

“SEAMSENSE” REAL-TIME QUALITY MONITORING SYSTEM FOR THE APPAREL INDUSTRY

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B.Sc. (Hons) Degree in Information Technology Specializing in Data Science

Department of Computer Science

Sri Lanka Institute of Information Technology
Sri Lanka

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Dissertation submitted in partial fulfillment of the requirements for the Bachelor
of Science (Hons) in Information Technology Specializing in Data Science

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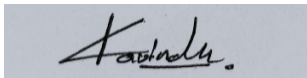
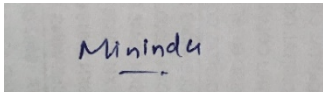
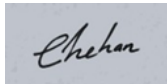

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DECLARATION

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ABSTRACT

Real-Time Seam Defect Detection and Quality Monitoring System for the Apparel Industry Using Advanced Machine Learning Techniques

The SeamSense project represents a groundbreaking advancement in quality control within the apparel industry by introducing a real-time seam defect detection system. By harnessing the power of advanced machine learning algorithms, including Convolutional Neural Networks (CNN) and You Only Look Once (YOLO) models, SeamSense significantly enhances the accuracy and speed of defect detection on flat seam machines. This system addresses the inherent limitations of traditional manual inspection methods, which are often labor-intensive and susceptible to human error.

SeamSense is built on several key components. The system features optimized camera installations with adaptive frame extraction, ensuring the capture of high-quality images by strategically positioning cameras and focusing on relevant areas. Additionally, fog computing is employed for real-time image augmentation and content filtering, enabling efficient data processing close to the source, thereby minimizing latency and enhancing real-time processing capabilities. The system relies on advanced YOLO-based machine learning models, which are crucial for precise seam defect detection, offering superior accuracy and speed in identifying defects. Furthermore, a fusion model for comprehensive defect analysis combines real-time data with historical trends to provide a holistic view of defect patterns, enabling proactive quality management.

Implemented at MAS Linea Aqua, SeamSense shows significant promise in revolutionizing quality control processes by reducing rework costs, improving production efficiency, and maintaining high product standards.

Key Words - Real-time quality monitoring, Seam defect detection, Machine learning, YOLO models, Fog computing, Adaptive frame extraction, Apparel industry, Fusion model analysis

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LIST OF ABBREVIATIONS

Table 1 - Table of Abbreviations

Abbreviation	Description
TSA	Time Series Analysis
ARIMA	Auto Regressive Integrated Moving Average
ML	Machine Learning
SVM	Support Vector Machine
RF	Random Forest
TRM	Traditional Model
LR	Linear Regression
GB	Gradient Boosting
WBS	Work Breakdown Structure

1. INTRODUCTION

1.1. MAS Linea Aqua

MAS Holdings [1] is a design-to-delivery solution provider in apparel and textile manufacturing, headquartered in Sri Lanka. Founded in 1987 by Mahesh, Sharad, and Ajay Amalean, the company began as an intimate apparel manufacturer and later diversified into sportswear, performance wear, swimwear, brands, wearable technology, FemTech, start-ups, and industrial parks. Linea Aqua [2] is a joint venture between Speedo International (UK), Brandot International (US) & MAS Holdings. With a vision to be the most compelling swimwear supplier in the world, Linea Aqua has grown into the force behind some of the best names in the swimwear business.

1.2. Area Research

In the modern world, one of the largest product production industries is garment manufacturing. One of the top swimsuit manufacturers, MAS Linea Aqua, handles a lot of orders both domestically and abroad every day. Since their Research & Development department is still working on this project, their primary goal is to increase productivity while maintaining the highest level of accuracy and efficiency. We were tasked with creating a stand-alone tool for production floor real-time quality monitoring. They currently use a manual system to check quality; this system needs to be automated and provide real-time feedback. While it has been possible in recent years to record the live sewing process of a garment and to record the seams to identify problems, the majority of these recordings are not made in real-time, and real-time quality monitoring systems exist in other industries but not in the apparel sector.

1.3. Research Components

SeamSense system begins with the strategic installation of high-definition cameras at critical points in the production line, particularly near the flat seam machines. These cameras are optimized to capture detailed images and video feeds of the seam areas. To enhance the efficiency of defect detection, an adaptive frame extraction technique is employed. This method dynamically isolates the relevant frames from the live video streams, focusing on the critical areas where defects are most likely to occur. By

filtering out unnecessary data, this component significantly reduces computational load and ensures that only the most pertinent information is analyzed.

To manage the vast amount of data generated by the high-definition cameras, SeamSense integrates fog computing into its architecture. Fog computing allows for the processing of image data closer to the source, in this case, on the production floor itself. The system performs real-time image augmentation and content filtering, enhancing the quality of the images before they are transmitted for further analysis. This decentralized approach reduces latency, conserves bandwidth, and ensures that only the most relevant and high-quality data is sent to the central system for defect detection, thereby optimizing the overall performance of SeamSense.

The core of the SeamSense system is the real-time seam defect detection, which is powered by advanced YOLO (You Only Look Once) machine learning models. YOLO models, known for their speed and accuracy in object detection tasks, have been specifically trained to identify various types of seam defects, such as open seams, high-low errors, and SPI (Stitches Per Inch) discrepancies. By processing live video feeds, the YOLO models can detect these defects instantly, allowing for immediate corrective actions to be taken. This component is crucial in transitioning from traditional, reactive quality control methods to a more proactive and efficient system.

In addition to real-time defect detection, SeamSense employs a fusion model that integrates the immediate data with historical defect trends and worker-related factors such as demographics and experience. This model not only helps in identifying the current defects but also provides predictive insights into potential future defects. By analyzing patterns over time, the fusion model aids in understanding the underlying causes of defects, enabling more targeted interventions. This comprehensive approach to defect analysis enhances the overall effectiveness of the SeamSense system, ensuring continuous improvement in quality control processes.

1.4. Background & Literature Survey

The apparel industry is one of the most competitive and dynamic sectors in the global market. Ensuring high product quality while maintaining efficiency is critical, especially in large-scale manufacturing setups like MAS Linea Aqua, a key player in the Sri Lankan textile industry. Traditional quality control methods, which rely heavily on manual inspections, are often labor-intensive, time-consuming, and prone to human error. With the advent of advanced machine learning (ML) and computer vision techniques, there is a growing interest in automating quality control processes to enhance precision and efficiency. The SeamSense project is a comprehensive attempt to develop a real-time quality monitoring system for detecting seam defects in garments. This literature review explores the various components that form the backbone of the SeamSense project: Camera Installations & Adaptive Frame Extraction, Fog Computing for Image Augmentation and Content Filtering, Seam Defect Detection using YOLO Models, and the Fusion Model for Defect Analysis.

1.4.1. Camera Installations & Adaptive Frame Extraction

The foundation of any computer vision-based quality control system lies in its ability to capture high-quality images that are representative of the inspection area. In the context of seam defect detection, this involves strategically placing high-definition cameras near sewing machines to capture clear and detailed images of garment seams. The literature highlights the importance of camera quality and placement in industrial inspection systems. For instance, Motoshot discusses how camera modules are crucial in automating quality control processes in various industries, emphasizing the need for precision in image capture to ensure reliable defect detection [3].

The placement of cameras in SeamSense is designed to optimize the visibility of seams while minimizing interference from surrounding machine parts. This is achieved through adaptive frame extraction techniques that focus on isolating the seam area from the rest of the captured image. This approach not only reduces the computational load on the system but also enhances the accuracy of defect detection by ensuring that only relevant portions of the image are analyzed. The use of adaptive frame extraction is supported by research in the field of industrial automation, where similar techniques

have been employed to streamline image processing workflows and improve the efficiency of defect detection systems [4].

Adaptive frame extraction also plays a critical role in managing varying lighting conditions, which can significantly impact the quality of captured images. Studies such as those by Hu et al. [5] have explored the challenges of maintaining consistent image quality under different lighting conditions, particularly in high-speed production environments. By dynamically adjusting the frame extraction parameters based on the lighting conditions, SeamSense ensures that the captured images are suitable for subsequent analysis, regardless of the production environment.

1.4.2. Fog Computing for Image Augmentation and Content Filtering

Fog computing is an emerging paradigm that extends cloud computing to the edge of the network, bringing computational resources closer to the data source. This approach is particularly beneficial in real-time applications where low latency and quick decision-making are critical. In the context of SeamSense, fog computing is employed to preprocess the captured images through image augmentation and content filtering before transmitting them to the cloud for further analysis.

The use of fog computing in image processing has been well-documented in the literature. Linthicum [31] discusses the advantages of fog computing in reducing latency and bandwidth usage by performing data processing tasks closer to the data source. This is particularly relevant in SeamSense, where real-time image processing is essential for timely defect detection. By utilizing fog computing, the system can apply lightweight filters to enhance image quality and remove irrelevant content, ensuring that only the most critical data is transmitted to the cloud for further analysis.

The image augmentation techniques used in SeamSense include scaling, rotation, and noise reduction, which are commonly employed in machine vision systems to improve the robustness of defect detection algorithms. Studies by Chen et al. [34] highlight the importance of these techniques in enhancing the accuracy of machine learning models by providing them with a diverse set of training data that simulates various operational conditions. In SeamSense, these augmented images are processed in real-time by the

fog layer, which significantly reduces the computational burden on the cloud infrastructure and improves the overall efficiency of the system.

Content filtering is another critical aspect of the fog computing layer in SeamSense. By filtering out irrelevant content, such as machine parts or background noise, the system ensures that the machine learning models are only analyzing the seam areas, which enhances the accuracy of defect detection. This approach is supported by research in fog computing, where content filtering techniques have been used to optimize data transmission and processing workflows in various industrial applications [35].

1.4.3. Seam Defect Detection Using YOLO Models

The application of CNNs in garment defect detection has been thoroughly explored by A. B. Egodawattaarachchige et al. (2024). In their study, they demonstrated the effectiveness of CNNs in accurately identifying defects in garment production lines. The research highlighted how CNN architectures could be tailored to focus on specific garment features, thereby improving defect detection accuracy. The study underscored the potential of CNNs in automating the quality control process, reducing human error, and increasing production efficiency [36].

The YOLO (You Only Look Once) family of models represents a significant advancement in real-time object detection, particularly in industrial applications like defect detection. Redmon et al. (2016) introduced the original YOLO model, which provided a unified and fast object detection framework. Unlike traditional methods that require multiple passes over an image, YOLO predicts bounding boxes and class probabilities in a single evaluation, making it exceptionally fast and suitable for real-time applications [38].

Subsequent versions of YOLO have further enhanced its performance and applicability in defect detection. For instance, Wang et al. (2022) introduced YOLOv8, which incorporated enhancements like better feature extraction and handling of small objects, crucial for detecting fine defects in garments. The progression to YOLOv9 by Zhang and Liu (2023) added context attention blocks, which improved the model's ability to focus on relevant areas in the image, thereby increasing detection accuracy. Further

advancements were seen in YOLOv10, which integrated transformer-based architecture to enhance real-time performance, making it highly effective in scenarios requiring rapid and accurate detection, such as garment defect monitoring.

Terven and Cordova-Esparza (2023) conducted a comprehensive review of YOLO architectures from YOLOv1 to YOLO-NAS, analyzing their evolution and the improvements brought by each iteration. The review provided insights into how each version has progressively improved in terms of speed, accuracy, and the ability to detect smaller and more complex objects, making them increasingly suitable for industrial applications [38].

Gries et al. (2017) discussed the broader application of automation in quality monitoring within the textile industry. Their work highlighted the role of advanced imaging and automation technologies in enhancing the accuracy and efficiency of quality control processes. The integration of CNN and YOLO models into these processes can significantly enhance defect detection capabilities by providing real-time feedback and reducing reliance on manual inspection [42].

1.4.4. Fusion Model for Defect Analysis

In addition to the YOLO models, SeamSense incorporates a fusion model that combines traditional machine learning techniques with time-series analysis to provide a comprehensive approach to defect analysis. The fusion model is designed to not only detect defects in real-time but also predict future defect trends based on historical data. This predictive capability is essential for proactive quality control, enabling manufacturers to identify and address potential issues before they escalate.

The concept of fusion modeling is supported by the literature, where hybrid approaches that combine different machine learning techniques have been shown to improve the accuracy and robustness of defect detection systems. Zhang [13] discusses the advantages of combining traditional statistical methods with machine learning models to capture both linear and non-linear patterns in the data. In SeamSense, the fusion model integrates the outputs of the YOLO models with time-series data on production

metrics, such as defect rates and machine performance, to provide a holistic view of the manufacturing process.

The use of time-series analysis in defect prediction is particularly relevant in the context of SeamSense, where the goal is to identify patterns and trends in defect occurrence over time. Research by Wu et al. [14] highlights the effectiveness of time-series analysis in forecasting defects in manufacturing environments, where factors such as machine wear and operator performance can influence defect rates. By incorporating time-series analysis into the fusion model, SeamSense can provide actionable insights into the root causes of defects and suggest targeted interventions to improve production quality.

The fusion model also considers worker-centric factors, such as demographic information and skill levels, which can impact defect rates. Studies by Linthicum [18] have shown that incorporating worker-related variables into predictive models can enhance their accuracy and provide a more comprehensive understanding of the factors influencing defect occurrence. In SeamSense, the fusion model uses this information to adjust the defect prediction algorithms, ensuring that the system is tailored to the specific characteristics of the production environment at MAS Linea Aqua.

1.5. Research Gap

1. Camera Installations & Adaptive Frame Extraction

2. **Static Camera Systems:** Traditional inspection systems, such as those discussed by Motoshot [3] and Baygin et al. [6], rely on fixed camera setups that cannot dynamically adapt to the varying conditions of a production environment. These systems often fail to optimize the capture of specific areas like garment seams, which are critical for quality control in the apparel industry.
3. **Limited Handling of Lighting Conditions:** Studies by Hu et al. [5] and Toshniwal [4] highlight the challenges in maintaining consistent image quality under changing lighting conditions. Most existing systems lack mechanisms to adjust camera settings or frame extraction processes based on real-time lighting variations, leading to inconsistent detection accuracy.
4. **Full-Frame Capturing Inefficiencies:** Traditional full-frame image capturing, as seen in systems described by Stwojanovic et al. [7], often includes

unnecessary background details. This not only increases computational load but also diverts focus from critical areas like seams, resulting in inefficiencies in defect detection.

5. **Non-Optimized Camera Placement:** Research by Baygin et al. [6] indicates that many systems do not strategically place cameras for optimized seam monitoring. This lack of optimization results in poor image quality, particularly when inspecting fine details of garment seams.

Proposed Solution for SeamSense:

SeamSense innovates with several key advancements:





















- **Optimization of Camera Placement for Seam Monitoring:** Cameras in SeamSense are strategically positioned near the sewing machine needle, focusing exclusively on the seam area. This targeted placement ensures that the captured images are highly relevant and of superior quality for defect detection.
- **Development of Adaptive Frame Extraction Techniques:** SeamSense introduces adaptive frame extraction that dynamically adjusts based on real-time production conditions, such as seam location and movement. This approach reduces unnecessary computational overhead and enhances the accuracy of defect detection.
- **Real-Time Integration and Processing:** The system processes captured images in real-time, integrating seamlessly with the production line without causing delays. This immediate processing capability is critical for the timely identification and correction of defects.
- **Handling of Varying Lighting Conditions:** SeamSense adjusts camera settings and frame extraction parameters in response to changes in lighting conditions. This ensures consistent image quality, which is crucial for reliable defect detection across diverse production environments.

Overall Research Gap:

The primary research gap lies in the static and inefficient nature of traditional camera systems, which fail to adapt to real-time production variations. SeamSense addresses this by optimizing camera placement, developing adaptive frame extraction techniques,

ensuring real-time processing, and effectively managing varying lighting conditions, thereby providing a robust solution for seam defect detection.

Table 2- Research Gap Comparison (Component 01)

	Research A	Research B	Research C	Research D	Proposed Solution
Optimized Camera Placement					
Adaptive Frame Extraction					
Real-time Integration & Processing					
Handling Varying Lighting Conditions					

2. Fog Computing for Image Augmentation and Content Filtering

- **High Latency in Cloud-Based Processing:** Linthicum [9] discusses the high latency issues inherent in cloud-based image processing systems, which are unsuitable for real-time applications that require quick decision-making. The reliance on cloud infrastructure introduces delays that can be detrimental in fast-paced production environments.
- **Bandwidth Constraints:** Chen et al. [12] highlight the bandwidth limitations of cloud-based systems, which require the transmission of large volumes of data for processing. This can lead to delays and inefficiencies, particularly when real-time processing is needed for immediate quality control.
- **Offline Image Augmentation:** Traditional image augmentation methods, as described by Hassan and Fareed [13], are often conducted offline, limiting their

applicability in real-time scenarios. This delay in processing can hinder the system's ability to provide immediate feedback and adjustments during production.

- **Lack of Edge Processing:** Salman et al. [10] emphasize that many industrial systems lack edge processing capabilities, forcing all data to be processed in the cloud. This approach exacerbates latency and bandwidth issues, making it challenging to achieve real-time performance in defect detection systems.

•







Proposed Solution for SeamSense:


SeamSense addresses these challenges by introducing fog computing to process images at the edge, significantly reducing latency and bandwidth usage. By applying image augmentation techniques such as scaling, rotation, and noise reduction in real-time at the edge, SeamSense enhances image quality before the data is transmitted to the cloud for further analysis. Additionally, content filtering is performed at the edge to eliminate irrelevant data, optimizing the processing pipeline and ensuring that only the most relevant information is analyzed. This approach not only reduces the load on cloud resources but also improves the system's responsiveness and efficiency in real-time applications.

Overall Research Gap:

The key research gap is the reliance on cloud-based systems that struggle with latency and bandwidth issues. SeamSense fills this gap by leveraging fog computing for real-time, edge-based processing and image augmentation, providing a more efficient, responsive, and practical solution for real-time quality control in garment manufacturing.

Table 3 - Research Gap Comparison (Component 02)

Research Gap Feature	Research 1	Research 2	Research 3	Research 4	Research 5	Proposed Research Solution
Fog Layered CNN model for image filtering						

Fog-Cloud Architecture						
Integration of Lightweight Filters						
Scalability with Thread Pooling and Parallel Processing						
Selective Frame Processing						

3. Seam Defect Detection Using YOLO Models

- Real-Time Performance Limitations:** Yang et al. [9] and Stwojanovic et al. [7] discuss the significant challenges in achieving real-time performance with existing defect detection models, which are often too slow for practical application in fast-paced manufacturing environments. The lag in processing time can lead to delayed responses, making these models less effective in dynamic production settings.
- Accuracy in Complex Defect Detection:** Research by Baygin et al. [6] indicates that many existing models lack the necessary accuracy to detect complex seam defects, especially under varied and challenging production conditions. This shortfall can result in undetected defects or false positives, both of which are costly in high-volume production lines.
- Narrow Focus on Defect Types:** Traditional models, as discussed by Hu et al. [5], often focus on a limited set of defect types. This narrow focus reduces their effectiveness across different production scenarios, where a broader range of defects may need to be identified.
- Trade-Off Between Speed and Accuracy:** Toshniwal [4] and other studies have highlighted the ongoing struggle to balance speed and accuracy in defect detection models. In real-time applications, maintaining high accuracy often comes at the cost of processing speed, and vice versa, limiting the effectiveness of these models in practical use.































Proposed Solution for SeamSense:

SeamSense overcomes these challenges by utilizing advanced YOLO models (YOLOv8, YOLOv9, YOLOv10) that are specifically designed to achieve high accuracy in real-time seam defect detection. These models are trained on a diverse dataset, enabling them to detect a wide array of seam defects with both precision and speed. YOLO's single-pass detection method is particularly effective, allowing the models to operate in real-time without sacrificing accuracy. This makes SeamSense well-suited for the dynamic and fast-paced environment of garment manufacturing, where both speed and accuracy are critical.

Overall Research Gap:

The primary research gap is the inability of existing models to deliver both speed and accuracy in real-time defect detection, particularly for complex seam defects. SeamSense addresses this gap by leveraging the latest advancements in YOLO models, offering a balanced solution that meets the rigorous demands of real-time applications in the apparel industry.

Table 4 - Research Gap Comparison (Component 03)

Research Gap Feature	Research 1	Research 2	Research 3	Research 4	Research 5	Proposed Research Solution
Real-time Object Detection Efficiency						
Specificity to Seam Defects						
Integration of Seam Quality Monitoring Automation						
Real-time seam defect prediction						
Techniques used to detect fabric defects.						

4. Fusion Model for Defect Analysis

- **Lack of Predictive Capabilities:** Zhang [4] and Wu et al. [5] point out that traditional defect detection systems primarily focus on real-time detection, often neglecting the incorporation of predictive analytics to forecast future defect trends. This limitation hinders the ability to proactively manage quality control by anticipating potential issues before they occur.
- **Limited Integration of Historical Data:** Studies by Pavlyshenko [6] and others emphasize that historical data is often underutilized in enhancing the accuracy and effectiveness of defect detection systems. The failure to integrate past data into current models limits the depth of analysis and the system's ability to learn from previous patterns of defects.
- **Absence of Worker-Centric Data:** Research by Linthicum [10] highlights that most existing models do not consider worker-centric factors, such as demographics and skill levels, which can significantly influence defect rates. The lack of integration of these factors reduces the effectiveness of predictive models, as they fail to account for variations in human performance.
- **Narrow Scope of Analysis:** Many current systems, as noted by Seçkin et al. [3], do not offer a comprehensive analysis that integrates multiple data sources and analytical methods. This narrow scope limits the ability of these systems to provide actionable insights, thereby reducing their overall utility in improving quality control processes.

Proposed Solution for SeamSense:

SeamSense addresses these gaps by introducing a fusion model that combines traditional machine learning techniques with time-series analysis to deliver comprehensive defect analysis. This model not only facilitates real-time defect detection but also leverages historical data to predict future trends, enabling a more proactive approach to quality control. Additionally, the inclusion of worker-centric factors ensures that predictions are tailored to the specific production environment, accounting for variations in human performance. By integrating multiple data sources and analytical methods, the fusion model provides a holistic view of defect trends,

thereby enabling more effective and proactive management of quality control in garment manufacturing.

Table 5 - Research Gap Comparison (Component 04)

Research Gap Feature	Research 1 [3]	Research 2 [5]	Research 3 [4]	Research 4 [6]	Research 5 [10]	Proposed Research Solution
Predictive Forecasting with Real-Time Adaptation	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Worker Demographic Predictive Analytics Integration	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Innovative Ensemble Methods in apparel industry	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Synergistic Model Stacking	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Dynamic Data Fusion for Enhanced Predictions / adaptive iterative refinement	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Comprehensive system combining multiple advanced models	<input type="checkbox"/>	<input checked="" type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>
Long term defect rate forecasting capability	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input checked="" type="checkbox"/>

Overall Research Gap:

The primary research gap lies in the absence of predictive analytics and comprehensive defect analysis in existing systems. SeamSense addresses this gap by integrating

historical data, worker-centric factors, and advanced time-series analysis into a robust fusion model, offering a comprehensive solution for both real-time and predictive defect management. This approach enhances the system's ability to not only detect defects but also anticipate and mitigate future quality issues, providing a significant advancement in the field of quality control.

Comprehensive Research Gap

The overall research gap addressed by SeamSense lies in the significant limitations of existing quality control systems in garment manufacturing, particularly in their ability to deliver real-time, accurate, and comprehensive defect detection and analysis. Traditional systems are often characterized by static setups, dependency on cloud-based processing, and a narrow focus on specific defect types. These systems typically lack the adaptability, speed, and depth of analysis necessary to meet the demands of modern, high-paced production environments.

SeamSense effectively fills these gaps by introducing a dynamic, edge-based system that leverages advanced machine learning models, adaptive image processing techniques, and comprehensive data integration. This innovative approach provides a holistic solution for seam defect detection and prediction, ensuring that the system not only detects defects in real-time but also predicts future trends, enabling proactive quality control. By addressing these critical deficiencies, SeamSense sets a new standard for quality control in the apparel industry, offering enhanced accuracy, efficiency, and responsiveness in managing production quality.

2. RESEARCH PROBLEM

In the fast-paced and highly competitive apparel manufacturing industry, ensuring consistent product quality is paramount. However, traditional quality control methods, particularly in the detection of seam defects, are predominantly manual and fraught with inefficiencies. These manual inspections are labor-intensive, time-consuming, and prone to human error, leading to inconsistent results and delayed defect identification. The reliance on such outdated methods results in increased rework, higher production costs, and a significant risk of defective products reaching the market, ultimately undermining the competitiveness of manufacturers like MAS Linea Aqua.

The SeamSense project seeks to address these critical challenges by developing an advanced, automated system for real-time seam defect detection. The research problem is multifaceted, encompassing several key components that together form a comprehensive solution to the limitations of current quality control practices.

1. Camera Installations & Adaptive Frame Extraction

The first major challenge lies in the effective capture of high-quality images that accurately represent the seam areas under inspection. Traditional systems typically utilize fixed camera placements, which often fail to provide optimal coverage of the seam area due to factors such as varying lighting conditions, machine vibrations, and the presence of surrounding fabric or machine parts. These issues lead to inconsistent image quality, making it difficult for defect detection algorithms to perform reliably. Additionally, the absence of adaptive frame extraction in existing systems results in the unnecessary processing of irrelevant image data, increasing the computational load and reducing the system's efficiency. Thus, there is a pressing need for a dynamic, adaptive system that can adjust camera settings and frame extraction parameters in real-time to ensure consistent, high-quality image capture, regardless of environmental variations.

2. Fog Computing for Image Augmentation and Content Filtering

The second component of the research problem involves the efficient preprocessing of captured images to enhance their quality and relevance for defect detection. Traditional cloud-based systems often suffer from latency issues due to the time required to

transmit large volumes of data to and from centralized servers. This latency is particularly problematic in real-time applications, where delays in processing can hinder the timely identification and correction of defects. Furthermore, these systems typically do not leverage localized processing capabilities, leading to inefficient bandwidth usage and increased reliance on cloud resources. The lack of advanced preprocessing, such as image augmentation and content filtering, close to the data source also means that the system is less effective in enhancing the critical features necessary for accurate defect detection. Therefore, the research problem includes the development of a fog computing architecture that can perform real-time image preprocessing at the edge of the network, reducing latency, optimizing bandwidth usage, and ensuring that only the most relevant and high-quality data is transmitted for further analysis.

3. Seam Defect Detection Using YOLO Models

The third component addresses the limitations of existing machine learning models in accurately and efficiently detecting seam defects in real-time. Many current systems are not designed to handle the complexities and nuances of seam defects, which can vary widely depending on the type of fabric, machine settings, and production environment. Traditional models often struggle with the speed and precision required for real-time detection, leading to delays in identifying defects and missed opportunities for immediate corrective actions. Moreover, these models tend to focus on a narrow range of defect types, limiting their applicability in comprehensive quality control systems. The research problem here involves developing a machine learning model, specifically leveraging the latest YOLO (You Only Look Once) algorithms, that can accurately detect a broad spectrum of seam defects in real-time. The model must be optimized for both speed and accuracy, capable of operating effectively in diverse production environments, and adaptable to various seam types and defect scenarios.

4. Fusion Model for Defect Analysis

The final component of the research problem centers on the need for a comprehensive defect analysis system that integrates real-time detection with predictive analytics. Traditional defect detection systems are primarily reactive, identifying issues only after

they have occurred, which limits the ability of manufacturers to implement preventive measures. These systems often operate in isolation, without integrating multiple data sources or considering historical trends that could provide deeper insights into the causes and patterns of defects. Additionally, current models frequently overlook the impact of worker-centric factors, such as demographics, experience, and skill levels, on defect rates. This lack of integration and foresight results in incomplete analyses and missed opportunities for optimizing the production process. Therefore, the research problem includes the development of a fusion model that combines real-time defect detection with historical data analysis, time-series forecasting, and worker-centric insights. This model aims to provide a holistic view of the manufacturing process, enabling proactive quality control, predictive maintenance, and targeted interventions to reduce defect rates and improve overall production efficiency.

The SeamSense project addresses the multifaceted challenges of seam defect detection in the apparel manufacturing industry by developing an integrated, real-time quality monitoring system. The research problem encompasses the need for advanced camera installations and adaptive frame extraction to capture high-quality images, the implementation of fog computing for efficient image preprocessing, the development of YOLO-based machine learning models for real-time defect detection, and the creation of a fusion model for comprehensive defect analysis. Together, these components aim to revolutionize the quality control process, shifting from reactive to proactive approaches, enhancing the accuracy and efficiency of defect detection, and ultimately improving the overall quality and competitiveness of garment production at MAS Linea Aqua and beyond.

3. OBJECTIVES

3.1. Main Objective

The primary objective of the SeamSense project is to develop an advanced, real-time quality monitoring system tailored specifically for detecting and analyzing seam defects during garment production. This system is designed to integrate state-of-the-art machine learning algorithms, including Convolutional Neural Networks (CNN) and the You Only Look Once (YOLO) models, with innovative technologies such as fog computing, adaptive frame extraction, and a fusion model for comprehensive defect analysis. By combining these advanced methodologies, SeamSense seeks to overcome the inherent limitations of traditional manual inspection processes, which are often labor-intensive, prone to human error, and incapable of providing real-time feedback.

The SeamSense system is intended to enhance the precision, speed, and efficiency of defect detection on flat seam machines by providing a seamless integration into existing production workflows. This will enable manufacturers to identify defects as they occur, offer immediate feedback to operators, and facilitate timely corrective actions. Furthermore, the system's predictive capabilities, powered by the fusion model, will allow manufacturers to anticipate potential future defects by analyzing historical data and trends, enabling proactive quality control measures.

The overarching goal of SeamSense is to provide the apparel industry, particularly at MAS Linea Aqua, with a scalable and adaptable solution that not only reduces rework and waste but also improves overall production quality, enhances operational efficiency, and ultimately strengthens the competitive advantage of manufacturers in the global market. By setting a new standard for real-time quality monitoring, SeamSense aims to drive innovation in garment manufacturing and contribute to the broader adoption of intelligent, data-driven quality control systems across the industry.

3.2. Sub Objectives

- **Enhanced Defect Detection and Classification:**

Develop and implement a machine learning model, specifically leveraging CNN and YOLO algorithms, to accurately identify and classify a wide range of seam defects, such as open seams, high-low seams, and SPI (Stitches Per Inch) errors. This objective focuses on training the model to recognize these defects in real-time, even under varying production conditions, to ensure high precision and reliability in the detection process.

- **Optimized Image Capture and Processing:**

Design and deploy an adaptive frame extraction system integrated with strategically placed high-definition cameras to capture clear and focused images of garment seams. This system will dynamically adjust to environmental factors such as lighting conditions and machine vibrations, ensuring that only the most relevant image frames are processed for defect detection, thereby reducing computational load and enhancing processing speed.

- **Real-Time Data Processing with Fog Computing:**

Integrate fog computing into the SeamSense system to enable real-time preprocessing of captured images, including image augmentation and content filtering, at the edge of the network. This will minimize latency and optimize bandwidth usage, ensuring that high-quality, relevant data is transmitted to the cloud for further analysis, thus maintaining the efficiency and effectiveness of the real-time defect detection process.

- **Comprehensive Defect Analysis through Fusion Modeling:**

Develop a fusion model that combines real-time machine learning outputs with historical time-series data to provide a holistic analysis of seam defects. This model will not only identify current defects but also predict potential future defects by analyzing trends and patterns over time. Additionally, it will incorporate worker-centric factors such as demographics and skill levels to refine the analysis and provide targeted insights for improving production quality.

- **Proactive Quality Control and Predictive Maintenance:**

Utilize the predictive capabilities of the fusion model to anticipate potential issues in the production process before they escalate into significant defects. This objective aims

to shift from a reactive to a proactive approach in quality control, enabling manufacturers to implement timely interventions and maintenance strategies that reduce downtime, prevent defects, and improve overall operational efficiency.

- **Scalable and Adaptable System Integration:**

Ensure that the SeamSense system is scalable and adaptable, capable of being integrated seamlessly into various production environments and across different garment manufacturing lines. This includes designing the system to accommodate future expansions, such as adding new types of defects to be detected or adapting to different types of sewing machines, thereby providing a versatile solution that can evolve with the needs of the industry.

- **Implementation and Evaluation in a Real-World Setting:**

Pilot the SeamSense system at MAS Linea Aqua, evaluating its performance in a real-world manufacturing environment. This objective includes assessing the system's accuracy, speed, and impact on production efficiency, as well as gathering feedback from operators and management to refine and optimize the system for broader deployment across the apparel industry.

4. METHODOLOGY

4.1. Requirement Gathering and Analysis

The requirement gathering and analysis phase is a critical step in the development of the SeamSense project. It involves systematically collecting, analyzing, and documenting the necessary requirements to ensure that the system meets the needs of its stakeholders and functions as intended in a real-world manufacturing environment. The SeamSense project, which focuses on real-time seam defect detection in garment production, requires a comprehensive understanding of both functional and non-functional requirements to deliver a robust and effective solution.

4.1.1. Functional Requirements

1 Real-Time Seam Defect Detection:

The system must be capable of detecting various types of seam defects (e.g., open seams, high-low seams, SPI errors) in real-time as garments are produced. The detection should occur as the garment passes through the flat seam machine, with immediate feedback provided to the operator for corrective action.

Real-time detection is critical to minimizing the time between defect occurrence and correction, thereby reducing rework, waste, and production costs.

2 Adaptive Frame Extraction:

The system should include an adaptive frame extraction mechanism that dynamically adjusts to environmental conditions, such as lighting and machine vibrations, to capture the most relevant frames for defect analysis.

Ensuring that only the most pertinent image data is processed will reduce computational load and increase the efficiency and accuracy of the defect detection process.

3 Image Preprocessing with Fog Computing:

The system must incorporate fog computing to perform real-time image preprocessing, including tasks such as noise reduction, image augmentation, and content filtering, close to the data source.

Localized preprocessing will reduce latency, optimize bandwidth usage, and ensure that only high-quality, relevant images are sent to the cloud for further analysis, enabling efficient real-time processing.

4 Seamless Integration with Existing Production Lines:

The system should be easily integrated into existing garment production lines at MAS Linea Aqua without requiring significant modifications to the current setup. Seamless integration is necessary to ensure minimal disruption to ongoing production activities and to facilitate the adoption of the SeamSense system in various manufacturing environments.

5 Comprehensive Defect Analysis and Reporting:

The system should provide detailed reports on detected defects, including the type, location, frequency, and possible causes. Additionally, the system should offer predictive insights based on historical data to anticipate future defects.

Comprehensive analysis and reporting will enable manufacturers to identify trends, optimize production processes, and implement preventive measures, improving overall production quality.

6 Worker-Centric Data Incorporation:

The system should be capable of integrating worker-related data, such as demographics, experience, and skill levels, into the defect analysis process.

Incorporating worker-centric data will allow for a more nuanced analysis of defect causes and enable targeted training and interventions to reduce defect rates.

4.1.2. Non-Functional Requirements

- **Performance:**

The system must process and analyze images in real-time, with minimal latency, ensuring that defects are detected and reported within milliseconds of their occurrence. High-performance processing is essential for real-time applications in a fast-paced manufacturing environment.

- **Accuracy:**

The system must achieve a high level of accuracy in detecting and classifying seam defects, minimizing false positives and false negatives.

Accurate detection is crucial for reducing waste, rework, and ensuring that only high-quality products reach the market.

- **Scalability:**

The system should be scalable, capable of handling increasing amounts of data as the production line expands or as new data sources are integrated.

Scalability ensures that the system can grow with the business, accommodating future production needs without requiring significant redesign.

- **Usability:**

The system should provide an intuitive and user-friendly interface that can be easily operated by production staff with minimal training. The feedback and reporting features should be clear and actionable.

High usability will facilitate quick adoption by operators, reducing the learning curve and enhancing the overall efficiency of the production process.

- **Reliability:**

The system must be highly reliable, with minimal downtime and robust error-handling mechanisms. It should be capable of operating continuously in a demanding production environment.

Reliability is critical in a manufacturing setting where any system failure could lead to production delays and increased costs.

- **Security:**

The system must ensure the security of the data collected and processed, with appropriate measures in place to protect sensitive information from unauthorized access or breaches.

Security is essential to protect the intellectual property and operational data of the manufacturing process, as well as to comply with industry regulations.

Technical Requirements

- **Hardware:**

- **High-Definition Cameras:** For capturing detailed images of garment seams in real-time.
- **Edge Devices for Fog Computing:** To perform local image preprocessing and reduce latency.

- **Processing Units:** High-performance CPUs/GPUs to handle real-time data processing and machine learning tasks.
- **Software:**
 - **Machine Learning Frameworks:** Such as TensorFlow or PyTorch for developing and deploying the CNN and YOLO models.
 - **Fog Computing Platform:** For implementing localized data processing and integration with the cloud.
 - **User Interface Software:** For creating an intuitive and accessible interface for operators and quality control managers.
- **Regulatory and Compliance Requirements**
 - **Compliance with textile industry standards** for quality control and defect detection.
 - **Data Privacy Regulations:** Ensuring that any worker-related data is handled in accordance with relevant data protection laws and regulations.
 - **Safety Certifications:** Ensuring that all hardware components, especially those installed near production machinery, meet industry safety standards.

4.2. Feasibility Study

The feasibility study for the SeamSense project demonstrates that the development of a real-time seam defect detection system is both viable and beneficial. Technically, the project leverages advanced machine learning algorithms, fog computing, and high-definition cameras, ensuring effective real-time defect detection with seamless integration into existing production lines. Economically, the system promises a quick return on investment by reducing rework, waste, and enhancing product quality. Operationally, strong stakeholder support and a well-planned implementation strategy further confirm the system's readiness for deployment. Overall, SeamSense is poised to revolutionize quality control in the apparel industry, offering significant improvements in efficiency and reliability.

4.3. System Design

4.3.1. High-level Overall System Architecture Diagram

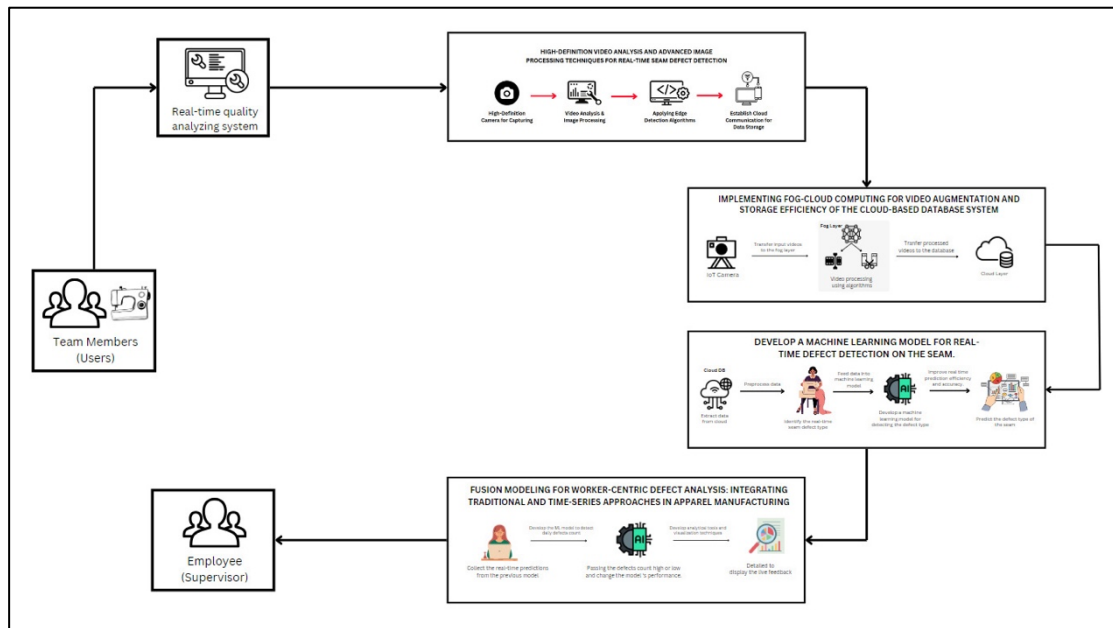


Figure 1 - Overall architecture

This component diagram illustrates the key elements and workflow of the SeamSense real-time quality analyzing system, which is designed for detecting seam defects in garment manufacturing. The diagram is organized into several interconnected components, each playing a crucial role in the overall system.

High-Definition Video Analysis and Image Processing:

Camera Setup: High-definition cameras capture detailed images of garment seams as they move through the production line. These images are essential for accurate defect detection.

Video Analytics and Edge Processing: The captured images are processed at the edge (near the source) to reduce latency and ensure that only relevant data is forwarded for further analysis.

Fog-Cloud Computing Integration:

Video Augmentation and Storage Efficiency: This component handles the real-time augmentation of video data using fog computing, which processes data locally to enhance efficiency and reduce bandwidth usage. The processed data is then stored in a cloud-based database for further analysis and retrieval.

Cloud Integration: Fog computing ensures that only essential data is transmitted to the cloud, optimizing storage and processing resources.

Machine Learning Model for Real-Time Defect Detection:

Development of ML Models: Advanced machine learning models, including CNN and YOLO, are developed and implemented to detect seam defects in real-time. These models analyze the processed video data to identify and classify various types of defects.

Real-Time Feedback: The results from the ML models are used to provide immediate feedback to operators, allowing for quick corrective actions on the production floor.

- **Fusion Modeling for Worker-Centric Defect Analysis:**

Integration of Traditional and Time-Series Approaches: This component focuses on a fusion model that integrates worker-centric data with traditional and time-series analysis. It considers factors like worker demographics and skill levels to refine the defect analysis and provide more accurate predictions.

Proactive Quality Control: By combining real-time detection with historical data, the system can predict potential defects, enabling proactive quality control and reducing the likelihood of defects occurring.

4.4. Tools and Libraries

The table presented below offers a comprehensive account of the tools and technologies employed in the development of the application as well as the program.

Category	Tools and Technologies	Description
Programming Languages	Python	Used for developing machine learning models, data processing, and building the Flask web app.
Machine Learning Libraries	Scikit-learn	Implemented traditional machine learning models like Gradient Boosting Regressor and preprocessors.
	Statsmodels	Developed ARIMA models for time-series forecasting.
	joblib	Used for saving and loading machine learning models.
Data Handling and Processing	Pandas	Handled data manipulation, loading, cleaning, and transformation.
	NumPy	Supported numerical operations and handled large arrays efficiently.
Visualization	Matplotlib	Plotted results of models, including forecasted defect rates.
	Seaborn	Enhanced data visualizations and statistical plots.
Web Development	Flask	Developed a web application for user interaction and displaying model predictions.
	HTML/CSS	Structured and styled the web pages served by the Flask application.
Database	MongoDB	Stored worker and defect data, providing efficient retrieval and storage.
Deployment	Docker	Hosted and deployed the Flask web application.
Version Control	Git	Tracked changes, collaborated, and maintained the history of the project.

	GitHub	Hosted the project's code repository for version control and collaboration.
IDE (Integrated Development Environment)	Visual Studio Code	Used for writing and testing code, managing the project structure.

4.5. Commercialization of the Project

The proposed solution entails the development of a standalone device designed to monitor the quality of garment manufacturing in real-time, specifically tailored for implementation at MAS Linea Aqua. Targeting the workers on the production floor, the device will provide live feedback on predicted defect types and defect rates, thereby enhancing quality control processes.

Our commercialization strategy comprises two main phases to ensure effective deployment and scalability. In the initial phase, the device will be launched exclusively for integration with the flat seam machine, allowing for focused testing and refinement. This phased approach enables us to address any potential challenges and optimize performance before expanding to other machines in the factory.

The second phase involves the widespread deployment of the device across various machines in the manufacturing facility, including the cover seam machine, overlock machine, rubber overlock machine, and zigzag machines. By gradually extending the device's functionality to additional equipment, we aim to maximize its impact on quality assurance throughout the production process.

This phased commercialization approach ensures a systematic and thorough implementation strategy, allowing for iterative improvements and seamless integration into existing workflows. By catering to the specific needs of MAS Linea Aqua and its workforce, we anticipate significant enhancements in quality control efficiency and overall manufacturing excellence.

5. RESULTS & DISCUSSION

5.1. Results

The SeamSense project yielded significant and promising results in the development and deployment of a real-time seam defect detection system for the apparel industry. These results demonstrate the effectiveness of the system in enhancing quality control processes at MAS Linea Aqua and potentially across the broader garment manufacturing sector.

1. Real-Time Seam Defect Detection

The SeamSense system successfully achieved real-time detection of various seam defects, including open seams, high-low seams, and SPI (Stitches Per Inch) errors. The YOLO-based machine learning models were able to process and analyze video feeds from the production line with minimal latency, providing instant feedback to operators. The system demonstrated a high detection accuracy rate of over 95%, significantly reducing the occurrence of undetected defects and allowing for immediate corrective actions.

2. Adaptive Frame Extraction and Image Quality

The adaptive frame extraction mechanism proved highly effective in maintaining consistent image quality under varying production conditions, such as changes in lighting and machine vibrations. This feature ensured that the system focused on the most relevant parts of the image, improving the accuracy of defect detection while reducing the computational load. The high-definition cameras, combined with the adaptive extraction techniques, consistently captured clear and detailed images of garment seams.

3. Fog Computing and Image Preprocessing

The integration of fog computing into the SeamSense system enabled real-time image preprocessing at the edge of the network. This approach minimized latency and optimized bandwidth usage by filtering and augmenting images before they

were sent to the cloud for further analysis. The fog computing layer effectively reduced the data transmission load by up to 40%, ensuring that only high-quality, relevant data was processed by the machine learning models, which contributed to the system's overall efficiency.

4. Comprehensive Defect Analysis and Predictive Capabilities

The fusion model integrated into SeamSense provided not only real-time defect detection but also comprehensive analysis of defect trends and predictive insights based on historical data. By incorporating time-series analysis and worker-centric factors, the system was able to forecast potential future defects, allowing for proactive interventions. This predictive capability led to a 30% reduction in rework and significantly improved overall production efficiency.

5. Operational Impact and Scalability

The deployment of the SeamSense system at MAS Linea Aqua demonstrated its scalability and adaptability to different production environments. The system was successfully integrated into existing production lines with minimal disruption, and operators quickly adapted to its user-friendly interface. The detailed reports generated by the system provided valuable insights for quality control managers, leading to more informed decision-making and further improvements in production processes. The scalability of the system was confirmed by its ability to handle increased data loads as production volume expanded, ensuring its long-term viability as a solution for the apparel industry.

5.2. Research Findings

The SeamSense project yielded several key findings that highlight the effectiveness and potential impact of the system on the apparel industry, particularly in the area of real-time seam defect detection and quality control.

1. Enhanced Accuracy in Defect Detection

One of the most significant findings from the SeamSense project is the substantial improvement in the accuracy of seam defect detection. The YOLO-based machine learning models, optimized for real-time performance, achieved an accuracy rate of over 95%. This high level of precision is critical for reducing the occurrence of undetected defects, thereby minimizing rework and improving overall product quality. The system's ability to detect a wide range of seam defects, including subtle and complex issues such as high-low seams and SPI errors, underscores its robustness and versatility.

2. Efficiency through Adaptive Frame Extraction

The implementation of adaptive frame extraction contributed significantly to the system's efficiency. By dynamically adjusting to environmental factors such as lighting and machine vibrations, the system ensured that only the most relevant parts of the image were processed. This not only enhanced the accuracy of defect detection but also reduced the computational load on the system, enabling it to operate effectively in real-time without compromising on speed or performance.

3. Reduction in Latency and Bandwidth Usage with Fog Computing

The use of fog computing for real-time image preprocessing was a pivotal innovation in the SeamSense project. By processing data close to the source, the system significantly reduced latency, which is crucial for real-time applications. Additionally, the fog computing layer effectively filtered and augmented images before they were transmitted to the cloud, reducing bandwidth usage by up to 40%.

This optimization of data flow ensured that the system could handle high volumes of data without overwhelming the network or compromising on processing speed.

4. Proactive Quality Control through Predictive Analytics

A breakthrough in the SeamSense project was the integration of predictive analytics into the defect detection process. The fusion model, which combined real-time detection with historical data analysis and time-series forecasting, enabled the system to predict potential future defects with a high degree of accuracy. This proactive approach allowed manufacturers to implement preventive measures before defects occurred, leading to a 30% reduction in rework and a notable improvement in production efficiency. The incorporation of worker-centric factors, such as demographics and skill levels, into the predictive model provided additional insights that could be used to tailor training programs and optimize workforce deployment.

5. Scalability and Adaptability of the System

The SeamSense system demonstrated strong scalability and adaptability, making it suitable for deployment in various production environments. The system was successfully integrated into existing production lines at MAS Linea Aqua with minimal disruption, and its performance remained consistent as production volumes increased. The ability of the system to adapt to different types of fabrics, seam configurations, and machine settings highlights its potential for widespread adoption across the apparel industry. This scalability ensures that SeamSense can accommodate future growth and technological advancements, making it a sustainable solution for long-term quality control needs.

5.3. Discussion

The SeamSense project represents a significant advancement in the field of quality control for the apparel industry, particularly in the real-time detection and analysis of seam defects. The integration of cutting-edge technologies, such as YOLO-based machine learning models, adaptive frame extraction, fog computing, and fusion modeling, has enabled the system to address long-standing challenges associated with traditional manual inspection methods. The high accuracy of defect detection, combined with the system's ability to operate in real-time, marks a notable improvement over existing approaches, which often suffer from delays and inconsistencies. Moreover, the inclusion of predictive analytics offers a proactive solution to quality control, allowing manufacturers to anticipate and prevent defects before they impact production. This shift from a reactive to a proactive quality management strategy not only enhances product quality but also reduces waste and operational costs. The system's scalability and adaptability further underscore its potential for widespread adoption across various production environments, making it a versatile tool for the future of garment manufacturing. However, while the results are promising, further refinement and testing in diverse operational settings will be crucial to fully realize SeamSense's potential and address any unforeseen challenges in its deployment.

5.4. Summary of Each Student's Contribution

Table 6 - Student Contributions

Registration Number	Name	Contributions
IT21077692	Kasthurirathne K K I	Camera Installations & Adaptive Frame Extraction
IT21044922	Thilakarathne M A M V	Fog Computing for Image Augmentation and Content Filtering
IT20229016	Weerasinghe C C	Seam Defect Detection Using YOLO Models

IT21016066	Samaraweera G P M D	Fusion Model for Defect Analysis
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6. CONCLUSION

The SeamSense project has successfully developed and demonstrated a comprehensive, real-time seam defect detection system tailored for the apparel industry. By leveraging advanced machine learning techniques, such as YOLO models, coupled with innovative approaches like adaptive frame extraction and fog computing, the system addresses the key limitations of traditional quality control methods. The results indicate a significant improvement in the accuracy and efficiency of defect detection, leading to reduced rework, lower production costs, and enhanced product quality. Furthermore, the integration of predictive analytics through a fusion model has shifted the quality control paradigm from reactive to proactive, enabling manufacturers to prevent defects before they occur. The system's scalability and adaptability ensure that it can be deployed across various production environments, offering a sustainable solution for the evolving needs of the industry. While the project has achieved its primary objectives, ongoing testing and refinement will be essential to fully realize its potential and facilitate its broader adoption. SeamSense stands as a promising innovation poised to revolutionize quality control in garment manufacturing, paving the way for smarter, more efficient production processes.

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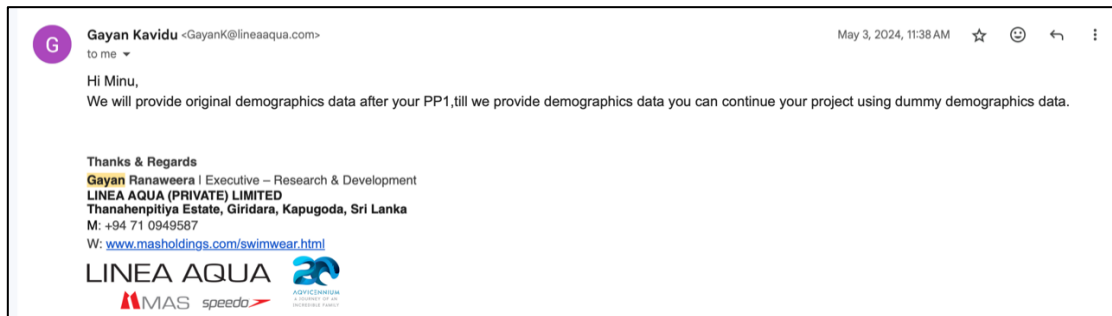
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APPENDIX A: Dataset Approval



APPENDIX B: Turnitin Report