286016

METAL SURFACE DEFECT DETECTION THROUGH MACHINE LEARNING

A PROJECT REPORT

Submitted by

DEEP AMISH SHAH

191310132127

In partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

in

Information and Communication Technology

Adani Institute of Infrastructure Engineering

Gujarat Technological university,

May 2022-23

Adani Institute of Infrastructure Engineering

Shantigram Township, Nr.Vaishnodevi Circle,

Sarkhej - Gandhinagar Hwy, PO, Adalaj, Gujarat 382421

CERTIFICATE

This is to certify that the internship report submitted along with the project entitled 'Metal Surface Defect Detection Through Machine Learning' Internship has been carried out by Mr. Deep Shah under my guidance in partial fulfillment for the degreeof Bachelor of Engineering in Information and Communication Technology, 8th Semester of Gujarat TechnologicalUniversity, Ahmadabad during the academic year 2022-23.

Dr. Nidhi Desai

Internal Guide

Dr. Ajay Kumar Vyas

Head ofthe Department

Gujarat Technological University

Adani Institute of Infrastructure
and Engineering

Centre for Product Design and Manufacturing

April 28, 2023

TO WHOMSOEVER IT MAY CONCERN

This is to certify that Mr. Deep Shah, from Adani university, Ahmedabad currently pursuing his 7th semester in Bachelor of Engineering in Information and Communication Technology (ICT), was an Intern at Smart Factory, Centre for Product Design and Manufacturing (CPDM) from February 1 to April 13, 2023. During this period, he has worked on:

"Metal Surface Defect Detection through Machine Learning" project to develop a computer vision system that can accurately detect and classify six types of metal surface defects - crazing, rolled, patches, pitted, inclusion, and scratches - using the Yolov8 algorithm for object detection. The system should be able to process custom data and provide accurate predictions. The project demonstrated the effectiveness of deep neural networks and convolutional neural networks in detecting and classifying metal surface defects within milliseconds, with the goal of improving quality control in the smart factory.

Professor Amaresh Chakrabarti
Centre for Product Design and Manufacturing
Indian Institute of Science

Adani Institute of Infrastructure Engineering

Shantigram Township, Nr.Vaishnodevi Circle, Sarkhej - Gandhinagar Hwy, PO, Adalaj, Gujarat 382421

DECLARATION

I hereby declare that the Internship report submitted on the topic 'Metal Surface Defect Detection Through Machine Learning' in partial fulfillment for the degree of Bachelor of Engineering in Information and Communication Technology to Gujarat Technological University, Ahmedabad, is a bonafide record of original project work carried out by me at Synersoft Tech under the supervision of Mr.Venu Allam and that no part of this report has been directly copied from any students' reports or taken from any other source, without providing due reference.

Name of the Student

Sign of Student

DEEP AMISH SHAH

Acknowledgement

I would like to express my sincere gratitude to all those who have supported me throughout my Semester 8 project. This project would not have been possible without their invaluable contributions, encouragement, and guidance.

First and foremost, I would like to thank my project supervisor, Mr. Venu Allam, for his unwavering support and valuable insights. His expertise, guidance, and patience played a pivotal role in shaping the direction and success of this project. I am truly grateful for their mentorship and for pushing me to deliver my best.

I would also like to extend my gratitude to the faculty members of Adani Institute Of Infrastructure Engineering, especially Dr, Nidhi Desai, for her support and constructive feedback. Her expertise and knowledge have been instrumental in expanding my understanding ofthe subject matter and refining my project.

Furthermore, I am thankful to my classmates Raj Shah and Rikin Patel who provided assistance, brainstorming sessions, and meaningful discussions throughout the project. Their collaborative spirit and enthusiasm have made this journey more enjoyable and rewarding.

Lastly, I would like to express my deepest gratitude to my family for their unconditional love, support, and understanding during this demanding period. Their encouragement and belief in my abilities have been my constant source of inspiration.

Although I have attempted to acknowledge everyone who has played a significant role in this project, there may be others whose contributions might have inadvertently been omitted. I extend my heartfelt thanks to all those who have supported me in any way, directly or indirectly, throughout this endeavor.

Thank you all once again for being an integral part of this project and for helping me accomplish my goals. Your support and contributions are deeply appreciated.

Sincerely,

Deep
Shah

Abstract

Centre for Product Design and Manufacturing, Indian Institute of Science, had initiated in 2014 India's first indigenous smart factory platform. With funding from Department of Heavy Industries (DHI), Government of India under its SAMARTH Udyog Bharat 4.0 programme, this is turning into a complete factory testbed with two parts: A labour-intensive toolroom with a connected set of legacy machines that represents the MSMEs of India, and An automation-intensive factory that integrates 3D (metal, polymer) printers, metal laser routers, 5 axis CNCs, using industrial robots, collaborative robots and automated guided vehicles.

The aim is to demonstrate the power of smart and connected intelligence in enhancing quality, productivity, efficiency, flexibility, and sustainability for manufacturing across sectors and for research into factories of the future.

The detection and classification of metal surface defects are essential in ensuring the quality of metal products. This study aims to develop a computer vision system using the Yolov8 algorithm for object detection that can accurately detect and classify six types of metal surface defects. The dataset used in this study contains 9600 images, with 70% of the data used for training, 15% for validation, and 15% for testing. The Yolov8 algorithm was implemented, and the system was trained to achieve a desired accuracy of 80% in detecting and classifying the six types of defects, including crazing, rolled, patches, pitted, inclusion, and scratches. The results indicate that the proposed system achieved an accuracy of 76.5% on the test data, indicating its effectiveness in detecting and classifying metal surface defects. The successful implementation of this system could significantly improve the efficiency and accuracy of metal surface defect detection in the smart factory.

List of Figures

Details of Chapters

Smart Factory -Demonstration

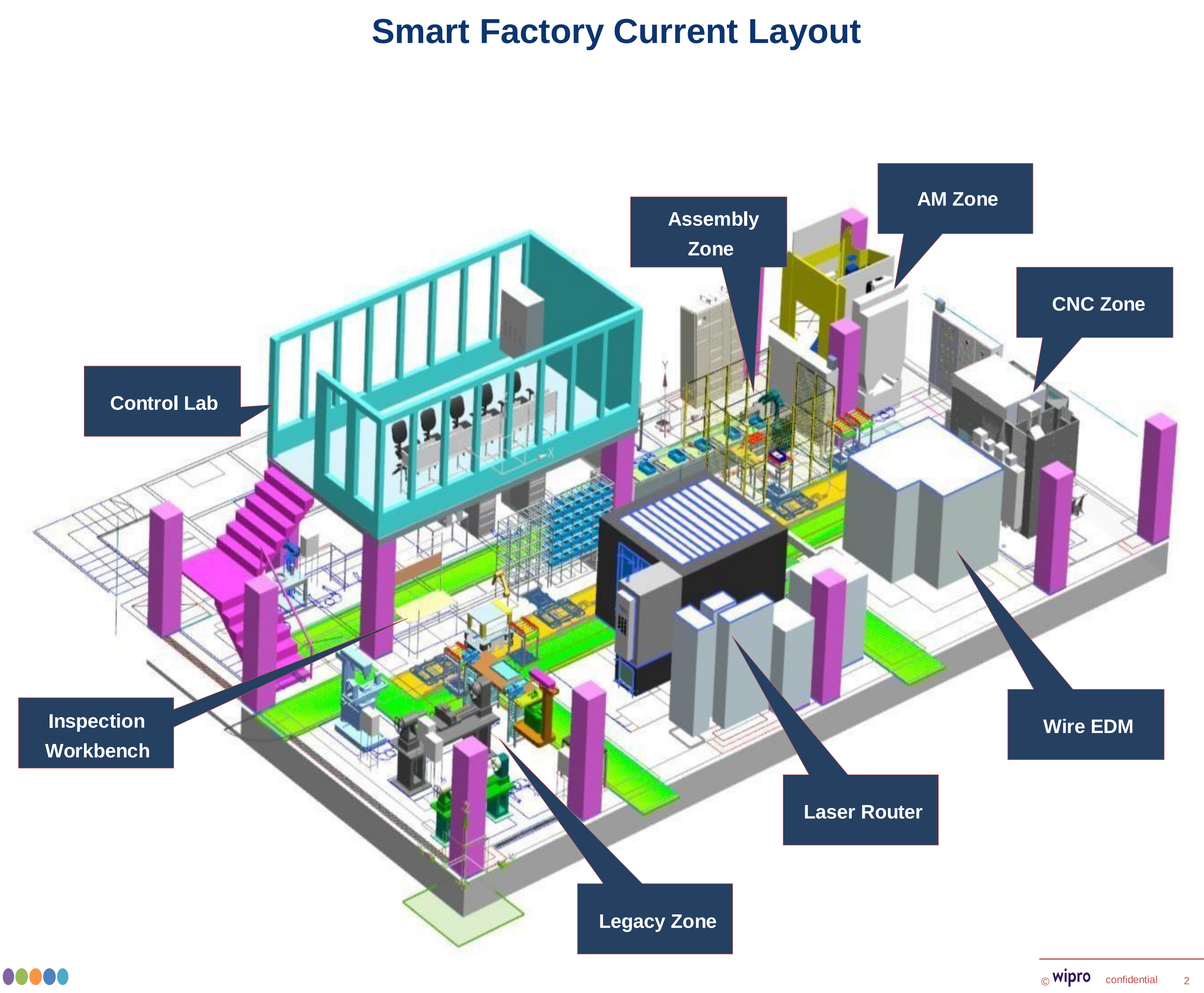


FIGURE 1: SMART FACTORY

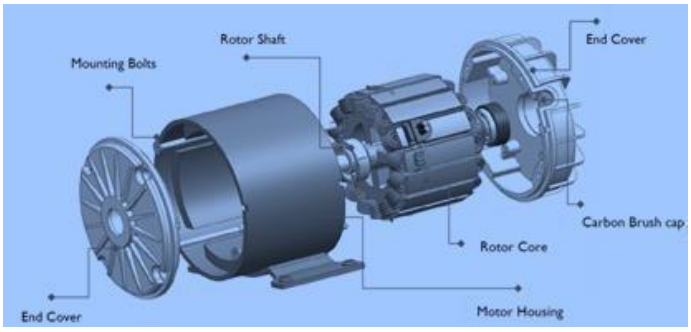


FIGURE 2: DC MOTOR

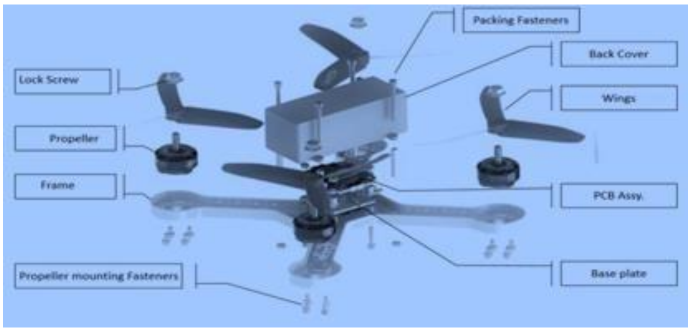


FIGURE 3: Drone

USE CASES MANUFACTURING IN SMART FCTORY

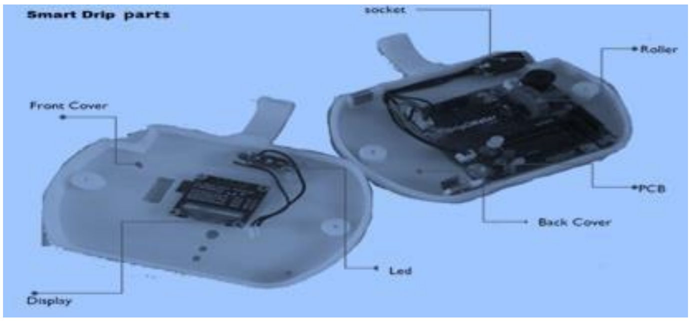


FIGURE 4: Smart Drip

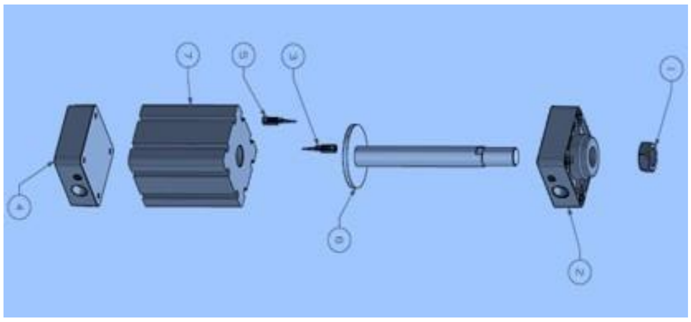


FIGURE 5 : Pneumatic Cylinder

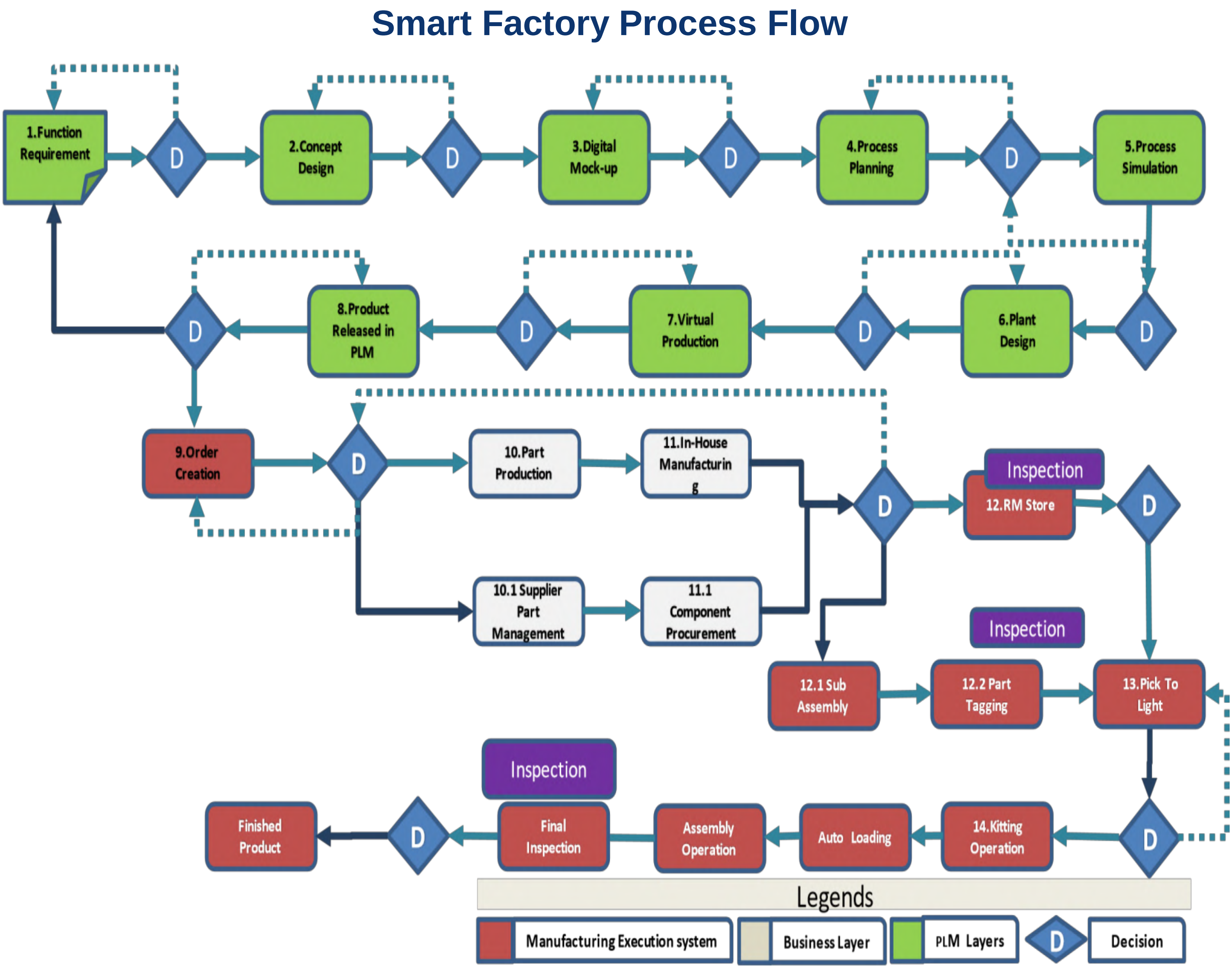
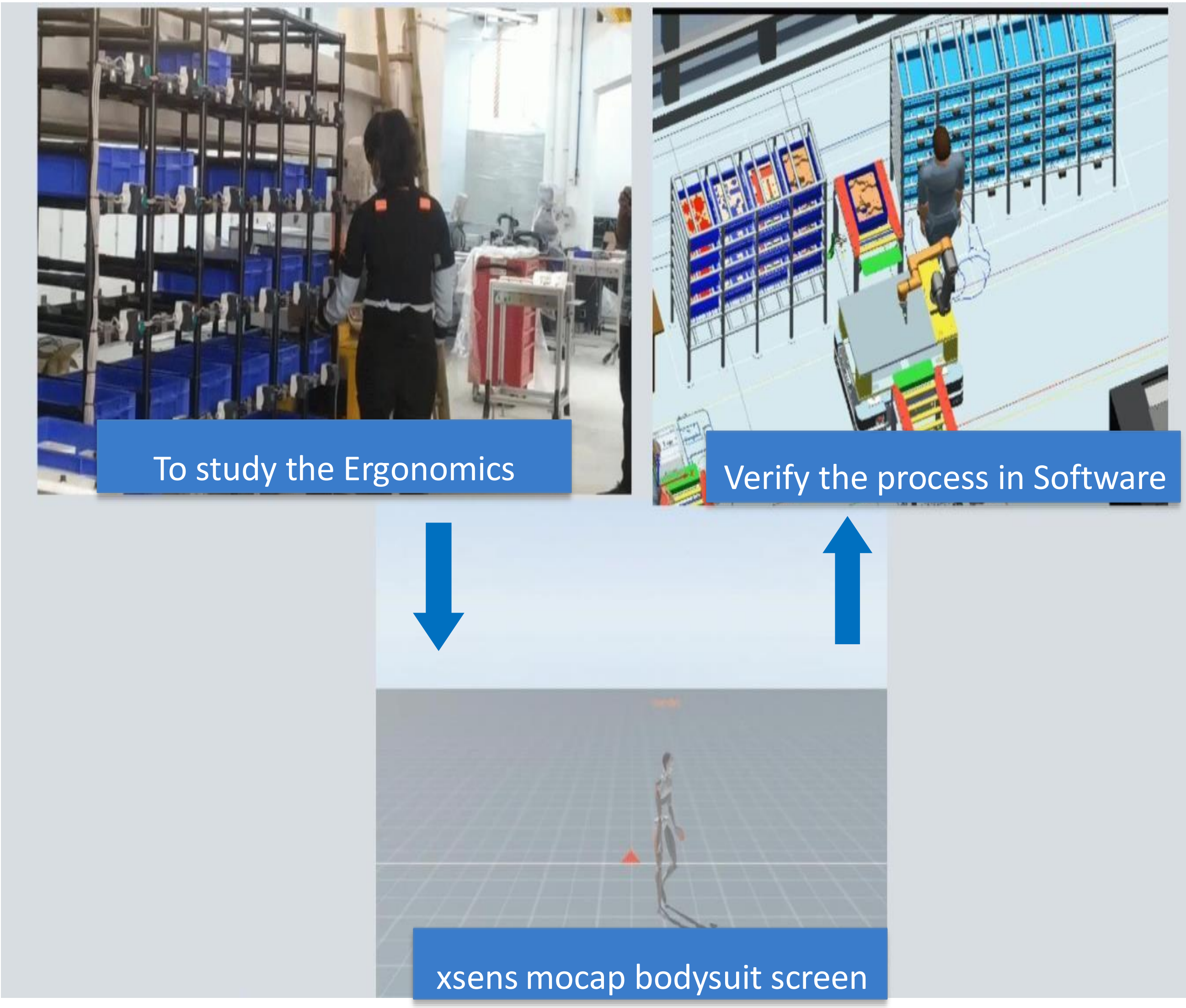


FIGURE 6: SMART FACTORY PROCESS DIAGRAM



MOCAP Integration

FIGURE 7: Digital Twin

Software Architecture

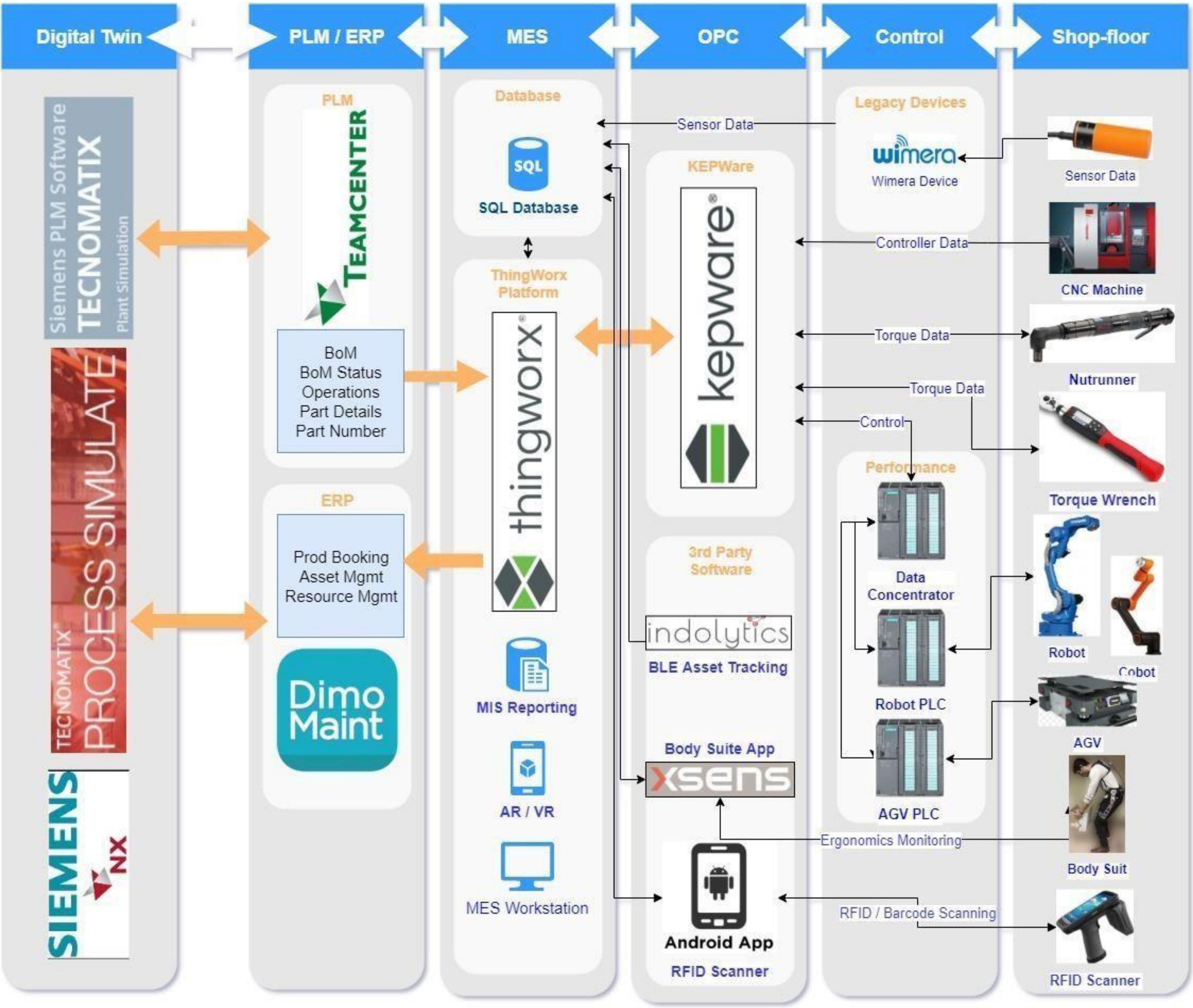
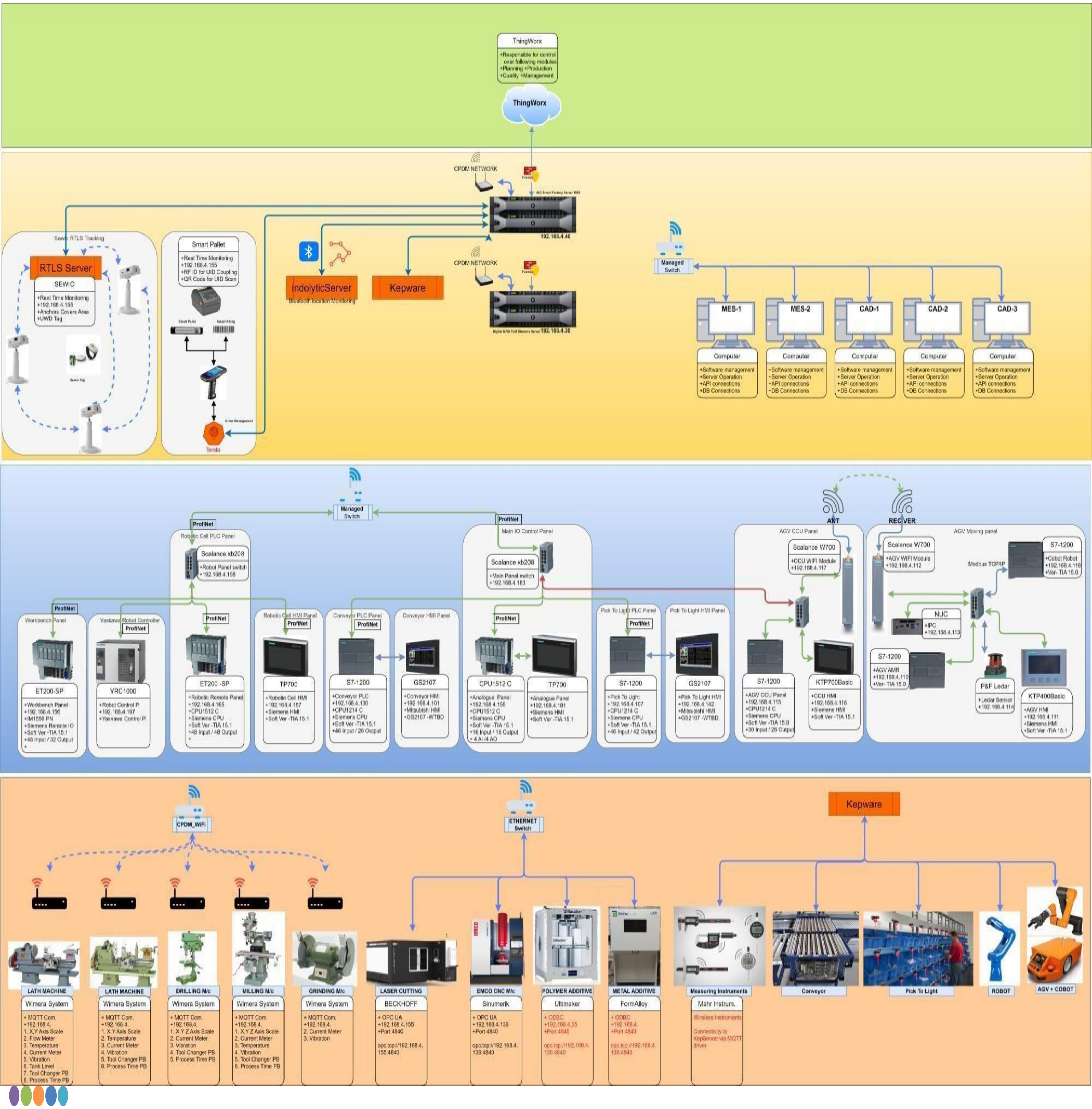
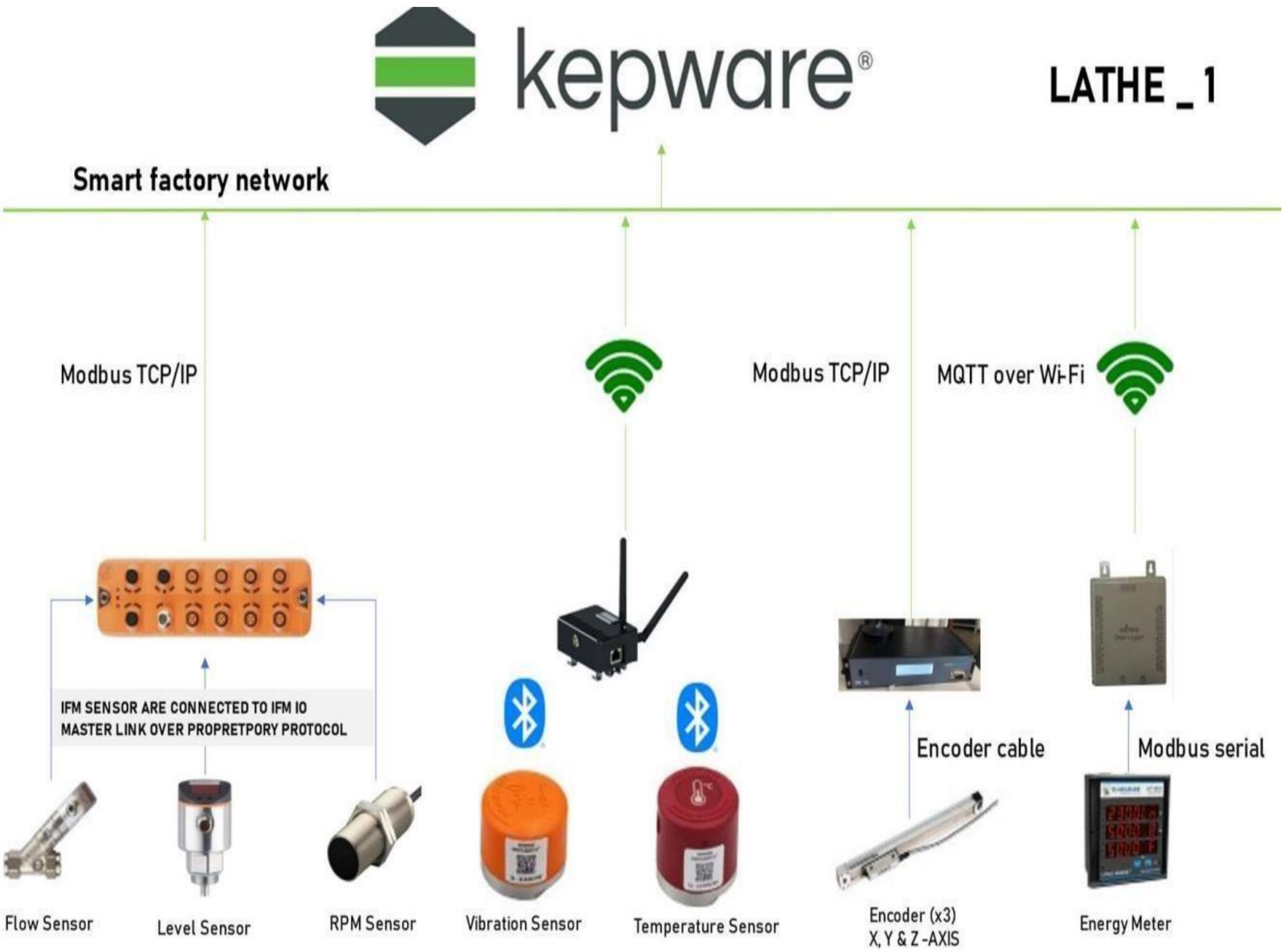


FIGURE 8: SOFTWARE ARCHITECTURE

Digital Factory Demonstration

IT-OT Factory Demonstration


ThingWorx
+Responsible for control over following modules +Planning +Production +Quality +Management
CPDM NETWORK
RTLS Server
SEWIO
Smart Pallet
indolyticServer
Kepware
MES-1
MES-2
CAD-1
CAD-2
CAD-3
Managed Switch
CPDM_WiFi
ETHERNET Switch
LATH MACHINE
DRILLING M/c
MILLING M/c
GRINDING M/c
LASER CUTTING
EMCO CNC M/c
POLYMER ADDITIVE
METAL ADDITIVE
Measuring Instruments
Conveyor
Pick To Light
ROBOT
AGV + COBOT


kepware
LATHE _ 1
Smart factory network
Modbus TCP/IP
Modbus TCP/IP
MQTT over Wi-Fi
IFM SENSOR ARE CONNECTED TO IFM IO MASTER LINK OVER PROPRETPORY PROTOCOL
Encoder cable
Modbus serial
Flow Sensor
Level Sensor
RPM Sensor
Vibration Sensor
Temperature Sensor
Encoder (x3) X, Y & Z -AXIS
Energy Meter

Physical Automation Demonstration

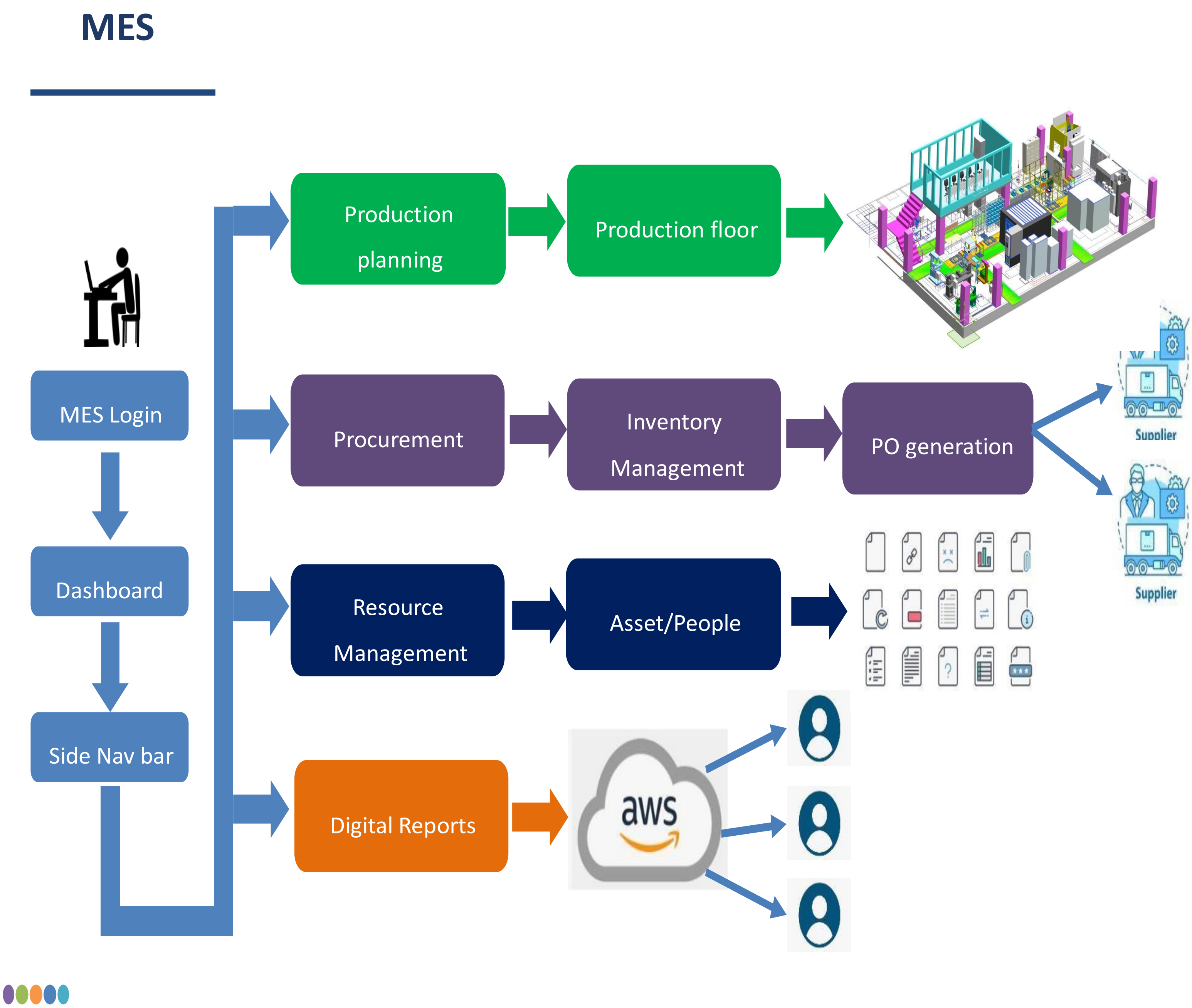
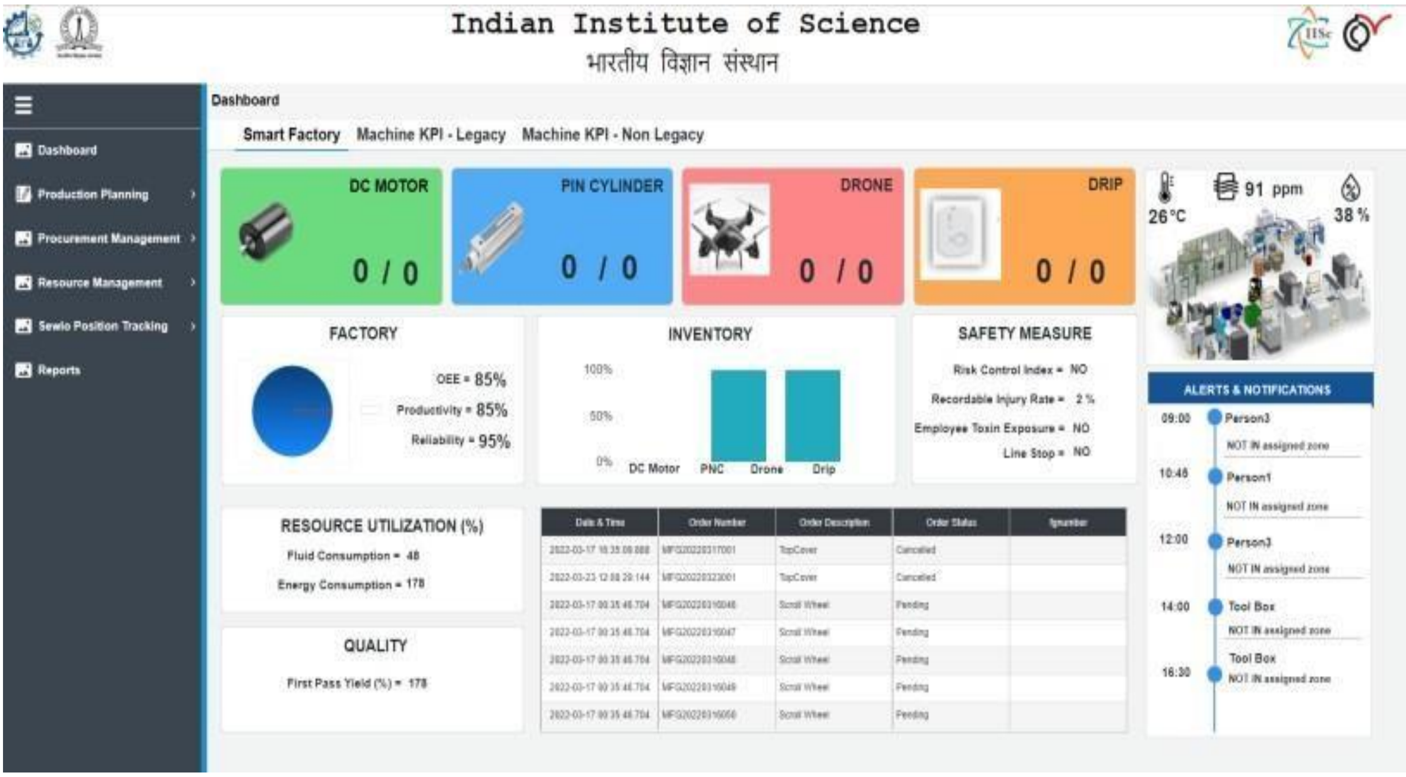
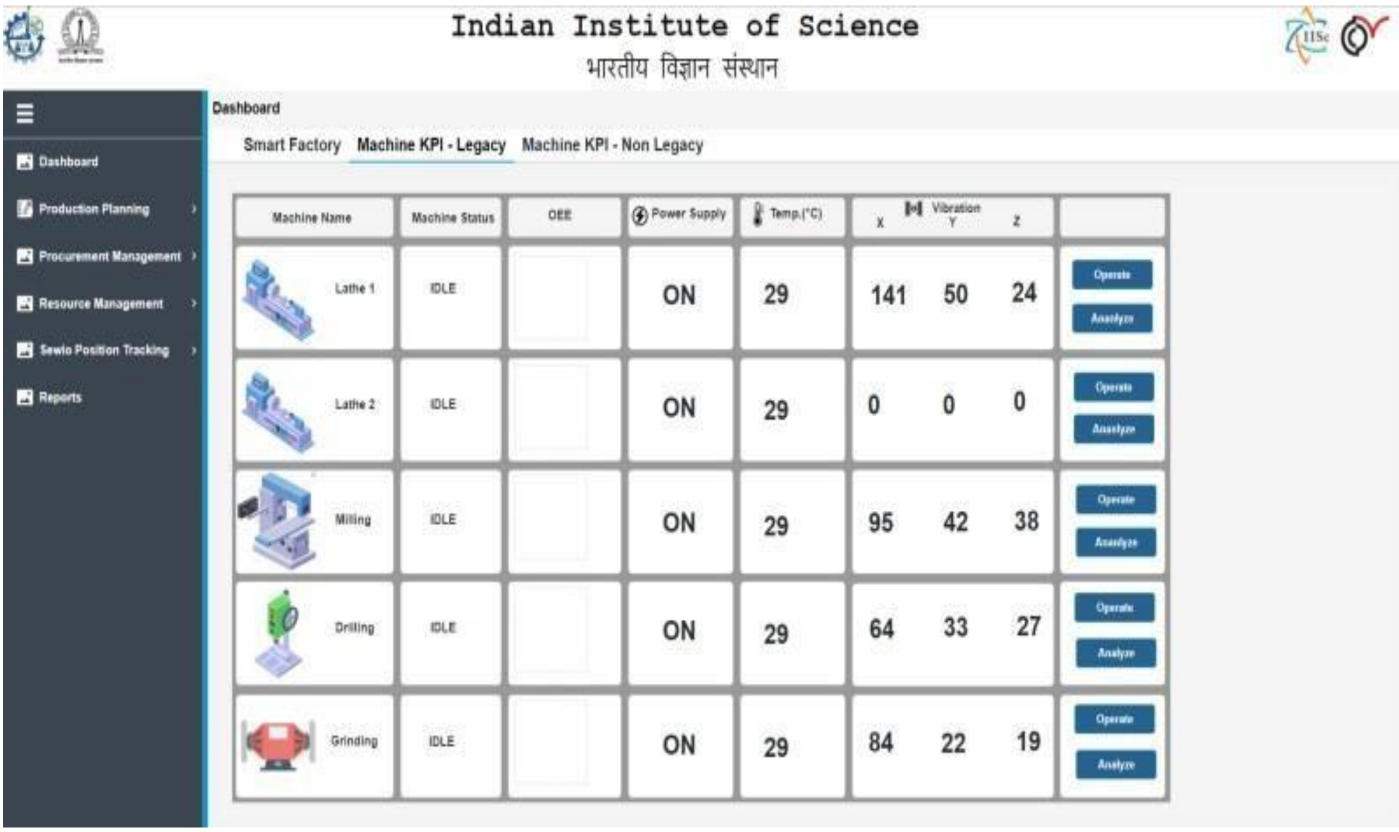


FIGURE 10: FRONTEND WORKFLOW

Factory Level Dashboard



Non-legacy Dashboard



Legacy Machine Dashboard

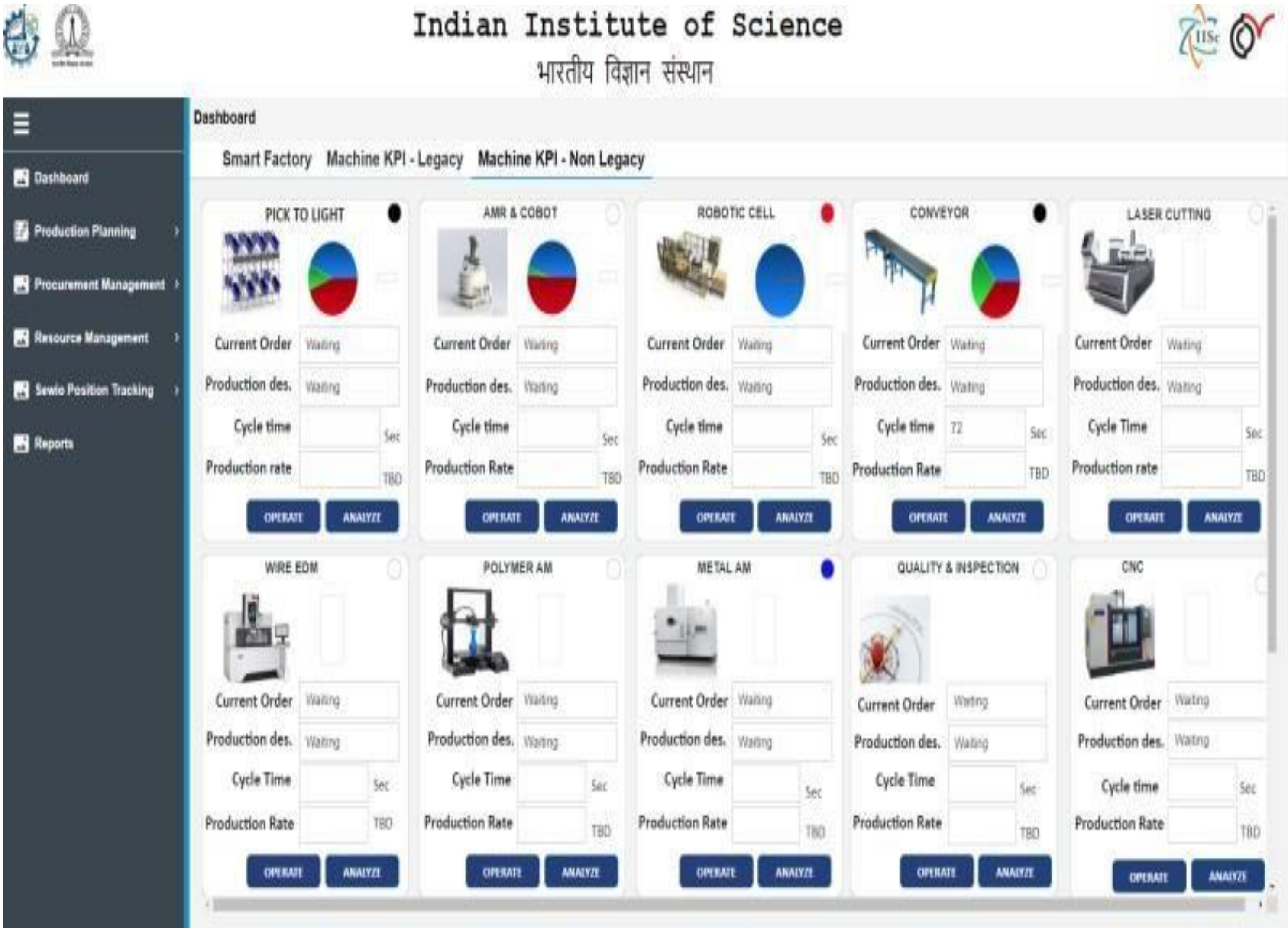


FIGURE 12: LEGACY, NON-LEGACY DASHBOARD

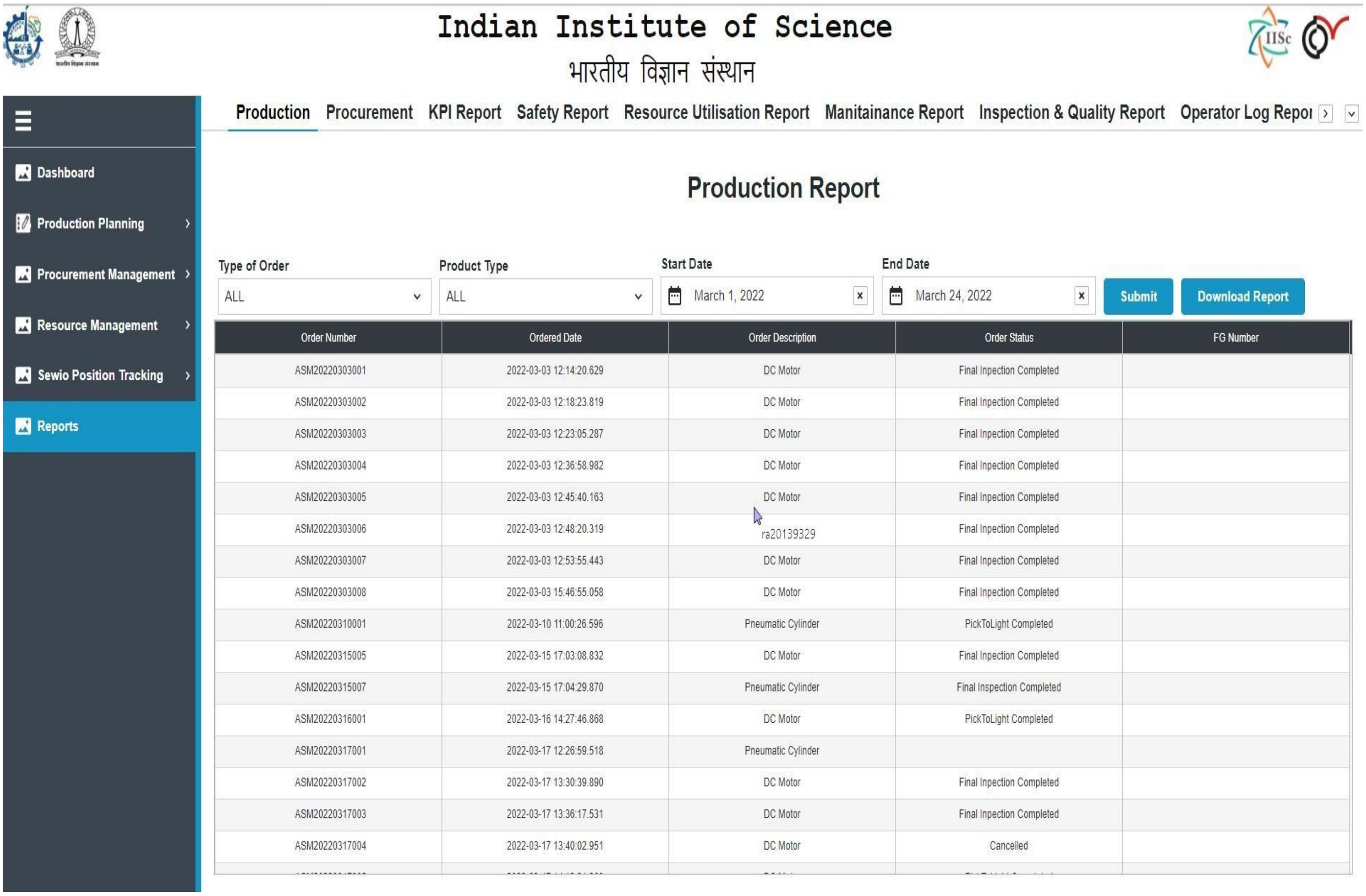


FIGURE 13: PRODUCTION REPORT

System Implementation:

1. Data Collection:

Inthis project, a total of 9400 images were collected from the NEU dataset, and 200 images captured from a mobile camera. The dataset was divided into 70% training, 15% validation, and 15% testing data, with 1440 images used for both the validation and testing sets. The NEU dataset provided a diverse range of metal surface defect types, including 1615 images of crazing, 1630 images of rolled, 1555 images of patches, 1490 images of pitted, 1560 images of inclusion, and 1750 images of scratches. The additional images captured from a mobile camera provided a real-world scenario for testing the model's effectiveness in detecting defects under different conditions. The use of this dataset enabled the development of a robust and accurate computer vision system for metal surface defect detection.

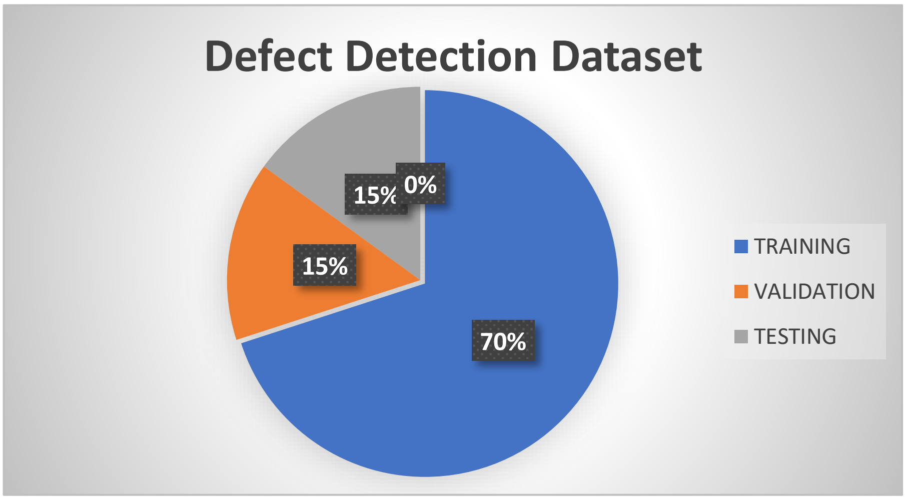


FIGURE 14: DATASET DISTIBUTION

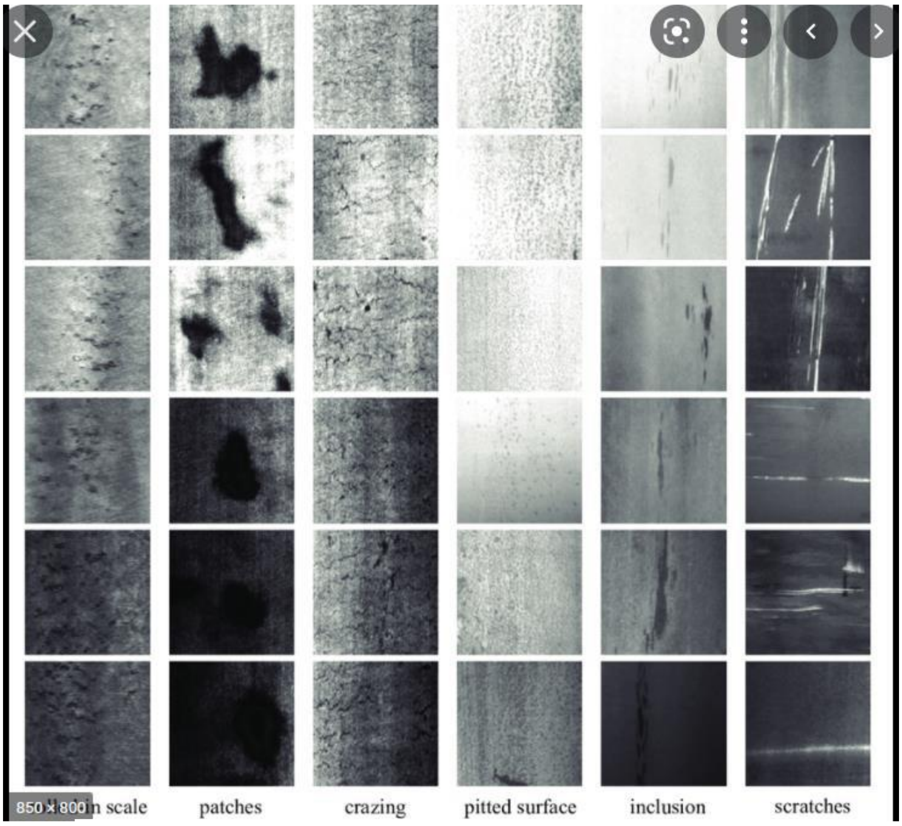


FIGURE 15: CLASSIFICATION OF DEFECTS

2.Image Annotation:

This step involves labelling the images with the appropriate classes or categories thatthemodel will learn to recognize. The annotation has been done by NEU dataset creator for 9400 images and other200 images were annotated manually.

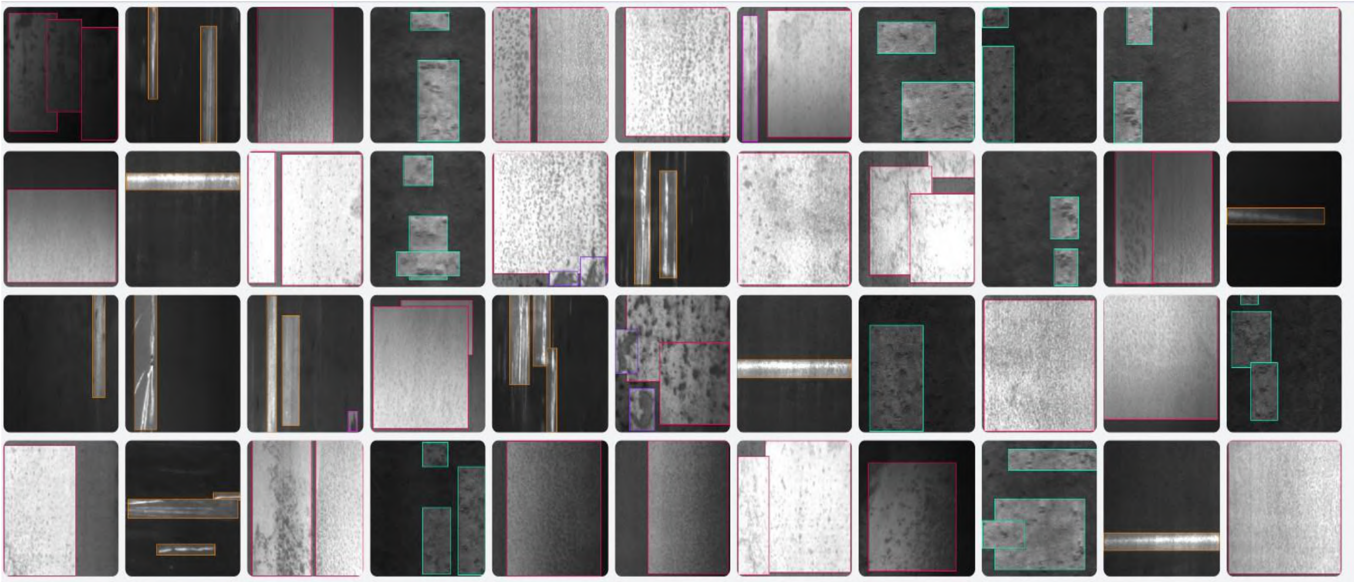


FIGURE 16: IMAGE ANNOATION

3.Train the Model:

CNN (Convolutional Neural Network)uses the raw pixel data of the image to train the model and then feature extraction is done automatically for better classification. It works in 2 steps- Feature Extraction and Classification. □

Convolution layer-In this layer filter is connected to input images to extract or distinguish its features. A filter is connected to the images at different times to make a feature map that classifies the input image.

Pooling layer- It is given as an input after the Convolutional layer is applied. This layer is added to diminish the dimensions of the map which preserves the important data or features of the input image set and decreases the computation period. Adding maximum pooling decreases the number of pixels in the output of the previous convolution level and decreases the dimensions of the image.

Fully connected layer- In the past 2 layers we have completed the Extraction methods, this layer comes under the Classification. This layer is used for input image classification into a label. It connects two things; one is the information extracted from the Convolution layer and the other is the Pooling layer classifies the input into the desired label and gives the output.

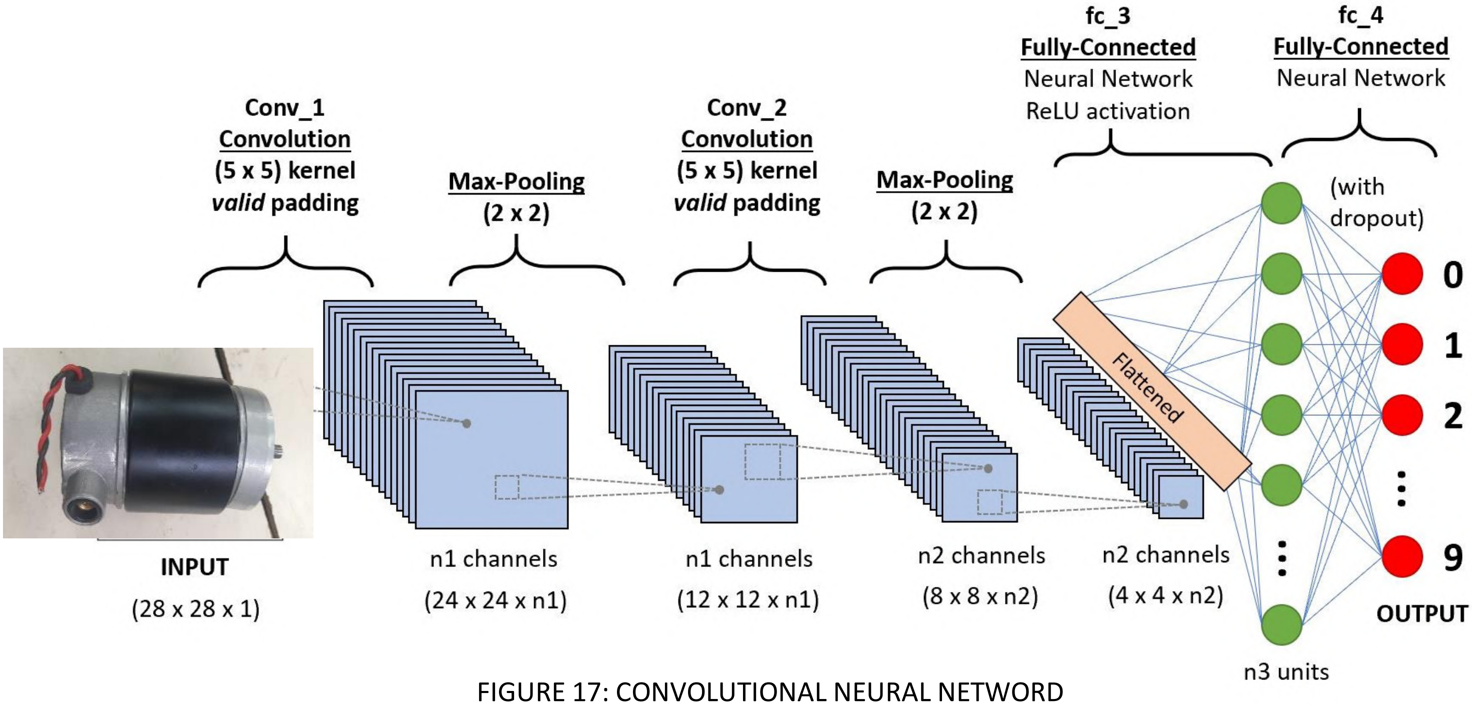


FIGURE 17: CONVOLUTIONAL NEURAL NETWORD

1. Evaluate the model:

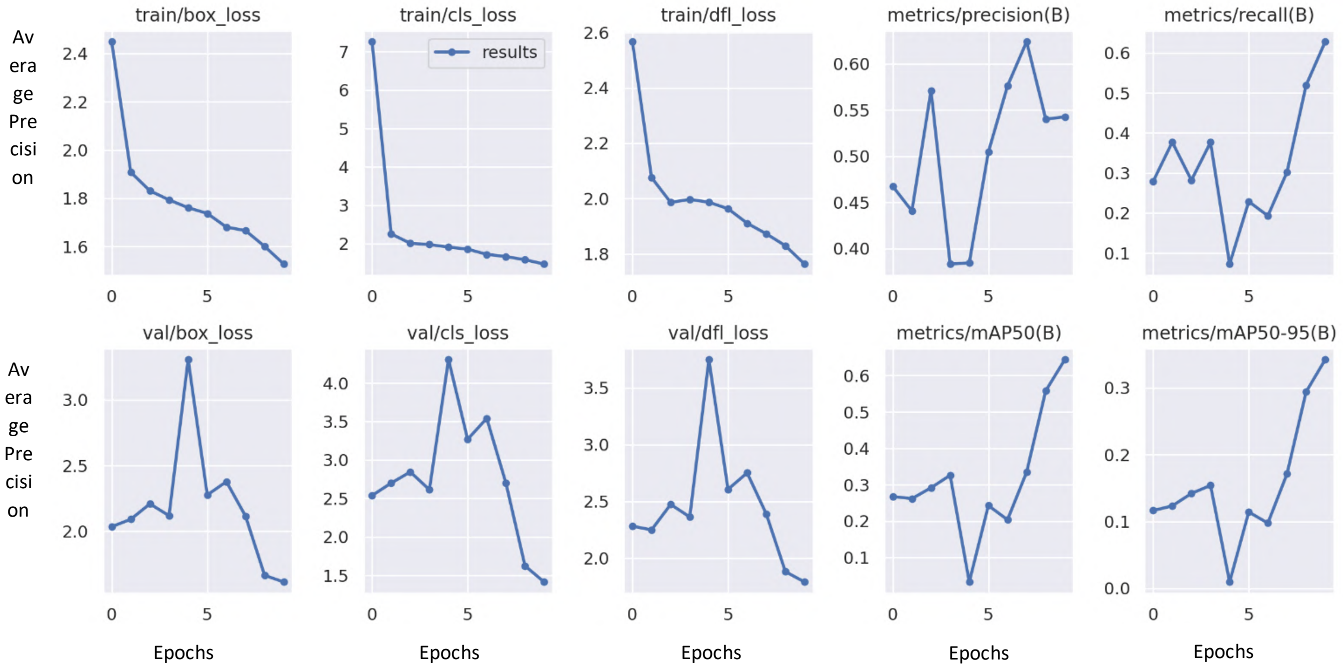


FIGURE 18: TRAINING CURVES

Evaluation of the model determines how well our model learns the patterns or features. As perthe above figure,the training loss indicates how well the model is fitting the training data, while the validation loss indicates how well the model fits new data. The results are predicted for 5 epochs on the x-axis, whereas the y-axis shows the Average Precision(AP). The graph also shows that during training precision is going up which means how accurately classes are being predicted. The recall measures the completeness of positive predictions.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

TP = True positive

TN = True negative

FP = False positive

FN = False negative

1. Epoch: An epoch is when all the training data is used at once and is defined as the total number of iterations of all the training data in one cycle for training the machine learning model.

2. Box Loss: The box loss represents how well the algorithm can locate the centre of an object and how well the predicted bounding box covers an object.

3. CLS Loss: a loss that measures the correctness of the classification of each predicted bounding box.

4. Precision: Precision is the proportion of correctly identified positive cases among all cases that the model predicted as positive. In other words, precision measures how accurate the model is when it predicts that something belongs to a certain class.

5. Recall: Recall is the proportion of correctly identified positive cases among all actual positive cases in the data. In other words, recall measures how well the model can identify all the positive cases, even if it also identifies some negative cases as positive.

Y-AXIS: In the YOLOv8 evaluation's graph, the y-axis usually represents the Average Precision (AP) value, which is a common metric used to evaluate the performance of object detection models. AP measures the accuracy of the model in detecting objects in an image, taking into account both the precision and recall of the model.

Therefore, the y-axis on the YOLOv8 evaluation's graph represents the AP value, which is an important metric for evaluating the performance of an object detection model.

X-AXIS: Number of iteration i.e. Epochs

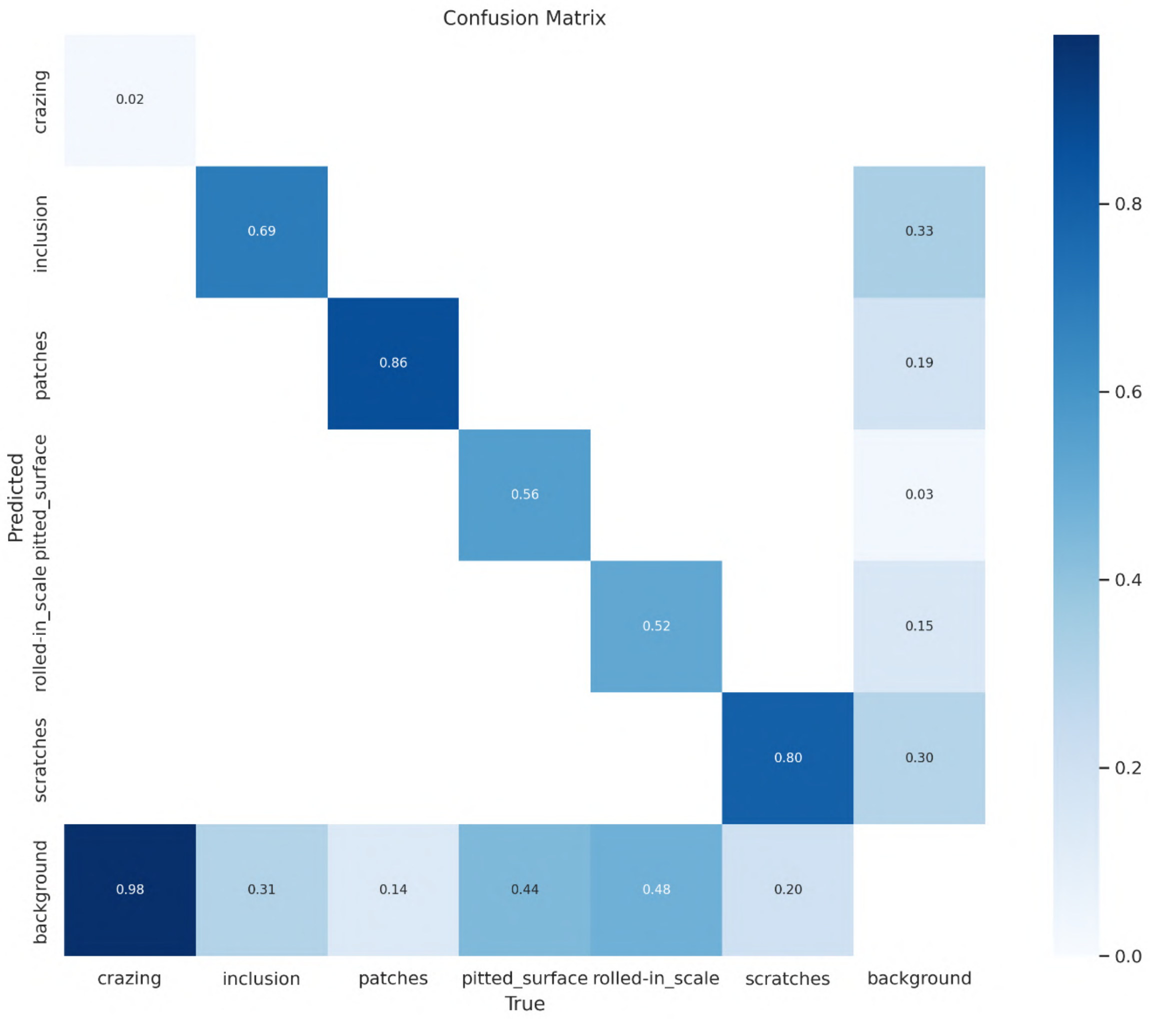
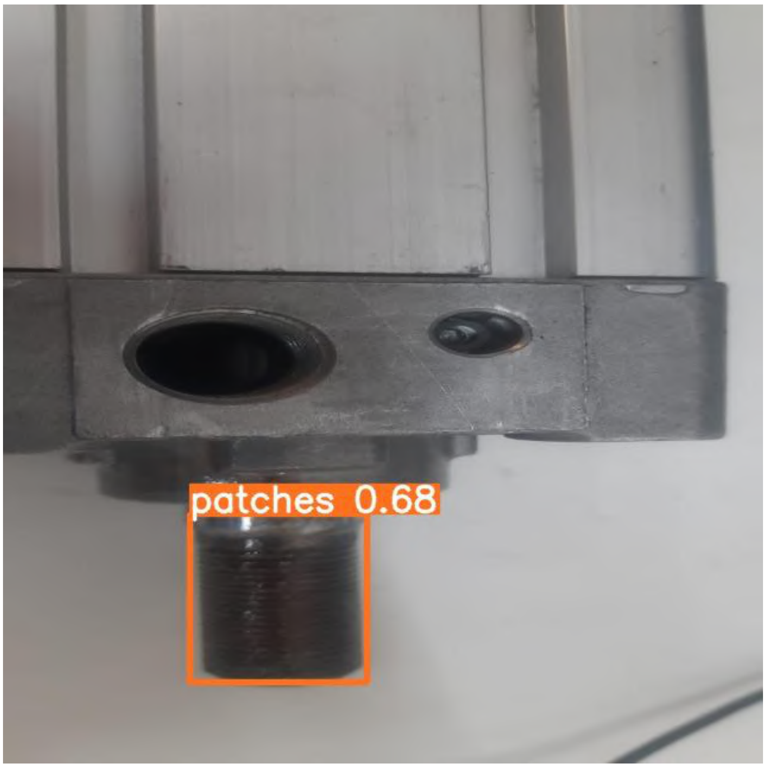
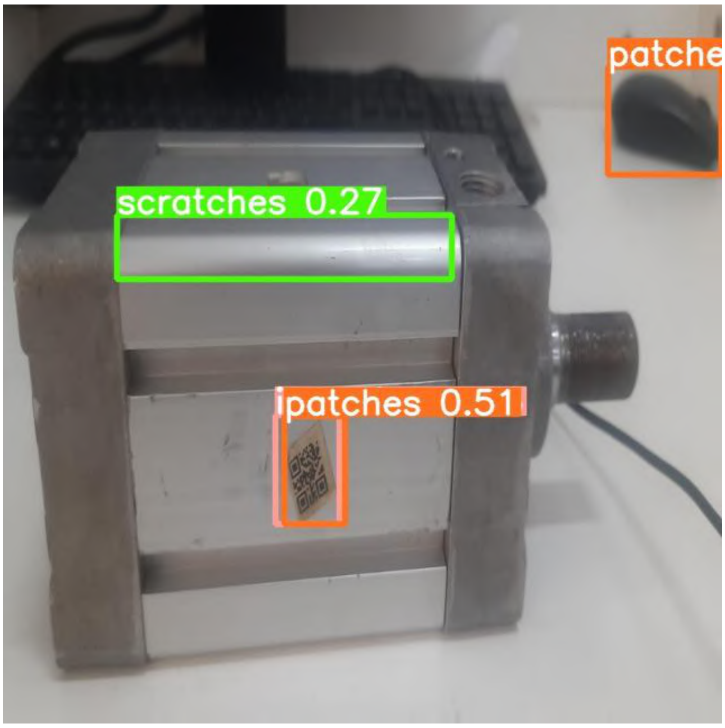


FIGURE 19: CONFUSION MATRIX

This Confusion Matrix indicates how well our model predicted on the test data. From the above matrix, we can say that for the crazing type of defect, our algorithm predicted 2% of the time the correct label. Same for the inclusion type of defect, our algorithm predicted 69% of the time correct label. For the patches type of defect, our algorithm predicted 86% of the time the correct label. For the pitted surface type of defect, our algorithm predicted 56% of the time the correct label. For the rolled-in scale type of defect, our algorithm predicted 52% of the time the correct label. For the Scratches type of defect, our algorithm predicted 80% of the time correct label.

5.Test on Custom Data





As a use case, two types of assembled products are used :

1. pneumatic cylinder (113 Images tested)
2. DC Motor (87 images tested)

As the above picture shows our algorithm predicts the patches on the surface of the pneumatic cylinder very accurately. In another image of a DC motor through computer vision,the machine learning algorithm is able to predict scratches on the metal surface.

The Algorithm also shows the probability of scratches or patches on the metal surface in the predicted image.

Execution:

1. First upload the images to the Predict folder for detection.

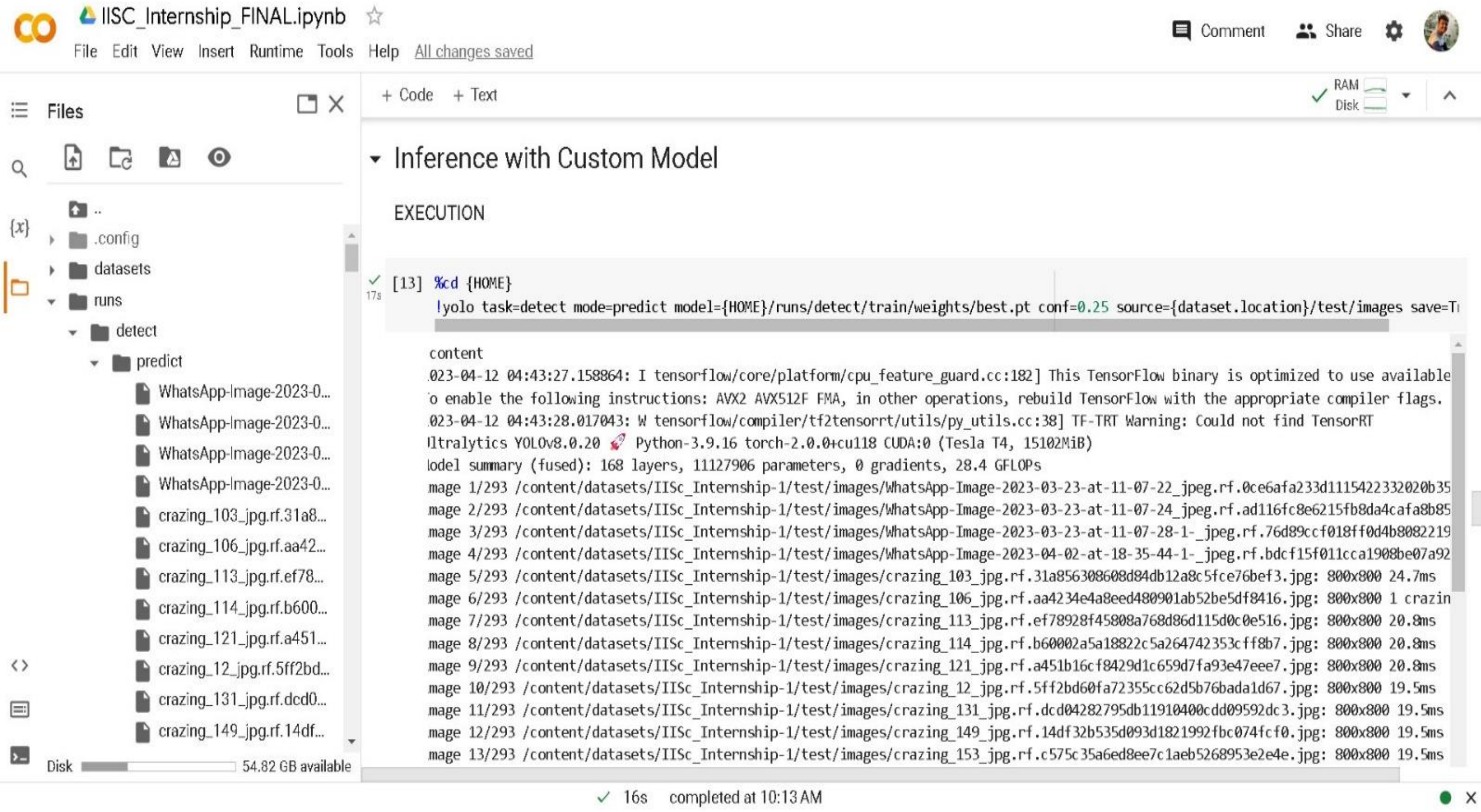
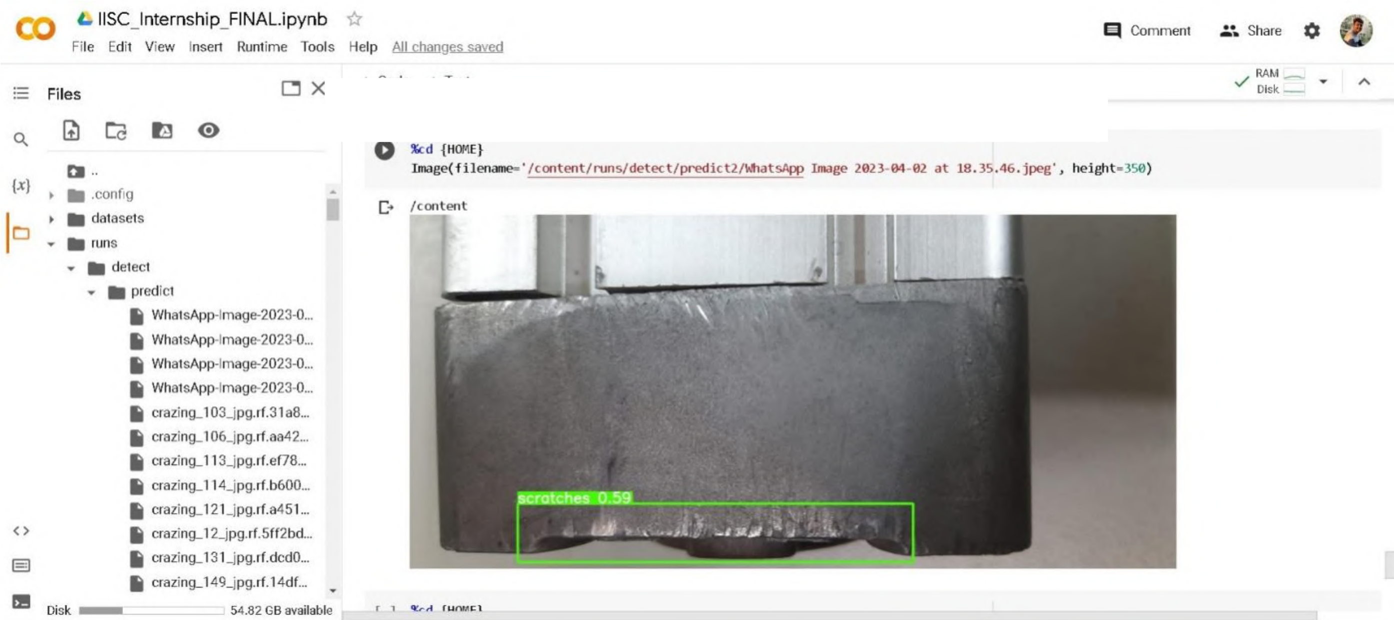


FIGURE 19: EXECUTION

2.Copy the path of the image which is supposed to be get detected.



3.Paste the Link into the cell and execute the command to generate the output.

FIGURE 20: PREDICTION

Validation Report

Introduction:

The aim of this work is to report the detection of metal surface defects in two use cases, namely a DC motor and a pneumatic cylinder. The detection of surface defects in metals was generated by using the Yolov8 algorithm to achieve results of high accuracy.

Methodology:

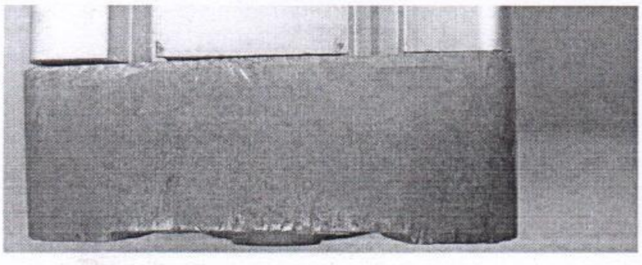
The detection of defects in the metal surface was performed using a Yolov8 algorithm that was trained on a set of images with known defects. The algorithm was then tested on 50 set of images of the DC motor and pneumatic cylinder to detect surface defects. The implementation of the algorithm was carried out to get accurate results.

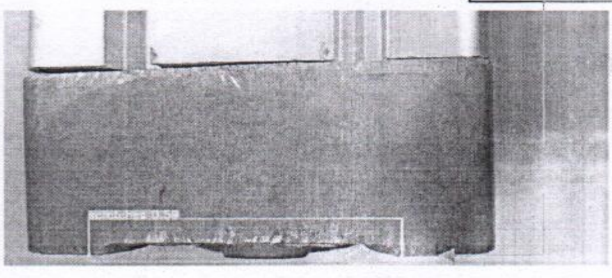
Results:

After testing the algorithm on 50 images, an accuracy of 76.5% was achieved. The accuracy concludes the ability of the algorithm to identify surface defects in 38 out of 50 images. The remaining 12 images were identified with defects, but the prediction of the algorithm was incorrect.

To reduce the incorrect predictions, the hyper-parameters of the algorithm were changed. By making these changes, the algorithm was tested which resulted in improved accuracy.

Scratches = 59%





EXPERIMENTS	CHANGES IN HYPER-PARAMETERS	ACCURACY
EXP 1: TRAINING IMAGES:1900 TESTING IMAGES:250	NO CHANGES	72.0%
EXP 2: TRAINING IMAGES:9600 TESTING IMAGES: 2400	DATA AUGMENTATION: ZOOM, FLIP, ROTATE, CROP	75.0%
EXP 3: TRAINING IMAGES:9600 TESTING IMAGES:2400	DATA AUGMENTATION + NUMBER OF EPOCHS(ITERATION)=10 + Learning rate=0.01	76.5%

Conclusion:

It is concluded that the detection of the metal surface defect was successfully performed on two use cases, the DC motor and pneumatic cylinder, using an algorithm that achieved an accuracy of 72% on the first run, and 76.5 after changing the hyper-parameters of the algorithm. The results achieved conclude the effectiveness of the algorithm in detecting surface defects but also emphasize the need for continuous testing and evaluation to improve accuracy and reliability.

Evaluation by: Evaluated on:13/04/2023.

Bharath -

Mr. Bharath G

Mr. Subhodeep Jana

Future Enhancement:

1. Segmentation
2. Measurement of Crack
3. Live on Camera

Conclusion:

In conclusion, the project focused on developing a computer vision model for detecting various types of defects on metal surfaces, including inclusion, patches, rolled-in scale, scratches, pitted surfaces, and crazing. Through the training of the model, an accuracy of 76.5% was achieved, indicating the potential usefulness of this approach in identifying and classifying defects in industrial settings. Further improvements in accuracy may be possible by refining the training process, increasing the size and diversity of the training dataset, or exploring alternative machine-learning techniques.

References:

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[4]“Keras”,Wikipedia.org https://en.wikipedia.org/wiki/Keras

[5]“ScikitLearnTutorial”,tutorialspoint.com https://www.tutorialspoint.com/scikit_learn/index.htm

Google colab code Link:

https://colab.research.google.com/drive/1vVNHuqdDl4NXwE8CHfZOmf2N61E1qzLH?usp=sharing