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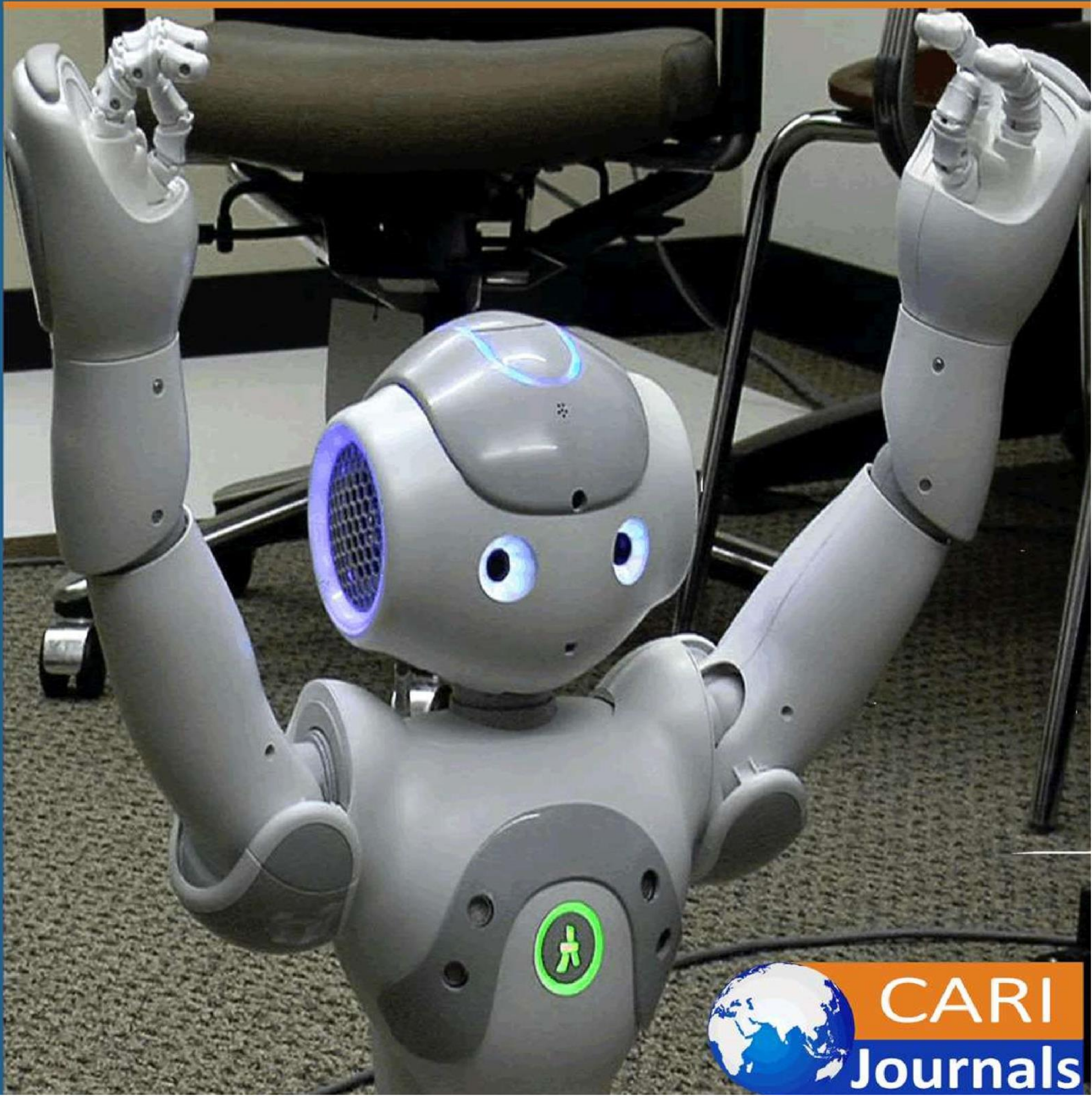

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A Review of Artificial Intelligence Techniques for Quality Control in Semiconductor Production

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Abstract

Purpose: Exploring AI techniques to improve the quality control of semiconductor production brings numerous advantages, such as enhanced precision, heightened efficiency, and early detection of issues, cost reduction, continuous enhancement, and a competitive edge. These benefits establish this area of research and its practical application in the semiconductor industry as valuable and worthwhile.

Methodology: It aims to highlight the advancements, methodologies employed, and outcomes obtained thus far. By scrutinizing the current state of research, the primary objective of this paper is to identify significant challenges and issues associated with AI approaches in this domain. These challenges encompass data quality and availability, selecting appropriate algorithms, interpreting AI models, and integrating them with existing production systems. It is vital for researchers and industry professionals to understand these challenges to effectively address them and devise effective solutions. Moreover, it aims to lay the groundwork for future researchers, offering them a theoretical framework to devise potential solutions for enhancing quality control in semiconductor production. This review aims to drive a research on the semi-conductor production with the AI techniques to enhance the Quality control.

Findings: The main findings to offer research is more efficient and accurate approach compared to traditional manual methods, leading to improved product quality, reduced costs, and increased productivity. Armed with this knowledge, future researchers can design and implement innovative AI-driven solutions to enhance quality control in semiconductor production.

Unique contribution to theory, policy and practice: Overall, the theoretical foundation presented in this paper will aid researchers in developing novel solutions to improve quality control in the semiconductor industry, ultimately leading to enhanced product reliability and customer satisfaction.

Keywords: *Artificial Intelligence, Process Optimization, Quality Control, Semiconductor Production, Technological Advancements.*

1. INTRODUCTION

Contemporarily, ever-evolving manufacturing and production processes have become more intricate, often consisting of multiple stages to cater to customers' needs. This presents major challenges regarding monitoring quality, as a copious amount of data is involved, and numerous factors interactively affect the final product's quality. The semiconductor industry stands at the forefront of technological advancements and drives innovation across various sectors. By assessing the execution of AI in managing the quality of semiconductor production, engineers and researchers can develop suitable algorithms and techniques that can be applied to other industries, thereby benefiting manufacturing processes as a whole. Concurrently, AI [1, 2] plays a pivotal role in ensuring the quality of semiconductor production. Through the utilization of ML (Machine Learning) and advanced techniques, AI has the probability to enhance the efficacy of quality control processes in varied ways. AI empowers semiconductor manufacturers to reach higher levels of quality control by harnessing its capacity to automate inspection procedures, analyse massive data quantity, and enable predictive maintenance.

As AI persists in progress, it is anticipated to enhance further the reliability, speed, and precision of quality control in semiconductor production. Considering this, different endeavours have been undertaken by existing works. In accordance with this, in the study [3], a smart framework has been used for real-time inspection and quality monitoring. The main objective has been to predict and determine any deviations in the quality of intricate and multi-level manufacturing systems at the initial possible phase. To accomplish this, a hybrid quality inspection approach has been developed that integrates predictive models with physical inspection. This approach has enhanced the quality monitoring process and assisted in minimizing inspection time, saving resources, and reducing costs. To build the model for quality monitoring, various ML techniques have been used, including SVM (Support Vector Machines), ANNs (Artificial Neural Networks), RF (Random Forest), and PCA (Principal Component Analysis). These techniques consider the cumulative impacts of varied manufacturing phases and the dynamic and unbalanced nature of the manufacturing processes. To evaluate the effectiveness of the endorsed framework, a large dataset has been used from the semiconductor manufacturing industry.

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Contrary to monitoring the production process for diagnostic purposes, the focus of this paper [4] has been on predicting the quality of the final product. Specifically, the attention has been directed towards the semiconductor industry, where the main intention has been to anticipate the performance of the complete microprocessors. The suggested approach has involved persistent updating of the estimated features of a product succeeding each of the manufacturing functions, permitting early potential issues identification. By utilizing such predictions, proactive measures could be taken to enhance the speed of slow wafers (a collection of microprocessors) or to alleviate the faster wafer's speed. Such predictions can also initiate suitable SCM (Supply Chain Management) actions.

This system [5] relies on an information system that incorporates real-time line data, as well as the intuition and experience of managers. To enhance yield enhancement, the execution of a DL (Deep Learning)-based system has been used. The suggested system is intended to construct an ideal decision-making framework using NN (Neural Networks) specifically designed for the manufacturing sector. Main intention has been to present a system design that could effectually support decision-making within the semiconductor industry, specifically for improvising production yield. To accomplish this, production data has been used consisting of 1,000 lots and 100 processes in the process of semiconductor manufacturing.

Through the suggested developed model, decision variables can be identified that maximize yields within the limitations of the production process. Such decision variables have been crucial in facilitating decision-making and enhancing the overall semiconductor production process. From the endeavours of existing works, it is clear that different studies have attempted to use diverse approaches, considering the diverse aspects of quality control in semiconductor production using AI. Owing to such diverse aspects, the current study intends to afford a theoretical overview of the use of AI for quality control in semiconductor production.

The main contributions of the study are,

- To scrutinize the existing work endeavors (between periods 2013 and 2024) with regard to the applications of AI in quality control of semiconductor production.
- To uncover the significant issues identified during the analysis of AI approaches in quality control of semiconductor production.
- To provide future researchers with a theoretical foundation for assisting them in bringing all probable solutions in this area for enhancing quality control.

2. REVIEW APPROACH

The study aimed to undertake the review using a sequence of procedures, as shown in Fig 1. In this case, papers were initially searched through Google Scholar with suitable keywords, namely, "AI for quality control in semiconductor production," "Artificial Intelligence for quality control," and "Defect detection in semiconductor production." Following this, papers were screened based on abstract and title. This was followed by eligibility checking about a year, keyword, and concept relevance. Then, irrelevant papers were excluded based on unsuitable concepts and inappropriate inferences. Lastly, the papers refined for undertaking the review were found to be 12.

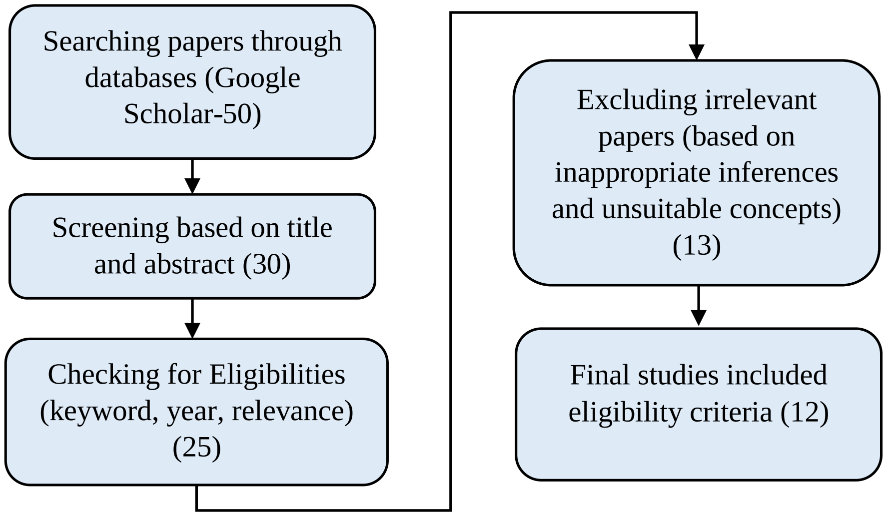

Figure 1. Survey Approach

3. AI IN SEMICONDUCTOR PRODUCTION

AI can greatly enhance quality control in semiconductor production across various domains. AI utilized for quality control in semiconductor production involves the formulation of equations and algorithms to represent the relationship between various variables and the quality of produced semiconductors. Here is an elaborated explanation of the mathematical modelling, along with definitions for the variables involved:

1) Variables

- X: Input variables or features that describe the semiconductor production process. These can include parameters such as temperature, pressure, time, chemical concentrations, and equipment settings.
- Y: Output variable representing the quality of the produced semiconductors. This can be a binary variable (good/bad) or a continuous variable (a quality metric).
- AI: AI algorithms used for modelling and prediction. This can include ML algorithms like NNs (Neural Networks), SVMs (Support Vector Machines), or DTs (Decision Trees).

2) Data Collection

- Historical data: Collect a dataset consisting of past semiconductor production records. Each record should include the input variables (X) and the corresponding quality assessment (Y) of produced semiconductors.
- Training data: Split the historical dataset into a training set and a validation set. The training set will be used to train the AI model, while the validation set will be used to evaluate its performance.

3) Model Development

- Feature selection: Identify the most relevant input variables (X) that have a significant impact on the quality of the semiconductors. This can be done using statistical analysis or domain expertise.
- Model architecture: Choose an appropriate AI algorithm and design its architecture. This involves determining the number of layers, nodes, activation functions, and other parameters specific to the chosen algorithm.
- Training: Use the training data to train the AI model. The model learns the relationship between the input variables (X) and the quality assessment (Y) by adjusting its internal parameters through an optimization process, such as gradient descent.
- Validation: Evaluate the trained model's performance using the validation set. This helps assess its ability to generalize and make accurate predictions on unseen data.

4) Model Deployment

- Once the AI model is trained and validated, it can be deployed for real-time quality control in semiconductor production.
- During production, the input variables (X) are continuously monitored and fed into the AI model.
- The model predicts the quality assessment (Y) of the semiconductors based on the input variables.

  If the predicted quality falls below a certain threshold, appropriate actions can be taken, such as adjusting process parameters or initiating corrective measures.

The mathematical modelling of using AI for quality control in semiconductor production aims to optimize the production process by predicting and maintaining high-quality standards. By leveraging historical data and advanced AI algorithms, this approach enables real-time monitoring and decision-making, leading to improved efficiency and reduced defects in semiconductor manufacturing. An aspect of controlling the quality in semiconductor production using AI is shown in Fig 2.

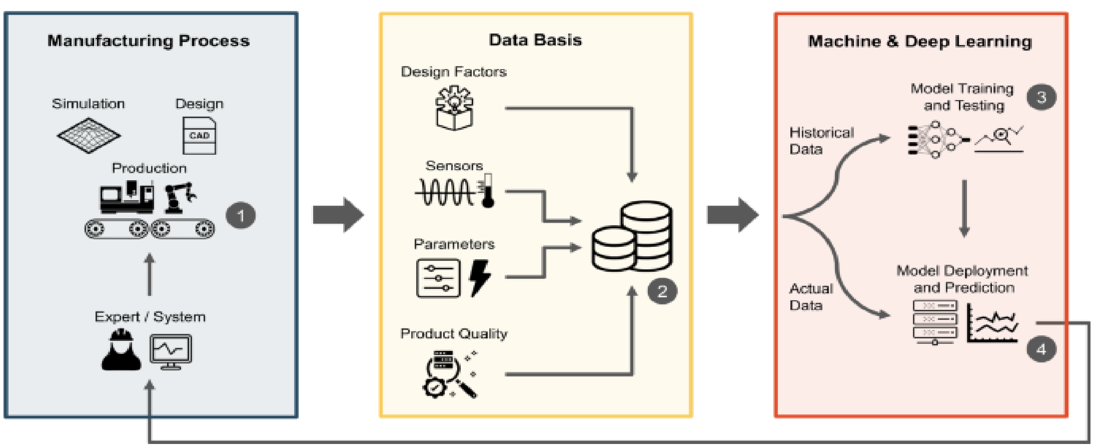

Figure 2. Predictive Quality Method

As shown in Fig 2, suitable process and quality-data is initially gathered. These are considered as a foundation to train the ML model. Following this, training model finds usage in estimating the quality for taking optimal decisions. AI is used in different dimensions for controlling the quality in semiconductor production. This involves defect detection, process optimization, and prognosticative maintenance, analyzing the root cause, real-time analysis, and feedback.

Defect Detection

AI finds use in assessing the sensor data or images from the manufacturing line to identify defects or abnormalities in semiconductor modules. Conventional EB (Electron Beam) and optical inspection systems rely on rule-based methodologies for detecting and classifying defects. However, these techniques are often rigid in their comparative processes, limiting their capabilities and requiring significant engineering time to classify minor defects. This rigidity is further exacerbated by the shrinking pattern dimensions in advanced nodes.

To address these challenges, a DL (Deep Learning) based approach has been endorsed that overcomes these limitations and enables accurate defect categorization and localization within a unified framework. Specifically, models have been trained based on CNN (Convolutional Neural Networks) using EB images of wafers having high resolution with deliberate defects of varied kinds. This training has permitted us to perform better in detecting and classifying defects.

Through the suggested method, a specificity rate of 100% and a high sensitivity rate of 97% have been attained. Performance has also been tested on images having dual distinct patterns. It has been found that modest retraining has been necessary for maintaining a high level of accuracy. Overall, by leveraging DL and AI, it is probable to significantly enhance quality control and defect detection in semiconductor manufacturing. This not only improves the complete production process but also alleviates the costs and averts perilous failures [6].

Process Optimization

AI algorithms cancan analyze vast amounts of data gathered at the production phase to discover correlations and patterns that could potentially impact the quality of a product. AI can optimize process parameters by utilizing these insights to enhance overall production efficiency, reduce defects, and improve yield.

Accordingly, in the study [7], a mathematical model has been suggested that addresses this multi-row facility layout issue by treating it as a predefined discrete points system, enabling the placement of processing modules at varied locations within the semiconductor fab plants. Given the substantial computational requirements, the PSO (Particle Swarm Optimization) algorithm has been employed to minimize the overall transportation distance amongst modules and solve the multi-row facility layout issue. The obtained results have represented that the PSO algorithm has been confirmed to be a suitable approach for resolving the multi-row facility layout issue in a shorter period.

According to technological advancements, advanced tools and techniques are now available for manufacturing semiconductor devices. As a fragment of this technological progress, optimizing manufacturing involves assessing various parameters, including measurements, temperature, and pressure. Over the years, numerous techniques have been employed, and one particularly efficient approach is using ANNs (Artificial Neural Networks). ANN consists of a few classes and enables the development of advanced methods for prognosticating manufacturing requirements.

The primary objective has been to optimize the fabrication process to achieve thin films with low-scale dimensions of a material, which can be applied to the semiconductor substrate. The main intention has been to optimize the parameters involved in processing, such as thin-film thickness and pressure. This optimization has been achieved by a diverse flow of Argon gas. By manipulating such parameters, the fabrication process could be enhanced at a significant rate. To train the NN (Neural Network), input parameters have been assumed, and contemplations have been made based on the figure-of-merits. This has ultimately resulted in the reduction of testing-time and streamlines the long and laborious fabrication process, avoiding the requirement for manual intervention [8].

Considering this, the research paper [9] has included an effectual data-driven methodology as NB (Naiive Bayes) for multi-objective optimization with the use of NN-based sensitivity evaluation for semiconductor devices. By undertaking sensitivity analysis, influential parameters can be quickly identified. Subsequently, probable design parameter candidates for customized solutions can also be chosen. These parameters are later acclimatized to stay within a certain range in accordance with the scaled sensitivities, assuring robustness against noise. The optimization process concentrates on the simultaneous meet up of the variation requirements and performance while considering the correlation among parameters.

Consequently, the suggested method has afforded multi-objective solutions that manage physical consistency, with an error margin (less than 1.7%). Then, a significant merit of this approach has been its computational efficacy. In comparison to the Bayesian optimization method for the optimization of the process, the suggested method has minimized the computational time by over 80%. This has made it highly effective across several industries, not just restricted to semiconductors. By leveraging the robustness of optimization, statistical modeling, and sensitivity analysis, a valuable framework has been offered for managing product quality and technology development within the manufacturing sector.

Predictive Maintenance

In the paper [10], several predictive models like ML on the SECOM (Semiconductor Manufacturing process dataset) have been used. This dataset consists of information about the semiconductor manufacturing process, including signals gathered from the devices. Nevertheless, the SECOM dataset has presented challenges associated with data pre-processing owing to its class imbalance and high dimensionality problem. Essential steps have been incorporated for pre-processing the data while executing various ML models.

To assess the performance of varied predictive ML classification models, a comparison and evaluation have been conducted using the ROC (Receiver Operating Characteristic) curve and accuracy as performance metrics. Through an extensive comparative study, it can be concluded that RF has underperformed on the SECOM dataset owing to class imbalance problems. Contrarily, LR (Logistic Regression) has performed considerably better, when integrated with PCA (Principal Component Analysis) to accomplish commendable accuracy. LR with FPR (False Positive Rate) has been the model that fits the dataset precisely.

Nevertheless, certain approaches fall short owing to class imbalance issues, and integrating certain hybrid approaches like evolutionary ML could be explored. The accuracy of the RF has been improved through the usage of the SMOTE technique. When employing the k-NN algorithm with cross-analysis, the mean cross-validation score was the highest.

Root Cause Analysis

AI can be utilized to determine the quality issues or root causes of defects by evaluating data from various sources, including sensor data, quality control records, and production logs. By pinpointing the underlying factors that subsidize the problem, manufacturers can take suitable actions to prevent identical issues from happening in the future. Failure analysis is crucial in assuring good quality in manufacturing the electronic component. Through failure analysis, it is probable to identify the flaws in components and attain a better comprehension of the strategies and reasons for failure, permitting remedial measures to enhance product reliability and quality.

However, few of such methods might not be appropriate for big datasets or might be intricate to fine-tune. In addition, some techniques might not be applicable to the textual data. Hence, the study [11] has developed a prognosticative model capable of finding failure conclusions in accordance with the discriminating features of failure descriptions. GA (Genetic Algorithm) has been integrated and utilized with a supervised learning approach to accomplish this. The main intention has been to optimize the prognostication of failure conclusions by considering relevant failure description features.

Real-Time Monitoring and Feedback

AI is capable of continuous monitoring of production processes, thereby affording immediate feedback to the operators. Through the analysis of real-time data, AI models possess the innate ability to identify any deviations from the desired quality standards. It is also capable of alerting operators to undertake prompt corrective actions. This assists in alleviating the probability of generating faulty components.

K-means clustering algorithm and association rules have been employed, along with real-time feedback control analysis. By integrating SPC and real-time feedback using historical process data, the system has been able to prognosticate the optimal process parameters for each subsequent lot. The suggested semiconductor system has the potential to be employed to evaluate the process data in conventional manufacturing industries. The results have illustrated how this system can improve the semiconductor manufacturing process regarding yield rate, processing capability, flexibility, and stability while concurrently minimizing costs. This has created a competitive merit for wafer fabs [12].

4. CHALLENGES AND FUTURE DIRECTIONS

The significant issues identified through the analysis of existing works are deliberated as follows,

- **Limited data availability:** Labeled data for training AI models in semiconductor production can be insufficient. Future studies should concentrate on developing methods to generate synthetic data or evaluate TL (Transfer Learning) approaches to utilize data from related domains [13].
- **Scalability:** Executing AI-based quality control systems in large-scale semiconductor production facilities can present difficulties. Future efforts should concentrate on developing scalable architectures and AI algorithms capable of dealing with the substantial velocity and volume of real-time generated data [14].
- **Interpretability and explainability:** AI models applied in quality control must deliver interpretable and explainable outcomes for establishing reliability among the stakeholders and operators. Future research should focus on developing AI techniques that can transparently explain the decisions made by the models [15].
- **Adaptability to process variations:** Semiconductor production processes can exhibit variations due to material differences or equipment disparities. Future research should explore AI techniques that can adapt and generalize effectively across diverse process variations, ensuring robust quality control [16].
- **Augmenting real-time decision-making:** Achieving optimal production rate and minimization of defects in semiconductor production requires executing decision-making processes in real-time. Future endeavors should highlight the advancement of AI approaches capable of promptly delivering accurate decisions to bolster real-time quality control practices [17].
- **Ensuring cost-effectiveness:** Adopting AI-based quality control systems encompasses substantial expenses, including data acquisition, infrastructure, and model development. Prospective studies should delve into economical alternatives, such as TL or harnessing existing data sources, to diminish the overall costs of incorporating AI into quality control processes [18].
- **Addressing ethical considerations:** Ethical concerns, like bias, data privacy, and fairness, must be appropriately addressed in AI-based quality control systems. Upcoming initiatives should establish comprehensive frameworks and guidelines that guarantee AI's ethical implementation and usage in semiconductor production quality control [19].
- **Nurturing Human-AI collaboration:** The collaboration between human operators and AI systems plays a pivotal role in achieving successful quality control outcomes. Future investigations should explore techniques for enhancing human-AI interactions [20].

5. COMPARATIVE ANALYSIS

Comparative analysis has been undertaken regarding method, algorithm and outcome in existing studies. The respective analytical results are presented in Fig 3.

Table 1. Comparative Analysis

References	Method	Algorithm	Outcome
[6]	DL	CNN - Automated Defect Classification Algorithm	Specificity – 100% Sensitivity – 97%
[9]	ML	NN - NB	Sensitivity – 90%
[7]	DL	ANN	Accuracy – 89%
[10]	ML	SMOTE Technique 1. MLP 2. LR 3. k-NN	Accuracy: • MLP -91.63% • LR – 94.64% • k-NN– 92.46% ROC curve: • MLP – 0.62 • LR – 0.66 • k-NN – 0.55
[11]	ML	Decision Tree Classifier & SVM 1. GA-DT 2. GA-SVM	Accuracy: • GA-DT: 84% • GA-SVM: 74% BLEU: • GA-DT: 0.72 • GA-SVM: 0.56 Cosine Similarities: • GA-DT: 0.85 • GA-SVM: 0.61

Figure 3. Comparative Analysis for Sensitivity and Accuracy

From Table 1, it has been found that the deep learning method has given more precise results when compared to the machine learning models. Similarly, Fig 3 shows the results for sensitivity and accuracy results, while using deep learning techniques. Hence, Table 1 explains the overall comparative studies from the pre-existing research.

6. CONCLUSION

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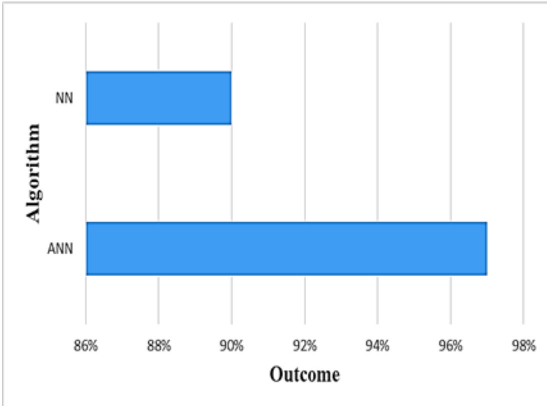

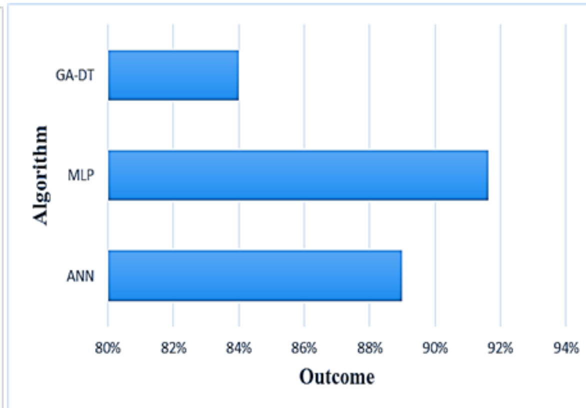

The study endeavored to undertake a precise review of the applications of AI in quality control for semiconductor production. A sequential procedure was undertaken to undertake the review wherein studies between 2013 and 2024 were considered. Different quality control aspects were presented, such as defect detection, process optimization, predictive maintenance, root cause analysis, and real-time monitoring and feedback. Common problems include limited data availability, complex defect patterns, scalability, interpretability, and explainability adaptability to process variations, augmenting real-time decision-making, ensuring cost-effectiveness, streamlining integration with current systems, addressing ethical considerations, and nurturing human-AI collaboration. To resolve such issues, the study uncovers certain future suggestions like the development of interactive decision support systems, ensuring the ethical implementation, seamless incorporation of strategies and standardized protocols, harnessing existing data sources to reduce overall costs, advancing AI approaches capable of making prompt and precise decisions to bolster real-time quality management practices, focus on introducing AI techniques that can transparently delineate the decisions undertaken by AI models. Such suggestions explored through this review will assist industry experts and stakeholders make suitable decisions for improving quality control in semiconductor production. To fully harness the potential of these techniques, it is crucial to have a deep understanding of the production process, high-quality data, and well-trained models. Regular updates and monitoring of the AI systems will also ensure their accuracy and effectiveness in improving the quality of semiconductor products.

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