-efficient-0.93
[11]	DL	LSTM-FFNN	Co-efficient-34.14%
[12]	ML	GMM-CNN & DNN	WAT-60
[13]	ML	AB, SGD, NNMLP, GB, RF, KNN, CART, NB,SVM	Accuracy • AB-97.88% • GB-97.88% • RF-97.88% • CART-97.82%

Table 2 describes about the overall pre-existing studies for the semi-conductor manufacturing. In AI methods, Deep and Machine learning methods was used to research the semi-conductor manufacturing**.**

From extensive review, it is found that several unresolved issues need to be addressed in future research. Firstly, it is crucial to consider additional parameters and process phases to develop a high-quality prediction model. This is especially important in semiconductor manufacturing, which comprises several process steps. There is a possibility that missing value count may increase with the addition of numerous processes. To overcome these challenges, a precise prognostication model that incorporates series metrology should be introduced.

Secondly, the paper [11] only focuses on suggesting a model for prognosticating edge yield. Therefore, further research should be conducted to extend the methodology for total yield prognostication. It is also recommended to explore the following topics in future studies:

1. Develop and test actual production verdicts such as rescheduling machine functions and lot dispatching. The significance of input data should be considered when making these decisions.
2. Include operators' working period and limitations of accessible material handling apparatus in the prediction model. This will provide a better comprehension of the production process
3. Moreover, observations have been limited to weekly data. However, future studies should consider measuring input data for each shift instead of each week. It is necessary to analyze the accumulated or sequence of values measured in consecutive shifts [13]

Future research can also be conducted to utilize the identified fault patterns in order to predict the impact of aging on modules or process tools for health management. The suggested framework can also be employed in various semiconductor manufacturing tools like PVD (Physical Vapour Deposition), diffusion, and etching for diverse applications. Contrarily, it is worth investigating the usage of model-building techniques and different data analysis, such as DL (Deep Learning) networks and image processing methods for assessing the CVD (Chemical Vapour Deposition) dataset [15].

In the future, focus has to be provided for methodological explorations to improvise model performance and enable dedicated analysis of minimal yield root causes. This analysis determines whether the causal factor is associated with WAT (Wafer Acceptance Test) or the production flow. This will permit quick identification of problems and afford effectual suggestions for improvising yield [12]. Various other future directions are projected in Fig 2.

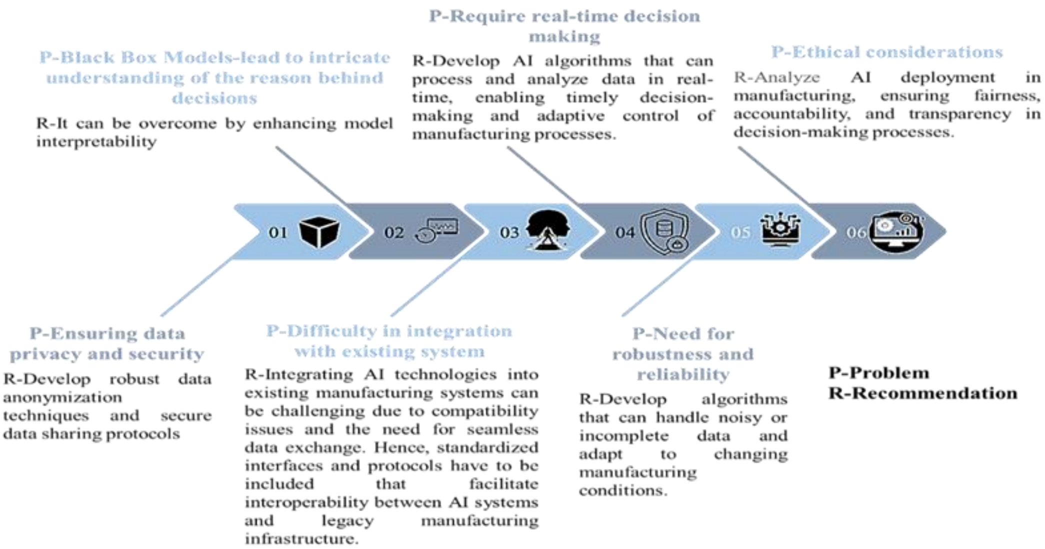

Figure 4: Various Other Future Directions

5. Conclusion

This study aimed to conduct a comprehensive survey between 2018 and 2023, examining cutting-edge research about the role of AI in optimizing the manufacturing processes of semiconductors. Furthermore, the study presented challenges and recommended solutions to guide future researchers in advancing this study area. From the initial analysis, it was discovered that further emphasis should be placed on developing robust techniques for anonymizing data and secure protocols for sharing data to safeguard intellectual property, thereby averting unauthorized access. Improvising the interpretability of models could also be a valuable research path, as it would enable engineers for attaining a comprehensive understanding of the underlying processes and foster trust in AI-driven decision-making. Furthermore, alternative techniques ought to be explored for improvising the flexibility of AI models, including developing algorithms capable of handling noisy or incomplete data and acclimatizing to altering manufacturing setups to ensure accountability, fairness, and transparency in processes for decision-making, ethical guidelines, and models have to be established to deploy AI in manufacturing. Overall, this review will serve as a valuable resource for semiconductor manufacturers, process engineers, researchers, technology providers, and industry decision-makers, offering valuable insights, recommendations, and potential avenues for further exploration in the implementation of AI in semiconductor manufacturing

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