Industrial Processes with Computer Vision: Approach to Identify and Monitor Productive Failures in Auto Parts Industries

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Introduction

Approach to Identify and Monitor Productive Failures in Auto Parts Industries

The importance of seamless production lines

The term "seamless production lines" refers to a smooth and continuous flow of processes from raw materials to finished products

Historical reliance on manual inspections

Manual inspections leverage human expertise, intuition, and sensory capabilities to identify defects, irregularities, or deviations in products.

Limitations of manual methods

- Time-consuming;
- Error-prone;
- Limited real-time capabilities;
- Unviable for today's mass production.

Some ways of monitoring defects

Visual Inspection:

Visual inspection involves human inspectors assessing products for defects using their eyes. This method is effective for detecting surface irregularities, color variations, and other visible defects.

Eddy Current Testing:

Eddy current testing is commonly used to detect surface and near-surface defects in conductive materials. It works by inducing electrical currents in the material and measuring the changes in the electromagnetic field caused by defects such as cracks or variations in conductivity.

Future is coming

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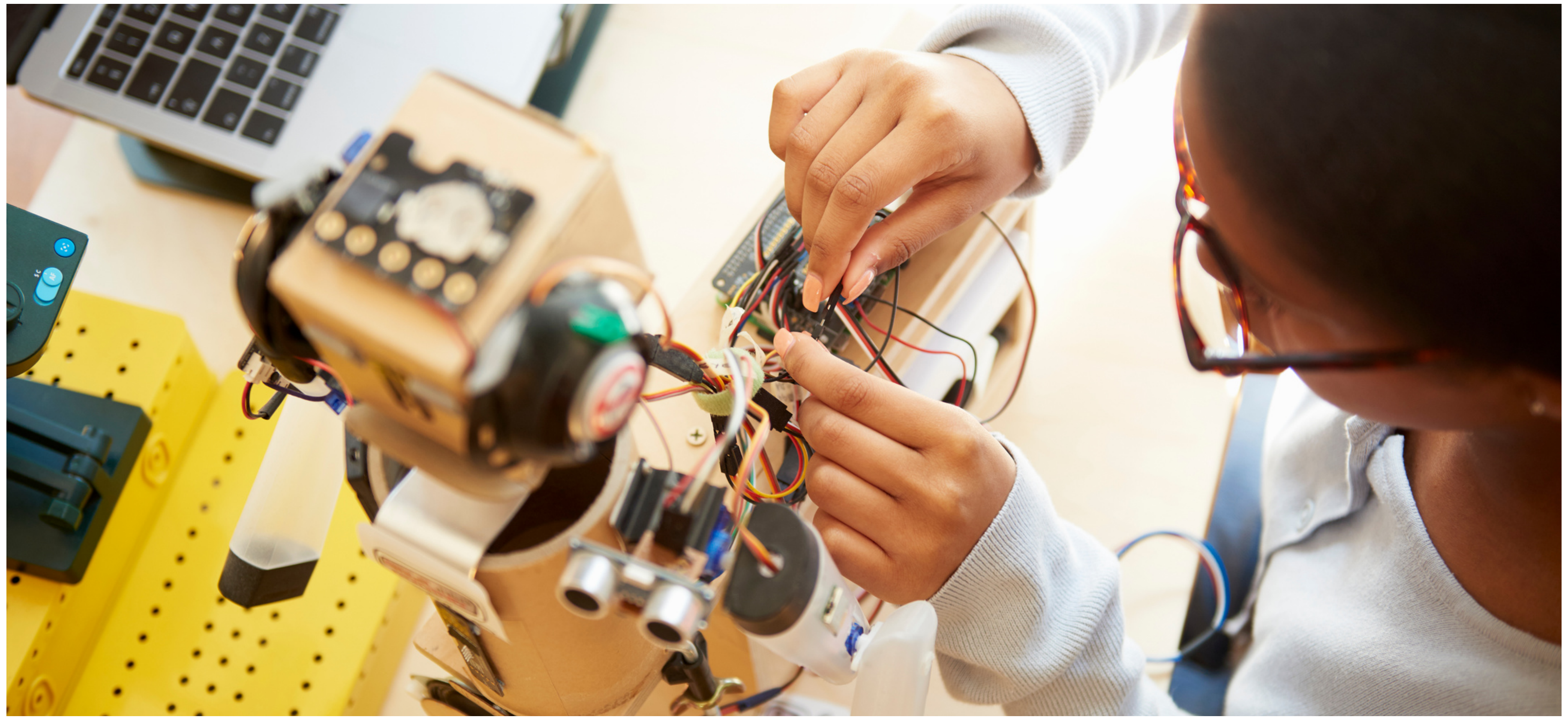
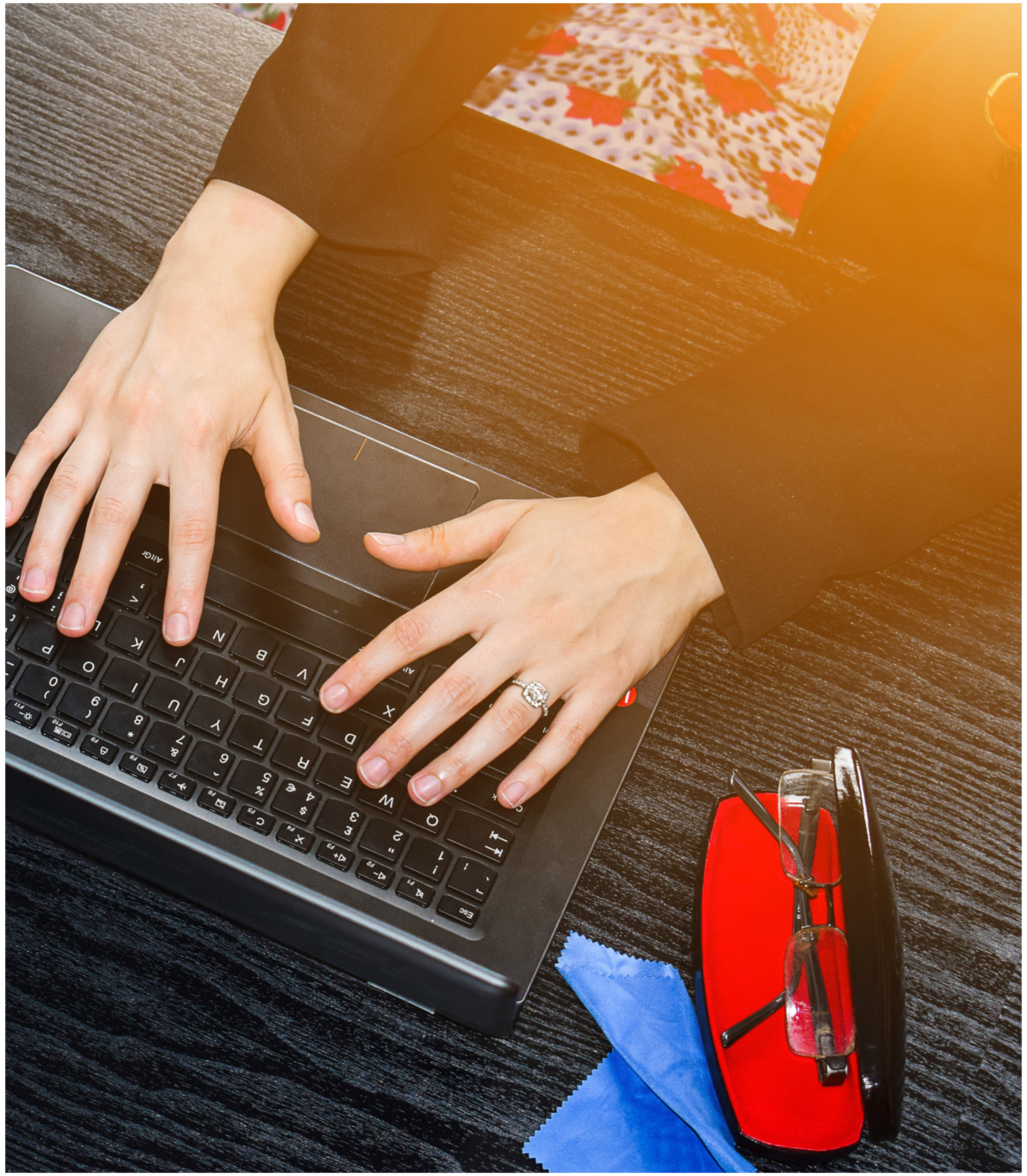


Advantages of

Computer Vision

- Eliminates limitations associated with human-based inspection
- Ensures consistent and objective assessments of product quality
- AI-powered algorithms operate tirelessly, providing round-the-clock monitoring capabilities



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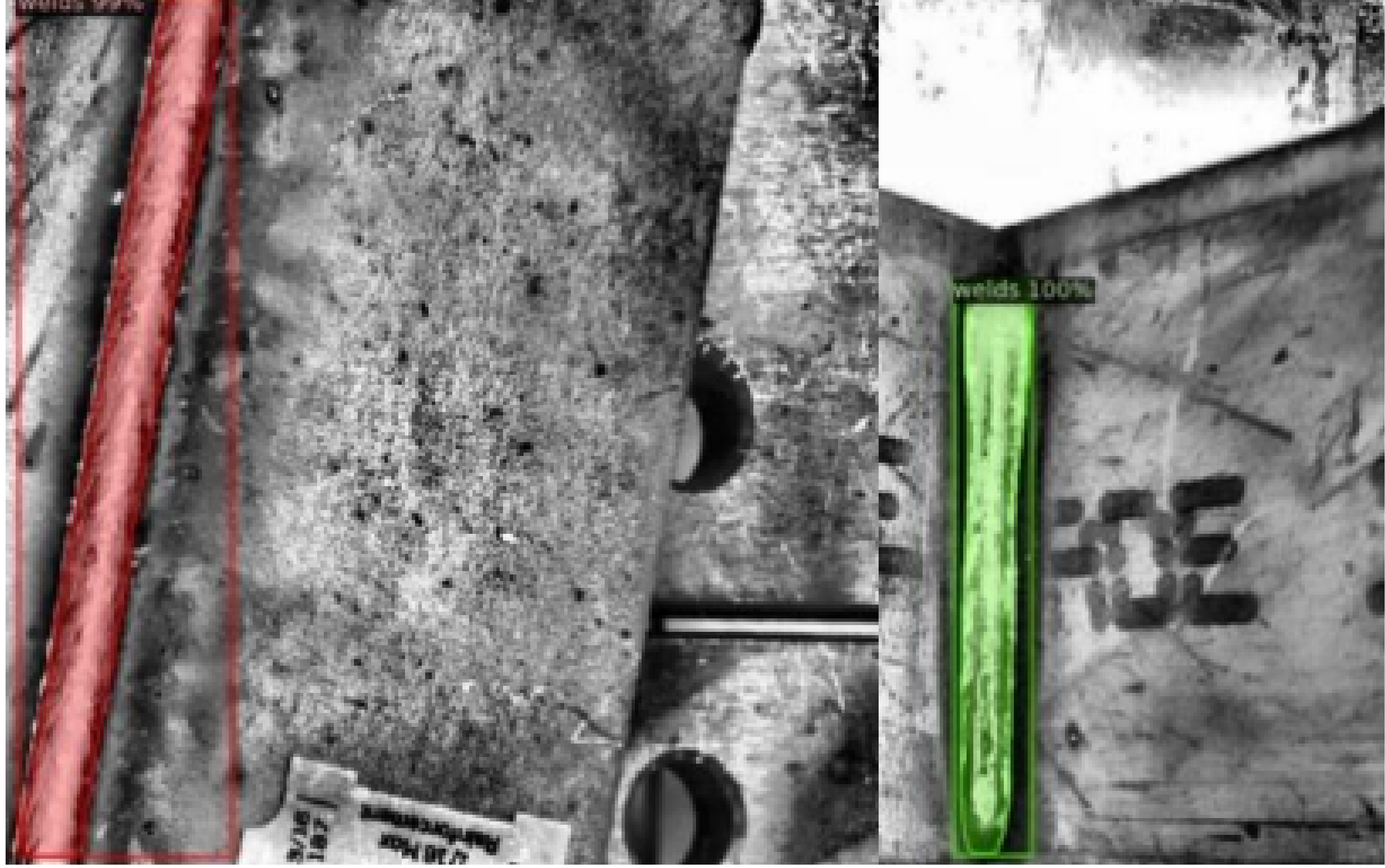
Research Methodology

The methodology used consists of collecting a database of images, exploratory analysis of the images and training various segmentation models using the Detectron 2 framework.

- Utilization of computer vision techniques such as classification and segmentation
- Collection of a comprehensive dataset comprising images at various production line stages
- Preprocessing steps including resizing, normalizing, and augmenting the images



The dataset has a total of 740 images already labelled and segmented

Detectron 2

Models

ResNet50-C4:

A popular deep convolutional neural network architecture with 50 layers. The C4 part indicates that it uses the "C4" feature pyramid network (FPN) structure.

ResNet50-DC5:

Similar to R50-C4, R50-DC5 also uses the ResNet-50 backbone but with the "DC5" FPN structure.

ResNet50-FPN:

This model also uses the ResNet-50 backbone, but it employs the standard FPN structure.

Detectron 2

Models

ResNet101-C4:

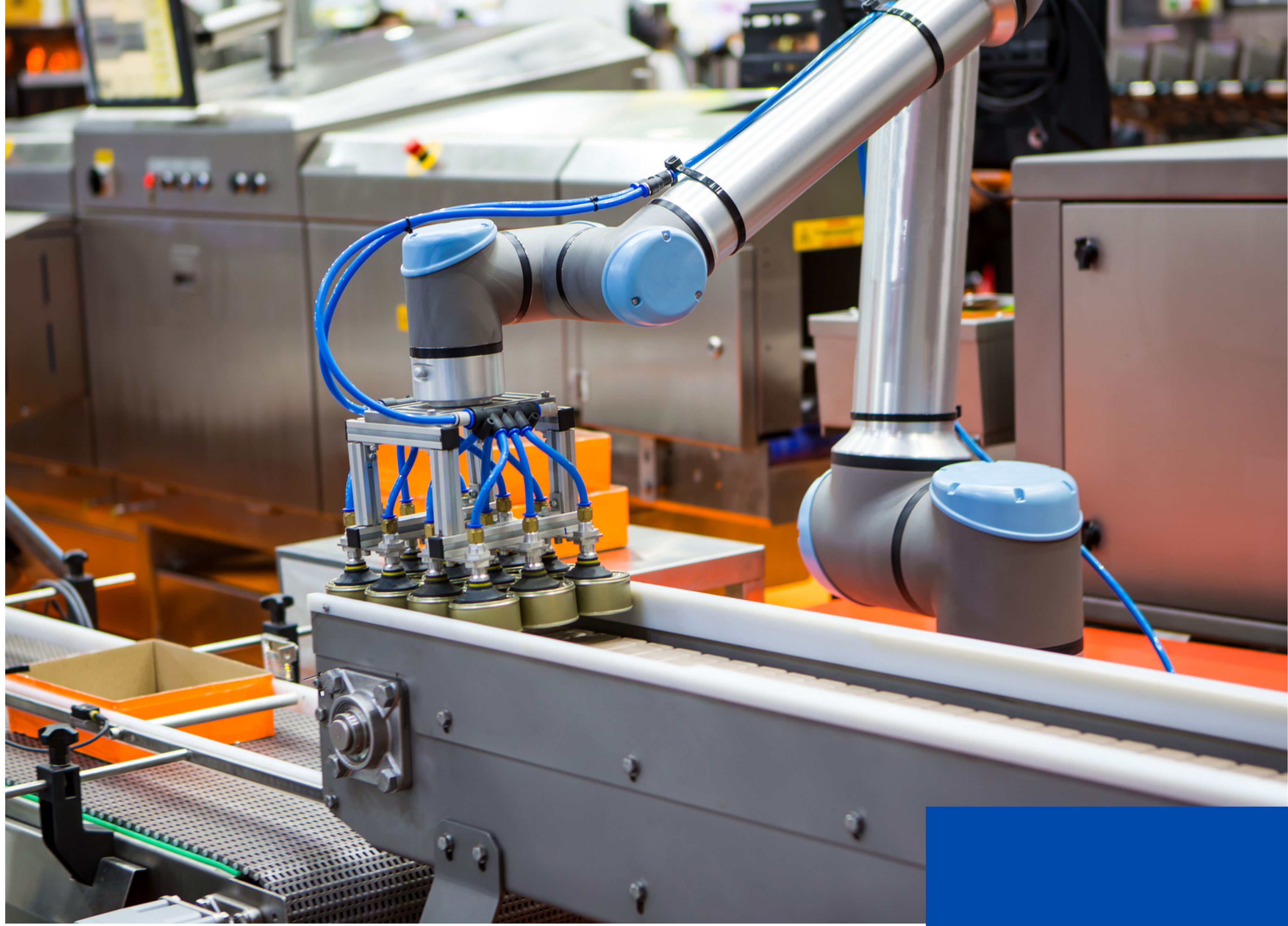
Uses ResNet101, a deeper variant of ResNet with 101 layers. The C4 structure indicates the use of the feature pyramid network.

ResNet101-DC5:

Utilizes the ResNet-101 backbone with the DC5 feature pyramid network. This combination provides a powerful setup for tasks

ResNet101-FPN:

Utilizes the ResNet101 backbone along with the standard FPN structure. This model benefits from the deeper ResNet architecture and the multi-scale feature fusion



X101-FPN:

Employs the "eXtended" version of the ResNet architecture (X101) combined with the FPN. X101 is a more powerful variant of ResNet, with increased model capacity.

Mainly Used

Computer Vision Validation Metrics

I. Accuracy

It represents the proportion of correctly predicted instances (both true positives (TP) and true negatives (TN) out of the total instances in the dataset.

II. Box Regression Loss

Evaluates the accuracy of the bounding box predictions made by the model during object detection tasks.

III. Classification Accuracy

Measures how well the model correctly classifies instances into their respective classes.

IV. False Negative Rate (FNR)

Is a measure of the error in the model's class predictions during object detection task

Mainly Used

Computer Vision Validation Metrics

V. False Positive Rate (FPR)

It measures the rate at which the model incorrectly classifies negative instances aspositive.

VI. Loss Mask

Evaluates the accuracy of the mask predictions made by the model during instance segmentation tasks

VII. Total Loss

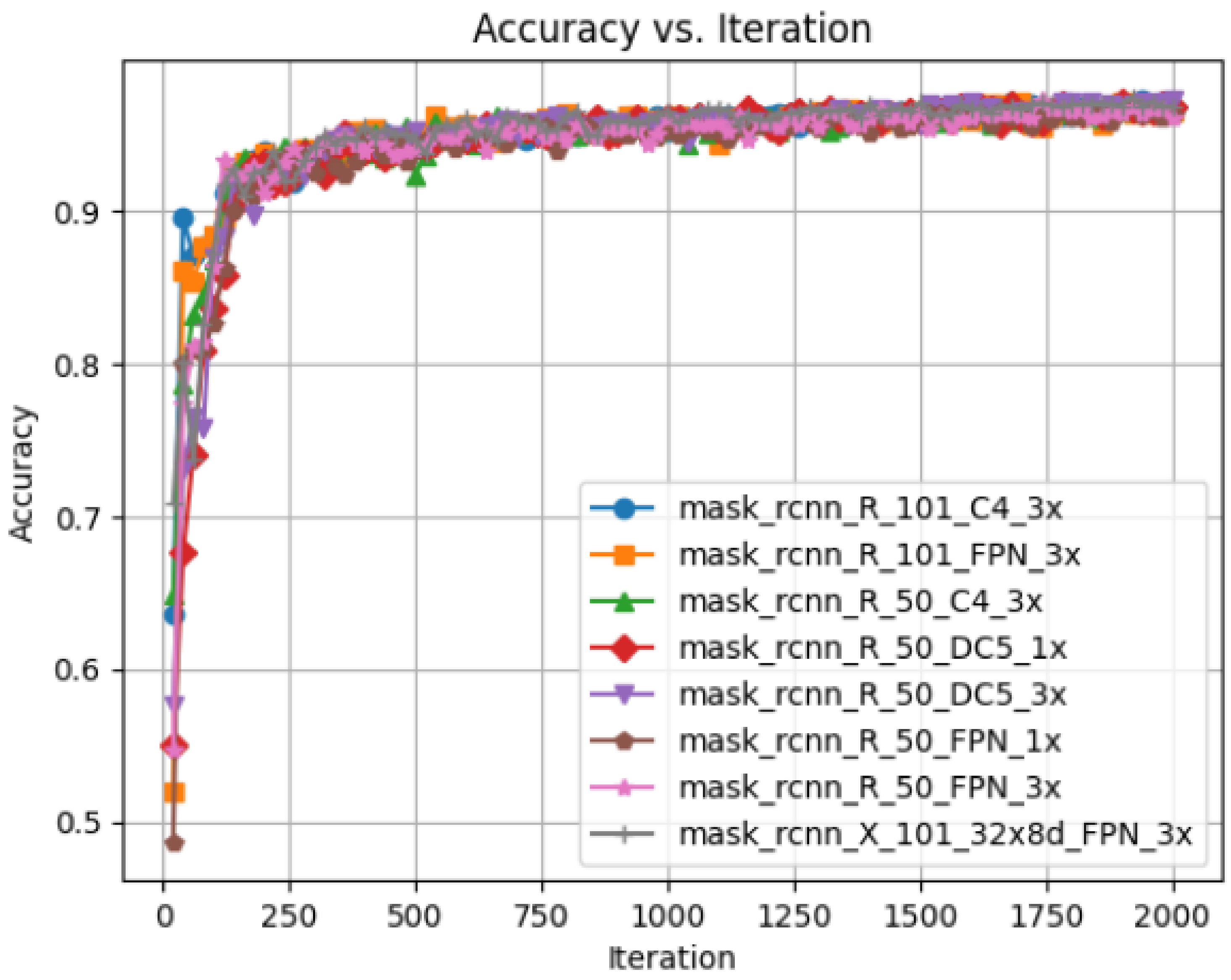
Is the sum of all individual losses in the model during training.

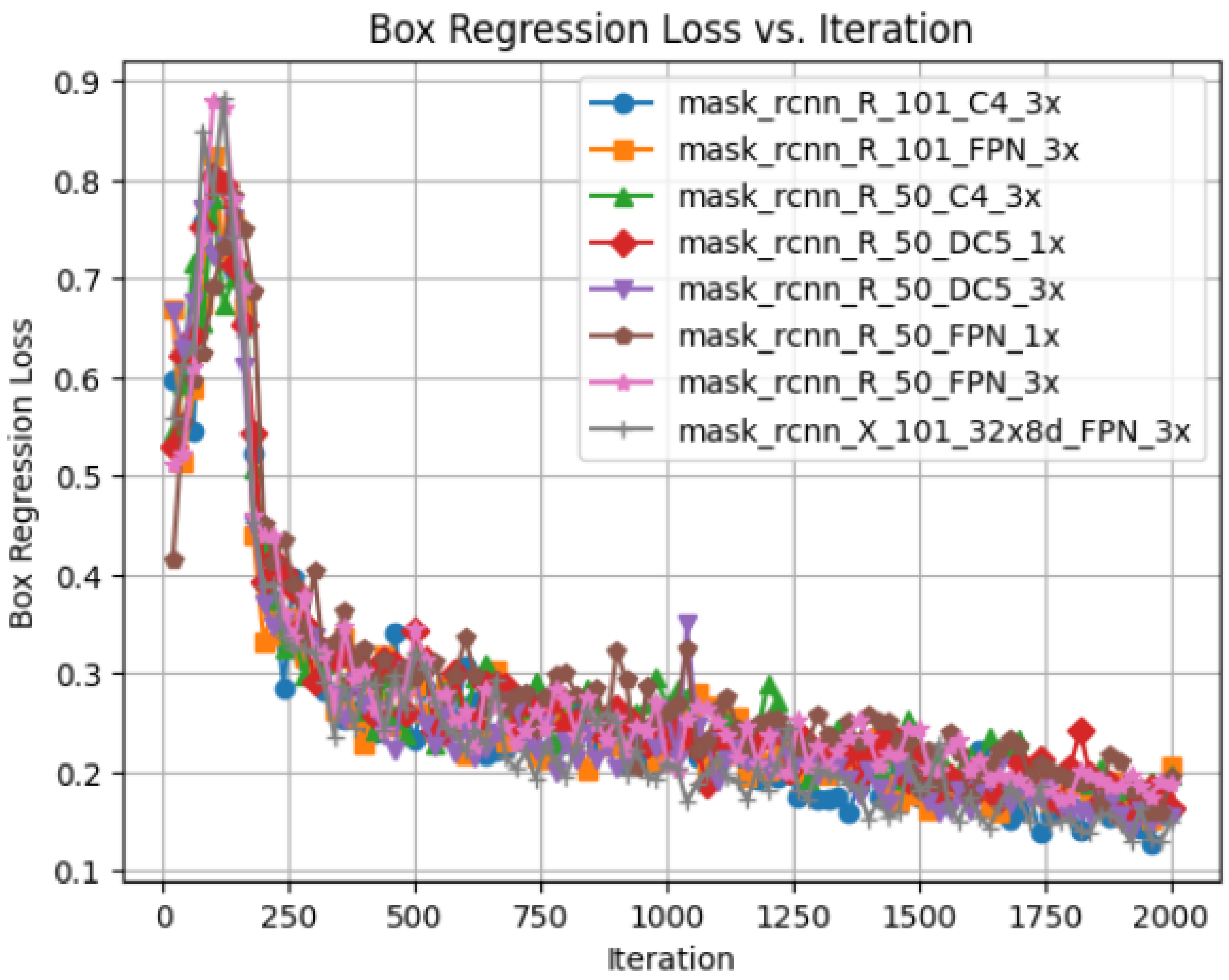
IX. Localization Loss in the RPN

It quantifies the difference between the and the ground truth bounding boxes used for training the RPN

Metric:

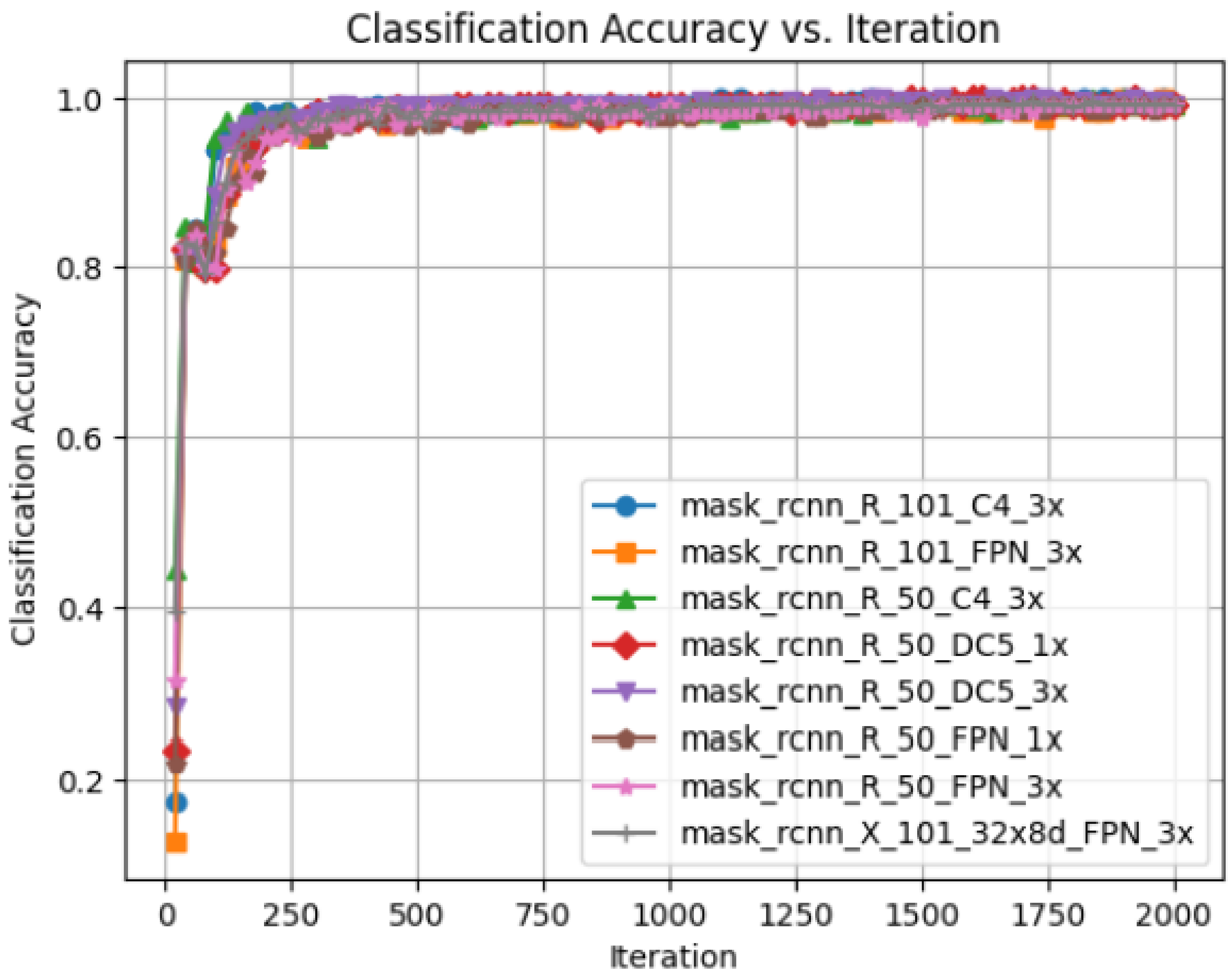
Accuracy & Box Regression

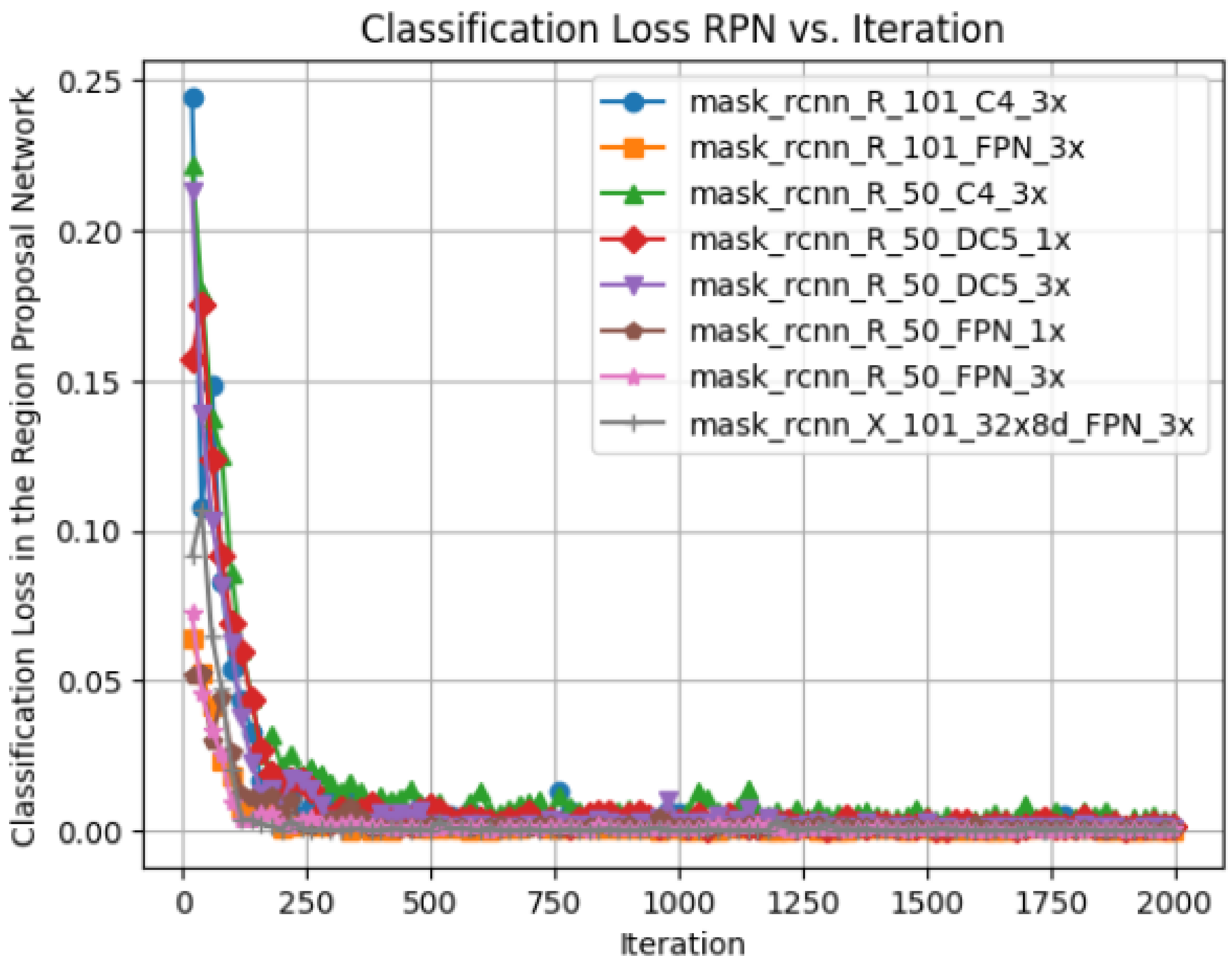




Metric:

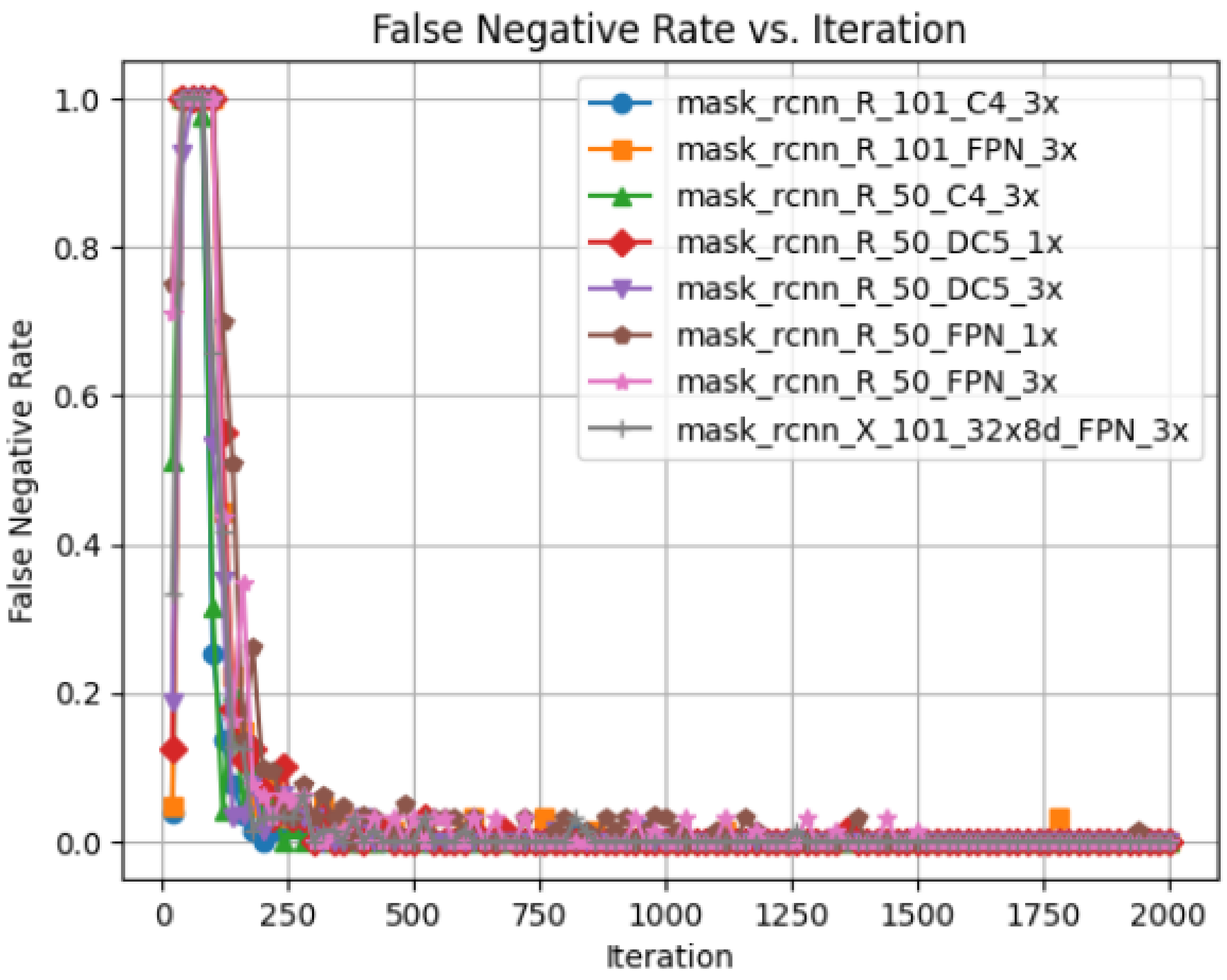
Class. Loss & Class. Accuracy

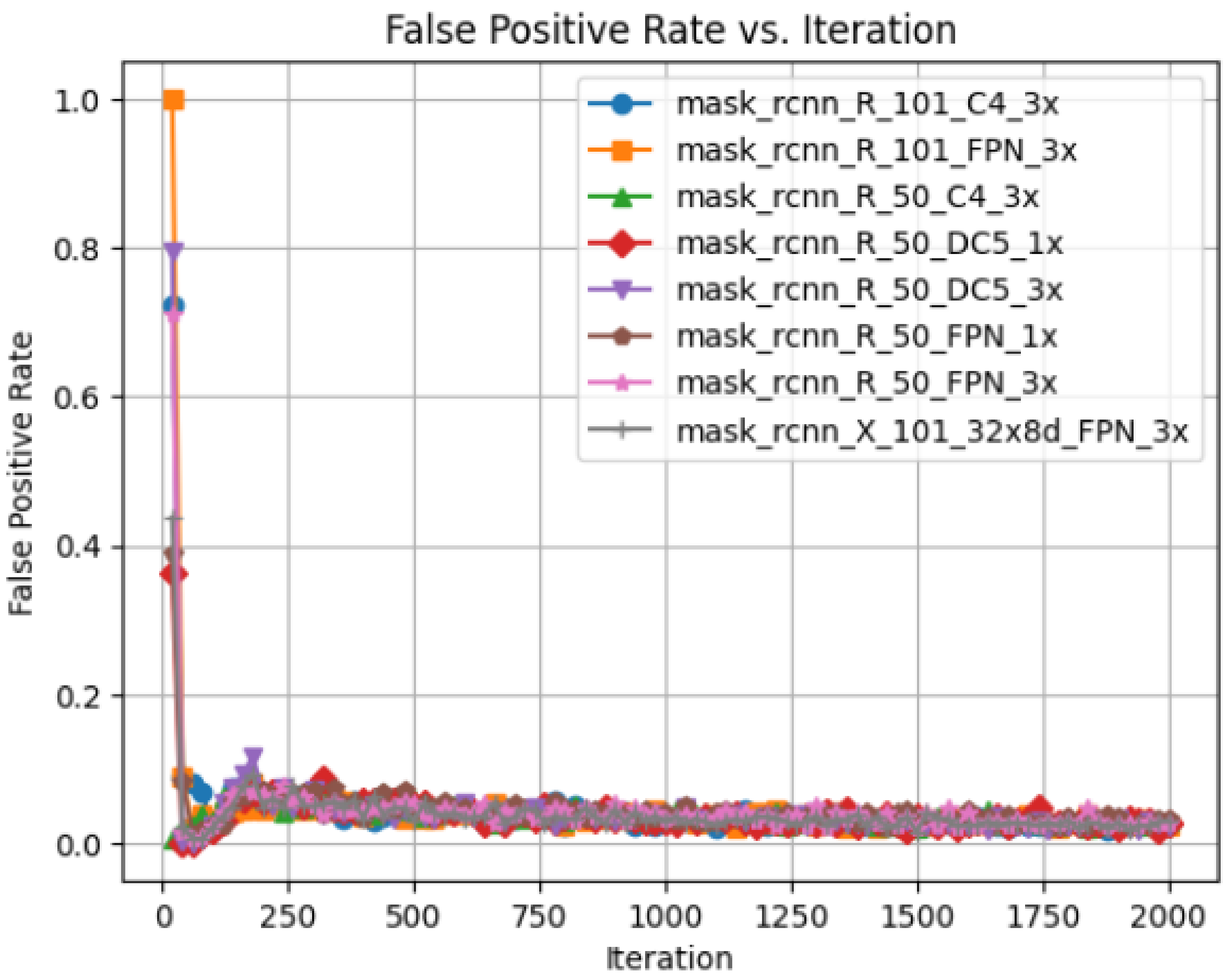




Metric:

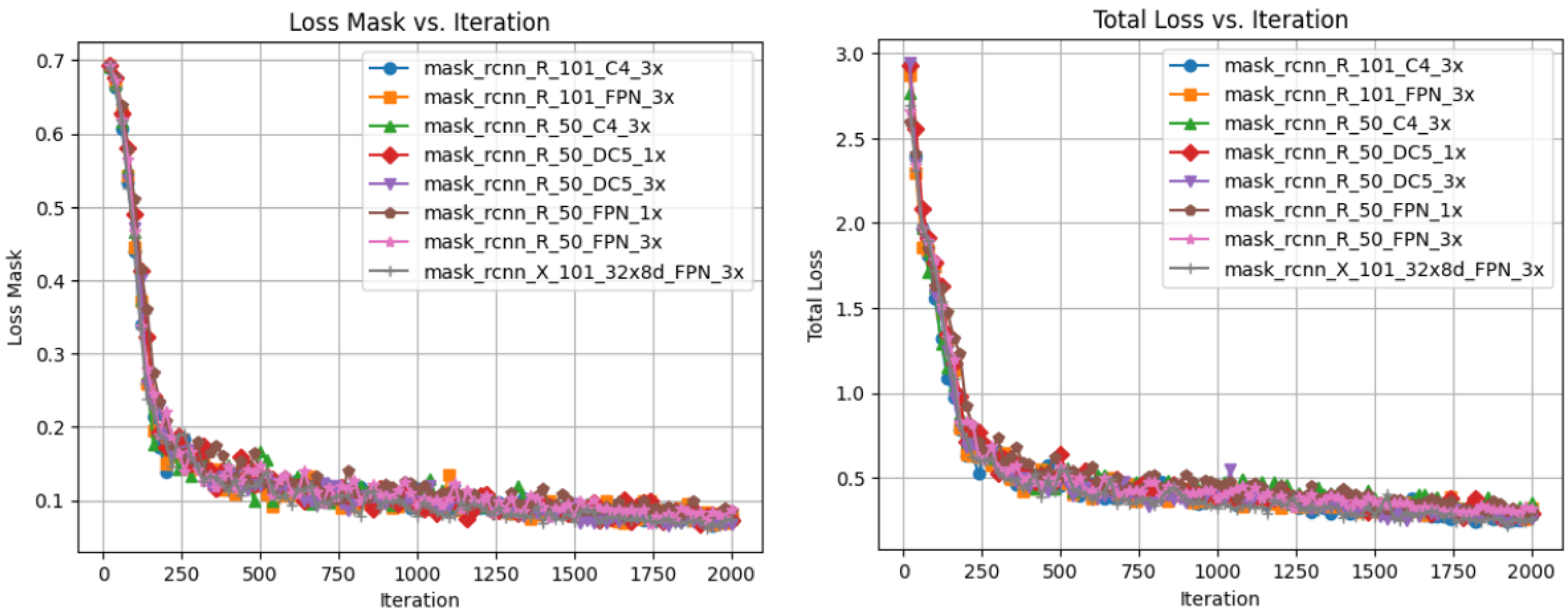
False Negative Rate & False Positive Rate





Metric:

Loss Mask & Total Loss



How the

AI System can be placed into production

Google Colab

Google Colab enables collaborative coding and sharing of Jupyter notebooks in the cloud, fostering team collaboration and agile machine learning model training.

Jetson Nano

Jetson Nano: The Jetson Nano, developed by Nvidia, is a compact and affordable computing platform designed for edge AI applications. With a focus on making AI more accessible.

Production

While no tests have been conducted, exploring model implementation on devices like the Jetson Nano could provide a cost-effective solution for deploying AI applications at the edge in production scenarios.

CONLUSION

By leveraging AI, the system has demonstrated success in detecting and preventing production line failures, resulting in heightened efficiency and cost reduction.

The conclusion notes that the choice of architecture for the segmentation task has shown little influence on the presented scenario, with similar results across different models. Future work is suggested to explore the implementation of the final model on a production device.

THANK YOU

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