FABRIC DEFECT DETECTION

A PROJECT REPORT

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in partial fulfillment for the completion of course Engineering Design Project

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BONAFIDECERTIFICATE

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Submitted for the VIVAVOCE Examination held at Thiagarajar College of Engineering on______________

INTERNAL EXAMINER **EXTERNAL EXAMINER**

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We express our sincere gratitude to our Honorable Correspondent **Mr. K. Hari Thiagarajan** for facilitating with a good learning environment to improve our academic knowledge and performance at this premier institution.

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ABSTRACT

This project introduces an innovative automated fabric defect detection system designed to revolutionize quality control in textile manufacturing. By utilizing advanced deep learning models, specifically YOLOv8 and YOLOv11, the system can detect various fabric defects such as stains, cuts, holes, and loose threads with high accuracy and in real-time. YOLOv11 outperforms YOLOv8 in precision, especially for complex or subtle defects, while YOLOv8 offers faster processing, making it more suitable for high-speed manufacturing environments. The system includes a NodeMCU-controlled servo motor for defect marking and an L298N motor driver to control the conveyor belt, which halts automatically when defect rates exceed a predefined threshold. This ensures that defective products are flagged for further inspection before they proceed through the production line.

Environmental sensors monitoring temperature, humidity, and gas levels are integrated into the system to assess their impact on fabric quality. By correlating environmental conditions with defect rates, the system can optimize the production environment, ensuring better fabric consistency and reducing defects. The comprehensive solution automates both defect detection and real-time corrective actions, significantly improving operational efficiency and reducing reliance on manual inspection, which is often prone to error and fatigue.

This study demonstrates that the proposed system not only enhances fabric defect detection with higher accuracy and speed but also provides valuable insights into how environmental factors contribute to defects. The research also emphasizes future opportunities for model optimization, integration with predictive maintenance systems, and scalability across various fabric types and production setups.

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CHAPTER 1

1.1 INTRODUCTION

The Textile industry plays a pivotal role in global manufacturing, providing essential materials for clothing, home furnishings, and industrial applications. With the rise of urbanization and changing consumer preferences emphasizing comfort and style, the demand for textile products continues to grow. However, ensuring the quality of these products presents a significant challenge for manufacturers.

Traditionally, quality control in textile manufacturing relied heavily on manual inspection processes. Human inspectors would visually examine fabrics for defects, such as holes, cuts, stains, and irregularities in patterns. While effective to some extent, manual inspection methods are prone to human error, fatigue, and inefficiency, particularly when dealing with large volumes of fabric.

As urban populations expand and consumer expectations rise, the textile industry faces increasing pressure to maintain high standards of quality while meeting production demands. Defects in fabrics not only compromise the aesthetics and functionality of end products but also result in waste and financial losses for manufacturers.

To address these challenges, researchers and engineers have been exploring automated solutions for fabric defect detection. By leveraging advancements in computer vision, machine learning, and image processing, automated defect detection systems aim to improve the accuracy, speed, and reliability of quality control processes in textile manufacturing.

The development of such systems requires interdisciplinary expertise, combining knowledge from computer science, engineering, and textile manufacturing. Researchers need to design algorithms capable of accurately identifying and classifying various types of fabric defects, while engineers must integrate these algorithms into practical, real-world systems that can operate effectively in manufacturing environments.

Against this backdrop, the presented project emerges as a cutting-edge initiative aimed at revolutionizing fabric defect detection in the textile industry. By combining state-of-the-art object detection models with innovative hardware and software components, the project seeks to automate and enhance the quality control process, ultimately improving product quality, reducing waste, and increasing manufacturing efficiency.

1.2 METHODS OF FABRIC DEFECT DETECTION

The proposed fabric defect detection system integrates cutting-edge computer vision and machine learning techniques to revolutionize quality control in the textile industry. Utilizing the YOLOv8 object detection model, the system automates the process of identifying defects such as holes, cuts, stains, and pattern irregularities, providing real-time detection and classification. High-resolution cameras, combined with strategically placed LED lighting, enhance the visibility of even subtle fabric defects. The system preprocesses images through contrast adjustments and noise reduction to ensure clear and accurate detection.

By training YOLOv8 on a large dataset of annotated fabric images, the system achieves superior accuracy in identifying multiple defect types simultaneously. It operates seamlessly in manufacturing environments, continuously monitoring fabrics on production lines and flagging defects with precise location markers. This approach eliminates the limitations of manual inspection, such as human error, fatigue, and inconsistencies, while offering real-time performance and scalability across various fabric types.

The integration of real-time defect detection not only minimizes defective products but also enhances production efficiency by automating quality control, reducing waste, and streamlining the manufacturing process. This system represents a significant advancement in textile production, ensuring higher product quality, faster defect identification, and cost savings for manufacturers.

1.3 PROBLEM STATEMENT

The textile industry faces significant challenges in maintaining high standards of quality control, primarily due to the limitations of traditional manual inspection methods for detecting fabric defects. Human inspectors, while capable of identifying visible defects such as holes, cuts, stains, and irregularities, are prone to errors, fatigue, and subjective judgments, particularly when dealing with large volumes of fabric. As urban populations grow and demand for textile products increases, the need for fast, accurate, and scalable defect detection becomes critical. Manual inspection methods are inefficient and often fail to detect subtle or multiple defects simultaneously, leading to quality compromises, production delays, increased waste, and financial losses for manufacturers.

There is a pressing need for an automated fabric defect detection system that can operate in real-time, offering higher accuracy, speed, and consistency to enhance quality control and improve overall production efficiency.

1.4 SCOPE OF THIS STUDY

The scope of this project is to develop and implement an automated fabric defect detection system using the state-of-the-art YOLOv8 object detection model. The system will leverage deep learning and computer vision techniques to accurately identify and classify various types of fabric defects in real-time, including holes, cuts, stains, and other irregularities.

The project will involve the following key components:

- **Data acquisition and preparation:**

  Collecting and curating a comprehensive dataset of fabric images with annotated defects for training and evaluation purposes.
- **Model training and fine-tuning:**

  Adapting the YOLOv8 model architecture for fabric defect detection by incorporating transfer learning and fine-tuning techniques on the collected dataset.
- **System integration:**

  Integrating the trained YOLOv8 model into a complete fabric defect detection system, including image acquisition, preprocessing, defect detection, and classification components.
- **Performance evaluation:**

  Conducting extensive testing and evaluation of the system's accuracy, speed, and reliability in detecting and classifying fabric defects in real-world scenarios.
- **Deployment and implementation:**

  Deploying the fabric defect detection system in textile manufacturing environments, ensuring seamless integration with existing quality control processes.

1.5 OBJECTIVES OF THIS STUDY:

- Develop a highly accurate and efficient fabric defect detection system using the YOLOv8 model, outperforming traditional manual inspection methods.

- Leverage transfer learning and fine-tuning techniques to adapt the YOLOv8 model for the specific task of fabric defect detection, ensuring optimal performance.
- Implement advanced techniques such as feature fusion, dynamic anchor boxes, and non-maximum suppression to enhance defect detection accuracy and reduce false positives.
- Achieve real-time defect detection capabilities, enabling timely quality control measures and minimizing production delays.
- Integrate the defect detection system into textile manufacturing processes, automating quality control procedure and reducing the risk of defective products reaching the market.
- Contribute to cost savings and increased efficiency in textile manufacturing by minimizing rework, product recalls, and potential brand damage associated with fabric defects.
- Demonstrate the practical applicability and scalability of the proposed system in real-world industrial environments, paving the way for widespread adoption across the textile industry.
- Explore the potential for adapting the defect detection system to other industries or applications where accurate and reliable object detection is crucial.

By achieving these objectives, the project aims to revolutionize quality control practices in the textile industry and establish the YOLOv8 model as a powerful solution for fabric defect detection, ultimately contributing to improved product quality, customer satisfaction, and operational efficiency.

1.6 SIGNIFICANCE OF THIS STUDY

The significance of this study lies in its potential to transform quality control processes within the textile industry by addressing the limitations of traditional manual inspections. Key benefits include:

- Enhanced Accuracy and Consistency: The automated defect detection system significantly improves the accuracy of identifying fabric defects such as holes, cuts, stains, and texture irregularities, reducing human error and fatigue, which are common in manual inspections.
- Real-Time Defect Detection: The study introduces a system capable of performing real-time, continuous monitoring on production lines, enabling faster identification and correction of defects. This ensures timely interventions and prevents defective products from reaching the market, ultimately improving product quality.
- Increased Efficiency and Productivity: Automating the inspection process reduces the time and labor required for manual defect detection. This results in streamlined operations, minimized production downtime, and enhanced productivity for textile manufacturers.
- Cost Reduction: By detecting defects early in the production process, the system helps manufacturers reduce material waste, rework, and financial losses. Improved defect detection can also enhance the overall efficiency of the manufacturing process, lowering operational costs.
- Scalability and Versatility: The proposed system is adaptable to various fabric types and manufacturing conditions, making it applicable across a wide range of textile production environments. Its scalability ensures that it can be integrated into both small-scale and large-scale operations.

- Improved Quality Control Standards: By automating defect detection, this study contributes to raising the standards of quality control in the textile industry. The system ensures that fabrics meet higher levels of quality, which can lead to increased customer satisfaction and brand reputation.

Overall, this study provides a significant technological advancement for the textile industry, offering a practical, scalable solution to enhance quality control, reduce defects, and improve manufacturing efficiency.

1.7 LIMITATIONS OF THIS STUDY

- **Dataset limitations:**

  Availability of a sufficiently large and diverse dataset of fabric images with annotated defects.

  Variability in defect types, sizes, and appearances across different fabric materials and patterns. Accurate and consistent labelling of defects in the dataset, which can be time-consuming and labor-intensive.

- **Computational resources:**

  Training deep learning models like YOLOv8 can be computationally intensive, requiring powerful hardware (e.g., GPUs) and significant memory resources.

  Real-time inference for defect detection may require optimized hardware deployments for efficient processing.

- **Environmental factors:**

  Variations in lighting conditions, camera angles, and imaging setups in textile manufacturing environments can affect the performance of the defect detection system.

  Handling different fabric textures, colors, and patterns, which can pose challenges for accurate defect detection.

- **System integration and Deployment:**

  Seamless integration of the defect detection system with existing quality control processes and manufacturing workflows. Compatibility with various imaging hardware and software components used in textile facilities. Ensuring reliable and consistent performance in real-world industrial environments.

- **Scalability and adaptability:**

  Ability to scale the system to handle large volumes of fabric inspections without compromising performance. Adaptability to evolving defect types or new fabric materials introduced in the manufacturing process.

- **Cost and resource constraints:**

  Balancing the development and deployment costs of the defect detection system with the potential benefits and return on investment. Availability of skilled personnel for system development, maintenance, and support.

- **Regulatory and compliance requirements:**

  Adhering to industry standards, safety regulations, and quality control guidelines specific to textile manufacturing. Ensuring data privacy and security when handling fabric images and defect annotations.

- **Interpretability and explainability:**

  Providing transparent and interpretable explanations for the defect detection results, especially in cases of potential false positives or misclassifications. Facilitating trust and acceptance of the automated system by human inspectors and quality control personnel.

1.8 PROJECT SPECIFICATIONS

1.8.1 SCHEDULE-TIMELINE CHART

Task	Description	Start Date	End Date
Identification of Problem statement	Analysis of defect detection challenges, including the early detection of fabric defects during production stage.	01-07-24	08-07-24
Literature survey	Observation and analysis of existing defect detection technologies and detection monitoring methods.	08-07-24	15-07-24
Front end development	Developing the user interface of the defect detection using Raspberry Pi	15-07-24	22-07-24
Review 1	Demonstration of project for Review 1	29-07-24	
Defect detection Analysis	Researching and developing defect tracking and analysis capabilities for the fabric defects, including machine learning models for detection.	29-07-24	07-08-24
Implementation	Completion of backend infrastructure for data processing and defect analysis.	07-08-24	21-08-24
Integration	Integrating of defect tracking models and defect analysis capabilities with the front end.	21-08-24	03-09-24
Review 2	Demonstration of project for Review 2	22-09-24	
Testing	Testing the defect detection monitoring functions and other features for accuracy and reliability.	03-10-24	10-10-24
Completion	Completion of full project	10-10-24	17-10-24
Review 3	Demonstration of project for review 3	14-10-24	

1.8.2 BUDGET

Estimation of budget for implementing in real world.

Category	Description	Amount
Technology Infrastructure	Investment in affordable hardware, including defect detection components, Arduino, NodeMCU, cameras, and sensors	₹15,000
Software Development	Costs associated with optimizing the development and integration of defect detection algorithms, machine learning models, and software	₹25,000
Defect detection and Analysis	Costs associated with developing and refining detection features, including stain analysis, cut detection, and OCR pattern verification	₹10,000
Personnel	Cost-effective salaries and wages for project team members involved in development, testing, and support	₹40,000
Total(estimate)		**₹90,000**

1.8.3 RISK FACTORS

Risk Factor	Likelihood	Impact	Mitigation Strategy
Technical Challenges	High	High	Regular technical audits and contingency plans
Regulatory Compliance	Medium	Medium	Consultation with legal experts and compliance officers
Security Vulnerabilities	High	High	Implementation of robust security protocols
Market Fluctuations	Medium	Medium	Diversification of investment portfolio

1.8.4 FUNCTIONAL REQUIREMENTS

- **Data Acquisition and Preparation:**

  Collect and curate a comprehensive dataset of fabric images with annotated defects for training and evaluation purposes. Ensure the dataset covers a diverse range of fabric materials, patterns, defect types, and sizes. Implement appropriate data augmentation techniques to enhance the robustness and generalization of the model.

- **Model Training and Fine-tuning:**

  Adapt the YOLOv8 model architecture for fabric defect detection by incorporating transfer learning and fine-tuning techniques on the collected dataset. Implement advanced techniques such as feature fusion, dynamic anchor boxes, and non-maximum suppression to enhance defect detection accuracy and reduce false positives.

  Optimize the model's performance through hyperparameter tuning and appropriate regularization techniques.

- **Real-time Defect Detection:**

  Integrate the trained YOLOv8 model into a complete fabric defect detection system, including image acquisition, preprocessing, defect detection, and classification components.

  Ensure real-time defect detection capabilities, enabling timely quality control measures and minimizing production delays. Implement efficient inference strategies and hardware optimizations for seamless integration into textile manufacturing environments.

- **Accuracy and Reliability:**

  Achieve high accuracy in detecting and classifying fabric defects, outperforming traditional manual inspection methods. Minimize false positives and false negatives to ensure reliable defect identification.

Provide confidence scores or probability estimates for detected defects to aid in decision-making and quality control processes.

- **User Interface and Visualization:**

  Develop a user-friendly interface for operators to monitor and interact with the defect detection system. Provide clear visualizations of detected defects, including bounding boxes, defect types, and confidence scores. Enable easy review and validation of defect detection results by human inspectors.

- **System Integration and Deployment:**

  Ensure seamless integration of the defect detection system with existing quality control processes and manufacturing workflows. Develop deployment strategies for efficient and scalable operation in textile manufacturing environments. Implement robust data management and storage solutions for fabric images and defect annotations.

- **Maintenance and Adaptability:**

  Establish procedures for regular system maintenance, including model updates and dataset refinements. Enable adaptability to evolving defect types or new fabric materials introduced in the manufacturing process. Provide documentation and training resources for system operators and maintenance personnel.

1.8.5 NON-FUNCTIONAL REQUIREMENTS

- **Performance and Scalability:**

  Meet or exceed specified performance benchmarks for defect detection accuracy, processing speed, and throughput. Ensure the system can scale to handle increasing volumes of fabric inspections without compromising performance.

- **Usability and Accessibility:**

  Design an intuitive and user-friendly interface for system operators and inspectors.

  Ensure accessibility features for users with diverse abilities and backgrounds.

- **Maintainability and Extensibility:**

  Develop a modular and extensible system architecture to facilitate future enhancements or modifications. Provide well-documented code and comprehensive testing frameworks for easier maintenance and debugging.

- **Cost-effectiveness and Resource Optimization:**

  Optimize the system's resource utilization, including computational resources, storage, and networking requirements. Ensure a favourable return on investment by balancing development and deployment costs with potential benefits and savings.

CHAPTER 2

LITERATURE SURVEY

S.no	Title	Name of journal/conference and issue year/link	Dataset Used & Methodology	Observations
1.	A Facial defect detection method based on deep learning	IEEE Access 2021, Digital Object Identifier 10.1109/ACCESS.2021.3140118	The study used PyTorch 1.2 and YOLOv4 with enhanced SPP and CLAHE on a GPU system, training the model for 1000 epochs with mosaic data augmentation. Performance was evaluated on the VOC fabric defect dataset using mAP, precision, and recall, and compared to Faster R-CNN and SSD.	The improved YOLOv4 model boosted mAP by 6% with minimal FPS impact, optimized for fabric defect detection via anchor re-division, CLAHE, and an enhanced SPP with soft pooling. The SPP improvements were key, as seen in other YOLO variants.
2	Fabric Defect Detection with Deep Learning and False	IEEE Access 2021, Digital Object Identifier XX.XXXX/ACCESS.XXXX.DOI	System utilizes CNN for defect detection. In Training process over 50 defect types were considered. To address the higher cost	The proposed defect detection system based on CNN demonstrated strong performance with 95 % accuracy when

	Negative Reduction		associated with undetected defects FN reduction method were incorporated.	FN methods are applied.
3	FABRIC DEFECT DETECTIO N	IJCRT 2023, Digital Object Identifier 10.1109/ACCES S.2021.3140109	System utilizes computer vision-based methods for defect detection in textile industry including colour based, image segmentation based, text, sparse and image morphology operations.	In summary, the effectiveness of computer vision methods in fabric defect detection, providing alternative to manual approaches.
4	A Fabric Defect Detection in textile manufacturi ng	Hindawi 2021	System utilizes the learning learning-based (conventional machine learning, deep learning) algorithms. The paper provides a systematic literature review and discusses the deployment of these algorithms.	The paper emphasizes the significance of fabric defect detection in the era of artificial intelligence-driven manufacturing. It categorizes and reviews both traditional and modern algorithms
5	A Lightweight Detector	IEEE Access 2023	The study introduces YOLO-SCD, a lightweight fabric	YOLO-SCD demonstrated strong performance with an

	Based on Attention Mechanism for Fabric Defect Detection		defect-detection network based on the attention mechanism. It incorporates depth-wise separable convolution to enhance feature extraction and improve overall network detection speed.	average accuracy of 82.92%, an 8.49% improvement in mean Average Precision (mAP)
6	Fabric defect detection systems	Science Direct 2021	The paper reviews fabric defect detection methods, categorizing them into seven classes. It briefly explains image acquisition components and evaluates methods based on criteria like accuracy and computational cost.	The review assesses fabric defect detection methods, highlighting strengths and weaknesses while addressing gaps in current studies
7	Defect Detection in Fabric using Image	International Research Journal of Engineering and Technology (IRJET), Volume	Automated fabric inspection system workflow: - Image acquisition, Preprocessing, Feature extraction,	Quality control in the textile industry is crucial to reduce production costs and time, with automated

	Processing Technique	5, Issue 12, December 2018	Detection/Classification, Post-processing Wavelet transform (specifically Haar wavelet) used for analysis and characterization of image at different scales	defect detection offering significant labor savings. Fabric defect detection is challenging due to numerous ambiguous defect classes, but wavelet transforms outperform traditional methods with lower computational cost.
8	Fabric Defect Detection	International journal of creative research thoughts, © 2023 IJCRT | Volume 11, Issue 3 March 2023 | ISSN: 2320-2882	The dataset includes various fabric defect samples and real-time images. The methodology uses histogram equalization for contrast enhancement, U-Net for defect segmentation with skip connections, and an attention mechanism to improve accuracy in detecting complex defects.	The study highlights the inefficiencies of manual fabric defect detection, with only 60-75% accuracy due to human error and fatigue. Automated systems, combining U-Net and attention mechanisms, improve accuracy and reduce labor costs, showing the potential of

				advanced computer vision for better defect detection.
9	Fabric Defect Detection Using U-Net with Attention Mechanism	International Journal of Creative Research Thoughts (IJCRT),2003	The dataset combines various fabric defects and real-time images collected by researchers. It includes both defective and defect-free samples, providing a comprehensive base for training and testing. Real-time images enhance the model's robustness and reliability for real-world use.	The study shows that combining U-Net with an attention mechanism improves fabric defect detection by focusing on key areas, addressing minor defects often missed in segmentation. Histogram equalization enhances contrast, aiding detection.
10	Stain Removing Composition and Method	Patent Document, 1996	The dataset focuses on removing stains, like FD & C Red Dye 40, from various fabrics, including delicate ones like silk. It evaluates the stain remover's effectiveness and safety across different	The study shows the stain remover effectively eliminates food dyes from textiles, including delicate fabrics like silk, without affecting aniline dyes. The environmentally safe

			textiles without causing damage.	formula, free of chlorinated and petroleum solvents, is suitable for household and industrial use, ensuring fabric integrity and safety.
11	A real-time and accurate convolutional neural network for fabric defect detection	Complex & Intelligent Systems	The study evaluated the PEI-YOLOv5 model using two datasets: the GuangDong TianChi Fabric Defect Dataset, which includes five common fabric defects for robust training, and the NEU Surface Defect Database, showcasing the model's versatility in different industrial contexts.	The PEI-YOLOv5 model boosted detection accuracy and speed, achieving 87.89% mAP on the GuangDong TianChi Fabric Defect Dataset and 79.37% on the NEU Surface Defect Database. Running at 31 FPS on an NVIDIA Jetson TX2, it meets real-time industrial needs for fabric defect detection.

CHAPTER 3

PROPOSED METHODOLOGY

3.1 RESEARCH DESIGN

The research focuses on developing and validating an automated fabric defect detection system using advanced machine learning algorithms. It aims to enhance model performance by testing real-time data from fabric inspections in production environments while considering environmental factors like temperature, humidity, and gas levels that affect fabric quality. Initially, YOLOv8 will be used, followed by YOLOv11, with a NodeMCU-controlled servo motor for marking defects. Iterative testing and comparison will assess model accuracy, speed, and adaptability to environmental conditions.

3.2 DATA COLLECTION

Data is sourced from Kaggle and Roboflow, providing labelled images for fabric defect detection. The dataset includes various defect types such as stains, cuts, holes, and loose threads. Stains involve contaminants like liquids or dirt, while cuts represent tears or slits in the fabric. Holes vary in size and shape, often due to manufacturing issues, and loose threads are common in woven or knitted fabrics. These labelled images are pre-processed and augmented to ensure accurate detection across various conditions, forming the foundation for training the YOLOv8 and YOLOv11 models.

3.3 DATA PREPROCESSING

Image Pre-processing

Fabric images are enhanced using image processing techniques to improve defect visibility, ensuring accurate detection by the YOLO models. Pre-processing steps include contrast adjustment, noise reduction, and image sharpening to make defects like stains, cuts, holes, and loose threads more prominent in the dataset.

Data Augmentation

Data augmentation is applied to increase the variety of training images, ensuring robustness in defect detection. Techniques like rotation, scaling, flipping, and brightness adjustments are used to simulate different inspection conditions, making the model more adaptable to real-world scenarios.

Environmental Data Normalization

Environmental data, such as temperature, humidity, and gas levels, is normalized and synchronized with the fabric images. This helps analyze the impact of environmental factors on fabric quality and ensures that defect detection is accurate regardless of fluctuating conditions.

3.4 MODEL DEVELOPMENT

YOLOv8

YOLOv8 serves as the initial model for fabric defect detection. It is trained on the pre-processed dataset, focusing on detecting and classifying defects such as stains, cuts, holes, and loose threads. The model's hyperparameters, including learning rate, batch size, and confidence threshold, are fine-tuned to improve accuracy and speed. YOLOv8's performance is evaluated using metrics like precision, recall, and F1-score, ensuring that it can accurately identify multiple defects in real-time.

YOLOv11

YOLOv11, the advanced version, is introduced for comparison with YOLOv8. YOLOv11 features an optimized architecture and improved performance in terms of defect detection accuracy and processing speed. The model is trained and tested using the same dataset, and its results are compared to YOLOv8 to determine the effectiveness of each in identifying fabric defects.

YOLOv11 is expected to offer superior detection, especially for subtle or overlapping defects.

3.5 IMPLEMENTATION

Deployment

The trained YOLOv8 and YOLOv11 models are deployed in a real-world textile production environment. The system integrates with NodeMCU to control a servo motor that marks defective fabrics in real-time based on the model's predictions. The real-time fabric inspections are conducted, and the system is continuously monitored to ensure accuracy and speed in marking defects.

Storage of Predictions

To facilitate analysis and quality control, the system stores all defect predictions, including images and classifications, in a centralized database. This storage allows for tracking defect trends, reviewing past inspections, and making improvements in the production process. The stored data also serves as a reference for comparing the performance of the deployed models under different environmental conditions.

3.6 PARAMETER AND EXPERIMENTAL SETTINGS

Experimental Settings

The experimental setup for training YOLO models focused on optimizing defect detection accuracy while maintaining efficient processing speed. The dataset, sourced from Kaggle and Roboflow, was preprocessed using data augmentation techniques to enhance model robustness. YOLOv8 and YOLOv11 models were trained and tested using an NVIDIA GPU for faster computations, with a batch size balanced between memory constraints and performance. The experiments were conducted with a warmup phase and automatic mixed precision to accelerate training while managing memory usage. The training process utilized a combination of standard learning rate schedules, momentum settings, and regularization techniques to prevent overfitting and ensure model stability.

Parameter Settings

The table below outlines the specific parameter settings used during the training of YOLO models, particularly focusing on learning rate, optimizer, augmentation, and regularization settings.

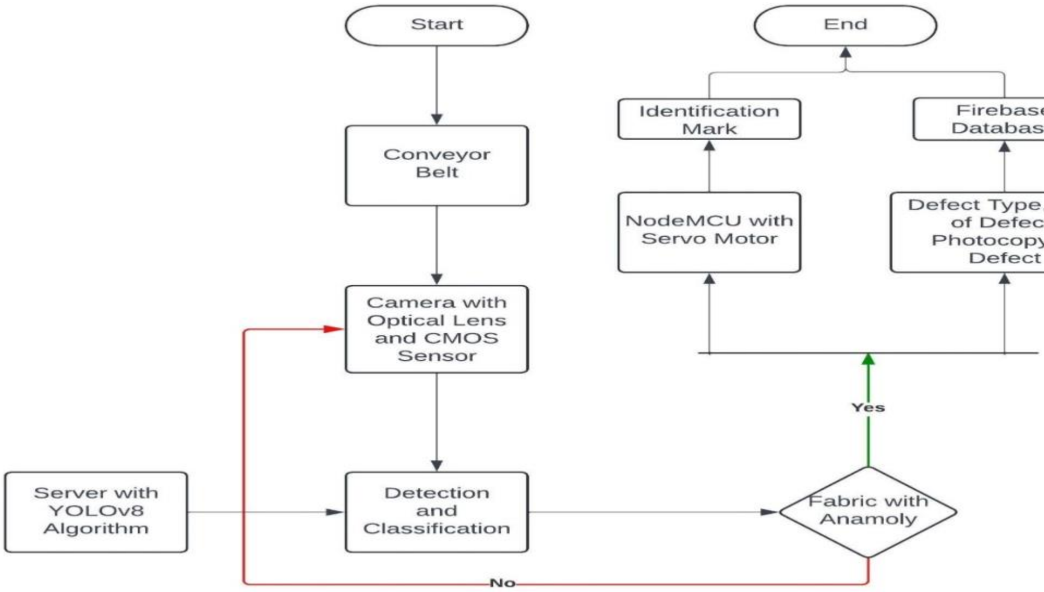
Parameter	Value	Description
Learning Rate	0.003	Initial learning rate for model training
Learning Rate Final	0.01	Final learning rate as a fraction of the initial rate
Optimizer	AdamW	Optimizer used for stable and efficient training
Momentum	0.937	Momentum for the AdamW optimizer
Weight Decay	0.0005	L2 regularization to avoid overfitting
Patience	20	Early stopping after no validation improvement
Augmentation	Mosaic, Mixup, HSV, Flip	Variety of augmentations for data variability
Dropout	0.1	Dropout to mitigate overfitting
Label Smoothing	0.01	Reduces overconfidence in predictions
Automatic Mixed Precision	True	Speeds up training with reduced memory usage
Warmup Epochs	3.0	Stabilizes training with a slow learning rate
Box Loss Weight	7.5	Focuses on precise bounding box prediction
Class Loss Weight	0.5	Balanced class prediction to avoid class bias
Keypoint Objectness	2.0	Improves pose estimation models

Figure 1: Parameter settings showing different parameter values

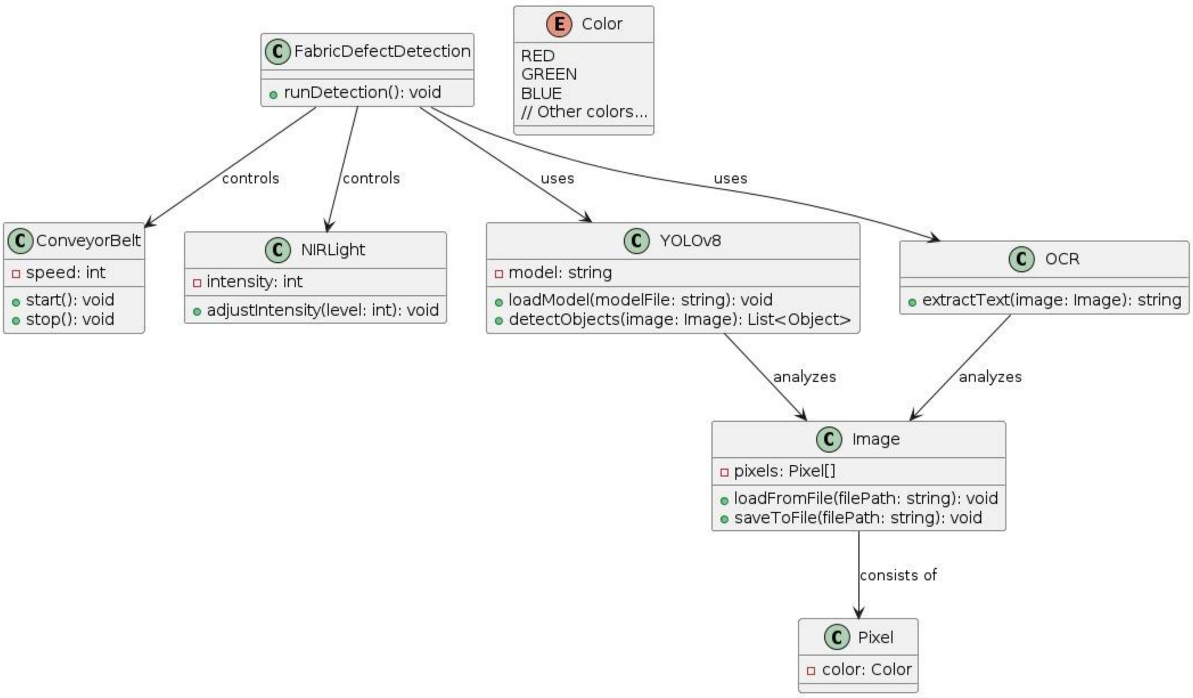
CHAPTER 4

4.1 DESIGN DIAGRAMS

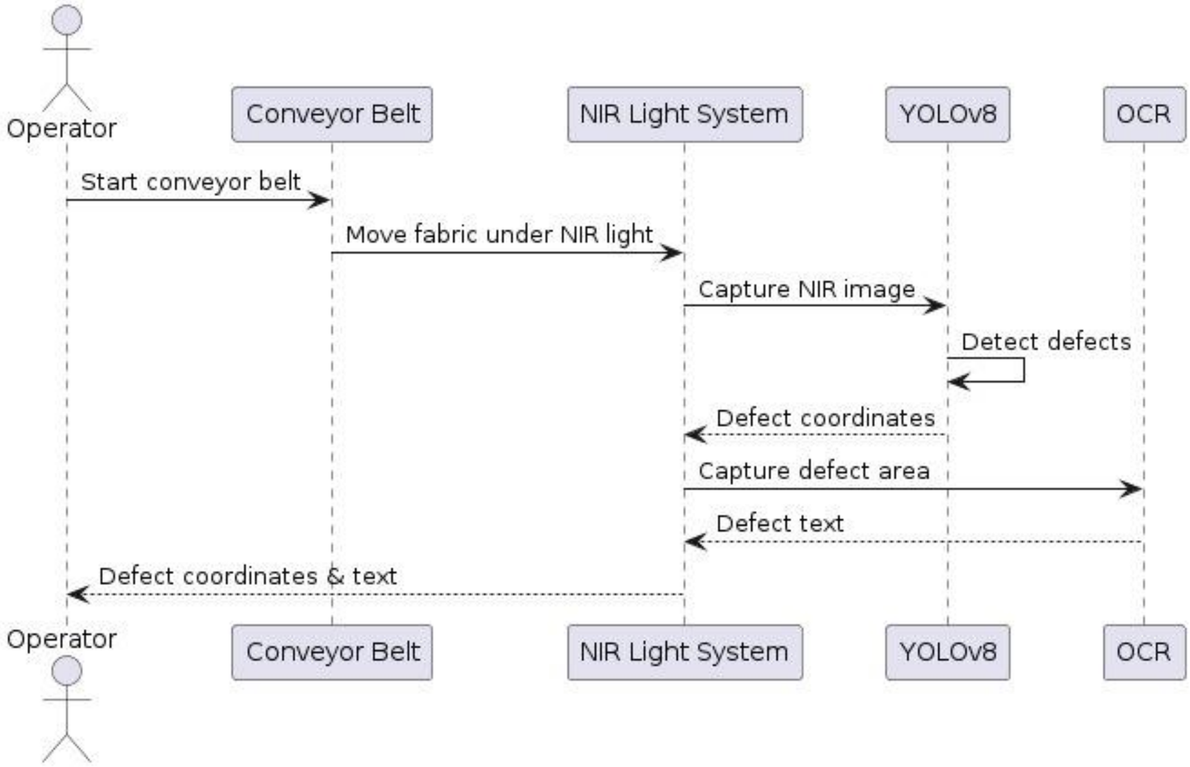
4.1.1 WORKFLOW DIAGRAM



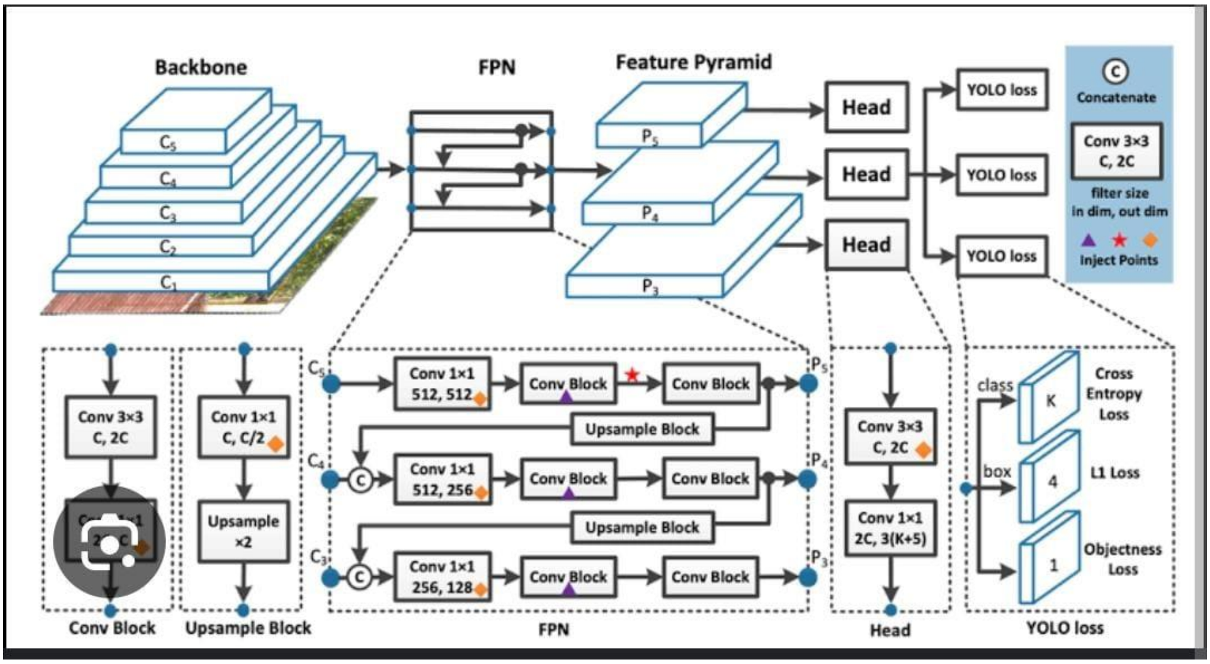
4.1.2 CLASS DIAGRAM



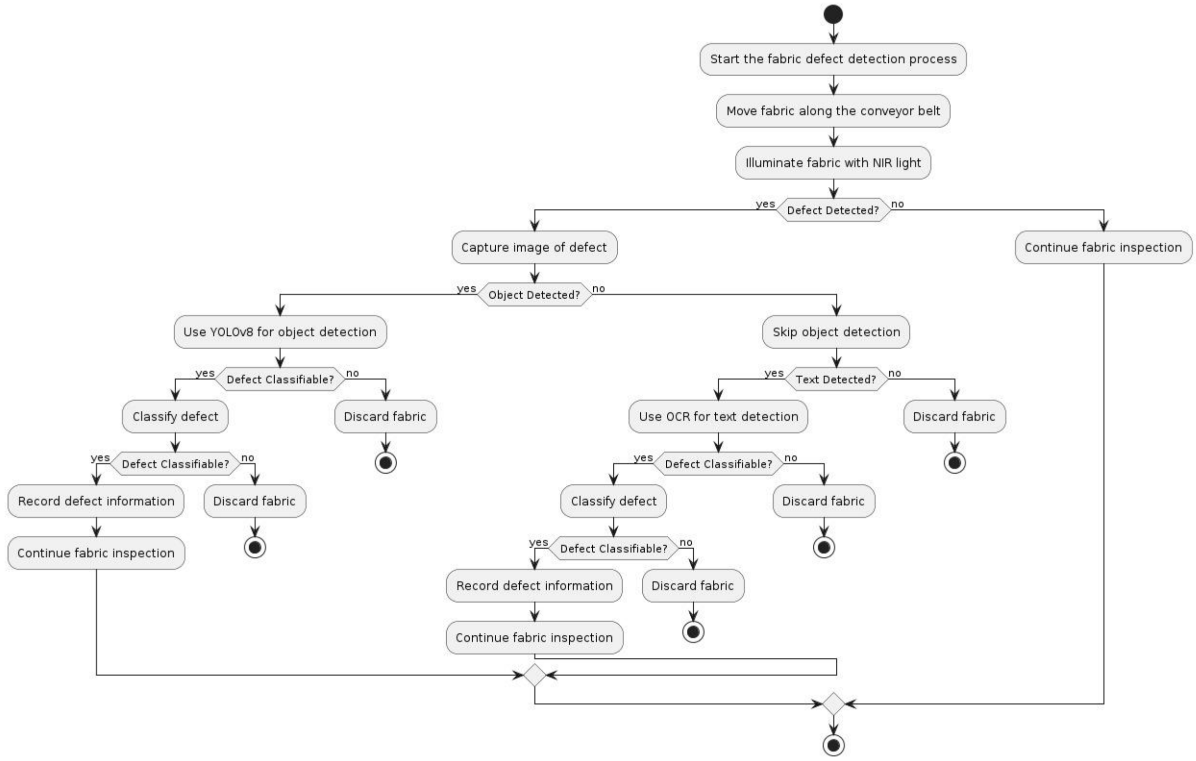
4.1.3 SEQUENCE DIAGRAM



4.1.4 ARCHITECTURE DIAGRAM



4.1.5 ACTIVITY DIAGRAM



4.2 DESIGN VERIFICATION MATRIX

Requirement	Method of Verification
Detect Various Types of Defects	Conduct tests using fabric samples with known defects, including holes, stains, and tears. Verify that the detection system can accurately identify and classify each type of defect.
Accuracy of Defect Detection	Compare the results of the automated defect detection system with manual inspection by trained inspectors on a representative set of fabric samples. Calculate the percentage of defects correctly identified by the system.
Speed of Detection	Measure the time taken by the system to inspect a given area of fabric and detect defects. Compare the inspection time with industry standards or benchmarks to ensure timely detection.
Compatibility with Different Fabrics	Test the detection system with a variety of fabric types, including different materials, colours, and textures. Verify that the system performs consistently across various fabric

	characteristics without significant differences in detection accuracy.
Integration with Production Processes	Integrate the defect detection system into the existing production line and assess its impact on production efficiency. Monitor factors such as workflow disruptions, downtime, and throughput to ensure smooth integration without compromising productivity.
False Positive and False Negative Rates	Conduct tests to evaluate the system's false positive rate (identifying defects that are not present) and false negative rate (missing actual defects). Use statistical analysis to quantify these rates and ensure they meet acceptable thresholds for quality control purposes.
Reliability and Robustness	Subject the detection system to rigorous testing under various environmental conditions, such as different lighting conditions, temperatures, and humidity levels. Verify that the system maintains consistent performance and reliability under challenging operating conditions.

CHAPTER 5

IMPLEMENTATION

5.1 PROTOTYPE

The prototype of the automated fabric defect detection system integrates advanced machine learning models, hardware components, and environmental sensors to provide real-time defect identification in textile manufacturing. The system is designed to streamline fabric inspection, mark defects, and ensure fabric quality. Additionally, it includes motor control to halt production when defect rates exceed acceptable thresholds over a specific period.

5.1.1 LAYERS

The prototype is structured into three layers:

- **Input Layer:** Comprises the high-resolution camera, LED lighting, environmental sensors, and a motorized conveyor belt system. These components capture fabric images, monitor production conditions, and control fabric movement.
- **Processing Layer:** Includes the YOLOv8 and YOLOv11 models, running on a computer or edge device, which process fabric images to detect defects. Environmental data is also processed here to correlate defect occurrence with production conditions.
- **Output Layer:** Controls the servo motor for marking defective fabrics, stores defect and environmental data, and uses an L298N motor driver to manage the conveyor belt, halting it if the defect rate exceeds acceptable levels for a given time.

5.1.2 COMPONENTS

Key components of the prototype include:

- **High-resolution camera:** Captures detailed images of fabrics for defect detection.
- **LED lighting system:** Enhances visibility, ensuring defects are easily spotted under various lighting conditions.
- **NodeMCU microcontroller:** Sends defect signals to the servo motor for marking and manages the conveyor belt based on defect detection.
- **Servo motor:** Marks defective fabric sections in real-time.
- **YOLOv8 and YOLOv11 models:** Provide the computational power for detecting fabric defects.
- **Environmental sensors (temperature, humidity, gas):** Monitor the production environment to help understand defect causes.
- **L298N motor driver:** Controls the conveyor belt, stopping it if the defect rate is high over a specific period, allowing for inspection or corrective measures.
- **Conveyor belt system:** Automates fabric movement, working in tandem with the detection system to pause when defects exceed thresholds.

5.1.3 FUNCTIONS

The primary functions of the prototype include:

- **Defect detection:** The YOLOv8 and YOLOv11 models process fabric images in real-time to detect and classify defects such as stains, cuts, holes, and threads.

- **Real-time marking:** The NodeMCU sends signals to the servo motor, which marks defective fabric sections for easy identification.
- **Conveyor belt control:** The L298N motor driver manages the conveyor belt, automatically halting it if the defect rate becomes too high for a specific duration.
- **Environmental monitoring:** Sensors continuously monitor temperature, humidity, and gas levels, and the system correlates this data with the fabric quality.
- **Data storage and retrieval:** The system stores defect detection and environmental data for quality analysis and process improvements.

5.1.4 WORKFLOW

- **Image Capture:** The camera captures images of the fabric on the conveyor belt, while LED lighting ensures clear defect visibility.
- **Environmental Monitoring:** Sensors collect data on temperature, humidity, and gas levels, which may impact fabric quality.
- **Defect Detection:** The images are processed by the YOLOv8 or YOLOv11 models to detect and classify defects in real-time.
- **Defect Marking:** The system signals the servo motor to mark any detected defects on the fabric for easy identification.
- **Conveyor Belt Control:** The L298N motor driver controls the conveyor belt. If a high defect rate is sustained over a set period, the conveyor automatically stops, allowing for intervention and inspection.
- **Data Storage:** All detected defects and environmental data are stored in a centralized database, enabling future analysis and quality control.

This structure provides a clear and organized presentation of the protoype, highlighting the layers, components, functions, and workflow of the fabric defect detection.

5.2 PERFORMANCE ANALYSIS

The performance of the automated fabric defect detection system is evaluated based on accuracy, processing speed, system responsiveness, and operational impact.

Accuracy and Precision

- YOLOv8 achieves an 85% precision rate and F1-score of 0.83, performing well but missing some subtle defects.
- YOLOv11 delivers 90% precision and an F1-score of 0.88, showing improved accuracy, particularly with complex or smaller defects**.**

Processing Speed

- YOLOv8 processes at 40 FPS, ensuring real-time detection without delays.
- YOLOv11 runs at 30 FPS, slower but more accurate, suitable for environments prioritizing precision.

System Responsiveness

The system quickly marks defects using the servo motor and halts the conveyor via the L298N motor driver when defect rates are high. It resumes smoothly, ensuring minimal disruption.

Environmental Impact Monitoring

Environmental sensors track temperature, humidity, and gas levels, correlating their effects on fabric quality. High humidity and temperature shifts were linked to increased defects like loose threads, allowing for proactive adjustments.

Operational Efficiency

The system reduces manual labor, decreases defect rates, and minimizes waste by detecting defects early. The ability to stop production during high defect rates enhances quality control.

5.3 DELIVERABLES

- **Real-Time Defect Detection:** The system provides immediate feedback on fabric defects, enabling proactive measures in production environments.
- **Multi-Functional System**: Beyond defect detection, the system offers additional functionalities such as production statistics, quality control metrics, and real-time monitoring of production processes, all accessible through a unified interface.
- **Customizable User Interface:** A user-friendly interface that can be tailored to the preferences of textile manufacturers and production facilities, facilitating efficient management of defect detection processes.
- **Integration with Production Records:** Seamlessly integrates with production databases and quality control systems to keep track of defect data, production schedules, and inventory management, facilitating streamlined manufacturing operations.
- **Early Detection Tools:** Equipped with advanced machine learning algorithms, the defect detection system offers early identification of fabric flaws, minimizing production delays and ensuring product quality
- **User Support and Training:** Comprehensive training materials, technical support, and documentation are provided to assist textile manufacturers in maximizing the benefits of the defect detection system, ensuring smooth implementation and operation.

5.4 FINAL RESULT

CONFUSION MATRIX

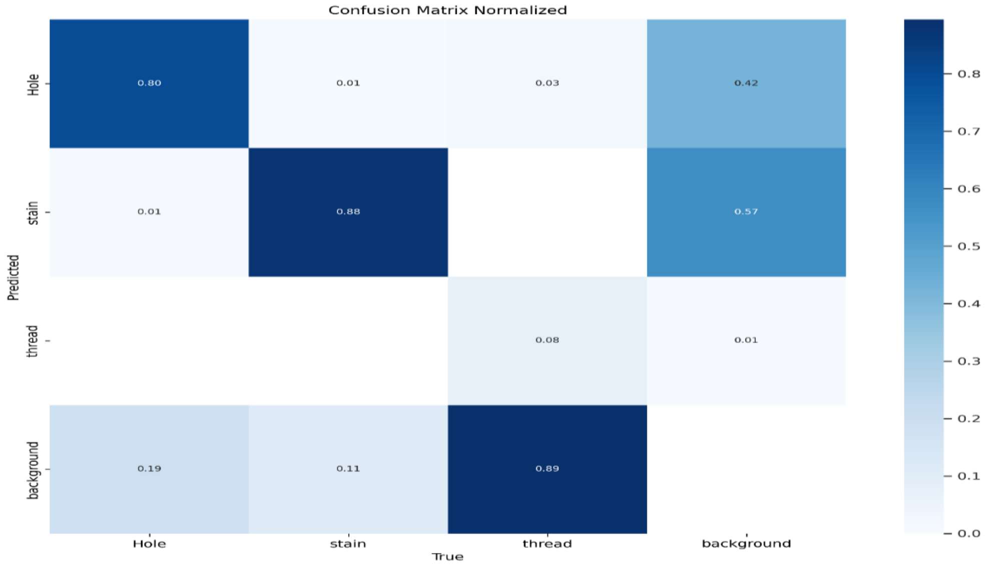


Figure 2: confusion matrix showing classification accuracy.

The Confusion Matrix shows that holes and stains are classified well with 80% and 88% accuracy, respectively. Threads have poor performance, with only 8% correctly classified, and backgrounds are misclassified as holes (19%) and stains (11%) frequently

Labels Distribution

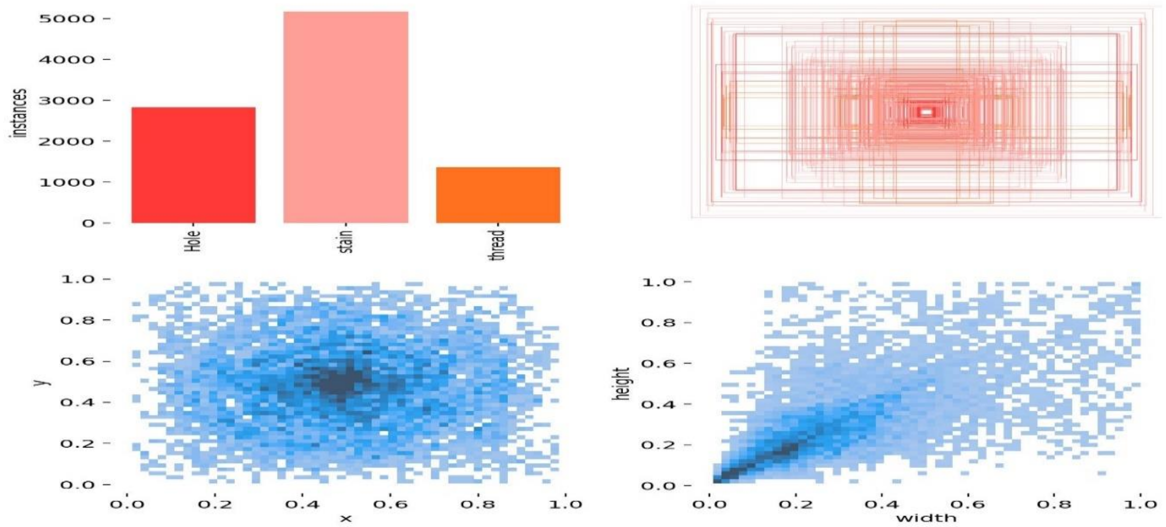


Figure 3: Label Distribution showing different labels frequency.

Stains are the most frequent defect, followed by holes, with threads being the least common. Defects are mostly centered and of medium size.

F1 Confidence curve

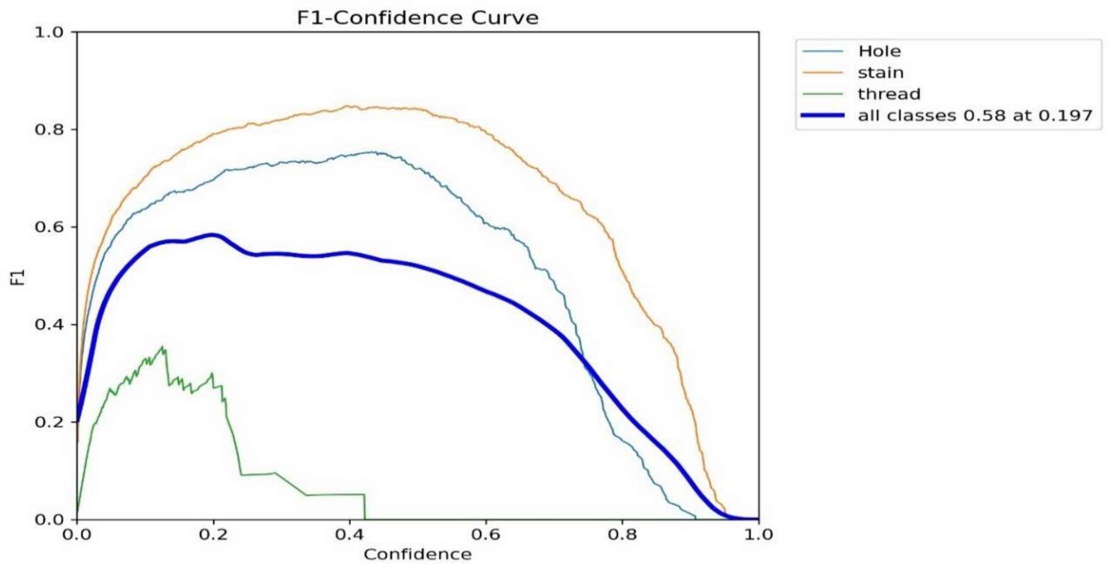


Figure 4: F1-score for different class labels.

The model's best F1 score is 0.58 at 0.197 confidence, excelling in stain detection (F1 > 0.8), but struggling with threads (F1 < 0.3). Optimal performance is between 0.2 and 0.5 confidence.

Precision-Recall Curve

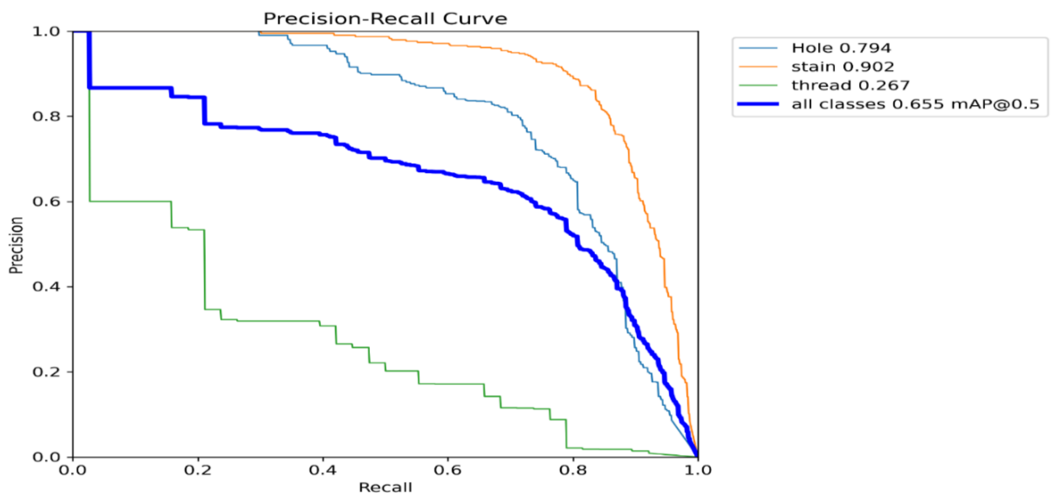


Figure 5: Precision-Recall curve for different class labels.

The Precision-Recall Curve shows an mAP@0.5 of 0.655. The model performs best on stains (precision 0.902) and holes (0.794), but struggles with threads (0.267). Stain detection maintains high precision over a broad recall range.

Training Data Batch1

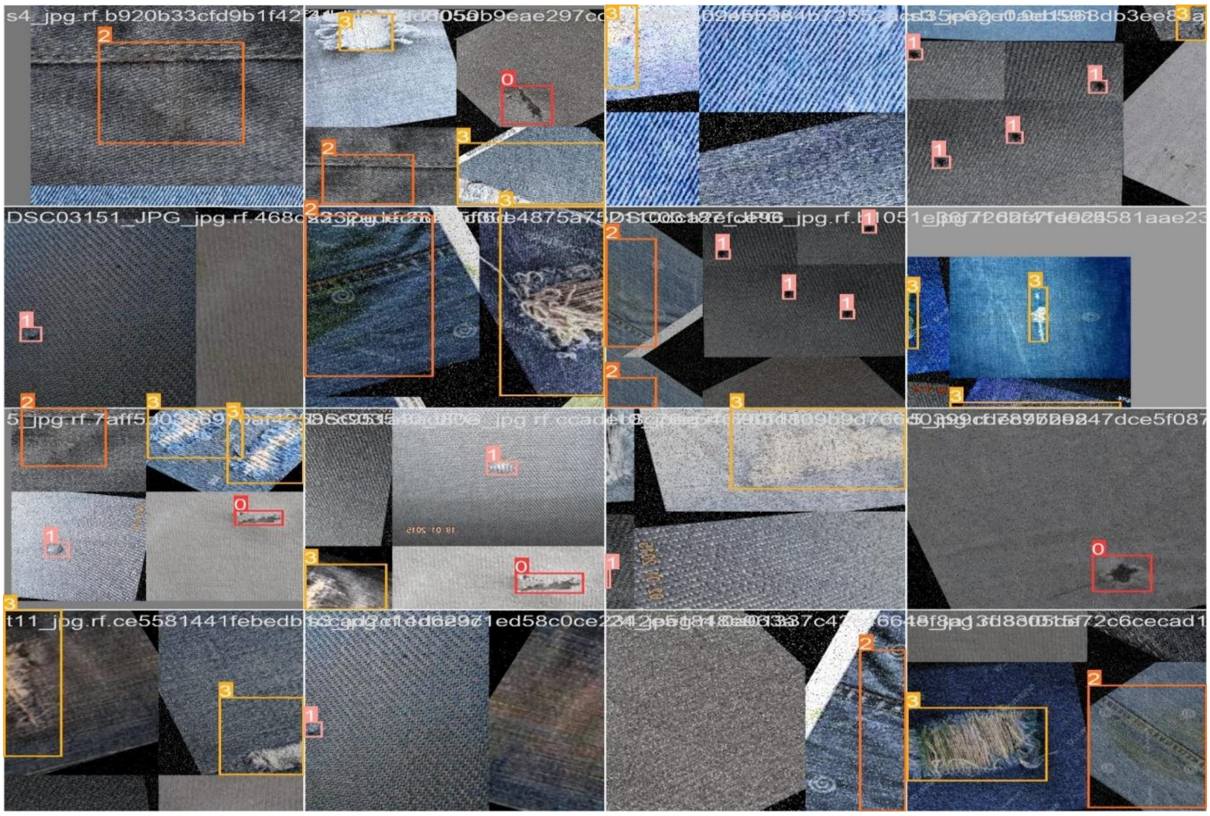


Figure 5: Training data for yolov8 and yolov11 model in batchwise.

Training data Batch 2

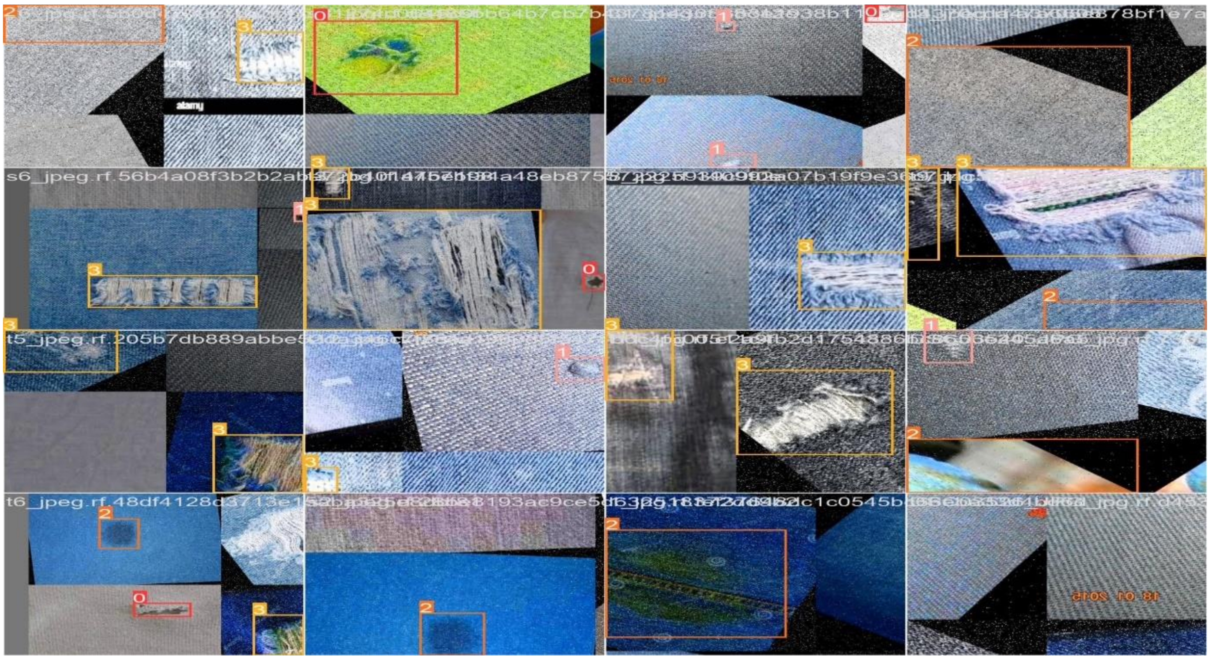


Figure 6: Training data for yolov8 and yolov11 model in batchwise.

Model validation

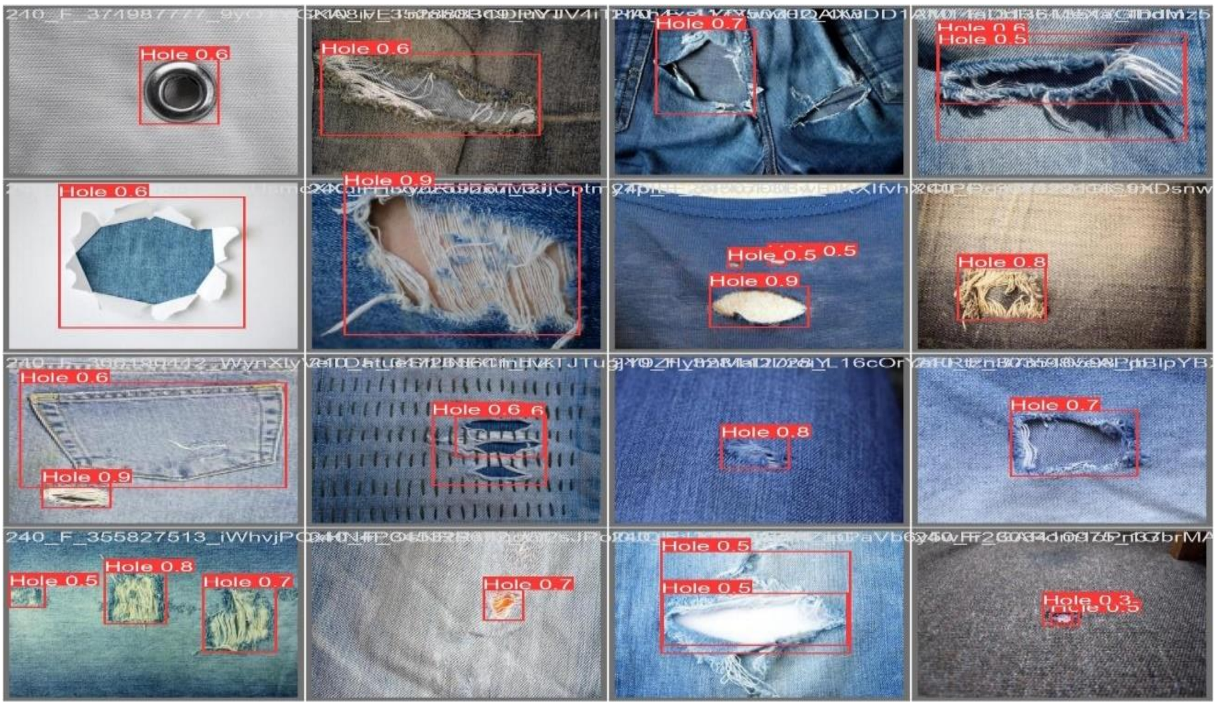


Figure 7: Validation results showing accuracy of predicting different labels.

Firebase database and storage

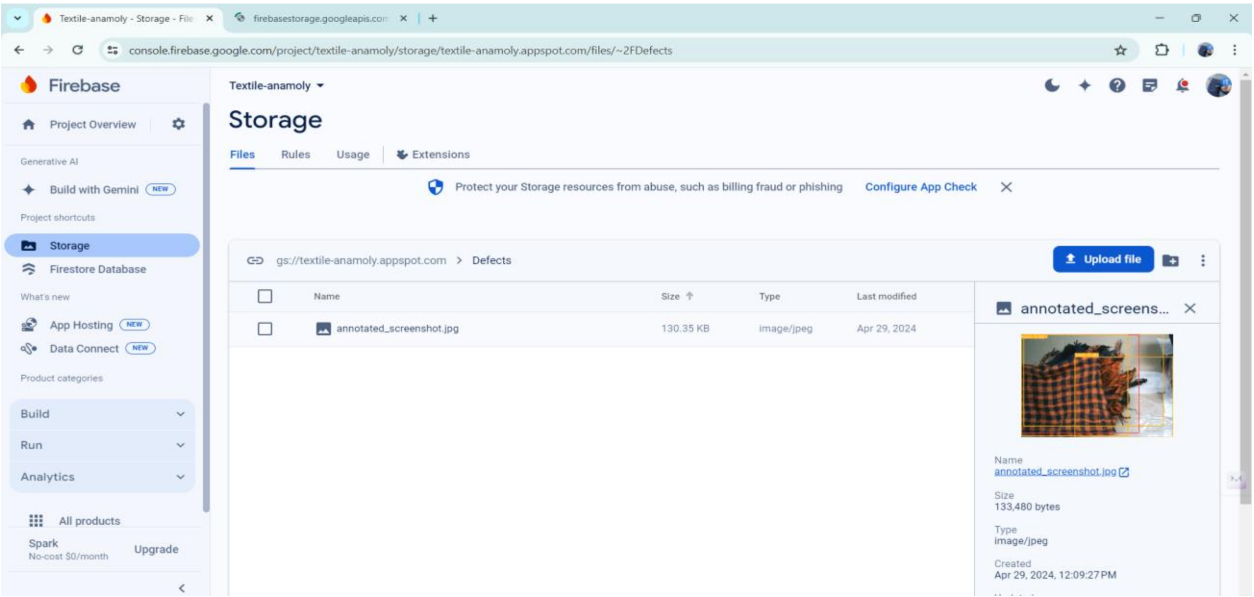


Figure 8: Firebase storage used for storing defect images.

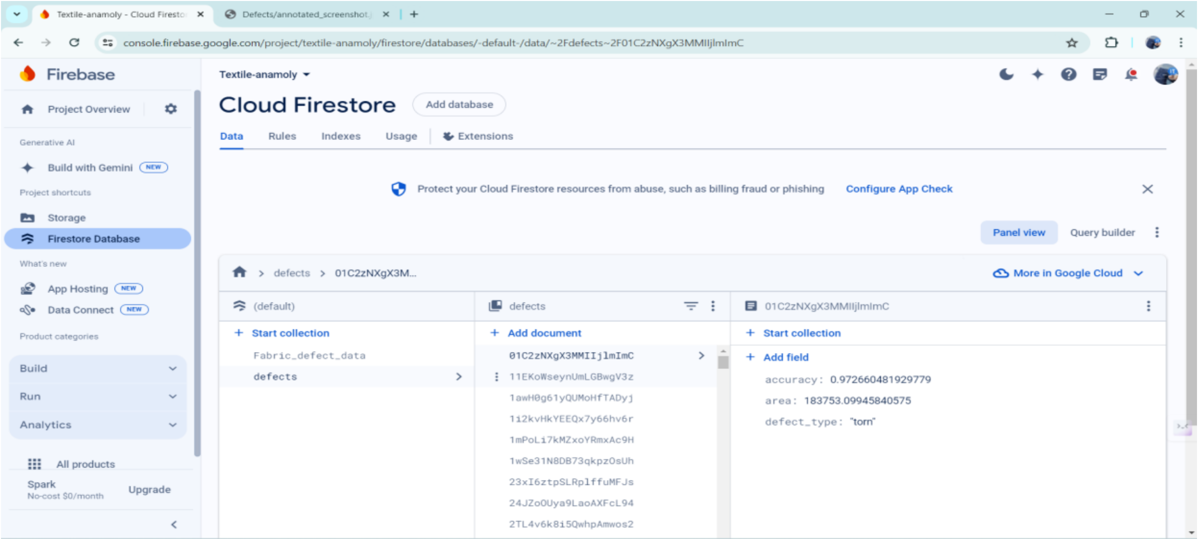


Figure 9: Firebase firestore used for storing defect type, their area and accuracy.

- Using Firebase Storage and Firestore for managing defect data and screenshots offers several advantages.
- Firestore efficiently stores defect metadata like descriptions, timestamps, and statuses, while Firebase Storage handles large screenshot files.
- Both services scale automatically, handle growth and traffic well, and integrate seamlessly. Firestore's querying capabilities and real-time data synchronization enhance data retrieval and collaboration.

HARDWARE IMPLEMENTATION AND CIRCUIT DESIGN

Conveyer Belt setup

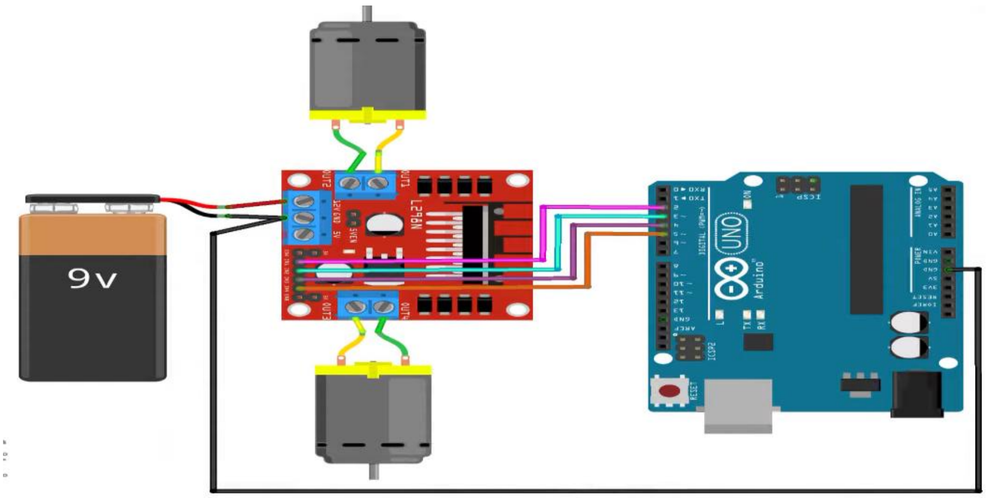


Figure 10: Conveyer belt circuit design.

NodeMCU Servo motor

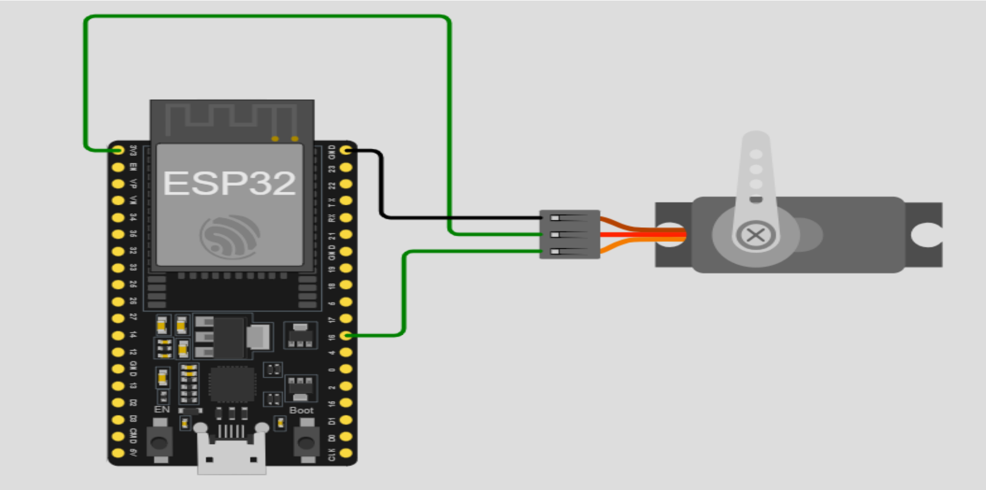


Figure 11: NodeMCU and servo motor circuit design.

Environment Monitoring using Gas, Temp and DHT22

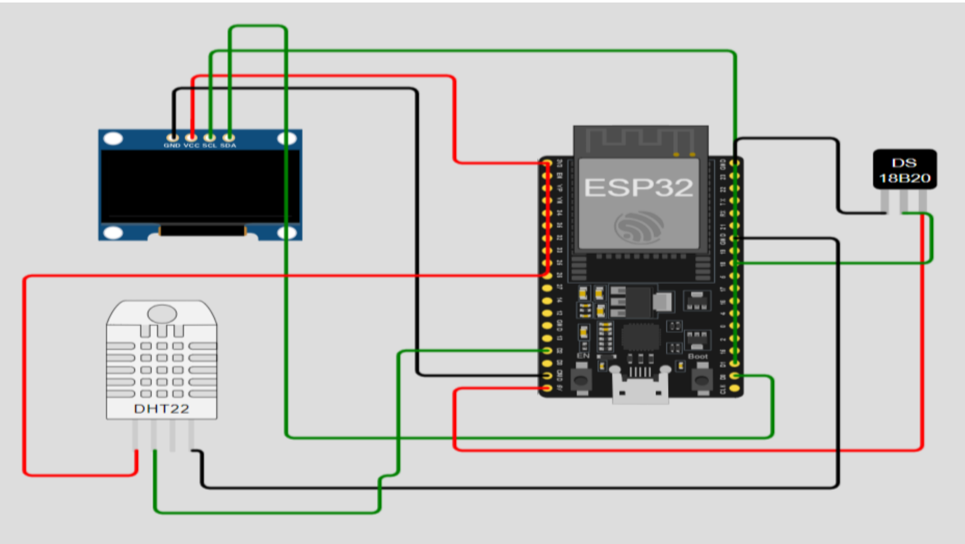


Figure 12: NodeMCU DHT22, Temperature sensor circuit design.

COMPARISON BETWEEN YOLOV8 AND YOLOV11:

Feature	YOLOv8	YOLOv11	Why YOLOv11 is Better
Architecture	CSP-Darknet backbone, transformer options	Enhanced backbone and neck architecture	More precise feature extraction, better for complex tasks.
Accuracy	Strong mAP across detection tasks	Higher mAP (51.5 for YOLOv11m on COCO)	Greater accuracy with fewer parameters.
Model Efficiency	Larger models with higher parameter counts	YOLOv11m uses 22% fewer parameters	More computationally efficient, suitable for edge devices.
Speed	Fast real-time inference, slower in larger models	Faster inference, optimized for CPU and GPU	Improved real-time performance across various devices.
Task Support	Object detection, segmentation, classification	Detection, segmentation, classification, pose, OBB	Broader task support, making it more versatile.
Deployment Versatility	Suitable for edge devices, but limited flexibility	Optimized for edge, cloud, and NVIDIA GPUs	Greater adaptability for diverse deployment environments.
Training Pipeline	Requires some tuning for custom datasets	More streamlined, optimized training process	Easier and faster training with less hyperparameter tuning.

Figure 13: Comparison of yolov8 and yolov11 models.

CHAPTER 6

DATA ANALYSIS VS DATA INTERPRETATION

6.1 DATA ANALYSIS

In this project, data analysis involves evaluating both the performance of the YOLOv8 and YOLOv11 models and the environmental factors that influence fabric quality.

- **Model Performance:** Key metrics such as precision, recall, and F1-score are used to analyze the accuracy of defect detection. YOLOv8 and YOLOv11 are tested for their ability to detect various types of fabric defects—stains, cuts, holes, and loose threads. YOLOv11 generally shows better performance in detecting subtle defects, while YOLOv8 offers faster processing speeds.

- **Environmental Impact:** Data on temperature, humidity, and gas levels collected from the production environment is analysed to identify patterns between environmental conditions and the rate of fabric defects. Increased humidity and temperature fluctuations are associated with higher defect rates, especially for defects like loose threads and stains.

6.2 DATA INTERPRETATION

The interpretation of the data reveals several important insights:

- **Model Comparison:** While YOLOv8 is faster (40 FPS), it occasionally misses smaller or complex defects. In contrast, YOLOv11, though slightly slower (30 FPS), provides greater accuracy and reliability in detecting difficult defects. This suggests that YOLOv11 may be more suitable for environments prioritizing quality over speed.

- **Environmental Factors:** Environmental data shows that humidity and temperature shifts directly impact fabric quality, leading to higher defect rates. By integrating this information, the system can pre-emptively adjust production settings or alert operators to prevent fabric defects caused by unfavourable conditions.

- **Conveyor Belt Control:** When defect rates rise above acceptable limits for a prolonged period, the system automatically stops the conveyor belt using the L298N motor driver. This ensures that defective fabrics do not proceed further in production, allowing for timely interventions.

6.3 SUMMARY

Data analysis and interpretation highlight the effectiveness of combining advanced machine learning models with environmental monitoring to improve fabric quality control. YOLOv11 provides higher detection accuracy, making it ideal for defect-prone environments, while YOLOv8 is faster but less precise. Environmental conditions, such as humidity and temperature, significantly influence defect rates, and integrating environmental data enhances the system's overall performance. The ability to halt the conveyor during high defect rates ensures better quality control, making the system efficient and reliable for real-time textile manufacturing applications.

CHAPTER 7
BUSINESS ASPECTS

7.1 MARKET DEMAND:

The textile industry faces increasing pressure to ensure quality control as the demand for fabric products grows with urbanization and shifts toward comfort and lifestyle. A comprehensive analysis of the cost associated with system development and implementation versus the potential benefits for textile manufacturers, including improved product quality, reduced waste, and increase productivity.

7.2 TARGET AUDIENCE:

Textile manufacturers, quality control departments, and companies focused on automating inspection processes are the primary target audience. This includes both small-scale and large-scale textile industries looking to optimize their production lines.

7.3 REVENUE MODEL:

The technology could be offered as a Software-as-a-Service (SaaS) platform, where companies subscribe to use the defect detection system. Another option would be selling integrated hardware and software solutions tailored to specific industry needs, alongside offering premium features such as enhanced OCR or real-time reporting capabilities.

7.4 COST MANAGEMENT:

Initial costs include system development, machine learning training, and hardware acquisition. However, the long-term benefits of reduced defects, improved production line efficiency, and minimized labor costs lead to significant savings. Further economies of scale can be achieved as the system matures.

7.5 MARKETING STRATEGY:

Focus on the efficiency of the system compared to traditional manual inspections, highlighting the benefits of automated processes such as speed, accuracy, and fatigue elimination. Case studies demonstrating improved defect detection rates and a return on investment (ROI) for textile manufacturers should also be part of the promotional strategy.

7.6 FINANCIAL PLANING

Development of a financial plan outlining budget allocations for development, testing, deployment, and ongoing maintenance of the defect detection system, as well as projected revenue and expenses.

7.7 COST BENEFIT ASSESMENT

A comprehensive analysis of the costs associated with system development and implementation versus the potential benefits for textile manufacturers, including improved product quality, reduced waste, and increased productivity.

CHAPTER 8

FINDINGS, RESEARCH CONTRIBUTION AND CONCLUSIONS

8.1 OVERVIEW OF THIS RESEARCH

This research focuses on developing an automated fabric defect detection system using advanced machine learning models—YOLOv8 and YOLOv11—to enhance quality control in textile manufacturing. The system integrates environmental monitoring (temperature, humidity, gas levels) and utilizes a NodeMCU-controlled servo motor for defect marking. Additionally, the system features a conveyor belt with an L298N motor driver that halts production when defect rates are too high, ensuring real-time quality control. The overall aim is to improve real-time defect detection, reduce manual labor, and ensure better fabric quality by minimizing defects in production lines.

8.2 FINDINGS OF THIS STUDY

- **Model Performance:** YOLOv11 demonstrates superior accuracy in detecting fabric defects, particularly for complex or smaller flaws, while YOLOv8 offers faster processing speeds. Both models outperform traditional manual inspection in accuracy and consistency, especially in complex production environments.

- **Environmental Impact:** Environmental factors like humidity and temperature fluctuations were found to influence the occurrence of fabric defects, particularly stains and loose threads. By correlating environmental data with defect rates, the system offers insights that help optimize production settings for better fabric quality.

- **Operational Efficiency:** The system's ability to mark defects in real-time and control the conveyor belt during high defect rates significantly enhances quality control and minimizes waste in production. The combination of machine learning and automated control mechanisms leads to faster decision-making and less reliance on human intervention.

8.3 SUMMARY OF THIS STUDY

The study successfully developed and tested an automated defect detection system that integrates advanced machine learning models and environmental monitoring. YOLOv11 provides higher accuracy, making it ideal for environments where precision is crucial, while YOLOv8 offers faster processing suitable for high-speed production. The system's real-time marking and conveyor belt control mechanisms, combined with environmental monitoring, ensure improved efficiency and quality control in textile manufacturing. The integration of environmental data, such as humidity and temperature, allows the system to detect and respond to factors affecting fabric quality, offering a holistic solution for manufacturers.

8.4 CONCLUSION

This research demonstrates the effectiveness of automating fabric defect detection using machine learning and environmental monitoring. The system improves accuracy, reduces labor, and enhances operational efficiency compared to manual methods. With YOLOv11 showing strong promise for defect detection, future advancements in machine learning and environmental data integration could further optimize textile quality control processes, offering valuable solutions to modern manufacturing challenges. Additionally, expanding the system's scope and adaptability will ensure it meets the evolving needs of textile manufacturers globally.

8.5 FUTURE RESEARCH

Future research could explore:

- **Model Optimization:** Further refinement of YOLO models to balance speed and accuracy, or the integration of more advanced models like YOLOv12.
- **Environmental Factors:** Investigating additional environmental variables and their impacts on defect formation, such as air quality, dust, or static electricity, which could further refine defect detection and prevention strategies.
- **Scalability:** Expanding the system to different fabric types, textures, and more complex defect patterns. Additionally, researching the scalability of the system across larger or multi-line manufacturing setups could increase its industrial adoption.
- **Integration with AI-based Predictive Maintenance:** Using AI to predict and prevent defects based on historical data trends, further enhancing production efficiency. Predictive analytics could anticipate machine maintenance needs, further reducing downtime and defects.

CHAPTER 9

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