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SHEET METAL SURFACE DEFECT DETECTION

Dr. Kannan K[1], Dinesh K[2], Arun Pratop K[3]
Professor & Head [1], Mechatronics Engineering, Kamaraj College of Engineering & Technology, Virudhunagar, Tamil Nadu, India
Department of Mechatronics Engineering [1,2], Kamaraj College of Engineering & Technology, Virudhunagar, Tamil Nadu, India

Abstract:
Detecting surface defects is essential for ensuring product quality and reducing waste in industrial environments. Conventional techniques typically depend on manual inspections or rudimentary automated Systems, which can be both labor intensive and prone to inaccuracies. This work presents an innovative solution utilizing Mask R-CNN, a cutting-edge deep learning framework designed for object detection and segmentation- Mask R-CNN is particularly adept at recognizing and outlining defects on intricate industrial surfaces by delivering accurate segmentation masks and bounding boxes. The model is trained On the NEU Surface Defect Database, which features a wide variety of defect images to ensure robust performance. To implement the Mask IR-CNN model in a real-time industrial setting, Raspberry Pi is employed, effectively running the defect detection model for onsite evaluations and prompt feedback. The system incorporates an LED-based feedback mechanism, facilitating swift and intuitive responses to detected defects, thereby improving operational efficiency and minimizing errors. Results indicate that the Mask R-CNN model successfully identifies and segments defects with a high degree of accuracy. The Raspberry Pi adeptly handles real-time processing and integrates with LED indicators, offering immediate and clear feedback.
Keywords: surface defects, product quality mask R-CNN, deep learning, segmentation, NEU surface defect database, real time processing.

1. Introduction:

1.1 Background on Surface Defect Detection:

Surface defect detection plays a critical role in manufacturing and quality assurance, ensuring that products meet industry standards. Identifying defects such as scratches and dents is essential for maintaining product integrity, reducing waste, and lowering production costs. Traditional methods, including manual inspections and basic image processing, are labour-intensive and prone to errors. However, advancements in computer vision have enhanced automation, enabling more precise, efficient, and consistent defect detection. Modern systems leverage deep learning algorithms to identify even subtle surface irregularities. Among these, Mask R-CNN has emerged as a preferred model due to its superior accuracy in detecting and segmenting defects compared to conventional techniques.

Respective meanings. By translating gestures into audible speech, the Digital Vocalizer facilitates real-time communication, breaking down the barriers that mute and deaf individuals face daily.

Our prototype focuses on creating a portable and user-friendly device that supports two-way communication. By converting specific hand gestures into audible speech, we aim to provide a practical solution that bridges the communication gap, promoting inclusivity and understanding.

This document outlines the design, implementation, and testing of the Digital Vocalizer system, detailing the hardware and software components involved. Our goal is to contribute to the

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development of assistive technologies that empower differently-abled individuals and foster a more inclusive society.

1.2 Overview of Mask R-CNN:

Mask R-CNN is a deep learning framework designed for image segmentation. It builds upon the Faster R-CNN architecture by incorporating a mask prediction branch, enabling pixel-level precision for tasks like surface defect detection. The system consists of two key components: the Region Proposal Network (RPN), which identifies potential object bounding boxes, and the mask prediction module, which generates binary masks to outline detected objects accurately. This two-stage approach allows Mask R-CNN to effectively recognize and separate multiple objects, even in cases of overlap or partial occlusion, making it highly suitable for defect detection applications.

1.3 Role of Raspberry Pi in Edge Computing:

In edge computing, the Raspberry Pi, a popular single-board computer, provides a small and affordable real-time processing option. It decreases reliance on centralized infrastructures and minimizes latency and bandwidth problems by processing data close to the source, in contrast to standard cloud-based systems. It is perfect for applications with limited space and energy because of its compact size and low power consumption. The Raspberry Pi effectively operates lightweight deep learning models, allowing data to be sent to distant servers with ease. It performs the Mask R-CNN model in this study, analyses camera pictures, finds surface flaws, and gives instant visual feedback via an integrated LED system. For firms looking for effective defect detection systems, its price and adaptability make it a desirable option.

1.4 Objectives:

The goal of this project is to use the Mask R-CNN model and a Raspberry Pi to develop a real-time surface defect detection system. Camera-captured photos will be analysed by the system, which will also segment and detect flaws and give immediate visual feedback. When a flaw is found, a red LED will turn on, and a green LED will show that there are no flaws. The goal is to improve the accuracy and efficiency of real-time defect identification during manufacturing by improving the Mask R-CNN model on Raspberry Pi. Furthermore, the incorporation of a dependable LED-based feedback system would facilitate the prompt evaluation of flaws by operators. By encouraging the use of edge computing technologies in manufacturing, this strategy lowers waste and improves product quality.

2. Literature Survey:

The paper "Steel Surface Defect Detection Algorithm Based on Improved YOLOv8n" by Feng Xiao et al. introduces an enhanced YOLOv8n model for detecting steel surface defects. The study improves detection accuracy and efficiency, addressing challenges related to small and complex defects often missed by conventional methods. By modifying the YOLOv8n architecture with deep learning techniques, the authors enhance feature extraction and localization precision. Their approach, compared with existing methods, demonstrates significant improvements in detection speed and accuracy, contributing to automated quality control in industrial applications.

The paper "Computer Vision for Industrial Defect Detection" by Johannes Landgraf et al. explores computer vision techniques for detecting defects in sheet metal production. The study discusses machine learning and image processing applications in automating surface defect detection. Various methods are evaluated for accuracy and real-time performance, considering challenges such as lighting conditions, complex textures, and defect variations. The research highlights the potential of computer vision to improve efficiency and quality control while addressing limitations and future developments in industrial defect detection.

The paper "A Survey of Vision-Based Methods for Surface Defect Detection and Classification in Steel Products" by Alaa Aldein M. S. Ibrahim and Raymond Tapamo provides a comprehensive

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review of vision-based techniques for steel defect detection. It analyses traditional and deep learning approaches, including image processing,

Machine learning, and neural networks. The survey emphasizes accuracy, computational efficiency, and real-time applicability. The shift toward deep learning for improved performance in complex defect scenarios is discussed, along with challenges in industrial implementation. The study offers insights into current trends and future research directions.

The paper "Surface Defect Detection of 'Yuluxiang' Pear Using Convolutional Neural Network with Class-Balance Loss" by Haixia Sun et al. presents a CNN-based method for detecting defects in Yuluxiang pears. The study addresses the issue of imbalanced datasets, where defective samples are significantly fewer than non-defective ones, reducing detection accuracy in traditional models. By integrating a class-balance loss function, the authors enhance CNN performance, improving defect detection in underrepresented classes.

The paper "Automatic Detection and Classification of Steel Surface Defects Using Deep Convolutional Neural Networks" by Shuni Wang et al. explores CNN-based automation for detecting and classifying steel surface defects. The proposed model effectively recognizes defects of varying shapes and sizes. Trained on a comprehensive dataset, the model achieves high accuracy in both detection and classification, outperforming traditional machine learning techniques in precision and speed. The study underscores the role of deep learning in enhancing quality control and reducing manual inspection efforts in steel manufacturing.

3. Methodology:

3.1. Proposed System:

The Fig, I show the experimental blocks of proposed steel plate defect detection system,

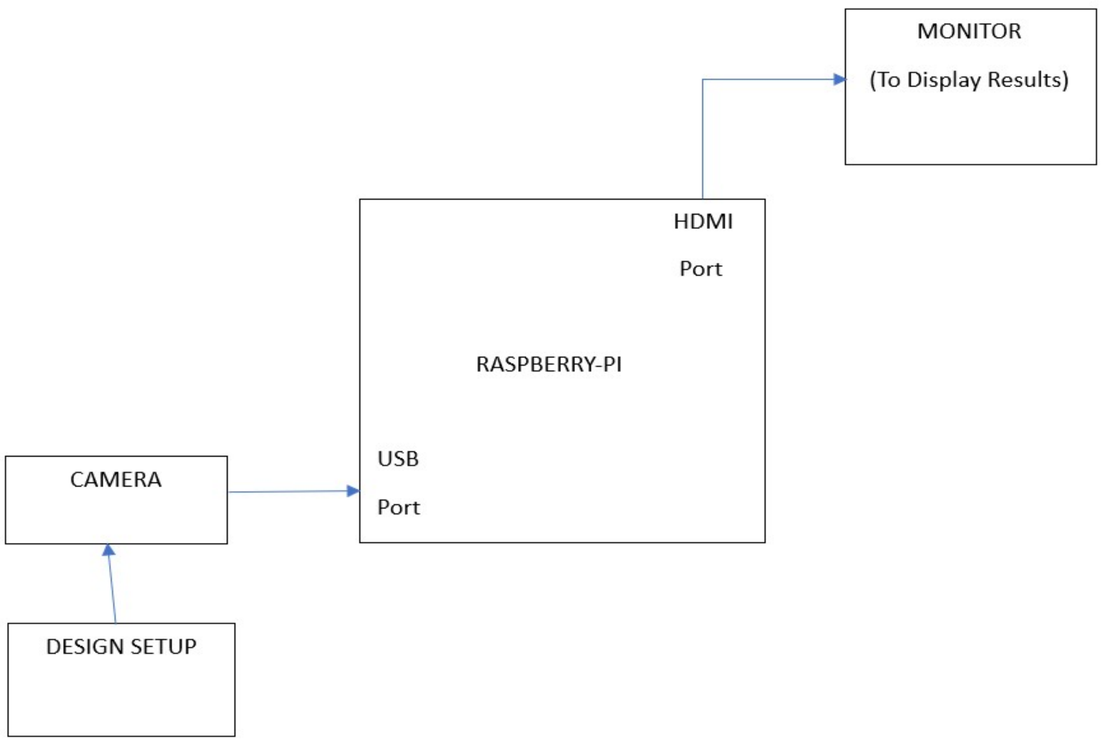

Figure.1: Block diagram of proposed System including Hardware

3.1.1. Image Input:

Experiments are carried out on a standard database in real-time in the suggested system. Steel plate defects are found using the North Eastern University (NEU) Surface Defect Database. There are six different kinds of defects in this database: inclusions, pitted surfaces, crazing, patches,

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rolled-in scale, and scratches. It consists of 1,800 bitmap pictures of faulty plates, each with a 200,000-pixel resolution. Examples of these six defect categories are shown in Figure 2.

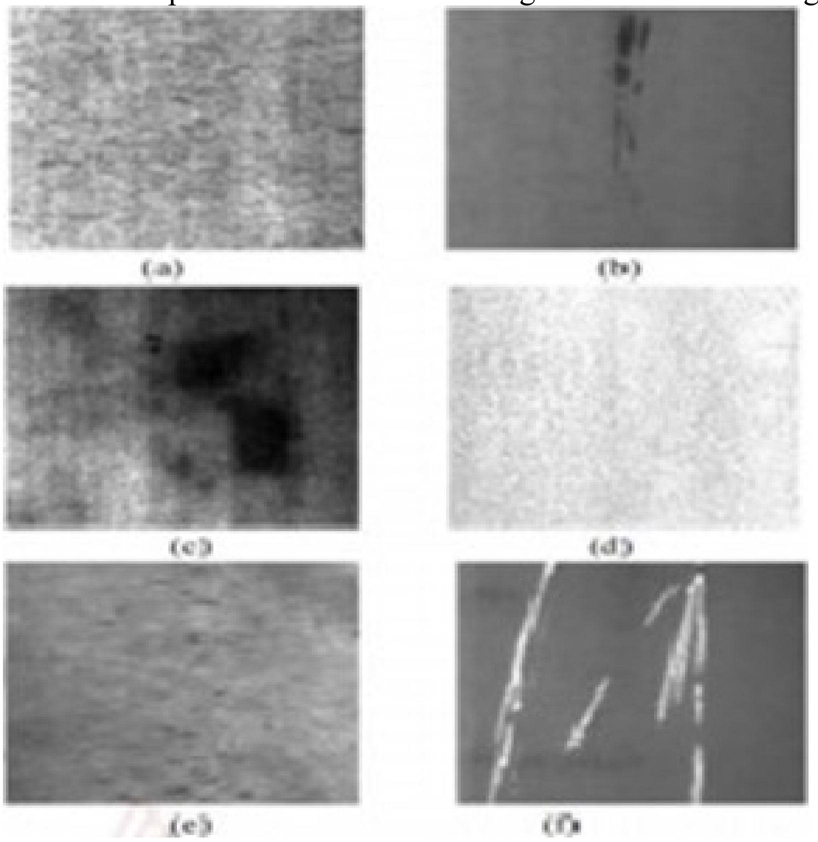

Figure.2: NEU surface defect database images (a) rolled-in scale (b) patches (c) crazing (d) pitted surface (e) inclusion (D) scratches

Similarly, experiments were conducted on real-time images. Steel surface sheets were collected from the industry, and images were captured using a webcam and stored in the database. Figure:3 presents examples of the real-time database images.

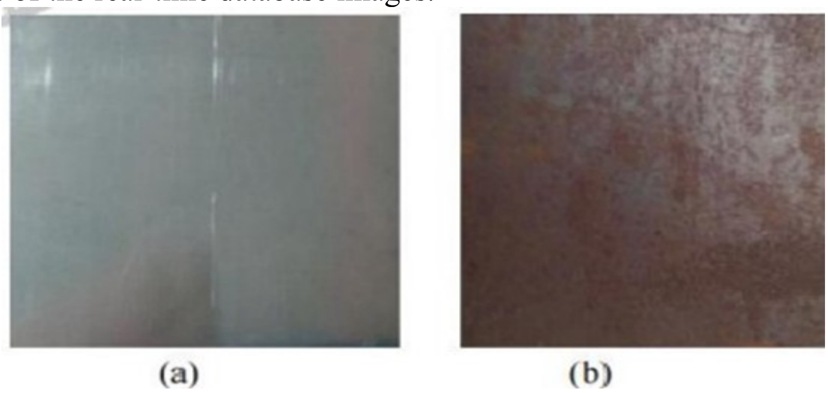

Figure.3(a): shows the normal (non-defective) plate and
Figure.3(b): shows the defective plate.

3.1.2 Image Preprocessing:

Any image processing technique starts with preprocessing. There are many sounds in the obtained image. Image preprocessing is required in order to eliminate noise. The median filter is utilized in this system to do this. The salt and pepper noise is successfully eliminated by the median filter since it appears as black and white dots. A kernel with a size of x 5 is applied across an image as a median mask in median filter processing. The centre element of the mask is assigned the median of the mask values.

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3.1.3 Extraction of ROI:

Region of Interest (ROI) detection is the initial step after preprocessing to find surface flaws in the metal. To ensure that only pertinent areas are examined, the steel surface section is chopped for additional processing because the input picture may contain non-metallic regions.

3.1.4 Reduction of Features:

Effective data categorization requires feature reduction. For dimensionality reduction, common methods include Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA). LDA has been tested on randomly generated data and is capable of handling scenarios with uneven within-class frequencies. Lower-dimensional feature vector approximation is made possible by PCA, which minimizes mean squared error while providing a linear representation of the original data. The main concept is to use a linear combination of leading eigenvectors to approximate the covariance matrix of the original data while maintaining the most important characteristics for classification.

3.2 Implementation:

The specification of hardware and software implementation is given below

3.2.1 Software specification:

- OpenCV 4.0
- Raspbian OS

3.2.2. Hardware specification:

- Steel plates size X IO cm
- Camera: Webcam SMP
- Raspberry Pi 4 Model B
- Monitor
- HDMI to micro-HDMI cable

3.3. Mask R-CNN Model Design and Training:

Mask R-CNN builds upon the Faster R-CNN framework by incorporating an additional branch dedicated to the prediction of segmentation masks. The architecture is composed of several essential components are:

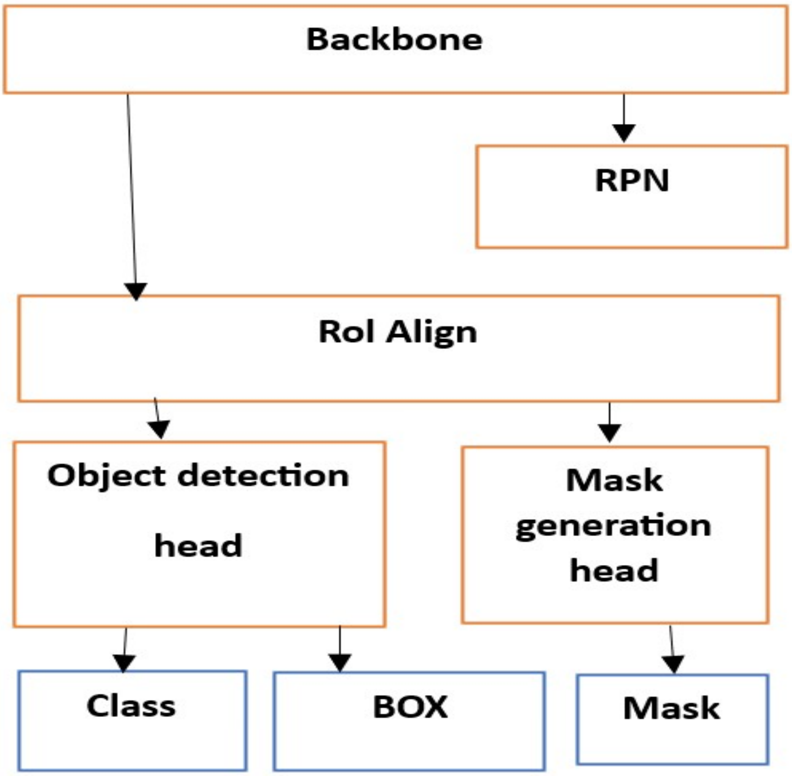

Figure.4: Basic Architecture of Mask R-CNN

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3.3.1 Image Processing's Backbone Network:

Captures complex visual patterns; generates feature maps based on the processing of incoming photos,

3.3.2 Proposal Network for Regions (RPN):

Produces region suggestions, or possible bounding boxes with flaws. During training, suggestions are improved for correctness.

3.3.3 ROI Alignment:

Effectively preserves the spatial integrity of object positions. Essential for accurate division.

3.3.4 Branch Segmentation:

Generates a binary mask for every flaw found, Allows precise segmentation at the pixel level.

3.4 Integration of Mask R-CNN with Raspberry Pi:

To optimize Mask R-CNN for the Raspberry Pi's limited processing power, techniques like model pruning and quantization are applied. Essential libraries such as Py-Torch and OpenCV are installed for image processing. The optimized model is deployed on the Raspberry Pi, running a Python script that captures images from a connected camera, processes them using Mask R-CNN, and displays defect detection results in real-time.

3.5 LED Indicator System:

Setting Up Hardware to Connect LEDs to a Raspberry Pi:

- Connecting LEDs: Red and green LEDs are connected to two GPIO pins using current-limiting resistors, and each LED's cathodes are connected to a shared ground pin.
- GPIO Pin Setup: The Raspberry-Pi's software architecture has LED pins set up as output pins. LEDs may be switched on or off in response to detecting findings thanks to GPIO pins.
- Algorithms for Finding Flaws and Turning on the Right LED.
- Image Acquisition: The Raspberry Pi uses a camera to take a picture.
- Defect Identification: The Mask R-CNN model is used to analyse the image.
- LED Control: If a defect is discovered, the GPIO pin activates a red LED; if not, a green LED.

3.6. OUTPUT:

Display**:** Detection results, including segmented image, sent to display for visualization.

4. Flow Chart:

The proposed System is to design and develop an automated System for sheet metal surface inspection which acts as an alternative to manual inspection is given below in the following flow chart. The flowchart you provided illustrates a system designed for detecting defects on sheet metal surfaces using a Mask R-CNN (Region-Based Convolutional Neural Network) model deployed On a Raspberry Pi and integrated with LED indicators. Here's a detailed explanation of each step in the flowchart:

Start: The process begins with the initialization of the system, likely triggered manually or by some automated event.

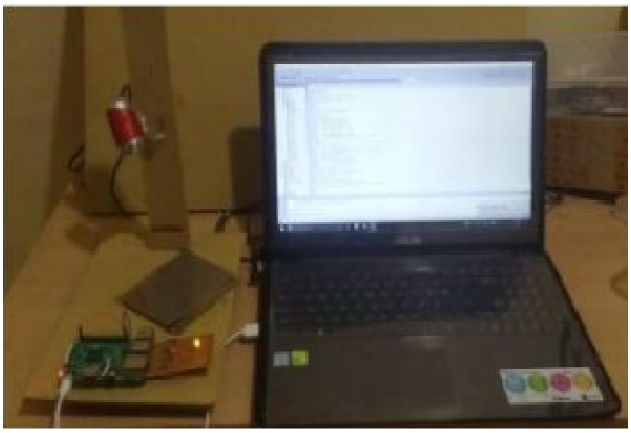

Figure.5: Hardware Module of the system

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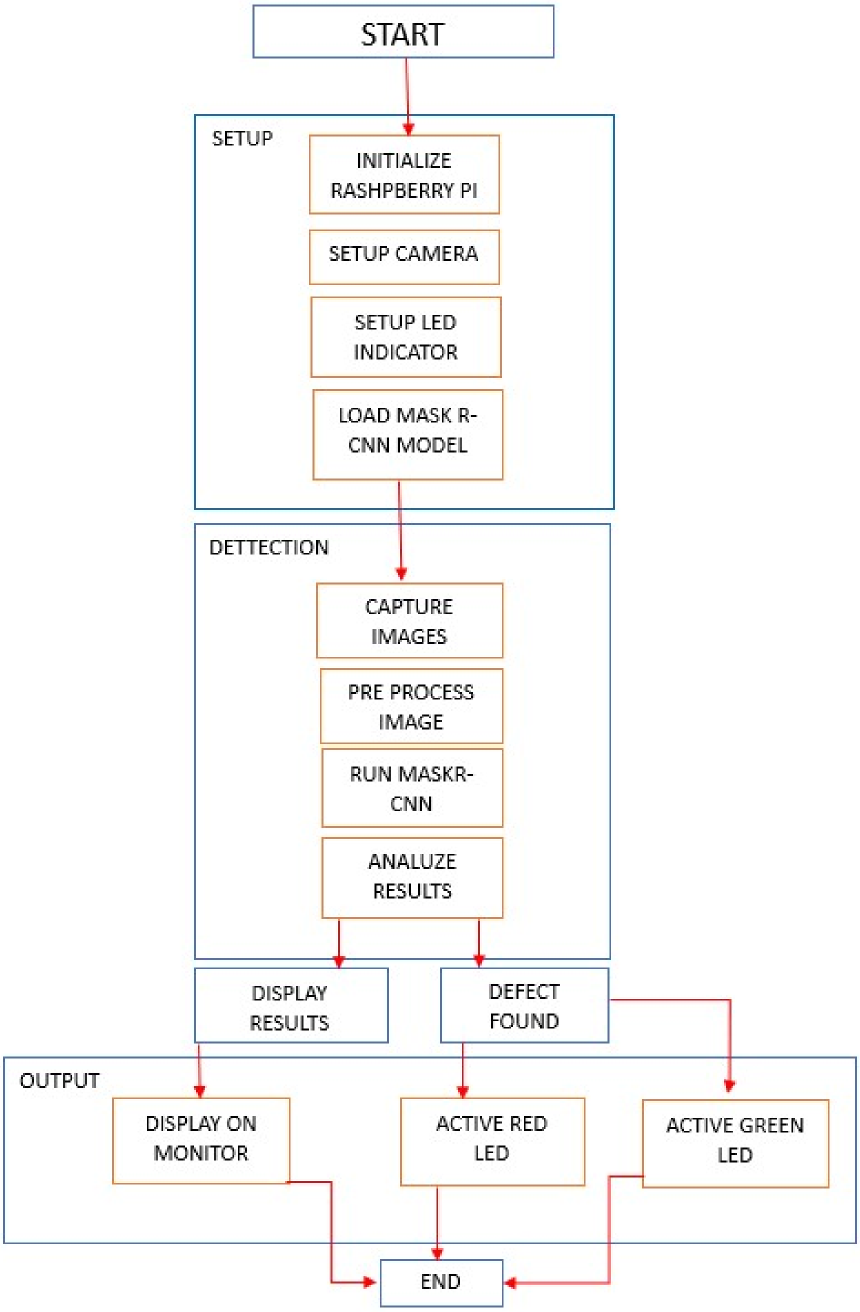

Figure.6: Flow chart of the proposed system

4.1 Setup Phase:

4.1.1 Initialize Raspberry Pi:

The Raspberry-Pi is powered on and initialized. This includes booting up the operating system and ensuring all necessary software components and services are ready.

4.1.2 Setup Camera:

The camera module connected to the Raspberry-Pi is set up, this includes initializing the camera, adjusting settings like resolution, focus, and other parameters necessary for capturing high-quality images of the metal surfaces.

4.1.3 Setup LED Indicators:

The LED indicators are set up and connected to the Raspberry-Pi's GPIO (General Purpose Input/Output) pins, The LED's will be used to signal the presence or absence of defects in the metal surface.

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4.1.4 Load Mask R-CNN Model:

The pre-trained Mask R-CNN model is loaded into the System's memory. This model is responsible for detecting and segmenting defects in the images captured by the camera,

4.2. Detection Phase:

4.2.1 Capture Image:

The camera captures an image of the metal surface that needs to be inspected.

4.2.2 Preprocess Image:

The captured image is pre-processed to enhance features relevant to defect detection. This step might include resizing the image, normalizing pixel values, or applying filters to remove noise.

4.2.3 Run Mask R-CNN:

The pre-processed image is passed through the Mask R-CNN model. The model analyses the image to detect any defects on the metal surface, It not only identifies the defects but also Segments the image to highlight the defectiveareas.

4.2.4 Analyse Results:

The results generated by the Mask R-CNN model are analysed. If any defects are detected, the system determines their nature and severity.

4.3 Indication Phase:

4.3.1 Defect Detected:

If a defect is found in the analysed image: Activate Red LED: The system activates the red LED indicator, signalling that a defect has been detected, this alert can be used to stop a production line or notify an Operator.

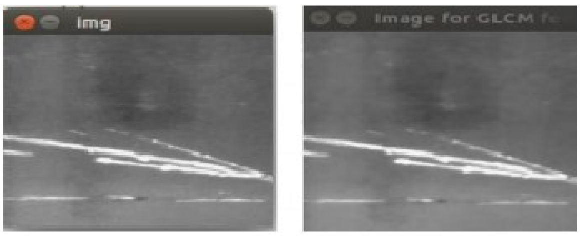
4.3.2 NO Defect Detected: If no defect is found:

Activate Green LED: The system activates the green LED, signalling that the metal surface is free of defects.

5. Result:

5.1 Qualitative analysis:

The proposed system utilizes the NEU Surface Defect Database, which includes six defect types (crazing, inclusion, patches, pitted surface, rolled-in scale, and scratches). Each defect category comprises 300 images, with the dataset split into 1,500 images for training and 300 for testing.



(a) (b)

Figure.7: Qualitative analysis of proposed system
(a) Input steel plate image (b) Pre-processed image

(c)

(c) Binarization shows the defects

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6.Conclusion:

This project successfully deploys a Mask R-CNN-based surface defect detection system on a Raspberry Pi using the NEU dataset. By combining deep learning with inexpensive hardware, it shows that it is possible to deploy sophisticated machine learning algorithms in environments with limited resources. The system effectively detects surface defects and gives real-time feedback via LEDs, making it appropriate for small-scale or cost-effective operations. Additionally, the ability to display detection results improves usability, highlighting the potential of edge AI in industrial automation and quality control.

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