

NAAN MUDHALVAN PROJECT

PHASE-3

IMPLEMENTATION OF PROJECT

TITLE : QUALITY CONTROL IN
MANUFACTURING

PRESENT BY :

310823205088 - SIDHRA FARHEEN S

310823205104 - THENMOZHI T

310823205070 - PRIYADARSHINI S K

310823205080 - SAKTHI SHREE I

310823205067 - POOVIZHI R

IMPLEMENTATION OF PROJECT

Title: AI-Driven Quality Control System for Automotive Manufacturing

OBJECTIVE :

The goal of Phase 3 is to implement a data-driven quality control system within the metal car body panel production line at AutoForm Industries. This initiative aims to address recurring surface defects—such as scratches, dents, and paint inconsistencies—that currently exceed the acceptable quality threshold of 2.5%. The target is to reduce this defect rate to below 1% through a combination of Statistical Process Control (SPC), Six Sigma methodologies, and AI-powered visual inspection.

1. Quality Variation Analysis

Overview :

This stage involves identifying the key contributors to quality defects in the production line. Factors like tooling wear, manual handling errors, and paint booth irregularities will be systematically analyzed.

Implementation :

- **Data Collection:** Historical defect logs, machine maintenance records, and operator feedback will be

- Root Cause Analysis: Techniques such as Fishbone Diagrams and Pareto Charts will be used to isolate major causes.

Outcome :

By the end of this step, a prioritised list of quality variation sources will be available to guide corrective action.

2. Computer Vision-Based Defect Detection

Overview :

An AI-based image inspection system will be developed to automatically detect surface defects in real-time during production.

Implementation :

- Model Training: Convolutional Neural Networks (CNNs) will be trained using labeled images of defective and non-defective panels.
- Integration: Cameras will be installed at inspection stations, and the model will flag defects above the threshold confidence level.

Outcome :

A functional computer vision system capable of identifying surface anomalies with high accuracy and minimal false positives.

Overview :

Using Six Sigma (DMAIC) methodology, the manufacturing process will be optimized to minimize variability and defects.

Implementation :

- Define & Measure: Key metrics like defect rate, cycle time, and process capability (C_p , C_{pk}) will be tracked.
- Analyze & Improve: Statistical tools will help identify variation trends; changes in procedures or equipment will be implemented accordingly.

Outcome :

Improved process consistency and a measurable reduction in defect rates.

4. Statistical Process Control (SPC) Implementation

Overview :

Real-time monitoring of critical quality parameters will be implemented using SPC tools.

Implementation :

- Control Charts: Variables such as paint thickness and surface smoothness will be tracked using X-bar and R charts.
- Alert System: Out-of-control conditions will trigger alerts for immediate intervention.

Outcome :

Consistent quality monitoring and rapid response to process deviations.

5. Testing and Feedback Collection

Overview :

The new quality control system will undergo pilot testing on a selected production line.

Implementation :

- Trial Runs: A sample batch will be monitored using the AI system and SPC tools.
- Feedback Loop: Operators and quality engineers will provide feedback on system usability and accuracy.

Outcome :

Insights gathered will guide fine-tuning before full-scale deployment.

CHALLENGES AND SOLUTIONS :

1. Data Imbalance in Vision Model :

Challenge: Rare defect types may not be well-represented in training data.

Solution: Employ data augmentation techniques to balance datasets.

Program code :

```
import tensorflow as tf

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv 2D,
    MaxPooling 2D, Flatten, Dense
from tensorflow.keras.preprocessing.image import Image
data generator

# Load and augment image data
train_gen = Image data generator(rescale=1./255,
    horizontal_flip=True, zoom_range=0.2)
train_data = train_gen.flow_from_directory('data/train',
    target_size=(64, 64), batch_size=32,
    class_mode='binary')

val_gen = Image data generator(rescale=1./255)
val_data = val_gen.flow_from_directory('data/val',
    target_size=(64, 64), batch_size=32,
    class_mode='binary')

# Build CNN model
model = Sequential([
    Conv 2D(32, (3,3), activation='relu', input_shape=(64,
64, 3)),
    Max pooling 2D(2, 2),
    Conv 2D(64, (3,3), activation='relu'),
    Max Pooling 2D(2, 2),
    Flatten()
```

```
Dense(1, activation='sigmoid') # Binary: Defect / No  
Defect  
)
```

```
model.compile(optimizer='adam',  
loss='binary_crossentropy', metrics=['accuracy'])  
model.fit(train_data, validation_data=val_data,  
epochs=10)  
model.save("defect_detector.h5")
```

2. Operator Resistance to Change :

Challenge: Staff may be reluctant to adopt AI-based inspections.

Solution: Conduct training sessions and involve operators in system testing.

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
# Simulated paint thickness data (in mm)
```

```
np.random.seed(0)
```

```
samples = np.random.normal(loc=0.8, scale=0.03,  
size=100)
```

```
mean = np.mean(samples)
```

```
std_dev = np.std(samples)
```

```
ucl = mean + 3 * std_dev
```

SPC Control Chart

```
plt.plot(samples, label="Measurements", marker='o')
plt.axhline(mean, color='green', label="Mean")
plt.axhline(ucl, color='red', line style='--', label="UCL")
plt.axhline(lcl, color='red', line style='--', label="LCL")
plt.title("SPC Control Chart - Paint Thickness")
plt.xlabel("Sample Number")
plt.ylabel("Thickness (mm)")
plt.legend()
plt.grid(True)
plt.show()
```

3. Real-Time Integration Issues :

Challenge: Linking AI systems with legacy machinery may pose difficulties.

Solution: Use middleware platforms to ensure smooth data exchange.

Assume specification limits (mm)

USL = 0.86

LSL = 0.74

$C_p = (USL - LSL) / (6 * std_dev)$

$C_{pk} = \min((USL - mean) / (3 * std_dev), (mean - LSL) / (3 * std_dev))$

print(f"Process Capability (Cp): {Cp: 2 f}")

Outcomes of Phase 3 :

1. Identified and documented key sources of surface defects.
2. Deployed a functional AI model for defect detection.
3. Implemented process improvements using Six Sigma tools.
4. Established SPC-based real-time monitoring.
5. Collected feedback for iterative system enhancement.

THANK YOU !!