### **Defect Detection in Manufacturing using AI**

**Author:** Sneha Kumari

#### 1. Introduction

In modern manufacturing, ensuring product quality is critical to maintaining competitiveness and customer satisfaction. Manual inspection of surface defects is labor-intensive, error-prone, and often inconsistent. This project presents an AI-powered **Defect Detection System** designed to automatically identify and classify surface defects in manufacturing materials using **Computer Vision** and **Deep Learning**. The system leverages Convolutional Neural Networks (CNNs) to detect six common types of surface defects, enabling faster, accurate, and real-time quality control.

### 2. Objectives

- Automate the identification of surface defects in manufacturing materials.
- Classify defects into six predefined categories: Crazing, Inclusion, Pitted Surface, Scratches, Rolled-in Scale, and Patch.
- Provide a simple, user-friendly interface for real-time defect detection.
- Facilitate data logging and reporting for industrial quality assurance.

#### 3. Dataset

The project uses the **NEU Surface Defect Database (NEU-DET)**, which contains steel surface images labeled into six defect categories:

### **Defect Type Description**

Crazing Fine cracks on the surface

Inclusion Embedded foreign particles

Pitted Surface Small depressions or holes

Scratches Surface scratches

Rolled-in Scale Material scale rolled into the surface

# **Defect Type** Description

Patch Uneven surface patches

The dataset is split into training and validation subsets, with images organized in corresponding class folders.

**Source:** NEU Surface Defect Database (NEU-DET)

### 4. Methodology

### 4.1 Data Preprocessing

- Images resized to 128×128 pixels.
- Normalization of pixel values to [0,1] range.
- Data augmentation (rotation, flipping, and scaling) applied to improve model generalization.

### **4.2 Model Architecture**

• Type: Convolutional Neural Network (CNN)

• Framework: TensorFlow / Keras

• Input: 128×128 RGB images

• Output: 6 classes

• **Optimizer:** Adam

• Loss Function: Categorical Cross-Entropy

• Validation Accuracy: ~94%

### 4.3 Training

• Data split: 80% training, 20% validation

Batch size: 32

• Epochs: 50

• Early stopping and model checkpoints implemented to prevent overfitting.

### 4.4 Deployment

- Streamlit web application for real-time defect detection.
- Users can upload an image, and the model predicts the defect type along with the confidence score.

### 5. Tech Stack

# **Languages & Libraries:**

- Python
- TensorFlow / Keras
- NumPy
- Pillow
- Streamlit

### Tools:

- Jupyter Notebook
- VS Code

# **Project Structure:**

## 6. Results

- The trained CNN model achieved a validation accuracy of ~94%, demonstrating strong capability in identifying surface defects.
- Example predictions:

### **Input Image Predicted Output**

Scratches (Confidence: 0.99)

Inclusion (Confidence: 0.97)

• Streamlit UI allows operators to upload images and receive instant defect predictions.

### 7. Advantages

- Reduces human error and manual inspection efforts.
- Real-time defect detection suitable for industrial production lines.
- Provides extensible data logging for quality control dashboards.
- Simple, intuitive interface for non-technical operators.

#### 8. Future Work

• Integrate live camera feed for continuous real-time defect detection.

- Expand dataset to cover additional materials beyond steel.
- Deploy using cloud platforms such as AWS or Streamlit Cloud for scalability.
- Implement **feedback-based retraining** to improve model performance over time.

### 9. Installation & Usage

### Clone the repository:

git clone https://github.com/yourusername/defect\_detection\_project.git cd defect\_detection\_project

### **Install dependencies:**

pip install tensorflow keras streamlit numpy pillow matplotlib

### Run the application:

streamlit run app.py

**Usage:** Upload an image from the validation set or new material image. The model predicts the defect type with confidence.

#### 10. Conclusion

This project demonstrates how **Al-powered computer vision** can effectively automate surface defect detection in manufacturing. By using CNNs, the system achieves high accuracy in identifying defects while providing a real-time, user-friendly interface. The framework can be extended to integrate with industrial production lines, improving overall product quality, efficiency, and operational consistency.

#### 11. References

- NEU Surface Defect Database (NEU-DET) NEU Surface Defect Database
- TensorFlow Documentation <u>TensorFlow</u>
- Keras Documentation <u>Keras: Deep Learning for humans</u>
- Streamlit Documentation Streamlit A faster way to build and share data apps