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DEPARTMENT OF MECHANICAL ENGINEERING

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Date:

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CERTIFICATE OF DECLARATION

DEPARTMENT OF MECHANICAL ENGINEERING

This is to certify that the Project-Thesis titled " **Steel Surface Defect Detection System using Deep Learning**" which is being submitted by **Priyanshu Singh (2020UME4055)**, **Rahul Ahuja(2020UME4064)**, **Rohit Yadav(2020UME4067)**, and **Ashish Raj (2020UME4059)**, to the Department of **Mechanical Engineering, Netaji Subhas University of Technology (NSUT) Dwarka, New Delhi,** in partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology, is a record of the thesis work carried out by the students under my supervision and guidance. To the best of my/our knowledge, the content of this thesis, in full or in parts, has not been submitted for any other Degree or Diploma.

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Date:

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ABSTRACT

Steel, a fundamental component in the machinery industry, plays a pivotal role, with the quality of its surface being a critical factor. The impact of steel surface defects on overall quality underscores the importance of surface defect detectors. Despite the global interest in this field, certain limitations persist, such as the restricted accessibility of datasets and the prevalence of small-scale public datasets. Moreover, existing research primarily focuses on model development, often neglecting considerations for real-time applications.

This paper delves into the feasibility of employing state-of-the-art deep learning methods, specifically YOLO (You Only Look Once) models, as real-time steel surface defect detectors. The study compares the performance of YOLOv3, YOLOv4, and YOLOv5, trained using a small-scale open-source NEU-DET dataset. The experimental findings reveal that YOLOv5 attains the highest accuracy, achieving an 89.6% mean Average Precision (mAP) on the NEU-DET dataset.

This research contributes to advancing the understanding of real-time steel surface defect detection through the comprehensive assessment of YOLO models' performance and their subsequent deployment on Nvidia devices. The findings provide valuable insights for optimizing real-time applications in the machinery industry.

TABLE OF CONTENT

TABLE OF EQUATIONS

TABLE OF FIGURES

TABLE OF TABLES

1. INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction to Steel

Steel is an alloy of iron and carbon, majorly iron, Carbon is added to steel to improve its strength and durability and fracture resistance is also increased as compared to pure Iron. An alloy, in particular, combines both metallic and non-metallic elements. Hence, steel is classified as an alloy because it merges the metallic attribute of iron with the non-metallic characteristic of carbon. Despite the relatively low carbon content, varying up to 2 percent, an increase in carbon concentration makes it brittle. To enhance its properties for specific purposes, various additives are added to steel.

Steel Structure of a Vehicle (Fig. 1)

Primarily employed as a building material, steel reigns as the most prevalent choice in the construction sector. Widely utilized in Civil Engineering, it finds application in crafting railway bridges, roof truss structures, and more. Noteworthy advantages of steel structures include their reduced weight compared to concrete alternatives. The advent of steel marked a transformative moment in the construction industry, replacing heavier and less durable structures that prevailed before its invention.

Steel Components (Fig. 2)

COMPOSITION OF ALLOYING ELEMENT IN STEEL:

Depending upon the type of steel, its composition varies; for example, based on the percentage of carbon content, it is classified as high, medium, or low carbon content steel. Likewise, different properties of steel also vary according to its compositions. Generally, steel is a composition of different materials like Chromium, Aluminum, Manganese, Iron, Phosphorus, Sulfur, Copper, Nickel, etc. Here a different composition of medium carbon steel is given, which helps to understand the steel composition.

Steel Tools (Fig. 3)

COMPOSITION:

Iron (Fe): The primary component of steel, providing its basic structure.

Carbon (C): Present in varying amounts, typically between 0.2% and 2.1%. The carbon content influences the mechanical properties of steel, such as hardness and tensile strength.

Alloying Elements: Additional elements, such as manganese, chromium, nickel, and others, are often added to enhance specific characteristics like corrosion resistance, toughness, and hardness.

PROPERTIES:

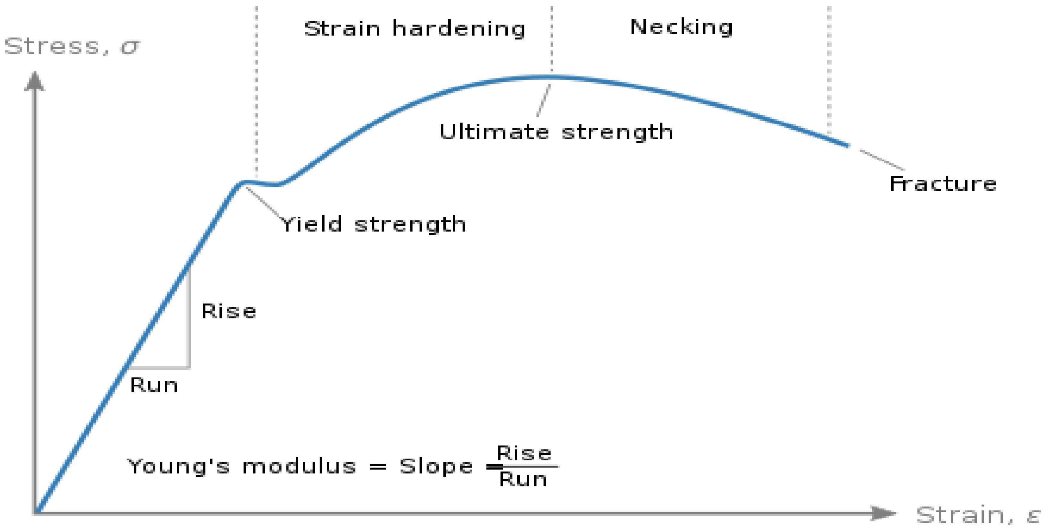
Strength: Steel is known for its high tensile strength, making it suitable for structural applications.

Ductility: Can be stretched without breaking, allowing for various forming processes.

Toughness: Resistant to fracture and can absorb energy without breaking, providing durability in challenging conditions.

Hardness: Alloying elements can increase hardness for applications requiring a tough, wear-resistant surface.

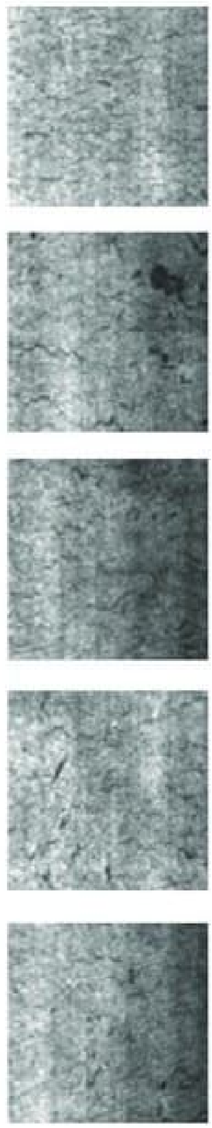
Corrosion Resistance: Stainless steel, in particular, exhibits excellent resistance to corrosion.



Stress Strain Curve for Steel (Fig. 4)

1.2 Introduction to Defects in Steel

(a) Crazing



crazing

Crazing in steel refers to the formation of fine cracks on the surface of the material. This defect is often observed in welded structures and can have detrimental effects on the mechanical properties of the steel. Crazing is a phenomenon characterized by the development of small, interconnected cracks on the surface of steel. These cracks are usually shallow and can resemble a network of fine lines, compromising the integrity of the material.

Causes of Crazing in Steel:

1) Welding Residual Stresses:

During the welding process, localized heating and cooling lead to the development of residual stresses in the welded region.

These stresses can promote the initiation and propagation of cracks, resulting in crazing.

2) Hydrogen Embrittlement:

The presence of hydrogen in the steel, often introduced during the welding process, can lead to embrittlement and crack formation.

Hydrogen diffuses into the steel matrix, weakening the material and making it susceptible to crazing.

3) Improper Heat Treatment:

Inadequate heat treatment of the steel, especially after welding, can contribute to the formation of microcracks and crazing.

Proper heat treatment is crucial to relieve welding-induced stresses and enhance the material's toughness.

4) High Cooling Rates:

Rapid cooling rates, typical in certain welding processes, can result in the formation of a brittle microstructure, making the steel prone to crazing.

Effects of Crazing in Steel:

1) Reduced Structural Integrity:

Crazing compromises the structural integrity of the steel, reducing its load-carrying capacity and overall strength.

2) Susceptibility to Fracture:

The presence of cracks makes the steel more susceptible to sudden fracture, especially under applied loads or external forces.

3) Diminished Fatigue Resistance:

Crazing can significantly reduce the fatigue resistance of the material, making it more prone to failure under cyclic loading conditions.

4) Aesthetic Concerns:

In addition to the mechanical implications, crazing can also affect the appearance of the steel surface, which may be undesirable in certain applications.

Mitigation Strategies:

1) Proper Welding Procedures:

Employing appropriate welding techniques and parameters can help minimize residual stresses and reduce the likelihood of crazing.

2) Hydrogen Control:

Implement measures to control and minimize the presence of hydrogen during welding, such as using low-hydrogen electrodes and ensuring proper shielding.

3) Optimized Heat Treatment:

Ensuring proper post-weld heat treatment helps relieve residual stresses and enhances the steel's toughness, reducing the risk of crazing.

4) Controlled Cooling Rates:

Managing the cooling rate during welding and heat treatment processes can prevent the formation of a brittle microstructure, mitigating crazing.

(b) Inclusion

Inclusion defects in steel refer to the presence of non-metallic particles or foreign materials within the steel matrix. These inclusions can have significant consequences on the mechanical properties of the material. Inclusion defects in steel involve the incorporation of non-metallic particles, such as oxides, sulfides, or silicates, into the steel matrix during its production or processing. These inclusions can be detrimental to the material's mechanical properties.

inclusion

Causes of Inclusion Defects:

1) Incomplete Deoxidation:

Incomplete removal of oxygen during the steelmaking process can lead to the formation of oxide inclusions. These inclusions are often present in the form of alumina or silica particles.

2) Inadequate Refining:

Insufficient refining of the molten steel can result in the retention of impurities, including non-metallic particles, leading to inclusion defects.

3) Contaminated Raw Materials:

The presence of contaminated raw materials, such as scrap metal with impurities, can introduce foreign materials into the steel, contributing to inclusion defects.

4) Refractory Wear:

Wear and degradation of refractory materials used in the steelmaking process can introduce refractory particles into the molten steel, causing inclusion.

Effects of Inclusion Defects:

1) Reduced Mechanical Properties:

Inclusions act as stress concentration points, reducing the material's strength, toughness, and overall mechanical properties.

2) Decreased Ductility:

Inclusion defects can lead to decreased ductility, making the steel more susceptible to brittle fracture under applied loads.

3) Impaired Fatigue Resistance:

Inclusions can initiate fatigue cracks, significantly reducing the material's resistance to cyclic loading and increasing the likelihood of premature failure.

4) Surface Defects:

Inclusions near the surface can cause surface defects, impacting the material's surface finish and potentially compromising its corrosion resistance.

Mitigation Strategies:

1) Optimized Steelmaking Processes:

Implementing optimized steelmaking practices, including thorough deoxidation and refining processes, helps minimize the formation of inclusions.

2) Quality Raw Materials:

Ensuring the use of high-quality raw materials with minimal impurities reduces the risk of introducing foreign particles into the steel.

3) Regular Maintenance of Equipment:

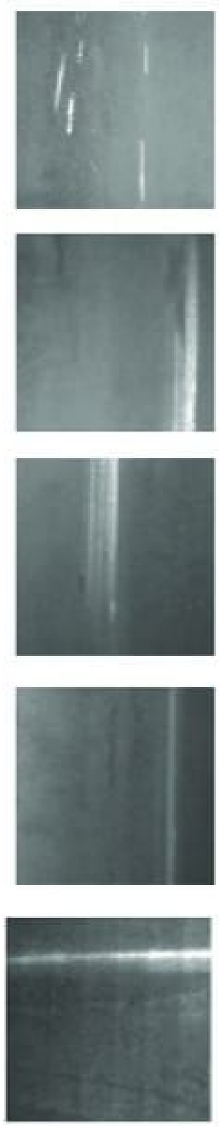
Regular maintenance and replacement of refractory materials in steelmaking equipment help prevent refractory wear and the introduction of refractory particles.

4) Advanced Quality Control Techniques:

Utilizing advanced quality control techniques, such as ultrasonic testing, to detect and assess the presence of inclusions helps ensure the quality of thesteel.

(c) Scratches

Scratches in steel refer to the presence of visible marks or abrasions on the surface of the material. While scratches themselves might not be considered a defect in the same sense as internal flaws, they can impact the appearance and potentially affect the material's performance in certain applications. Scratches in steel manifest as superficial marks or abrasions on the surface of the material. These scratches can vary in depth and length, and they are typically the result of mechanical actions or contact with abrasive surfaces during handling, processing, or other stages.



scratches

Causes of Scratches:

1) Handling and Transportation:

Rough handling during transportation or material handling processes can result in scratches on the steel surface.

2) Processing Equipment:

Contact with abrasive tools or surfaces during cutting, machining, or other processing steps can cause scratches.

3) Storage and Stacking:

Improper storage or stacking of steel products can lead to surface abrasions as materials rub against each other.

4) Foreign Particles:

Presence of foreign particles on surfaces, such as dirt or abrasive substances, can cause scratches when the steel comes into contact with them.

Effects of Scratches:

1) Aesthetic Concerns:

Scratches affect the visual appearance of the steel, potentially diminishing its aesthetic quality.

2) Corrosion Susceptibility:

Scratched surfaces may be more prone to corrosion, as the protective oxide layer can be compromised, exposing the underlying steel to environmental factors.

3) Fatigue Performance:

While minor scratches may not significantly impact fatigue resistance, deep or numerous scratches can contribute to fatigue failure under cyclic loading conditions.

4) Surface Integrity:

Deep scratches may compromise the surface integrity, affecting the smoothness and potentially the functionality of the steel in certain applications.

Mitigation Strategies:

1) Careful Handling:

Implementing proper handling procedures during transportation and processing to minimize the risk of abrasions.

2) Protective Coatings:

Applying protective coatings or films to the steel surface can help reduce the likelihood of scratches and enhance corrosion resistance.

3) Quality Control Measures:

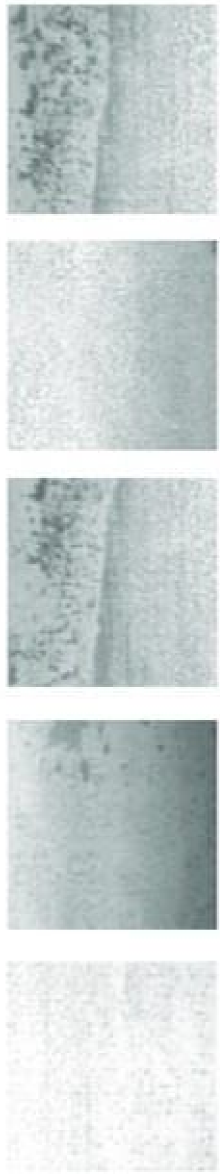
Implementing rigorous quality control measures to identify and address scratches during various stages of production and handling.

4) Proper Storage:

Ensuring proper storage conditions and practices to prevent abrasions from stacking or movement of steel materials.

(d) Pitted Surface

A pitted surface defect in steel refers to the presence of small, localized cavities or depressions on the material's surface. These pits can vary in size and depth, and their formation can be influenced by various factors. Pitted surface defects in steel are characterized by the formation of small, often circular or irregularly shaped, cavities or pits on the surface of the material. These pits can be the result of corrosion, erosion, or other environmental and processing factors.



pitted surface

Causes of Pitted Surface Defects:

1) Corrosion:

The most common cause of pitted surfaces in steel is corrosion. Exposure to corrosive environments, such as saltwater, acidic solutions, or atmospheric contaminants, can lead to the localized breakdown of the protective oxide layer on the steel surface.

2) Chemical Attack:

Exposure to chemicals or harsh substances during processing, cleaning, or industrial operations can contribute to the formation of pits on the steel surface.

3) Microbial Corrosion:

Microbial activity, such as the presence of certain bacteria, can contribute to localized corrosion and pitting on the steel surface.

4) Abrasion:

Mechanical abrasion, caused by the contact of steel surfaces with abrasive materials or particles, can lead to the formation of pits.

Effects of Pitted Surface Defects:

1) Reduced Strength and Toughness:

Pits can act as stress concentration points, reducing the overall strength and toughness of the affected steel area.

2) Increased Corrosion Susceptibility:

Pitted surfaces are more prone to further corrosion as the protective oxide layer is compromised, leading to accelerated material degradation.

3) Surface Roughness:

Pitted surfaces can result in increased surface roughness, affecting the aesthetic quality and potentially interfering with functional requirements.

4) Fatigue Failure Risk:

In cyclic loading conditions, such as those experienced in structural components, pitted surfaces can contribute to fatigue failure by initiating cracks.

Mitigation Strategies:

1) Protective Coatings:

Applying corrosion-resistant coatings to the steel surface can provide a barrier against environmental factors and prevent or slow down the formation of pits.

2) Proper Material Selection:

Choosing steel alloys with improved corrosion resistance for applications in harsh environments can reduce the likelihood of pitted surface defects.

3) Regular Maintenance:

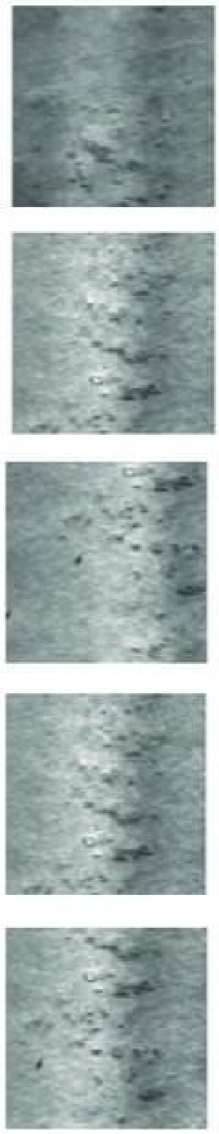
Implementing regular inspection and maintenance practices to identify and address pitted surfaces before they progress and cause more significant damage.

4) Environmental Control:

Controlling the environment in which steel is used or stored to minimize exposure to corrosive elements can help prevent the formation of pitted surface defects.

(e) Rolled in Scale

Rolled-in scale in steel refers to the presence of scale—thin layers of iron oxides—incorporated into the surface of the steel during the rolling process. This defect occurs when the scale is not effectively removed or separated from the steel surface during hot rolling. Rolled-in scale in steel is a surface defect where thin layers of iron oxides, known as scale, are embedded or incorporated into the surface of the steel during the hot rolling process. Scale is a byproduct of the oxidation of the steel surface at elevated temperature.



rolled in scale

Causes of Rolled-in Scale:

1) Ineffective Scale Removal:

During the hot rolling process, the steel surface develops an oxide scale due to exposure to high temperatures. If the scale removal mechanisms, such as descaling equipment, are ineffective, the scale can be rolled into the steel surface.

2) Insufficient Descaling Equipment:

Inadequate or malfunctioning descaling equipment, which is designed to remove the scale before further processing, can lead to the incorporation of scale into the steel surface.

3) High Rolling Temperatures:

Elevated rolling temperatures can promote the formation of a thicker and more adherent scale. If not properly managed, this scale can become rolled into the steel surface.

Effects of Rolled-in Scale:

1) Reduced Surface Quality:

Rolled-in scale impairs the visual appearance and surface quality of the steel, affecting its aesthetic appeal and potentially hindering its functional performance.

2) Surface Roughness:

The presence of scale on the steel surface can contribute to increased surface roughness, impacting the material's texture and finish.

3) Corrosion Susceptibility:
Scale can create crevices and imperfections on the steel surface, making it more susceptible to corrosion by providing sites for corrosive agents to attack the material.
4) Weakened Mechanical Properties:
In severe cases, rolled-in scale can act as stress concentration points, potentially leading to reduced mechanical properties and structural integrity.

Mitigation Strategies:

1) Effective Descaling Practices:
Implementing efficient descaling techniques and equipment during the hot rolling process is crucial to minimize the formation and incorporation of scale into the steel surface.
2) Optimized Rolling Parameters:
Controlling and optimizing the rolling parameters, including temperature and speed, helps manage scale formation and facilitates its removal during subsequent processing.
3) Quality Control Measures:
Implementing rigorous quality control measures to inspect and detect rolled-in scale during various stages of production, ensuring timely intervention and corrective actions.
4) Surface Treatment:
Utilizing surface treatment methods, such as pickling or shot blasting, to remove any residual scale and enhance the surface finish of the steel.

1.3 Motivation

The motivation driving the formulation of the mathematical model for steel surface defect detection using YOLO stems from a compelling intersection of industrial imperatives. In the dynamic landscape of manufacturing, the need for real-time detection and classification of defects on steel surfaces is pivotal, prompting the utilization of YOLO—a model recognized for its rapid processing capabilities. This initiative aligns with the broader trend of automation in smart factories, offering enhanced operational efficiency, reduced manual intervention, and a proactive approach to quality control. By integrating YOLO's versatility to handle diverse defect patterns and its adaptability to edge devices, the model stands poised to address the pragmatic challenges of industrial environments. The research seeks to bridge the gap between theoretical advancements in computer vision and their practical implementation in smart factory ecosystems, fostering continuous improvement, interdisciplinary collaboration, and a trajectory towards more efficient and automated quality control processes within the manufacturing continuum. Ultimately, the motivation lies in the transformative potential of YOLO, promising a harmonious integration of real-time capabilities and adaptive defect detection mechanisms into industrial workflows.

1.4 Key Challenges

The development and implementation of the mathematical model for steel surface defect detection using YOLO, along with efforts to address dataset limitations through generative AI techniques, are confronted with several key challenges:

1. Dataset Diversity Constraints:
   The existing datasets for metal surface detection lack the necessary diversity and comprehensiveness, impeding the model's ability to be trained and evaluated effectively.

2. Complexity in Defect Patterns:
   Metal surface defects exhibit intricate and diverse patterns, introducing complexity for the model in generalizing and accurately detecting a broad spectrum of anomalies.

3. Performance Evaluation Gaps:
   The absence of thorough studies assessing the performance improvements of deep learning algorithms in the realm of metal surface detection creates a knowledge gap, hindering a clear understanding of algorithmic effectiveness.

4. Industrial Deployment Complexity:
   The practical implementation of the model in real-world industrial environments presents challenges related to scalability, real-time processing demands, and seamless integration with existing systems.

By actively acknowledging and systematically addressing these challenges, the research endeavors to elevate the robustness, reliability, and practical utility of the mathematical model for steel surface defect detection.

1.5 Problem addressed in thesis

In the production workflow of industrial products, various factors such as equipment, human intervention, environmental conditions, and processing technologies can contribute to surface defects. These defects not only compromise product quality and pricing but also introduce potential risks and disruptions to subsequent stages in the production process. Recognizing the significance of this issue, the deployment of surface defect detectors has become pivotal in manufacturing.

Presently, human inspections remain a common practice, but their efficiency varies and is subject to human error. Consequently, there is a growing demand for alternative solutions, with automated inspection systems emerging as a viable option. With the rise of computer vision and deep learning, defects on product surfaces are now treated as specific objects, offering a transformative approach to industrial inspections in sectors such as wood, tiles, fabric, and steel.

The steel production industry, as a heavyweight player in manufacturing, has attracted substantial attention from researchers and companies seeking efficient methods for detecting and classifying surface defects on steel. However, challenges persist, including the need for real-time performance, limited dataset sizes, small target dimensions, and imbalanced sample identification. Moreover, real-world scenarios in industrial settings demand an end-to-end system, encompassing camera setups for image acquisition, edge computing devices hosting deep learning models, and display screens for the supervision of detection and classification results.

This report explores the feasibility of employing state-of-the-art one-stage (SOTA) detector algorithms from the YOLO family to address the aforementioned challenges. Specifically, our contributions are outlined as follows:
We evaluate and compare the real-time performance of YOLOv3, YOLOv5, and YOLOv7 in detecting steel surface defects. Our experiments involve training these pre-trained models from the YOLO family using transfer learning techniques on the NEU-DET dataset.

1.6 Approach to the Problem and Organization of the Thesis

Employing a multifaceted strategy to address the complexities of steel surface defect detection, the core of our approach involves harnessing the capabilities of cutting-edge YOLO family models. This includes YOLOv3, YOLOv4, and YOLOv5, each carefully chosen based on its architectural nuances and suitability for the specific use case. The goal is to capitalize on the strengths of each model while mitigating their respective limitations. To counteract the scarcity of diverse datasets, generative AI techniques are implemented for intelligent data augmentation, enhancing the model's ability to generalize across a spectrum of defect patterns.

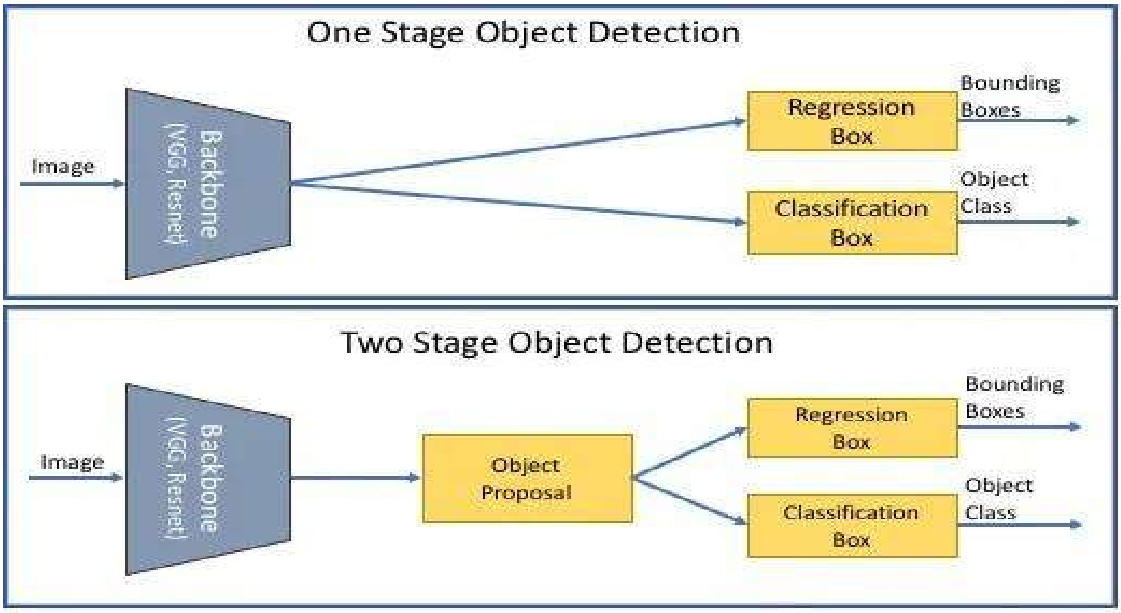
The thesis is meticulously organized into distinct sections to provide a structured and thorough exploration of the proposed mathematical model for steel surface defect detection. Commencing with background and literature review sections, the foundational context for the research is established. Subsequent sections delve into the intricacies of the YOLO architecture, delineating the model's loss functions and evaluation metrics. The mathematical formulations are presented systematically, ensuring clarity in comprehending the model's complexities.

Continuing, the thesis elaborates on experimental methods and materials, delineating datasets, preprocessing steps, and training procedures. The results section meticulously presents the outcomes of comprehensive experiments, featuring precision-recall curves, F1 scores, and mean average precision (mAP) values. Practical considerations for industrial deployment are discussed, emphasizing real-time analysis and seamless integration with existing systems.

In conclusion, the thesis provides a critical discussion of results, highlighting the model's strengths and areas for improvement. Acknowledging encountered limitations and challenges, the thesis suggests recommendations and avenues for future work. Overall, the thesis is meticulously organized to offer an in-depth exploration of the mathematical model's development, evaluation, and potential applications in the domain of steel surface defect detection.

2. MATHEMATICAL MODELING/EXPERIMENTAL METHODS AND MATERIALS

2.1 Yolo algorithm overview



Block Diagram of YOLO (Fig. 5)

This section provides an overview of the YOLO (You Only Look Once) algorithm, focusing on its evolution through different versions.

The YOLO algorithm distinguishes itself from conventional anchor-based models, such as Faster R-CNN and SSD, by treating object detection as a regression task without Region of Interest (ROI) detection. Instead, YOLO divides the image into SxS grids for object detection. If an object's centroid falls within a grid, that grid is responsible for detecting the object. YOLO predicts multiple bounding boxes with distinct confidence scores, indicating the likelihood of containing an object. Additionally, it predicts class probabilities per grid, irrespective of the number of bounding boxes, enabling final object detections.

YOLOv1:

- YOLOv1 is a fast, single-stage object detector suitable for real-time applications.
- Drawbacks include the limitation of each grid to have only one class and challenges in detecting small objects when they are close or overlap.

YOLOv2 to YOLOv4:

- Subsequent updates from v2 to v4 address limitations of the previous versions, mainly focusing on improving the backbone, a critical component of YOLO's structure.

YOLOv5:

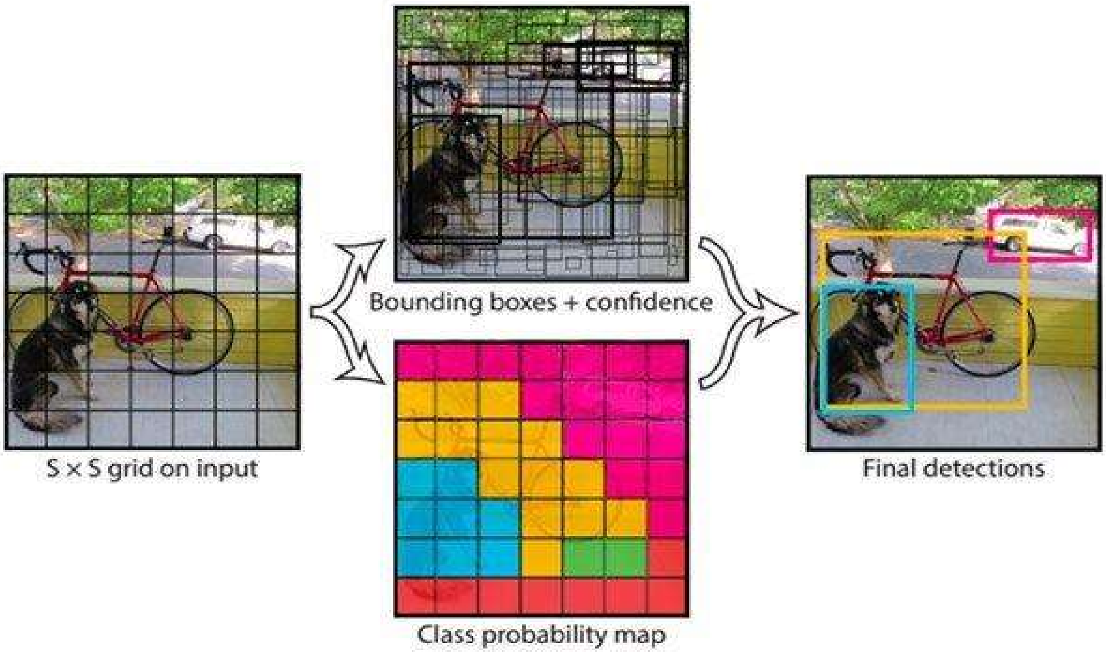
- YOLOv5, introduced as the PyTorch implementation of YOLOv4, emphasizes exportability for deployment across various environments.
- Notable updates in version 6, including YOLOv5 nano, aim for reduced parameters and size, making it suitable for lightweight devices like mobiles and CPUs.

YOLOv7:

- YOLOv7, released in June 2022, represents the state-of-the-art (SOTA) object detector in the YOLO family.
- It introduces Extended Efficient Layer Aggregation Network (E-ELAN) and Model Scaling for Concatenation (MSC) for improved structural efficiency and versatility.
- YOLOv7 achieves high accuracy and real-time performance, making it a leading object detector.

Device	Configuration
Operating System	Windows 11
Processor	Intel® i5
GPU	RTX 2080 10 G × 2
GPU Accelerator	CUDA 11.2, Cudnn 8.1
Framework	PyTorch 1.9.1
Compiler IDE	Pycharm
Scripting language	Python 3.6

2.2 Yolo architecture



Working of YOLO (Fig. 6)

1. YOLO Architecture:

Bounding Box Parameters:

$$b_x, b_y : \text{Bounding box center coordinates (normalized)}$$
$$b_w, b_h : \text{Bounding box width and height (normalized)}$$

Class Probabilities:

$$P_c : \text{Probability of object presence in the bounding box}$$
$$P_{\text{class}} : \text{Class probabilities for each defect type}$$

Model Prediction:

$$\hat{Y} = \{b_x, b_y, b_w, b_h, P_c, P_{\text{class}}\}$$

Model Output:

$$\hat{Y}_{i,j,k} : \text{Model prediction for grid cell at position } (i, j) \text{ and anchor box } k$$

2. Loss Function:

Localization Loss:

$$L_{\text{loc}} = \lambda_{\text{coord}} \sum_{i=0}^{S-1} \sum_{j=0}^{S-1} \sum_{k=0}^{B-1} \left[\left(\hat{Y} i, j, k - Y i, j, k \right)^2 \right]$$

Equation 1

Measures the error in predicting the bounding box parameters.

Classification Loss:

$$L_{\text{class}} = \lambda_{\text{class}} \sum_{i=0}^{S-1} \sum_{j=0}^{S-1} \sum_{k=0}^{B-1} \left[\left(\hat{P}\text{class}, i, j, k - P\text{class}, i, j, k \right)^2 \right]$$

Equation 2

Measures the error in predicting the class probabilities.

Overall Loss:

$$L = L_{\text{loc}} + L_{\text{class}}$$

Equation 3

The combined loss for training the YOLO model.

3. Precision and Recall:

True Positives (TP):

TP: The number of correctly predicted defect bounding boxes.

False Positives (FP):

FP: The number of predicted defect bounding boxes that do not correspond to a real defect.

False Negatives (FN):

FN: The number of real defect bounding boxes that were not predicted.

Precision:

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

Equation 4

The ratio of correctly predicted positive instances to the total predicted positives.

Recall (Sensitivity):

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

Equation 5

The ratio of correctly predicted positive instances to the total actual positives.

4. F1 Score:

F1 Score:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Equation 6

A harmonic mean of precision and recall, providing a balanced metric.

5. Thresholding for Precision-Recall Curve:

Precision-Recall Curve:

- Varying the confidence threshold to construct a curve.

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

Equation 7

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

Equation 8

6. Mean Average Precision (mAP):

Average Precision (AP):

$$\text{AP} = \int_0^1 \text{Precision}(R)\, dR$$

Equation 9

Area under the precision-recall curve.

Mean Average Precision (mAP):

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

Equation 10

Average of AP values across different defect classes.

7. Training Objective:

Modified Training Objective:

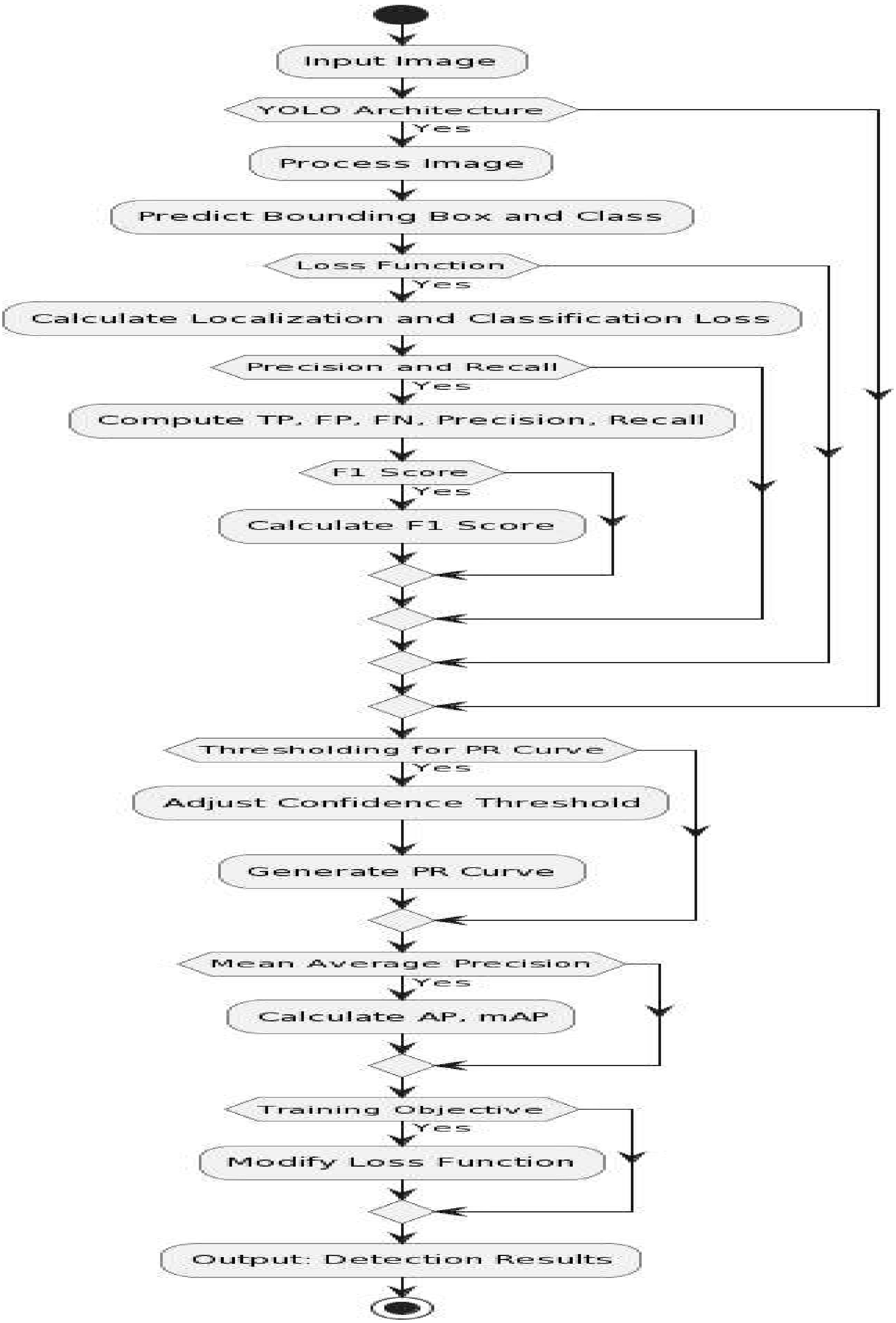
$$L = L_{\text{loc}} + L_{\text{class}} + \lambda_{\text{prec}} \cdot \text{Precision} + \lambda_{\text{rec}} \cdot \text{Recall}$$

Equation 11

Adjusted loss function considering class-specific precision and recall.

- Here, λ_{prec} and λ_{rec} are coefficients for balancing the contributions of precision and recall to the overall loss.

This comprehensive mathematical model details the YOLO architecture, loss functions, and evaluation metrics essential for steel surface defect detection. The provided breakdown aims to offer a thorough understanding of each component and its role in the detection process.



Flow Chart of YOLO (Fig. 7)

3. RESULTS AND DISCUSSION

Our dataset has a total of 1800 images and each defect has an approximate 300 images. The training was done using 100 epochs for 1800 images on YOLO v3, YOLO v4 and YOLO v5.

We use F1 score and Mean Average Precision as the criteria to compare the YOLOv3, YOLOv4, and YOLOv5 algorithms. F1 score is the harmonic mean of precision and recall. It is the model's test accuracy. The highest possible value of F1 score is 1, which indicates perfect precision and recall. The lowest possible score is zero, which indicates either the precision or recall is zero. Mean Average Precision is calculated by taking mean of average precision of all the classes. Mean Average Precision can be calculated by taking the mean of Average Precision. Mean Average Precision can be considered a measure to calculate the accuracy of machine learning algorithms. FPS has been used to calculate the speed of the algorithm.

Average Precision is calculated from the precision-recall curve. Mean average Precision is calculated by taking the mean of average precision of all the classes.

Precision can be calculated as the ratio of true prediction is to the total number of predictions. For example, if a model makes 50 predictions and all of them are correct, the precision is 100 percent. If a model makes 50 predictions and 25 of them are correct then the precision is 50 percent.

Recall can be calculated as the ratio of true objects to the total number of objects present in an image. For example, if a model detects 50 true objects and there are 100 true objects in the image, then recall is calculated to be 50 percent.

Having only high precision or having only high recall does not guarantee high precision. There should be a balance between both precision and recall in for an object detection algorithm to be considered as accurate. This is the reason why we look at the F1 score to decide whether a model is accurate or not.

$$F1score = 2 * \frac{(precision * recall)}{precision + recall},$$

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive},$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative},$$

Equations 12.1, 12.2 and 12.3

For training the neural network, we first used YOLOv3. Similarly, we used YOLOv4 and YOLOv5 for training, with the exact same parameter assignment that we used for YOLOv3.

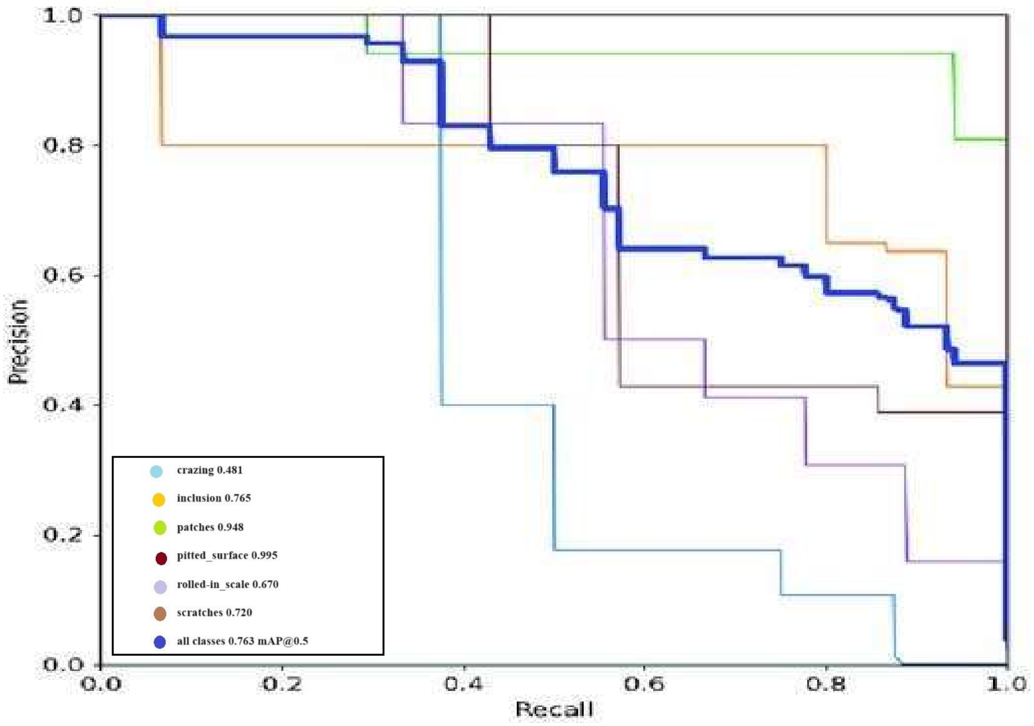
YOLOv5 presents higher Mean Average Precision and F1 score compared to YOLOv3 and YOLOv4. This shows that YOLOv5 can detect objects more accurately compared to the other algorithms.

In this we also found that YOLO v3 is faster algorithm as compared to other algorithms. The accuracy of YOLO v5 is higher than YOLO v4 because it uses auto learning bounding boxes.

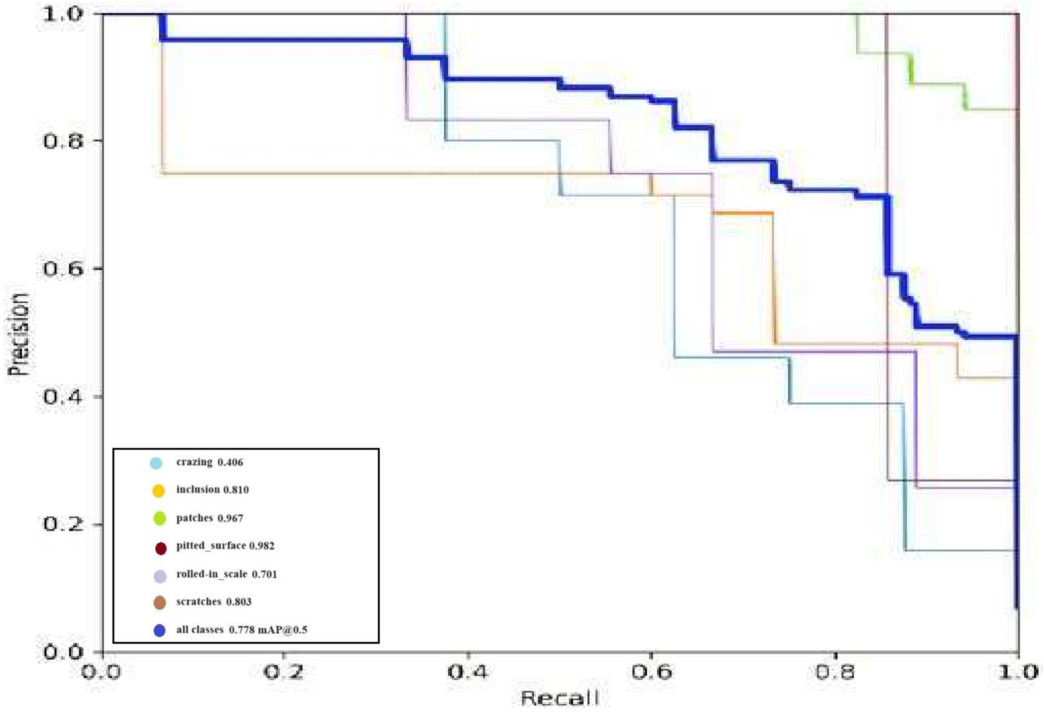
YOLOv3 has a high precision but its recall is low, and this shows that the model needs improvement. For an algorithm to be considered efficient, there must be a perfect balance between precision and recall and that is reflected by the F1 score of the algorithm. In YOLOv4 and YOLOv5 the precision and recall are balanced. This is the reason why F1 score of YOLOv4 and YOLOv5 are higher compared to YOLOv3 but YOLOv3 has higher precision. We see that the models in YOLOv4 and YOLv5 have balanced precision and recall which results in a high F1 score.

DataSet Number	Training/Testing Set	Defect Name	Defects
1800 images	Training set (1400 images)	Crazing	
		Inclusion	
		Patches	
		Pitted Surfaces	
		Rolled-in scale	
		Scratches	
	Testing set (400 images) 845 labels	Crazing	140
		Inclusion	187
		Patches	190
		Pitted Surfaces	78
		Rolled-in scale	130
		Scratches	120

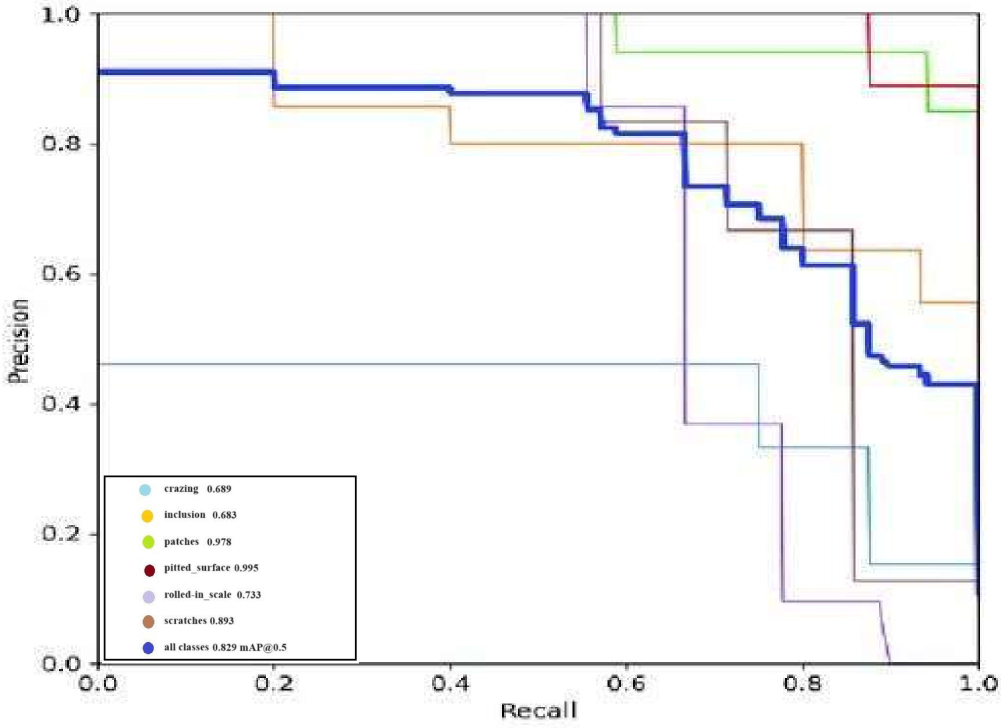
Dataset Distribution (Table 2)



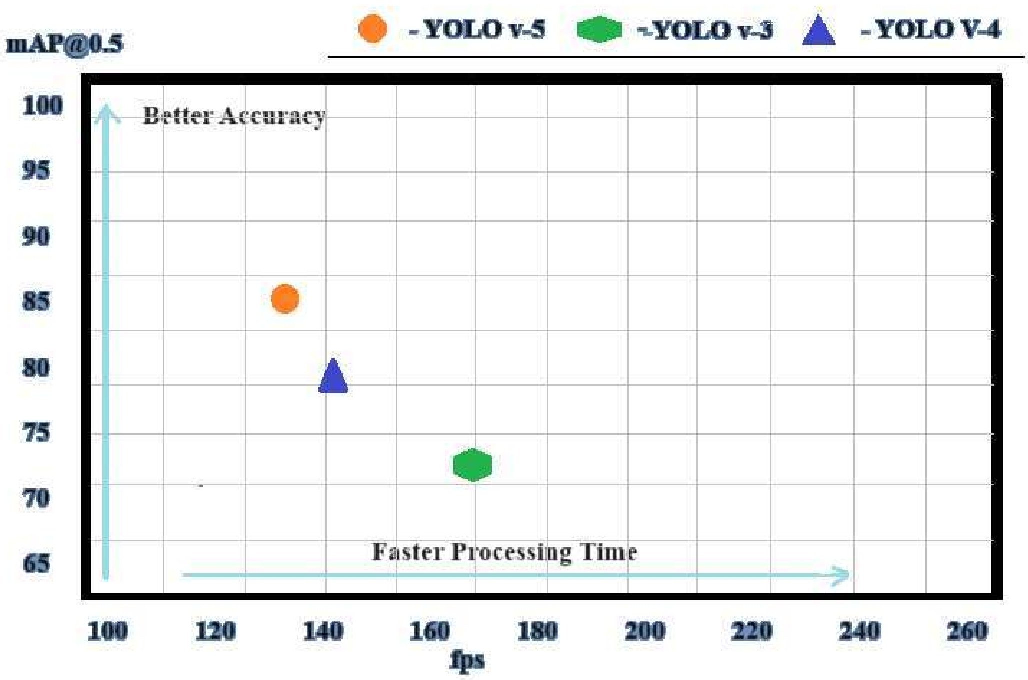
Precision vs Recall for YOLO v3



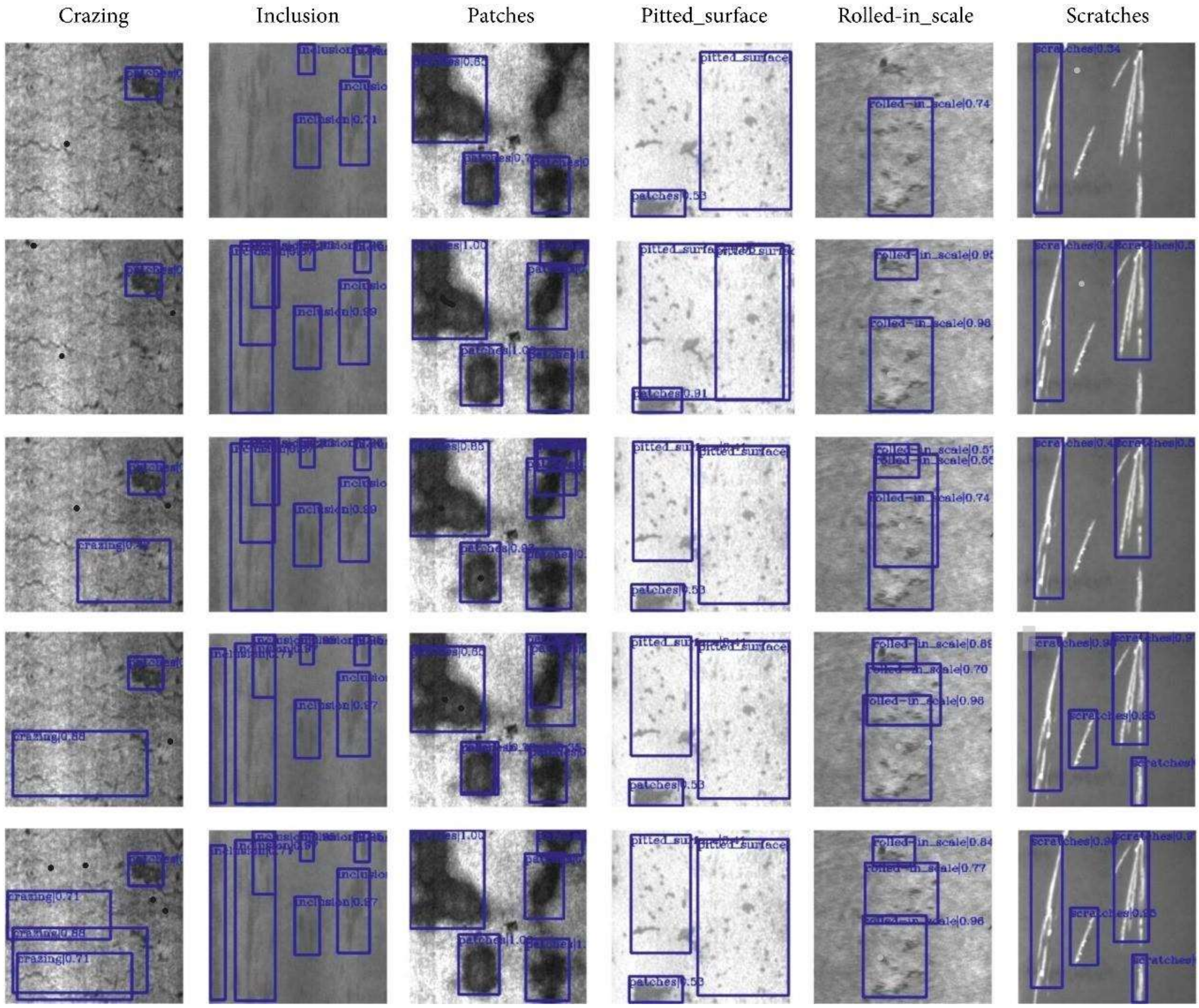
Precision vs Recall for YOLO v4



Precision vs Recall for YOLO v5



Comparison between YOLO Models



Steel Surface Defects Detected (Fig. 12)

4. CONCLUSIONS AND FUTURE WORK

4.1 Task, Achievement, and Possible Beneficiaries

In this study, we assess the efficacy of state-of-the-art YOLO family models for real-time detection and classification of steel surface defects, emphasizing accuracy and real-time analytical capabilities. The primary objective is to affirm the practicality of deploying YOLO models on diverse devices for applications within smart factory environments. This research encompasses a comprehensive comparative analysis of YOLO models, coupled with the development and deployment of a real-time steel surface defect detector, contributing to the acceleration of future investigations and bridging the divide between research endeavors and practical industrial implementation.

Beyond these foundational attributes, our customized application incorporates additional functionalities. Notably, it allows for the preservation of detected results in either image or video formats based on input data, adding a layer of versatility to the system. Furthermore, the application facilitates the calculation of real-time mean average precision (mAP) accuracy, offering a valuable metric that can seamlessly integrate into smart factory applications.

This study holds significance for a broad spectrum of stakeholders, including researchers, industrial practitioners, and technology developers. Researchers stand to benefit from the insights gained through the comparative analysis of YOLO models, potentially inspiring advancements in object detection methodologies. Industrial practitioners can leverage the developed real-time defect detection application to enhance quality control processes within manufacturing settings. Additionally, technology developers may find value in the customizable features of the application, offering a robust foundation for further innovation in real-time defect detection systems. Overall, this work contributes to the practical integration of cutting-edge computer vision technologies into industrial workflows, fostering efficiency and precision in defect detection on steel surfaces.

4.2 Review of Contributions

Conceptualization, Priyanshu Singh; investigation, Rohit Yadav; methodology, Rahul Ahuja.; project administration, Ashish Raj, Priyanshu Singh, Rahul Ahuja, Rohit Yadav; software, Rahul Ahuja.; supervision, Priyanshu Singh; validation, Priyanshu Singh, Rahul Ahuja; writing—original draft, Ashish Raj; writing—review and editing, Ashish Raj and Rohit Yadav. All authors have read and agreed to the published version of the manuscript.

4.3 Scope for Future Work

The potential scope for future work related to the mathematical model for steel surface defect detection using the YOLO architecture is multifaceted and includes various avenues for improvement and exploration. Researchers could delve into expanding and diversifying the dataset to improve the model's generalization, collecting comprehensive and varied examples of steel surface defects. Advanced pre-processing techniques may be explored to optimize the input data, investigating image enhancement methods, noise reduction, and other data augmentation strategies to enhance model robustness. Algorithmic enhancements to the YOLO architecture or alternative object detection models could be investigated, involving modifications to the backbone architecture, loss functions, or the incorporation of attention mechanisms to boost detection accuracy.

Efforts could also be directed towards optimizing the model for real-time performance, crucial for industrial settings, through techniques such as model quantization, pruning, or specialized hardware accelerators. Integration with existing industry standards and quality control systems is another avenue, ensuring compatibility with established manufacturing protocols. Enhancing the model's explainability and interpretability would contribute to stakeholders' understanding and trust in the model's predictions.

Continuous model monitoring and updating mechanisms should be developed to adapt to evolving defect patterns, environmental changes, or variations in manufacturing processes. Ethical considerations and bias mitigation strategies are vital, addressing potential biases in the training data and ensuring fair and unbiased model predictions, especially in diverse industrial settings. User-friendly interfaces can be designed for effective interaction, including intuitive visualization tools and dashboards for quality control professionals to interpret and act upon the model's output. Moreover, seamless integration with broader smart factory ecosystems, incorporating Industry 4.0 principles for enhanced automation, data sharing, and interoperability, represents a significant area for exploration.

By addressing these future research directions, the mathematical model can be refined, adapted, and expanded to meet the evolving needs of the steel manufacturing industry, contributing to advancements in quality control and defect detection processes.

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