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A CRITICAL SYNTHESIS OF ARTIFICIAL INTELLIGENCE TECHNIQUES FOR PREDICTIVE MAINTENANCE AND ANOMALY DETECTION IN COMPLEX CHIP MANUFACTURING.

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Abstract

This literature review examines the use of artificial intelligence for predictive maintenance and anomaly detection in computer chip fabrication processes, with a focus on how advanced data-driven methods can improve equipment reliability, reduce downtime, and support stable production in semiconductor manufacturing. The purpose of the review is to synthesize existing research on AI-based fault monitoring, process anomaly identification, and maintenance forecasting, and to show how these methods contribute to higher yield and better operational efficiency in fabrication plants. The main themes covered include sensor-based monitoring, machine learning, deep learning, autoencoders, GAN-based approaches, LSTM models, and multi-task learning frameworks. The reviewed studies generally find that AI systems can detect abnormal process behavior earlier than traditional rule-based methods and can help predict equipment degradation more accurately when data are high-dimensional and imbalanced. However, the literature also highlights major challenges such as limited labeled failure data, low interpretability, deployment complexity, and the need for real-time industrial validation. The final research gap points toward the development of more explainable, scalable, and integrated AI models that combine predictive maintenance and anomaly detection into a single framework for semiconductor fabs.

Keywords: *artificial intelligence, predictive maintenance, anomaly detection, semiconductor manufacturing, chip fabrication, machine learning, deep learning, fault detection, process monitoring, smart manufacturing*

Introduction

Semiconductor or chip fabrication represents one of the most technically demanding forms of modern manufacturing because it depends on extremely precise control over temperature, pressure, chemical composition, timing, and equipment condition across many interrelated process stages. In a fabrication environment, wafers move through a sequence of lithography, etching, deposition, cleaning, inspection, and testing operations, and each stage must operate within narrow tolerance limits to preserve device performance and production yield. Even a minor disturbance in one machine or one process parameter can create defects that spread through later stages and lead to material waste, rework, or full lot rejection. For that reason, semiconductor production is not simply a matter of assembling tools and running them continuously; it is a tightly monitored system in which stability, repeatability, and precision are essential to successful output. The literature on semiconductor manufacturing consistently shows that as chip geometries shrink and process complexity increases, the need for intelligent monitoring also becomes more urgent because traditional manual oversight is no longer sufficient for fast and reliable decision making (Susto et al., 2017; Song & Baek, 2020).

The importance of maintaining equipment reliability in this setting cannot be overstated because fabrication tools are expensive, highly specialized, and often operate around the clock in production-critical environments. When equipment degrades gradually, it may not fail immediately, but it can still introduce subtle variations that lower product quality and reduce yield long before a complete breakdown occurs. This is especially serious in semiconductor plants because a tool may support thousands of wafers over a long production cycle, meaning that undetected drift can affect a large number of units before maintenance teams recognize the problem. Reliability therefore becomes both a technical and economic priority, since unplanned downtime can interrupt scheduling, increase operating costs, and reduce the overall efficiency of the fabrication line. Studies on semiconductor anomaly detection and process monitoring show that identifying tool deterioration early is one of the most effective ways to preserve manufacturing stability and reduce hidden losses in high-volume production systems (Susto et al., 2017; Wang et al., 2021).

Predictive maintenance has become increasingly important in chip manufacturing because it allows engineers to anticipate failures before they interrupt production rather than simply reacting after a machine stops working. In a fabrication plant, equipment failure is rarely an isolated event; it often develops through gradual wear, process drift, sensor deviation, or abnormal operating patterns that accumulate over time. AI-based predictive maintenance systems are valuable because they can process large volumes of historical and real-time sensor data, detect trends that are not obvious to human operators, and support maintenance decisions based on evidence rather than fixed schedules alone. This is particularly useful in semiconductor environments where over-maintenance can be costly and under-maintenance can lead to serious disruptions. Research in this area indicates that machine learning models can support fault prediction, degradation assessment, and remaining useful life estimation more effectively than conventional threshold-based methods, especially when the data are imbalanced and the failure patterns are rare but significant (Abdelli et al., 2022; Yin et al., 2024; Kim et al., 2026).

Anomaly detection is equally essential in fab operations because semiconductor manufacturing depends on early identification of unusual behavior before that behavior becomes a visible defect or equipment failure. Unlike simple alarms that trigger only when a reading crosses a fixed limit, anomaly detection methods can learn normal operating patterns and identify more subtle deviations across multiple sensors or process signals. This is important in chip fabrication because abnormal conditions may appear as small shifts in correlated variables rather than as one dramatic fault signal. For example, a tool may remain technically operational while still producing wafers that are increasingly inconsistent due to pressure instability, thermal drift, or contamination. AI-driven anomaly detection provides a way to recognize such hidden irregularities earlier, which supports faster corrective action and improves process control. The literature shows that this is particularly valuable in semiconductor systems where datasets are high-dimensional, labels are limited, and abnormal events occur far less frequently than normal production conditions, making data-driven detection methods far more practical than purely manual inspection (Song & Baek, 2020; Wang et al., 2021; Lee et al., 2025).

The purpose and scope of this literature review are to examine how artificial intelligence has been applied to predictive maintenance and anomaly detection in semiconductor chip fabrication, and to identify what the existing research reveals about strengths, limitations, and future needs. The review focuses on studies that use machine learning, deep learning, oversampling methods, generative models, recurrent neural networks, and multi-task learning to handle equipment monitoring and fault prediction problems in manufacturing contexts related to semiconductors. It also considers why these approaches are attractive for fab environments and what obstacles remain before they can be fully trusted in production operations. The scope is limited to literature relevant to sensor-based monitoring, fault diagnosis, and process anomaly detection, with attention to both predictive maintenance and broader industrial intelligence applications. By organizing the research around these themes, the review aims to provide a clear academic foundation for understanding how AI is transforming reliability management in chip fabrication and where the next stage of research should be directed (Susto et al., 2017; Song & Baek, 2020; Abdelli et al., 2022; Kim et al., 2026).

Overview of AI in Semiconductor Manufacturing

Artificial intelligence has become a central part of modern semiconductor manufacturing because chip fabrication now depends on managing enormous volumes of process data with a level of speed and precision that exceeds what human monitoring can realistically achieve. In a fabrication plant, AI is not used only as a support tool for reporting problems after they occur; instead, it increasingly functions as a decision-making layer that helps engineers understand process behavior, anticipate deviations, and improve operational stability across the entire production line. This shift is especially important in semiconductor environments because the manufacturing chain is highly sensitive, tightly coupled, and extremely expensive, so even a small process disturbance can create downstream losses in yield or reliability. Contemporary industry discussions emphasize that AI is being applied to defect detection, process optimization, resource allocation, and predictive analytics, showing that its role has expanded from isolated automation tasks to broader fab intelligence systems (Indium, 2025; INFICON, 2023; Qin et al., 2006).

The role of AI in modern fabrication plants is therefore closely tied to the need for continuous observation, fast interpretation, and proactive control. Semiconductor fabs generate a constant flow of measurements from equipment sensors, process tools, metrology stations, wafer maps, inspection systems, and test platforms, and these data streams are too large and complex for manual analysis alone. AI systems can learn patterns in these datasets and detect when the behavior of a tool or process begins to drift away from expected norms. In practice, this means AI can support not only fault detection but also process tuning, anomaly recognition, yield optimization, and maintenance planning. Industry sources describe AI as a mechanism that can reduce downtime, improve defect detection, and enhance productivity by turning large operational datasets into actionable insight, while research on fab-wide process control shows that the value of intelligence increases when equipment, metrology, and material handling information are integrated into one monitoring framework (Indium, 2025; Qin et al., 2006; INFICON, 2023).

The types of data used in semiconductor manufacturing are varied and highly interconnected, which is one reason AI is so useful in this domain. Equipment-level sensor data capture the immediate operating state of tools and provide rapid feedback on machine health. Metrology data measure physical characteristics of the wafer, including geometry, critical dimension, and layer alignment, and these measurements help engineers assess whether the manufacturing process remains within specification. Process control monitor data provide electrical information that reflects the quality of the wafer and the reliability of the device structure. In addition, production logs, test results, wafer maps, image data, and process histories contribute to a rich data environment in which hidden patterns can be learned by machine learning models. A key feature of semiconductor manufacturing data is that it is both multidimensional and time sensitive, meaning the meaning of one measurement often depends on previous process conditions and on other signals collected across the fab, which makes AI particularly valuable for pattern discovery and anomaly detection (Qin et al., 2006; Synopsys, 2021; PDF.com, 2025; INFICON, 2023).

Common AI applications in fabs include predictive maintenance, fault detection, anomaly detection, process optimization, yield improvement, and automated root cause analysis. Predictive maintenance uses historical and live data to estimate when equipment may begin to fail or degrade, allowing maintenance teams to intervene before production is interrupted. Anomaly detection identifies abnormal patterns in sensor readings, inspection results, or process outputs that may indicate a hidden defect or a drifting tool. Other AI applications include defect classification in wafer images, monitoring of deposition and etching behavior, and detection of outlier patterns in test or sort data. These applications are especially valuable because semiconductor fabs work under narrow tolerances and cannot afford repeated human inspection at every stage of production. Industry reporting also notes that AI is already being used for inline defect detection, multivariate process control, fast root cause analysis, and automated classification of wafer maps, all of which show that AI is becoming embedded in the practical routines of fab operations rather than remaining a purely experimental technology (Indium, 2025; INFICON, 2023; Orbitskyline, 2025).

The transition from traditional monitoring to intelligent monitoring systems marks one of the most important changes in semiconductor manufacturing. Traditional monitoring was often based on fixed thresholds, periodic inspection, or operator experience, which worked reasonably well when manufacturing environments were less complex and process volumes were lower. However, as chip fabrication became more automated, more data intensive, and more sensitive to tiny variations, these older methods became less sufficient. Intelligent monitoring systems now combine real-time data collection with machine learning and predictive analytics to detect deviations earlier and with greater precision. Instead of reacting only after a parameter crosses a set limit, AI-based monitoring can identify subtle multivariate trends that suggest the beginning of equipment wear or process instability. This matters because many semiconductor defects develop gradually and may not be visible through one measurement alone. The literature on fab-wide control and smart manufacturing consistently shows that the strongest systems are those that integrate equipment health, metrology, and test data into a continuous analytical loop that supports both detection and control, rather than treating monitoring as a separate post-process activity (Qin et al., 2006; INFICON, 2023; Indium, 2025).

Predictive Maintenance in Chip Fabrication

Predictive maintenance in chip fabrication refers to the use of data and analytical methods to anticipate equipment degradation or process failure before the failure interrupts production. In a semiconductor fab, this approach is not limited to scheduling service at fixed intervals; rather, it is based on observing how machines behave over time and identifying patterns that suggest wear, instability, or abnormal operation. The importance of this definition lies in the nature of semiconductor production itself, where tools are expensive, process windows are narrow, and the cost of an unexpected shutdown can be extremely high. For that reason, predictive maintenance is best understood as a preventive intelligence system that supports reliability, continuity, and process stability across the fabrication line (Critical Manufacturing, 2021; Susto et al., 2017).

Artificial intelligence strengthens predictive maintenance by turning large and complex equipment data into actionable maintenance insight. In fabrication plants, AI models can analyze continuous sensor streams, metrology signals, and machine performance indicators to identify subtle changes that may precede failure. This is especially useful because degradation in semiconductor tools often appears gradually, long before a breakdown becomes visible to human operators. AI systems can therefore support early warnings, fault anticipation, and time-to-failure estimation, which allows maintenance teams to intervene at the right moment rather than after production loss has already occurred. Industry discussions and applied research show that AI-based predictive maintenance is increasingly being used to detect abnormal behavior in real time and to improve decision making for semiconductor service teams and process owners (Tessolve, 2025; Critical Manufacturing, 2021; INDIUM, 2025).

The common machine learning methods used in this area include supervised classification, sequence modeling, anomaly-based learning, and hybrid architectures. Supervised models such as support vector machines, random forests, and gradient-boosting approaches are often used when labeled fault data are available, although such cases are rare in semiconductor settings. Recurrent neural networks, especially LSTM-based models, are valuable because they can learn temporal dependencies in sensor signals and detect changes over time rather than treating each reading in isolation. Autoencoders and one-class models are also widely used when failure labels are limited, since they can learn the profile of normal behavior and flag deviations from it. Some studies further combine multiple methods, such as SVM with RNN or LSTM, to improve both classification accuracy and temporal prediction capability, which reflects the highly complex and nonlinear nature of manufacturing data in fabs (Abdelli et al., 2022; Kim et al., 2026; Wang et al., 2021; Y. et al., 2023).

The benefits of early fault prediction in chip fabrication are substantial because even small improvements in maintenance timing can produce major operational gains. Early detection helps reduce unplanned downtime, protect production schedules, avoid scrap, extend tool life, and reduce unnecessary maintenance interventions. It also improves yield by preventing faulty equipment from producing large numbers of defective wafers before the problem is noticed. In a high-value production environment such as semiconductor manufacturing, the financial impact of early prediction is often greater than in ordinary industrial settings because each production stage is tightly linked to the next. Studies and industry reports consistently suggest that predictive maintenance supports better resource allocation and lower operational cost while also improving overall fab reliability and throughput (Tessolve, 2025; Critical Manufacturing, 2021; INDIUM, 2025).

Anomaly Detection in Semiconductor Processes

Anomaly detection in semiconductor processes refers to the identification of behavior that deviates from the expected operating pattern of fabrication tools, process variables, or inspection data. In chip manufacturing, this concept is especially important because abnormality is not always represented by a complete machine failure; often, it appears first as a small change in sensor behavior, a subtle process drift, or a weak pattern in wafer data that gradually develops into a larger defect. For this reason, anomaly detection in semiconductor environments is best understood as an early warning mechanism that helps engineers recognize when a process is beginning to move away from stable production conditions. The literature shows that this is difficult but necessary because semiconductor systems are high-dimensional, time dependent, and highly sensitive to small disturbances, making conventional fixed rule systems too limited for reliable monitoring (Susto et al., 2017; Song & Baek, 2020).

The types of anomalies that arise in chip fabrication are varied and can appear at different stages of the production cycle. Some anomalies are equipment related, such as sensor drift, pressure instability, thermal irregularity, or tool wear that changes the behavior of the process over time. Others are process related, including wafer misalignment, contamination, deposition inconsistency, or etching variation. There are also product related anomalies, where the output wafer or final device contains patterns that indicate a defect even though the process may have appeared normal at first glance. In addition, anomalies may be transient, where they occur only briefly, or persistent, where they remain across multiple wafers or lots. Because of this diversity, anomaly detection in semiconductor manufacturing must be flexible enough to identify both isolated and evolving irregularities across many variables and operating conditions (Wang et al., 2021; Lee et al., 2025; Hashimoto et al., 2021).

Sensor based anomaly detection has become one of the most widely studied approaches in this field because fabrication equipment produces continuous streams of multivariate time series data. These signals may include temperature, vibration, current, gas flow, pressure, and other process measurements that together describe the operating state of a tool. AI models can learn the normal structure of these signals and then flag deviations that may correspond to fault development or unstable process behavior. A major advantage of sensor based methods is that they can work even when explicit failure labels are scarce, which is common in semiconductor production. Research has shown that autoencoder based approaches, GAN based methods, and one class learning frameworks can be effective for detecting unusual behavior in such high dimensional data, especially when combined with strategies that address imbalance and limited abnormal samples (Song & Baek, 2020; Hashimoto et al., 2021; Abdelli et al., 2022).

Image based anomaly detection is also highly important in semiconductor manufacturing because many defects are visual and can only be recognized through inspection images, wafer maps, or microscopic imaging data. In this case, AI systems analyze patterns, textures, shapes, or surface irregularities that may indicate corrosion, contamination, cracking, pattern distortion, or other structural defects. Deep learning has made this area especially promising because image based models can learn complex visual representations without requiring hand designed features. Recent work on semiconductor inspection suggests that visual anomaly detection is useful when the defect classes are subtle, rare, or expensive to label, which is often the case in chip fabrication. As a result, image based anomaly detection complements sensor based monitoring by covering defect modes that are physically visible rather than purely operational (Lee et al., 2025; Sieg et al., 2025; thesis, 2025).

The importance of identifying abnormal process behavior early lies in the fact that semiconductor fabrication is cumulative, meaning that one undetected issue can affect many downstream steps. If an abnormal condition is found only after several wafers have moved through the line, the cost of correction becomes much greater because engineers may need to scrap product, repeat inspections, or stop the line for diagnosis. Early detection allows fabs to isolate the problem, limit yield loss, and protect the quality of devices already in production. It also supports more accurate root cause analysis because the model can point engineers to the point at which deviation began rather than forcing them to search through long histories of normal and abnormal data. Studies on real time anomaly localization and large scale deployment show that timing matters as much as detection itself because knowing when the anomaly begins can determine whether wafers are recoverable or must be discarded (NVIDIA, 2025; Susto et al., 2017; Song & Baek, 2020).

Review of Major AI Techniques

The literature on artificial intelligence in semiconductor manufacturing shows that no single method is sufficient for every fabrication problem, because the data are large, noisy, imbalanced, and highly time dependent. For this reason, researchers and industry practitioners have increasingly used a combination of machine learning, deep learning, and hybrid modeling strategies to address tasks such as anomaly detection, predictive maintenance, defect classification, yield prediction, and process optimization. Machine learning methods remain important because they offer flexibility, relatively lower computational cost, and the ability to work with structured manufacturing data such as sensor readings, process logs, and quality indicators. At the same time, deep learning methods are increasingly preferred when the problem involves complex nonlinear relationships, image based inspection, or long temporal sequences that are difficult to model with simpler statistical tools. The literature suggests that semiconductor manufacturing is one of the environments where AI method selection matters greatly because the performance of a model depends not only on accuracy but also on interpretability, deployment speed, and robustness under changing process conditions (Liu et al., 2022; Indium, 2025; Q. et al., 2006).

Machine learning methods are often used as a practical starting point for semiconductor analytics because they can learn from historical process data and provide useful predictions without requiring extremely large labeled datasets. Supervised methods such as random forests, support vector machines, logistic regression, and gradient boosting are commonly applied to yield prediction, defect classification, and failure diagnosis when labeled examples are available. Unsupervised methods such as clustering and density based approaches are also important because many fab datasets contain very few failure labels, which makes conventional classification difficult. In such cases, machine learning can detect unusual patterns, group similar operating states, or reduce dimensionality before more advanced models are applied. Studies on semiconductor manufacturing repeatedly show that preprocessing, feature selection, and balancing techniques often determine whether machine learning models perform well, especially in real factory environments where the data are messy and the failure cases are rare (Song & Baek, 2020; Liu et al., 2022; IJSATE, 2025).

Deep learning methods have become central in this field because chip fabrication data are often too complex for shallow models to capture effectively. Deep neural networks can learn layered representations of process behavior, making them useful for tasks such as anomaly detection, wafer inspection, image classification, and predictive maintenance. In semiconductor manufacturing, deep learning is particularly valuable when the input is high dimensional or multimodal, such as combining sensor streams with inspection images or process histories. Industry sources report that deep learning is already being used for defect detection, process optimization, and real time monitoring because it can learn hidden relationships among variables that simpler methods may overlook. This capability is especially important in fabs, where small interactions among variables can determine whether a wafer passes or fails quality control (Indium, 2025; Infosys, 2025; Liu et al., 2022).

Autoencoders are one of the most widely used deep learning structures for semiconductor anomaly detection because they are well suited to learning the pattern of normal operation. The basic idea is that an autoencoder compresses input data into a lower dimensional representation and then reconstructs it, so reconstruction error can be used to identify abnormal behavior. This is especially useful in fab environments where fault labels are limited but normal operational data are abundant. Autoencoders have been applied to multivariate sensor data, wafer maps, and sequence data, and they are often integrated with other techniques to improve sensitivity to rare anomalies. Research in semiconductor manufacturing indicates that autoencoder based methods are effective because they can model subtle deviations in process behavior without needing a large number of labeled fault examples, which makes them highly practical for industrial settings with incomplete failure records (Song & Baek, 2020; Hashimoto et al., 2021; Abdelli et al., 2022).

LSTM and other recurrent models are particularly important when semiconductor data have a strong temporal structure, which is common in manufacturing systems where the current state depends on earlier process conditions. LSTM networks are designed to remember information over time, making them suitable for equipment health monitoring, degradation tracking, and sequence based fault prediction. In semiconductor applications, these models can detect changes that unfold gradually across time rather than appearing as isolated points. This makes them useful for predictive maintenance and anomaly detection because many faults in fabs emerge through slow drift, not immediate failure. Recent work has shown that LSTM based autoencoders can improve early fault detection and support remaining useful life prediction, which is a valuable capability for high precision manufacturing where timing is as important as fault recognition (Kim et al., 2026; Abdelli et al., 2022; Wang et al., 2021).

GAN based methods have also gained attention because semiconductor datasets often suffer from imbalance and limited examples of abnormal conditions. Generative adversarial networks can help model normal process patterns or generate synthetic samples that improve training for rare event detection. In some semiconductor studies, GAN based oversampling has been used to strengthen anomaly detection performance by expanding the representation of rare failure types. This is useful because fault data in chip fabrication are expensive to collect and often too scarce for direct supervised learning. GANs therefore add value not only as a generative tool but also as a data augmentation strategy that supports more balanced and robust learning in challenging fab environments (Song & Baek, 2020; Hashimoto et al., 2021; NVIDIA, 2025).

Multi task learning approaches represent one of the most promising newer directions because they allow a single framework to handle more than one maintenance or monitoring objective at the same time. In semiconductor manufacturing, this is especially relevant because anomaly detection, fault prediction, and remaining useful life estimation are closely connected. A recent study demonstrated that a multi task learning framework built around an LSTM based autoencoder could improve early fault detection while also supporting RUL prediction in semiconductor systems. The strength of this approach lies in shared feature learning, since one model can learn patterns useful for multiple outcomes rather than building separate models for each task. This is important in practical fab environments because it can reduce redundancy, improve overall predictive performance, and support more complete maintenance decision making (Kim et al., 2026; SUAS, 2026).

Overall, the literature shows that AI methods in semiconductor manufacturing have evolved from simpler prediction tools to more integrated, adaptive, and hybrid architectures. Machine learning remains useful for structured data and baseline prediction, deep learning is dominant for complex nonlinear patterns, autoencoders are effective for unsupervised anomaly detection, LSTM models capture temporal degradation, GANs help manage imbalance, and multi task learning offers a more unified maintenance framework. The central message across the research is that method choice should follow the data structure and operational need of the fab, since no single model can solve all monitoring problems equally well. This is why semiconductor manufacturing has become a strong testing ground for advanced AI methods that balance accuracy, scalability, and interpretability in demanding industrial conditions (Liu et al., 2022; Indium, 2025; Kim et al., 2026; Song & Baek, 2020).

Applications in Real Fabrication Environments

In real fabrication environments, artificial intelligence is not used as a theoretical add on but as a practical layer of intelligence that supports daily decisions in semiconductor production. The most immediate application is tool health monitoring, where AI systems observe machine behavior across long operating periods and identify signs of wear, drift, or instability before a breakdown occurs. This matters because semiconductor tools are costly and highly specialized, so even a short interruption can affect production flow and create large financial loss. AI based monitoring can combine vibration, pressure, thermal, and electrical signals to determine whether a tool is still functioning within acceptable conditions or whether it is beginning to produce unstable output. In practice, this allows maintenance teams to move from reactive repair to planned intervention, which is more efficient and less disruptive. Studies and industry reports show that predictive analytics and machine learning are increasingly being used for this purpose because they make it possible to recognize hidden deterioration patterns that human inspection might miss (Critical Manufacturing, 2021; Tessolve, 2025; Abdelli et al., 2022).

Wafer process monitoring is another major real world application because wafer fabrication depends on a sequence of tightly controlled steps in which temperature, chemical concentration, time, and pressure must remain within a narrow operating range. AI systems help by continuously analyzing process data and detecting whether the behavior of a batch or tool begins to diverge from expected performance. This is particularly valuable in lithography, deposition, etching, and cleaning stages, where even a small deviation can lead to structural defects or yield loss. AI based monitoring is useful not only because it identifies abnormal readings but also because it can connect patterns across multiple sensors and process stages. That means a model may detect the early sign of a problem even when no single variable appears alarming by itself. Industry literature on semiconductor optimization emphasizes that AI driven process monitoring improves consistency by converting complex fab data into actionable alerts and recommendations, allowing engineers to correct process drift before it spreads through subsequent production steps (Indium, 2025; INFICON, 2023; Qin et al., 2006).

Fault detection and classification represent one of the most important ways AI supports production quality in fabrication plants. Once an abnormal condition is identified, it is not enough to know that something is wrong; engineers also need to understand what kind of fault is occurring and how severe it may be. AI models can classify defects by type, such as contamination, misalignment, particle intrusion, pattern distortion, or sensor failure, which helps maintenance and process teams respond more precisely. Classification is especially valuable because different faults require different actions, and treating all anomalies in the same way can waste time or fail to solve the underlying problem. Research on semiconductor manufacturing shows that AI based classification systems improve the speed and consistency of defect identification, while industry reports describe their use in real inspection workflows where rapid sorting of fault types helps reduce bottlenecks and improve line efficiency (Susto et al., 2017; Wang et al., 2021; Image based industry sources, 2025; NVIDIA, 2025).

Yield improvement is another direct and highly significant application because every defect prevented or detected early has the potential to save large numbers of wafers from being wasted. AI contributes to yield improvement by identifying parameter combinations that are associated with low quality output and by helping engineers adjust process windows before losses become severe. In production settings, this means AI can support yield analysis, root cause identification, and recipe optimization across different tool sets. The value of this capability is especially clear in advanced node manufacturing, where process tolerances are extremely tight and defect rates must remain very low for production to remain profitable. Studies and industrial analyses report that AI can reveal recurring defect patterns, support faster troubleshooting, and help teams make more informed decisions about process tuning and maintenance scheduling. This makes yield management more proactive and less dependent on delayed manual review (Indium, 2025; Yieldwerx, 2025; Y. Lee et al., 2025; Qin et al., 2006).

Defect detection and process control are closely linked in semiconductor fabrication because detecting defects early is only useful if the process can also be corrected in time. AI based inspection systems can analyze wafer images, microscope data, and production signals to locate defects and classify them with much greater speed than traditional manual review. These systems are increasingly used in inline inspection, where wafers are checked during production rather than only at the end of the line. The combination of defect detection with process control allows fabs to create a feedback loop in which abnormal patterns trigger immediate investigation or automatic adjustment. This is one reason AI has become central to intelligent manufacturing, since it does not simply observe defects but also supports the control of process behavior in response to those defects. Reports on AI driven wafer inspection and semiconductor quality management indicate that automated detection improves accuracy, reduces false alarms, and helps factories maintain tighter process stability while keeping throughput high (Overview.ai, 2026; Robovision, 2024; Inficon, 2023; Qing et al., 2006).

Advantages of AI-Based Approaches

AI-based approaches offer several important advantages in semiconductor manufacturing because they help fabs respond to problems earlier, more accurately, and with less manual effort than traditional monitoring systems. One of the most significant benefits is reduced downtime. In a chip fabrication environment, equipment failure can interrupt an entire production sequence, and even short stoppages can create expensive delays because process steps are tightly connected and wafers may need to wait, be reprocessed, or be discarded. AI helps reduce this risk by identifying warning signs before a failure occurs, allowing maintenance teams to intervene at a planned time instead of reacting after the machine has already stopped. This predictive ability is especially valuable in semiconductor plants because unplanned downtime is not only costly but can also affect surrounding tools, production schedules, and delivery commitments. Research and industry practice consistently show that early anomaly detection and predictive maintenance help plants preserve continuity and avoid avoidable interruptions in high-value manufacturing lines (Susto et al., 2017; Song & Baek, 2020; Critical Manufacturing, 2021; Tessolve, 2025).

AI also improves production efficiency by making monitoring and decision making faster and more consistent. Traditional monitoring methods often rely on fixed thresholds, periodic checks, or operator experience, which can slow response time and miss subtle process drift. By contrast, AI systems can analyze large volumes of sensor data and identify patterns that signal instability long before those patterns become visible in final product quality. This allows engineers to correct process issues earlier, maintain smoother throughput, and reduce the number of defective wafers moving through the line. Efficiency improves further because AI can handle many variables at once, which is important in semiconductor fabrication where the state of the process depends on multiple interacting signals rather than one simple measurement. Industry reports on semiconductor process optimization emphasize that AI can streamline inspection, diagnosis, and quality control, making fab operations more responsive and more productive overall (Indium, 2025; INFICON, 2023; Qin et al., 2006).

A further advantage is better equipment reliability, which is one of the central goals of intelligent manufacturing. Semiconductor tools are expensive, sensitive, and often designed to operate with minimal tolerance for variation, so reliability is a critical factor in both cost and output quality. AI contributes to reliability by learning normal operating behavior and identifying early signs of degradation, drift, or instability. This means that equipment can be serviced based on actual condition rather than only according to a calendar schedule, which is usually a more accurate and efficient strategy. Over time, this condition-based approach helps keep machines in a healthier operating state, reduces the chance of catastrophic failure, and improves confidence in the stability of the fabrication line. Studies on predictive maintenance and anomaly detection in semiconductor systems show that AI is especially useful for detecting these gradual changes because human observation alone is often too slow or too limited to capture them in time (Abdelli et al., 2022; Wang et al., 2021; Kim et al., 2026).

Lower maintenance cost is another important benefit because AI helps prevent both unnecessary maintenance and expensive emergency repair. In traditional maintenance systems, machines are often serviced on a fixed schedule even if they do not need attention, which can waste labor, spare parts, and production time. At the same time, some failures still occur unexpectedly because the schedule is not responsive enough to actual machine condition. AI reduces this inefficiency by supporting more targeted maintenance decisions. When maintenance is based on evidence from equipment data, teams can focus on the tools that genuinely show signs of wear and avoid over servicing healthy machines. This more precise allocation of resources lowers operating costs and improves the value of maintenance work. Industry sources and applied research both suggest that the combination of early prediction and anomaly analysis can reduce the total cost of ownership in fab operations by limiting both sudden failure and unnecessary intervention (Critical Manufacturing, 2021; Tessolve, 2025; Yin et al., 2024; Song & Baek, 2020).

AI-based approaches also support higher yield and better product quality, which may be the most important outcome from a manufacturing perspective. In semiconductor fabrication, yield loss can result from very small process deviations that affect large numbers of wafers if not detected quickly. AI helps improve yield by identifying when process conditions begin to drift away from normal behavior and by guiding corrective action before the deviation becomes a major defect source. It also improves product quality by helping with defect detection, classification, and process control, which reduces the number of faulty units that reach later production stages. The literature shows that better defect detection and predictive monitoring are directly linked to fewer scrap losses, more stable process output, and stronger overall fab performance. In advanced semiconductor environments, where each wafer carries significant value, even a small increase in yield can have a major financial impact. For this reason, AI is often viewed not just as a technical tool but as a strategic enabler of quality improvement and competitive manufacturing performance (Susto et al., 2017; Indium, 2025; Robovision, 2024; Yieldwerx, 2025).

Limitations and Challenges

Despite the growing promise of artificial intelligence in semiconductor manufacturing, the literature makes it clear that several limitations continue to constrain practical adoption. One of the most persistent problems is the issue of imbalanced datasets. In fabrication environments, normal operating records are abundant because equipment usually runs without incident, while true failure examples are relatively rare. This creates a training environment in which models may learn normality very well but fail to recognize rare anomalies with the same reliability. As a result, even a model with strong overall accuracy may still perform poorly on the exact cases that matter most for maintenance and quality control. Studies on semiconductor anomaly detection show that imbalance is not a minor preprocessing concern but a structural challenge that affects model design, evaluation, and real-world usefulness, especially when failure types are diverse and unevenly represented (Song & Baek, 2020; Susto et al., 2017; Abdelli et al., 2022).

A related limitation is the lack of labeled failure data. In many semiconductor fabs, failures are infrequent, expensive, and sometimes difficult to isolate precisely, which means that engineers often do not have enough labeled examples to train fully supervised learning systems. This scarcity is especially problematic because deep learning methods often perform best when large annotated datasets are available. In practice, researchers are therefore forced to rely on unsupervised, semi-supervised, or weakly supervised approaches, each of which comes with tradeoffs in reliability and interpretability. The absence of comprehensive labels also makes it difficult to verify whether an anomaly detected by a model corresponds to a true fault, a harmless variation, or a sensor artifact. The literature suggests that this lack of labeled fault history remains one of the strongest barriers to building highly robust predictive maintenance systems in semiconductor production, and it is one reason why hybrid and transfer learning strategies are being explored more actively (Kim et al., 2026; Wang et al., 2021; Song & Baek, 2020).

Another major challenge lies in the noise and complexity of fab sensor data. Semiconductor manufacturing generates a very large number of measurements across different tools, process stages, and inspection systems, but these signals are not always clean or directly comparable. Some sensors drift over time, some measurements are missing or delayed, and others are influenced by external process conditions that are not immediately obvious. In addition, many variables are strongly correlated, which makes it difficult to separate meaningful change from routine fluctuation. This complexity means that AI systems must be able to handle high dimensional, noisy, and often time dependent data without producing excessive false alarms. Research on semiconductor monitoring repeatedly shows that data quality and feature complexity can significantly affect model performance, especially when the abnormal condition is subtle rather than obvious. For this reason, robust preprocessing, feature engineering, and model calibration remain essential parts of any practical fab monitoring pipeline (Qin et al., 2006; Hashimoto et al., 2021; Abdelli et al., 2022).

Limited explainability of AI models is another serious issue because semiconductor engineers need to understand why a model has identified a process or tool as abnormal before they act on it. Many advanced AI models, especially deep neural networks, can produce accurate results but still function as black boxes. This creates hesitation in industrial settings where decisions about maintenance, process adjustment, and product hold require strong justification. If a model cannot clearly show which sensor signals, time periods, or process behaviors led to a warning, then operators may be reluctant to trust it fully. The literature increasingly recognizes that explainability is not optional in semiconductor applications because these systems operate in high cost environments where false positives and false negatives both carry substantial consequences. Studies on multi task learning and complex anomaly detection point to the need for more interpretable models that can support not only detection but also engineer confidence and actionable diagnosis (Lee et al., 2025; Kim et al., 2026; NVIDIA, 2025).

Deployment and real time monitoring issues also remain important barriers to full scale adoption. Semiconductor fabs require monitoring systems that operate continuously, react quickly, and integrate smoothly with existing equipment and production software. A model that performs well offline may still be difficult to deploy if it demands too much computation, produces alerts too slowly, or cannot adapt to changing tool conditions. Real time systems must also deal with concept drift, meaning that a model trained on past data may become less accurate as equipment ages, recipes change, or operating conditions shift. This creates the need for ongoing model retraining, system validation, and infrastructure support. The literature indicates that real world deployment is often more difficult than model development because the factory environment demands low latency, high reliability, and minimal disruption to production. As a result, even strong academic results may not translate directly into fab use unless the AI system is carefully engineered for continuous industrial operation (Critical Manufacturing, 2021; Tessolve, 2025; Abdelli et al., 2022; Kim et al., 2026).

Research Gaps

A major gap in the current literature is the need for more explainable AI systems that can support semiconductor decision making in a way engineers can trust and act upon. Although many models have shown strong performance in anomaly detection and predictive maintenance, their internal reasoning is often difficult to interpret, which becomes a problem in a fab environment where every intervention has technical and financial consequences. In practice, process and maintenance engineers need to know not only that a system has flagged abnormal behavior, but also which variables, time periods, or process interactions contributed to that decision. Without that level of transparency, model output may remain useful for screening but insufficient for high stakes operational use. The literature therefore points toward the development of explainable frameworks that can translate model predictions into meaningful diagnostic insight for real manufacturing teams (Lee et al., 2025; Kim et al., 2026; NVIDIA, 2025).

Another important gap is the need for integrated predictive maintenance and anomaly detection models. Much of the existing research treats these tasks separately, even though in semiconductor manufacturing they are closely related and often arise from the same underlying process behavior. An anomaly may indicate early degradation, and degradation may eventually lead to failure, which means that a unified framework could offer a more complete and operationally useful solution than isolated models. The literature increasingly suggests that multi task learning and hybrid architectures can reduce redundancy while improving maintenance forecasting and fault detection at the same time. However, this integrated approach is still underdeveloped in many semiconductor applications, especially in deployment ready environments. As a result, there is a clear need for models that connect abnormality detection, prognostics, and maintenance planning within a single predictive system (Kim et al., 2026; Abdelli et al., 2022; Song & Baek, 2020).

The literature also reveals a need for robust models that can work across different fabs, tools, and process conditions. Semiconductor manufacturing is highly heterogeneous, and a model trained in one production line may not automatically generalize to another because equipment configurations, recipes, process parameters, and data distributions can differ substantially. This issue of transferability limits the practical value of many promising academic models, especially when they are evaluated only on a single dataset or a narrow operational environment. Future research therefore needs to emphasize cross fab robustness, domain adaptation, and model transferability so that AI systems can be deployed more broadly rather than remaining limited to one experimental setting. This gap is particularly important for global semiconductor production, where companies often operate multiple fabs with different technological conditions and maintenance practices (Qin et al., 2006; Susto et al., 2017; Kim et al., 2026).

A further gap concerns multimodal data integration. Much of the existing research focuses on either sensor data or image data, but semiconductor manufacturing generates both, along with test results, process logs, and quality histories. Since defects and equipment issues may be visible in only one type of data or may emerge more clearly when multiple data sources are combined, future systems should be designed to integrate these modalities in a more coherent way. Multimodal AI could improve both sensitivity and interpretability by linking process signals with visual evidence and historical context. However, this area still requires stronger methodological development, better alignment of data streams, and more comprehensive evaluation in real fab conditions. The literature suggests that integrating these sources could produce more reliable anomaly detection and better root cause analysis, but practical deployment remains limited (Hashimoto et al., 2021; Lee et al., 2025; NVIDIA, 2025).

Finally, there is a strong need for real world industrial validation. Many studies demonstrate promising results in controlled experiments or benchmark datasets, but fewer have been tested at scale inside active semiconductor fabs under production constraints. This matters because industrial environments involve noise, changing equipment behavior, rare fault events, and operational requirements that are much more complex than laboratory conditions. Without large scale validation, it is difficult to know whether a model will remain stable, useful, and trustworthy when faced with the realities of continuous manufacturing. The literature therefore highlights the importance of moving beyond proof of concept studies toward implementations that can be tested, monitored, and refined in actual fabrication settings. Only through such validation can AI systems become truly reliable tools for semiconductor predictive maintenance and anomaly detection rather than promising academic prototypes (Critical Manufacturing, 2021; Tessolve, 2025; Abdelli et al., 2022).

Future Scope

The future of artificial intelligence in chip fabrication is likely to move toward more self learning maintenance systems that can continuously improve from new production data without requiring constant manual reconfiguration. In a semiconductor environment, this kind of adaptive intelligence is especially valuable because equipment behavior changes over time, process recipes evolve, and operating conditions are never perfectly stable for long periods. Self learning systems could help maintenance teams identify degradation patterns earlier, refine prediction accuracy over time, and respond more flexibly to new fault signatures that were not present in the original training data. The literature already suggests that static models are often limited by concept drift and changing fab conditions, so future research will need to focus on adaptive models that can learn from ongoing sensor streams and improve their own decision boundaries as the production environment changes (Kim et al., 2026; Abdelli et al., 2022; Tessolve, 2025).

Real time AI monitoring platforms are also an important direction because semiconductor manufacturing depends on rapid response and continuous control. A model that works only after offline analysis cannot fully meet the needs of a live fab, where even a short delay in detection can allow defects to spread through multiple wafers or lots. Future systems are therefore expected to combine streaming data analytics, edge computing, and automated alert generation so that engineers can receive meaningful warnings while the process is still recoverable. This will likely strengthen the connection between anomaly detection and process control, making AI not just a diagnostic tool but an operational layer embedded directly into fab decision making. Industry discussions already point toward increasing demand for AI systems that can support real time inspection, predictive diagnostics, and automated response at production speed (Critical Manufacturing, 2021; Indium, 2025; NVIDIA, 2025).

Hybrid models that combine sensor and image data represent another promising direction because semiconductor faults are often visible in more than one form of evidence. A process anomaly may first appear in sensor drift, then later become visible in inspection images or wafer maps, which means that single modality systems may miss part of the story. By integrating multivariate sensor streams with visual inspection data, future models could improve both detection accuracy and diagnostic depth. This would also support more reliable root cause analysis because the model would be able to connect physical process behavior with visual defect patterns. The literature suggests that multimodal learning can become especially powerful in semiconductor settings if it is designed to handle asynchronous data, uneven sampling, and different feature types from process and inspection systems (Hashimoto et al., 2021; Lee et al., 2025; Overview.ai, 2026).

Transfer learning is another important future direction because fabs differ substantially in equipment type, process design, and operating context. A model trained in one facility may not generalize well to another unless it is adapted to the new environment, which makes transfer learning highly relevant for practical deployment. Future research should therefore focus on methods that can reuse knowledge from one fab or one tool class and apply it effectively to another with minimal retraining. This would reduce the cost of implementation and make AI systems more scalable across the semiconductor industry. The need for transferability is especially strong in global manufacturing networks where companies operate multiple fabs with different configurations but similar monitoring goals. Research in this area is likely to become more important as AI moves from isolated pilot projects to broader industrial adoption (Qin et al., 2006; Kim et al., 2026; Song & Baek, 2020).

Integration with Industry 4.0 and smart manufacturing is perhaps the broadest and most strategic future scope for this field. In the coming years, AI is likely to become part of a larger digital manufacturing ecosystem that includes connected sensors, digital twins, automated scheduling, cyber physical systems, and intelligent quality control. In that environment, predictive maintenance and anomaly detection will not function as separate tools but as part of a continuous feedback loop that links equipment health, process stability, and production performance. This shift would allow semiconductor factories to become more resilient, more responsive, and more efficient in managing both cost and complexity. The literature and industry practice both indicate that the semiconductor sector is moving steadily toward this kind of smart factory model, where AI plays a central role in manufacturing intelligence and operational coordination (Indium, 2025; INFICON, 2023; Critical Manufacturing, 2021).

Conclusion

The literature reviewed in this study shows that artificial intelligence has become an essential part of modern semiconductor manufacturing because it supports predictive maintenance, anomaly detection, process monitoring, and quality improvement in highly complex fabrication environments. Across the reviewed research, AI methods such as machine learning, deep learning, autoencoders, LSTM networks, GAN based models, and multi task learning have demonstrated strong potential for identifying abnormal behavior, supporting early fault prediction, and improving overall fab performance. At the same time, the literature also makes clear that these methods are still challenged by imbalanced datasets, limited failure labels, noisy sensor conditions, and the difficulty of deploying interpretable models in real time production systems. Together, these findings show that while the field has advanced considerably, it still requires further work before AI can be fully trusted as a seamless operational layer in every semiconductor fab (Song & Baek, 2020; Wang et al., 2021; Kim et al., 2026).

The importance of AI in chip fabrication lies in its ability to transform manufacturing from a largely reactive process into a more predictive and adaptive system. Rather than waiting for equipment to fail or defects to appear in finished product, AI allows engineers to detect subtle warning signs earlier and make decisions based on continuous evidence. This is especially important in semiconductor environments where process windows are extremely narrow and the cost of error is very high. By improving reliability, reducing downtime, and supporting better yield outcomes, AI contributes directly to both technical stability and economic efficiency. The reviewed literature therefore positions AI not as an optional enhancement but as a core capability for the future of chip fabrication and advanced manufacturing more broadly (Susto et al., 2017; Abdelli et al., 2022; Indium, 2025).

The future potential of this field is substantial because the next generation of semiconductor manufacturing will likely depend even more heavily on adaptive, integrated, and intelligent monitoring systems. As fabs become more automated and data rich, AI will be increasingly important for linking predictive maintenance, anomaly detection, defect recognition, and process control into one coherent framework. The most promising future systems will probably be those that combine real time monitoring, multimodal learning, and explainable decision support so that engineers can trust the outputs and act on them quickly. This suggests that the research direction is moving toward more practical, scalable, and context aware AI systems that can operate reliably under industrial constraints rather than only in controlled experimental settings (Lee et al., 2025; NVIDIA, 2025; Critical Manufacturing, 2021).

In closing, the literature demonstrates that AI has already begun to reshape the way semiconductor fabs monitor equipment, detect anomalies, and manage maintenance, but its full value will depend on how effectively future research addresses interpretability, robustness, and deployment at scale. The direction of the field is clear: smarter, faster, and more integrated manufacturing systems will increasingly depend on AI as a core enabler of reliability and process excellence (Kim et al., 2026; Song & Baek, 2020; Tessolve, 2025).

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