A Project Report on

Defining top quality issue and taking correcting action on them

By

Virendra Pardeshi (22210908)

Tanvi Patil (22210259)

Kunal Jadhav (22211100)

Guide

Mr. D. B. Nalawade

Department of Mechanical Engineering

Vishwakarma Institute of Information Technology, Pune

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Vishwakarma Institute of Information Technology, Pune

C E R T I F I C A T E

Virendra Pardeshi (22210908)

Tanvi Patil (22210259)

Kunal Jadhav (22211100)

has successfully completed the project work entitled ***"Defining top quality issue and taking correcting action on them"*** under my supervision, in the partial fulfilment of *Third Year B. Tech - Mechanical Engineering*.

Date:

Place: Pune

Name of the guide

Guide

Examiner

Dr. Pravin P Hujare

Project Coordinator

Dr. Sandeep S Kore

Head of the Department

Seal of the Departmen

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We look forward to leveraging the knowledge and experience gained from this phase to successfully complete the project.

Yours sincerely,

Virendra Pardeshi

Tanvi Patil

Kunal Jadhav

ABSTRACT

Effective quality control is essential for maintaining high standards and ensuring customer satisfaction in manufacturing processes. However, many companies still rely on manual inspection methods, which can lead to inconsistencies, human error, and delays in production workflows. This project focuses on the design and implementation of **an automated defect detection system for quality control**, leveraging machine learning and image processing techniques to enhance accuracy and efficiency.

The proposed system uses **MATLAB and a trained machine learning model** to classify metal parts as defective or normal based on image analysis, eliminating the need for manual inspection. Comparative analysis highlights the benefits of automation over traditional inspection methods, emphasizing improved precision, speed, and reduced operational costs. This system enables real-time defect identification, streamlined data analysis, and proactive quality control measures, ultimately enhancing product consistency and operational effectiveness. This report provides an overview of the development process, challenges encountered, and the positive impact of automated defect detection on quality control, offering a practical solution for businesses seeking to optimize inspection processes and uphold product standards.

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Nomenclature

1.ML	-	Machine Learning
2.IP	-	Image Processing
3.CNN	-	Convolutional Neural Networks
4.QC	-	Quality Control

1.INTRODUCTION

In manufacturing, effective quality control is essential for maintaining high standards, reducing waste, and enhancing customer satisfaction. Many companies, however, continue to rely on manual inspection processes to identify product defects, which can introduce human error, inefficiencies, and delays. As production lines and quality standards become increasingly complex, there is a growing need for automated solutions that can streamline defect detection and reduce reliance on manual inspection.

This project focuses on developing **an automated defect detection system** designed to improve quality control in the manufacturing industry. By leveraging **machine learning (ML) and image processing (IP)** techniques, the proposed system aims to enhance the accuracy, speed, and consistency of defect detection. This system will utilize **MATLAB** to process images of metal parts, identifying and classifying defects with minimal human intervention. The automated approach offers a practical and efficient solution for manufacturers, particularly small to mid-sized enterprises, who seek to maintain high product standards without incurring the costs of manual inspection or complex systems.

The objective of this project is to establish a reliable **method for detecting and categorizing defects, ultimately improving overall quality control**. Automated defect detection will ensure consistency in inspections, provide real-time analysis, and enable faster decision-making. Through comparative analysis of automated versus manual inspection methods, this report will demonstrate the advantages of adopting machine learning for quality control, including increased efficiency, reduced error rates, and enhanced customer satisfaction.

1.1 Machine Learning and Image Processing in Defect Detection

Automated defect detection combines Machine Learning (ML) and Image Processing (IP) to classify parts as defective or non-defective by analysing visual data. These technologies improve the speed, accuracy, and consistency of quality control processes, addressing the limitations of manual inspection. This section provides an overview of how ML and IP work in defect detection, types of defect detection methods, and a comparison to demonstrate why our chosen approach offers the best solution for our objectives.

1.1.1 How Machine Learning and Image Processing Work in Defect Detection

Machine learning models are trained on labelled image data to recognize patterns associated with defects. Image Processing techniques prepare images for analysis by enhancing key features and reducing noise. Here's an outline of the basic workflow:

1. **Image Acquisition**: Images of metal parts are captured using cameras. Each image is labelled as "defective" or "non-defective."
2. **Image Preprocessing**: IP techniques are applied to normalize and enhance images, adjusting aspects like lighting, contrast, and scale to ensure consistent input for the ML model.
3. **Feature Extraction:** Key features relevant to defect detection, such as texture, edges, and contours, are highlighted through filters or transformations.
4. **Model Training and Prediction**: The ML model is trained on these processed images, learning to recognize and classify defects based on the extracted features. After training, the model can analyse new images in real time and categorize them with high accuracy.

By combining these steps, ML and IP enable a reliable automated process for identifying defects, significantly reducing reliance on manual inspection.

1.1.2 Types of Defect Detection Methods

Several methods exist for detecting defects in manufacturing using ML and IP, each with distinct strengths and limitations:

1. **Traditional Image Processing Methods**: These involve manually defined algorithms that detect defects based on specific features like size, shape, or colour. While effective for simple inspections, they lack flexibility and accuracy for complex or subtle defects.
2. **Statistical Methods**: Techniques like Principal Component Analysis (PCA) and Gaussian Mixture Models (GMM) analyse variations within images to identify anomalies. These are suitable for detecting minor defects but often struggle with complex defect patterns.
3. **Deep Learning-Based Methods**: Convolutional Neural Networks (CNNs) and other deep learning models have gained popularity for defect detection due to their ability to automatically learn complex features. CNNs are highly effective for image-based classification tasks, as they can learn hierarchical features directly from raw image data.
4. **Hybrid Approaches**: Some systems combine traditional IP techniques with deep learning models to optimize performance. These methods leverage the strengths of both approaches but often require extensive computational resources.

1.1.3 Advantages of Machine Learning and Image Processing in Defect Detection

- **Consistency and Accuracy**: ML models provide high consistency by removing human variability, ensuring that each part is inspected uniformly.
- **Real-Time Analysis**: Automated systems allow for rapid detection, enabling real-time quality control on production lines.
- **Scalability**: Once trained, ML models can be applied across multiple defect types and products, adapting to various inspection requirements.
- **Cost-Effectiveness**: Automated inspection reduces the need for extensive manual labour, leading to lower operational costs over time.

1.1.4 Limitations of Machine Learning and Image Processing

- **Data Dependency:** ML models require a large, high-quality labelled dataset for training. Limited data can reduce model accuracy and generalizability.
- **Computational Requirements:** Some ML methods, especially deep learning models, require significant computational resources, which can be costly.
- **Complexity in Implementation:** Setting up an automated defect detection system involves multiple technical steps, from data collection to model tuning, which can be complex and time intensive.

1.1.5 Comparison and Selection of the Best Method

After evaluating the available methods, our project adopted a Convolutional Neural Network (CNN)-based approach for defect detection. This decision was based on the following factors:

- **Feature Learning Capability**: Unlike traditional or statistical methods, CNNs learn relevant features automatically, which makes them highly effective for complex defect patterns.
- **High Accuracy with Small Dataset**: With a limited dataset of 13 defective and 11 normal images, CNNs still offer reliable performance through transfer learning, leveraging pre-trained models and fine-tuning them on our specific dataset.
- **Efficiency in Real-Time Applications**: CNNs allow for quick and accurate classifications, suitable for real-time defect detection in production environments.

In conclusion, the CNN-based method offers the best balance of accuracy, adaptability, and efficiency for our defect detection system. This approach addresses the limitations of traditional methods while maximizing the strengths of machine learning and image processing, making it ideal for consistent and automated quality control.

1.2 MATLAB for Automated Defect Detection

MATLAB is a powerful computing environment and programming platform that excels in data analysis, visualization, and the development of algorithms, making it an ideal choice for implementing automated defect detection. Its versatility, built-in image processing and machine learning toolboxes, and user-friendly interface enable efficient development and testing of defect detection models. MATLAB's strengths in rapid prototyping, visualization, and ease of integration make it an appealing choice for quality control projects in manufacturing.

1.2.1 MATLAB as a Machine Learning and Image Processing Tool

MATLAB provides an extensive set of tools for image processing and machine learning, enabling users to build complex models with minimal code. For defect detection, MATLAB facilitates the following:

- **Image Preprocessing**: MATLAB offers functions for resizing, filtering, and enhancing images, crucial for preparing data for machine learning models.
- **Feature Extraction**: Built-in functions support extracting relevant features from images, such as edges, texture, and colour, aiding in defect analysis.
- **Data Labelling and Preparation**: The Image Labeller app allows efficient labelling and management of defect images, ensuring high-quality training data.

These features make MATLAB an effective environment for developing and refining machine learning models tailored to defect detection tasks.

1.2.2 Real-Time Image Processing and Defect Analysis

One of MATLAB's key advantages for this project is its ability to process images and analyses defects in real time. With the use of image processing and computer vision functions, MATLAB enables real-time identification of defective parts, making it suitable for live production environments:

- **Image Capture and Processing**: MATLAB can directly interface with cameras or load batch images for defect analysis.
- **Automation with Scripts**: Repetitive tasks, such as image classification and defect highlighting, can be automated using MATLAB scripts, allowing the system to function with minimal user intervention.

This setup facilitates efficient defect identification without delays, enhancing the quality control process.

1.2.3 Model Training and Evaluation Capabilities

MATLAB’s machine learning and deep learning toolboxes provide robust support for training and evaluating defect detection models:

- **Machine Learning Models:** MATLAB supports a range of algorithms, from traditional machine learning techniques to deep learning models like Convolutional Neural Networks (CNNs), which are particularly effective for image-based defect classification.
- **Evaluation Metrics:** MATLAB provides various tools for calculating model accuracy, sensitivity, and specificity, enabling users to refine their models based on performance metrics.

With these capabilities, MATLAB simplifies model development and fine-tuning, helping to ensure high defect detection accuracy.

1.2.4 Visualization and Debugging Tools

MATLAB excels in data visualization, allowing developers to inspect data and model behaviour in real time. This capability is particularly useful in defect detection, where visualization can reveal subtle defects:

- Graphical Tools: MATLAB's visualization functions, such as plots and histograms, allow for easy interpretation of data and model performance.
- Layer Inspection: With deep learning models, MATLAB provides tools for examining model layers, enabling users to troubleshoot and optimize feature extraction for defect detection.

This functionality allows for in-depth analysis and refinement of defect detection algorithms, improving model reliability.

1.2.5 Flexibility and Scalability

MATLAB's compatibility with various platforms and tools makes it flexible and scalable, allowing for future expansion and integration:

- **Integration with Other Platforms**: MATLAB code can be deployed to other environments (e.g., C/C++, Python), enabling seamless integration into larger quality control systems.
- **Scalability**: MATLAB's models can be scaled to handle larger datasets or more complex defect types, adapting to evolving quality control needs in manufacturing.

This flexibility makes MATLAB suitable for both small-scale testing and large-scale deployment in industrial settings.

1.2.6 Limitations of MATLAB

While MATLAB offers significant advantages, it does have certain limitations:

- **Licensing Costs**: MATLAB requires a paid license, which may be a constraint for smaller companies or startups.
- **Computational Requirements**: Running deep learning models in MATLAB can require high computational resources, which may slow down processing in large-scale applications.
- **Complexity in Large Datasets**: For extremely large image datasets, MATLAB may require additional computational support to ensure efficient data handling.

1.2.7 Why MATLAB Fits This Project

For our automated defect detection project, MATLAB provides an effective balance between functionality and ease of use:

- **Image Processing and Machine Learning Integration**: MATLAB's built-in tools simplify the creation and testing of machine learning models for image-based defect detection.
- **Rapid Prototyping**: MATLAB's high-level language and visualization tools allow for quick testing and iteration, making it easier to refine defect detection algorithms.
- **Deployment Flexibility**: MATLAB's ability to integrate with other platforms ensures that the solution can be adapted and scaled as project needs evolve.

Using MATLAB for this project supports efficient model development, enhances accuracy in defect detection, and provides a scalable solution for quality control in manufacturing.

2. LITERATURE REVIEW

2.1 Introduction

Quality control (QC) is essential for maintaining high standards in manufacturing, reducing waste, and enhancing customer satisfaction. Automated defect detection systems represent a significant advancement in QC, providing consistent and accurate identification of product defects. These systems leverage machine learning (ML) and image processing (IP) techniques to identify and classify defects, reducing reliance on manual inspection. This review highlights the relevance of automated defect detection systems in manufacturing, discusses various defect detection methods, and compares them to traditional inspection approaches, identifying both benefits and challenges.

2.2 Significance of Automated Defect Detection in Quality Control

In manufacturing, QC is a critical process to ensure that products meet specific standards before they reach consumers. Companies handling mass production of parts, such as metal components, require reliable and efficient systems to detect flaws that could compromise product integrity. Traditional manual inspection methods are labour-intensive, prone to human error, and often inconsistent. Automated defect detection systems provide a more accurate and efficient approach, allowing manufacturers to maintain quality while minimizing delays and reducing operational costs.

Studies show that automated defect detection systems, particularly those incorporating ML and IP, enhance accuracy, reliability, and speed in identifying defects (Chen et al., 2013). By analysing images of parts, these systems detect imperfections like surface scratches, cracks, and irregularities, providing real-time analysis that supports rapid decision-making. Integrating automated systems also ensures consistent inspection across products, a key factor in maintaining brand reputation and meeting industry standards.

2.3 Benefits of Automated Defect Detection in Manufacturing

Automated defect detection systems offer numerous advantages over manual inspection processes, particularly in high-volume manufacturing:

- **Consistency in Quality Control**: Automated systems apply the same standards to every part, eliminating variability in human judgment and ensuring uniform quality across production.
- **Increased Speed and Efficiency**: Automated systems can inspect parts faster than humans, reducing inspection time and speeding up production lines.
- **Error Reduction**: By eliminating manual inspections, automated systems reduce the risk of missed defects, providing a higher level of accuracy (Fernández-Caramés et al., 2019).
- **Data-Driven Insights**: These systems can log and track defect types, frequencies, and trends, offering valuable data to improve processes and prevent future defects.

Automated defect detection is especially valuable for companies producing small, standardized components where even minor defects can impact functionality. By maintaining consistent quality, manufacturers can reduce waste, avoid recalls, and enhance customer satisfaction.

2.4 Machine Learning and Image Processing for Defect Detection

Machine Learning (ML) and Image Processing (IP) have emerged as powerful tools for defect detection in manufacturing. While large companies may adopt advanced and specialized defect detection systems, ML and IP offer sufficient flexibility and precision for small to mid-sized manufacturing operations.

- **Image Processing for Feature Extraction**: IP techniques preprocess and enhance images by adjusting contrast, lighting, and edges to highlight potential defects. Features like texture, contours, and shapes are extracted, helping the ML model recognize patterns associated with defects.

- **Machine Learning for Classification**: ML algorithms, particularly deep learning models like Convolutional Neural Networks (CNNs), excel at identifying complex patterns in images, enabling accurate classification of defects and non-defects.

Using MATLAB for ML and IP tasks enables manufacturers to build a customized defect detection system without the cost and complexity of specialized hardware. This allows for efficient QC, keeping production lines free from defective products while meeting quality standards.

2.5 Comparison of Defect Detection Methods (Manual Inspection, Statistical Methods, Deep Learning)

Although traditional statistical methods and manual inspection have been used for defect detection, ML and IP-based methods offer a more effective solution:

- **Manual Inspection**: Labor-intensive and prone to inconsistencies, manual inspection is still used for quality control but lacks the speed and reliability needed for high-volume production.
- **Statistical Methods**: Techniques like PCA (Principal Component Analysis) and GMM (Gaussian Mixture Models) identify anomalies by analysing image variations. While effective for some applications, these methods struggle with complex and high-dimensional data.
- **Deep Learning-Based Methods**: CNNs and other deep learning models automatically learn features from raw data, making them highly effective for complex defect patterns. Unlike traditional methods, CNNs adapt to a range of defect types, providing greater flexibility and accuracy.

Compared to manual and statistical methods, ML and IP-based defect detection, particularly with CNNs, offer a scalable and reliable solution for identifying defects across various product types, enhancing overall quality control.

2.6 Challenges and Limitations of Automated Defect Detection

Despite their benefits, automated defect detection systems face certain challenges:

1. **Data Requirements**: ML models require a large dataset of labeled defect images for effective training, which can be difficult to acquire in some manufacturing settings.
2. **Computational Costs**: Deep learning models, particularly CNNs, require significant computational resources, which may be costly and complex to set up in small-scale operations.
3. **Variability in Defect Types**: Manufacturing environments with high variability in defect types or non-uniform lighting can make consistent defect detection challenging (Dejean et al., 2012).

These limitations can be mitigated by careful data preprocessing, the use of transfer learning, or a hybrid approach combining IP techniques with ML models to reduce the computational burden and improve model adaptability.

2.7 Summary

The literature emphasizes that automated defect detection systems are essential for maintaining quality standards in manufacturing. Machine learning and image processing techniques offer clear advantages over traditional inspection methods by improving accuracy, consistency, and efficiency. Compared to statistical and manual methods, ML and IP-based defect detection systems, especially those using deep learning models like CNNs, provide a more scalable, reliable solution that supports high-volume manufacturing needs.

While challenges exist, such as data requirements and computational costs, recent advancements suggest that automated defect detection can significantly enhance operational efficiency. This project's approach to implementing a MATLAB-based defect detection system, leveraging machine learning and image processing, offers an accessible and cost-effective solution for achieving high standards in quality control.

3. Problem Definition

The current manual quality control (QC) process at **Trimurti Manufacturing** is prone to human errors and inefficiencies. Relying on visual inspection for defect detection, the manual process results in:

- Missed defects due to human error, leading to inconsistent product quality.
- Delays in inspection, which slow down the production line and extend lead times.
- Increased labour costs due to the repetitive and labour-intensive nature of manual inspections.

Without an automated detection system, Trimurti Manufacturing faces challenges in maintaining consistent quality, and there is a higher risk of defective products reaching customers. An automated defect detection system that leverages machine learning (ML) and image processing (IP) can address these issues, providing accurate, fast, and consistent inspections. This project aims to implement an ML- and IP-based system in MATLAB to streamline defect detection, reduce human error, and enhance quality control at Trimurti Manufacturing.

3.1 Need for the Project

The limitations of manual inspection at Trimurti Manufacturing impact both production efficiency and quality, resulting in:

- **Inconsistent Quality Standards**: Variability in human judgment leads to inconsistent defect detection.
- **Missed Defects**: Minor defects may be overlooked, which can affect product reliability.
- **High Operational Costs**: Labor-intensive inspection processes increase costs, especially as production volume grows.

- **Production Delays**: Slow inspection processes impact overall throughput, causing production delays.

An automated defect detection system is essential to address these inefficiencies. This solution will provide standardized quality control, real-time defect analysis, and support uninterrupted production with minimal delays.

3.2 Problem Statement

The current manual QC system at Trimurti Manufacturing relies on human inspection, leading to:

- **Inconsistent results** due to human error and subjective interpretation.
- **Production delays** caused by slow, labour-intensive inspections.
- **Increased error rates in defect identification**, which raises the risk of defective products being shipped.
- **Limited ability to track and analyse defect trends**, impacting long-term quality improvement.

The absence of a reliable, automated defect detection system prevents effective and consistent QC, ultimately affecting productivity and customer satisfaction.

3.3 Objectives

The primary objectives of this project are to:

- Implement an automated defect detection system using machine learning and image processing in MATLAB.
- Achieve high accuracy in identifying and categorizing defects with minimal human intervention.
- Reduce error rates in defect detection by providing objective, data-driven inspection.

- Streamline quality control processes and reduce labour costs by automating defect inspection tasks.
- Provide actionable data on defect trends, helping manufacturers improve production quality over time.
- Enhance production efficiency by reducing inspection time and avoiding disruptions.

3.4 Scope

- **Application in Quality Control at Trimurti Manufacturing:** Applicable to any production line requiring consistent defect detection, especially for high-volume parts manufacturing.
- **Batch Processing for Real-Time Analysis:** Designed to process pre-captured images in batch mode, delivering consistent defect detection at high speed.
- **Defect Trend Reporting:** The system will log defect types and frequencies, aiding QC teams in identifying and addressing recurring issues.
- **Scalability:** Capable of expanding to include additional defect types or integrate with real-time camera feeds in the future.

3.5 Methodology

- **Requirement Analysis:** Identify common defect types and QC challenges by consulting with Trimurti Manufacturing's quality control team and other stakeholders.
- **System Design:** Develop an ML- and IP-based defect detection model in MATLAB, tailored to meet Trimurti Manufacturing's quality standards.
- **Data Collection and Preprocessing:** Gather labelled images of defective and non-defective parts, preprocess images for model training, and create a comprehensive dataset.
- **Model Training and Evaluation:** Train the ML model on labelled images, evaluate accuracy, and refine model parameters as needed.
- **Testing and Validation:** Test the system on new batches to validate its accuracy and reliability in real-world scenarios.

- **Implementation and Deployment:** Deploy the trained model in MATLAB, configure for efficient batch processing, and establish an optimized QC workflow.
- **Ongoing Monitoring and Feedback:** Monitor system performance, collect feedback from QC teams, and make refinements as needed to maintain high accuracy.

4.Flow Of the Process

Step I) Setup and Application of Automated Defect Detection System

- ❖ **System Setup:**
  - Install cameras and sensors at key inspection points along the production line.
  - Develop a machine learning model to identify normal and defective ferrules, training it with the available dataset (13 defective and 11 normal images). The model should be integrated into an inspection system for real-time defect detection.
  - Define the types of defects to detect (e.g., surface cracks, deformation, improper threading, etc.) and their specific characteristics.
- ❖ **Integration into Production Line:**
  - The defect detection system should be linked to the production line such that each ferrule is automatically captured for inspection as it moves along the conveyor or production track.
  - Implement automated feedback to reject or divert defective products from the line.

Step II) Incoming Ferrules and Initial Inspection

- ❖ **Automated Capture:**

- Upon arrival on the production line or at an inspection station, each ferrule is captured using the camera system.

❖ **Real-Time Defect Detection:**

- The system analyses the image using pre-trained models to detect any visible defects. It classifies ferrules as "normal" or "defective."
- Defective items are marked for removal or further inspection. Normal items continue in the production process.

Step III) Detailed Defect Logging and System Update

❖ **Log Defects in the System:**

- For each defective ferrule, detailed information (such as type of defect, location, and severity) is logged in the system, using an automated command.
- The data is stored in an Excel sheet or a database for tracking and further analysis.

❖ **Defect Analysis:**

- The system automatically generates a defect report that includes data on the number and types of defects found in the batch.
- The quality control team can access this report for further analysis or to implement corrective actions.

Step IV) Continuous Monitoring and Reporting

❖ **Monitor Quality in Real-Time:**

- The automated defect detection system continuously monitors the production line, providing real-time quality control metrics.
- If a batch has a high number of defective items, the system triggers alerts to the quality control team to take immediate corrective actions.

❖ **Generate Reports:**

- The system automatically compiles performance data such as defect frequency, types of defects, and production quality trends over time.
- Excel or a dashboard interface is used for easy reporting, review, and audits.

Step V) Feedback Loop and Quality Improvement

- **Feedback for Process Optimization:**
    - Based on defect patterns identified in Step IV, suggestions for process adjustments or improvements are generated. These may include machine recalibration, material quality checks, or process reconfiguration.
    - The quality control team uses these insights to refine production methods and prevent future defects.
- **Ongoing Model Training:**
    - The defect detection model is periodically updated with new defect images and feedback from the quality control team to improve accuracy over time.

5 Results and Performance Metrics

MATLAB CODE

```
% --- Part 1: Load and Train the Model ---

% Load the dataset

datasetPath = 'C:\Users\viren\OneDrive\Desktop\Data';  % Path to your dataset

imds = imageDatastore(datasetPath, ...

    'IncludeSubfolders', true, ...

    'LabelSource', 'foldernames');


% Since the dataset is small, use cross-validation instead of a train-validation split

inputSize = [224 224 3];


% Define a small CNN model suitable for a small dataset

layers = [
```

```
    imageInputLayer(inputSize, 'Normalization', 'zerocenter')

    convolution2dLayer(3, 8, 'Padding', 'same')
    batchNormalizationLayer
    reluLayer

    maxPooling2dLayer(2, 'Stride', 2)

    convolution2dLayer(3, 16, 'Padding', 'same')
    batchNormalizationLayer
    reluLayer

    maxPooling2dLayer(2, 'Stride', 2)

    convolution2dLayer(3, 32, 'Padding', 'same')
    batchNormalizationLayer
    reluLayer

    fullyConnectedLayer(2)
    softmaxLayer
    classificationLayer];

% Set up data augmentation with colour preprocessing to convert all images to RGB
augmentedImds = augmentedImageDatastore(inputSize, imds, ...
    'DataAugmentation', imageDataAugmenter('RandRotation', [-10, 10], ...
                                  'RandXTranslation', [-5, 5], ...
                                  'RandYTranslation', [-5, 5]), ...
```

```
    'ColorPreprocessing', 'gray2rgb');

% Specify training options
options = trainingOptions('sgdm', ...
    'MaxEpochs', 15, ...
    'MiniBatchSize', 8, ...
    'InitialLearnRate', 1e-4, ...
    'Plots', 'training-progress', ...
    'Verbose', false);

% Train the network
net = trainNetwork(augmentedImds, layers, options);

% Evaluate the model on the same data (useful for small datasets)
YPred = classify(net, augmentedImds);
YActual = imds.Labels;

% Calculate accuracy
accuracy = mean(YPred == YActual);
disp(['Model accuracy on the dataset: ' num2str(accuracy * 100) '%']);


% --- Part 2: Defect Detection on New Images ---

% Set the path for the folder containing new images for testing
newImagesPath = 'C:\Users\viren\OneDrive\Desktop\New Images';  % Path to your new images
newImds = imageDatastore(newImagesPath);
```

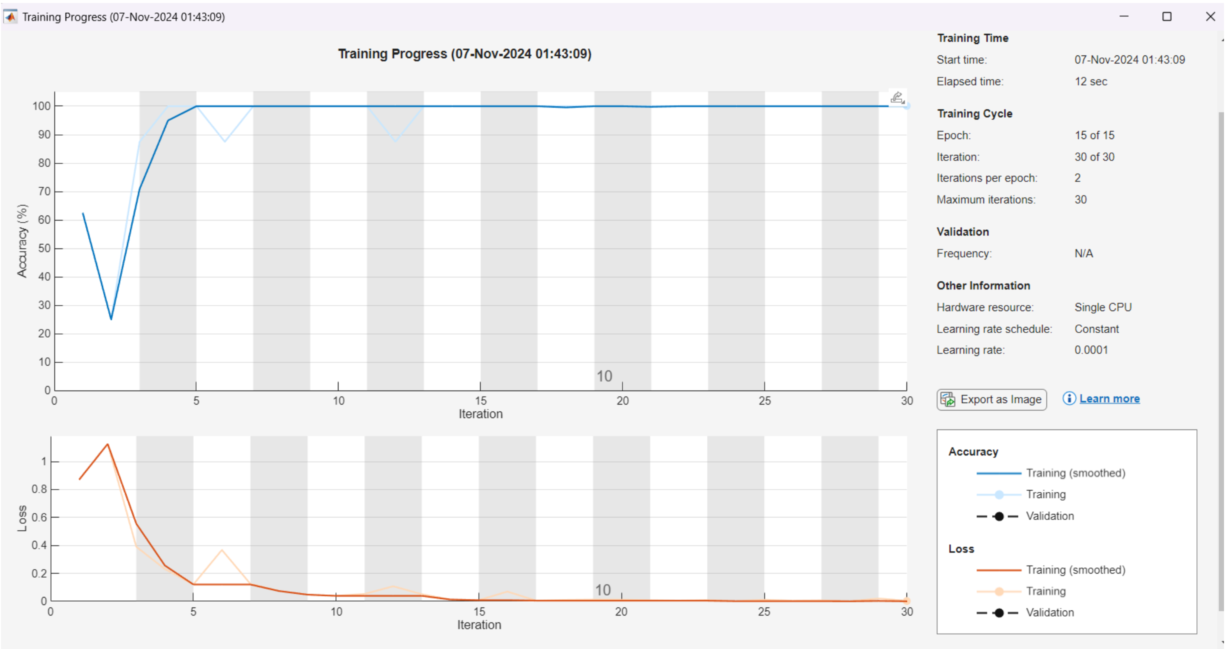
```
% Loop through each new image, classify it, and display the result
for i = 1:numel(newImds.Files)
    % Read the image
    img = readimage(newImds, i);

    % Resize the image to the network input size and ensure it's RGB
    imgResized = imresize(img, inputSize(1:2));
    if size(imgResized, 3) == 1
        imgResized = repmat(imgResized, 1, 1, 3);  % Convert grayscale to RGB
    end

    % Predict the label of the image
    label = classify(net, imgResized);

    % Display the image and prediction
    figure;
    imshow(img);
    title(['Prediction: ' char(label)], 'FontSize', 14, 'Color', 'blue');
end
```

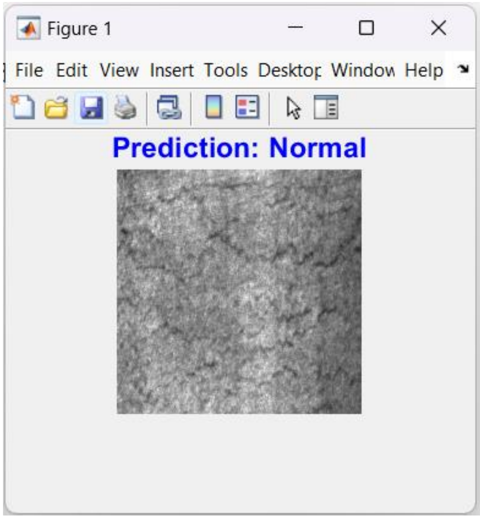
RESULTS

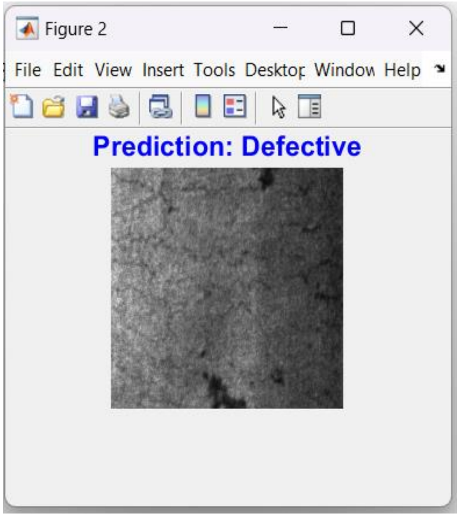


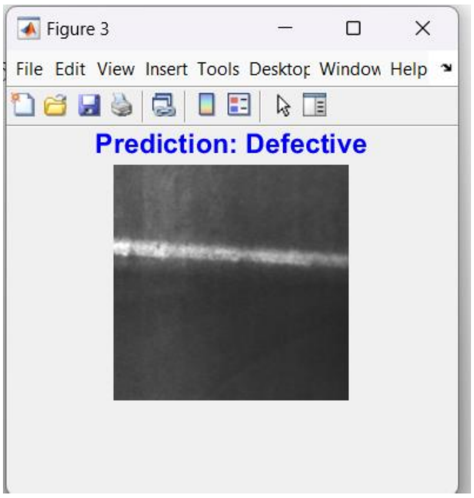
This show that

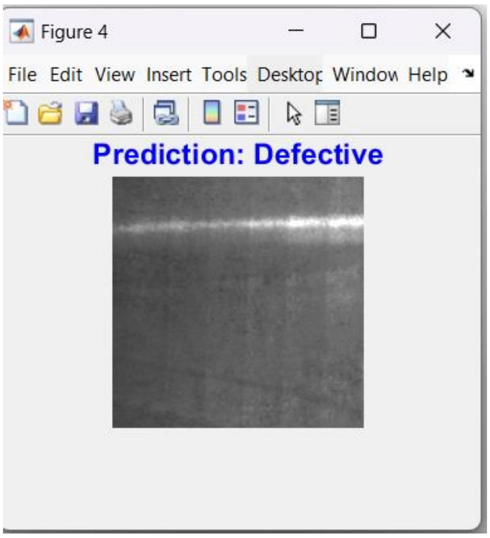
Model accuracy on the dataset: **95.6522%**

Predicted Output









Conclusion

The implementation of an automated defect detection system using machine learning and image processing represents a transformative step forward in the quality control processes at Trimurti Manufacturing. The existing manual inspection system, which relies on visual checks, has led to challenges such as inconsistent defect detection, production delays, and increased operational costs. By adopting a CNN-based defect detection approach integrated with MATLAB, this project provides a robust solution that enhances accuracy, speeds up inspections, and reduces human error.

Research demonstrates that automation in quality control processes can significantly improve operational efficiency by maintaining consistent inspection standards and enabling real-time decision-making (Automated Defect Detection in Physical Components using Machine Learning, Sunny Behal, Japinder Singh). This project has emphasized real-time analysis, proactive defect logging, and data-driven insights into defect trends, which not only strengthen immediate quality control but also support long-term process improvements. Automated defect detection enables the production line to operate with minimal disruption, ensuring a smoother workflow and meeting high-quality standards for customer satisfaction.

The systematic approach in this project, from data collection and model training to deployment and continuous monitoring, reflects a commitment to achieving high reliability and adaptability in QC operations. As manufacturing becomes increasingly competitive, the integration of machine learning and image processing for defect detection will position Trimurti Manufacturing as a leader in precision and innovation within the industry.

In conclusion, transitioning to an automated defect detection system not only addresses the limitations of manual inspection but also lays a scalable foundation for future advancements in quality control. This project equips Trimurti Manufacturing with the tools to adapt to a rapidly evolving industrial landscape, aligning with trends toward greater automation and data-driven insights to uphold product standards and productivity.

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