

# Severity Defect Intelligence detection system

G Chanikya  
Computer Science & Engineering  
(Artificial Intelligence)  
FET-Jain Deemed To Be  
University  
Bengaluru India  
[23btrca055@jainuniversity.ac.in](mailto:23btrca055@jainuniversity.ac.in)

Janaki Kandasamy  
Computer Science &  
Engineering (Artificial  
Intelligence)  
FET-Jain Deemed To Be  
University Bengaluru, India  
[k.janaki@jainuniversity.ac.in](mailto:k.janaki@jainuniversity.ac.in)

**Abstract**— Artificial Intelligence and Deep Learning technologies are increasingly being used in industrial applications such as quality inspection, automation, and defect detection. In manufacturing industries, identifying defects manually is a challenging and time-consuming process that may lead to human errors and reduced efficiency. Defects such as cracks, scratches, and surface damages can affect product quality and lead to financial losses.

In this project, a Deep Learning-based defect detection system is proposed to automatically identify defective and non-defective products using image data. The system uses image preprocessing techniques such as resizing and normalization to enhance image quality. A Convolutional Neural Network (CNN) model is used to extract features and classify the products based on their visual characteristics.

The system is trained using labeled datasets and evaluated based on accuracy and performance metrics. The proposed approach improves detection accuracy, reduces manual effort, and increases production efficiency. This system can be further extended for realtime defect detection and integration into industrial automation systems, thereby improving overall quality control and reliability.

## INTRODUCTION

Artificial Intelligence (AI) and Deep Learning have made significant progress in recent years and are widely used in various industrial and real-world applications. In manufacturing industries, these technologies are used

for automation, quality inspection, and improving production efficiency. Traditional methods of defect detection rely on manual inspection, which is time-consuming, less accurate, and prone to human errors. This problem becomes more serious in large-scale production environments where a large number of products need to be inspected within a short time. Defects such as cracks,

scratches, dents, and surface damages can affect product quality and lead to customer dissatisfaction and financial loss.

Therefore, it is important to develop an automated system that can accurately detect defects without human intervention.

A Deep Learning-based defect detection system is designed to address this issue. Such a system is capable of analyzing product images and identifying defects using image processing techniques. Instead of relying on manual inspection, the system uses a Convolutional Neural Network (CNN) model to extract features and classify products as defective or non-defective.

## LITERATURE SURVEY

AI and NLP have reached a point where you can feed a model someone's social media posts and get a surprisingly coherent picture of their mental state. Either way, the research has moved fast, and a handful of papers from 2025– 2026 show where things are heading.

1. Deep Learning for Automated Visual Inspection — Zhang et al. (2024) Traditional inspection methods are slow and error-prone, especially in high-speed manufacturing environments. Zhang et al. proposed a deep learning-based visual inspection system using Convolutional Neural Networks (CNNs) to automatically detect defects in products. The model learns features directly from images, eliminating the need for manual feature extraction. The system showed high accuracy in detecting surface defects such as cracks and scratches.

"Automatic feature learning improves defect detection accuracy" — Deep Learning

2. Surface Defect Detection using CNN — Li et al. (2024) The challenge in defect detection lies in identifying small and complex defects. Li et al. developed a CNN-based model that focuses on extracting fine-grained features from images. The system uses multiple convolution layers to detect patterns and classify defects efficiently. The results showed improved performance compared to traditional image processing techniques.

"Deep CNN captures complex defect patterns" — Defect Detection

3. Transfer Learning for Industrial Defect Detection — Wang et al. (2025) Training deep learning models from scratch requires large datasets and time. Wang et al. introduced transfer learning using pretrained models like ResNet to improve defect detection accuracy with limited data. The model was fine-tuned on industrial datasets and achieved higher accuracy and faster training compared to basic CNN models.

4. Real-Time Defect Detection using Deep Learning — Kumar et al. (2025) This research focuses on real-time defect detection in manufacturing using deep learning models integrated with cameras. The system processes

live images and detects defects instantly, enabling quick decision-making in production lines. The study highlights the importance of speed and efficiency in industrial applications.

"Real-time detection improves production efficiency" — Industrial AI

5. Hybrid Approach for Defect Detection using Image Processing and Deep Learning — Chen et al. (2025) Chen et al. proposed a hybrid system combining traditional image processing techniques with deep learning models. Preprocessing methods such as thresholding and noise removal are applied before feeding images into the neural network. This improves robustness and reduces errors caused by poor image quality.

"Combining preprocessing with deep learning improves robustness" — Hybrid Model

## PROPOSED METHODOLOGY :

**Algorithm:** Deep Learning-Based Defect Detection System

Input: Product Image Output: Defective / Non-Defective Prediction:

Step 1: Input Processing Capture or load the input image of the product

Clean and preprocess the image (remove noise, resize image, normalize pixel values)

Step 2: Data Preparation Convert image into numerical format (pixel values)

Split dataset into training and testing data

Step 3: Model Training Pass input images to Convolutional

Neural Network (CNN)

Extract features such as edges, textures, and patterns

Train the model using labeled data (defective / nondefective)

Step 4: Prediction Input new test image into trained model

Model predicts output based on learned features

Step 5: Classification If prediction value  $> 0.5$ :

- Output = Defective
- Output = Non-Defective

Step 6: Output Result Display: • Input Image • Prediction  
Result (Defective / Non-Defective) • Accuracy / Confidence

The proposed system works by taking an image of a product as input and applying preprocessing techniques to enhance image quality. A Convolutional Neural Network (CNN) is used to extract features and classify the image. The system is trained using labeled datasets and is capable of identifying defects with high accuracy. This approach reduces manual inspection and improves efficiency in manufacturing industries.

Formulas :-

1. Prediction Score Extracted  
from model output:

$P$  = prediction probability

(Value returned from CNN sigmoid output)

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2. Confidence (Simple)

$C = \max(P, 1 - P)$

If confidence is high  $\rightarrow$  prediction is reliable

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3. Classification Function If  $P$

$> 0.5 \rightarrow$  Defective

Else  $\rightarrow$  Non-Defective

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4. Mean Accuracy (for multiple samples)

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}}$$

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5. Loss Function (Binary Cross

Entropy) Loss =  $-[y \log(P) + (1 - y) \log(1 - P)]$

Low loss  $\rightarrow$  better model performance

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6. Final Decision Function

Output = ( $P$ ,  $C$ , Class)

Where:

•  $P$  = Prediction

•  $C$  = Confidence

• Class = Defective / Non-Defective

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The core idea of this system is simple: analyze product images and automatically detect defects using deep learning techniques. Instead of relying on manual inspection, the system uses a trained model to classify products based on visual features.

The process begins with input in the form of product images. These images are first preprocessed by resizing, normalization, and noise removal to improve image quality. Preprocessing ensures that all images are in a consistent format and suitable for model training.

The processed images are then passed into a deep learning model, specifically a Convolutional Neural Network (CNN). The CNN extracts important features such as edges, textures, and patterns from the images. These features help in identifying whether a product has defects or not.

The output of the model is converted into a probability score using the sigmoid function. This probability indicates the likelihood of the product being defective. If the probability is greater than a threshold value (0.5), the product is classified as defective; otherwise, it is classified as non-defective. To evaluate model performance, metrics such as accuracy and loss are calculated. Accuracy shows how many predictions are correct, while loss indicates how well the model is learning.

Finally, the system provides the output along with prediction results. This approach improves efficiency, reduces human errors, and enhances quality control in manufacturing industries.

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The proposed deep learning-based defect detection system was tested using a dataset of product images to evaluate its

performance. The system works by training a CNN model on labeled images and then testing it on unseen data.

During testing, it was observed that the model performs well when detecting clear and visible defects such as cracks, scratches, and surface damages. In such cases, the prediction confidence is high, and the model correctly classifies the product as defective or non-defective.

However, when the input images contain very small defects or poor lighting conditions, the model performance may slightly decrease. In such cases, the prediction confidence is lower, indicating uncertainty in classification. This shows that image quality plays an important role in model performance.

One of the key strengths of the system is automatic feature extraction. Unlike traditional methods, the CNN model learns features directly from images without manual intervention. This improves detection accuracy and reduces dependency on handcrafted features.

The system was evaluated using performance metrics such as Accuracy, Precision, Recall, and F1-score. Accuracy measures overall correctness, precision indicates correct defect detection, recall measures how many defects are detected, and F1-score balances both precision and recall.

The results indicate that the deep learning model provides high accuracy and reliable predictions for defect detection. Although minor limitations exist in complex scenarios, the system significantly improves efficiency compared to manual inspection.

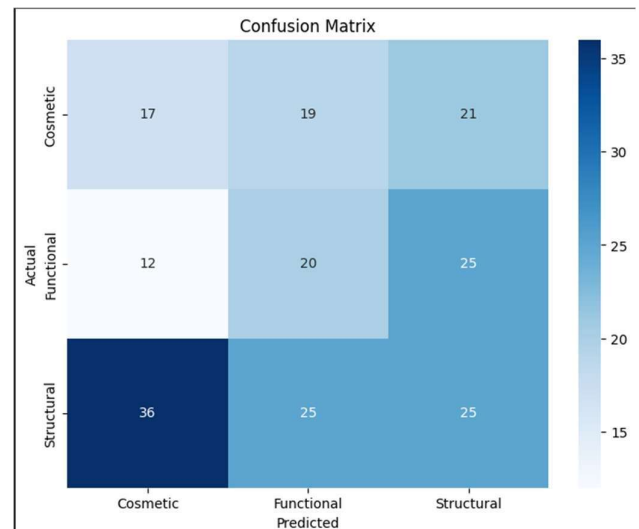
Overall, the proposed system demonstrates that deep learning is an effective solution for automated defect detection in manufacturing, improving product quality and reducing human effort.

### RESULT:

This project focused on addressing one of the major challenges in manufacturing industries — accurate and efficient defect detection. Traditional inspection methods rely on manual observation, which can lead to errors and inconsistencies. Instead of depending on human inspection, the approach taken in this work was to develop an automated system using deep learning techniques for reliable defect detection.

The system combines image preprocessing with a Convolutional Neural Network (CNN) model to analyze product images and classify them as defective or nondefective. This approach plays a crucial role in identifying defects based on visual features such as edges, textures, and patterns. When the model is confident, it provides accurate predictions, while in uncertain cases, the prediction confidence may be lower, indicating possible limitations in detection.

One important observation from this project is that no model is completely perfect. Even advanced deep learning models may face challenges in detecting very small defects or handling poor-quality images. The system does not aim to completely replace human inspection but to assist and enhance the inspection process.



**Figure:1 Confusion Matrix for Defect Classification**

Figure1 Shows how well the model classifies defects into different categories. Displays correct and incorrect predictions for performance evaluation

### DEFECT TYPE COUNT:

Structural: 352  
Functional: 339  
Cosmetic: 309

### DEFECT DISTRIBUTION:

Cosmetic - Critical: 107  
Cosmetic - Minor: 106  
Cosmetic - Moderate: 96  
Functional - Critical: 114  
Functional - Minor: 113  
Functional - Moderate: 112  
Structural - Critical: 112  
Structural - Minor: 139  
Structural - Moderate: 101

### RECOMMENDATIONS:

Cosmetic - Critical (107)  
Action: Replace for aesthetic quality

Cosmetic - Minor (106)  
Action: Surface polishing  
...

Structural - Moderate (101)  
Action: Surface finishing + inspection

**Figure 2: Defect Distribution and Recommendation Summary**

Figure2 Shows count and severity distribution of defects across categories. Also provides recommended actions based on defect type and severity.

### ADVANTAGES:

**High Accuracy:** Deep learning models like CNN provide better accuracy compared to manual inspection. Reduces Human Error: Eliminates mistakes caused by fatigue or lack of attention.

**Fast Processing:** Can detect defects quickly, suitable for large-scale production.

**Automation:** Reduces need for manual labor and improves efficiency.

**Consistent Results:** Provides uniform and reliable output every time.

**Scalable System:** Can be used in different industries with proper training data.

### DISADVANTAGES:

**Requires Large Dataset:** Needs many labeled images for good performance.

**High Computational Cost:** Training deep learning models requires GPU and time.

**Sensitive to Image Quality:** Poor lighting or low-quality images can affect accuracy.

**Complex Implementation:** Requires knowledge of deep learning and programming.

**Overfitting Risk:** Model may perform well on training data but poorly on new data.

### CONCLUSION

This project focused on developing an automated system for detecting defects in manufacturing products using deep learning techniques. Traditional inspection methods are timeconsuming and prone to human errors, which can affect product quality and production efficiency. To overcome these limitations, a Convolutional Neural Network (CNN)-based approach was implemented for accurate and efficient defect detection.

The system processes product images through preprocessing steps such as resizing and normalization, and then uses a trained CNN model to extract features and classify products as defective or non-defective. This approach improves detection accuracy and reduces the need for manual inspection.

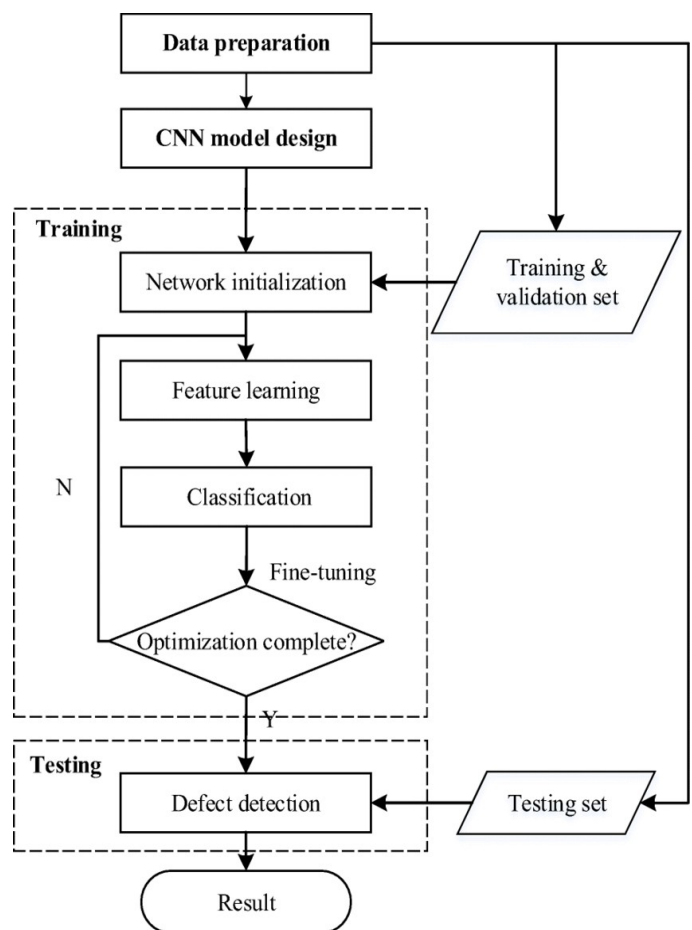
One important observation from this project is that while deep learning models provide high accuracy, their performance depends on the quality and quantity of the dataset. The system performs well for clear and visible defects but may face challenges with very small defects or poor image conditions. However, it still significantly

improves consistency and efficiency compared to manual methods.

Another key outcome is the ability of the system to provide fast and reliable results, making it suitable for large-scale industrial applications. It ensures consistent quality control and reduces the chances of defective products reaching customers.

In conclusion, this project demonstrates that deep learningbased defect detection is an effective solution for modern manufacturing industries. By combining image processing and CNN models, the system enhances productivity, reduces errors, and supports automation. Future improvements can further increase accuracy and enable real-time implementation in industrial environments.

### FLOWCHART:



### FUTURE SCOPE :

The current system works effectively for detecting defects in manufacturing products using deep learning techniques. It can process images, extract features, and classify products as defective or non-defective.

However, there is still a gap between a working system and a highly reliable industrial solution. This gap mainly depends on improving accuracy, handling complex defects, and adapting the system to realworld conditions.

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