AI Agents in the Manufacturing Industry, Enhancing Manufacturing Excellence

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Abstract: The rapid expansion of digital technologies and the growing demands of industrial standards are elevating the manufacturing sector to a more advanced level. This study proposes the integration of AI agents, specifically AI callbots, into the manufacturing environment and examines performance factors, downtime, meaningful insights, and decision-making. The study further investigates the use of AI callbots in optimizing performance, reducing downtime, and promoting prompt decision-making. The challenges of conventional systems are thoroughly examined, including troubleshooting latency, inconsistent data management, and a lack of real-time monitoring. The proposed solution considers the employment of AI agents combined with machine learning algorithms and natural language processing, facilitating human-machine integration, predictive maintenance, and timely scheduling. The methodology encompasses the optimal use of a unified namespace, enhancements in digital twin technology, and the application of augmented reality and virtual reality with real-time feedback adaptation. The results indicate a substantial increase in efficiency, client satisfaction, and compliance with industrial standards. The article concludes stating AI Agent as an effective AI-driven tool offering a sustainable approach in achieving manufacturing excellence.

Keywords: CNC fault detection; digital twins; food and beverage optimization; Industry 4.0; MedTech applications; machine learning; motor fault prediction; predictive maintenance; real-time data analytics; robots and cobots; variable speed drives; virtual inspections

1. Introduction

The manufacturing industry, in the context of ongoing globalization and the rapid growth of smart technology, plays a prominent role in holistic growth and development. The sector plays a key role in socio-economic development and aids in attaining sustainable developmental goals. Advancements in digital technologies and the need for optimum productivity make the industry address the requirement for automation, data analytics, and modern applications of Artificial intelligence. Improved productivity, reduced downtime, and enhancement in operational efficiency demand the incorporation of smart technologies. In evolving techno-space data management and monetization, predictive error detection, and real-time decision-making emerge as a crucial element in the operational sector.

Existing System

The legacy manufacturing industry was characterized by manual or semi-automated processes, unchangeable production lines, static data, unpredicted downtime, delayed troubleshooting, paper-based documentation, and limited flexibility in on-demand manufacturing [1]. The instances include manual assembly lines, mechanical CNC systems, etc. Decision-making was derived from experience and intuition. The commencement of digital computing and basic automation increased performance through Enterprise Resource Planning (ERP), Programmable Logical Controls (PLC), Computer Aided Manufacturing (CAM), etc. Later Industry 3.0 standard was developed integrating advanced applications in Automation and Internet of Things (IoT) enabled systems. Artificial Intelligence was employed for detecting anomalies and optimizing processes. Recent advancements in AI include machine learning algorithms, AI-powered chatbots for predictive maintenance, meaningful insights, quality control, and resource allocation in operational environments. Owing to rapid growth and development, the existing system exhibits limitations and becomes ineffective in this Industrial era [2].

Limitations in the Existing System

The reality of technological emergence reveals the flaws and limitations of the existing operations. Rapid growth in industry and the exponential intensity of demand impact on the authenticity and efficiency of data. Broadly in an industrial environment of large data sets the quality of data, secrecy of data, and safety measures for data need to be maintained (Jiawen Xu, Matthias Kovatsch, Denny Mattern, Filippo Mazza, Marko Harasic & Lucia, 2022). The inefficiency within an AI-based system arises due to an unskilled workforce. The reduction in human interaction reduces the expertise of the workforce. AI automation enhances routine tasks, but the lack of an AI-trained workforce hinders efficiency. AI technology limits the interaction between machines and humans, hence lacking collaboration. For a manufacturing landscape with emerging technology, seamless collaboration augments productivity [3].

There are indicative gaps in the system concerning the exponential growth of the manufacturing industry. Though the prediction capability and automation have been improved, distinct gaps are found in regulatory affairs, real-time adaptability, skilled workforce, digital twin application, asset management, cyber security, and complying protocols.

The legacy system often encounters inconsistent data management involving procurement, analysis, processing, and adequate response, affecting production efficiency. Inaccurate data entry and vested human interest corrupt the data, henceforth leading to misinterpretation and alterations. Frequent follow-ups and compilation are needed for the data to comply with the industrial regulations. Manual documentation and data management may lead to delayed and error audits, hindering efficacy [4]. Data scalability is essential in a dynamic production environment. Existing systems have a restricted capacity for data elasticity.

The existing system offers restricted troubleshooting capacities. The procedures used for the vulnerabilities are provided in the SOP. The inability to ascertain the exact SOP from the document control prolongs the downtime. The on-call support may necessitate specific time for the supporter to avail clear information and additional time for the remedy. The existing facility provides has limitations in rectifying the problem in the short term. The time delay incurred in texting the problem, appropriate interpretation of the problem, and providing adequate solutions may result in unnecessary delays in the industry. The unexpected disruption of workflow ends up in the misinterpretation of issues. Appropriate understanding in the least amount of time is needed for rectification [5].

Manual errors and discrepancies may arise in the industrial environment due to oversight. This could result in communication errors. Human interaction has a constrained capacity to resolve the issues. Modern AI-integrated systems are employed to mitigate the vulnerabilities [6].

AI call-bots reduce data redundancy and latency, providing meaningful and dynamic insights for decision-making. The intrinsic and multifaceted data structures can be communicated through voice commands thereby addressing the challenges posed by the signage and symbols in industrial areas. Accurate and consistent rapid responses protect the system from unexpected failures [7].

Though the existing system is empowered with AI, it lacks adaptability to a custom setting, real-time interactions, and autonomous decision-making. The gap lies in the need for a seamlessly integrated, autonomous learning AI system that supports extensive datasets with accurate predictions, and meaningful insights without human interaction [8]. AI callbots utilize NLP and its wider application to interact with humans with voice or text. AI call bots work in a multi-tasking operational mode on both back end and front-end services. Remote availability beyond time and geographical constraints makes AI callbots a viable solution to improve maintenance scheduling and production performance [9].

2. Materials and Methods

The research is aimed at gaining excellence in productivity by integrating AI Agent call bot to the existing manufacturing operational environment. The methods employed encompasses data processing and management, System Design, AI Models and performance evaluation metrics

Database Processing and management

Complex and intrinsic data without losing inherent authenticity and reliability is vital in the operational environment. The external and internal data sources are collected, processed and interpreted in such a way that the whole system operates on a synchronous platform. The data is collected from IoT sensors, PLCs, SCADA systems, and Internet IoT devices are integrated into a Unified Namespace (UNS). UNS serves as the necessary component of the manufacturing unit. UNS forms a single data structure feeding inputs from sensors, actuators, cameras, and control systems leveraging the maintenance schedules [10]. UNS facilitates collecting data from different sources, translating it, adding context to it, and feeding it as input to the progressive levels. UNS ensures reduced data latency, improving efficiency in data interactions such as collection, processing, and interpreting [10].

UNS includes photogrammetry and 3D scanning techniques which aids in generating accurate digital twins according to the data provided. UNS provides real-time data integration and facilitates data normalization making data easier to use, analyze, and query. It reduces redundancy by cleaning the data, henceforth increasing the accuracy of the data. The use of single and data protects data from potential threats. The efficient working of the whole operational environment can be monitored at ease [11].

System Design-

The manufacturing industrial landscape is rapidly evolving. The efficiency of the operational sector is determined by anomaly detection and predictive maintenance. The production index is indicative and proportional to the duration required to analyze, detect, and rectify anomalies. Presently, the AI integrated system has the chatbot facility which facilitates human-machine interaction. The limitation to interpret messages in panic situation may tend the maintenance to fail. This may be hazardous to the whole system. AI callbots gain momentum in this scenario. They are the automated system that uses Natural Language Processing (NLP) and machine learning algorithms in human interaction[12]. The AI call bot can handle multiple tasks, ranging from real-time data interaction to troubleshooting. The call handling facility can be employed through Twilio which enables real time voice interaction. Bland AI facilitates meaningful decision making as per requirement using NLP based query resolution and contextual analysis.

Machine Learning algorithms are used to train the machine how to interpret and handle the data efficiently. The methods used may vary with operating sectors. The ML algorithms in this scenario are used to increase performance and reduce untimely downtime and failure. For this we can use an ensemble method and Neural network method. The Gradient boosting method a subset of ensemble method, is suitable for better learning. It generates the models sequentially, learning from the errors of the predecessor. In industrial setting GBM have the ability to capture the non-linear relationship which is quite effective in foreseeing equipment failure [13].

Long Short-Term Method falls under Recurrent neural network method, which analyses the data sequentially and identifies the temporal dependencies, thereby receiving meaningful insight in error detection. LSTM was integrated with RUL (Remaining Useful Life) prediction, which aided in determining long term dependencies. It facilitated the analysis of both global and local context of the equipment, generating a real-time assessment of the lifespan of the machine. The hybrid LSTM – Support Vector Regression (SVR) is also used for RUL prediction. This approach generated health index curves and by employing K means clustering to degradation paths. The facilitation in determining the lifespan of the equipment. [14]. The IoT devices are integrated and dynamically monitored for the real time data for prompt anomaly detection and revival. IoT devices depict the system's machine condition, contextual information, and temporal features. Appropriate communication aids in receiving the life condition of the machine [15].

Evaluation-

Incorporation of AI Agents in manufacturing seeks to improve performance, reduce downtime, and optimize production performance. The effectiveness is assessed in the following performance metric. The role of AI Agent in human error mitigation and operational discrepancy is crucial in the manufacturing industry. Accurate machine learning algorithms help the system in forecasting errors. The NLP call-bots facilitate the human-machine interaction at ease. The operational system failure can be promptly addressed and rectified. Error mitigation, Overcoming oversight vulnerability, Data interpretation delays, Human AI Interaction. It reduces misinterpretation [16]. The error mitigation index determines the quality of the product and precision.

Recent studies show that AI-driven predictive management system can reduce unplanned downtime by 40%, enhancing productivity. Advanced algorithms, real-time data analytics, voice guided queries, real-time feedback loops, and automated decision making significantly enhance the performance [17].

The integration of AI Agent exponentially decreases downtime through prediction maintenance and automation. Automated troubleshooting Call-bot addresses the issues promptly thereby reducing the manual intervention delays. Smart integration helps in optimized workflow automation enhancing resource allocation [18]. The process bottlenecks have been mitigated.

3. Results

The results evolved from the test cases and from the discussions ensure that incorporation of AI Agent in manufacturing system enhances productivity and efficiency to greater extent. The incorporation enhanced functionalities and minimized unnecessary downtimes by a significant percentage, and exponentially increased productivity. The results are derived from a structural analysis by comparing AI Driven approaches with legacy systems. The factors analyzed are issue resolution, real-time decision making and validation, and benefits in predictive maintenance. The findings are as follows:

AI Performance Overtime

AI powered assistance improves its efficiency as it handles more data effectively. AI Agents in Gazer 3D model utilizes IoT data, IIoT data, historical logs, Machine learning algorithms to refine and validate the data output in a given manufacturing environment. There is a considerable amount of 40% reduction in unnecessary downtime under the incorporation of predictive and prescriptive maintenance[19].

Comparative Analysis: Ai Vs. Manual Approach

Significant improvement is evident when AI Agent was incorporated as a AI powered call assistant for a field staff. Table 1 describes Average Downtime, Incident Response Time, Issue Escalation efficiency, and workforce productivity. An Average of 25% work force productivity was increased after AI implementation which is an indicative growth on productivity. The prompt response time and reduced latency in action makes a system robust and stable.

Table 1:Comparative Analysis

Metric	Before AI Implementation	After AI Implementation
Average Downtime (Min)	120	65
Incident Response Time (Min)	15	5
Issue Escalation Efficiency (%)	60	80

Workforce Productivity	+25

Performance Analysis

AI Agent incorporation ensures a better productive index, compared to the legacy manual approach. The Figure 1 represents the performance difference in the field of Linguistic Queries, Real time IoT integration Advanced predictive analysis, and reduction in downtime. AI callbots emerge as a cutting-edge technology in the field of manufacturing industry reducing distressed human interference, enhancing troubleshooting and maintenance. Real-time monitoring of both machine data and external environment ensures meaningful decision making and valuable insights. Predictive analysis aids in decreasing anomalies and unnecessary downtime in the industry. There is an imperative performance gain of 15% more compared to the traditional system.

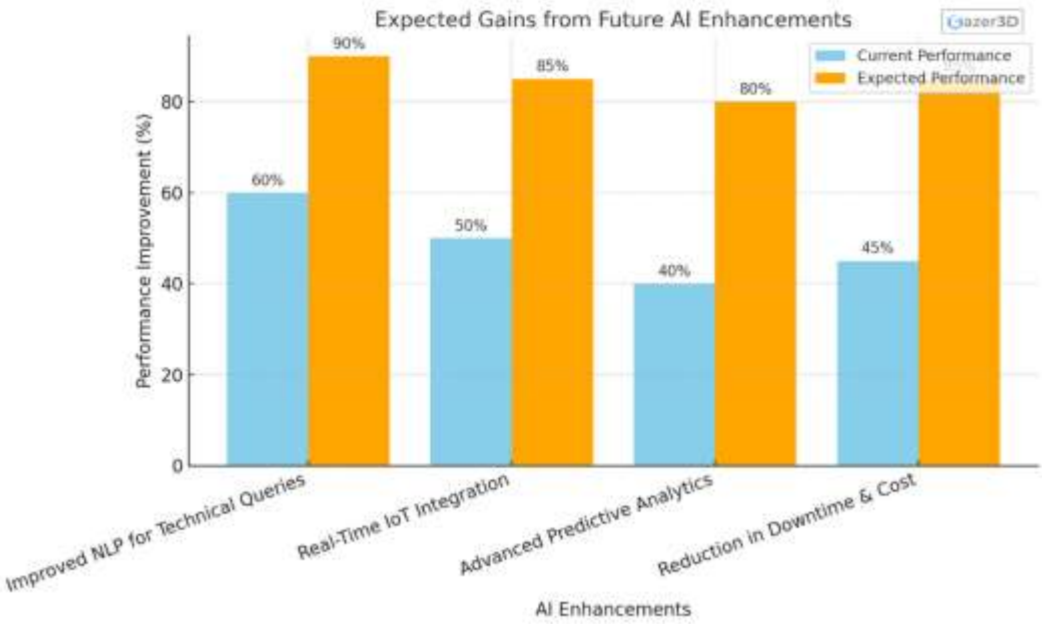

Figure 1: Gains from AI enhancement

User Satisfaction and Field Impact

Incorporation of AI Agent exponentially increased user satisfaction to a considerable amount in different parameters. Key parameters analyzed are Ease of Use, Response time Satisfaction, Problem Resolution, and Overall Effectiveness. Prior to AI integration, the data collection and retrieval were a complex and intrinsic process, which delayed the output. AI Agent simplifies the troubleshooting process by generating SOP promptly and appropriately. Diagnosing faults manually involves latency. This delayed the overall efficiency. Escalations need manual intervention. AI Agent escalates the issue after the threshold time ends, which reduces the average response time exponentially. Identifying potential issues in its acute stage was another major challenge in the legacy system. AI Agents play a key role in identifying potential issues and escalating it before entering critical situations. AI Agent further reduces cognitive load, which enhances the efficiency of the human workforce. The Table 2 the scenario with valid data.

Table 2:User Satisfaction Scores

Parameter	Score (Before AI)	Score (Before AI)
Ease of Use	5.5/10	9/10
Response Time satisfaction	4/10	8.5/10
Problem Resolution	6/10	9/10
Overall Effectiveness	5/10	9.2/10

Benchmarking Against Standards

Gazer 3D AI Driven solution marked remarkable performance in relation to contemporary industrial standards. The key parameters valuated are Incident Resolution Time, Cost savings on Maintenance, First time Resolution Rate, and User satisfaction score. These benchmarking aids the system to analyse the effectiveness and reliability as shown in Table 3. The Gazer 3D adoption is aligned and compared with the global standards, ensuring compatibility. The values can be streamlined across the globe. ISO22400 defines the performance metrics as Mean Time to Repair (MTTR), Mean Time between failures (MTBF), and Overall Equipment Efficiency (OEE). The parameter analysis reveals that AI-driven predictive maintenance reduced MTTR by 40%, MTBF by 30%, and OEE by 88%, which inherently proves the benefits of the system. The incident resolution time is reduced to 5% compared to the industrial standard. The cost savings and maintenance have been increased to 30% compared to the industrial standard, which is 20%. Further, a user satisfaction score of 9.2 out of 10 proves the AI segment to be reliable, effective and stable in the manufacturing industry.

Table 3:Benchmarking Standards

Metric	AI Powered Assistant	Industry Average
Incident Resolution Time	5min	12 min
Cost Savings on maintenance	30%	20%
First time Resolution Rate	90%	75%
User satisfaction score	9.2/10	8/10

4. Discussions

AI Agents, utilizing the advanced AI driven capabilities aids in progressive growth and development of the machine system. As in the Figure 2, AI Agent simultaneously interact with the set inputs and the operational environment, dynamically adapting the system for optimum productivity. The abilities, goals and the attained knowledge is fed to AI Agent, which in turn translate to action and adapting and changing the action responses according to the observation and past experiences from the environment.

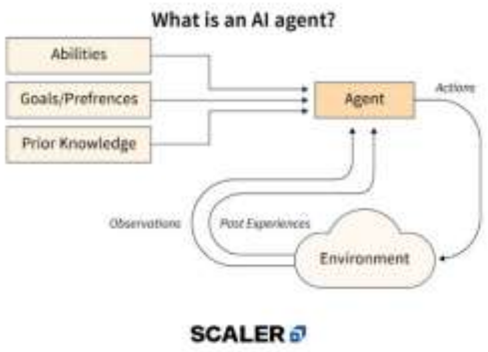

Figure 2:AI Agent Scenario

AI Agent is used for learning, adapting and deriving meaningful insights and decisions based on data with certain principles. AI Agent gathers and processes data from various input sources, including IoT sensors, historical logs, and real-time operational metrics. This data renders the basis for analytics and decision making. AI Agent employs particular Machine Learning Algorithms to identify the patterns, predict outcomes, and adjust to environmental changes. Appropriate and necessary decisions such as adequate maintenance, work flow optimization, operational discrepancy identification, and operational alerts to the workforce are done by AI Agent through predefined goals and the insights derived from the data analysis. AI Agent enhances interactive human environment by providing actionable insights, automating repetitive tasks, and delivering real-time recommendations. The Figure 3 shows the executional pattern where the AI Agent has three components: perception, brain, and action, respectively. AI driven Gazer 3D can be enhanced utilizing AI Agents.

AI Agent in Gazer 3D:

The integration of AI Agent in Gazer 3D transformed the manufacturing industry by enhancing decision making and operational intelligence. AI Agent leverages machine learning, IoT analytics to rectify discrepancies, scheduling maintenance, and befitting workforce interaction. Key application includes

1. On-call Assistant

AI callbot plays a key role in identifying emergencies and informing the responsible personnel regarding the urgency in their absence. Communication can occur with the remotely located operational environment with established SOPs. The AI Agent processes incoming queries using conversational call bots, facilitating phone guidance and escalating critical issues when human intervention is vital. The human operators can ask AI Agent for live data insights, thus handling the emergencies effectively. AI Call bot provides step-by-step instruction based on received inputs and contextual knowledge. For instance, whenever a malfunction in the machine is detected, over odd time, the information is passed to the responsible personnel with appropriate suggestions to prevent untimely damages. The on-call assistant work flow is depicted in the Figure 4. The AI agent evaluates the situation, categorizes the priority, and provides the guidance accordingly. The integration of Augmented Reality and the Verbal communication (NLP) enhances the industrial scenario in receiving vital inputs and contextual information of the operational environment at a remote. Figure 5 depicts the Conversational AI workflow in the industrial setting.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 02 | Feb - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

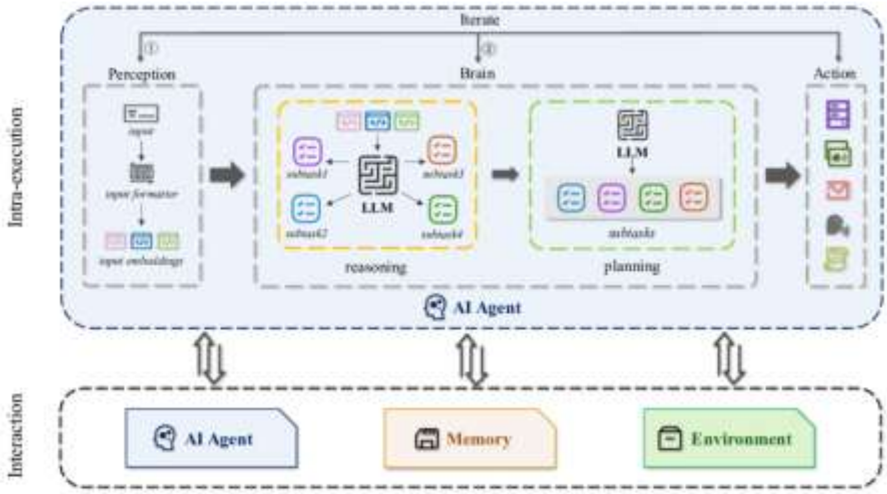

Figure 3:General Workflow of AI Agent

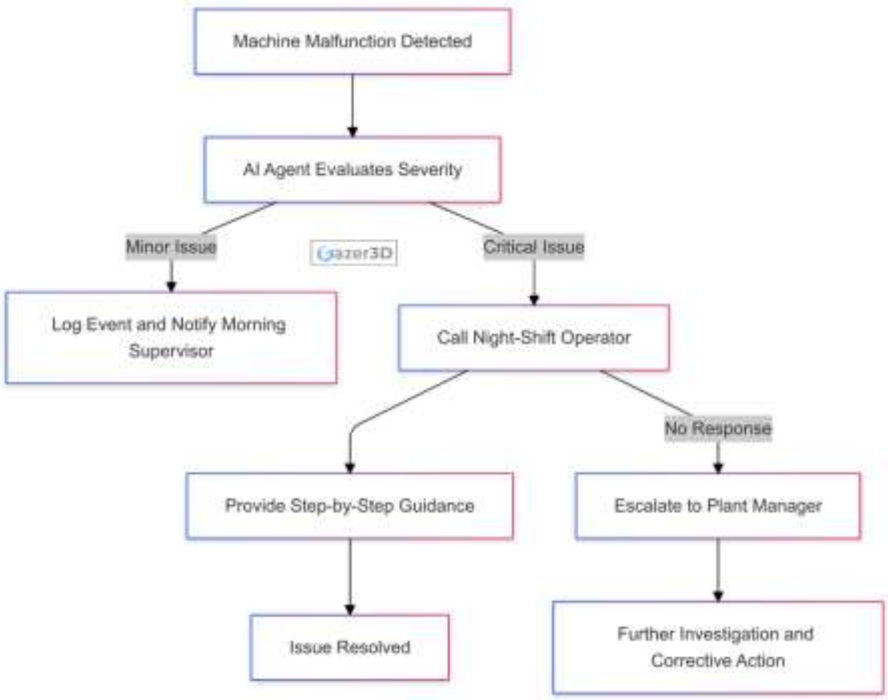

Figure 4:On-call AI Assistant workflow

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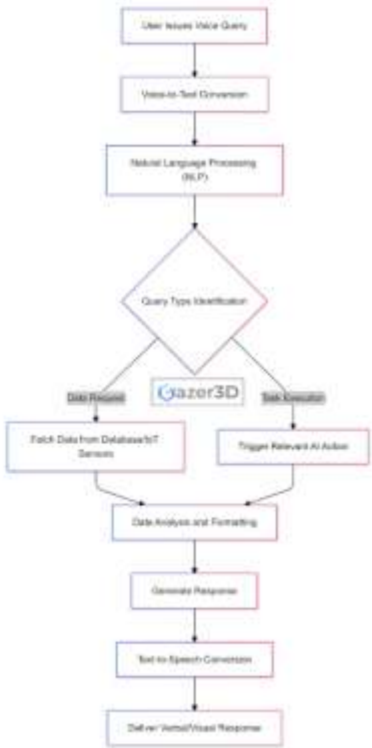

Figure 5:AI Query workflow from voice input to Response

2. Predictive and Prescriptive Maintenance

AI Agents are incorporated and employed for efficient maintenance in an operational environment. They take inputs from IoT sensor data streams in real time and identify potential threats in advance. In Predictive Maintenance, the explanatory variable (independent variable) and the response variables (Dependent variable) obtained from the IoT devices are analyzed through regression analysis, which helps to determine the future trend and to gain meaningful insight [20]. Anomaly detection techniques are used to detect errors and downtime promptly. AI agents are involved in recommending precise actions such as part replacement, adjusting operational parameters, etc. For instance, the Figure 6 shows the workflow of an anomaly detection where a motor showing unusual vibration may trigger the AI Agent to alert the personnel. The AI agent recommends the suggestable remedy.

3. Digital Twin Enhancement

Digital Twin acts as the virtual replica model of the real-time physical entity. As shown in Figure 7 AI Agent, fed by the real-time sensor values helps to modify the digital twin model. This helps to determine the prospects and anomalies of the system in advance. The deficiencies of insufficient modeling accuracy and restricted universality can be mitigated through consistent feedback from AI Agents [21]. For instance in a Pharmaceutical industry the disital twin of a production line is employed to optimize bacth processes, ensuring stringent quality standards. DT can be modified with real-time monitoring and feedback thereby improving predicitve maintenance which optimizes the productional efficiency [22].

4. AI Driven Scheduling and Resource Optimization

Legacy maintenance systems were operated manually. Manual scheduling has its own limitation. The high idle time results in unnecessary delay and error prone schedules results in suboptimal task allocation hindering work force efficiency. On the contrary, AI driven scheduling has enormous benefits compared to the former. It reduces idle time and unnecessary delays through optimal task allocation; and real-time monitoring and adjustments leads to higher workforce efficiency. The impact of AI Driven scheduling in depicted in the Figure 8.

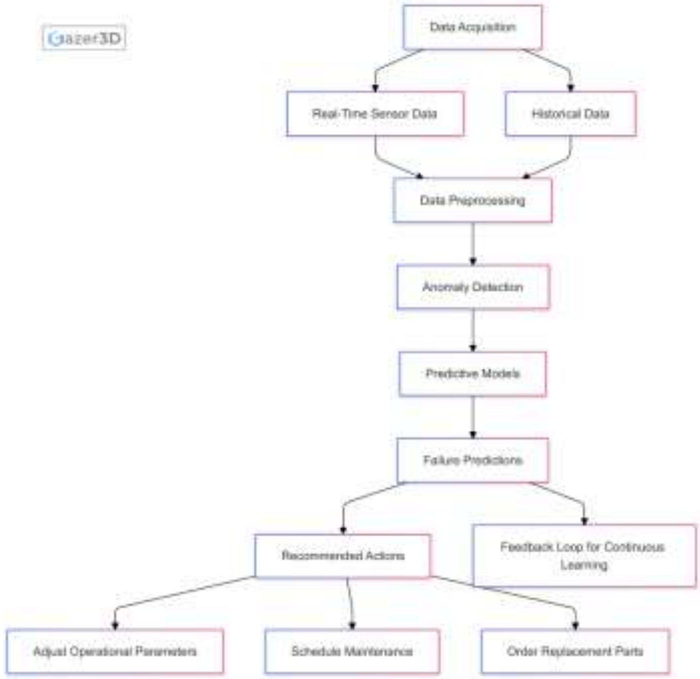

Figure 6:Predictive Analysis and Prescriptive Action Process

Figure 7:Correlation between Digital Twin Usage and Operational Efficiency

5. AR/VR Overlays

The manufacturing industry requires a skilled workforce to the optimum. Due to spatial and time constraints, optimum training is not possible to a certain extent. AR/VR overlays help the system to overcome the limitation by presenting adequate and communicable data virtually or in an augmented way. Broadly, AR/VR technologies can be used in Assembly guidance, maintenance/repair, product design and development, layout planning, warehouse management, quality control, and simulation. Manufacturing industries operating at human vulnerability utilize AR/VR technologies [23]. AI Agents superimpose real-time metrics like temperature, vibration, and pressure levels onto physical machinery during inspections, aiding the personnel to identify the parameters certainly during the assessment. The Virtual reality techniques guided by AI can be used for training purposes. For instance in the Energy sectors engineers utilize VR simulations of turbines to train for complex repairs, thereby reducing the risk of errors during real-time operations. AR Devices such as Head Mounted Display (HMD), Handheld Display (HHD), or Spatial Display (SD) can be employed for effective AR/VR Visualization [24].

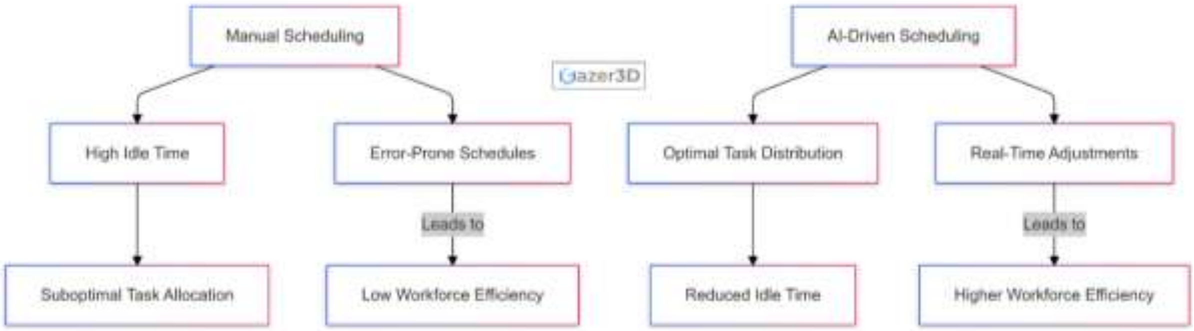

Figure 8:Impact of AI Driven Scheduling on Workforce Efficiency

6. Emergency Response and Crisis Management

The most prominent advancement in AI Driven manufacturing environment is it crisis management capacity. AI agents powered with call bots alerts the responsible personnel of critical anomalies through calls or voice automated alerts. AI agent suggests actionable insights. The escalations can be reported to the apellate authority. The affected systems can isolated from the whole system. The industry which handles accuracy, health and hygeine needs to be scrutinized precisely. The Figure 9 shows a situation in Food and Beverage industry where a critical anomaly is detected. The AI Agent may alert the responsible personnel and may suggest actionable insight. The Emergency protocols are iterated to resolve the issues promptly. This can be deployed in remotely located industries.

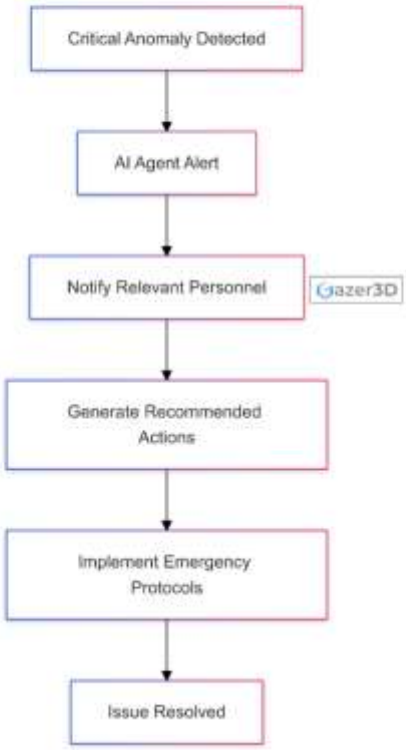

Figure 9:Emergency workflow orchestrated by AI Agents

7. Energy Efficiency and Sustainability

Industrial environments rely on renewable and no renewable energy sources. Operational efficiency demands optimum usage of renewable energy by enhancing greener practices. AI Agents can monitor energy consumption patterns and recommend energy-saving measures. AI Agent may predict wasteful energy consumption and resource utilization facilitating waste reduction. AI Agent can identify power usage of idle equipment in the electronics industry [25].

8. Advanced Data Security and Compliance

Data Security plays the key role in manufacturing industry. The AI detects unusual patterns in data access or operaitonal behaviour hence ensuring data integrity. Construction industry, one of the most hazardous industry with high fatality rate and least digitized scenario faces the issue of data integrity more. AI driven tools are used in construction communication where effective and secured communication is essential for timely and on-budget completion, AI Agents can gnerate detailed report on compliance ensuring adherence to regulatory standards like General Data Protection Risks(GDPR), ISO, and cyber security attacks [26].

In Medical Device industry Figure 10 AI ensures compliance of rules with FDA regulations by logging and analyzing the device performance metrics. The collected data is examined for compliance, subsequently audited with the generated reports and submitted to the regulatory body for approval [27].

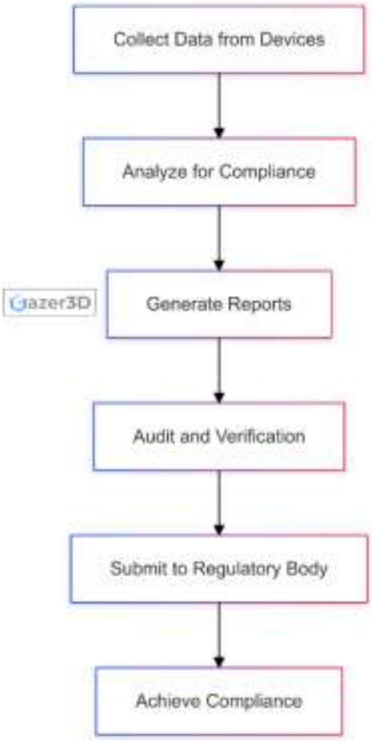

Figure 10:Compliance Reporting workflow powered by AI

CONCLUSION

The integration of AI agents into the field of manufacturing presents clear benefits over the legacy systems. The analysis and synthesis of the legacy manufacturing interface leads to the exploration of limitation and inefficiencies of the same. AI Agent addresses the typical lags incurred into the system and offers predictive maintenance, voice enabled callbots, and various ML models. The advancement in human machine interaction aids the industry to have a better productive index and reduced unpredictive downtime. AI Agents facilitiates the system to comply with the industrial standards offering interoperability [28] [29]. The seamless integration of AI Agents in digital twin modelling, predictive maintenance, AR/VR faculty, and panic scenario managament, makes the manufacturing industry robust, stable and versatile. The present test cases are executed in a contolled environment, while the near future presents further opportunities in real-time industrial settings.

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