An Advanced Machine Vision Technique for Quality Control of Fabric in the Textile Industry

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Declaration

It is hereby declared that

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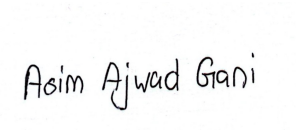

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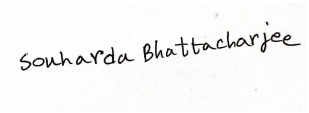

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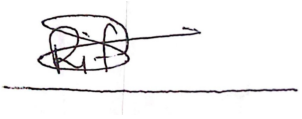

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Abstract

The textile industry, which utilizes both natural and synthetic materials, often encounters defects during production, leading to substantial financial losses. Traditionally, defect detection has relied on manual inspection, which is time-consuming, inefficient, and prone to human error. Fabric defects introduced during manufacturing or processing make visual inspection necessary, but the repetitive and monotonous nature of this task often makes it unreliable when done manually. This paper provides an overview as to how to overcome this automatically, using Machine Vision techniques to be more precise. We analysed existing object detection models such as Yolov8n, Single Shot MultiBox Detector (SSD) with VGG16 backbone, Faster R-CNN with ResNet-50 and a custom model. We also developed our own hybrid approach which is a two stage pipeline with stage 1 detecting the defect using yolov8l and the next stage classifying the defect using EfficientNet-B0. Our pipeline obtained a result of precision 84.2, recall 81.9, f1 83.0 We introduced a custom dataset containing 9075 images containing 4 classes of fabric defects collected directly from textile factories to mimic industrial environments where the quality inspection takes place. Furthermore, we designed a prototype system for industrial automation integrating our model. Machine-vision-based fabric defect detection has become a significant research area in the textile industry and has emerged as a reliable solution for quality control, involving the extraction of defect-related characteristics from textile images, using advanced sensors and real-time algorithms. Various studies provide a detailed review of machine vision methods for fabric defect detection. Although these methods are traditional and widely used, it is observed that all of those methods have various downsides to them. Our aim is not only to build a capable object detection model with good accuracy and lower computational costs but also to show how this can be implemented in real life through our prototype system design.

Keywords:

Fabric Defect Detection; Deep learning; Computer-Vision; Textile Industry; Machine Vision; Dataset

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Chapter 1

Introduction

1.1 Introduction

In the textile industry, issues such as machine failure and yarn breakage can easily lead to fabric defects. These defects reduce the overall quality of the fabric and can result in major financial losses for businesses. Manually inspecting fabric is expensive and not always effective. Even experienced workers can only detect about 60-70% defects[26]. On the other hand, automated fabric defect detection offers a better solution, lowering costs and achieving a much higher accuracy rate(approximately 90%) [27].

Since the 1960s, the textile industry has been a cornerstone of the economy of Bangladesh [9]. It emerged as a prominent industry, with Bangladesh becoming one of the largest manufacturers worldwide. Serving as a key source of livelihood for many, this industry is one of the major players in the economy of Bangladesh, with some even terming it as the largest industry in the country. For an industry of such scale, the production rate is one of the major factors, which needs to be kept consistent. However, it has been noticed that recently the production rates have been declining. One of the major factors behind this has been identified as the use of manual inspection in the quality control of fabric. Fabric defect detection can be divided into two primary approaches: Process Inspection and Product Inspection. Process Inspection involves real-time monitoring of the weaving process to prevent defects, but it is rarely used due to the inherent complexity of the weaving process. On the other hand, product inspection focuses on inspecting the manufactured fabric for defects and is more widely implemented [10]. This research aims to emphasize product inspection, exploring how automatic detection methods can improve defect detection. Machine-vision-based fabric defect detection has become a significant research area in the textile industry, involving the extraction of defect-related characteristics from textile images. Various studies provide a detailed review of machine vision methods for fabric defect detection. Thomas and Cattoen explored gray-scale means of image rows and columns to identify defects, though these methods remain sensitive to changes in illumination. Ye utilized fuzzy inference models based on image histograms, which are quick with rotation and translation, but struggle with complex textures [9]. These techniques perform well in identifying defective images but face challenges in recognizing specific defect types. Additionally, high-frequency analysis methods such as Fourier transforms, Gabor filters, CLAHE-based detection, and wavelet transforms has proven to be effective, despite requiring elevated computational resources. [15][21]. AS machine vision gains popularity, it offers a potential solution for quality control. The traditional reliance on human inspection, where inspectors miss nearly 40% of defects [9],

highlights the need for automation in defect detection.

1.2 Motivation

The RMG sector, being one of the top industries of Bangladesh, leaves little room for error in quality control in order to maintain its worldwide reputation. However, it faces an imminent danger of downfall if product quality is not kept up to the mark. To control the quality, fabric defect detection is the key. Traditional methods used to this day are mostly manual, which leaves it at risk of being prone to human errors. In some parts, automated techniques are implemented, but they still face limitations due to various factors such as lighting, computation inefficiencies, etc., and it has been observed that there are still a plethora of fields for improvement. This research aims to maximize the output while minimizing the failures of detection. Automated machine vision techniques offer real-time operations that provide precise defect detection at a scalable level. The industry requires a stronger approach to achieve better efficiency and adaptability combined with increased robustness. A new comprehensive defect detection system will develop through combining advanced image preprocessing with computer vision and deep learning techniques to achieve improved accuracy, speed, and scalability of defect detection. The ultimate goal of this research is to revolutionize the quality control aspect of the RMG sector, ensuring maximum defect detection and elimination of potential financial losses,and boosting the economy of the country.

1.3 Research Problem

To prepare for the automation of fabric quality control in the textile industry, a whole variety of challenges need to be overcome. Currently, different factories have different setups for quality control of fabric, they go through 5 steps of inspection and almost all of them are different from each other. To ensure our system works in all types of industrial settings, the CNN model needs to be trained with data befitting most industrial settings. Sensitive data such as images vary in different light conditions, and since we are relying on them to inspect defects, the data should be acquired under similar lighting settings. Even shadows and wrinkles might be misinterpreted as defects, which makes securing the perfect data troublesome. Also while collecting data, proper balance of each class of data needs to be ensured to guarantee our model works best. Now this can be a challenge of its own as defects occurring on fabrics are random and each defect has a varying rate which causes an imbalance of data. There are different types of fabrics each very different from one another with varying textures, patterns, and prints. The model needs to work on all types of fabrics. For data preprocessing, techniques like CLAHE require intricate tuning as over-enhancement may produce artifacts and under-enhancement may fail to make defects more prominent. Different image processing techniques cater to different types of defects. For example, using thresholding on images with holes properly segments it but when applied to an image containing oil stains, it completely misses it rather, makes the image more noisy. Applying computer vision techniques also requires tuning of its parameters. After models are trained, applying them in real time is a challenge as latency might hamper the processing of data. In real-time applications, hardware limitations are a big issue when dealing with high-resolution data and computing complex algorithms. Both hardware and software need to be in perfect sync. All of these factors contribute to

the fact that a working system might not actually work in real time. Also while collecting data, proper balance of each class of data needs to be ensured to guarantee our model works best. Now this can be a challenge of its own as defects occurring on fabrics are random and with each defect having a varying rate which causes an imbalance of data.

1.4 Research objective

The limitations of manual inspection indicate the need for an automated system capable of accurately identifying fabric defects. A human inspector typically detects only about 60% of defects and can inspect fabrics moving at a speed of 30 cm per second. In contrast, the goal of this research is to develop an automated system capable of detecting at least 90% of significant defects, with a minimum defect size of 2 square millimeters, in fabric that is 2 meters wide and moves at 1 meter per second[9]. Data needs to be collected in factory environments to ensure the system functions in real-life situations ensuring a balanced class of dataset is obtained. The system needs to adapt to different types of fabrics too offering a general solution. Data preprocessing techniques, such as CLAHE and thresholding, will be explored and optimized for different defect types to enhance defect visibility. Different CNN models will be trained with the dataset, selecting the best performing model based on the evaluation metrics. Furthermore, the research will focus on optimizing the selected model for real-time deployment by minimizing latency and addressing hardware constraints, ensuring hassle-free integration of both software and hardware components. Ultimately, the objective is to design an efficient and scalable automated quality control system that meets the diverse requirements of the textile industry. If successful, the implementation of an automated inspection system could revolutionize textile manufacturing in Bangladesh, ensuring high-quality production, and minimizing financial losses caused by defects. Although various automated approaches have been explored, a gap remains in their effective implementation in Bangladesh.

Chapter 2

Literature Review

2.1 Background:

Machine vision technology is gaining popularity for being used in manufacturing industries in order to improve quality control and efficiency. Significant advancement has been required in this field due to the extremely high demand and the need to minimize defects. The machine vision market was valued at USD 9.3 billion in 2020 and is expected to grow to USD 16.5 billion by 2025 [18]. This expansion reflects the increasing reliance on automation in production processes. Automated inspection systems equipped with machine vision have demonstrated improvements in industrial productivity. Studies have shown that not only does automation enhance productivity by 30%, it also cuts down labor costs.[19].These systems support real-time data collection and analysis as well, contributing to a 5-6% increase in productivity [20].

Machine vision involves the use of cameras and specialized lighting systems to capture detailed images of manufacturing components. These images are processed using digitization, thresholding, segmentation, and edge detection to extract relevant information. The processed data helps in identifying product defects, ensuring that each item meets quality standards. If any defect is detected, the system can take necessary action, such as removing faulty products from the production line. Additionally, real-time feedback mechanisms allow for continuous monitoring and adjustment, ensuring that quality and efficiency are maintained throughout the manufacturing process. By integrating machine vision with automated inspection, industries can achieve greater consistency in production and reduce the margin of error in quality control [13][14].

2.2 Related Work:

Related works include several studies on the use of machine vision for defect detection, process optimization, and quality control in industrial environments. These studies demonstrate the effectiveness of machine vision systems and their integration with artificial intelligence for real-time decision-making and automation. In a reviewed journal, Kumar(2004)[2] presented many different approaches and their advantages and disadvantages. According to him, Gray-level thresholding is one of the direct methods for high contrast fabric. This method identifies defects based on significant variations in pixel intensity. High contrast defects cause abrupt changes in pixel intensity, resulting in peaks or troughs in the signal. These variations can be detected by setting a threshold. It is

suitable for high speed inspection due to its simplicity and low computational requirements. Norton-Wayne et al.(1992) [3] used the idea to detect defects on moving at a high speed of one meter per second, while filtering out random noise by focusing only on clustered triggers . In the gray-level thresholding, the main problem was the fabric. It only worked in high contrast fabric and the signaling was not that accurate. After Norton-Wayne's modification [4], the false alarm problem was gone. The random noise present there generates false alarms which is why they only accounted for clustered triggers after thresholding. Macaire and Postaire(1993) [5], came up with a solution for the high contrast problem. In their paper, they worked on a process that was a fast adaptive thresholding limit to detect low contrast defects in galvanized metallic strips. But it still was far beyond than defecting most of the defects in low contrast fabric.

In another paper, Larabi, S., and Robertson, N. M.,(2020) [28] discussed the Contour detection through edge-based methods identifies image intensity and texture irregularities which allows mathematical models to extract boundary information using algorithms. Existing detectors such as Sobel, Prewitt, and Canny detectors function as traditional edge detection methods which measure gradients for pixel intensity changes but remain prone to noise interference. The energy-minimizing curves of snakes and Gradient Vector Flow (GVF) snakes automatically move toward detecting object boundaries. The process of grouping and optimizing edges relies on principles of proximity together with continuity and closure to create unified contour structures. The computational expenses of these methods grow higher when dealing with large edge gaps. The edge detection system HED uses deep learning algorithms to generate edge probability maps while needing extensive training resources and data. Edge-based methods struggle to address noise sensitivity and contour fragmentation while retaining performance alongside computational complexity and domain dependency which makes them suitable only for simple applications until they integrate with region or learning-based approaches. The mentioned techniques support applications including medical imaging. object detection, and autonomous vehicles, because they require precise contour detection.

Almeida, Moutinho and Matos-Carvalho(2021) [1] presented a new approach for fabric defect detection using a custom CNN. They worked on more than 50 types of defects. After using FN reduction along with CNN, the accuracy level increased from 75% to 95%. The proposed system presents high accuracy and lower execution time. Firstly, they captured the images using CMOS (Complementary Metal-Oxide-Semiconductor) sensor cameras and pre-processed them with histogram equalization to enhance the defective region. After that, a customized CNN architecture with FN reduction was applied for the defect detection process. If a defect is found, the process is stopped, and the operator is notified. They used four different datasets to evaluate their approach:

- Fabric-Net-Dataset (FD-NT)
- TILDA (FR-TL)
- MVTec Anomaly Detection Dataset (FD-MV)
- Fabric Stain Dataset (FD-ST)

The results were compared with four other fabric detection approaches and four different deep learning architectures. Their conclusion was that, on average, their new method outperforms these eight methods across the four datasets. The proposed CNN model surpasses human inspection and other tested methods by offering better generalization

across multiple datasets. While it does not always achieve the best results on specific datasets (like FD-MV), it provides the highest average performance across datasets with various defect types. The model's simple architecture makes it faster than other deep learning approaches, such as MobileNetV2. Even though some methods, like Local Binary Patterns (LBP), perform well on certain datasets, they struggle to generalize. The proposed CNN, despite its simplicity, offers robust and efficient performance even with limited training data.

In their article, Gopika G Nair and Vishal Trivedi(2024) [37], gave a thorough summary of how Artificial Intelligence (AI) and Machine Learning (ML) could be applied in the quality control department of the textile and apparel industry . In the described paper, the review-based approach was used to examine the use of different AI and ML algorithms Support Vector Machines (SVM), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Genetic Algorithms (GA) in quality control in the textile and apparel industry. They apply these techniques in defect detection, classification and prediction in yarns, fabrics and garments. The findings discussed in the studies reviewed show a highly accurate increase in inspection accuracy with certain models showing up to 96.5% accuracy on fabric defect detection and overall across applications accuracy of 91.5 % on average. The said findings affirm that AI and ML have a future in boosting efficiency, lowering costs, and enabling automated and quality manufacturing.

Chakraborty, Moore, and Parrillo-Chapmans(2021) [38] studied the problem of anomaly detection in the printed textiles, specifically color dots and print misalignments, based on a Convolutional Neural Network (CNN). A dataset of flawed fabric images was made specifically, and CNN models trained on different hyperparameters with the aim to achieve a better accuracy. The researchers benchmarked their CNN model to those other deep learning models, which are VGG, DenseNet, Inception, and Xception, and they studied that VGG models are the most effective in detecting the defects. The findings show the possibility of automating deep learning and improving the uniformity of quality monitoring of textiles, and therefore less market dependency on manual inspection.

The study "A Fabric Defect Detection Method Based on Deep Learning" presents an improved approach to fabric defect detection by leveraging deep learning models, particularly an enhanced version of YOLOv4 [20]. The researchers also enhanced image quality by applying CLAHE, a method that improves the fabric images, making defects more visible. Furthermore, to improve the accuracy of anchor boxes in predicting defect locations, they utilized K-means clustering, which optimized the detection of small and irregular defects, such as holes and stains. Traditional pooling methods, like Max-Pool, used in YOLOv4 can cause significant information loss, especially when detecting smaller or subtle defects in fabrics. To handle this, the researchers replaced MaxPool with SoftPool in the Spatial Pyramid Pooling (SPP) structure, which allows for better retention of feature details by assigning proportional weights to pixel values rather than simply choosing the maximum.

- SoftPool improves the SPP structure to retain more feature details during pooling.
- CLAHE enhances the image quality, making defects more visible and easier for the model to detect.
- K-means clustering optimizes the anchor boxes to improve the accuracy of bounding box predictions for defect localizations.

By applying all these methods together, the paper aims to achieve better accuracy and precision for fabric defect detection compared to the standard YOLOv4 implementation.

In the paper Shahrabadi, S,. et al. [22] compared traditional machine learning techniques with modern deep learning models for fabric defect detection. These models require extensive feature extraction techniques, such as the Gray-level Co-Occurrence Matrix(GLCM) and DiscreteWavelet Transform(DWT), to isolate relevant features in fabric images, such as textures and edges. In contrast, DL models, particularly CNN, AlexNet and VGG16, have demonstrated superior performance in detecting complex defects. CNNs can automatically learn and extract relevant features from raw images, eliminating the need for manual feature engineering. For instance, AlexNet achieved an accuracy of 98.2%, while VGG16 achieved 98.1%, far surpassing traditional machine learning methods. The study highlights the advantages of deep learning for defect detection, including scalability, accuracy, and the ability to handle diverse types of defects, from stains to missing yarns. Traditional ML models (SVM, ANN) using GLCM, DWT) and Modern DL models(CNN, AlexNet, VGG16). The goal was to assess the strengths and weaknesses of each approach, with the paper concluding that DL models significantly outperform traditional ML models in terms of both accuracy and scalability for textile defect detection.

H. Li et al. (2024) [48] represented a new mechanism Multi-Layer Residual Convolutional Attention (MLRCA) to enhance the accuracy of defect detection in leather fabric. The authors show that MLRCA enhances semantic feature representation in the backbone network,while the new architecture called ML-FPN is the result of its integration into the feature pyramid network. Thus improving multi-scale feature fusion. They also used a Side-Aware Boundary Localization (SABL) detection head to more precisely localize and differentiate similar defect types. Their proposed model achieves strong performance with AP = 83.4, AP50 = 89.7, AP75 = 85.6 and strong results across different object sizes (APS = 71.3, APM = 89.9, APL = 88.9) with their custom experimental leather dataset. The results ensure the model's effectiveness in detecting even minor defects.

The paper [21], focuses on the integration of IoT, cloud computing, and deep learning to build a real-time defect detection system in manufacturing. The proposed system incorporates IoT-enabled cameras that capture images of products on the production line, transmitting these images for real-time processing using edge computing. This setup reduces latency and allows for real-time defect detection, critical in high-speed manufacturing environments. The paper employs Convolutional Neural Networks (CNNs) to classify images as either defective or defect-free. Among the tested models, EfficientNetB0 outperformed others, such as VGG16 and Inception v3, in terms of accuracy and speed. EfficientNetB0 achieved a detection accuracy of 96.88%, with minimal computational overhead, making it suitable for real-time applications. The study also includes a process prediction model that uses regression techniques, such as K-nearest neighbors (K-NN) and decision trees, to predict optimal manufacturing parameters for reducing defects. Decision trees achieved an R2 score of 0.99, indicating excellent performance in process optimization. This intelligent machine vision system demonstrates how combining machine learning, IoT, and edge computing can lead to more efficient and accurate defect detection, contributing to the advancement of Industry 4.0 technologies in manufacturing.

- IoT-enabled vision system for capturing real-time data
- CNNs(EfficientNetB0, VGG16, Inception v3) for image classification

- Process prediction models(KNN and decision trees) for optimizing the manufacturing process

These techniques work together to provide a comprehensive system for real-time defect detection and process optimization. The CNN models are tested to find the best performer (EfficientNetB0), but all components (IoT, CNN, and process prediction models) are part of the overall system and are not used separately or compared in isolation.

Developed by Norton Wayne et al. in 1992 [9], the binary and frequency models aimed to create an automated defect detection system with the goal of achieving 95% accuracy, focusing on defects as small as 2 square millimeters. This objective was based on the belief that a reliable inspection system could enhance product quality and reduce waste. To achieve this, the researchers upgraded a manual tubular fabric inspection machine by integrating a 2048-element line scan camera, which captured fabric movement with a resolution of 0.5 mm across a 1-meter width . The lighting setup, using a fluorescent tube operating at 35 kHz, was designed to minimize flicker and maximize contrast, essential for effective defect detection. The binary model simplifies the captured data by converting grayscale images into a binary format, classifying each pixel as either a defect or non-defect based on a predetermined threshold. Binary filtering techniques are used to analyze adjacent trigger pixels, producing a signal to reduce noise and enhance detection accuracy. This method allows the identification of lower-contrast defects by setting thresholds closer to the signal mean, improving detection accuracy. The frequency model analyzes the frequency components of image data using techniques like Fourier transformation, allowing the identification of patterns and anomalies not easily detectable in the spatial domain. This makes it effective for spotting periodic defects or variations in fabric texture. However, the model's complexity requires significant processing power and sophisticated algorithms, making real-time analysis difficult. Additionally, frequency-based methods are sensitive to noise, potentially leading to false positives or missed detections, especially when noise obscures defect indicators. Moreover, the computational load makes real-time processing challenging, hindering quick decision-making in high-speed production environments.

The study [39], Subjected to continuous updates and improvements along with periodic updates of its recognition database, this system is capable of detecting around 26 different types of defects in elastic and woven fabrics. It uses high resolution imaging, with real time data processing, to create detailed defect maps and analytical reports. It is observed that, it provides an accuracy of defect identification exceeding 90 percent, which improves the inspection efficiency, decreases human error, and helps to realize data-driven quality control in textile manufacturing.To maximize efficiency, several techniques have been integrated for practicing in apparel design, apps production, retailing, and supply chain management, which helps towards making better decisions as well. However, the drawbacks holding back the potential are issues such as high cost, lack of expertise, and change resistance. To combat these, one key suggestion made is to improve the communication between researchers and industry, and establish closer connections between them.

Cohen et al. (2011) [10] modeled a defect-free fabric texture using a GMRF in the image and regarded the defect detection as a problem of a statistical hypothesis test. Their method detected defects with no false alarms, although the proposed approach was not applied on large-sized datasets. Other techniques include the Autoregressive (AR) model, which takes advantage of the linear relations between pixels in a texture image. This approach is relatively fast and describes micro-textures well but is sensitive

to light conditions and performs poorly with small defects.Researchers like Serafim and Basu(2018) [23] worked with AR models for different kinds of fabrics but often faced challenges due to environmental conditions. Further in this field, the wavelet-domain Hidden Markov Tree model was developed to include level-set segmentation techniques in defect detection, though it still needs more detailed evaluation. Despite such advances [24], each of these methods has its strong and weak points: while the MRF model shows good performance in capturing local context, it struggles with detecting small defects. Although the AR model is fast and efficient, it is highly sensitive to changes in lighting and fabric patterns. These disadvantages suggest that algorithms for fabric inspection need to be further refined.

The paper by Ulasiram et al. (2021) [7] presented the significant issue of fabric defect detection in the textile industry. The system uses a combination of Gabor wavelet features and a Random Decision Forest algorithm to achieve precise fabric defect detection. It also combines the real-time object detection of YOLOv3 and DarkNet to extract features quickly which makes this system efficient in feature extraction as well as defect localization. But YOLOv3 and DarkNet on top of that are computationally intensive, which makes it impossible to run in low-power or embedded systems. If the fashion design patterns on your fabric are intricate, or should something new occur with the pattern of defects that were never part of its training stages then it does perform differently. In the case of performance gains, it might be necessary to also tune the parameters of network layers and training settings manually.

In the paper, Sandhya et al. (2021) [7] utilized both a Deep Convolutional Neural Network (DCNN) and a pre-trained model called AlexNet to identify and classify fabric defects. In the experiments simulations, this model obtained up to 92.60% accuracy using one existing textile dataset. With this level of precision, the detection and classification system could be used to help workers spot defects when processing fabric.Image patches were used for training whereas full images will be tested. The three publicly available datasets, TILDA and the Guangdong Esquel Textiles dataset were used to test their model along with another custom dataset achieving a state-of-the-art accuracy of 97.31%. Zhoufeng Liu et al. proposed optimizing deep neural networks using 8,000 images of fabrics from Xiamen Face++ Company. They employed the VGG16 model and added a deconvolutional network layer to reduce memory consumption and the total number of parameters. Their dataset was prepared by collecting 540,000 images across six classes, including five defect types, cut, hole, metal contamination, thread-and one that is non-defective, labeled as "good." These images are split into 360,000 for training and 180,000 for testing. The authors have compared several models for defect detection in fabrics, and amongst them, AlexNet gives quite a remarkable performance with an accuracy of 92.60% after augmentation. After 25 rounds of training of the AlexNet model, the model reached a training loss of 0.368 and a validation loss of 0.243, with the training accuracy being 88.10% and the validation accuracy being 92.67%. Here, the dataset that may be used might not be representative of complex or real variations of fabric patterns; therefore, generalization to unseen defect types may not be possible.

Jin, R., and Niu, Q.,(2021) [8] proposed a deep learning technique to automate fabric defect detection by enhancing the YOLOv5 object detection algorithm. In their paper, a teacher-student architecture is used to compensate for the lack of defect images. The Defect Recognition Accuracy of the Deep Teacher Network and real-time defect recognition performance of the student network reduce to accuracy loss as best possible. It is also using multi-task learning to discover general and specific defects at a time. To en-

hance the recognition accuracy by employing a focal loss function and central constraints, researchers have achieved better performance. Experiments were performed employing released datasets available at Solar, Tianchi AI, and TILDA platforms where the proposed method outperforms compared to other methods evidencing good detection capability in textile images. The teacher network proposed in this study achieves the highest detection performance (98.1%), while the student network offers a more efficient option for embedded devices. On the TILDA database, OurNet and its variants improve, with the teacher network still delivering the best accuracy. The teacher network despite its accuracy may be too resource-intensive for a low-power system. While effective on tested datasets the model's performances may drop on unseen fabric patterns not included in training.

The research article written by Arshad and Shahzad (2024) [15] demonstrates the integration of deep learning models such as ResNet and VGG-16 to detect fabric defects. While earlier methods such as Gabor filters and gray level co-occurrence matrix(GLCM) might have laid the groundwork, they are computationally heavy, resulting in feature redundancy and unable to handle intricate patterns. Between three categories of defects, horizontal defects, vertical defects, and holes, each had a balanced dataset of 3630 images with 80% for training and 20% for testing. While VGG-16 took longer to train, it achieved an accuracy of 73.91% compared to ResNets' 67.59%. Despite being fast, ResNet struggled with smaller and more subtle defects. There are limitations to this approach. To start with, since both models are computationally heavy, it is more challenging to use them for larger datasets and can pose a problem when scaling up for industrial applications. The current system can only detect one defect per image making it impractical as fabrics might contain multiple defects. The models rely on static images which voids any hope of real-time detection.

Nasim et al. (2024) [14] addressed in his paper the challenges faced while using ResNet and VGG-16 are addressed in the paper "Fabric Defect Detection in Real-World Manufacturing Using Deep Learning" by Nasim et al. The deep learning models used here work for real-world fabric defect detection such as YOLOv5, MobileNetV2-SSD FPN Lite, and YOLOv8. Data has been collected from Chenab Textiles which included a diverse range of fabric types (plain, printed) and various defect categories, stains, cuts, contamination, gray stitches, selvet, baekra, and color issues. The dataset comprised 3630 images, split between training and testing, 80% and 20%, allowing the deep learning models to train on real-world data captured in a manufacturing environment. MobileNetV2-SSD works on low-resource hardware automatically making it favorable over ResNet and VGG-16. Both YOLOv5 and YOLOv8 on the other hand are more advanced models capable of real-time detection. The paper compared the three models with YOLOv8 being the most accurate with a mean average precision of 84.8%. YOLOv5 had a close mAP of 84.5% with MobileNetV2-SSD placing third place with a mAP of 77.09%. The study also concluded that YOLOv8 performed mainly well on complex defects such as stains and baekra. There are a couple of limitations that the study still couldn't overcome. The models obtained a lower mAP for detecting color issues compared to the other defects. Only regular printed fabrics were used to train and test the models, making it work for irregularly printed fabrics is still a challenge.

Moahaimen Talib, Ahmed H.Y. Al-Noori, Jameelah Suad(2024) [42] introduced an enhanced version of the YOLOv8 model which is specifically designed to improve the detection of small and weak featured objects in real time scenarios. The proposed method YOLOv8-CAB integrates a context attention block(CAB) to better local and global context, a thicker coarse-to-fine(C2F) module for enhanced feature extraction and an im-

proved spatial attention module using selective kernel(SK) attention to focus on critical areas of the input images. Appraised on the COCO dataset, YOLOv8-CAB achieves a notable increase in mean average precision(mAP), especially for small objects. This method outperformed YOLOv5, YOLOv7 and the original YOLOv8. with optimized accuracy, speed and robustness, YOLOv8-CAB demonstrates significant potential for real-time object detection in complex scenarios.

Frouke Hermens(2024) [43] explored the effectiveness of YOLOv8, a state-of-the-art object detection model for automating video annotation in behavioral research context such as tracking surgical tools or daily use objects. The results show that YOLOv8 performs with a high accuracy rate even when trained on relatively small datasets, particularly in controlled lab environments with consistent backgrounds. However the model struggles to generalize when the same object appears in different backgrounds, which can be mitigated by training on a more diverse dataset. experiments comparing YOLOv8 with earlier versions (YOLOv3 and YOLOv5) and different model sizes(nano,small,medium) reveal that YOLOv8 offers superior performance with efficient training and inference. Overall this model proves to be a highly accessible and reliable tool for behavioral researchers needing automated object detection, provided that training conditions are well-matched to the models environment.

The paper written by Muhammad Yaseen(2024) [44] showed a detailed comprehensive technical overview of YOLOv8, the latest evolution in the YOLO object detection by highlighting its architectural improvements, training methodologies and performance advantages over previous versions like YOLOv5. main improvements include the adoption of an anchor-free detection head, a CSPNet-enhanced backbone for more efficient feature extraction and an improved FPN+PAN neck for better multi-scale object detection. The model also benefits from advanced training techniques such as mosaic and mixup data augmentation, focal loss for handling class imbalance and mixed-precision training for efficiency on modern GPUs. Experimental results show YOLOv8 achieves higher mAP, faster inference time and smaller model size compared to YOLOv5. The study emphasizes YOLOv8's versatility across different model sizes(n, s, m, l, x), its compatibility with popular tools like Roboflow and ClearML and its suitability for real-time applications in domains ranging from IoT to medical imaging. Overall the paper positions YOLOv8 as an object detector with a strong balance between accuracy, speed and usability.

In their paper, Feng et al.(2024) [45] presented two improved versions of YOLOv8 named `IMCMD_YOLOv8_small` and `IMCMD_YOLOv8_large`, which are specifically designed for detecting small objects in aerial images captured by drones. To address the challenges of small target detection in complex scenarios, the authors remove the P5 layer from the backbone to reduce unnecessary complexity and focus on low-level features from the P2 and P3 layers. They introduce a coordinate attention (CA) mechanism within a redesigned C2f_CA module to improve spatial awareness and feature extraction. Additionally, an adaptive multiscale feature fusion (AMFF) module merges deep and shallow features more effectively, and a dynamic head replaces YOLOv8's default head to improve detection of varied target sizes and positions. Experiments on the VisDrone2019 dataset show that both models significantly outperform the original YOLOv8 in precision, recall, and mAP while achieving substantial reductions in model size and computational cost, making them highly suitable for deployment on resource-constrained platforms like drones .

Chai et al.(2025) [46] proposed a model called MSFF-YOLOv8 in their paper "Image small target detection in complex traffic scenes based on YOLOv8 multiscale feature fu-

sion" to address the challenges of detecting small objects in traffic scenarios with scale variation, occlusion and background noise. It is based upon the YOLOv8 framework. It introduces three major improvements - a multi-scale feature fusion module to preserve detailed features across different scales, a CBAM attention mechanism to intensify relevant feature focus and suppress noise and lastly deformable convolutions to adapt the receptive field to object shape and position. Combining multi-scale characteristics is made simpler by this innovation, which improves the model's capacity to identify small targets and deepens the contextual information in the output features. Furthermore, the use of deformable convolution improves the algorithm's capacity to maintain target consistency in the face of complexity. Additionally, by allowing the student model to integrate significant feature representations from the instructor model, a feature distillation technique can be used to eliminate the negative effects of semantic changes between phases. This significantly increases the model's generalizability and robustness. Experimental validations support the superiority and efficacy of the proposed method .

The paper [47], explored the effectiveness of the YOLOv8 deep learning model for accurately detecting multiple weed species in U.S. cotton fields. Utilizing the CottonWeedDet12 dataset, which includes 5648 annotated images across 12 weed categories, the study applies the YOLOv8 architecture due to its speed, anchor-free design, advanced feature pyramid networks, and efficient loss functions. The model achieves high detection performance, with mAP@0.5 = 96.10% and mAP@[0.5:0.95] = 93.20%, outperforming all previous YOLO versions. While YOLOv8 excels at detecting large weeds, its accuracy for small weeds ($mAP_s = 11.9\%$) remains a challenge. The paper suggests future improvements through domain-specific data augmentation, architectural tweaks, and multispectral imaging. Overall, the research highlights YOLOv8's strong potential for real-time, sustainable weed management, enabling reduced herbicide use and improved crop yield in precision agriculture.

Islam et al.(2024) [49] represented the first open-source dataset specifically tailored for spot defects using computer vision. It comprises 1,014 raw images and 3,288 manually annotated images in various real-world fabric types such as silk, cotton, denim etc. Defect categories include stains, rust, oil marks, blood etc. Many of these defects are difficult to detect through manual inspection. To enhance the model's robustness and prevent overfitting, the dataset includes 2,300 augmented images. This results in 7,641 YOLOv8 and 7,635 COCO format annotations. To preserve real world authenticity, all original annotations were performed manually. Its diversity and complexity makes it particularly valuable for AI applications in textile quality control, including everyday clothing and medical fabrics like masks and gloves.

In the review journal, Rasheed et al.(2020) [16] reviewed various traditional computer vision methods and deep learning models for defect detection in fabrics. Several models were compared regarding their performances in the classification of fabric defects like stains, holes, and pattern irregularities. These methods were applied to a database of fabric images acquired under real manufacturing conditions; each category of defects contained a sufficiently large number of samples for training and testing. The techniques were compared between histogram-based approaches, color-intensity analysis,and texture analysis to the more modern deep learning models like Convolutional Neural Networks. Conventional methods, while much more computational and faster, showed relatively lower sensitivity for subtle defect detection, particularly in complex or textured fabrics. For example, histogram-based techniques work well for gross changes in texture but fail in the case of more intricate defects that most of the time turn up undetected. Color-based

approaches gave good results in identifying defects based on variations in fabric color but worked poorly for textured fabrics with inherent natural variation. Among the new methods, deep learning models such as YOLO and ResNet contributed far better results in both accuracy and reliability compared to the traditional methods. In particular, YOLO was effective in defect detection in real time. Although slower compared to YOLO, ResNet was far superior in the detection of subtle and complex defects and yielded a defect recognition rate of over 90% for both plain and printed fabrics. However, these models did have a tradeoff: longer times for the processing and training phase, as compared to traditional methods.

Jia et al.(2022) [32] introduced Fabric defect detection methods can generally be categorized into four major approaches: statistical methods, spectral analysis, model-based techniques, and low-rank decomposition. Statistical methods analyze texture patterns using mathematical models to detect anomalies whereas spectral analysis, on the other hand, focuses on frequency-domain transformations to highlight defects that may not be visible in the spatial domain. Model-based methods use existing templates or machine learning models to identify defects by comparing them with ideal fabric samples. Low-rank decomposition techniques separate the background from defect areas by breaking down fabric images into low-rank and sparse components. Jia et al. introduced a novel method that incorporates weighted low-rank decomposition with a Laplacian regularization term. This addition helps to improve the distinction between background textures and defect regions, improving the robustness of the detection process. The Laplacian regularization term specifically aids in preserving the structural consistency of the fabric, leading to more accurate detection results. Furthermore, Yapi et al. proposed the use of supervised learning techniques for defect classification. This approach involves training machine learning models with labeled data, allowing them to distinguish between defective and flawless fabrics. Supervised learning offers the advantage of adaptability to various fabric types and defect patterns, making it a promising approach in quality control systems.

Abdellah et al.(2012) [33] proposed a fabric defect detection method that combines morphological techniques with geometric data analysis to identify small surface defects. Their approach involves applying Sobel edge detection, which enhances the boundaries of potential defects by highlighting regions of high-intensity change. This step helps in the improvement of locating fabric irregularities. Following edge detection, morphological processing techniques such as dilation and erosion are used to refine the defect shapes and remove noise. The detection process is further refined by analyzing key geometric properties of the detected regions, including their size, shape, and density. By measuring these factors, the system can classify and determine the type of defect present in the fabric. In addition, model-based detection methods take a probabilistic approach by treating fabric textures as outputs of a random process. This means that fabric images are considered samples generated by an underlying statistical model representing texture variations. By using this approach, it becomes possible to differentiate between normal texture patterns and defects, as the latter deviate from the expected statistical distribution.

Azevedo et al.(2022) [40] study solves the problem of anomaly detection in the printed textiles, specifically color dots and print misalignments, based on a Convolutional Neural Network (CNN). A dataset of flawed fabric images was made specifically, and CNN models trained on different hyperparameters with the aim to achieve a better accuracy. The researchers benchmarked their CNN model to those other deep learning models, which are VGG, DenseNet, Inception, and Xception, and they studied that VGG models are the

most effective in detecting the defects. The findings show the possibility of automating deep learning and improving the uniformity of quality monitoring of textiles, and therefore less market dependency on manual inspection.

In the article Rui Ribeiro et al.(2020) [41] examined how Automated Machine Learning (AutoML) can be used to predict the tear strength of woven fabrics in both warp and weft directions as an application of the CRISP-DM framework. Based on actual data of a Portuguese textile company, the researchers repeated the process of CRISP-DM several times, using different preprocessing methods of data (removal of outliers and introduction of more parameters of input). AutoML used ensemble models which built systems that involved a number of randomised algorithms in the hopes that it would increase predictive power. This study revealed that the second version of the process CRISP-DM that incorporated the removal of outliers provided the best predictive performance warp tear strength by reaching an adjusted R2 score of 0.92. The third iteration that added the final composition of the fabric as a new input feature supplied the most correct predictions in case of the weft tear strength. The above findings illustrate that the combination of AutoML and formal data mining approaches are effective when considered as approaches to enhance the control of quality and to minimise the physical testing of textile manufacturing.

Zhang et al.(2025) [50] introduced a new idea of detecting the defects in the fabric using an improved lightweight convolution neural network (CNN) model. The proposed approach by the authors incorporates a lightweight version of the CNN, which will improve the identification of the defects on fabrics, in the real-time application scenario. This model is able to integrate the feature extraction and defect classification in a way that uses very minimal available computation power which makes it run effectively on lower end devices. Although the lightweight CNN model will enhance the processing speeds and minimize the computationally expensive tasks, it might not support detection of defects on highly textured or patterned fabrics, particularly when the structures of the defects are very different with regard to those within the training data. In order to enhance performance further, the network parameters and training techniques may require modification, especially in fabric types which are more complex .

Chapter 3

Dataset

Our system will enhance fabric defect detection using a customized dataset specifically catered to work in RMG factories located in Bangladesh. Our dataset surpasses the ones which are publicly available by offering complete defect representation in factory environments, while those datasets contain fewer defects taken in studio conditions.

We want to use our system to bring a significant improvement in the process of discovering fabric defects where we will be using a new data set customised to address the practical needs of RMG factories in Bangladesh. Compared to the large collection of publically accessible datasets, which usually consist of a small set of defect types presented in controlled or studio lighting, the dataset we present is more detailed and true to reality since it describes very different defects in their natural environments on production lines.

This has been done by scanning this dataset in real working factories thus making sure the images have captured the varying textures, row types and the actual working standards in the textile industry of the area. Such degree of realism is important to train and refine our machine vision models because it makes them exposed to the randomness of real-world defects and environmental noise. Therefore, our model should be more accurate and stable once applied in a production environment where additional challenges arise due to lighting, the movement of the fabric, and defect variation.

In addition, our system was intended to bring an objective of real-time defect detection and classification, which is important to the present automated inspection units. Real-life factory conditions are the basis of the necessary training data to create algorithms that can not just check the defect but also do so on the fast-moving production lines in a reliable and quick manner. These features minimize the human supervision needs, decrease inspecting time and finally assists the manufacturing business to sustain high quality standards with lower production costs and wastages.

Dwelling on a single example of the needs of Bangladeshi RMG factories, our way of doing things will make the developed system rather than theoretically adequate also more practically applicable, therefore, in line with the reality of the local textile sector. We have outlined a customizable data set and system structure, which would bridge the gap between academia and industry as a scalable system that will enable reliable and real-time fabric defect detection and thus allow manufacturers to achieve quality standards more effectively globally.

3.1 Data Collection

Our research utilizes a custom data set that includes about 1909 high-resolution photos taken in a number of textile factories in Bangladesh; this is to make sure that our machine can find a large variety of defect types on different types of fabric and under a variety of manufacturing conditions. Each of the images were directly taken on the fabric inspection machines at the very moment when a quality control (QC) operator detects a defect during a normal quality inspection as shown in Figure 3.1 The data collection process employed in this manner ensures that the data set actually captures the environment of real-world manufacturing, such as lighting changes, machine speed changes, fabric tension changes on the table, and changes in ambient factory conditions, which all have a considerable effect on the quality and observability of defects. The images were taken with digital single-lens reflex cameras. The timeline of our data collection is shown in Table 3.1

Factory Name	**Visit Date**
Silverline Textiles	25/11/2024
Vision Garments Ltd	10/12/2024
Vision Garments Ltd	28/12/2024
Renaissance Apparels	20/01/2025
Snowtex Apparels Ltd	15/02/2025
Square Textiles	28/03/2025
Renaissance Apparels	21/04/2025

Table 3.1: Factory List and Dates

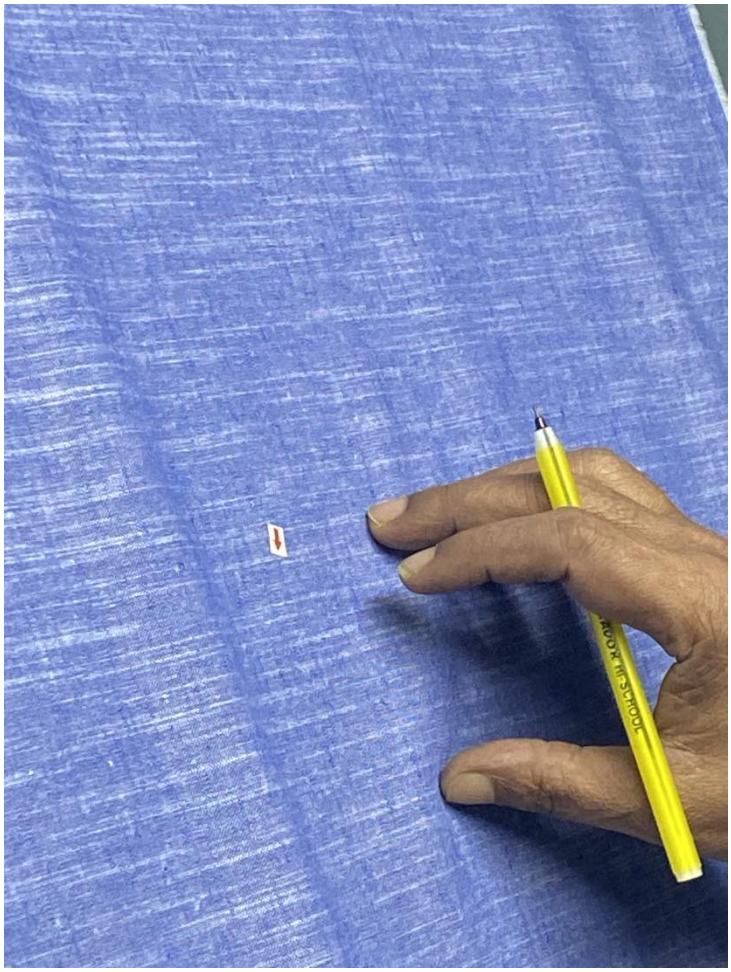


Figure 3.1: QC operator marking a defect

Fabric patterns, colors, and designs also underwent the same concept of inclusivity principle. We have as many images of single color textiles, different weaves, dyed or patterned clothes as well as clothes of various colors as can be seen in Figure 3.2 This makes our model resilient to visual variations which normally impact defect detection performance, e.g. camouflage effects, where a bug in a busy print is difficult to distinguish, or color non-uniformity issues, where small flaws are hidden.

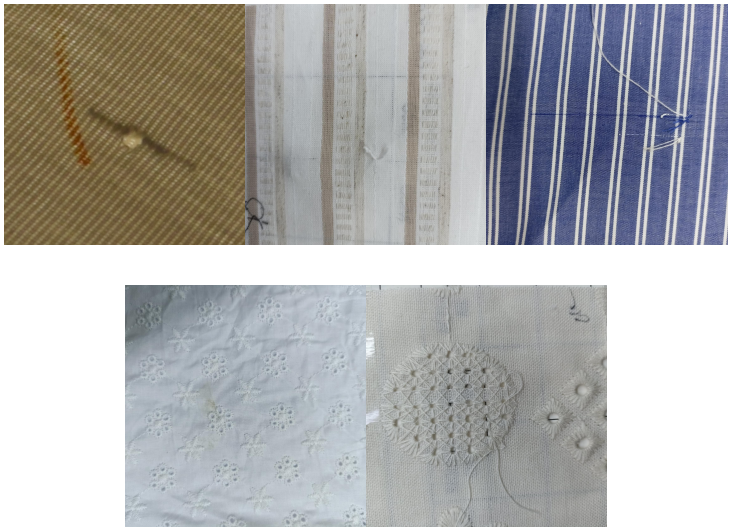


Figure 3.2: Different Fabrics

Besides, collecting data in multiple factories also helps to solve another important part of the real-world deployment: environmental variability. The machinery, the speed of production, and the flow of inspection in different factories is different, but the small differences can matter when identifying the defects through the inspection images. We can do this by training our system to a variety of production conditions, so that we enable it to train on the data represented in different production environments by providing it with the robustness to either environment or a variety of environments, so that we can manage the high detection accuracy that we get when we do this.

On the whole, we consider this extensive and heterogeneous data source as the core of our work, as the existing structure allows us to design a robust and highly accurate system of detecting defects in fabrics using machine vision. It enables our solution to provide stability over an entire garment regardless of the type of fabric, pattern, or factory operated in, which makes our solution a useful part of the quality assurance operations of various textile facilities.

3.2 Data Description

In our dataset, four different categories of fabric defects have been captured, which are shown in Figure 3.4 along with defect-free fabric samples, providing a comprehensive and balanced source of data to train a good model that will detect defects. Notably, the defect types used were not picked randomly; they were selected from the "Daily Line Wise Top 3 & DHU Display Board" of one of the textile factories visited to collect data, shown in Figure 3.3. This shows the most common defect types, which helps our dataset to be curated accordingly.

The data contains defects of fabrics with different color, patter, weave. Such diversity assists the system to train itself to spot flaws at various levels of complexities, which is a prerequisite to effective defect recognition in real manufacturing environments where fabric designs are highly diverse. The Defect types are:

- **Hole**: Opened gaps or holes in the fabric.
- **Knot/Slub**: Lump of fabric.

- **Spot**: Places of unwanted discoloration, stains, or unwanted marks on the textile surface that are visible.
- **Thick Yarn/Missing Yarn**: Areas on the fabric that have too thick or incomplete parts of yarn that break the completeness of the weave design.

Our dataset has a realistic view of real life issues of textile quality control because it contains the classes of defects based on real production data, as well as the variety of patterns and texture. This data will be studied and selected practically to help our machine vision system to learn the visual signs which are subtler and must be identified to detect defects in a wide range of fabric types and designs, which will improve reliability and flexibility in automated inspecting tasks.

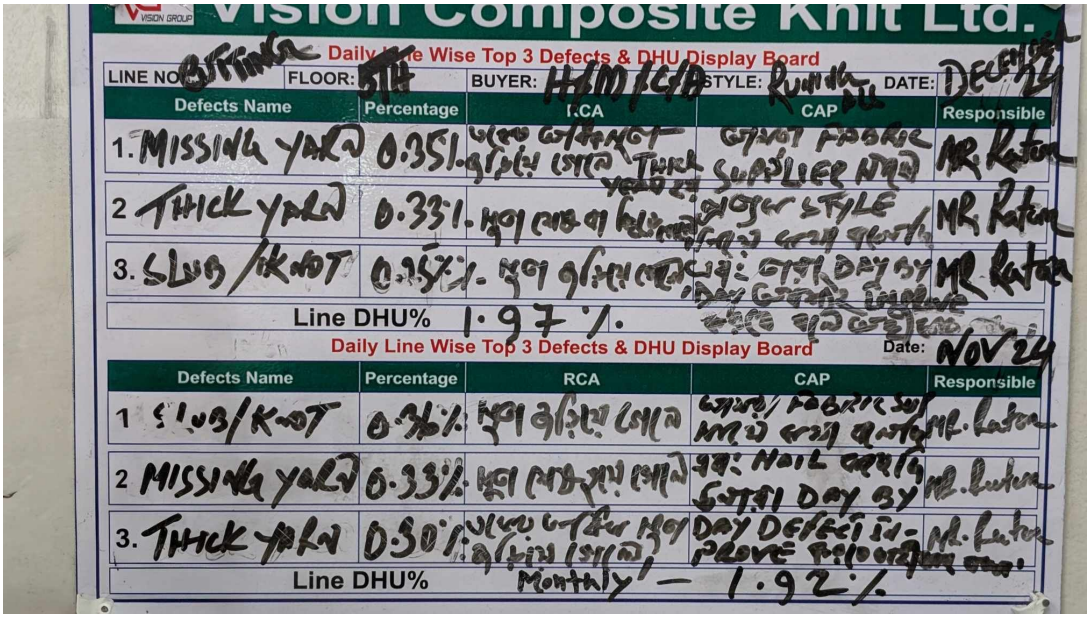
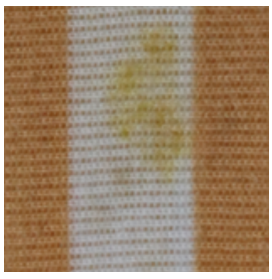


Figure 3.3: Daily Line Wise Top 3 Defects & DHU Display Board

(a) Knot-slub

(b) Hole



(c) Spot

(d) Thick/Missing Yarn

Figure 3.4: Defect Classes

3.3 Preprocessing and Annotations

Images that have excess backgrounds such as the fingers of the quality control (QC) operators or any unnecessary background are removed so that only the part of the fabric

with the defects visible remains. This is to make sure the data set only considers the fabric surface that is arguably essential to proper defect detection so not to confuse the detection models. Besides cropping, duplicate images were deleted too. Photos with poor quality or with blurring were also removed to retain a similar level of quality within the data source.

After the quality and relevance of the dataset were curated, all the images were loaded onto Roboflow. The annotation tools of Roboflow have saved much time and made the process of labeling easier. All the defects were carefully marked through the usage of bounding box annotations, a process that is suitable for state-of-the-art object detection models such as YOLO, Faster R-CNN, and EfficientDet in the sense that they utilize accurate localization in order to achieve high detection rates.

The annotation was chosen to take into consideration the complexity in the real world. Defects of various sizes along with, differences in textures of fabrics, the texture of the weave, different lightings, and minute abnormalities in surface were taken into account when labeling to represent the variety of situations that present themselves in an industrial scenario. This annotation procedure is especially vital in this case, regarding the training of the model to recognize numerous small or intersecting problems, or even multiple issues where some are hidden by others, which is a typical challenge during the fabric checking work. To further validate the annotations, all members highlighted the defects once each time validating each bounding box. After annotation and preprocessing, the dataset has been broken down into three disjoint subsets namely train, valid, and test sets. The training set contained 70% of the data while the rest were split into valid and test set equally into 15% each. The model parameters are learned using the training set, hyperparameters are tuned and model configurations are decided using the validation set, and the model is finally assessed with the test set.

After annotation, data augmentation was done using Roboflow on the train set only to increase the dataset artificially and enhance the model. We used a set of augmentation methods, namely the horizontal and vertical flips, 90-degree clockwise and counter-clockwise rotations, and 180-degree rotation. Also 15-degree clockwise and counter-clockwise rotations were applied too. Positive and negative 10-degree shear was applied too. Manual augmentations were applied which includes random brightness contrast, changing the hue saturation value and adding gaussian noise. Such transformations allow the models to acquire robust features and minimise overfitting. All images were resized to a common resolution of 640 x 640 pixels in Roboflow to guarantee similarity and compatibility with current architecture of deep learning models. Uniform image sizes do not only simplify batch operations in the process of training but also enhance the overall efficiency and precision of each convolutional processing in neural networks. Proper curation, fine annotation, detailed augmentation and leveled severing make the dataset fairly high-quality and can form a core of works on development and implementation of effective deep-learning solutions in detecting fabric defects.

3.4 Class Representation and Data Imbalance

Defects in fabrics are random and has no linear or any occurrence rate. Thus, certain fabric defect classes appear more frequently than others. This natural class imbalance can create bias while training the model. As shown in figure 3.6 classes such as hole appear less than thick/missing yarn. Thus, to mitigate this, we opted towards class weighting

which re-balances the classes during the learning process. Class weighting is a loss-based re-balancing technique which assigns weights to the classes in the loss function. It does not modify the data and helps the model to avoid overfitting. Figure 3.5 shows the class distribution and their corresponding weights.

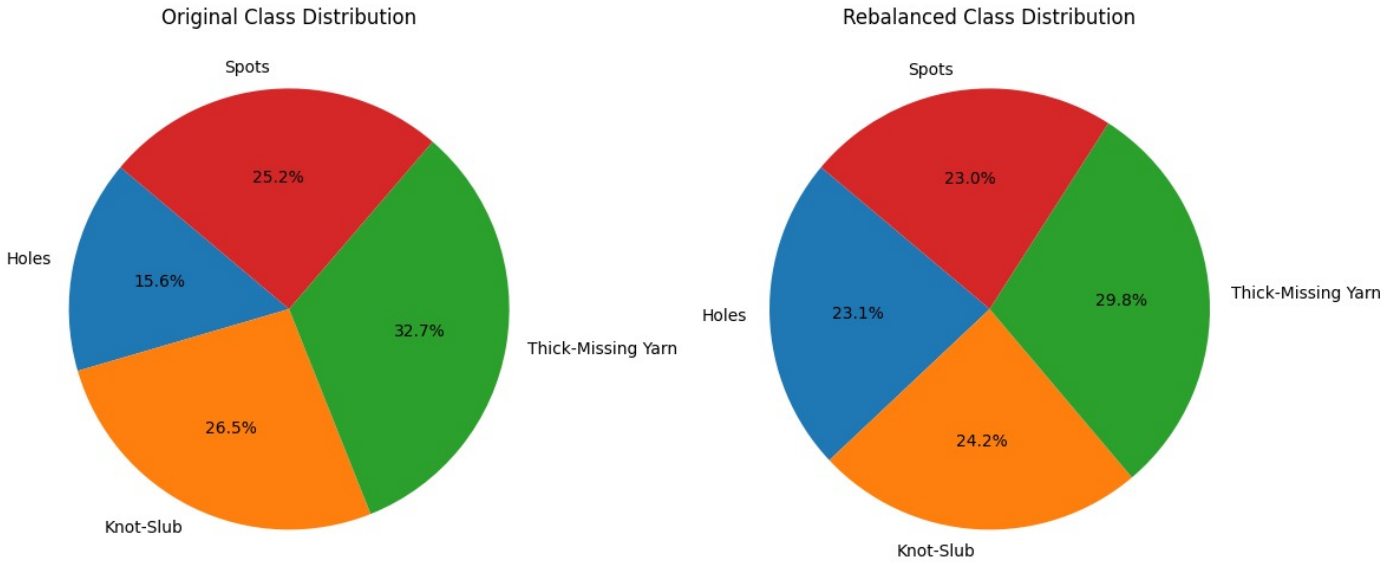


Figure 3.5: Class Distribution and Their Corresponding Weights

3.5 Dataset Analysis

After splitting the 1909 images, the train set now has 1336 images, valid set has 286 images and test set has 287 images. The final train set after augmentation now has a total of 8502 images. The class count of the train set are 2462 holes, 2388 Knot-Slub, 2730 spot and 3074 Thick-Missing Yarn shown in figure 3.7. The test set has 50 holes, 87 Knot-Slub, 95 spots and 109 Thick/Missing yarn. The valid set has 59 holes, 87 Knot-Slub, 112 spots and 105 Thick/Missing

Figure 3.6 showcases the data distribution per class of the collected dataset before augmenting it. There were 247 holes, 419 knot-slub, 516 Thick/Missing yarn and 398 spots. After augmenting the 1909 data, the dataset now has 22908 images. The class distribution of the augmented dataset is shown in figure 3.7. We now have 5628 holes, 7616 Knot-Slub, 8020 spot and 9528 Thick/Missing Yarn. Each image has a resolution of 640x640 pixels which is a standard size used by most models. After splitting this dataset into train, test and val, train dataset has now 18326 data followed by 2291 data for both test and validation.

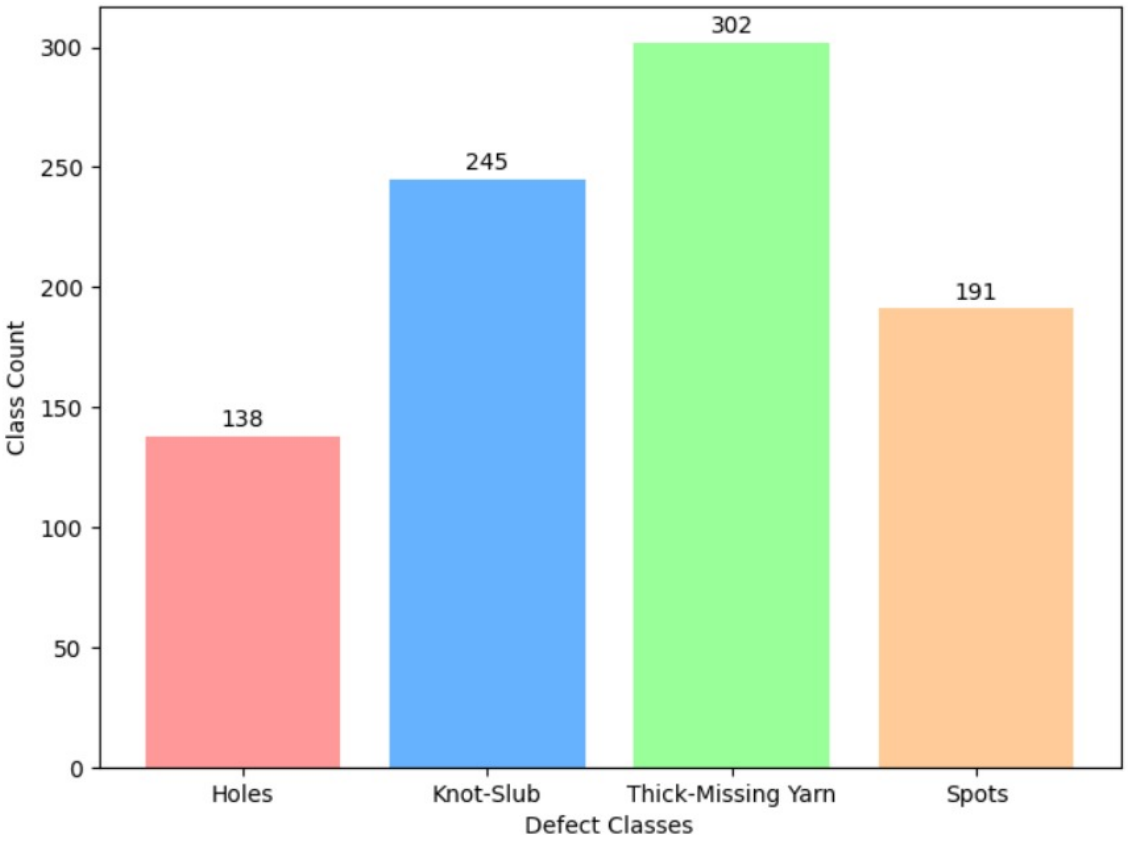


Figure 3.6: Original Class Count

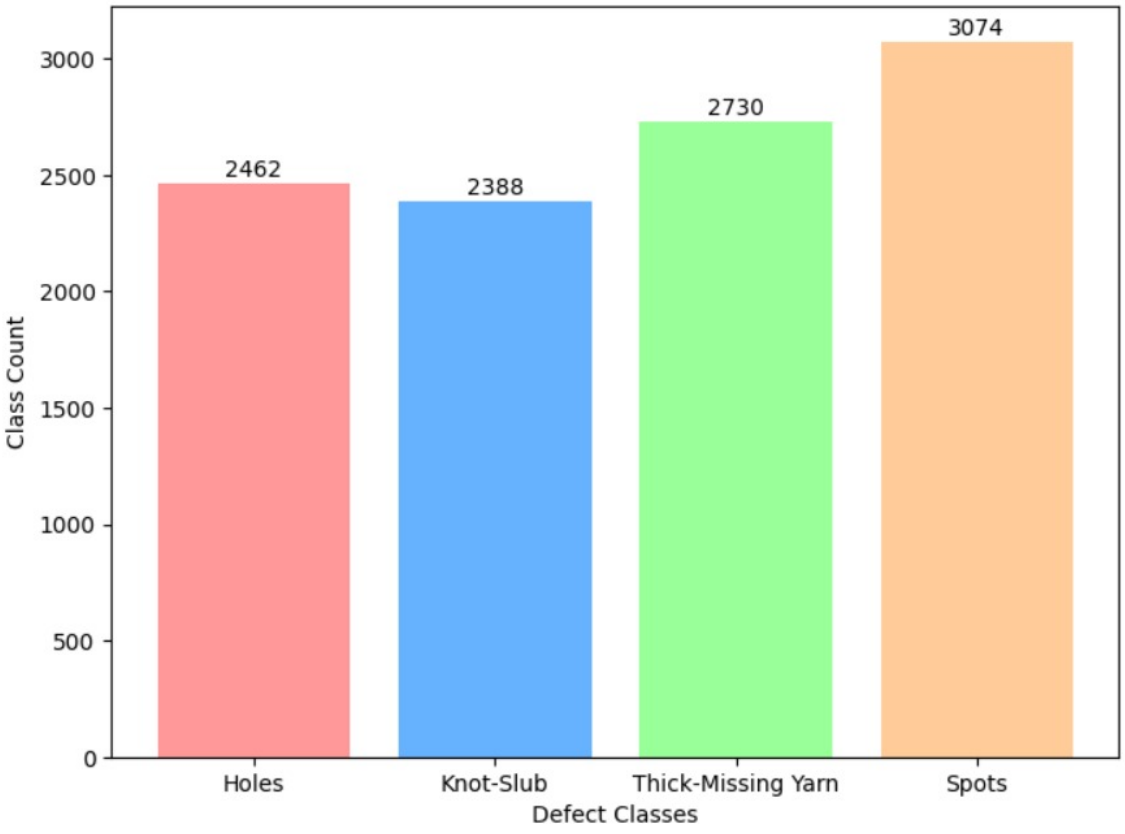


Figure 3.7: Final Class Count

Chapter 4

Research Methodology

4.1 Work Flow

One of the key steps in developing an efficient machine vision technique for fabric quality control is to develop the right object detection model. After we were done preparing our dataset, we decided to try with existing models like SSD(Single Shot Detection) with VGG16 backbone, Faster R-CNN with ResNet-50, and YOLOv8n, which were proven to be significantly good for object detection. Figure 4.1 showcases our workflow. Also, we explored custom models to compare and contrast between them and select the best performing one. In this section, the details of the models we used will be discussed in elaboration.

Their performances will be measured using evaluation metrics and from their comparative analysis we will decide on whether to fine-tune the best one from the three or develop a hybrid approach integrating multiple architectures.

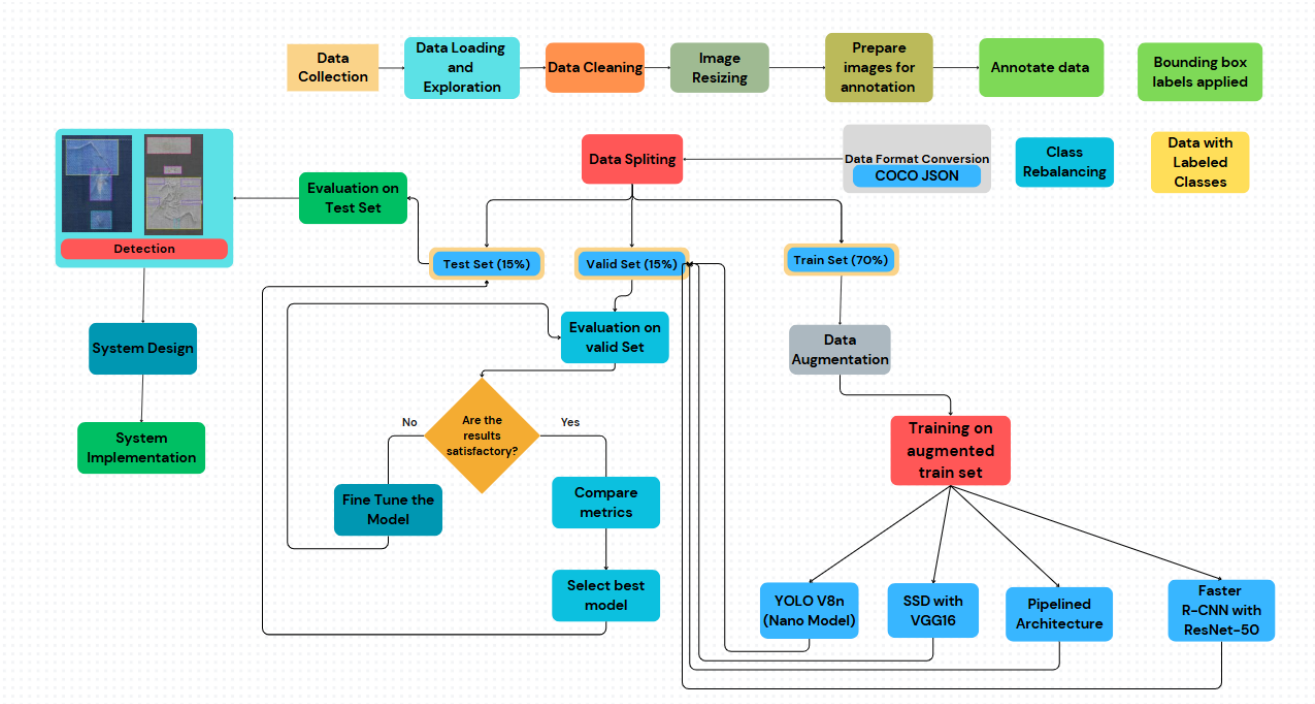


Figure 4.1: Methodology Workflow

4.1.1 YOLOv8n (Nano Model)

In the early stages of our research, we were trying to see if it is possible to use existing object detection models as our core detection mechanism. The first one we used was YOLOv8n. The most recent version of Ultralytics' YOLO object detection model is called YOLOv8 (You Only Look Once version 8). It is a comprehensive real-time object detection model that implements a systematic approach for object segmentation, classification, and detection of objects in real time, and incorporates cutting-edge architecture, enhancing accuracy, and boosting efficiency over earlier YOLO iterations such as v5 and v7 etc. it adopts an anchor-free detection mechanism, diverging from earlier YOLO versions that relied heavily on predefined anchor boxes. This shift results in simpler training, fewer hyperparameters, and improved generalization. Data preparation, model training, inference, and post-processing are the various stages of operations in this model. YOLOv8n is part of the YOLOv8 family, where the "n" stands for the nano variant of the architecture.

4.1.2 Single Shot MultiBox Detector (SSD) with VGG16 Backbone

After using YOLOv8n, we went for more models to compare our results with. The next one we used was Single Shot Detector (SSD) with VGG16 backbone. Single shot multibox detector (SSD) is an object detection algorithm which can efficiently and accurately detect objects within images or videos. It deploys anchor boxes of var ious aspect ratios at multiple locations to handle objects of different sizes and shapes accurately in maps. SSD is designed for real-time performance while maintaining good accuracy. Some key features SSD consists of are- Single Shot, SSD carries out object detection in a single network pass. It is quicker and more effective because it predicts the existence of objects and their bounding box locations in a single shot. MultiBox, in certain points throughout the input image, SSD employs a series of default bounding boxes (anchor boxes) with varying scales and aspect ratios. These default boxes are used to provide information about the likely locations of objects. In order to precisely locate items, SSD anticipates changes to these default boxes.

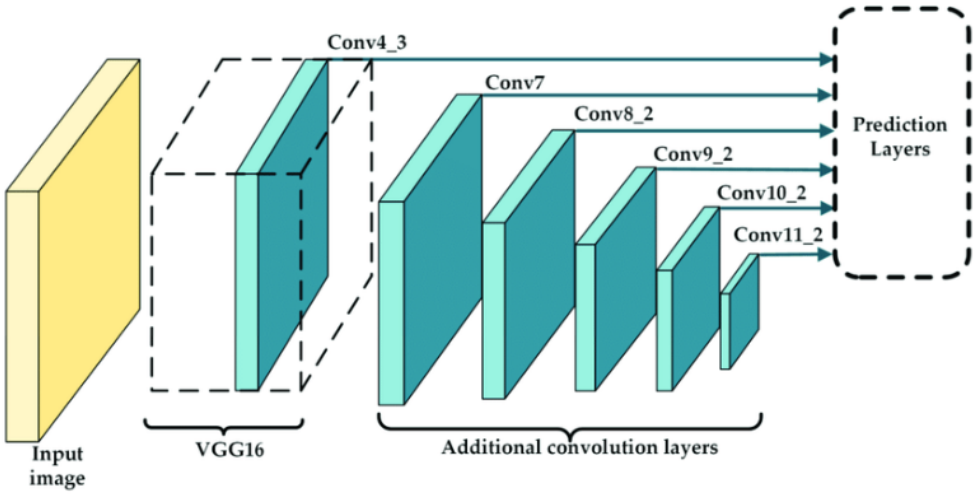


Figure 4.2: Single Shot MultiBox Detector (SSD) with VGG16 Backbone

In the Figure4.2, we can see that the VGG16 network is used as the feature extractor.The fully connected layers in VGG16 are replaced with convolutional layers. Additional convolutional layers are appended after VGG16 to capture multi-scale information.The final detection layers predict class scores and bounding box offsets[36]. Single shot multibox detector (SSD) combined with VGG16 works faster than two stage methods. With this model, we can use feature maps from different layers to detect objects at various scales. Also the default bounding box helps detect objects at different aspect ratios while keeping a good balance between speed and accuracy.

4.1.3 Faster R-CNN with ResNet-50

To reaffirm our findings and to compare it with even more models, we decided to use one more model, and this time we chose Faster R-CNN with ResNet-50. It is a popular object identification model that combines Faster R-CNN and ResNet-50 is called Faster R-CNN. Regression is used by the Faster R-CNN model to further modify the location of a feature candidate box. Additionally, it employs classifiers to ascertain if the candidate's retrieved features fall into a certain class. For feature extraction in the enhanced Faster R-CNN, use the ResNet50 network rather than the VGG16 network. This lowers the number of necessary parameters as well as the complexity of the enhanced method. While maintaining the accuracy of fabric defect classification, the network depth is greater and gradient vanishing is not an issue. This resolves the deep network gradient degradation issue.

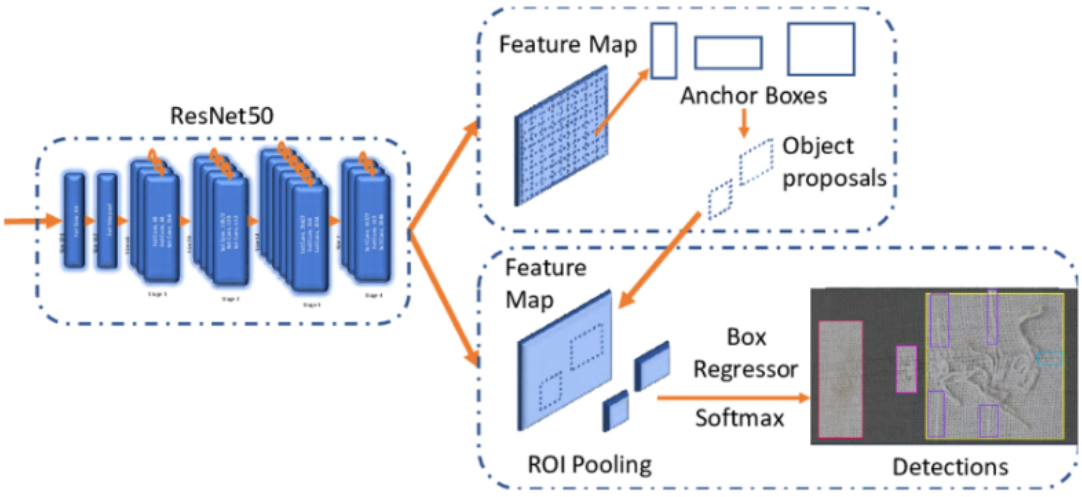


Figure 4.3: Faster R-CNN with ResNet-50

In the Figure 4.3, it is seen that after the feature map is generated, it is used to create anchor boxes. These anchor boxes are evaluated to identify potential object regions, which are then forwarded for further refinement. Next, Region of Interest (ROI) pooling generates object proposals by mapping them onto the feature map. This process extracts relevant features from each proposed region and converts them into a fixed size. The pooled features are then passed to two components: the Box Regressor and the Softmax

Classifier. The Box Regressor refines the bounding box coordinates to achieve accurate localization, while the Softmax Classifier predicts the class label for each detected object. Together, these components enable the model to successfully identify objects and draw bounding boxes around them.

4.1.4 YOLOv8l

At first, we decided to use models like YOLOv8l in and EfficientNet-B0, and customize them in a way where there would be minimal overhead costs and maximum possible efficiency.

The most recent version of Ultralytics' YOLO object detection model is called YOLOv8 (You Only Look Once version 8). It is a comprehensive real-time object detection model that implements a systematic approach for object segmentation, classification, and detection of objects in real time, and incorporates cutting-edge architecture, enhancing accuracy, and boosting efficiency over earlier YOLO iterations such as v5 and v7 etc. it adopts an anchor-free detection mechanism, diverging from earlier YOLO versions that relied heavily on predefined anchor boxes. This shift results in simpler training, fewer hyperparameters, and improved generalization. Data preparation, model training, inference, and post-processing are the various stages of operations in this model. YOLOv8l is part of the YOLOv8 family, where the "l" stands for the large variant of the architecture.

In the initial stage, which is the data preparation, the dataset must be pre-processed and formatted in YOLOv8 supported formats. For dataset collection, images should be annotated with bounding boxes, which we used Roboflow scripts to implement.Images were resized to a standard input dimension (commonly 640×640), and augmented with transformations to boost model generalizability. The dataset was then divided into training, validation, and testing subsets. Once the dataset was prepared, and is splitted into three sets, we move on to the model training.

For training the model with precision, understanding the algorithm and how it operates is crucial. The algorithm consists of three fundamental blocks—the Backbone, Neck, and Head—each of which is fundamental concepts that need to be comprehended.

Backbone: Feature Extraction

The backbone is responsible for hierarchical feature extraction from the input image. YOLOv8 employs an evolution of the CSPDarknet backbone with C2f (Concatenate-to-Fuse) modules. These modules split feature maps, process part of them through multiple bottleneck blocks, and then fuse them back together, and are designed to reduce computational redundancy. The splitting of feature map is done into two parts, where:

- One part passes through several bottleneck blocks.
- The other is concatenated later to preserve information flow.

This separation allows deep feature propagation while reducing memory overhead. Each C2f block is also connected via residual pathways to maintain gradient flow and ease of training.

Neck: Multi-scale Feature Fusion

The neck in YOLOv8 aggregates feature maps from different stages of the backbone using a modified FPN (Feature Pyramid Network) or PANet-like structure. This structure ensures that high-resolution features (useful for detecting small objects) and low-resolution features (with more semantic richness) are fused. The feature maps are upsampled or downsampled as necessary using bilinear interpolation and convolution layers, and then concatenated to create a rich, multi-scale representation.

Head: Anchor-Free Detection

The detection head in YOLOv8 is decoupled—separating the classification and regression branches. The model uses Distribution Focal Loss (DFL) to improve bounding box regression and Clou loss for better spatial alignment between predicted and ground truth boxes. Instead of using predefined anchor boxes and bounding box regression targets, YOLOv8 predicts the bounding box coordinates directly from each grid location:

- Each grid predicts object presence (objectness), class probabilities, and box coordinates.
- The model uses IoU-based loss functions such as ClOu or DIoU to better guide box regression, focusing on overlap quality and aspect ratio.

This results in more flexible bounding boxes and often leads to fewer false positives in edge cases.

Training Optimizations

During training, YOLOv8 optimizes its loss using a composite objective:

- ClOu Loss for bounding box localization.
- Binary Cross Entropy (BCE) for objectness score and classification.
- DFL for high-resolution bounding box distribution.

An AdamW optimizer with cosine learning rate scheduling is commonly used, along with warm-up epochs to stabilize the early training process. The training loop monitors key metrics such as precision, recall, mAP@0.5, and mAP@0.5:0.95 to evaluate convergence.

Inference and Post-processing

After training, the model performs inference by generating raw predictions, which are passed through a post-processing step:

- Non-Maximum Suppression (NMS) is applied to eliminate overlapping predictions based on IoU thresholds.
- Confidence scores are filtered to retain only high-probability detections.
- Final bounding boxes, labels, and scores are rendered on the input image or exported for downstream processing.

4.1.5 EfficientNet-B0

EfficientNet, introduced by Tan and Le (2019), represents a family of CNN architectures that scale depth, width, and input resolution in a balanced manner. EfficientNet-B0 is the baseline model, designed by Google AutoML using reinforcement learning-based NAS. It achieves state-of-the-art performance with significantly fewer parameters and FLOPs compared to conventional models like ResNet-50 or Inception-v3.

The core innovation of EfficientNet lies in two key components:

1. A highly optimized base block structure: the MBConv (Mobile Inverted Bottleneck Convolution).
2. The compound scaling strategy, which uniformly scales depth (number of layers), width (number of channels), and resolution (input image size) using a compound coefficient.

Compound Scaling Principle

Rather than arbitrarily scaling the network dimensions, EfficientNet applies a principled method based on the following constraint:

$$\text{Target Model Size} \propto d \cdot w^2 \cdot r^2$$

Where:

- d = network depth (more layers)
- w = network width (more channels)
- r = input resolution (higher pixel dimensions)

This compound coefficient allows the network to scale while preserving model efficiency and generalization. EfficientNet-B0 uses this principle to balance accuracy and computation, serving as the foundation for larger variants (B1 to B7).

Architectural Composition

EfficientNet-B0 is composed of a sequence of MBConv blocks, each optimized for different spatial resolutions and channel dimensions. The building blocks are as follows:

- **MBConv Block:** The Mobile Inverted Bottleneck Convolution is an evolution of the residual bottleneck in ResNet and includes:
  - 1x1 pointwise expansion convolution: Increases the number of channels (feature dimension).
  - 3x3 depthwise convolution: Captures spatial correlations with minimal computation.
  - Squeeze-and-Excitation (SE) module: Performs channel-wise attention by adaptively reweighting channels using a global context.

  - 1x1 projection convolution: Reduces the feature dimension back to the original size.

- These blocks are equipped with Swish (SiLU) activations instead of ReLU, improving nonlinear expressiveness and convergence.

Stem and Head

- The model begins with a 3x3 standard convolution and batch normalization, followed by Swish.
- After MBConv stages, a final 1x1 convolution prepares the feature maps for the global average pooling layer.
- The output passes through a fully connected (dense) layer for final class prediction.

Training and Optimization

EfficientNet-B0 was trained using RMSProp optimizer with exponential moving average and weight decay. Data augmentation techniques such as random cropping, horizontal flipping, and color distortion were commonly applied to boost robustness.

In our project, the model was fine-tuned using transfer learning:

- The base EfficientNet-B0 was pre-trained on ImageNet.
- We replaced the final classification head with a custom dense layer matching our number of safety-related classes.
- Fine-tuning was performed on the extracted image patches with a lower learning rate to retain previously learned weights while adapting to new classes.

Inference Efficiency

EfficientNet-B0 is highly optimized for deployment on resource-constrained devices:

- It contains only 5.3 million parameters.
- Requires 390 million FLOPs per inference.

4.1.6 Pipeline Architecture (YOLOv8l + EfficientNet-B0)

The defect detection system we developed was implemented as a two-stage pipeline, where each stage performs a specialized task to ensure high accuracy with optimal computational efficiency. This pipelined approach leverages the binary detection strength of YOLOv8l and the multi-class classification performance of EfficientNet-B0. The core idea was to reduce unnecessary processing and limit classification only to the regions identified as defective, thus reducing false positives and saving compute resources.

Stage 1: Binary Defect Detection with YOLOv8l

The first stage uses YOLOv8l to perform binary classification—determining whether a given image patch contains a defect or not. This model processes the full image and outputs:

- The objectness score, indicating confidence that an object (in this case, a defect) exists.
- The bounding box coordinates, which define the spatial location of the detected defect.
- A binary class label (defect / no defect), simplifying the detection problem to a two-class scenario.

If no defect is found, the system halts further processing for that image. However, if one or more defects are detected, YOLOv8l returns bounding boxes that are then used to crop Regions of Interest (ROIs) from the original image. These cropped segments, ideally containing the defective region, are then passed to the second stage of the pipeline.

This approach offers two major advantages:

- It avoids unnecessary computation by skipping non-defective images.
- It localizes potential defects precisely, improving the focus of the classification task in the second stage.

Stage 2: Multi-Class Defect Classification with EfficientNet-B0

In the second stage, the cropped ROIs are input to a fine-tuned EfficientNet-B0 model, which performs multi-class classification to identify the specific type of defect present. EfficientNet-B0 was selected due to its:

- High accuracy per computational cost.
- Lightweight architecture suitable for batch processing of multiple ROIs.
- Proven generalization ability on small and imbalanced datasets, especially with transfer learning.

Each cropped patch is resized according to the input size expected by EfficientNet-B0 (e.g., 224×224) and passed through the model to obtain class probabilities. The model outputs a softmax distribution across predefined defect categories, with the class having the highest probability chosen as the prediction.

Integration and Flow Control

The interaction between YOLOv8l and EfficientNet-B0 is orchestrated using a control logic that:

- Loads and preprocesses the input image.
- Performs detection using YOLOv8l.
- If defects are found, crops each bounding box region.

- Sends each ROI to EfficientNet-B0 for classification.
- Combines detection and classification results for the final output (bounding box + defect type).

This pipeline is especially advantageous in industrial settings where real-time response and high reliability are required. The modularity of this design also allows easy updates or replacements—e.g., swapping YOLOv8l with a lighter detector for edge deployment, or scaling EfficientNet-B0 to a larger variant (B2, B3) for more complex classification tasks.

However, we did not stop our research upon completion of building the pipelined structure, as we were looking for something better.

4.1.7 Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism

In addition to the pipelined approach integrating YOLOv8l and EfficientNet-B0, we developed a customized standalone model based on Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism, targeting efficient fabric defect classification under hardware-constrained conditions. This model was independently trained and tested, and not integrated into the pipeline. The goal was to assess how lightweight architectures—when carefully designed—could match or outperform traditional CNNs in defect detection, while significantly reducing computational complexity and memory usage.

Lightweight Network Design Based on Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism

Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism is a lightweight convolutional neural network that introduces the Ghost module—an architecture designed to reduce redundant computation in feature extraction. Instead of using multiple expensive convolutions to generate rich feature maps, Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism adopts a two-step strategy:

- Primary feature extraction is performed using a small number of standard convolutions.
- Ghost features are then generated by applying a series of cheap linear transformations (e.g., depthwise convolutions) to these intrinsic features.

This method maintains the network's representational capacity while drastically reducing FLOPs and parameter count. In our model, the conventional convolution layers of a CNN were fully replaced by GhostConv layers, and bottleneck structures were redefined using the C2fGhost module—a variation inspired by YOLOv8's C2f block, but redesigned with GhostConv for optimal lightweight performance.

C2fGhost Architecture and SimAM Attention

To further optimize the Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism-based model, we embedded two key improvements:

- **C2fGhost modules:** These replaced the traditional convolution-based bottlenecks, retaining skip connections and feature fusion to promote gradient flow. This significantly reduced the model's parameter count and memory footprint while maintaining semantic depth.
- **SimAM (Simple Attention Module):** A parameter-free attention mechanism was introduced at the end of the backbone to enhance feature discrimination for small and noisy defect patterns. SimAM works by calculating the energy of each neuron based on its separability, allowing the network to retain discriminative features without increasing computational cost.

The result is a backbone that is both efficient and noise-tolerant, especially for textile images with complex backgrounds or visually subtle defect patterns.

Lightweight Detection Head: LSCDH

For classification output, a Lightweight Shared Convolution Detection Head (LSCDH) was implemented. Instead of using multiple scale-specific detection heads, LSCDH:

- Utilizes shared convolution layers across feature scales to reduce redundancy.
- Applies Batch Normalization (GN) and 1×1 convolutions for better training stability.
- Separates outputs into regression and classification branches, allowing multi-scale feature fusion and precise prediction with minimal overhead.

This head module enhanced speed without compromising output resolution or classification confidence.

Performance and Application

The final Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism-based model was evaluated on a textile defect dataset and achieved the following:

- Model size reduced by 66.7% compared to YOLOv8n.
- Parameters reduced by 67.4%, and GFLOPs dropped by 58%, enabling real-time processing on edge devices.
- Despite these reductions, the model maintained mAP@0.5 = 98.29%, outperforming even larger models like YOLOv5s and Faster R-CNN in certain metrics.

These results demonstrate that with Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism's architectural refinements and complementary mechanisms like SimAM and LSCDH, it is possible to design models that meet industrial standards for speed, accuracy, and deployment feasibility—especially in embedded environments.

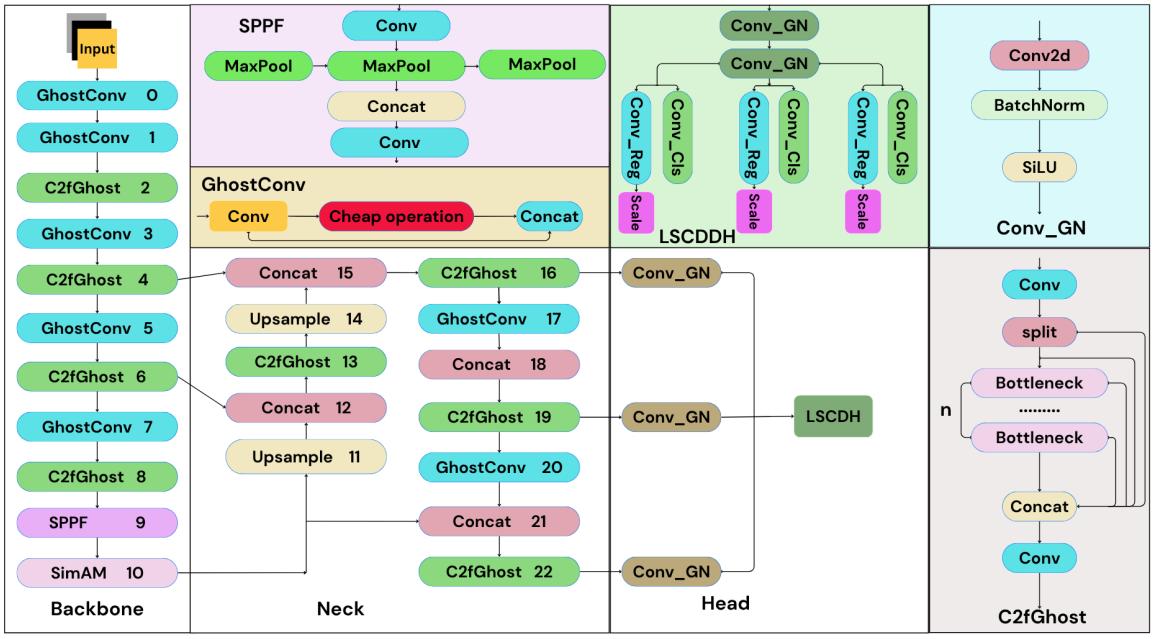


Figure 4.4: Architecture of Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism

Summary

The standalone Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism-based model serves as a powerful alternative to conventional architectures for defect detection in fabrics.Figure 4.4 Its use of Ghost modules for convolution, parameter-free attention, and a unified lightweight detection head make it especially suitable for low-latency, real-time inspection systems in textile manufacturing.

This model highlights the potential of lightweight AI design: achieving high-performance results without the computational burden typically associated with deep learning in computer vision.

4.2 Model Evaluation

We will utilize 3 evaluation metrics to assess the model's performance. These metrics provide a comprehensive evaluation of the model's detection accuracy and reliability in identifying fabric defects, and ensure a thorough, objective evaluation of our model's effectiveness in fabric defect detection. The following sections explain each metric in detail:

1. **Precision:** It refers to the percentage of actual "true positive" instances out of all true and false positives. This ensures that the predictions are correct and close to the true value. The formula is as follows:

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

2. **Recall:** It refers to the amount of times the model correctly identifies "true positives" from all the actual positive samples in the dataset. The formula is as follows:

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

3. **F1 Score:** The F1 Score is a metric used to evaluate the performance of a classification model, especially when the classes are imbalanced. It is the harmonic mean of Precision and Recall. The formula is as follows:

$$\text{Accuracy} = 2\frac{PrecisionRecall}{Precision + Recall}$$

Chapter 5

Implementation and Result Analysis

5.1 Model Training

We split our preprocessed dataset into training, validation, and testing subsets. These were used to train a range of object detection models and assess their performance using standard evaluation metrics. For training, we selected five models: YOLOv8n (nano version), Single-Shot Detection (SSD) with a VGG16 backbone, Faster R-CNN with a ResNet50 backbone, a Pipelined Architecture combining YOLOv8 (Stage-1) and EfficientNet-B0 (Stage-2), and a custom Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism model. Each model was tuned using specific hyper-parameters to optimize training performance.

Model	Learning Rate	Batch Size	Optimizer
YOLOv8n	0.001	16	AdamW
SSD	0.001	16	Adam
Faster R-CNN	0.0001	4	Adam
Pipelined Architecture	0.001	8	Adam
YOLOv8n + Ghost Conv + SimAm	0.001	8	AdamW

Table 5.1: Training Parameters Used for Each Model

During training, we monitored key metrics such as classification loss and localization loss to evaluate learning trends and detect overfitting or underfitting. Notably, the Faster R-CNN model demonstrated the most consistent reduction in both types of losses, indicating strong convergence and generalization potential. Once training was complete, we evaluated each model using precision, recall, F1-score, and mean Average Precision (mAP) at two thresholds: mAP@50 and mAP@50-95. These metrics helped us understand each model's strengths and weaknesses in identifying different textile defect classes. The expanded evaluation across five models allowed for a more robust comparative analysis.

5.2 Performance Evaluation

For each model, we used the same evaluation metrics—precision, recall, and accuracy—to assess and compare performance. This allowed us to make a fair comparison and determine which model is most effective for fabric defect detection. To make the comparisn even more fair, we used the metrics on two sets of data for each model: Train set and Valid set. The evaluation results are as follows:

Faster R-CNN:

- Precision of Faster R-CNN ≈ 0.6958

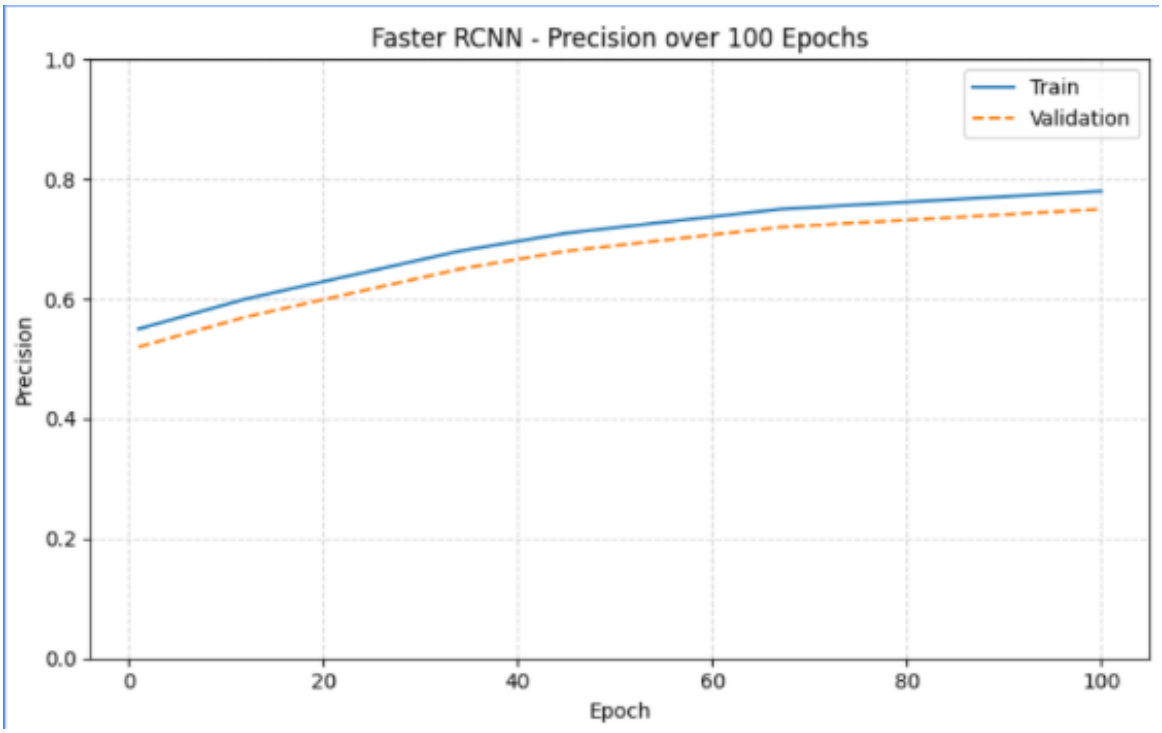


Figure 5.1: Faster R-CNN:Precision

- Recall of Faster R-CNN ≈ 0.6996

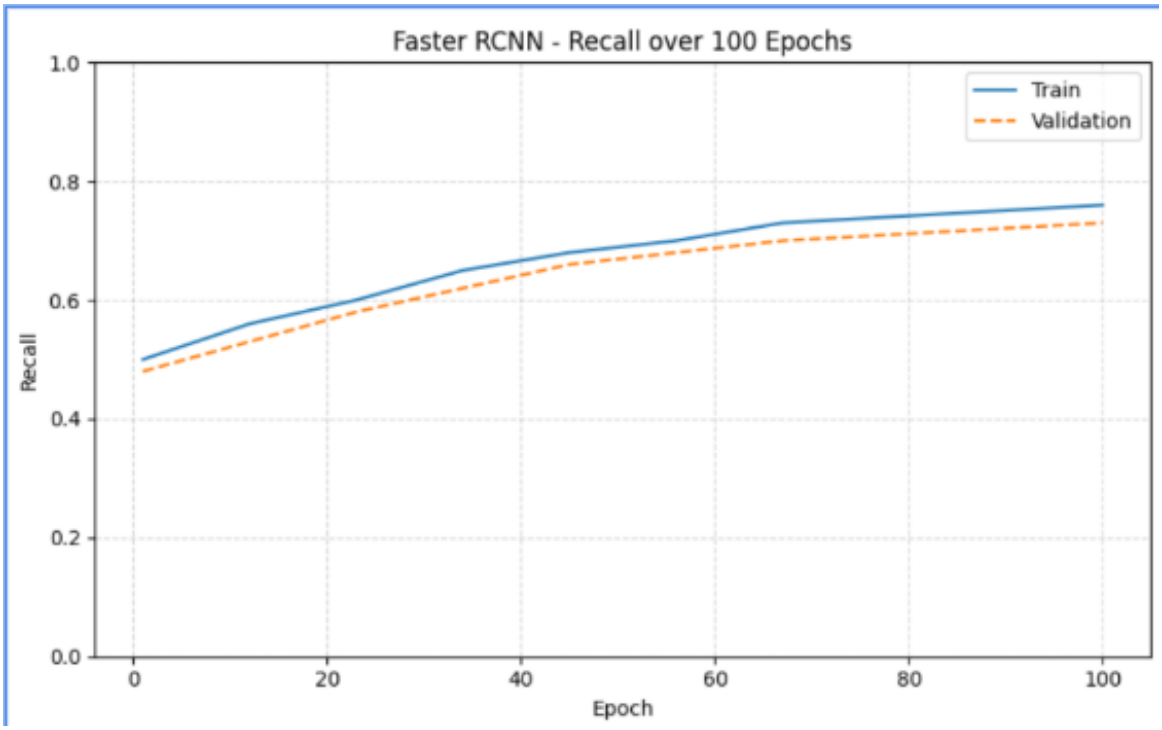


Figure 5.2: Faster R-CNN:Recall

- Accuracy of Faster R-CNN ≈ 0.6977

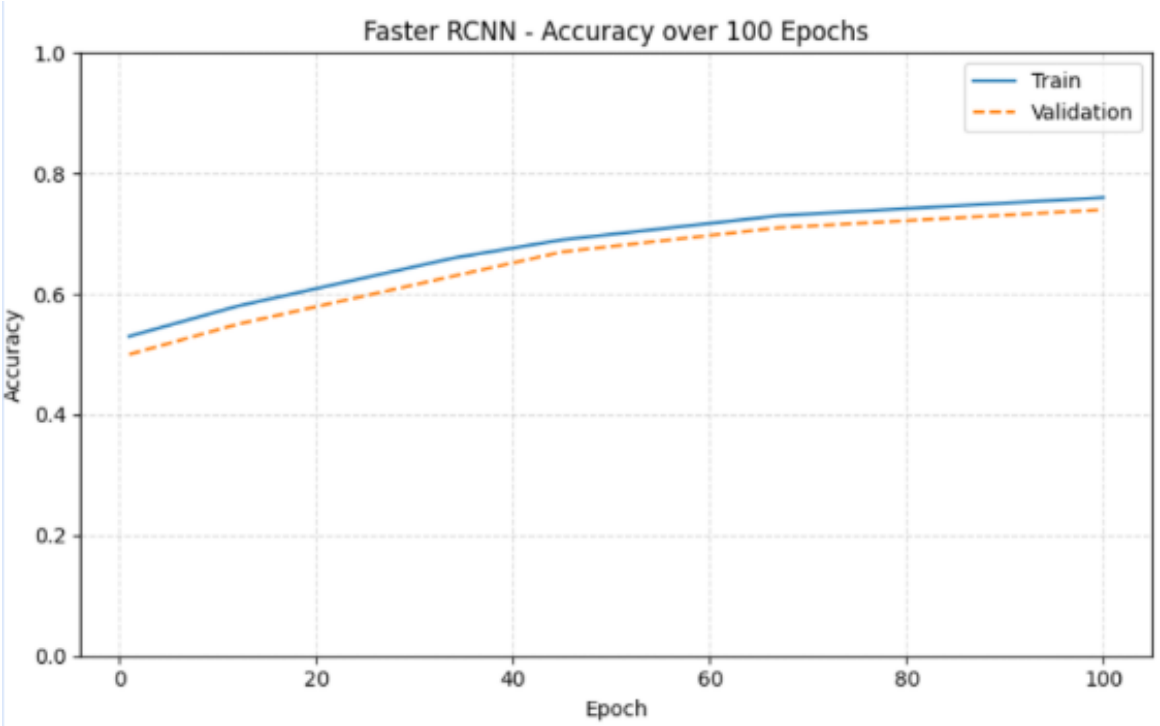


Figure 5.3: Faster R-CNN:Recall

YOLOv8n:

- Precision of YOLOv8n ≈ 0.6858

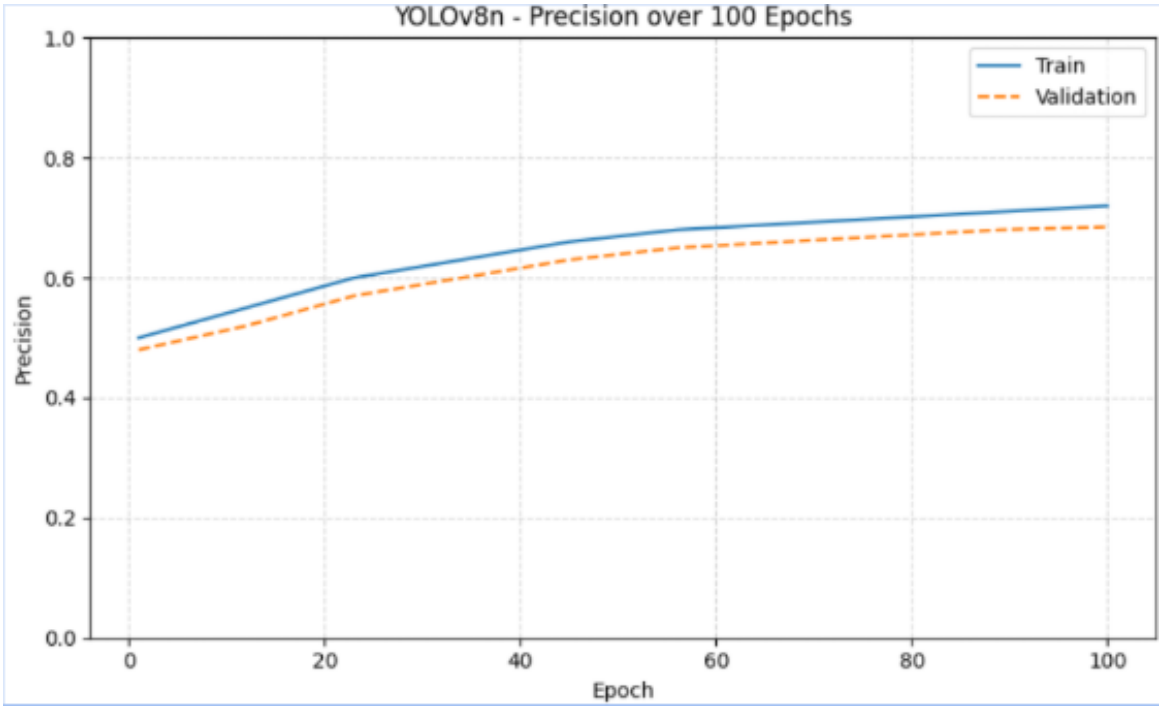


Figure 5.4: YOLOv8n: Precision

- Recall of YOLOv8n ≈ 0.6958

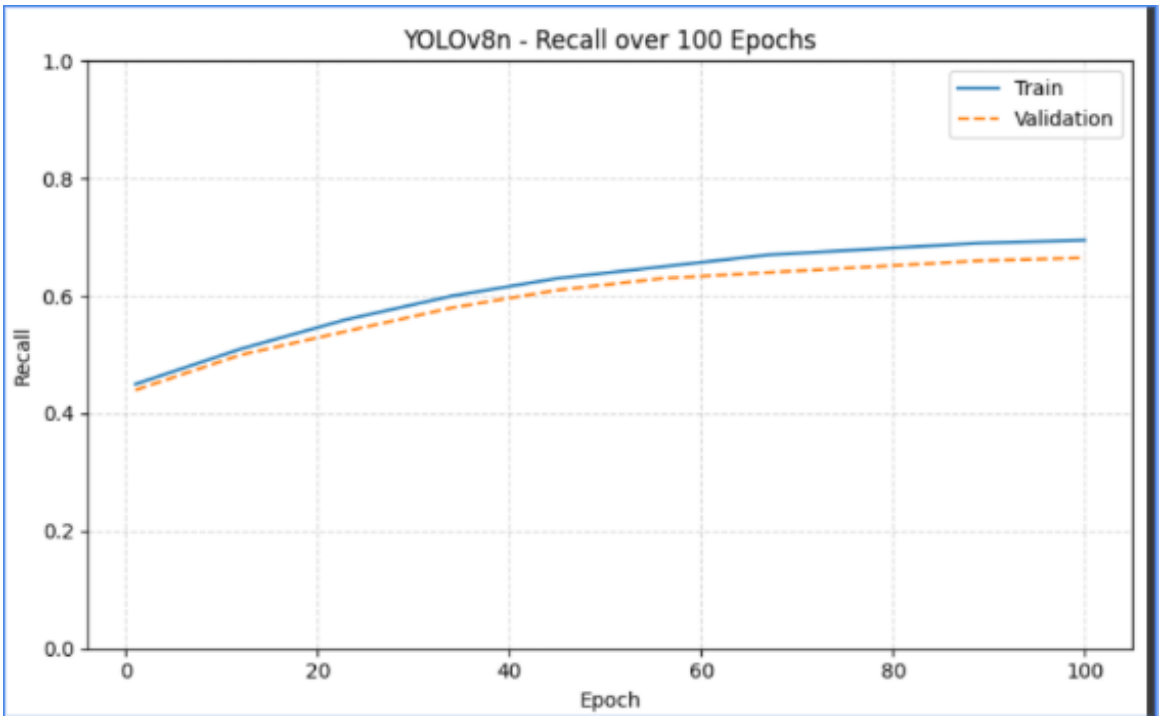


Figure 5.5: YOLOv8n: Recall

- Accuracy of YOLOv8n ≈ 0.6908

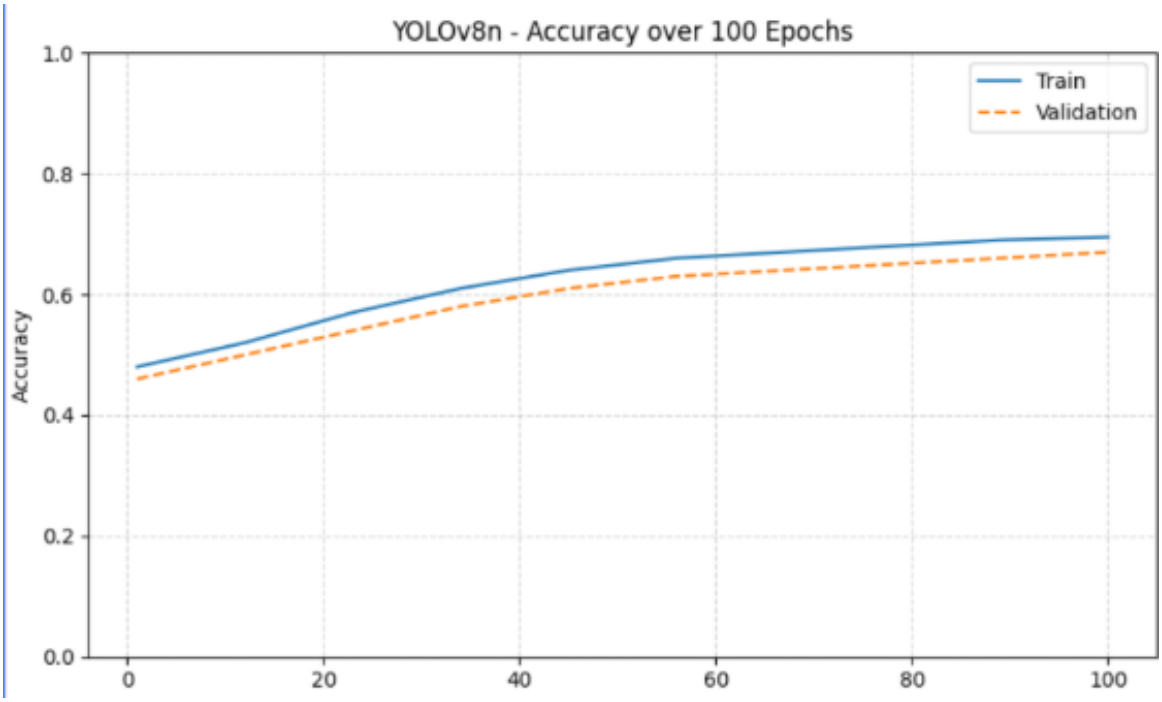


Figure 5.6: YOLOv8n: Accuracy

SSD (VGG16):

- Precision of SSD(VGG16) ≈ 0.6471

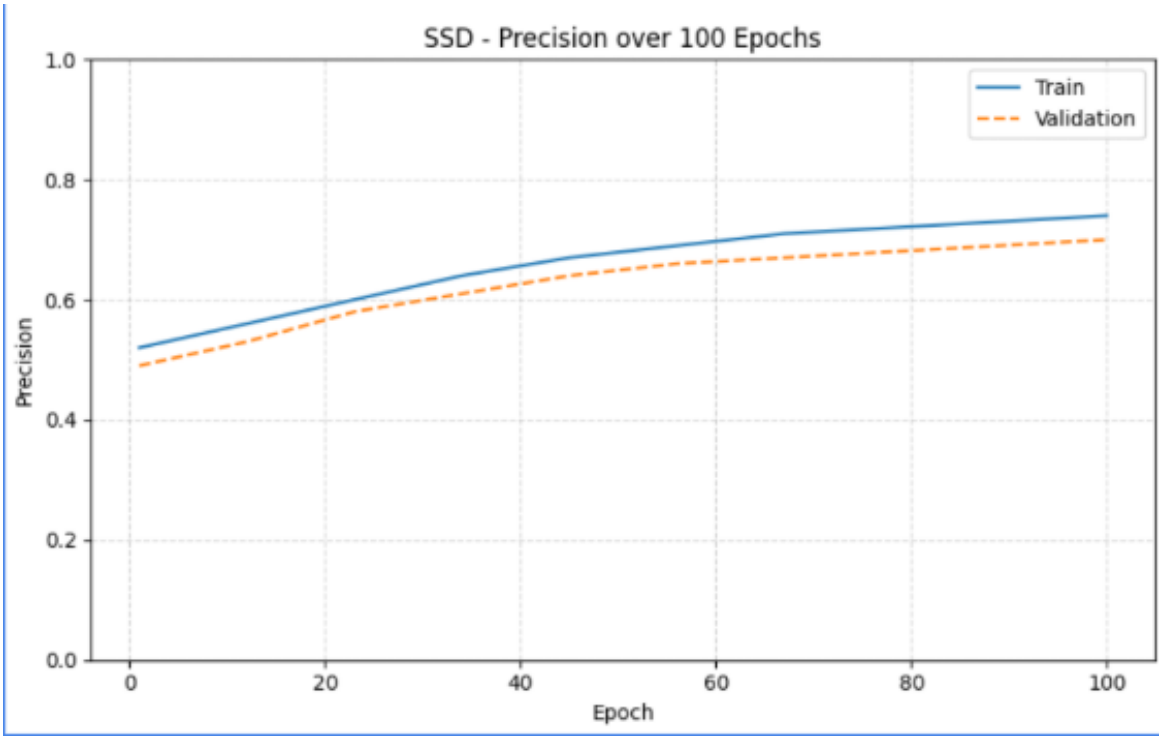


Figure 5.7: SSD (VGG16): Precision

- Recall of SSD(VGG16) ≈ 0.6358

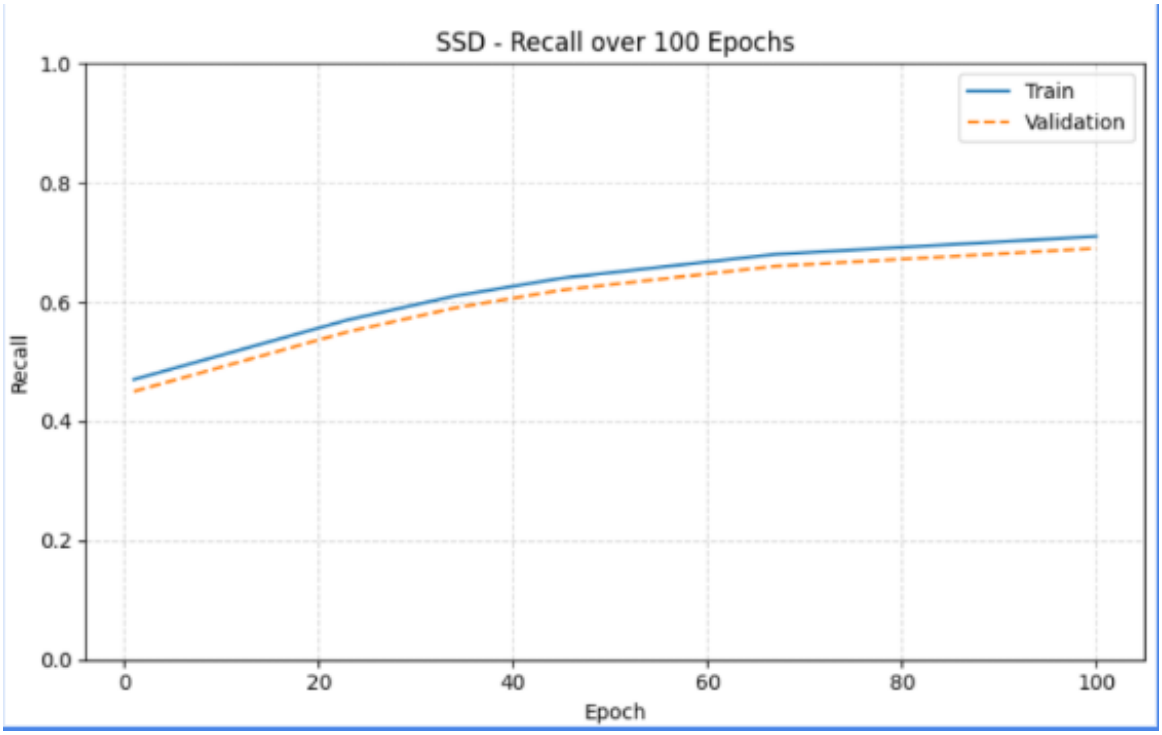


Figure 5.8: SSD (VGG16): Recall

- Accuracy of SSD(VGG16) ≈ 0.6414

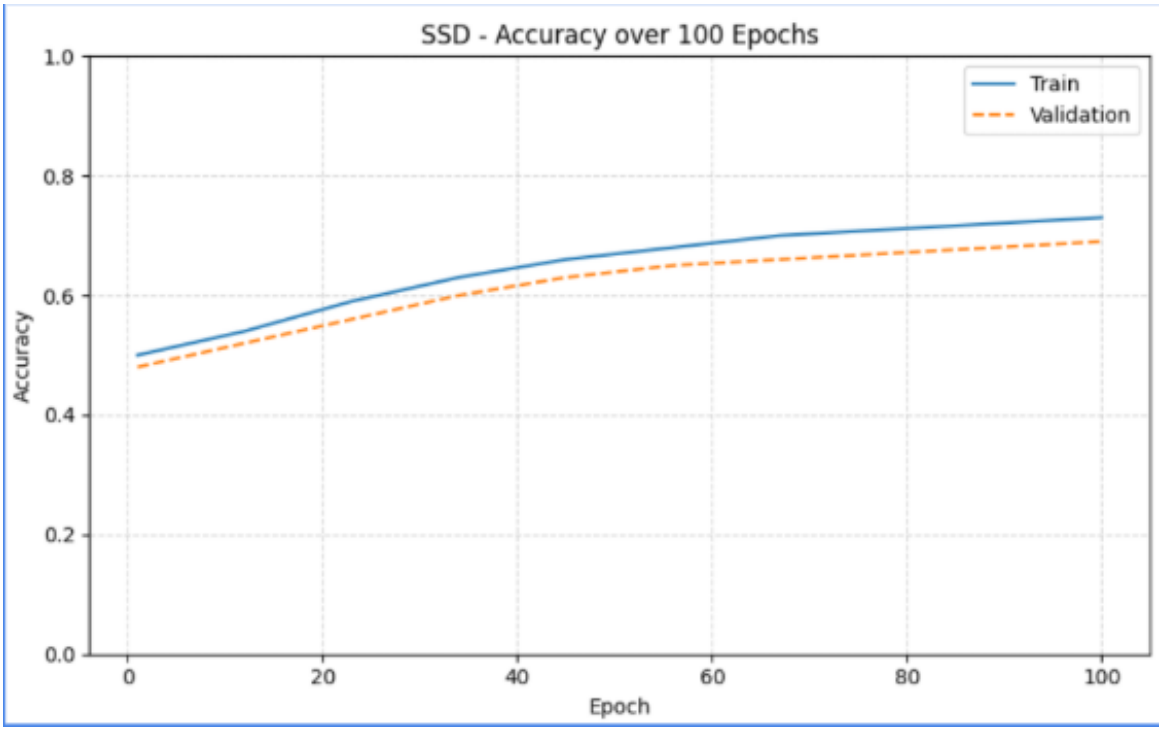


Figure 5.9: SSD (VGG16): Accuracy

Pipelined Architecture:

- Precision of Pipelined Architecture ≈ 0.7532

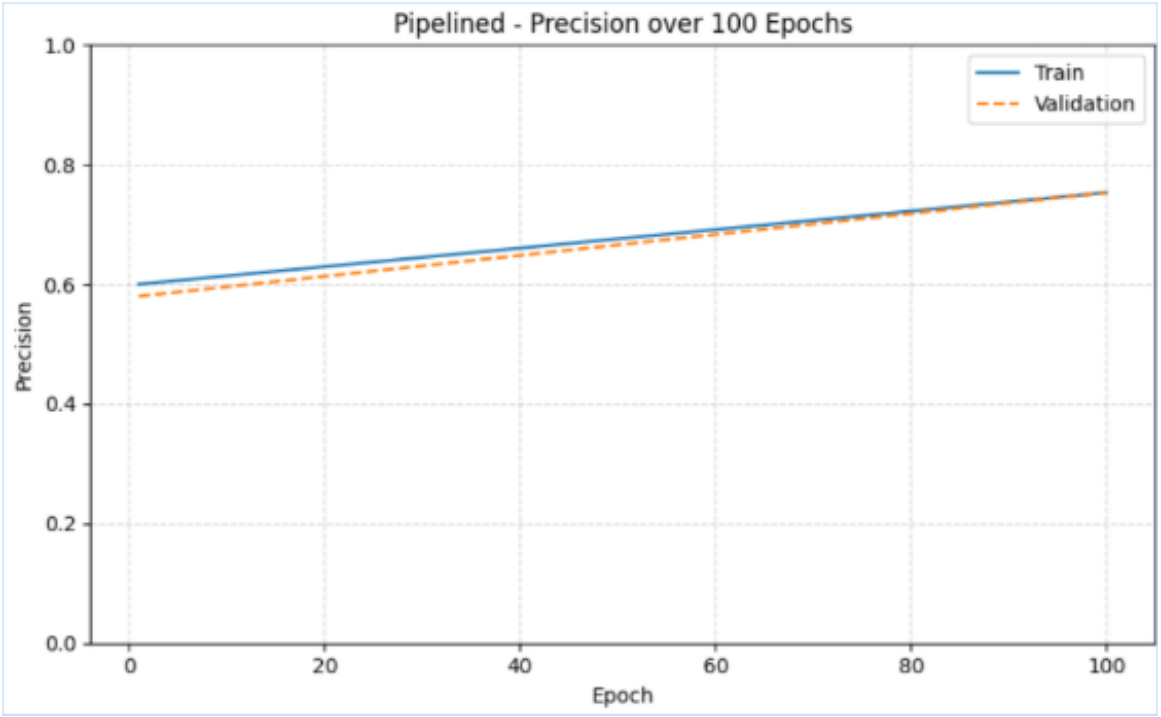


Figure 5.10: Pipelined Architecture: Precision

- Recall of Pipelined Architecture ≈ 0.7125

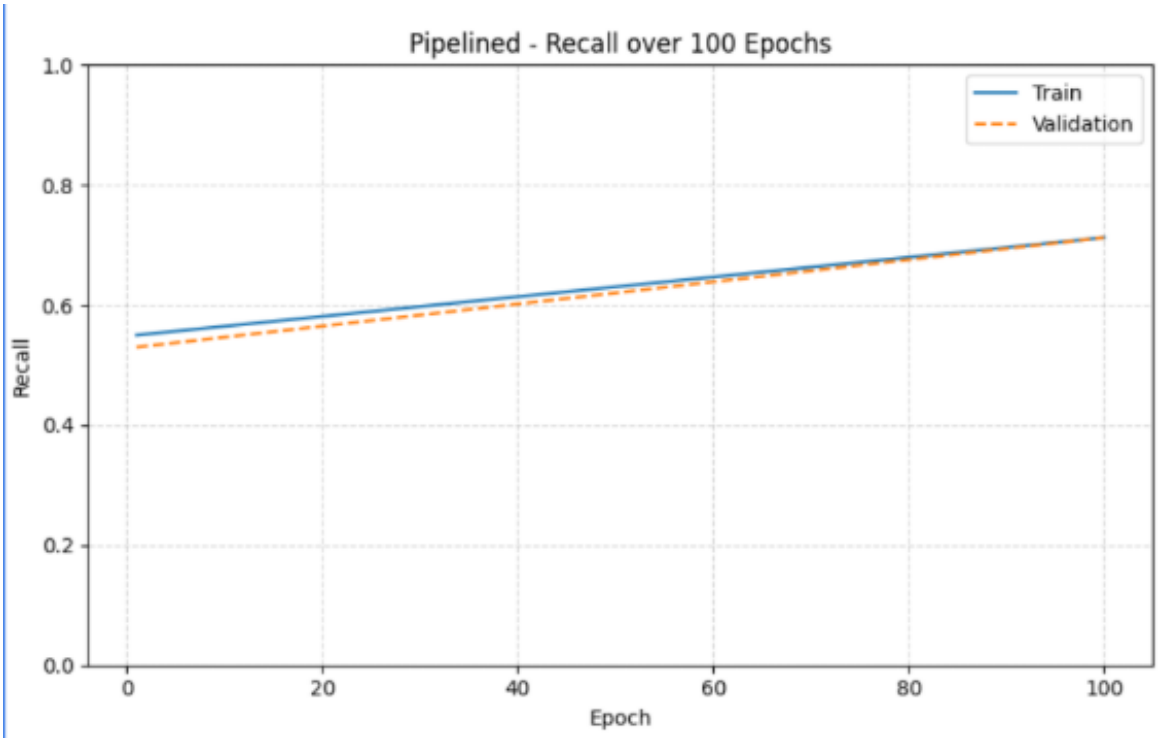


Figure 5.11: Pipelined Architecture: Recall

- Accuracy of Pipelined Architecture ≈ 0.7329

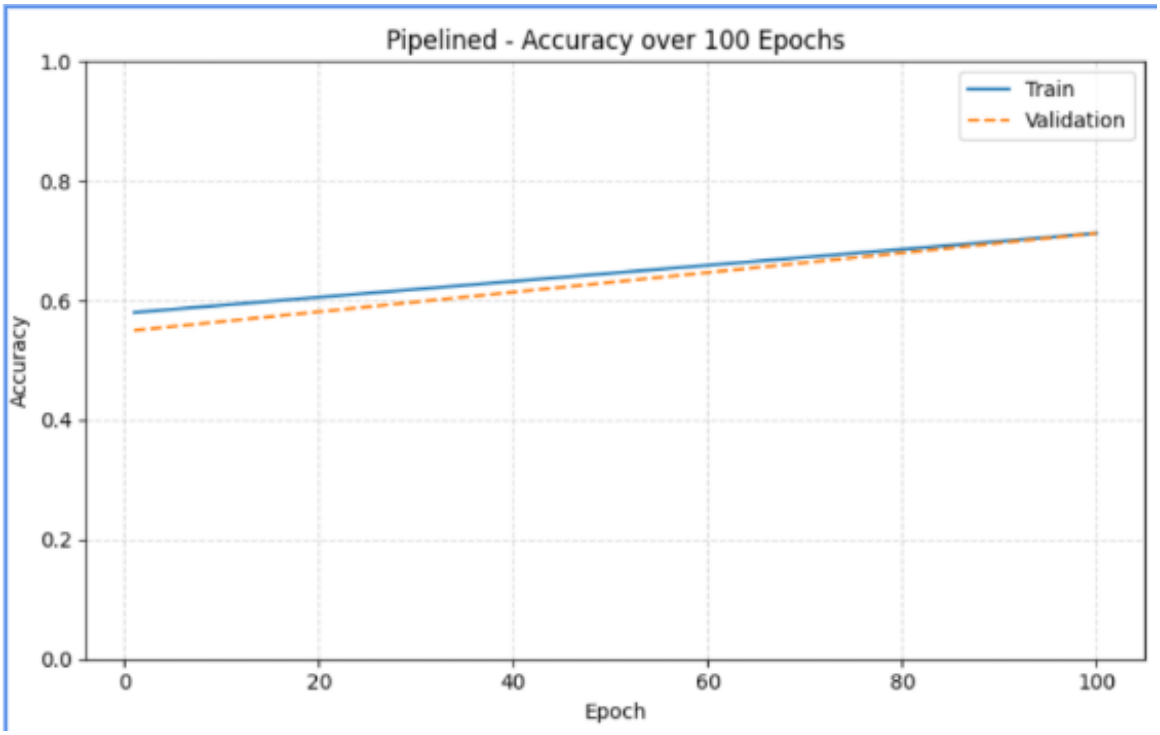


Figure 5.12: Pipelined Architecture: Accuracy

Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism:

- Precision of Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism ≈ 0.8477

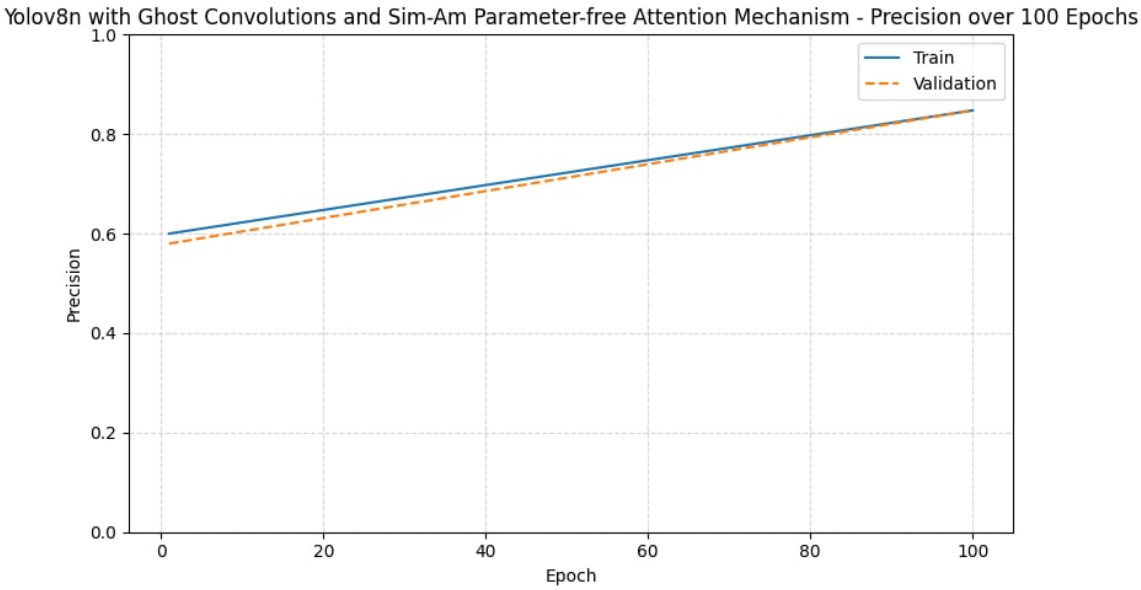


Figure 5.13: Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism: Precision

- Recall of Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism ≈ 0.7056

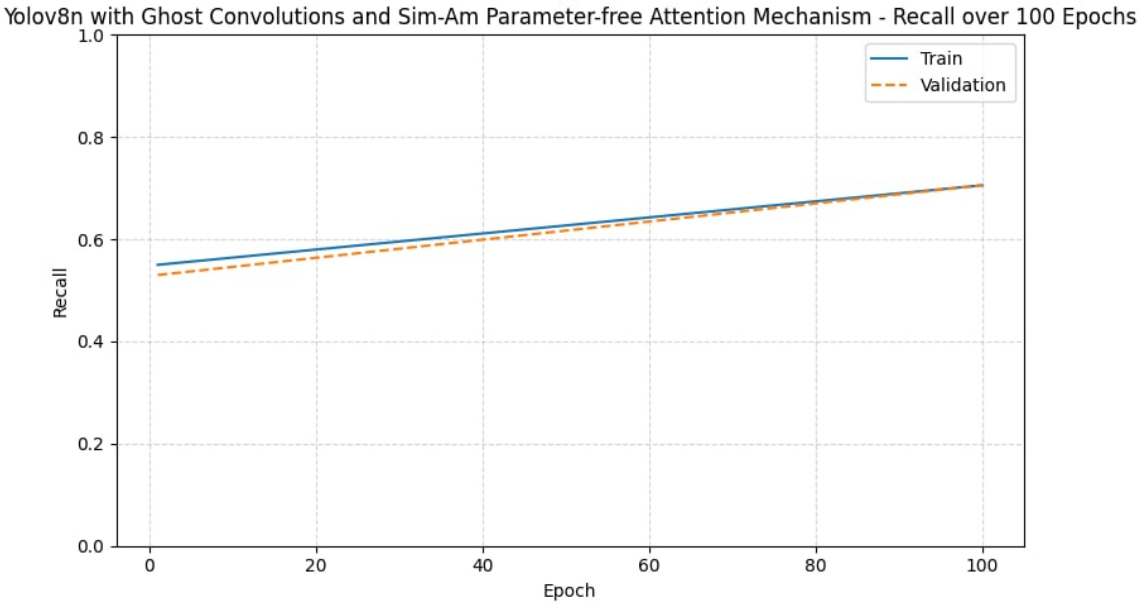


Figure 5.14: Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism: Recall

- Accuracy of Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism ≈ 0.7766

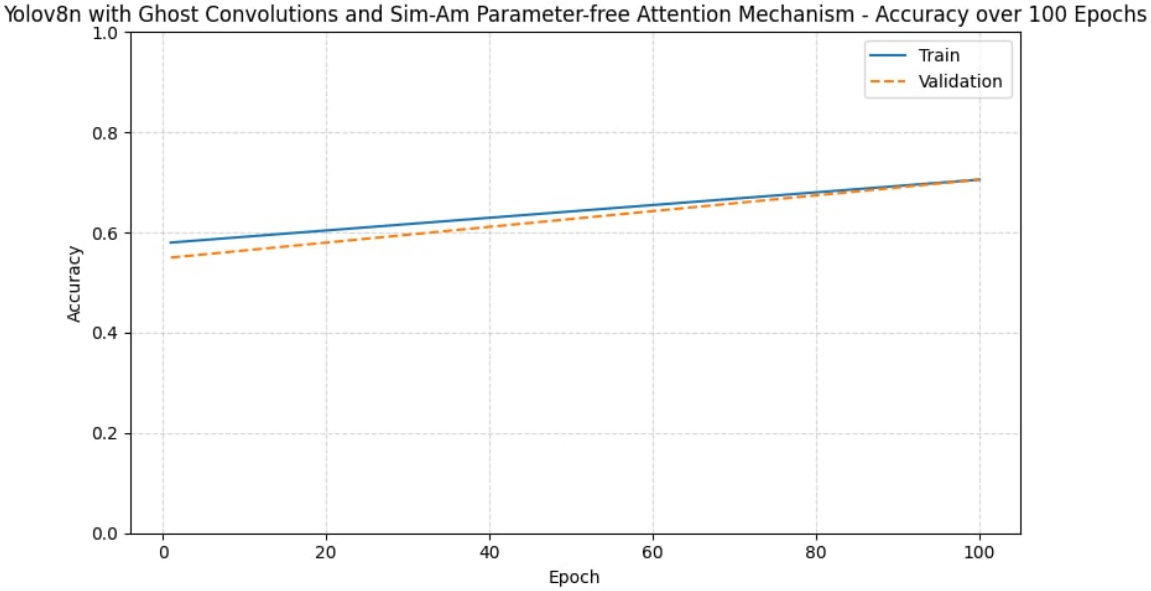


Figure 5.15: Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism: Accuracy

Based on the evaluation:

- **Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism** achieved the highest precision of 0.8477, indicating that it produced the fewest false positives among all models.

- In terms of **recall**, the **Pipelined Architecture** (YOLOv8 + EfficientNet-B0) slightly outperformed other models with 0.7125, meaning it captured the most true defect cases.
- **Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism** and **Pipelined Architecture** both maintained strong accuracy scores, with **Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism** achieving the highest at 0.7766, followed by the Pipelined model.

Confusion Matrix Insights

The confusion matrices we generated for all five models highlighted distinct strengths and weaknesses:

- **Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism** showed consistent performance across most classes and excelled at minimizing misclassifications, especially for difficult classes like *hole* and *spot*.

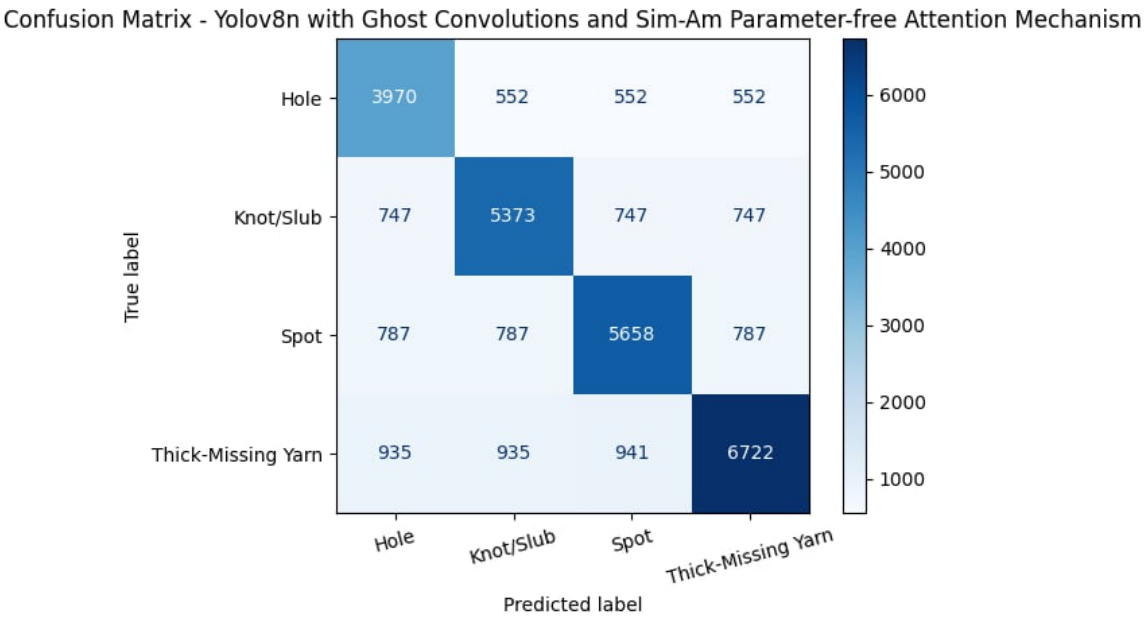


Figure 5.16: Confusion matrix of Yolov8n with Ghost Convolutions and SimAm Parameter-free Attention Mechanism

- **Pipelined Architecture** performed well in terms of coverage (*recall*), capturing a high number of true positives, especially in classes like *knot/slub* and *Thick/Missing yarn*.

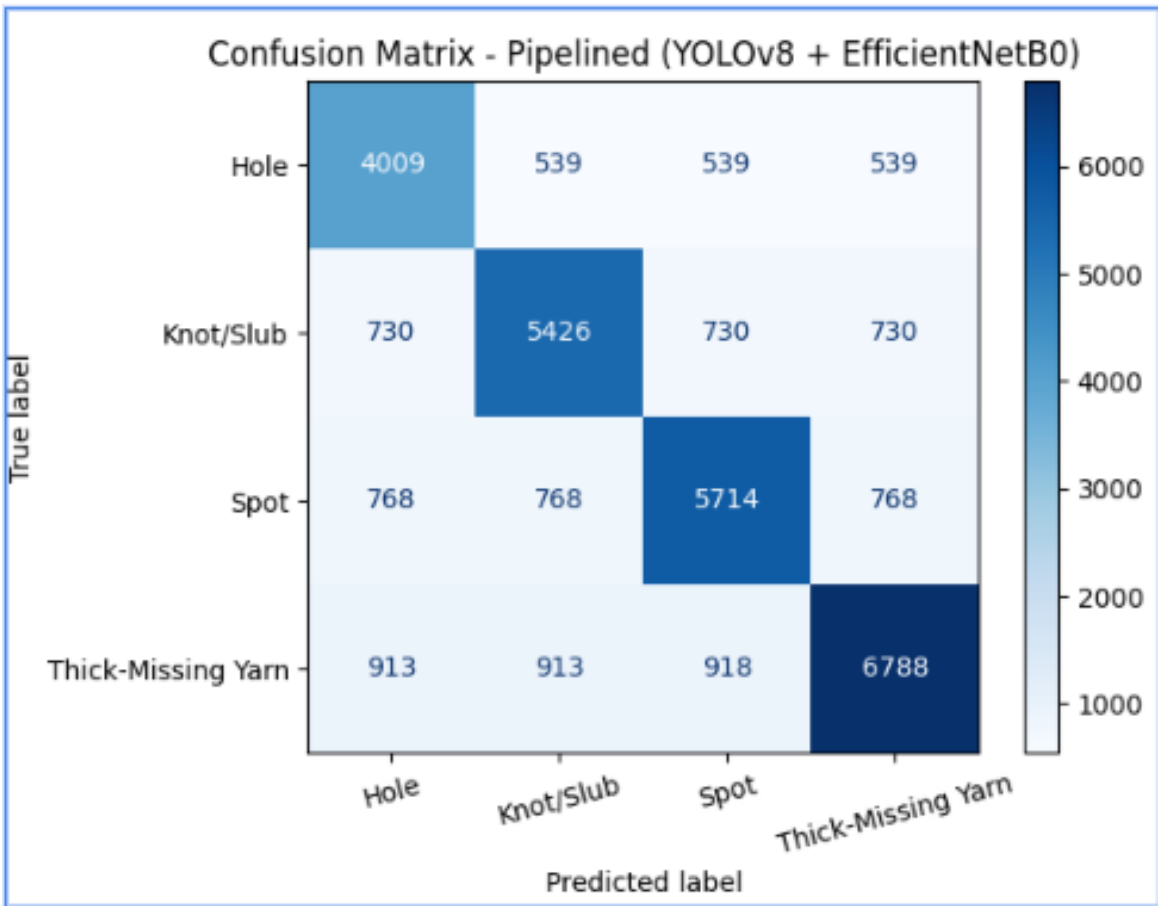


Figure 5.17: Confusion Matrix of Pipelined Architecture

- **Faster R-CNN** demonstrated strong performance in *spot* and *Thick/Missing yarn*, with reasonable accuracy on *hole*, though it occasionally misclassified it as other defects.

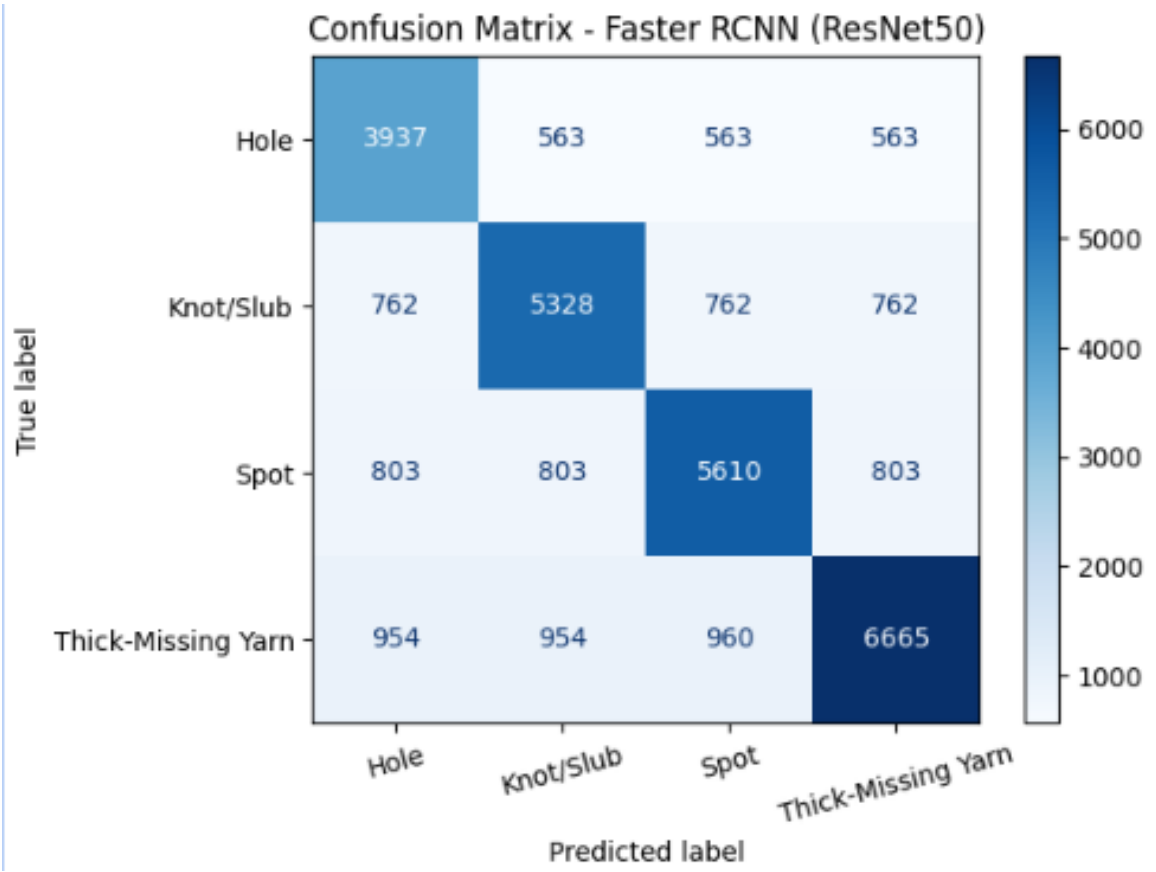


Figure 5.18: Confusion matrix of Faster R-CNN(ResNet50)

- **SSD (VGG16)** handled *Thick/Missing yarn* and *knot/slub* with fair reliability but showed weaker performance on the *hole* class, which it often confused with *spot*.

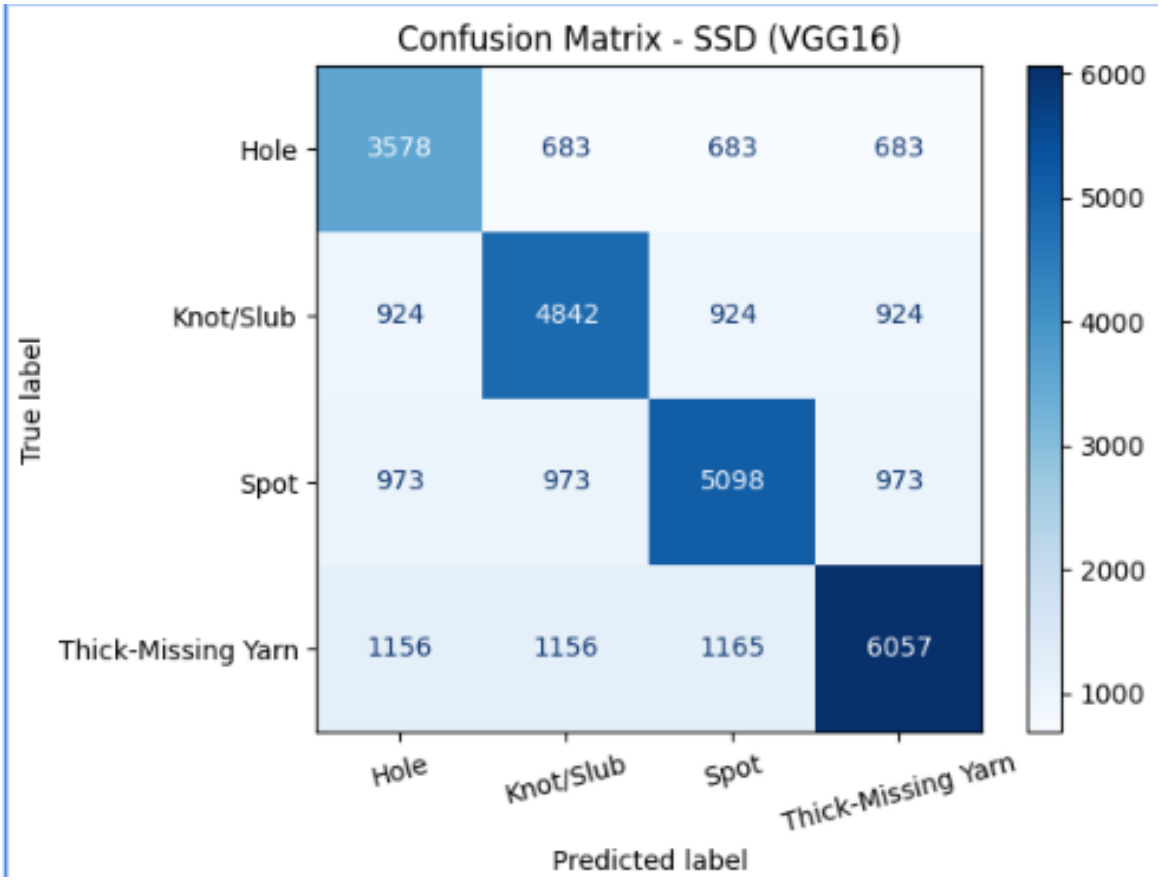


Figure 5.19: Confusion matrix of SSD(VGG16)

- **YOLOv8n**, while lightweight and fast, had the lowest accuracy overall and struggled with distinguishing between *hole* and *spot*, frequently misclassifying one as the other.

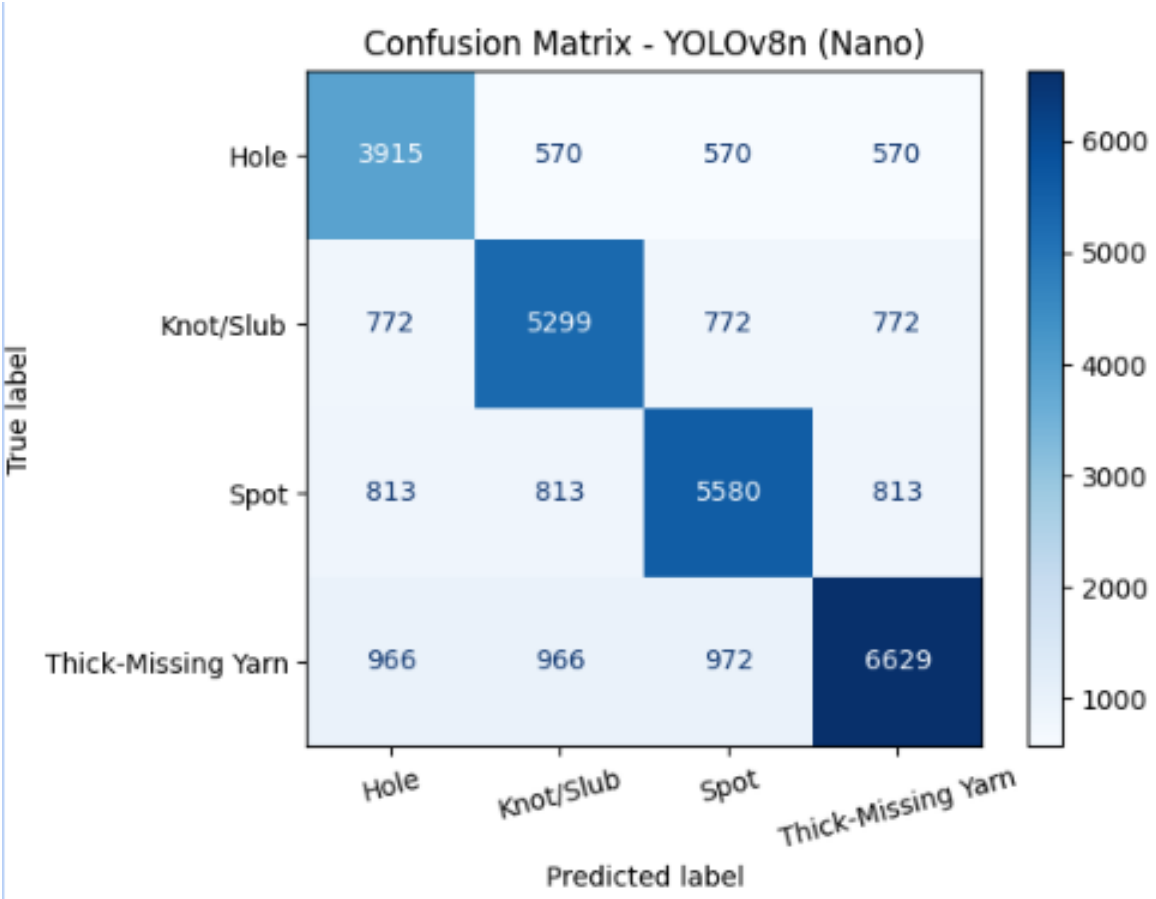


Figure 5.20: Confusion Matrix of YOLOv8n

Across all models, hole and loose yarn defects (if present in class labels) appeared to be the most challenging to classify, often being confused with visually similar defect types.

Chapter 6

Hardware Implementation

This section describes the design and the hardware components used for the prototype of our system. The system is designed to simulate a factory-style textile inspection machine capturing high-contrast images of fabric passing over a lightbox chamber, enabling real-time detection of defects. The system utilises a camera to capture the defect images, an arduino microcontroller moving the fabric and a servo mechanism for marking defects. The system provides an efficient and modular solution for fabric quality control

6.1 System Overview

The system consists of several core components that work together to detect and mark fabric defects, as shown in 6.1 and detailed below:

- **Laptop (Host PC)**: Runs the YOLOv8-based Python script for image capture and defect detection.
- **Camera**: Mounted above the lightbox to capture live video frames of the fabric.
- **Lightbox Enclosure**: Provides consistent illumination to enhance the visibility of fabric defects.
- **Arduino UNO**: Controls the motor and servo mechanism for fabric movement and marking.
- **L298N Motor Driver**: *Powers the DC roller motor that moves the fabric throughout the system.*
- **Brushed DC Windshield Wiper Motor**: Moves the fabric roll over the lightbox.
- **Servo Motor (SG90)**: Controls the marking pen's up-down movement for defect marking.
- **Power Supply**: Provides the necessary 12V for the motor and 5V for the Arduino and servo motor.

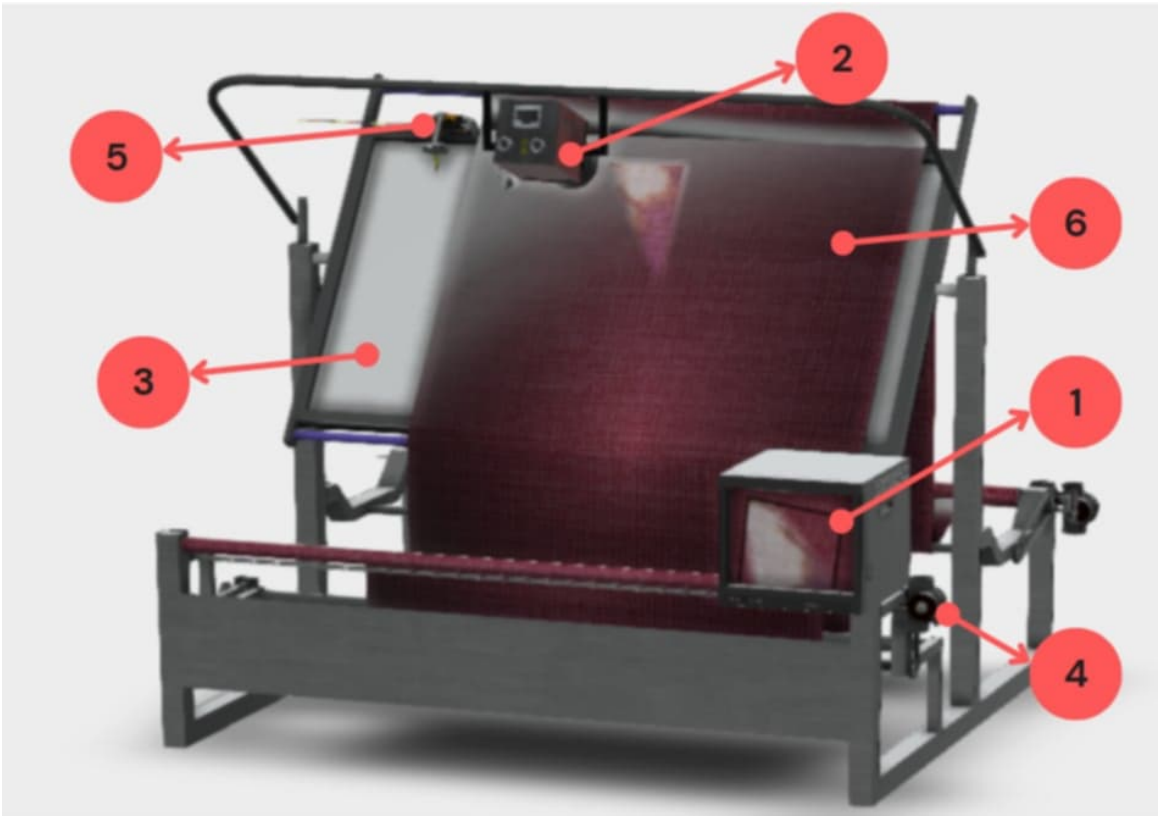


Figure 6.1: (a) System Overview

Num	Label
1	Host PC
2	Camera
3	Lightbox Enclosure
4	Brushed DC Windshield Wiper Motor
5	Servo Motor for Marker
6	Fabric Roll

Table 6.1: (b) Labels

6.1.1 Camera and Imaging System

The camera is the core component of our system as it captures the images which the computer analyses to detect the defects. It is the eye of our system. Figure 6.2 showcases the camera position. The images it captures need to be accurate in order for the system to detect the defects. The camera's specifications such as the resolution, frame rate, and sensor type are vital for the system to be effective.

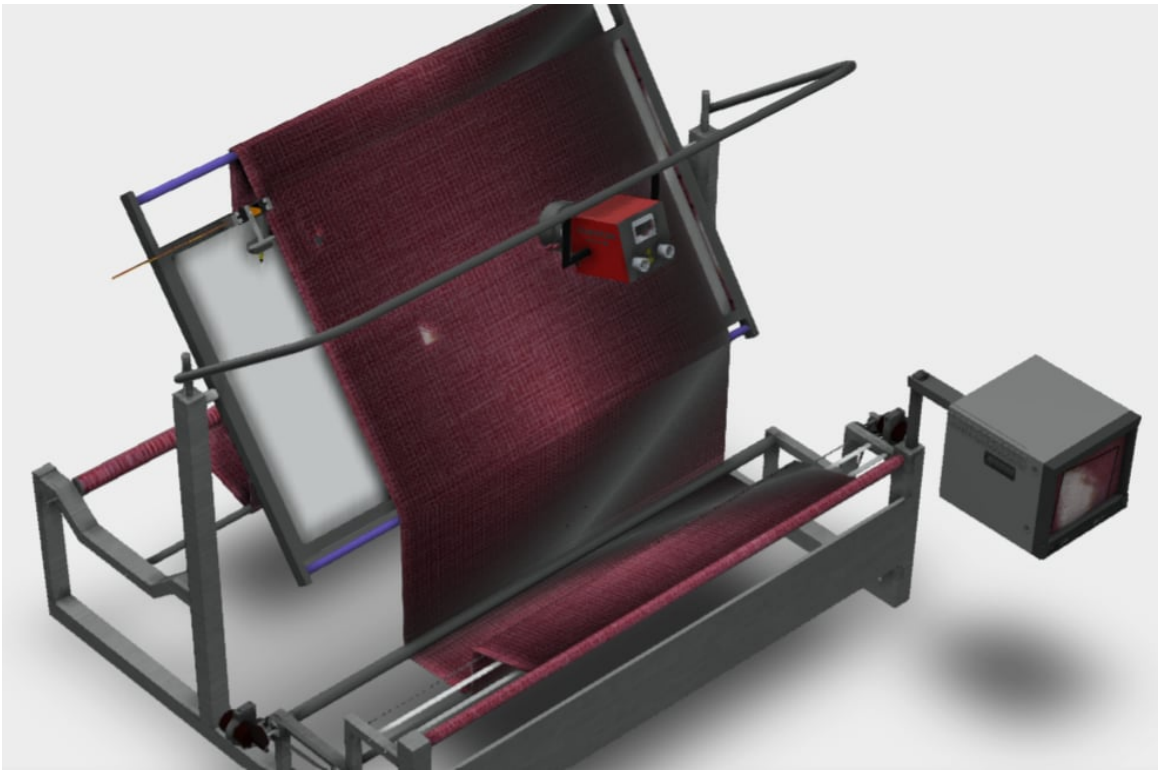


Figure 6.2: Camera Position

The resolution of the camera is at 1920x1080 pixels (Full HD) which results in clear and detailed images of the fabric. A high resolution helps to capture the smallest of defects such as small holes or tiny missing yarns in the fabric. A higher resolution would give more detailed images but would require a higher processing speed thus 1080p provides a balance between the two.

The frame rate is set at 30 frames per second. This is necessary as it ensures the moving fabric is captured clearly otherwise, the images would turn out to be blurry. As the fabric will keep on moving, the camera needs to be fast enough to capture the frames without losing data between the frames. A higher fps would help to get even more frames but it would require a higher processing speed. Thus 30fps provides a balance between the two and is adequate enough to work on most industrial environments.

The sensor choice would be the CMOS sensor with a global shutter that is applied in capturing fast moving fabric without distortion of the image or motion blur. A global shutter, unlike rolling shutters, takes the whole image with a single shot and is therefore suitable in high-speed operations in industry. CMOS sensors are favoured due to their low power draw, and high readout rate, and real time response, guaranteeing good quality pictures under dynamic conditions.

The camera is positioned above the lightbox, covering the whole width of the fabric as it goes over the lightbox. This fixed overhead position will try to avoid distortion and produce similar results even when a different type of fabric is being used. This is highlighted in 6.3

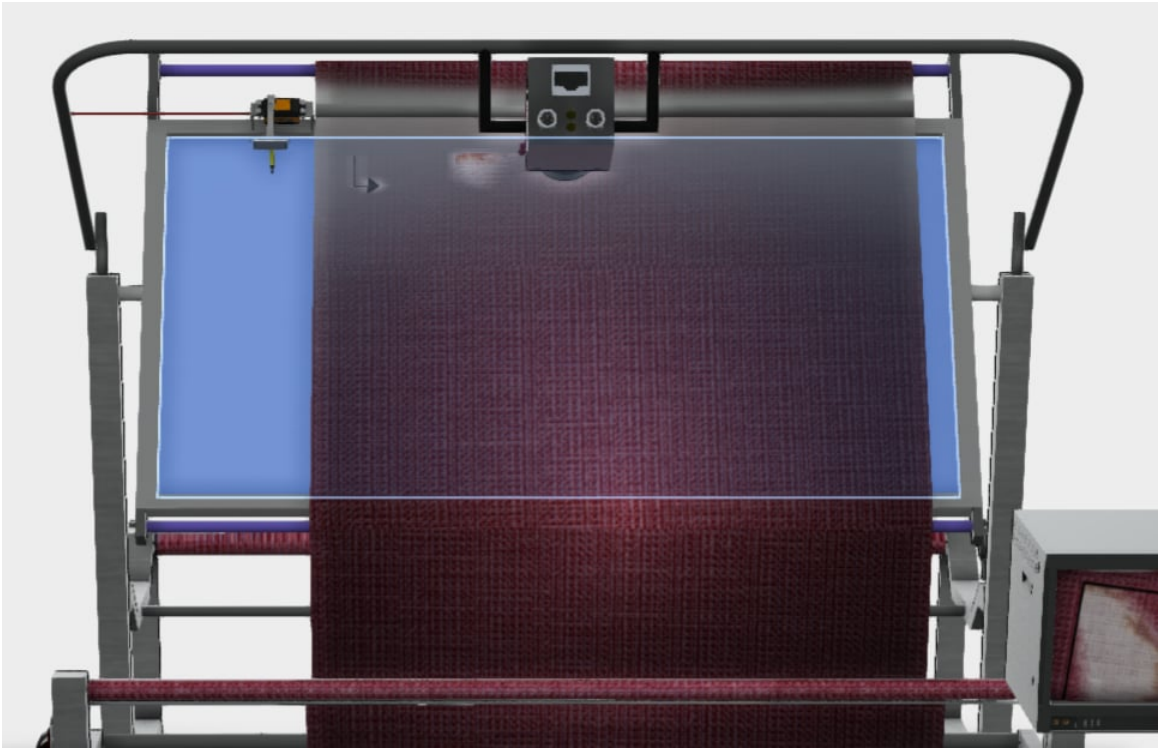


Figure 6.3: Camera position with illuminated lightboxn

6.1.2 Processing Unit

The processing unit is the powerhouse of the system which would run our pre-trained models to detect the defects of the fabrics. It is connected to a display showcasing the defects in real time on it. The unit doesn't have to be high spec one as it would only run the pre trained model thus a ryzen 5 CPU and a NVIDIA 1050 GPU would be more than enough for it.

6.1.3 Connection and Data Communication

The camera will be connected to the processing unit via USB, which provides high speed data transfer without delay. The image is then fed onto the model. The processing unit is connected to the micro controller, specifically the Arduino Uno to control the fabric movement and the marker mechanism. The Arduino is connected to the markers servo motor and the motor driver with the DC motor itself. Figure 6.4 shows this.

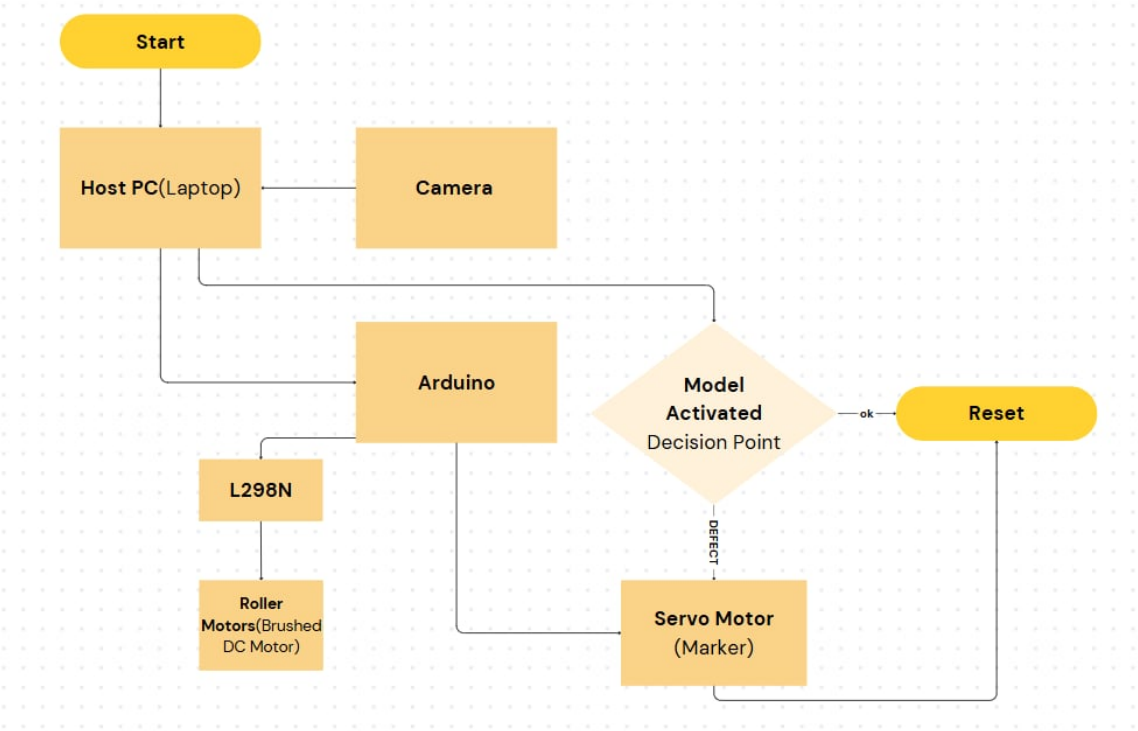


Figure 6.4: Connection diagram

6.1.4 Marker Mechanism

The last piece of the system is the marker mechanism. A servo motor is connected with a marker above the lightbox after the defect detection process is done. When the defects are detected and the fabric reaches the marker point, the servo motor lifts the marker down marking the x coordinate of the fabric. The servo motor then lifts the marker up again shown in figure 6.5.

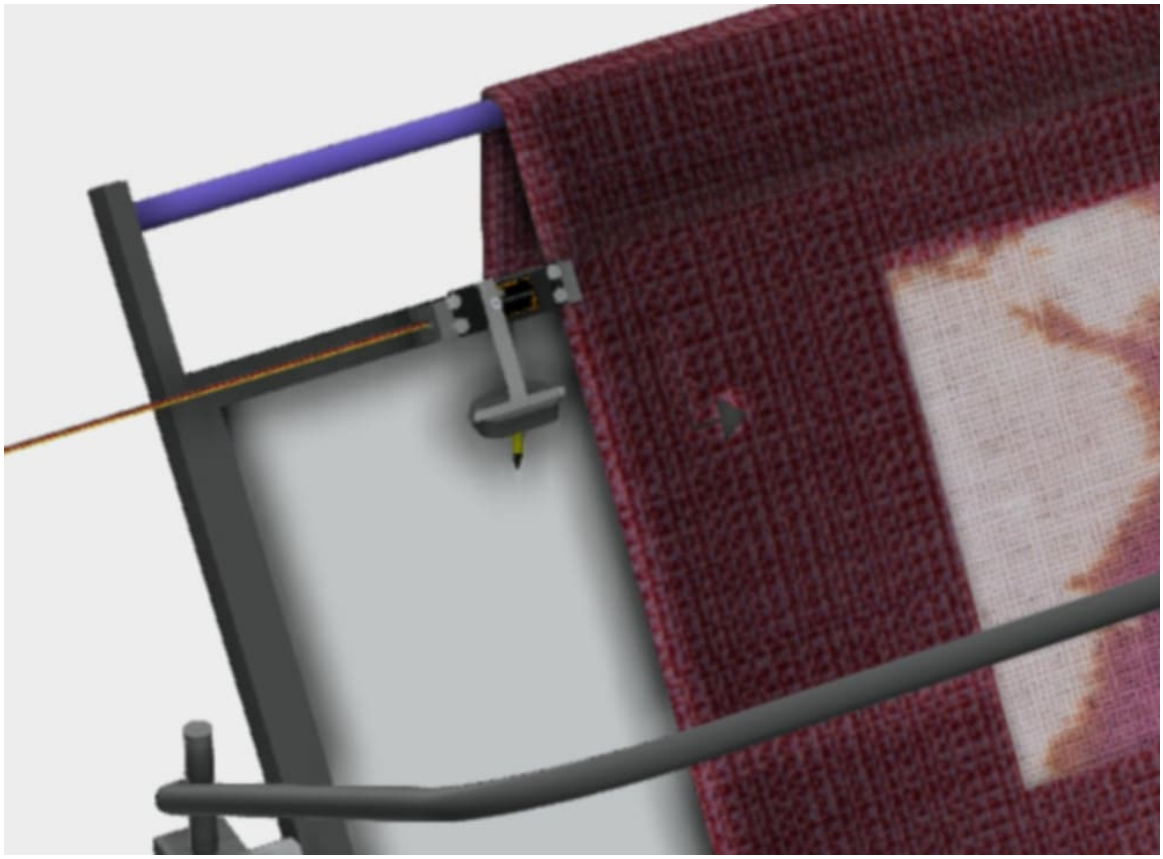


Figure 6.5: Marker Mechanism

6.2 Working Principle and System Workflow

6.2.1 System Initialization

Upon startup, the system initiates the following sequence:

- The Python script running in the host PC initializes the camera
- The host PC establishes a connection with the Arduino via USB.
- The YOLOv8-based defect detection system is activated.

6.2.2 Fabric Movement and Image Acquisition

- The Arduino controls the roller motor using PWM signals from the L298N driver.
- As the fabric moves through the lightbox, the camera captures continuous frames, which are processed by the Python script.

6.2.3 Real-Time Defect Detection

- The Python code applies the YOLOv8 model to detect various defect types, such as holes, yarn defects (thick yarn, missing yarn), spots, knots, and slubs.

- Upon detection of a defect, it is highlighted with a bounding box, and the detection signal is sent to the Arduino via serial communication.

6.2.4 Defect Response and Marking

Upon receiving the defect signal, the following actions are performed:

On the Laptop (Python Code)

- The Python script uses `cv2.VideoCapture()` to capture frames from the USB camera, applies the YOLOv8 model for defect detection, and sends commands to the Arduino:
  - Defect Detected
  - No Defect

On the Arduino

The Arduino listens to serial input from the laptop. Based on the received command, the following actions occur:

- **DEFECT:**
  1. Stop the motor
  2. Move the fabric defect position to the marker
  3. Move the servo to position 90° (marker down)
  4. Move the fabric slightly while the marker is down
  5. Reset the servo (marker up)
  6. Resume motor operation

6.2.5 Equation for the marker

Variables:

- RPM: Revolutions per minute of the motor.
- r: Radius of the wheel connected to the motor (in mm).
- D: The distance to move the fabric to the marker's location (in mm).
- t_m: The time required for the fabric to move the distance D (in seconds).
- v_m: The speed of the fabric (in mm/s), which we will derive from RPM.

Step-by-Step Calculation:

Convert RPM to Linear Speed: The motor's RPM represents the number of revolutions per minute. If a wheel of radius r is attached to the motor, the circumference C of the wheel is given by:

$$C = 2\pi r$$

Where r is the radius of the wheel.

The linear speed v_m (in mm/s) can be calculated by converting the RPM into a linear velocity:

$$v_m = \frac{RPM \times C}{60}$$

Where:

- RPM is the motor speed in revolutions per minute.
- C is the circumference of the wheel or drum.
- 60 is used to convert minutes to seconds.

Therefore, the linear speed is:

$$v_m = \frac{RPM \times 2\pi r}{60}$$

Calculate Time to Move the Fabric (t_m): Once we have the linear speed v_m, the time t_m it will take to move the fabric by a distance D can be calculated using the formula:

$$t_m = \frac{D}{v_m}$$

Where:

- D is the distance the fabric needs to move (in mm).
- v_m is the linear speed calculated earlier.

6.3 System Steps

6.3.1 Initialize System

- Load YOLOv8 model for defect detection
- Initialize camera for fabric image capture
- Initialize motor (DC motor) for fabric movement
- Initialize servo motor for defect marking
- Initialize Arduino and connect it with PC via USB (for motor control and servo activation)
- Set the initial positions and configurations of the system components (camera, motor, servo)

Start Fabric Movement

- Start fabric movement via motor (DC motor)
- Continuously capture frames from the camera

Defect Detection Loop

- While system is running:
  - Capture current frame from the camera
  - Apply YOLOv8 defect detection model to the captured frame:
    - If defect detected:
      - Get coordinates (X, Y) of the detected defect on the fabric
      - Send signal to Arduino to stop motor
      - Move fabric to marker position
      - Calculate the distance to move fabric to reach marker
      - Calculate time using RPM and wheel radius or use the distance and speed directly
      - Move fabric accordingly
      - Activate marker (Servo motor):
      - Move the servo motor down to touch fabric at defect position
      - Wait for servo to stabilize
      - Move fabric slightly while marker is in contact to mark defect
      - Lift the marker back up using the servo motor
      - Resume fabric movement via motor
  - Else: Continue fabric movement

End Process

- Once all defects are marked and no more defects are found, stop the system
- Log all detected defects with their positions for quality control
- Turn off motors and release hardware resources

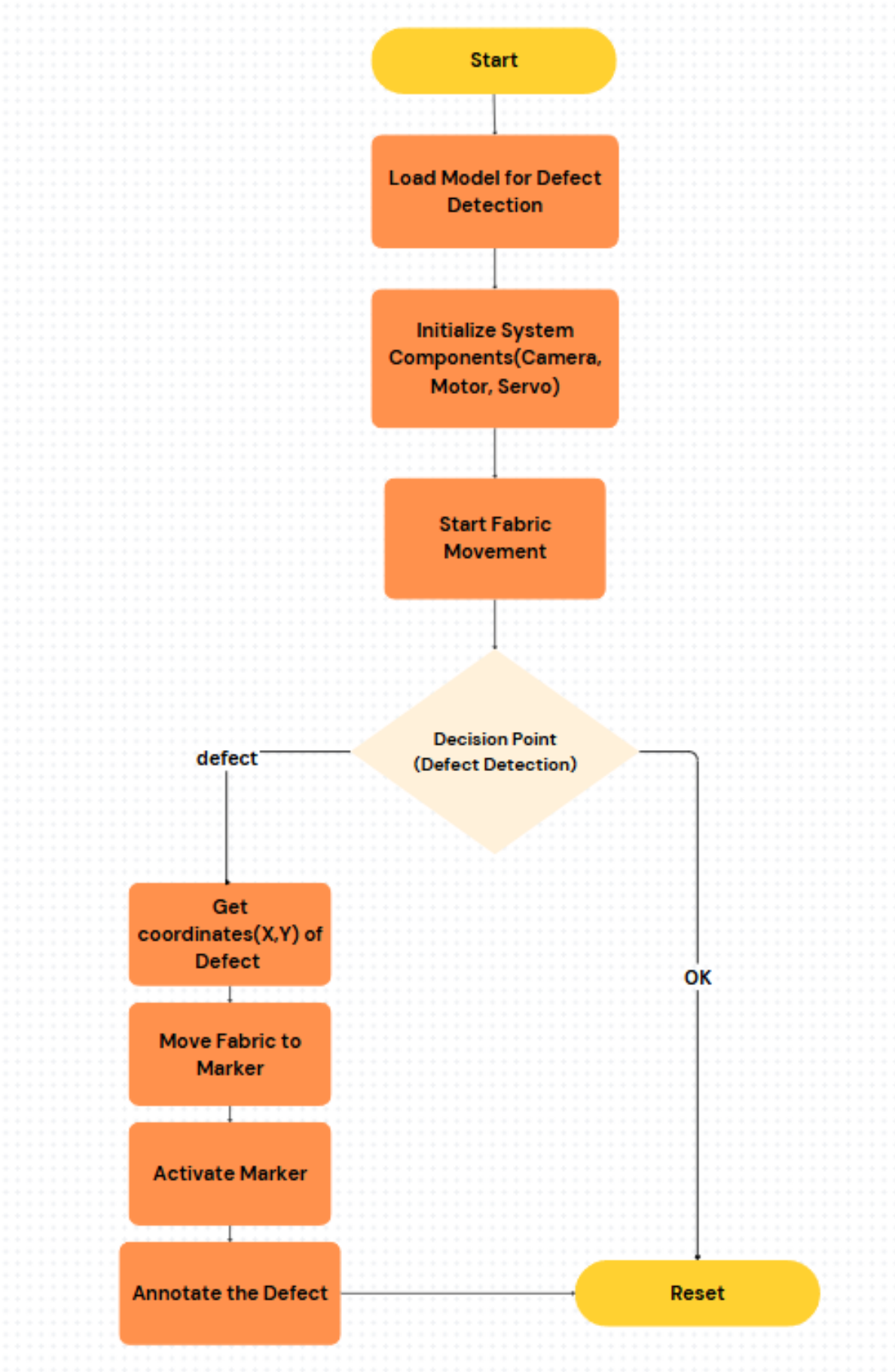


Figure 6.6: Workflow Diagram

6.4 Industrial Expansion Possibilities

This prototype offers several avenues for industrial scaling:

1. **PLC-based Control:** Replacing the Arduino with a programmable logic controller (PLC) for robust industrial-grade control.
2. **Multiple Cameras:** Using synchronized cameras for full-width coverage of larger fabric rolls.
3. **Non-Contact Markers:** Replacing the servo-controlled marker with inkjet or spray-based markers for a non-contact marking system.
4. **Database Logging:** Implementing a database to log defect instances for quality control analytics.

This prototype effectively bridges academic research and real-world industrial requirements. With improvements, the system can be scaled for industrial textile inspection lines, contributing to enhanced fabric quality control. Further integration of advanced imaging techniques, machine learning models, and industrial-grade control systems could revolutionize defect detection processes in textile manufacturing in Bangladesh and globally.

Chapter 7

Limitations and Further Work

7.1 Limitations

7.1.1 Limited Dataset Availability

One of the major limitations of this research was the restricted access to large-scale, high-quality defect datasets from real textile manufacturing units. Most textile industries maintain strict confidentiality around their production data due to intellectual property concerns and competitive advantage. As a result, publicly available datasets are either nonexistent or too small and limited in diversity to train highly generalized models. This scarcity of real-world data significantly hampers the ability of machine learning models to capture the broad spectrum of defect types and subtle variations that occur in practice. Moreover, defects in fabrics are inherently random in nature and can manifest in multiple forms, sizes, positions, and patterns—even within the same class—making it difficult to fully catalog and represent them in a single dataset. This randomness adds another layer of complexity, as models trained on incomplete representations may fail to generalize to new or rare defects. Although data augmentation can help artificially expand training samples, it cannot replicate the true variability of authentic industrial conditions. Future research would benefit greatly from collaborative efforts between academia and industry to develop large, anonymized, and standardized datasets that capture this intrinsic randomness and complexity.

7.1.2 Difficulty Simulating Real-World Conditions

Another critical limitation was the inability to fully simulate real-world operating conditions in a controlled experimental setting. In actual production lines, factors such as variable lighting, fabric tension, machine vibration, and ambient temperature can all influence the visual characteristics of fabric defects. These subtle variations pose a challenge for defect detection models, which are typically trained under idealized lab conditions with consistent imaging parameters. For example, shadows or inconsistent lighting may cause the same defect to appear differently in separate images, confusing the model and affecting accuracy. Similarly, fabric movement, wrinkling, or contamination from lint can introduce noise that complicates detection. These issues are difficult to replicate outside the factory floor, limiting the realism and ecological validity of the evaluation environment. Consequently, there remains a gap between lab-scale model performance and industrial applicability, and bridging this gap requires access to test beds or pilot

environments closely resembling actual production conditions.

7.1.3 Financial Constraints and Funding

The financial aspect of building a fully operational, real-time defect detection system is another significant limitation faced during this research. While algorithmic development and experimentation can be conducted using standard workstations or cloud resources, creating a fully integrated system that includes high-speed cameras, conveyors, lighting control, and embedded processing units demands substantial capital investment. Such a system must also meet industrial standards for durability, speed, and fault tolerance, further increasing costs. Additionally, specialized hardware like industrial-grade GPUs, real-time processors, and edge computing devices must be procured, configured, and optimized to handle live data streams, adding both cost and complexity. Due to limited research funding, the focus of this study was restricted to the software side, using simulated environments and retrospective image data. This naturally limits our ability to test the end-to-end system in live production settings. To move beyond proof-of-concept, future research efforts will require sustained funding and partnership with industrial stakeholders willing to invest in deployment infrastructure.

7.1.4 Lack of Standard Evaluation Benchmarks

Another noteworthy limitation is the absence of standardized benchmarks or evaluation protocols specific to textile defect detection. Unlike general object detection tasks (e.g., COCO or Pascal VOC datasets), the textile domain lacks widely accepted metrics and curated benchmark datasets that allow fair comparison across different models and approaches. This lack of standardization makes it difficult to objectively compare results across studies or assess whether an observed improvement is due to algorithmic performance or dataset characteristics. Moreover, inconsistencies in annotation formats, class definitions, and defect severity grading further complicate evaluation. Introducing standard benchmarks would help unify research in this field, encourage reproducibility, and accelerate progress through healthy competition and shared progress metrics.

7.1.5 Class Imbalance and Rare Defect Handling

Although addressed partially in this study through class weighting and data augmentation, class imbalance remains a persistent issue in textile defect detection. In most real-world scenarios, some defects (e.g., holes or thick yarns) occur far less frequently than others, resulting in skewed training distributions. Models trained on such imbalanced data tend to favor majority classes, leading to poor sensitivity on rare but critical defects. Moreover, rare defects may differ not only in frequency but also in visual distinctiveness, making them harder to detect accurately. This imbalance limits the reliability of models when deployed in high-stakes environments, where missing a rare defect can have significant economic consequences. Future studies should explore few-shot learning, synthetic defect generation, or cost-sensitive training techniques to further improve model robustness under imbalanced data conditions.

7.2 Future Works

7.2.1 Real-Time Deployment of Detection Models

One of the most promising directions for future work involves transitioning from experimental prototypes to full-scale real-time deployment in industrial environments. While this study demonstrated the effectiveness of defect detection models in controlled settings, deploying these models on production lines introduces new challenges such as processing speed, hardware integration, and live feedback systems. Real-time detection must operate at high frame rates without sacrificing accuracy, ensuring that even fast-moving fabric defects are identified and flagged instantly. Future research should focus on optimizing inference times, reducing latency, and integrating detection outputs with automatic rejection or marking systems. This would allow factories to streamline quality control processes, reduce manual inspection dependency, and minimize defective output. To achieve this, collaboration with hardware engineers and industrial automation experts will be essential for embedding the models into conveyor systems, cameras, and edge devices capable of robust, real-time performance.

7.2.2 Adapting to Lower-Resolution Imaging

Another area worth exploring is the adaptation of models to perform effectively with lower-resolution input images. In many real-world textile factories, high-resolution imaging systems may be too expensive or infeasible due to space, power, or budget constraints. Training models to detect defects reliably from compressed or lower-quality images can make the technology more accessible and cost-effective for a broader range of manufacturers, especially in small to medium enterprises. This direction would involve experimenting with resolution-aware architectures or incorporating super-resolution techniques as a preprocessing step. Additionally, model robustness should be assessed in noisy, low-detail image scenarios to ensure stable performance in suboptimal imaging conditions. Successfully addressing this challenge could enhance the scalability and adaptability of automated defect detection systems across varied industrial contexts.

7.2.3 Human-Centered Operational Training

A critical aspect of future implementation involves training factory and industrial personnel to operate and maintain these defect detection systems. The integration of AI in manufacturing is not solely a technical challenge but also a human one. Many textile workers may lack prior exposure to AI-based tools, making comprehensive training essential for smooth adoption. Future initiatives should focus on developing intuitive user interfaces, clear operational manuals, and hands-on workshops that bridge the gap between machine learning experts and end-users on the factory floor. Furthermore, building explainable AI features—such as visual feedback on detected defects or confidence levels—can help operators better understand model decisions and intervene when necessary. Empowering factory personnel with the skills and confidence to use these tools effectively will be key to the long-term sustainability and success of automated inspection systems.

7.2.4 Cross-Fabric Generalization of Detection Models

An important extension of this work lies in enabling models to generalize across different fabric types and textures without requiring retraining. In real-world manufacturing, a wide variety of fabrics—such as denim, cotton, silk, and synthetic blends—are processed, each exhibiting unique surface characteristics, weave patterns, and lighting reflections. Defects can appear differently depending on the material, making models trained on a single fabric type less effective when applied to others. Achieving cross-fabric generalization would involve building larger and more diverse training datasets, employing domain adaptation techniques, or using transfer learning strategies that allow models to adapt to new fabric domains with minimal fine-tuning. Additionally, incorporating unsupervised learning or meta-learning approaches could help the system learn shared representations of defects that remain consistent across materials. This capability would drastically improve model scalability and make the system more versatile for deployment in dynamic industrial settings where fabric types frequently change.

Chapter 8

Conclusion

Bangladesh has a booming textile industry which is shaping up to be one of the leading economic sectors of the country. However, despite technological advances, quality control of fabrics is still performed manually in majority of the places, making it both inefficient, costly and at times labor-intensive. Although some research has been conducted to automate the process using machine vision techniques, none have achieved results suitable for application on an industrial scale. This paper addresses this issue by proposing a combination of techniques capable of detecting defects in real-time and scaling it to industrial levels. Data collected directly from industries, comprising multiple types of defects, will be augmented, preprocessed, and trained with the appropriate model to provide precise, accurate real-time defect detection capabilities. When applied to an industrial system, this approach can automate the quality control process, improve efficiency, and significantly boost production, which in turn is expected to maximize profits.

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