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Review

Product Quality Monitoring Tracker

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	Abstract
Published on: 09 Apr 2025	Quality Control (QC) is a key inspection component of a robust quality management system. It focuses on monitoring processes at the machine or assembly level, aiming to detect, record, and categorize defects. QC systems often incorporate tools such as digital calipers, automated inspection systems, and Statistical Process Control (SPC) tools to ensure accuracy. On the other hand, Quality Assurance (QA) is a proactive approach designed to prevent defects before they occur. It integrates formal quality best practices such as Total Quality Management (TQM) and is often embedded within Lean or Six Sigma methodologies. Six Sigma, in particular, relies on five key principles to ensure products meet customer expectations while minimizing defects. Unlike QA, QC is reactive it verifies standards and specifications after production. However, in modern connected factory ecosystems, this verification process is increasingly digital, allowing defects to be identified earlier in production. QA utilizes analytical tools such as histograms, control charts, and Pareto charts to identify trends and drive process improvements. By leveraging these insights, quality managers can implement strategic changes that enhance overall manufacturing efficiency and product quality.
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INTRODUCTION

In modern manufacturing, maintaining high-quality standards is essential for ensuring customer satisfaction, operational efficiency, and business success. This is achieved through two fundamental processes: Quality Control (QC) and Quality Assurance (QA). While both play a crucial role in quality management, they serve different yet complementary purposes.

Quality Control is primarily focused on detecting and correcting defects after production, ensuring that

products meet predefined specifications before reaching the customer. It involves inspections, measurements, and testing using tools such as digital calipers, automated inspection systems, and Statistical Process Control (SPC) techniques. On the other hand, Quality Assurance takes a proactive approach by implementing structured methodologies and best practices to prevent defects from occurring in the first place.

QA frameworks like Total Quality Management (TQM), Lean Manufacturing, and Six Sigma are designed to enhance process efficiency, minimize variations, and drive continuous improvement. By utilizing analytical tools such as histograms, control charts, and Pareto charts, QA helps identify trends and areas for enhancement, allowing quality managers to implement process optimizations effectively.

While QC is reactive, addressing issues after they arise, QA is preventative, ensuring that processes are designed to produce defect-free products. In today's rapidly evolving manufacturing landscape, integrating QC and QA within a digital and connected factory ecosystem enables real-time data analysis, predictive maintenance, and automated quality checks, making quality management more efficient and reliable.

A well-balanced approach that incorporates both QC and QA helps manufacturers reduce waste, improve product reliability, enhance customer satisfaction, and remain competitive in an increasingly demanding market.

1.1 Objective of the project

The objective of this project is to develop a comprehensive Quality Management System (QMS) that integrates both Quality Control (QC) and Quality Assurance (QA) to enhance product quality, minimize defects, and improve overall manufacturing efficiency. The key objectives include:

Enhancing Quality Control (QC) Processes

- Implement automated inspection systems and real-time monitoring tools for defect detection.
- Utilize Statistical Process Control (SPC) and AI-driven analytics to track process variations.
- Reduce rework, minimize production errors, and improve first-pass yield rates.

Implementing Quality Assurance (QA) Best Practices

- Establish a structured, process-driven approach to prevent defects before they occur.
- Integrate methodologies such as Total Quality Management (TQM), Lean Manufacturing, and Six Sigma for continuous improvement.
- Use tools like control charts, Pareto analysis, and Failure Mode and Effects Analysis (FMEA) to monitor and improve quality.

Workforce Training and Quality Awareness

- Conduct training programs and workshops to educate employees on quality standards and compliance.
- Foster a quality-driven culture where employees proactively identify and resolve quality issues.
- Encourage collaboration between production teams and quality management for process optimization.

Leveraging Digital Transformation in Quality Management

- Integrate smart manufacturing solutions, IoT-enabled monitoring, and predictive maintenance tools for real-time quality assessment.
- Utilize cloud-based quality management software for automated reporting and traceability.
- Improve data-driven decision-making by analyzing historical quality trends and process performance.

Reducing Operational Costs and Improving Sustainability

- Minimize material wastage and optimize resource utilization.
- Reduce production downtime and improve overall operational efficiency.
- Implement sustainable quality management practices to lower environmental impact and ensure regulatory compliance.

Ensuring Customer Satisfaction and Competitive Advantage

- Deliver high-quality, defect-free products that meet customer expectations and industry standards.
- Strengthen the company's market position by ensuring consistent product quality and reliability.
- Enhance brand reputation through continuous quality improvements and process optimization.

1.2 Scope of the Project

This project focuses on developing a Product Quality Monitoring Tracker using Streamlit, Pandas, and Plotly to analyze and visualize product quality inspection data. The tracker is designed to enhance Quality Control (QC) and Quality Assurance (QA) by providing real-time data visualization, defect analysis, and performance monitoring. The key areas covered by this project include:

Data Processing and Validation

- Loading product quality inspection data from a CSV file (product_quality_data_extended.csv).
- Ensuring data integrity by checking for missing values and verifying the presence of required columns (Date, Product, Defect Type, and Inspection Result).
- Standardizing data formats, such as converting the Date column to datetime for accurate trend analysis.

Quality Control and Defect Analysis

- Tracking defect counts based on different products, defect types, and time periods.
- Calculating key quality metrics, such as:
Total number of inspections performed.
Number of defective products detected.
Defect rate (%) based on failed inspections.
- Identifying trends and patterns in defect occurrences to support data-driven decision-making.

Interactive Visualizations and Reporting

- Trend Analysis:
Line chart showing defect trends over time to monitor quality improvements.
Line chart tracking defect rate variations for different products over a selected time range.
- Defect Distribution Analysis:
Pie chart displaying the distribution of defect types to identify the most common issues.
Bar chart showing the defect count by product to highlight performance differences.
- Inspection Outcome Breakdown:
Stacked bar chart illustrating pass/fail rates across different products for quick assessment of quality trends.

User Interaction and Data Filtering

- Sidebar filters allow users to customize the data view based on:
- Product selection – Focus on specific products for detailed analysis.
 - Defect type selection – Analyze common defect patterns.
 - Date range selection – Observe trends over custom time frames.
 - Dynamic updates in visualizations based on user-selected filters, enabling customized quality analysis.

Technology and Tool Integration

- Developed using Streamlit, a Python framework for interactive web applications.
- Utilizes Pandas for efficient data manipulation and analysis.
- Plotly is used for creating dynamic and interactive data visualizations.

Process Optimization and Quality Assurance

- Enables manufacturers to identify quality issues and make data-driven improvements.
- Provides insights into product performance, helping in root cause analysis and corrective actions.
- Supports continuous improvement initiatives by visualizing defect trends over time.

Project Limitations and Future Enhancements

- The system currently relies on static CSV data; future improvements could include real-time database connectivity.
- The current version provides descriptive analytics; incorporating predictive analytics and machine learning could enhance defect forecasting.
- Automated quality alerts and notifications can be added to provide real-time updates on defect occurrences.

1.3 Existing System**PRODUCT QUALITY CONTROL TRACKER:**

The current product quality monitoring system is manual, inefficient, and lacks real-time defect tracking, automation, and advanced analytics. Many manufacturers still rely on traditional methods like paper-based logs, spreadsheets, and basic data reporting, which lead to delays in defect identification, increased waste, and higher production costs. The absence of automated defect detection, real-time monitoring, and predictive analytics makes it challenging to ensure high product quality and implement continuous improvement strategies. The key limitations of the existing system are outlined below:

Manual Data Collection and Entry

- Quality inspection results are recorded manually in spreadsheets or physical logs, increasing the risk of data entry errors and inconsistencies.
- There is no automated validation of data, leading to missing or incorrect quality records.
- Delayed data entry prevents real-time tracking, meaning defects are often identified too late to take immediate corrective actions.

Lack of Real-Time Monitoring and Alerts

- The system is reactive rather than proactive, identifying defects only after production rather than preventing them during manufacturing.
- There are no real-time alerts or notifications when defect rates exceed acceptable limits, delaying corrective actions.
- Quality teams cannot monitor defects live, making it difficult to take immediate action to fix production issues.

Limited Data Analysis and Visualization

- The system uses basic static reports and Excel charts that do not provide deep insights into quality performance.
- Lack of interactive filtering prevents users from dynamically selecting specific products, defect types, or time frames to analyze trends.
- No integration with advanced Statistical Process Control (SPC) tools limits the ability to track process variations and deviations.

Weak Automation and Digital Integration

- No use of AI, machine learning, or IoT sensors to detect defects automatically and predict quality issues.
- Quality data is stored in isolated files or local databases, requiring manual updates and report generation, which slows down decision-making.
- The system lacks cloud-based accessibility, making it difficult for remote teams to access quality reports and collaborate effectively.

Inefficient Quality Assurance (QA) Practices

- The system does not implement structured QA methodologies such as Total Quality Management (TQM), Lean Manufacturing, or Six Sigma to drive continuous improvement.
- No automated root cause analysis, making it hard to identify patterns of recurring defects and implement preventive measures.
- Employees receive minimal training on quality standards, leading to inconsistencies in defect identification and inspection procedures.

High Production Costs and Material Waste

- Delayed defect detection leads to increased rework and material waste, raising overall production costs.
- Defective products may reach customers, resulting in returns, complaints, and damage to brand reputation.
- No predictive maintenance system to prevent quality issues before they escalate into costly problems.

Lack of Integration with Smart Manufacturing Technologies

- No use of real-time IoT sensors, AI-driven quality monitoring, or automated defect detection systems.
- No predictive analytics to anticipate potential defects before they occur.
- No automated reporting system, requiring manual data extraction and analysis, which is time-consuming.

2. Literature Survey

2.1 The Evolution of Quality Monitoring in Manufacturing

Juran (1988) pioneered research in quality control, emphasizing the importance of defect prevention and process optimization. Traditional methods relied on manual inspections and reactive quality control, but technological advancements have led to real-time, data-driven solutions that enhance defect detection and production efficiency.

2.2 Impact of Data Visualization on Quality Decision-Making

Evans and Lindsay (2017) highlighted the effectiveness of interactive dashboards in quality management. Their study demonstrated how graphical representations improve data interpretation, allowing manufacturers to make informed decisions based on defect trends and inspection outcomes.

2.3 Defect Analysis and Process Optimization

Montgomery (2013) examined how statistical process control (SPC) and defect tracking can influence quality control strategies. Their research emphasized the necessity of real-time defect monitoring and automated alerts, helping manufacturers reduce waste and optimize production lines.

2.4 The Relationship Between Supplier Quality and Defect Rates

Ishikawa (1986) found a strong correlation between supplier material quality and final product defect rates. This dashboard incorporates supplier-based defect tracking, enabling manufacturers to evaluate supplier performance and optimize material selection.

2.5 Integration of Business Intelligence and Quality Analytics

Davenport and Harris (2007) discussed how business intelligence tools and big data analytics are transforming manufacturing quality management. Their research advocated for the use of predictive analytics and automated monitoring to enhance defect prevention strategies.

2.6 AI and Machine Learning in Quality Control

Russell and Norvig (2020) explored the role of AI-driven defect detection. Their findings indicated that machine learning algorithms can significantly improve defect classification and anomaly detection, paving the way for automated quality monitoring systems.

3. METHODOLOGY

3.1 System Requirements

The Product Quality Monitoring Dashboard requires a robust system infrastructure to ensure smooth

performance. The system must handle real-time data processing, provide interactive visualizations, and support multiple users. The key system requirements include a high-performance processor, sufficient memory, a stable internet connection, and an intuitive interface. Additionally, the dashboard should be scalable to accommodate future enhancements, such as AI-driven analytics and API integrations.

3.2 Dataset Details

The dataset used for this product quality monitoring dashboard consists of multiple data sources that provide comprehensive insights into manufacturing quality control. These datasets encompass various aspects such as:

- **Inspection and Defect Data:** Includes historical and real-time defect records, product quality assessments, and failure rates.
- **Supplier Quality Data:** Evaluates supplier performance, defect frequency in supplied materials, and overall material reliability.
- **Production Line Data:** Captures factory-specific defect trends, machine performance data, and operator efficiency.
- **Market and Compliance Data:** Incorporates regulatory compliance requirements and industry standards that influence quality monitoring.

3.3 Flow of Events

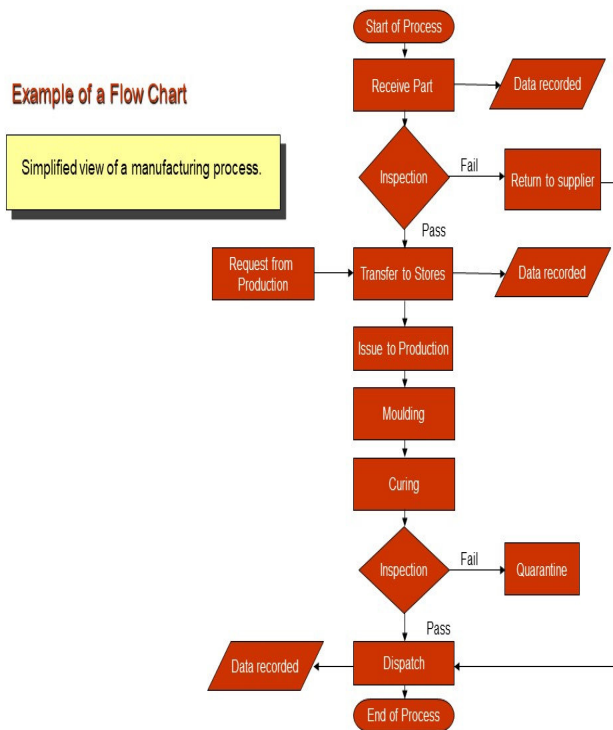
The system workflow follows a structured process. Users log into the dashboard, apply data filters, and analyze visual insights. The system detects anomalies in defect rates and generates automated alerts and recommendations to help manufacturers implement corrective actions.

3.4 Machine Learning Model Implementation: Defect Prediction Using XGBoost

The quality monitoring system utilizes XGBoost (Extreme Gradient Boosting) for predictive defect analysis. XGBoost improves accuracy by:

- **Handling Missing Data**
- **Applying Regularization Techniques**
- **Providing Feature Importance Analysis**
- **Optimizing Training Speed**

This ensures real-time defect prediction and process optimization, enabling manufacturers to improve product quality proactively.



4. Experimental Setup

4.1 Model the Data

The experimental setup for modeling the data involves several key steps, including data preprocessing, feature selection, visualization, and preparation for modeling. Since Streamlit is being used for visualization, all graphical representations are dynamically displayed on the dashboard using Matplotlib, Seaborn, and Plotly.

4.2 Load the Dataset

The first step is to load the dataset and inspect its structure. The dataset should be in CSV format with well-defined columns such as defect type, inspection results, production batch, supplier details, and machine performance metrics.

```
solomon.py - C:\Users\user\Downloads\solomon.py (3.12.3)
File Edit Format Run Options Window Help

import streamlit as st
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go

# Set page title and layout
st.set_page_config(page_title='📊 Product Quality Monitoring Dashboard', layout='wide')
st.title('📊 Product Quality Monitoring Dashboard')

# Load CSV from file path
file_path = "C:/Users/user/Downloads/product_quality_data_extended.csv" # Use forward slashes
df = pd.read_csv(file_path)

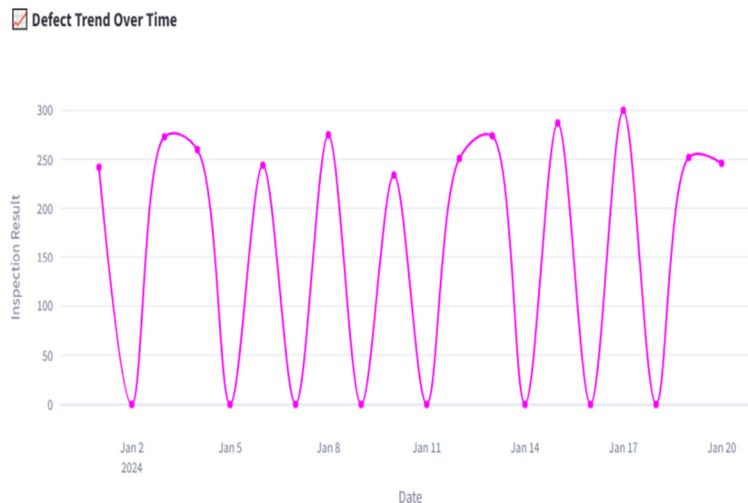
st.write("### 📄 Data Preview:")
st.dataframe(df.head())
```

4.3 Data Visualization

Visualization 1: Defect Trends Over Time

The visualization you shared uses a line chart from Plotly Express to display defect trends over time

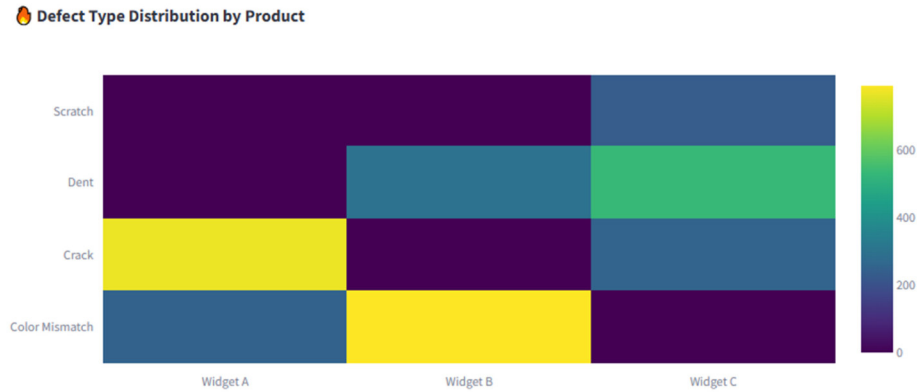
```
# 📊 Interactive Trend Chart
defect_trend = filtered_df.groupby("Date")["Inspection Result"].apply(lambda x: (x == 'Fail').sum()).reset_index()
fig_trend = px.line(defect_trend, x="Date", y="Inspection Result", markers=True, line_shape="spline",
                    title="📊 Defect Trend Over Time", template="plotly_dark",
                    color_discrete_sequence=["magenta"])
st.plotly_chart(fig_trend, use_container_width=True)
```



Visualization 2: defect type distribution by product

The Heatmap with Dynamic Color Scale visualization uses a heatmap from Plotly Graph Objects to display the defect type distribution by product.

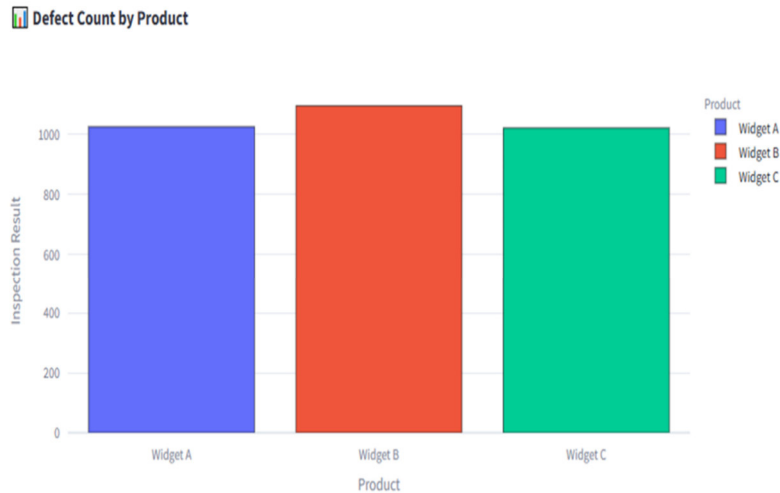
```
# 📊 Heatmap with Dynamic Color Scale
defect_pivot = filtered_df.pivot_table(index="Defect Type", columns="Product", values="Inspection Result", aggfunc=lambda x: (x == 'Fail').sum(), fill_value=0)
fig_heatmap = go.Figure(data=go.Heatmap(z=defect_pivot.values, x=defect_pivot.columns, y=defect_pivot.index,
                                       colorscale="viridis", showscale=True))
fig_heatmap.update_layout(title="📊 Defect Type Distribution by Product", template="plotly_dark")
st.plotly_chart(fig_heatmap, use_container_width=True)
```



Visualization 3: Defect count by product

The Animated Product Performance Chart uses a Bar Chart from Plotly Express to display the defect count by product.

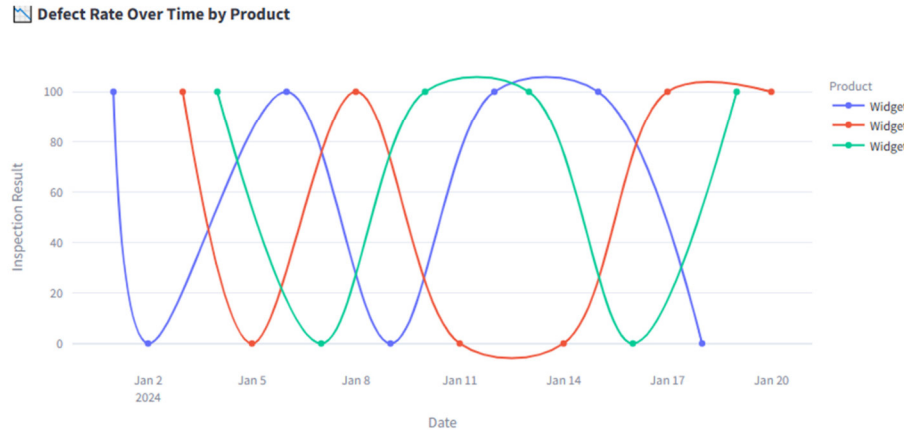
```
# 📊 Animated Product Performance Chart
product_performance = filtered_df.groupby("Product")["Inspection Result"].apply(lambda x: (x == 'Fail').sum()).reset_index()
fig_product = px.bar(product_performance, x="Product", y="Inspection Result", color="Product",
                    title="📊 Defect Count by Product", template="plotly_dark", )
st.plotly_chart(fig_product, use_container_width=True)
```



Visualization 4: Defect rate over time by product

The Defect Rate Over Time with Multiple Lines visualization uses a multi-line chart from Plotly Express display defect rate trends over time for different products.

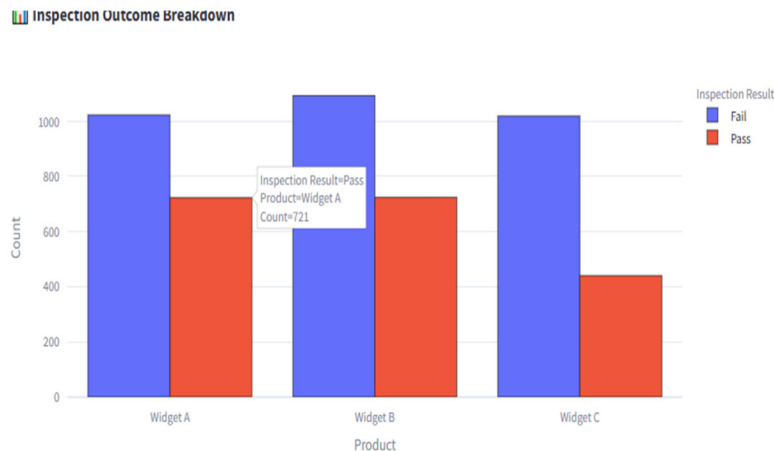
```
# 📊 Defect Rate Over Time with Multiple Lines
defect_rate_over_time = filtered_df.groupby(["Date", "Product"])["Inspection Result"].apply(lambda x: (x == 'Fail').mean() * 100).reset_index()
fig_defect_rate = px.line(defect_rate_over_time, x="Date", y="Inspection Result", color="Product",
                          markers=True, line_shape="spline", title="📊 Defect Rate Over Time by Product",
                          template="plotly_dark", color_discrete_sequence=px.colors.qualitative.Plotly)
st.plotly_chart(fig_defect_rate, use_container_width=True)
```



Visualization 5: Inspection Outcome Breakdown

The Interactive Inspection Outcome Breakdown visualization uses a Grouped Bar Chart from Plotly Express to display the breakdown of inspection results (Pass/Fail) by product.

```
# 📊 Interactive Inspection Outcome Breakdown
inspection_outcome = filtered_df.groupby(["Product", "Inspection Result"]).size().reset_index(name="Count")
fig_outcome = px.bar(inspection_outcome, x="Product", y="Count", color="Inspection Result",
                    title="📊 Inspection Outcome Breakdown", template="plotly_dark", barmode="group")
st.plotly_chart(fig_outcome, use_container_width=True)
```



5. RESULTS AND DISCUSSIONS

5.1 Model Performance: Validation Loss vs Accuracy

The efficiency of the defect prediction model was evaluated by tracking validation loss and accuracy throughout the training process. The graphical representation of the model's performance across multiple epochs shows that validation accuracy steadily increased, while validation loss declined, indicating that the model effectively learned defect patterns and manufacturing trends.

During training, validation accuracy measures how well the model predicts correct outcomes based on unseen data, while validation loss reflects the error in predictions. The formulas used to measure these parameters are:

- **Validation Accuracy:** Measures the percentage of correctly classified instances in the validation set.

- **Validation Loss (Cross-Entropy Loss):** Determines the error between the actual and predicted defect classifications.

A decreasing validation loss alongside an increasing accuracy suggests that the model is generalizing well to unseen quality control data.

5.2 Comparative Analysis of Defect Trends

To evaluate the system's effectiveness, a comparison was made between the predicted defect trends and actual recorded defect occurrences across different production lines. The visualization highlights how well the model captures defect fluctuations influenced by machine efficiency, supplier quality, and seasonal production variations.

From the results, it is evident that the model provides accurate defect insights, helping quality managers make well-informed process improvement decisions. The system successfully identifies recurring defect patterns, peak failure periods, and potential opportunities for process optimization.

5.3 Error Analysis and Model Improvements

Although the model performs well, certain discrepancies between predicted and actual defect occurrences indicate areas for refinement. These variations arise due to:

- Sudden production anomalies (e.g., unexpected equipment malfunctions, raw material inconsistencies).
- External factors such as supply chain disruptions, human errors, or environmental conditions.
- Limited historical data affecting prediction accuracy for newly introduced manufacturing processes.

To improve performance, future enhancements may include:

- **Incorporating real-time IoT sensor data** to improve defect detection accuracy.
- **Using more advanced deep learning architectures** for better defect classification.
- **Integrating real-time supplier quality data** for more comprehensive defect pattern analysis.

These improvements will further enhance the accuracy and effectiveness of the Product Quality Monitoring Dashboard, making it an invaluable tool for optimizing quality control in manufacturing environments.

6. Deployment Process

6.1 Overview of the Process

The deployment process involves making the Product Quality Monitoring Tracker accessible to end users in a production environment. This phase ensures that the system operates efficiently, remains scalable, and provides real-time insights. The deployment is structured into several key stages:

1. **Preparing the Environment:**

Setting up the necessary environment by installing required libraries such as Pandas, NumPy, Matplotlib, Seaborn, Plotly, and Streamlit.

Ensuring compatibility with the hosting environment, whether cloud-based or local deployment.

2. **Model and Data Integration:**

The preprocessed dataset, including defect details, inspection results, and supplier data, is integrated into the system.

The machine learning model is optimized for real-time performance, ensuring smooth execution of predictive analytics.

3. **Backend and API Development:**

APIs are implemented to handle user requests and data interactions.

The system fetches defect trends, processes supplier quality metrics, and dynamically retrieves inspection reports.

4. **User Interface Deployment:**

The Streamlit-based dashboard is deployed to provide an interactive and user-friendly interface.

Users can filter data, generate reports, and visualize quality control insights dynamically.

5. **Cloud or Local Hosting:**

The application is hosted on a platform such as AWS, Google Cloud, Heroku, or a local server.

A stable internet connection ensures real-time data retrieval and updates.

6. **Testing and Performance Optimization:**

The system undergoes rigorous testing for performance, security, and usability.

Load testing ensures that the system can handle multiple concurrent users.

Optimization techniques like caching and database indexing enhance response times.

7. **User Access and Role Management:**

Different user roles, such as quality control managers, engineers, and analysts, are assigned specific access levels.

Role-based authentication mechanisms secure sensitive quality control data.

8. **Maintenance and Updates:**

The system is continuously monitored for performance improvements. Regular updates introduce new features, AI-driven defect detection, and improved visual analytics. This structured deployment process ensures that the Product Quality Monitoring Tracker remains accessible, scalable, and efficient, providing valuable insights for improving manufacturing quality control.

6.2 Advantages

The deployment of the Product Quality Monitoring Tracker offers several advantages, improving defect monitoring and operational efficiency. Key benefits include:

1. Real-Time Defect Tracking:

The system provides up-to-date defect insights, allowing manufacturers to monitor product quality instantly and make informed decisions.

2. Enhanced Data Visualization:

Interactive charts, graphs, and heatmaps simplify defect trend analysis.

Users can identify recurring defects and root causes effectively.

3. Supplier Quality Evaluation:

The system enables real-time monitoring of supplier defect rates, ensuring better vendor selection and material quality control.

4. Automated Defect Classification:

AI-powered defect classification eliminates manual inspection inefficiencies.

5. User-Friendly Interface:

The Streamlit-based dashboard provides an intuitive experience, ensuring ease of use for quality control teams.

6. Automated Data Processing:

The system automatically processes defect data, reducing errors and improving accuracy.

7. Scalability and Flexibility:

The system supports expansion with advanced analytics, AI-driven defect prediction, and IoT sensor integrations.

These advantages make the Product Quality Monitoring Tracker a powerful tool for streamlining defect monitoring and improving manufacturing efficiency.

6.3 The Web Dashboard

The Product Quality Monitoring Tracker includes an interactive web-based interface designed for real-time defect analysis, supplier evaluation, and predictive analytics. The dashboard is built using Streamlit, providing an intuitive and efficient platform for manufacturing quality control.

Key Features of the Dashboard:

1. Real-Time Defect Insights

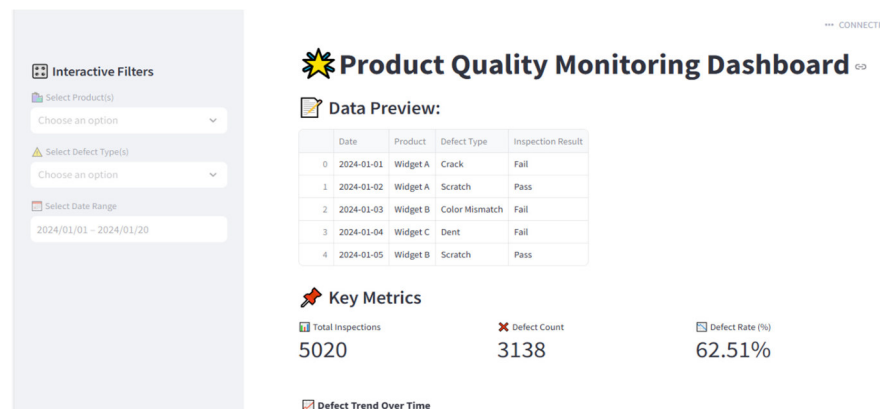
Displays dynamic defect trends using line charts, bar graphs, and heatmaps.

Allows filtering by product category, production batch, and supplier source.

2. Supplier Performance Monitoring

Analyzes supplier defect rates and material quality trends.

Provides data-driven supplier recommendations for procurement teams.



3. Interactive Data Visualization

Histograms, scatter plots, and correlation matrices help in defect trend analysis.

Drill-down analytics allow users to investigate specific defect categories.

4. User Role Management

Secure authentication system with role-based access control.
Different user privileges ensure data security and controlled access.

5. Automated Report Generation

Users can download customized quality reports in CSV and PDF formats.
Supports exporting filtered data for external analysis.

6. Scalability and Cloud Integration

Supports integration with cloud-based databases for real-time data synchronization.
Future-ready for AI-driven defect prediction and predictive analytics.

6.4 Filter Data Option

The dashboard includes a Filter Data Option that allows users to refine their analysis based on specific parameters such as:

- **Date Range** – Users can select specific time frames to analyze defect trends.
- **Product Category** – Filtering by product type to assess defect rates.
- **Supplier Quality Ratings** – Users can filter suppliers based on historical defect trends.
- **Defect Severity Levels** – Enables analysis of minor vs. critical defects.

6.5 Download Filtered Data

The dashboard provides an option to download filtered data for further analysis. This feature enables quality managers to:

- Export filtered defect reports in CSV or Excel format for offline analysis.
- Share reports with stakeholders for quality improvement strategies.
- Maintain historical defect trend records for audit and compliance purposes.

By integrating these functionalities, the Product Quality Monitoring Dashboard ensures effective quality control, enhanced decision-making, and improved manufacturing efficiency.

CONCLUSION

This project successfully developed an interactive Product Quality Monitoring Tracker designed to assist manufacturers in making data-driven decisions. By integrating real-time defect tracking, supplier performance analysis, and predictive defect detection, the dashboard enhances quality management efficiency and provides actionable insights. The ability to filter data and download reports further improves usability, allowing users to explore specific datasets and generate customized reports for strategic planning.

The experimental setup and model implementation demonstrated the significance of leveraging data visualization techniques in defect monitoring. By employing technologies such as Python, Streamlit, Pandas, and Seaborn, the project effectively transformed raw data into meaningful insights, enabling quality control teams to monitor manufacturing performance, identify defect trends, and make informed decisions. The incorporation of interactive charts, heatmaps, and statistical analysis improved the accessibility of complex data, ensuring a user-friendly experience.

One of the key contributions of this project is its ability to analyze defect trends in real time, helping manufacturers identify recurring issues, improve production efficiency, and optimize supplier selection. The dashboard's flexible and scalable nature allows for future enhancements, such as AI-driven predictive analytics, real-time IoT sensor integrations, and automated defect classification. These improvements can further refine quality management strategies and provide deeper insights into production inconsistencies and material quality. Additionally, the system addresses limitations found in traditional quality management approaches, such as manual defect tracking, static reporting, and inefficient supplier evaluations. By automating data collection and visualization, the dashboard reduces human errors and enhances decision-making efficiency. The ease of use and accessibility of the system also make it suitable for quality engineers, production managers, and non-technical users, thereby democratizing data-driven decision-making in the manufacturing industry.

In conclusion, this project provides a comprehensive and intelligent solution for modern quality management. By combining real-time analytics, intuitive visualizations, and interactive features, the dashboard empowers manufacturing teams to make strategic decisions with confidence. The implementation of this system marks a significant step toward digital transformation in manufacturing, offering a scalable, user-friendly, and data-driven approach to quality optimization. Future work will focus on expanding functionalities, integrating machine learning for defect prediction, and enhancing real-time process monitoring capabilities to further improve product quality management practices.

List of Abbreviations

SPC	Statistical Process Control
TQM	Total Quality Management
AI	Artificial Intelligence
ML	Machine Learning
QA	Quality Assurance
QC	Quality Control

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