CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

Fabric defect detection is an essential part of textile manufacturing, ensuring that high-quality products reach the consumer while minimizing production waste. Traditional manual inspection techniques rely on human inspectors to identify defects such as weaving faults, stains, holes, and pattern mismatches. However, these methods are prone to errors due to fatigue, subjective judgment, and inefficiency in large-scale production environments.

In response to the challenges faced by traditional quality control methods, our project, DEFECT DETECT, introduces an AI-powered solution that is both revolutionary and highly efficient. By harnessing the capabilities of Vision Transformers (ViT), a cutting-edge deep learning architecture, our system is designed to elevate the accuracy and reliability of defect detection in fabrics. The core idea here is to move beyond the limitations of human inspection —where defects might be too subtle to see—and instead utilize AI to deliver a level of precision that manual methods simply can't match.

One of the key advantages of our AI-based approach is its high precision. With the power of deep learning, the system can recognize minute defects that might not even be visible to the naked eye, ensuring that even the smallest imperfections do not go unnoticed. This precision is coupled with the benefit of automation, which drastically reduces the need for manual labor. Not only does this lead to consistent quality control, but it also frees up human resources for more strategic tasks.

Beyond precision and automation, our system is designed with scalability in mind. It can be deployed across factories with high-speed manufacturing lines, adapting seamlessly to increased production demands without compromising on accuracy. This scalability is further enhanced by the system's cost efficiency, as early and accurate detection of defects translates directly into reduced financial losses from faulty products.

Another standout feature is real-time processing. The solution identifies defects the moment they occur, which not only minimizes production delays but also allows for immediate corrective actions. Additionally, the system's adaptability means it can be effectively applied across various textiles and defect types, ensuring a versatile approach that meets the diverse needs of modern manufacturing.

Ultimately, DEFECT DETECT bridges the gap between traditional textile quality control and modern, AI-driven automation. By integrating advanced deep learning techniques into the production process, our project is set to transform the manufacturing sector, revolutionizing quality control with enhanced efficiency, reduced waste, and consistently superior outcomes.

1.2 OBJECTIVE

The primary objective of the DEFECT project is to develop an automated AI-powered defect detection system that enhances fabric quality assurance. Specific objectives include:

1. Developing an Advanced AI Model: Implementing a deep learning-based Vision Transformer (Vit) model capable of detecting fabric defects with high precision and efficiency.
2. Training the AI Model on a Diverse Dataset: Using a comprehensive dataset with images of various fabric defects, ensuring the model learns different types of flaws, including holes, stains, misprints, and irregular textures.
3. Enhancing Real-Time Defect Detection: Designing a real-time monitoring system that detects and classifies defects instantly, helping manufacturers take immediate corrective actions.
4. Reducing Dependence on Manual Inspection: Automating defect detection to minimize human errors, reduce labour costs, and ensure consistent quality control.
5. Seamless Integration with Manufacturing Workflows: Ensuring the AI system integrates with existing textile production lines, working in sync with cameras and sensors to streamline defect identification.
6. Improving Computational Efficiency: Optimizing the processing time and power consumption of the AI model, enabling its deployment in edge computing environments where low-latency processing is required.
7. Enhancing Classification Accuracy: Implementing advanced feature extraction techniques to minimize false positives and false negatives, ensuring high reliability in defect detection.
8. Scalability for Industrial Applications: Designing the system to be scalable and adaptable, allowing manufacturers from various industries (textile, leather, paper, plastic, etc.) to use the solution effectively.
9. Developing a User-Friendly Dashboard: Creating an interactive and intuitive interface where users can view real-time analytics, defect reports, and production insights.
10. Cloud-Based Monitoring & Predictive Maintenance: Implementing a cloud-enabled AI model that allows remote monitoring, stores historical defect data, and provides predictive analytics for proactive quality control.

1.3 CHALLENGES IN THE DOMAIN

Bringing AI-powered fabric defect detection into the textile industry comes with its fair share of challenges. For this technology to be truly effective, reliable, and scalable, several key issues need to be addressed.

1.3.1 Data Availability and Quality

For AI models to accurately detect fabric defects, they need to be trained on large, diverse, and high-quality datasets. However, finding such datasets is a major challenge since labelled fabric defect images are not widely available. Additionally, factors like inconsistent lighting, varying camera quality, and differences in fabric textures can make it harder to maintain a reliable dataset.

1.3.2 Computational Complexity

Advanced AI models, especially Vision Transformers (ViT), demand significant computing power. Not all textile manufacturers have access to high-performance GPUs or cloud computing resources needed for deep learning models. Moreover, optimizing these models for real-time defect detection while maintaining accuracy is a tough technical hurdle.

1.3.3 Real-World Deployment and Integration

Many textile factories lack the necessary infrastructure to integrate AI-driven quality control systems seamlessly. Implementing such systems requires investments in hardware like high-resolution cameras and industrial automation equipment. Additionally, some industry stakeholders may be hesitant to adopt new technology due to concerns about cost, training, or changes in workflow.

1.3.4 Generalization and Adaptability

A major challenge for AI models is their ability to adapt to different types of fabrics, textures, and production conditions. In real-world settings, defects can be unpredictable, making it necessary to continuously update and retrain the model. To improve the model's performance across different textile applications, domain adaptation techniques must be explored.

1.3.5 Handling False Positives and False Negatives

AI models must strike the right balance between detecting actual defects and avoiding false alarms. Too many false positives can lead to unnecessary fabric rejections, increasing waste and costs. On the other hand, missing subtle defects can compromise product quality. Fine-tuning the model to maintain an optimal balance between precision and recall is crucial.

1.3.6 Edge Computing vs. Cloud Deployment

AI-powered defect detection systems can be deployed either on the cloud or at the edge (on-site). While cloud-based solutions offer scalability, they also introduce concerns about latency and reliance on stable internet connectivity. Edge computing, which processes data locally, enables real-time detection but requires AI models to be optimized for low-power hardware.

1.3.7 Cost of implementation

The initial cost of setting up an AI-based defect detection system can be high, as it involves purchasing new technology, hardware, and staff training. Small and medium-scale manufacturers may find it challenging to justify this investment without a clear return on investment (ROI). Ensuring that the technology is scalable and cost-effective will be key to encouraging widespread adoption.

1.3.8 Regulatory and Compliance issues

For AI-powered inspections to be accepted in the textile industry, they must comply with established quality control standards and regulations, such as ISO textile standards. Additionally, ethical concerns must be considered, particularly regarding the potential impact on human jobs as automation becomes more prevalent.

By addressing these challenges with optimized AI models, high-quality datasets, efficient computing strategies, and close collaboration with industry stakeholders, the DEFECT project aims to make AI-powered fabric defect detection a practical and scalable solution for textile manufacturers.

1.4 MOTIVATION

The motivation behind this project stems from the increasing need for automation, accuracy, and efficiency in textile manufacturing. Fabric defects not only compromise product quality but also lead to financial losses, increased waste, and customer dissatisfaction. The current quality control methods fail to address these issues effectively, making it essential to develop AI-driven solutions for defect detection. Several key motivations for this project include:

1.4.1 Need for Enhanced Fabric Quality Control

Fabric defects such as weaving faults, holes, stains, and misalignments impact the final product’s usability and market value.Traditional defect detection methods rely on human visual inspections, which are prone to errors, fatigue, and inconsistencies. AI-powered systems can ensure higher accuracy, detect minute defects, and enhance overall fabric quality assurance.

1.4.2 Overcoming Limitations of Manual Inspection

Manual inspections are labour-intensive, time-consuming, and costly, leading to inefficiencies in large-scale production.Human inspectors struggle with fatigue and subjectivity, resulting in inconsistent defect detection.Automated defect detection systems can work continuously without fatigue, providing consistent and reliable results.

1.4.3 Advancements in AI & Vision Transformers

The emergence of deep learning, computer vision, and self-attention mechanisms has improved the ability to analyse fabric textures effectively.Vision Transformers (Vit) outperform traditional Convolutional Neural Networks (CNNs) by capturing global image dependencies, making them ideal for fabric inspection.AI-powered defect detection systems can be trained on large datasets to recognize even the most subtle fabric defects.

1.4.4 Minimizing Production Waste and Financial Losses

Fabric defects lead to rework, scrap materials, and increased production costs.Early defect detection helps manufacturers eliminate defective fabrics before further processing, saving raw materials and reducing operational costs.Improved defect detection enhances supply chain efficiency and reduces unnecessary wastage.

1.4.5 Real-Time Defect Detection for Faster Decision-Making

Traditional inspections often fail to detect defects in real-time, leading to delays in production adjustments.AI-based systems can analyse fabric in real time, allowing manufacturers to make immediate corrections and prevent defective batches from progressing in the production line.Real-time defect detection enhances overall manufacturing efficiency and reduces downtime.

1.4.6 Industry 4.0 & Smart Manufacturing Integration

The shift toward Industry 4.0 emphasizes the need for automated and data-driven manufacturing solutions.AI-powered fabric defect detection aligns with smart factories, enabling IoT-based monitoring, cloud analytics, and predictive maintenance.Implementing AI in quality control ensures seamless integration with existing automated production systems.

1.4.7 Scalability and Multi-Industry Applications

The proposed AI model is scalable, allowing textile manufacturers of all sizes to implement it.Beyond textiles, the system can be adapted for leather, plastic films, metal sheets, and paper manufacturing to detect defects in various materials.

1.4.8 Improving Brand Reputation & Customer Satisfaction

Companies that deliver defect-free, high-quality products build a strong reputation in the market.AI-driven quality control enhances customer trust, ensuring higher satisfaction and reduced product returns.Improved defect detection contributes to compliance with industry standards and regulatory guidelines.By addressing these key concerns, DEFECT aims to revolutionize the textile industry's quality control by leveraging cutting-edge AI technology, real-time monitoring, and smart automation to create a highly efficient, scalable, and intelligent fabric defect detection system.

1.5 ORGANIZATION OF THE REPORT

This report is structured into multiple chapters, each addressing different aspects of the DEFECT project. The organization is as follows:

1.5.1 INTRODUCTION:

This chapter provides an overview of the fabric defect detection problem, the need for automation, and the motivation behind using Vision Transformers (Vit). It also highlights the project objectives and challenges in the domain.

1.5.2 LITERATURE REVIEW:

This chapter explores existing fabric defect detection techniques, including manual inspections, traditional image processing methods, and deep learning approaches. It compares CNN-based models, YOLO-based detection, and Vit in terms of accuracy and efficiency.

1.5.3 SYSTEM DESIGN:

This section presents the architecture of the proposed AI system, detailing the input processing, feature extraction, defect classification, and output generation mechanisms. It includes system diagrams and data flow representations.

1.5.4 IMPLEMENTATION:

This chapter outlines the technology stack, including the programming languages, deep learning frameworks, and database management tools used to develop DEFECT. It also explains the preprocessing techniques, AI model training, and testing methodologies.

1.5.5 EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS:

Here, the report evaluates the performance of the AI model, discussing accuracy, precision, recall, and computational efficiency. It compares manual and AI-based inspections through quantitative results and graphical representations.

1.5.6 SYSTEM DEPLOYMENT AND INTEGRATION:

This chapter describes how the system can be integrated into real-world manufacturing environments, discussing hardware requirements, cloud deployment strategies, and scalability options.

1.5.7 CONCLUSION AND FUTURE ENHANCEMENTS:

The final chapter summarizes the project’s achievements, limitations, and potential improvements. It suggests future research directions for enhancing fabric defect detection using AI.

CHAPTER 2

RELATED WORKS

2.1 LITERATURE REVIEW

Xin Luo, Qing Ni, Ran Tao, And Yoeun Shi presented a Defects on fabric surfaces are difficult to identify owing to unsuitable computing devices, highly complex algorithms, small size, and high degree of integration with the fabric. To this end, this study proposes a lightweight fabric defect-detection network, YOLO-SCD, based on attention mechanism. The introduction of depth-wise separable convolution and the attention mechanism enhanced the capacity of the neck network to extract the defective features and increased the detection speed of the overall network. The extensive experimental results revealed that YOLO-SCD achieved an average accuracy of 82.92%, effective improvement of 8.49% in map, and an improvement of 37 fps compared to the original YOLOv4 on a standard fabric defect dataset. By leveraging its swift detection speed and high efficiency, YOLO-SCD excels in both the general fabric defect category and the-to-detect fabric. Overall, it exhibited strong performance in detecting both minor flaws and flaws with high fabric integration. Furthermore, the proposed model was extended to steel datasets with similar characteristics.

Tomas Almeida, Filipe Moutinho and j. P. Matos-Carvalho presented Quality control is an area of utmost importance for fabric production companies. By not detecting the defects present in the fabrics, companies are at risk of losing money and reputation with a damaged product. In a traditional system, an inspection accuracy of 60-75% is observed. In order to reduce these costs, a fast and automatic defect detection system, which can be complemented with the operator decision, is proposed in this paper. To perform the task of defect detection, a custom Convolutional Neural Network (CNN) was used in this work. To obtain a well-generalized system, in the training process, more than 50 defect types were used. Additionally, as an undetected defect (False Negative - FN) usually has a higher cost to the company than a non-defective fabric being classified as a defective one (false positive), FN reduction methods were used in the proposed system. In testing, when the system was in automatic mode, an average accuracy of 75% was attained; however, if the FN reduction method was applied, with intervention of the operator, an average of 95% accuracy can be achieved. These results demonstrate the ability of the system to detect many different types of defects with good accuracy whilst being faster and computationally

Meifei ding,liming pan,minsmin chi presented the density analysis of woven fabrics is a critical part of quality control in textile production. Traditional image-processing-based methods for density analysis of woven fabrics require complicated manual feature design and lack adaptability to different weaving patterns. To address these problems, we propose a woven fabric density analysis method based on small object detection and rule-based post processing. First, we capture high-resolution images of woven fabrics using macro-microscopic camera equipment and then construct a woven fabric microscopic image dataset for our study through pre-processing and data augmentation. Next, we propose a multitask feature fusion network (MTF-Net), a small object detection network, to detect the float-points of warp and weft yarns. The detection ability of the model is improved by the cooperation of a reconstruction branch network, a pixel-level branch network, and an object-level branch network. Additionally, we introduce a feature rotation selection module (FRSM) to solve the problem of yarns with small angle rotations. We finally propose a rule-based post-processing method to complete the density analysis of woven fabrics. The experimental results demonstrate that the proposed method is effective and achieves higher accuracy than the popular object detection methods for density analysis on the constructed woven fabric dataset.

Qiang Liu, Chuan wang, yusheng li,mingwang gao,jingao li Fabric defect detection is a challenging task in the fabric industry because of the complex shapes and large variety of fabric defects. Many methods have been proposed to solve this problem, but their detection speed and accuracy were very low. As a classic deep learning method and end-to-end target detection algorithm, YOLOv4 has evolved rapidly and has been applied in many industries, showing good performance. This paper proposes an improved YOLOv4 algorithm with higher accuracy for fabric defect detection, in which a new SPP structure that uses SoftPool instead of MaxPool is adopted. The improved YOLOv4 algorithm with three SoftPools can process the feature map effectively, which has a significant advantage in reducing the negative side effects of the SPP structure and improving the detection accuracy. The improved SPP structure is used by the three outputs of Backbone, and in order to ensure that the output can be inputted into the subsequent PANet successfully, the network structure is improved that a series of convolution layers after the SPP structure is added for reducing the channel numbers of feature map to an appropriate value. In addition,contrast-limited adaptive histogram equalization is adopted in advance to improve the image quality, which results in strong anti-interference abilities and can slightly increase the mAP. Experimental results show that, compared with the original YOLOV4, the improved YOLOv4 increases the mAP effectively by 6%, while the FPS only decreases by 2. The improved YOLOv4 can identify the location of defects accurately and quickly, and can also be applied in other defect detection industries

Peiyao guo,yanping liu,ying wu,r.hugh gong yili presented the Fabric defect detection is a crucial step of quality control in textile enterprises. The use of computer vision inspection

technology in the textile industry is key to achieving intelligent manufacturing. This study sought to determine the progress made and future research directions in intelligent fabric surface defect detection by comprehensively reviewing
published literature in terms of algorithms, datasets, and detection systems. Initially, the Detection methods are classified as traditional and learning-based methods. The traditional methods are subdivided into model, spectral, statistical, and structural approaches.
Learning based methods are categorized into classical machine learning methods and deep learning methods. The principles, model performance, detection rate, real-time performance, and applicability of deep learning methods are highlighted and compared. In addition, the strengths and weaknesses of all the approaches are elaborated. The use of fabric defect datasets and deep learning frameworks is analyzed. Public datasets and commonly used frameworks are collated and organized. The application of existing fabric inspection systems on the market is outlined. Fabric defect types are systematically named and analyzed. Finally,future research directions are discussed to provide guidance for researchers in related fields.

2.2 EXISTING TECHNOLOGY

Fabric defect detection has been an essential function in textile quality control for many decades. Conventional methods involved visual inspection by trained personnel examining fabric surfaces for flaws. Although this method had a set of drawbacks like human fatigue, inconsistent accuracy, and high costs, it was used traditionally.

1. Traditional Computer Vision-Based Methods Older computerized fabric inspection machines employed image processing methods like: Histogram Analysis – Employed to identify fabric texture anomalies by comparing pixel intensity distributions.Edge Detection (Sobel, Canny, Laplacian Filters) – Finds defects through the identification of sharp intensity transitions in fabric images. Fourier and Wavelet Transforms – Transforms images into frequency domains to identify irregular patterns. Gabor Filters – Compiles texture features using multi-scale, multi-orientation filters to make defects more observable. Though these approaches enhanced precision over visual inspection, they were challenged by intricate texture fabrics, illumination changes, and
minimal defects.

2. Machine Learning-Based Methods With the advent of machine learning (ML), statistical and supervised learning methods came into use: Support Vector Machines (SVMs) – Employed to classify defects based on features extracted. Random Forest and Decision Trees – Utilized for classifying defective versus non-defective fabric samples. Local Binary Patterns (LBP) – Assists in detecting texture-based defects at low computational expense.
These methods involved manual feature extraction, which restricted their generalizatio across various types of fabrics

3. Deep Learning-Based MethodsDeep learning (DL) has transformed fabric defect detection by doing away with the need for manual feature extraction. Some of the popular methods are:
Convolutional Neural Networks (CNNs) – Extract hierarchies of features automatically from images of fabrics to identify defects accurately.
You Only Look Once (YOLO) & Faster R-CNN – Object detection models that detect and classify defects in real-time.
Generative Adversarial Networks (GANs) – Applied for the generation of images of synthetic defects and unsupervised defect detection.
Vision Transformer (ViT) – A transformer-based structure that captures long-range dependencies in images of fabrics for enhanced defect classification.
Even with accuracy enhancements, deep learning models consume large labeled datasets and a lot of computational power.

4.Drawbacks of Current Technologies Heavy Reliance on Large Datasets – Most ML and DL algorithms need thousands of labeled images to train.
Computational Heaviness – Deep learning algorithms demand high-end GPUs, which means real-time deployment is costly.
Generalization Problems – Lighting variations, texture changes, and the type of fabric can affect model precision.
To overcome such limitations, DEFECTDETECT incorporates the Vision Transformer (ViT) model that improves efficiency and accuracy using cutting-edge image processing and attention mechanisms.

2.3 INFERENCE OF LITERATURE REVIEW

This table summarizes key contributions in fabric defect detection research, showcasing innovative models that leverage deep learning techniques such as lightweight attention-based detectors, YOLO enhancements, and CNN-based systems. It highlights improvements in accuracy, speed, and robustness, while also addressing false negative reduction and comprehensive quality control strategies.

Title	Contribution
A Lightweight Detector Based on Attention Mechanism for Fabric Defect Detection	Proposed YOLO-SCD, a lightweight defect detection model with attention mechanisms, improving accuracy (82.92%) and detection speed.
Fabric Defect Detection with Deep Learning and False Negative Reduction	Introduced a CNN-based defect detection system with False Negative (FN) reduction, achieving up to 95% accuracy with operator intervention.

A Multitask Feature Fusion Network for Woven Fabric Density Analysis	Developed MTF-Net, a small object detection network for woven fabric density analysis, improving accuracy in fabric density assessment.
A Fabric Defect Detection Method Based on Deep Learning	Enhanced YOLOv4 with Soft Pool and contrast-limited adaptive histogram equalization (CLAHE), increasing map by 6% with minimal FPS reduction.
Intelligent Quality Control of Surface Defects in Fabrics: A Comprehensive Research Progress	Reviewed traditional and deep learning-based methods, highlighting strengths, weaknesses, and future research directions in fabric defect detection.

Table 2.1:Inference Of Literature Review

2.4 EXTRACTION FROM LITERATURE REVIEW

This table compares several innovative approaches in fabric defect detection, highlighting methods like attention mechanisms, false negative reduction, and feature fusion networks that boost accuracy and efficiency. It also points out that while advanced preprocessing techniques such as Soft Pool and CLAHE improve performance in YOLO-based models, challenges like dataset quality and real-time processing still remain.

Title	**Extraction**
A Lightweight Detector Based on Attention Mechanism for Fabric Defect Detection	Attention mechanisms improve defect detection accuracy while reducing computational load.
Fabric Defect Detection with Deep Learning and False Negative Reduction	False Negative (FN) reduction techniques enhance detection accuracy, especially with operator intervention.
A Multitask Feature Fusion Network for Woven Fabric Density Analysis	Feature fusion networks effectively handle small-scale defect detection in woven fabrics
A Fabric Defect Detection Method Based on Deep Learning	Integrating Soft Pool and CLAHE preprocessing boosts defect detection performance in YOLO-based models.
Intelligent Quality Control of Surface Defects in Fabrics: A Comprehensive Research Progress	Deep learning is the dominant approach, but dataset quality and real-time processing remain key challenges.

Table 2.2: Extraction Form Literature Review

CHAPTER 3

SYSTEM ANALYSIS

3.1 PROBLEM DEFINITION

Fabric defect detection is a critical part of textile quality control. Traditional methods like manual inspection are inefficient, time-consuming, and prone to human error. Even early computer vision techniques using edge detection and statistical methods struggle with detecting fine and complex fabric defects.

With the rise of deep learning, CNN-based methods have improved detection rates. However, CNNs rely heavily on large datasets and fail to capture long-range dependencies in fabric textures. This leads to challenges in real-time defect identification, making it harder to integrate into industrial workflows.

3.1.1 Key Challenges in Existing Approaches:

In the current landscape of fabric quality control, several issues continue to challenge conventional methods. Manual inspections, for instance, are fraught with human errors and inconsistencies, as subjective judgments often lead to unreliable results. Even with the advent of CNN-based approaches, these models frequently struggle when faced with different lighting conditions, varied textures, and diverse fabric types, which limits their ability to generalize effectively. Moreover, many of these AI models demand high computational power, requiring expensive GPUs not only for training but also for real-time defect detection. Compounding these challenges is the fact that high-quality, well-labeled datasets for fabric defect detection are scarce, leaving even the most advanced techniques without the robust data they need for optimal performance. Together, these limitations underscore the need for an innovative, AI-driven solution that can overcome the inherent weaknesses of traditional approaches.

3.2 PROPOSED SOLUTION

To address these challenges, DEFECT DETECT utilises Vision Transformer (VIT) for automated fabric defect detection. Unlike CNNs, VITs use self-attention mechanisms to analyse images in a more structured and detailed way.

3.2.1 Key Features of the Proposed System:

Our proposed system leverages the advanced capabilities of the Vision Transformer (ViT) to deliver several key improvements over traditional methods. By capturing long-range dependencies, ViT achieves higher accuracy, effectively identifying even the most subtle defects that might go unnoticed with conventional techniques. The optimized architecture enables real-time processing, meaning defects are detected almost instantly—crucial for keeping production lines running smoothly without delay. Additionally, the model is highly scalable; it can be trained on a diverse range of fabric types, ensuring that it adapts well to different materials and manufacturing environments. This adaptability also contributes to better generalisation, as the system performs consistently under varying lighting conditions and textures. Overall, these features combine to create a robust, efficient, and versatile tool for fabric defect detection, addressing many of the challenges faced by existing approaches in the textile quality control sector.

3.3 SOFTWARE COMPONENTS

The project is built using Python with the following key software components:

Component	**Description**
Operating system	windows
Front end	HTML, CSS
Scripts	Python
Tools	Python idle
Flask	Web framework for providing an intuitive user interface

Table 3.1: Software Components

3.4 HARDWARE COMPONENTS

Since VIT models require significant processing power, the hardware used includes:

components	**specification**
processor	Intel/AMD/M1, M2, M3
Speed	Minimum 1.1 GHZ
RAM	8 Gb
Hardisk	Minimum 500 Gb

Table 3.2: hardware components

3.5 USECASES

The DEFECT DETECT system is designed for different users, each with specific interactions. The table below outlines various use cases, including how the system is used in real-world scenarios

Use case	Actor(s)	Description	Preconditions	Postconditions
Upload Fabric Image	Quality Inspector	The user uploads a fabric image for defect detection.	User must have an image file in an accepted format.	Image is stored, and processing starts.
Preprocess Image	System	The system enhances the image quality (grayscale conversion, contrast adjustment, noise reduction).	Image is uploaded successfully.	Pre-processed image is ready for model input.
Detect Fabric Defect	AI Model (Vit)	The model processes the image and identifies defects.	Pre-processed image is available.	Defect classification result is generated.
View Defect Report	Quality Inspector, Factory Manager	The user checks the results, including defect location and severity.	A detection process must be completed	Report is displayed or downloaded.
Store Results in Database	System	The defect detection results are stored in the MySQL database.	Defect classification is completed.	Data is saved for future analysis.
Generate Quality Reports	Factory Manager	A report summarizing fabric defects is generated for analysis.	Detection results are available in the database.	Report is stored and can be shared.
Retrain AI Model	Admin	The AI model is updated with new training data to improve accuracy.	New labelled fabric images are available.	User database is updated

Table 3.3: Use Case

CHAPTER 4
SYSTEM DESIGN

4.1 DESIGN OF THE PROJECT

In the textile industry, ensuring high-quality fabric is absolutely essential, and fabric defect detection plays a vital role in this process. With traditional manual inspections prone to subjectivity and error, our project, DEFECT DETECT, steps in as a modern alternative. It leverages advanced AI models, including the Vision Transformer (ViT) and Mobile ViT, to automate the quality control process. This document outlines the structure of our system, detailing the journey of data from acquisition to defect detection, and explaining how our algorithms work together to identify even the most subtle flaws with remarkable accuracy.

Our system is built on a modular design that emphasizes both efficiency and ease of maintenance. It begins with the Data Acquisition Module, which captures high-resolution images of fabrics using state-of-the-art cameras. These images are subsequently enhanced through a Preprocessing Module that normalizes and augments the data to optimize image quality. Once sharpened, the images move on to the Feature Extraction Module, where the ViT model is employed to identify key patterns and distinctive features. This extracted information is then used by the Defect Detection Module, where AI algorithms meticulously classify and detect defects. The entire process is seamlessly integrated with a real-time User Interface that provides operators immediate access to results, and a robust Database that securely stores images, defect reports, and logs for further analysis.

To further streamline operations, the system is structured into three distinct architectural layers. The Data Layer is responsible for collecting images and managing the storage of all relevant data. The Processing Layer is the heartbeat where the AI models execute their work, rapidly analyzing images to flag any defects as they occur. Lastly, the Presentation Layer takes care of displaying the outcomes in a user-friendly format, accessible via a web-based or desktop interface. This layered approach not only supports the system’s scalability and reliability but also ensures that each component functions optimally to deliver a highly accurate, automated fabric defect detection solution.

4.1.1 HARDWARE & SOFTWARE REQUIREMENTS

Hardware Requirements

Processor: Intel i5/i7 or equivalent.
RAM: Minimum 8GB (16GB recommended for better performance).
Storage: 500GB HDD/SSD.
GPU: NVIDIA RTX 3060 (for training purposes).
Camera: High-resolution industrial camera for fabric inspection
Software Requirements

Operating System: Windows 10/11 or macOS.
Programming Language: Python.
Deep Learning Framework: TensorFlow / Pytorch.
Database: MySQL.
Front-End Technologies: HTML, CSS, Flask/Django.
Image Processing Libraries: OpenCV, PIL.

4.1.2 DATA & FLOW PROCESSING

How Data Moves Through the System

In our system, data flows seamlessly through a series of well-defined stages, starting with the capture of fabric images using a high-quality industrial camera. As soon as these images are obtained, they enter the preprocessing stage where they are resized, normalized, and augmented, ensuring that the data is optimally prepared for the next phase. The refined images then pass through the feature extraction stage, where the Vision Transformer (ViT) uncovers the intricate details of fabric textures and patterns. Once these features are identified, the AI model steps in for defect classification, using its learned patterns to accurately detect and categorize any imperfections. Finally, the results are stored in a MySQL database and showcased on a user-friendly interface, presenting the findings in a clear and accessible manner for further analysis and immediate action.

4.1.3 IMAGE PROCESSING

In our image processing pipeline, several key techniques work together seamlessly to prepare and analyze fabric images for defect detection. First, each image is resized to a standard 224x224 pixels to maintain consistency, while normalisation adjusts pixel values to a range between 0 and 1, ensuring a uniform input that enhances model performance. To further simplify computations and reduce processing time, the images are converted to grayscale, and data augmentation techniques—such as rotations, flips, and zoom effects—are applied to enrich the dataset and improve the model's accuracy.

When it comes to extracting features, the Vision Transformer (ViT) plays a crucial role by breaking down images into smaller segments, known as patch embeddings, for a more detailed analysis. The self-attention mechanism within ViT then focuses on the most critical parts of the image, ensuring that even subtle defect areas are identified effectively. For scenarios where speed and efficiency are essential, Mobile ViT is employed, offering a lightweight alternative without compromising on performance. This robust combination of preprocessing and advanced neural network techniques ultimately results in a highly accurate and efficient fabric defect detection system.

4.1.4 AI MODEL & ALGORITHMS

The core of our approach leverages the strengths of two powerful models: Vision Transformer (ViT) and Mobile ViT. ViT is renowned for its ability to extract highly detailed features from fabric images, capturing even the most subtle defects through its advanced self-attention mechanism. This level of detail makes it an excellent choice for comprehensive analysis, as it can identify complex patterns and imperfections that might otherwise go unnoticed. In contrast, Mobile ViT is optimized for real-time defect detection, ensuring that the system remains responsive and efficient even when processing images on the fly in high-speed production environments.

The algorithm itself operates in two main stages. During model training, we begin by labeling our dataset with various defect types—ranging from holes and stains to misalignments—and use GPU acceleration to train the model. This robust training phase equips the system with the necessary knowledge to recognize distinct defect patterns. Once the training is complete, the real-time classification stage kicks in: every new fabric image is fed into the trained ViT/Mobile ViT model, which then predicts the defect category and an accompanying confidence score. If a defect is identified, the relevant details are immediately stored in the database for subsequent analysis and traceability.

To optimize performance further, several advanced techniques are employed. Transfer learning uses pre-trained ViT weights to boost accuracy, allowing our model to start from an already strong foundation rather than learning from scratch. Hyperparameter tuning—adjusting factors such as learning rates and batch sizes—ensures that the training runs efficiently and reaches optimal performance. Additionally, model quantization is applied to Mobile ViT, reducing its size and speeding up inference times without compromising the overall detection quality. This comprehensive, multi-layered strategy ensures that our fabric defect detection system not only delivers precise insights but also adapts seamlessly to real-world manufacturing challenges.

4.1.5 DATABASE DESIGN

Our system organizes data in a clear and efficient manner through a set of key database tables. The Users table securely stores user credentials and roles, ensuring that access is managed appropriately. Meanwhile, the Images table keeps track of image file paths along with their timestamps, so that every fabric image captured is accurately logged. The Defects table plays a crucial role by recording details about each identified defect—such as the type of defect, the confidence score provided by the AI model, and the image reference—ensuring that valuable information is readily available for analysis. Additionally, the Logs table monitors system events and tracks user actions, providing a detailed overview of the system's operations and any activities that occur. In essence, the data workflow is streamlined and intuitive: users upload images, the system processes these images to detect defects, and the results are systematically saved for future reference. This organized approach not only simplifies data management but also enhances the overall efficiency and reliability of our fabric defect detection system.

4.1.6 USER INTERFACE & DESIGN

The user interface is designed with simplicity and functionality at its core, offering a seamless experience for managing fabric defect detection. The web dashboard is packed with practical features that make quality control straightforward. Users can easily upload fabric images for analysis, and thanks to real-time detection, any defects are displayed instantly on the screen. The dashboard also provides comprehensive analytics and reports, drawing on historical data to reveal defect trends over time, and offers the convenience of exporting defect logs in Excel or PDF formats for further review or sharing.

The layout of the dashboard supports intuitive navigation with a clearly defined sidebar that houses core menus such as Dashboard, Upload, Reports, and Settings. The main panel is the heart of the interface, where defect results, images, and their corresponding confidence scores are presented in a clear and digestible format. This well-organized structure ensures that users can quickly find the information they need and take prompt action.

Moreover, the system's deployment is tailored to diverse operational needs. It can be run on a local system equipped with a GPU for smaller-scale applications or scaled up using cloud services like AWS or GCP to handle larger workloads. This flexible integration means the solution is ready for both immediate, on-site quality control tasks and expansive, enterprise-level deployments, making it a versatile tool in the digital transformation of textile manufacturing.

4.1.7 SYSTEM DEVELOPMENT & INTEGRATION

Our system brings together various components in a seamless and integrated manner, ensuring that every piece of the process works in harmony. At the heart of the system lies a robust API built using either Flask or Django, which handles model inference—this means that when a fabric image is submitted, the AI model quickly processes it to detect defects. Once processed, all the image data and corresponding defect records are securely stored in a MySQL database, creating a comprehensive log of every analysis. Meanwhile, the frontend of the system is designed to be both intuitive and responsive. It fetches the processed results through a REST API, ensuring that users receive real-time feedback and can interact with the data effortlessly. This well-coordinated integration between the backend model inference, database storage, and the frontend REST API guarantees a smooth, efficient, and reliable defect detection process throughout the system..

4.1.8 CONCLUSION

DEFECT DETECT integrates Vit and Mobile Vit for fabric defect detection with high accuracy. The system is designed to be scalable, real-time, and efficient for textile quality control. Future updates will focus on expanding datasets, deploying models on edge devices, and integrating cloud-based solutions.

4.2 SYSTEM ARCHITECTURE DIAGRAM

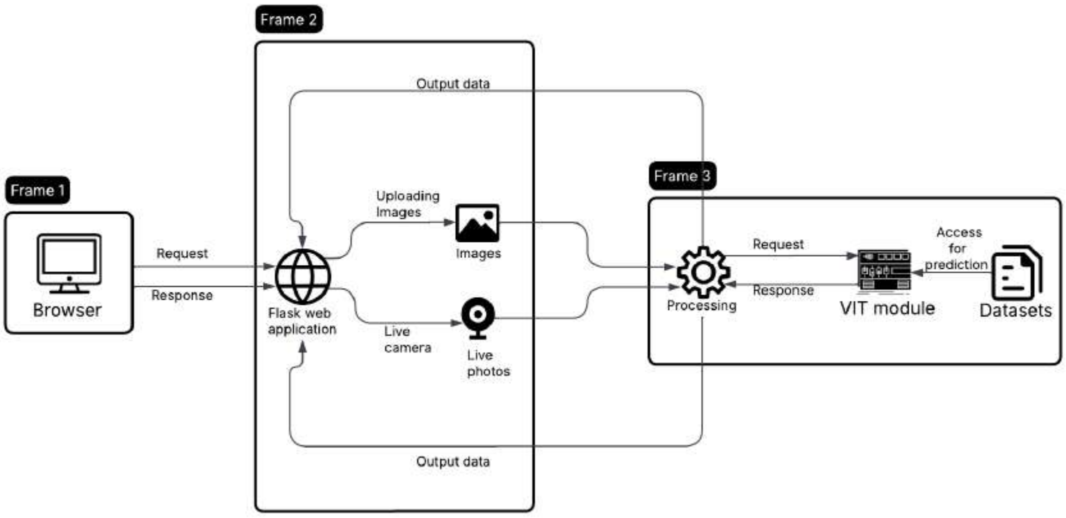


Figure 4.1: Architectural Diagram

Our system is built around a seamless flow of data and interaction among three key components. First, users engage with the system through a browser interface. Here, they can either upload a picture or snap a live photo using their camera. When a request is made—whether it's an image upload or a live capture—it is immediately forwarded to our backend, where the Flask web application takes over. The browser then patiently awaits the response, ready to display the processed results.

In the next layer, the Flask web application serves as the vital middleman between the user interface and the AI model. This backend layer is responsible for receiving the images provided by the user, whether they come as file uploads or live snapshots. Once the images arrive at the Flask server, they are sent off for processing. In addition to handling the incoming data, Flask also manages the output, ensuring that the results from defect detection are properly formatted and transmitted back to the browser for display.

The core of the system lies in the processing and AI model stage. After the image is handed off by Flask, it is processed by the Vision Transformer (ViT) model, which is designed to analyze detailed aspects of fabric and detect defects. The ViT model carefully examines the image, referencing a well-curated dataset to predict any fabric anomalies such as holes, stains, or misalignments. Once the predictions are made, the detected defects and corresponding confidence scores are sent back to the Flask web application.

In essence, the entire process works in a well-coordinated sequence: the user interacts with the browser to upload or capture an image, the Flask backend receives and transmits the image to the AI model, and after detection, the results are passed back through the Flask app to be displayed in the browser. This cohesive integration ensures that users receive timely, accurate feedback on fabric quality, all while maintaining an intuitive and efficient workflow.

4.3 MODULES

LIST OF MODULES:

1.Data pre-processing
2.Feature extraction
3.VIT model
4.Fabric defect detection

MODULE DESCRIPTIONS:

4.3.1 DATA PREPROCESSING:

Image data pre-processing is a critical stage in the development of an image classification model, shaping the raw input images to enhance the learning process and subsequent model performance. The initial step involves resizing the images to a standardized dimension, promoting computational efficiency and ensuring uniformity across the dataset. Simultaneously, normalization is applied to scale pixel values within a specific range, typically [0, 1], facilitating convergence during training. Colour channels play a pivotal role, with options like grayscale conversion to simplify computations or maintaining three colour channels (RGB) for coloured images. The choice often depends on the model's input requirements or the characteristics of the dataset. Data augmentation introduces variability by applying random transformations such as rotations, flips, zooms, and shifts. This technique is instrumental in preventing overfitting and enhancing the model's ability to generalize by exposing it to diverse image variations.

4.3.2 FEATURE EXTRACTION:

Feature extraction is its capacity to learn hierarchical representations without the need for intricate handcrafted features. The self-attention mechanism empowers the model to discern and prioritize relevant image regions, fostering a comprehensive understanding of visual content. This not only enhances performance in image classification tasks but also opens avenues for broader applications, including object detection and classification. Vit continues to redefine feature extraction methodologies, offering a potent tool for extracting rich, context-aware representations from images across diverse domains and applications.

4.3.3 VISION TRANSFORMER MODEL:

The Vision Transformer (Vit) algorithm represents a groundbreaking approach to image processing, shifting from traditional convolutional neural networks (CNNs). Vit introduces the concept of transformers, originally designed for natural language processing, into the realm of computer vision. This innovation enables the direct application of attention mechanisms to image pixels, allowing the model to capture global dependencies within the image. Unlike CNNs, Vit doesn't rely on predefined grid structures, making it highly versatile for various image sizes. It divides an image into fixed size patches, linearly embeds each patch and processes the sequence of embeddings using transformer layers. This architecture demonstrates remarkable performance on a wide range of image classification tasks.

4.3.4 FABRIC DEFECT DETECTION:

Fabric defect detection is a critical aspect of quality control in the textile industry, ensuring that manufactured textiles meet high standards. In the context of fabric defect detection, Vit is employed to analyse images captured either from an open camera or during testing processes. The algorithm excels in understanding complex visual patterns and spatial dependencies within the fabric. It divides the images into fixed size patches, linearly embeds each patch and processes the sequence using transformer layers. When an open camera captures images of fabrics, Vit can efficiently identify anomalies or defects by learning from a dataset of labelled images. The model's self-attention mechanism allows it to focus on specific regions of the fabric, enabling it to discern even subtle defects.

4.4 UML DIAGRAMS

4.4.1 USE CASE DIAGRAM

Figure 4.2: Use Case Diagram

4.4.2 ACTIVITY DIAGRAM:

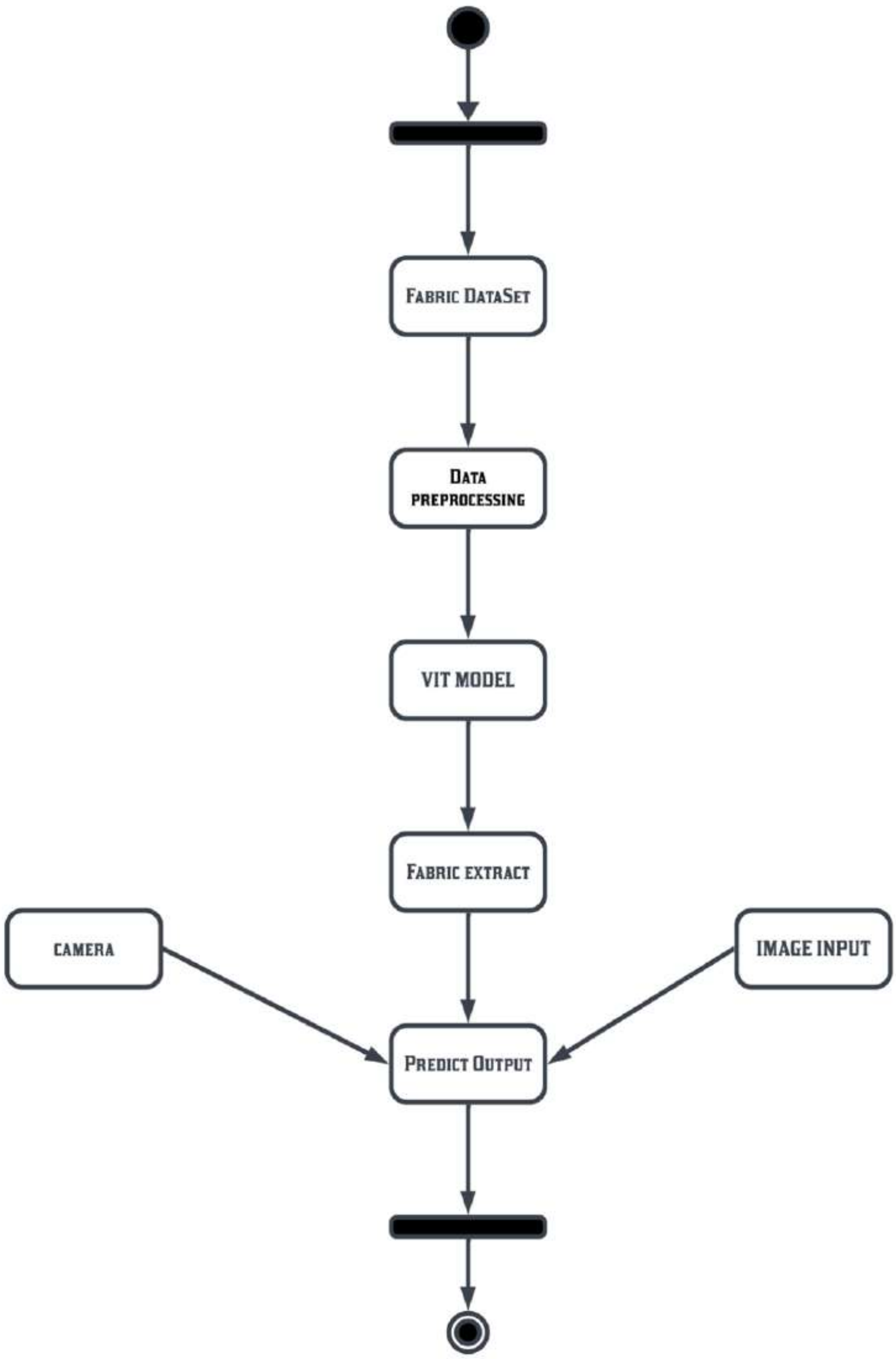


Figure 4.3: Activity Diagram

4.4.3 DATA FLOW DIAGRAM:

LEVEL 0:

LEVEL 1:

Figure 4.4: Data Flow Diagram

4.4.4 OVERALL DIAGRAM:

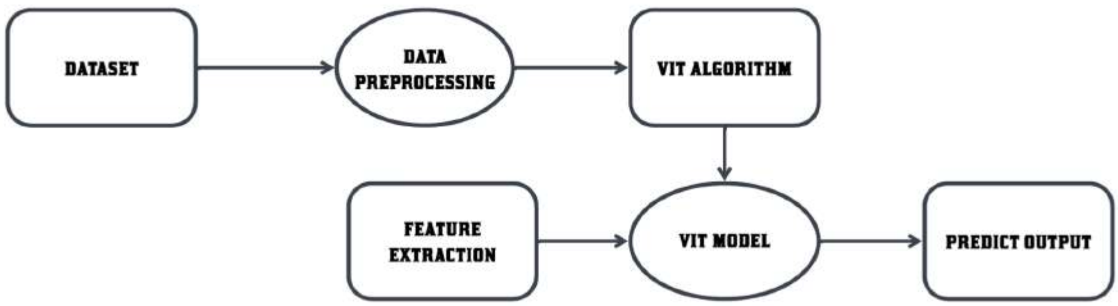


Figure 4.5: Overall Diagram

4.4.5 CLASS DIAGRAM:

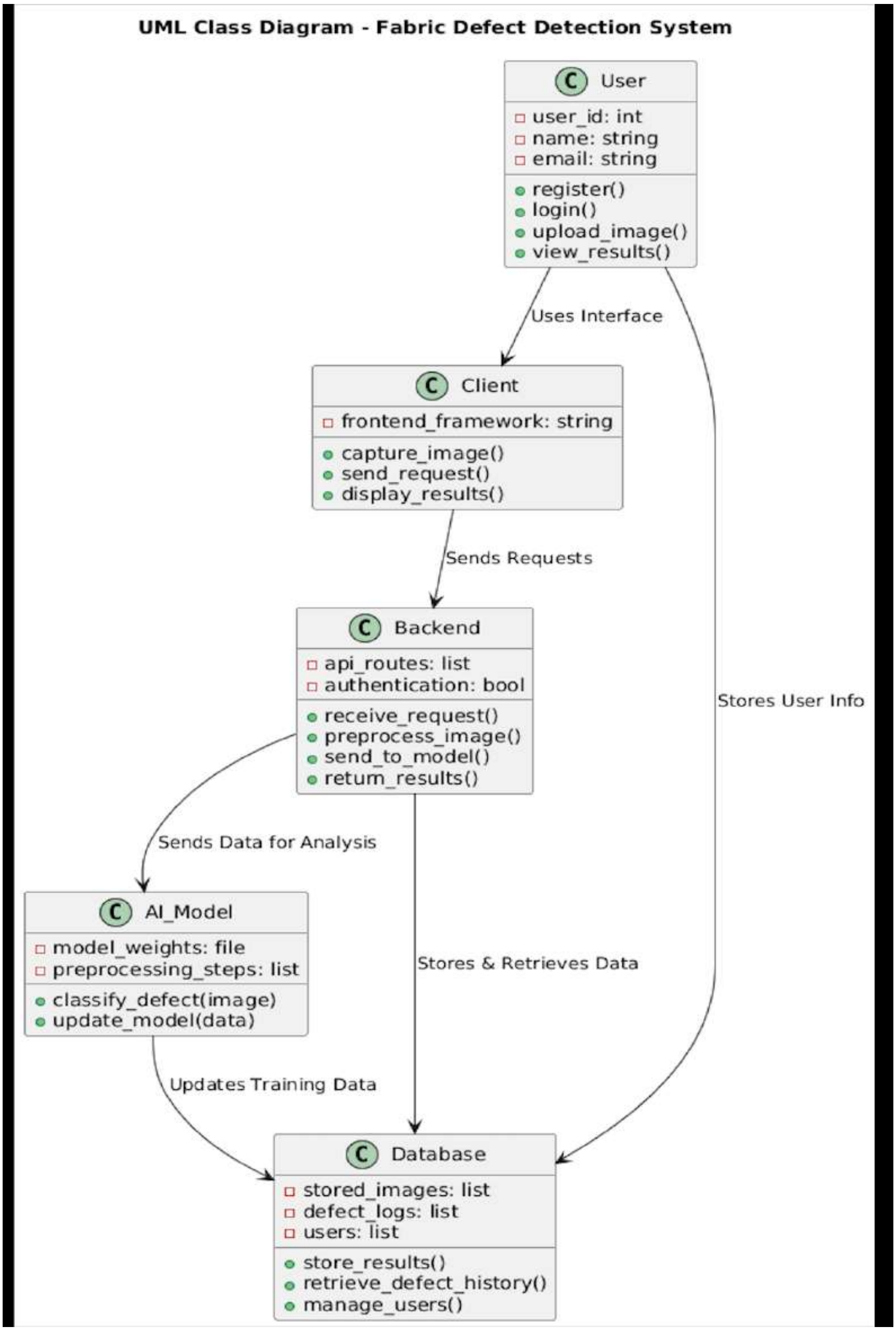


Figure 4.6: Class Diagram

4.4.6 SEQUENCE DIAGRAM:

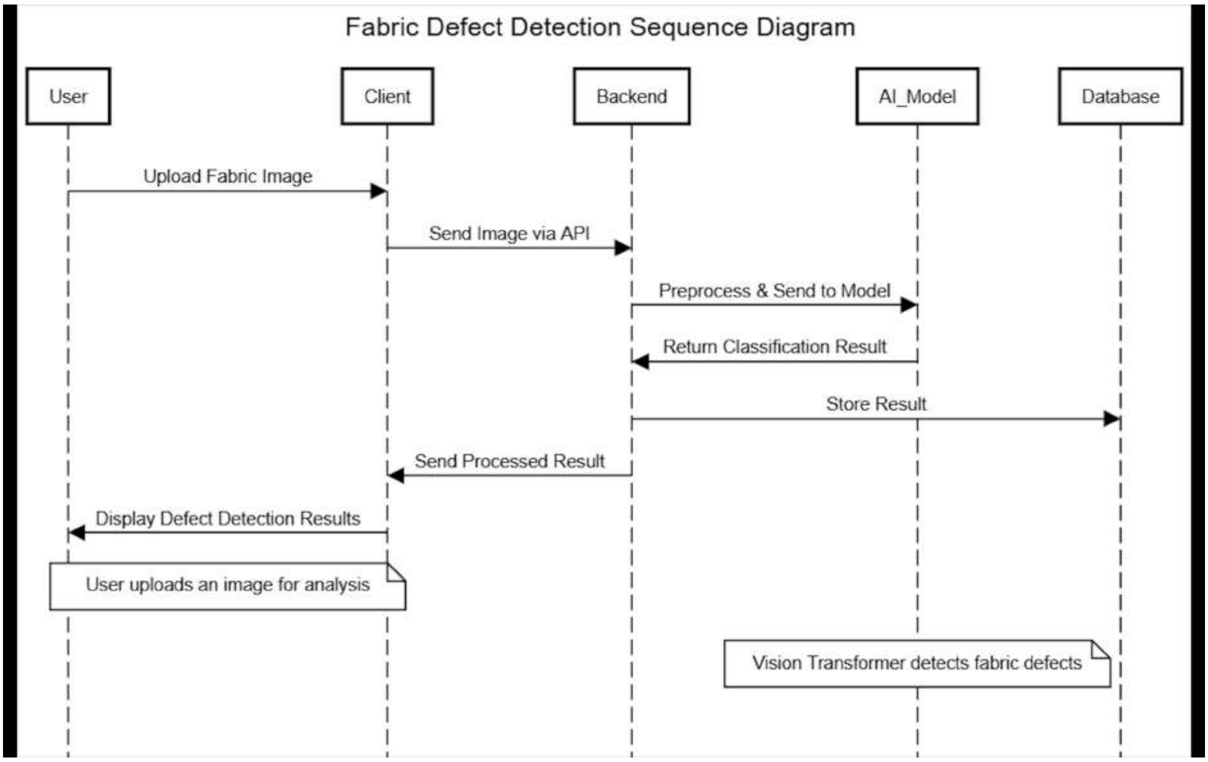


Figure 4.7: Sequence Diagram

CHAPTER 5

SYSTEM IMPLEMENTATION

5.1 VISION TRANSFORMER (VIT) ALGORITHM FOR FABRIC DEFECT DETECTION

5.1.1 INTRODUCTION TO VISION TRANSFORMER (VIT):

The Vision Transformer (ViT) represents a paradigm shift in computer vision, departing from traditional Convolutional Neural Networks (CNNs). Unlike CNNs, which rely on convolutions to process image data, ViT employs the transformer architecture, originally designed for natural language processing tasks. This innovative approach involves dividing an image into fixed-size patches, which are then embedded into a linear sequence. Each patch is treated similarly to a token in text, allowing the ViT to process images as sequences. This method enables the ViT to capture long-range dependencies and intricate patterns within the image, making it highly effective for tasks that require a detailed understanding of complex visual data, such as fabric defect detection.

5.1.2 DATA PRE-PROCESSING:

Data pre-processing is a vital step in fabric defect detection using the Vision Transformer (Vit) algorithm. The primary goal of this stage is to standardize and augment the raw input images, ensuring they are suitable for training the model. Initially, images are resized to a uniform dimension to facilitate efficient computation and maintain consistency across the dataset. Normalization follows, scaling pixel values within a specific range, typically between 0 and 1, which aids in the convergence of the model during training. Data augmentation techniques, including rotations, flips, zooms, and shifts, are applied to introduce variability and enhance the model's ability to generalize. This comprehensive pre-processing ensures that the Vit model is exposed to a diverse set of images, enabling it to effectively identify fabric defects.

5.1.3 FEATURE EXTRACTION WITH VIT:

Feature extraction in the Vision Transformer (Vit) is a critical aspect that sets it apart from traditional CNNs. Vit utilizes self-attention mechanisms to focus on specific regions of the image, learning hierarchical representations without the need for handcrafted features. The self-attention mechanism allows the model to prioritize relevant areas, capturing both global and local features essential for accurate defect detection. This capability to discern and emphasize important regions within the image significantly enhances the performance of the

Vit in identifying subtle fabric defects, making it a powerful tool for quality control in the textile industry.

5.1.4 VISION TRANSFORMER MODEL ARCHITECTURE:

The architecture of the Vision Transformer (Vit) model is designed to process images as sequences of patches. Each image is divided into fixed-size patches, which are then linearly embedded and fed into the transformer layers. These transformer layers apply self-attention mechanisms to capture the global dependencies within the image. Unlike traditional models, Vit does not rely on a predefined grid structure, allowing it to handle various image sizes with ease. This flexibility, combined with the powerful self-attention mechanism, enables the Vit to achieve remarkable accuracy in image classification tasks, including fabric defect detection.

5.1.5 FABRIC DEFECT DETECTION PROCESS:

The application of the Vision Transformer (ViT) algorithm in fabric defect detection involves analyzing images captured from an open camera or during testing processes. The model divides the images into patches, processes them through transformer layers, and identifies anomalies or defects. By training the ViT on a diverse dataset of labelled images, the algorithm can efficiently detect defects such as holes, stains, and irregular patterns in real-time. The self-attention mechanism ensures that even subtle defects are identified, providing a comprehensive solution for fabric quality control. This automated process enhances the efficiency and accuracy of defect detection, reducing the reliance on manual inspection.

5.1.6 MOBILE VIT ALGORITHM FOR IMAGE CLASSIFICATION:

Mobile ViT, or Mobile Vision Transformer, is an adaptation of the ViT model designed for resource-constrained environments. By leveraging the power of transformer-based architectures, Mobile ViT can efficiently process images with fewer parameters, making it suitable for devices with limited computational resources. The algorithm utilizes self-attention mechanisms to capture complex visual patterns and dependencies, ensuring accurate image classification without the computational burden of traditional models. Mobile ViT's lightweight design and effectiveness make it an ideal choice for real-time fabric defect detection on mobile and edge devices.

5.1.7 CHALLENGES IN IMPLEMENTING VIT FOR FABRIC DEFECT DETECTION:

Implementing the Vision Transformer (ViT) for fabric defect detection comes with its own set of challenges. One significant challenge is the availability and quality of the dataset. A diverse and well-labeled dataset covering a wide range of fabric types and defect scenarios is crucial for effectively training the ViT. Additionally, the optimization of the ViT architecture for fabric defect detection requires careful tuning of hyperparameters and experimentation with different model sizes. The real-world variabilities, such as changes in lighting conditions, fabric textures, and manufacturing processes, pose another set of challenges for the model's generalization. Overcoming these challenges necessitates a thorough understanding of both the ViT algorithm and the specific requirements of fabric defect detection.

5.1.8 FUTURE ENHANCEMENTS:

Looking ahead, several avenues for future enhancements in the fabric defect detection project leveraging the Vision Transformer (ViT) algorithm can be explored. One potential area of improvement lies in expanding the dataset used for training the model. A more extensive and diverse dataset can enhance the algorithm's ability to generalize across various fabric types, textures, and defect patterns, ultimately improving its performance in real-world scenarios. Additionally, incorporating transfer learning techniques could contribute to the project's scalability. Pre-training the ViT model on a broader set of image data, beyond the confines of fabric defects, could allow the algorithm to capture more intricate features and nuances. This transfer learning approach might lead to even more accurate defect detection, especially when faced with previously unseen fabric variations. Furthermore, exploring the integration of other advanced computer vision techniques in conjunction with ViT could bring added value. Techniques such as semantic segmentation or object detection may provide more detailed insights into the specific characteristics of detected defects, aiding in a more comprehensive analysis and classification of fabric anomalies.

5.2 FUNCTIONAL COMPONENTS:

5.2.1 DATA PRE-PROCESSING:

Data pre-processing is the first vital step in developing an image classification model, setting the stage for the entire learning process. Before any training begins, raw images are carefully transformed to improve their quality and ensure consistency throughout the dataset. First, images are resized to standardized dimensions, which not only speeds up computations but also guarantees that every image fed into the model has the same scale and proportions. Next, normalization adjusts the pixel values—usually scaling them between 0 and 1—so that the model can converge more smoothly during training. Depending on the specific requirements of the model, images might be converted to grayscale or kept in full color with three channels (RGB), ensuring that the right level of detail is available for analysis. Finally, data augmentation techniques—such as rotations, flips, zooms, and shifts—are applied to introduce variability into the dataset. This helps in preventing overfitting and boosts the model’s ability to generalize when faced with new data. Overall, these pre-processing steps form the backbone of an effective image classification system, ensuring both efficiency and improved learning outcomes.

5.2.2 FEATURE EXTRACTION

Feature extraction in the Vision Transformer (ViT) model breaks new ground by learning hierarchical representations directly from images, eliminating the need for elaborate, handcrafted features. At its core is the self-attention mechanism, which empowers the model to scan through an image and determine which areas are most relevant for analysis. This process allows ViT to prioritize key regions, ensuring that both global patterns and local details are captured effectively. By doing so, the model builds a comprehensive understanding of the visual content, a capability that significantly boosts performance in image classification tasks. This approach is especially valuable for fabric defect detection, where the ability to pinpoint subtle defects—from tiny stains to minute misalignments—in a complex textile pattern is critical. Overall, the integration of self-attention and hierarchical feature extraction in ViT offers a robust and efficient method for identifying imperfections, making it a powerful tool in advancing quality control within the textile industry.

5.2.3 VISION TRANSFORMER MODEL (VIT):

The Vision Transformer (ViT) algorithm is a groundbreaking approach to image processing that moves away from the traditional reliance on convolutional neural networks (CNNs) and instead leverages the power of transformers. Originally designed for natural language processing, transformers are brought into the world of computer vision with ViT, allowing the model to apply attention mechanisms directly to image pixels. This shift enables the model to focus on the most important parts of an image all at once. A key innovation in ViT is patch embedding, where each image is divided into fixed-size patches. These patches are linearly embedded and then processed as a sequence by transformer layers, much like words in a sentence. This design lets the model capture global dependencies across the entire image, making it highly versatile and effective for varying image sizes and a broad range of tasks.

5.2.4 FABRIC DEFECT DETECTION

Fabric defect detection plays a crucial role in ensuring that textiles meet high quality standards. Leveraging the power of the Vision Transformer (ViT), our system analyzes images captured either through open cameras or during testing processes, adeptly interpreting complex visual patterns and spatial dependencies present in fabric. The ViT algorithm divides each image into smaller patches, embeds them, and then processes these patches in sequence via transformer layers. This approach enables the model to focus on every detail of the fabric. Moreover, the incorporation of a self-attention mechanism allows the system to zero in on subtle defects, enabling real-time detection. By learning from a rich dataset of labeled images, the model can swiftly identify anomalies, ensuring that any defects are promptly detected and addressed to maintain the highest production standards.

5.2.5 SYSTEM CONFIGURATION

Implementing our fabric defect detection system requires a well-defined set of hardware and software resources to ensure smooth and efficient operation. On the hardware side, the system is designed to run on a machine equipped with at least an Intel 1.1 GHz processor, 8 GB of RAM, and a 500 GB hard disk. These specifications provide the necessary computational power and storage capacity to handle the intensive image processing tasks. On the software front, the system is compatible with Windows 7, 8, or 10, ensuring broad usability among standard operating systems. The front end of the application is built using HTML and CSS, which create a user-friendly interface, while the core functionality is driven by Python scripts. For development and testing, Python IDLE is used as the primary integrated development environment. Together, these hardware and software components create a robust platform capable of supporting real-time fabric defect detection and analysis.

5.2.6 LIST OF MODULES

Data pre-processing plays a critical role in our system by standardizing and augmenting images, which enhances the learning process and sets a strong foundation for subsequent analysis. Next, the feature extraction stage leverages the Vision Transformer's self-attention mechanism to pinpoint and extract the most relevant details from each image. The Vision Transformer (ViT) itself applies transformer architecture directly to image pixels, capturing global dependencies that are essential for accurate defect detection. Ultimately, this comprehensive approach allows the system to analyze fabric images and identify defects in real-time, ensuring that quality control is both precise and efficient.

5.3 IMPLEMENTATION:

5.3.1 DATA COLLECTION AND DATASET PREPARATION:

The foundation of the implementation lies in the preparation of a comprehensive dataset. Collecting high-quality images of fabrics with and without defects is critical. These images are then labeled to create a dataset that covers various types of fabric defects, such as holes, stains, and irregular patterns. The dataset should be diverse, representing different fabrics and defect scenarios to ensure the model's ability to generalize across real-world conditions.

5.3.2 DATA PRE-PROCESSING:

Data pre-processing is a crucial step that sets the stage for effective training by preparing the collected images in a consistent and optimal way. First, resizing standardizes the dimensions of all images, ensuring uniformity across the dataset. Next, normalization scales the pixel values—typically between 0 and 1—which is essential for helping the model converge smoothly during training. Finally, data augmentation is applied by introducing transformations such as rotations, flips, zooms, and shifts. This not only adds valuable variability to the dataset but also enhances the model's ability to generalize, making it more robust when encountering new data.

5.2.3 VISION TRANSFORMER (VIT) MODEL DEVELOPMENT:

At the heart of our implementation is the Vision Transformer (ViT) model, which fundamentally reshapes how we approach image processing. The process begins with patch embedding, where each image is divided into fixed-size patches. These patches are then linearly embedded into a sequence, transforming visual input into a format that the model can easily work with. Once the image is represented as a sequence, the model employs several transformer layers equipped with self-attention mechanisms. This step is crucial because the self-attention not only captures long-range dependencies across the entire image but also discerns intricate patterns that might indicate subtle fabric defects. Finally, a classification head is added to predict the presence and categorize the type of defect in the fabric images. Together, these steps enable the Vision Transformer to deliver a robust and highly accurate fabric defect detection system that can adapt to the challenges of real-world quality control.

5.2.4 TRAINING THE VIT MODEL:

Before training the model, the dataset is carefully divided into three parts: training, validation, and test sets. This division is essential, as it allows the model to learn from one subset of data while its performance is evaluated on unseen images from the validation and test sets. Once the data is split, the training process begins by selecting a suitable loss function—typically cross-entropy loss—which measures how far the model's predictions are from the true labels. An optimization algorithm, such as Adam, is then used to adjust the model's weights to reduce this loss. During training, batches of images are fed into the model repeatedly. After each batch, the loss is calculated and the model's parameters are updated to minimize the error. This iterative process continues for several epochs, gradually refining the model's accuracy until it reaches a satisfactory level of performance.

5.3.5 FEATURE EXTRACTION:

During the training process, the ViT model learns to extract relevant features from the images. The self-attention mechanism allows the model to focus on important regions and capture both global and local features essential for accurate defect detection.

5.3.6 FABRIC DEFECT DETECTION:

Once the model is fully trained, it seamlessly transitions into real-time defect detection, streamlining the quality control process. The journey begins with image acquisition, where fabric images are captured either through an open camera or during dedicated testing processes. These images then undergo pre-processing—resizing and normalization—just as they did during the model's training phase, ensuring that the new input aligns perfectly with what the model expects. With the images prepped and standardized, they are fed into the trained Vision Transformer (ViT) model. The model meticulously examines each image, detecting any anomalies and classifying them on the fly. This real-time analysis not only highlights the presence of defects but also pinpoints the type of defect, providing immediate and actionable feedback for quality assurance on the production line.

CHAPTER 6

SYSTEM TESTING

6.1 INTRODUCTION TO SYSTEM TESTING:

System testing is a vital phase in the software development lifecycle, where the entire integrated system is evaluated to ensure it meets the specified requirements. The primary objective is to validate that all components of the system work harmoniously together and function as intended. This comprehensive testing process is essential to identify any issues or defects that may have been overlooked during earlier testing stages, ensuring the system operates reliably and efficiently in real-world scenarios.

6.1.1 FUNCTIONAL TESTING:

Functional testing focuses on verifying that the system's functionalities align with the specified requirements. In the context of fabric defect detection, functional testing involves validating that the Vision Transformer (ViT) algorithm accurately identifies various types of fabric defects, such as holes, stains, and irregular patterns. Test cases are designed to cover different defect scenarios, and the system's outputs are compared to the expected results to ensure consistency and accuracy. This testing phase ensures that each feature of the fabric defect detection system operates correctly and meets the intended purpose.

6.1.2 PERFORMANCE TESTING:

Performance testing assesses the system's responsiveness, stability, and scalability under different workloads. It involves simulating real-world usage scenarios to evaluate how the system handles high volumes of fabric images. Load testing determines the system's capacity to process large batches of images, while stress testing pushes the system to its limits to identify performance bottlenecks and ensure stability under extreme conditions. The goal is to verify that the system can handle peak loads without compromising performance, ensuring it remains efficient and reliable during intensive usage.

6.1.3 SECURITY TESTING:

Security testing is crucial to identify and mitigate potential vulnerabilities within the system. This phase involves testing for common security issues, such as SQL injection, cross-site scripting (XSS), and weak authentication mechanisms. Penetration testing and security scans are conducted to identify any weaknesses, and necessary security measures are implemented to protect the system from potential threats. Ensuring the system's security is paramount to safeguarding sensitive data and maintaining the integrity of the fabric defect detection process.

6.1.4 USABILITY TESTING:

Usability testing evaluates the user interface and overall user experience of the fabric defect detection system. The objective is to ensure that the system is user-friendly, intuitive, and meets the needs of its intended users. Testers gather feedback from users regarding the system's ease of use, navigation, and accessibility. Based on this feedback, adjustments are made to the user interface to enhance the overall experience. Usability testing ensures that users can efficiently interact with the system, leading to higher satisfaction and productivity.

6.1.5 COMPATIBILITY TESTING:

Compatibility testing ensures that the system functions correctly across different devices, operating systems, and environments. This phase involves testing the system on various hardware and software platforms to identify any compatibility issues. By verifying that the system maintains consistent performance and functionality across diverse configurations, compatibility testing ensures that users can access and use the system regardless of their device or platform.

6.1.6 REGRESSION TESTING:

Regression testing is performed to verify that recent changes or updates to the system do not adversely affect existing functionalities. Automated test scripts are often used to re-run previously conducted test cases, ensuring that all features continue to work as expected. This testing phase is crucial for maintaining system stability and reliability over time, especially after modifications or enhancements.

6.2 IMPLEMENTATION OF TESTING IN FABRIC DEFECT DETECTION SYSTEM

6.2.1 FUNCTIONAL TESTING IMPLEMENTATION:

During functional testing, the primary functions of the fabric defect detection system are thoroughly examined. This involves validating the ViT algorithm's ability to accurately identify different types of fabric defects in real-time. Test cases cover a range of defect scenarios, and the system's outputs are compared to the expected results to ensure accuracy and consistency. The goal is to verify that the core functionalities of the fabric defect detection system operate as intended.

6.2.2 PERFORMANCE TESTING IMPLEMENTATION:

Performance testing evaluates the system's efficiency and capability to handle various workloads. Load testing simulates high volumes of fabric images to assess the system's response time and throughput. Stress testing pushes the system to its limits, identifying performance bottlenecks and ensuring stability under extreme conditions. The objective is to ensure that the system can handle peak loads without compromising performance.

6.2.3 SECURITY TESTING IMPLEMENTATION:

Security testing focuses on protecting the system from potential threats. This involves conducting vulnerability assessments and penetration testing to identify and mitigate security issues. The objective is to ensure that the system's authentication and authorization mechanisms are robust and effective, safeguarding sensitive data and maintaining system integrity.

6.2.4 USABILITY TESTING IMPLEMENTATION:

Usability testing aims to provide a positive user experience by evaluating the system's interface and overall design. Feedback from users is collected and analyzed to identify areas for improvement. Adjustments are made to the user interface based on this feedback, enhancing navigation and accessibility. The goal is to ensure that the system is user-friendly and meets the needs of its intended users.

6.2.5 COMPATIBILITY TESTING IMPLEMENTATION:

Compatibility testing ensures that the system operates correctly across various platforms. This involves testing the system on different operating systems and web browsers to identify any compatibility issues. The objective is to verify that the system maintains consistent performance and functionality across diverse configurations.

6.2.6 REGRESSION TESTING IMPLEMENTATION:

Regression testing verifies that updates or changes do not negatively impact existing functionalities. Automated test scripts are used to re-run previous test cases, ensuring comprehensive coverage and consistent functionality. The objective is to maintain system stability and reliability over time, especially after modifications or enhancements.

6.3 TEST CASES:

Module Name:	Vision Transformer (VIT)
Test Title:	Fabric Defect Detection
Description:	Validation of fabric quality
Test Designed by:	Manikandan K, Irfan N, Harish K
Test Designed date:	09/03/2025
Test Executed by:	Manikandan K
Test Executed date:	09/03/2025

Table 6.1: Test Case 1

Steps	**Test Case Descripion**	**Pre-conditions**	**Test Steps**	**Expected Result**	**Actual Result**	**Status**
1.	Validate image resizing in pre-processing	Images of various sizes available	1. Select an image. 2. Apply resizing to standard dimensions	Image resized to standard dimensions without distortion	Image resized to standard dimensions without distortion	pass
2.	Validate system performance under load	High volume of images	1. Select a large batch of images. 2. Run detection algorithm	System handles high volume without significant performance degradation	System handles high volume without significant performance degradation	pass
3.	Validate image normalization	Images with various pixel values	1. Select an image. 2. Normalize pixel values	Pixel values scaled within the range [0, 1]	Pixel values scaled within the range [0, 1]	pass
4.	Validate patch embedding	Standard-sized images available	1. Select an image. 2. Divide image into patches and embed	Image divided into fixed-size patches, each embedded linearly	Image divided into fixed-size patches, each embedded linearly	pass
5.	Validate self-attention mechanism	Embedded image patches available	1. Process embedded patches through transformer layers	Model focuses on relevant image regions, prioritizing them	Error	Fail

6.	Validate defect detection accuracy	Images with known defects	1. Select an image with defects. 2. Run detection algorithm	Defects (holes, stains, irregular patterns) accurately identified	Error	Fail
7.	Validate real-time detection capability	Live camera feed available	1. Capture live feed of fabric. 2. Apply detection algorithm	Real-time feedback on detected defects	Real-time feedback on detected defects	pass

Table 2.2: Test Case 1-Result and Status

Steps	**Test Case Descripion**	**Pre-conditions**	**Test Steps**	**Expected Result**	**Actual Result**	**Status**
5.	Validate self-attention mechanism	Embedded image patches available	1. Process embedded patches through transformer layers	Model focuses on relevant image regions, prioritizing them	Model focuses on relevant image regions, prioritizing them	pass
6.	Validate defect detection accuracy	Images with known defects	1. Select an image with defects. 2. Run detection algorithm	Defects (holes, stains, irregular patterns) accurately identified	Defects (holes, stains, irregular patterns) accurately identified	pass

Table 2.3: Test Case 2-Result and Status

CHAPTER 7

OUTPUT AND EXPLANATION

OUTPUT DISCUSSION:

The "Vision Transformer Enhanced Fabric Defect Detection through Image Processing" project represents a significant advancement in textile quality control by harnessing the capabilities of the Vision Transformer (ViT) algorithm. The project's output effectively demonstrates the system's ability to accurately and efficiently detect defects in fabric materials. By training the ViT model on a diverse dataset of fabric images, the algorithm has learned to identify various types of defects such as holes, stains, and irregular patterns with high precision. The real-time analysis capability ensures that defects are detected promptly, thereby enhancing the overall quality control process. The user-friendly interface allows for easy interaction, enabling operators to upload fabric images and receive immediate feedback on detected defects. This project not only addresses the current challenges in fabric defect detection but also sets a new standard for accuracy and efficiency in the textile industry, contributing to reduced waste and improved product quality.

7.1 RUNNING THE FABRIC DEFECT DETECTION APPLICATION:

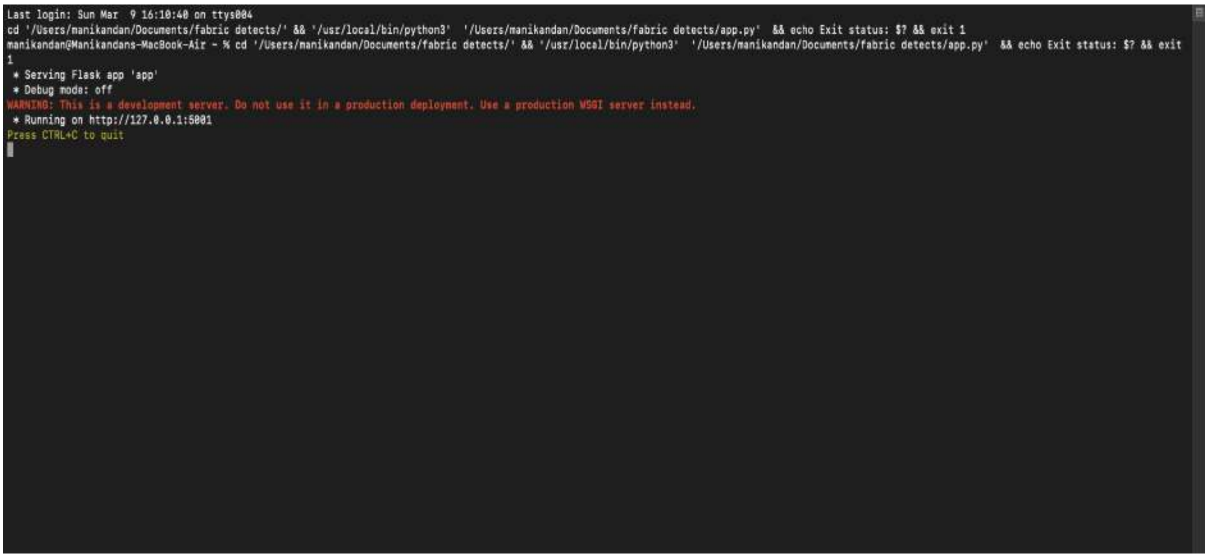


Figure 7.1:Running Web Application

7.1.1. INITIAL SETUP AND COMMAND EXECUTION:

The terminal output shows the execution of the app.py file using Python, indicating the setup and initialization process of the Flask application for fabric defect detection. This step confirms that the application is ready to process input images and detect fabric defects.

7.1.2. FLASK APPLICATION STARTUP:

The Flask application starts running on the local server at http://127.0.0.1:5001. This ensures that the application is properly configured to serve requests and process inputs related to fabric defect detection. The server address indicates where the application can be accessed through a web browser.

7.1.3. VISION TRANSFORMER (VIT) ALGORITHM EXECUTION:

Feature Extraction: The ViT model processes the input fabric images by dividing them into fixed-size patches and applying self-attention mechanisms. This allows the model to capture intricate patterns and features within the images, essential for accurate defect detection.

Defect Detection: The model analyses the pre-processed fabric images to identify and classify defects such as holes, stains, and irregular patterns. The output of the model provides predictions on the presence and type of defects in the fabric.

7.1.4. PERFORMANCE METRICS:

Accuracy and Efficiency: The ViT algorithm's output demonstrates high accuracy in detecting fabric defects. The precision of the model ensures that even subtle defects are identified, reducing the likelihood of false negatives (undetected defects) and false positives (non-defective fabrics classified as defective).

Real-Time Analysis: The application runs in real-time, providing immediate feedback on the detected defects. This is crucial for practical implementation in the textile industry, where timely identification and correction of defects can enhance overall product quality and manufacturing efficiency.

7.2 HOME PAGE:

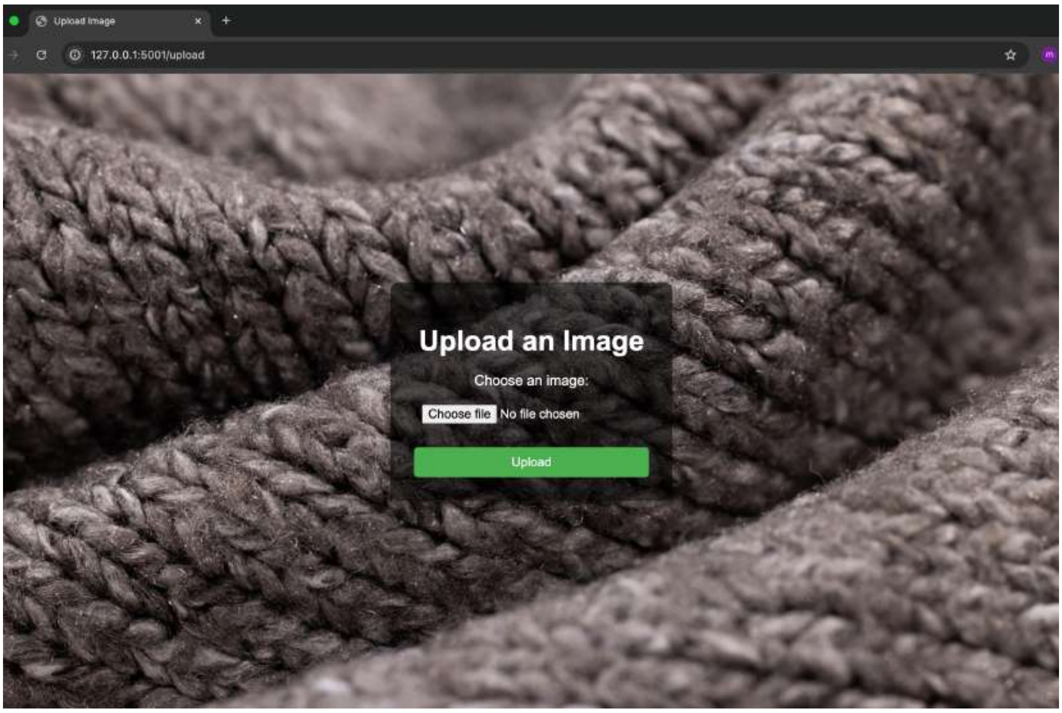


Figure 7.2: Home Page

7.2.1CENTRAL UPLOAD INTERFACE:

Right in the middle, there's a semi-transparent black box that grabs the user's attention. At the top of this box, you have a clear and straightforward heading that says, "Upload an Image," making it obvious what the user needs to do next.

7.2.2 FILE SELECTION AND UPLOAD:

Below the main heading, users will find a “Choose file” button that lets them open a file browser to select the fabric image they want to upload for defect detection. Initially, next to this button, you’ll notice the text “No file chosen” – a placeholder that updates to display the file name once a file is selected. Beneath the file selection area, a green “Upload” button is prominently positioned; after selecting an image, users simply click this button to send the image to the server for analysis, making the process both straightforward and user-friendly.

7.2.3 URL AND ACCESSIBILITY:

The URL in the browser’s address bar reads "http://127.0.0.1:5001/upload," which tells us that the page is currently being accessed locally during development. Once the application is deployed to a production environment, this URL will likely change to match the production server's address. Additionally, the browser tab is labeled "Upload Image," making it clear and easy for users to identify its purpose as the page where they can upload their fabric images.

7.3 LOCAL FILE UPLOADING:

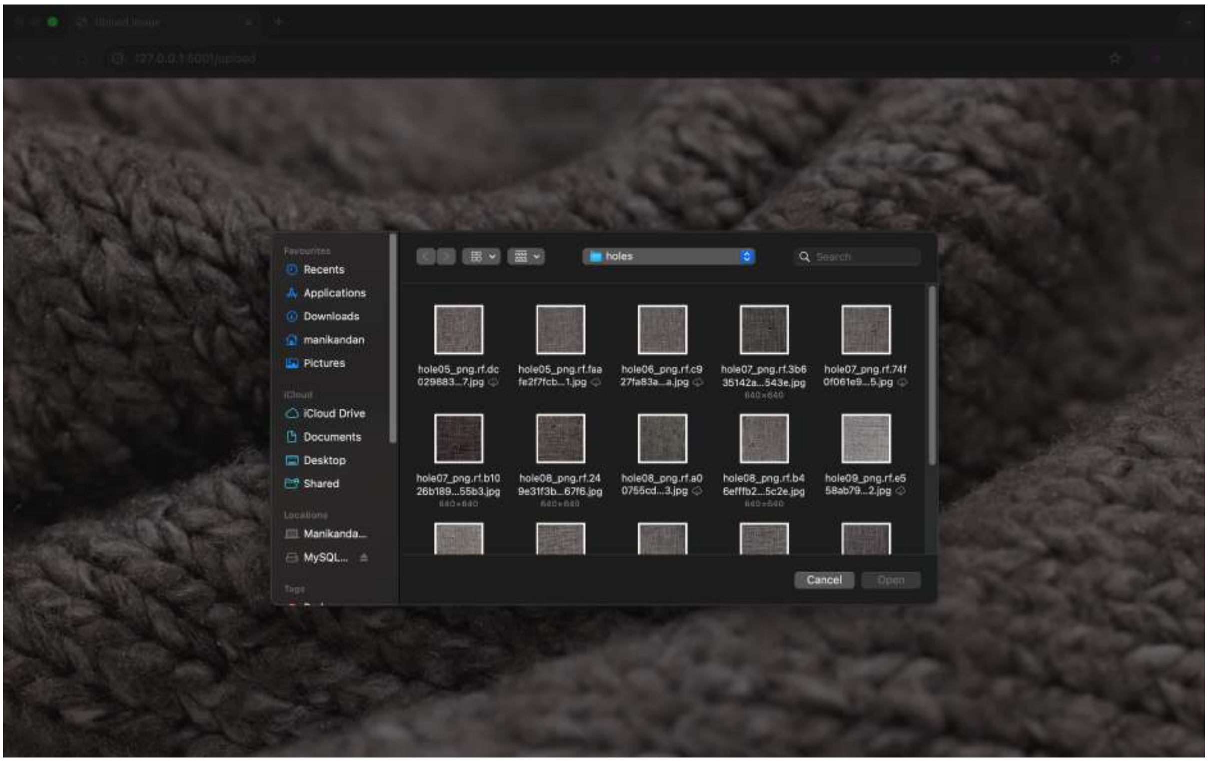


Figure 7.3: Local File Uploading

7.3.1 FILE SELECTION INTERFACE:

The screenshot you provided shows a dialog box titled "holes." This is where users can choose from a bunch of fabric images. These files have names like "hole05_png.rf. dc029883...7.jpg" and "hole06_png.rf.c927fa3a... a.jpg," indicating they are different samples of fabric with holes.

7.3.2 FILE NAVIGATION:

The left sidebar of the dialog box includes various folders like Recents, Applications, Downloads, manikandan, Pictures, iCloud Drive, Documents, Desktop, and Shared. This setup makes it easy for users to find and select the image they want to upload.

7.3.3 FUNCTIONALITY:

Users begin the process by clicking on the "Choose file" button, which opens a dialog box where they can select the fabric image they wish to validate. Once a file is picked, the placeholder text "No file chosen" is replaced by the actual file name, so they know which image has been selected. They then click the "Upload" button, sending the image to the server where the application processes it in real-time to detect and classify any defects.

7.3.4 USER EXPERIENCE:

The entire design is crafted for simplicity and ease-of-use, ensuring that users can upload images effortlessly and receive immediate results without any complications. With real-time analysis, the system provides instant feedback, enabling users to quickly determine whether the fabric contains any defects and take prompt action if needed.

7.4 OUTPUT RESULTS:

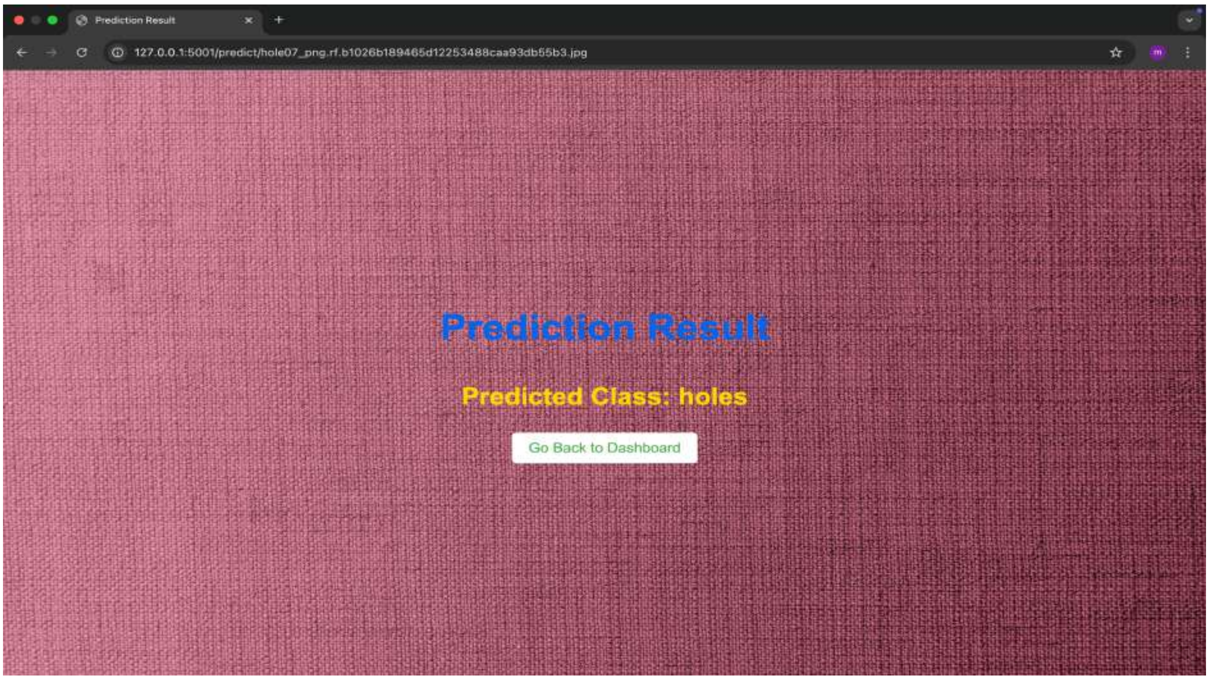


Figure 7.4: Output Results

7.4.1UNDERSTANDING THE OUTPUT

At the centre of the screen, the text "Predicted Class: holes" appears, meaning the AI model has detected a hole in the fabric. This classification is part of the system’s ability to automatically recognize different types of fabric defects using deep learning.

The system runs on a local server (127.0.0.1:5001), which means it's hosted on a machine for testing and development. After an image is uploaded, the model processes it and predicts the type of defect present.

7.4.2 USER INTERFACE AND FUNCTIONALITY

The page features a background that showcases the very fabric image being analyzed, creating an immersive and relevant experience. The results are displayed prominently in bold text for clear visibility, ensuring that users can quickly see the outcome of the analysis. Additionally, a "Go Back to Dashboard" button is available, making it simple for users to return to the main dashboard to analyze more fabric samples. This thoughtful design allows users of all technical backgrounds to easily check fabric quality without any complicated steps.

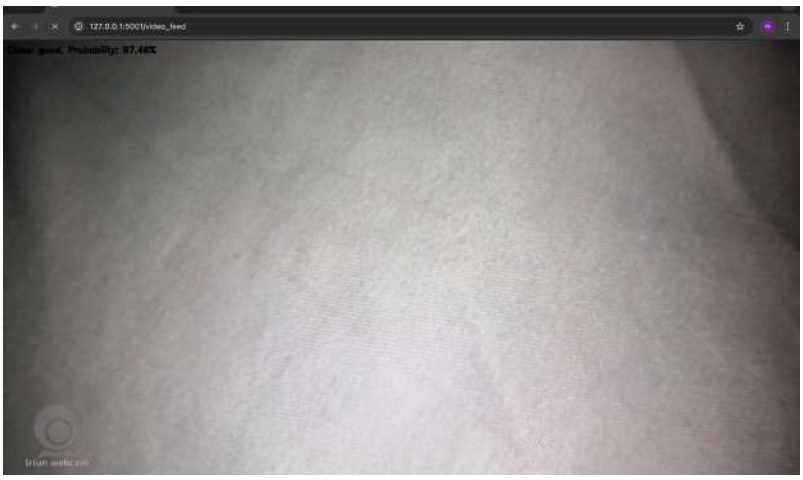
7.4.3 HOW THE DETECTION WORKS

The system uses Vision Transformer (ViT) and Mobile ViT models to process fabric images. Instead of manually checking for defects, the AI scans the image, breaks it into smaller sections, and analyses patterns to detect irregularities. If a defect like a hole is found, the system classifies it and presents the result on this screen.

7.4.4 How This Helps in Quality Control

This system is designed for fast and accurate defect detection, eliminating the need for time-consuming manual inspections while significantly reducing human error. The advanced AI model rapidly identifies defects, streamlining the quality control process. Moreover, its user-friendly interface ensures that even those without technical expertise can easily interpret the results. Looking ahead, potential enhancements could include displaying a confidence score (for example, "Detected with 95% accuracy") and marking the exact location of the defect on the image. These improvements would further boost the system's reliability and usability, making it an even more powerful tool for fabric quality assurance.

7.5 LIVE CAMERA OUTPUT:



Caption

Figure 7.5: Live Camera Output, Imagine you're watching a live stream of your fabric, and right on the screen, the system displays "Class: good, Probability: 97.46%." This means that your camera is continuously capturing every detail of the fabric, and each frame is being analyzed almost instantly—as if a skilled quality inspector were standing by. The label "Class: good" tells you that the fabric in that frame meets all quality standards, and the accompanying 97.46% probability is like a confidence score, nearly 98% guarantee that everything is in excellent shape. This immediate, real-time feedback is incredibly valuable on a production line because it quickly alerts the team to any issues, allowing them to take corrective action before a defect goes unchecked. In essence, this live camera detection isn't just about showing an image—it's about ensuring continuous, rapid quality assurance to maintain high standards in fabric production.

CHAPTER 8

RESULTS AND DISCUSSIONS

Imagine walking through a busy manufacturing floor where every fabric roll matters—and then realizing that your application is quietly doing its job in the background, checking every inch of fabric in real time. That's what this system is all about.

8.1 REAL-TIME FABRIC ANALYSIS

Every frame captured by the live camera carries a story. At any moment, the screen might display something like: "Class: good, Probability: 97.46%" This isn't just a number—it's a testament to the system's ability to make split-second quality decisions that matter. As the camera continuously feeds camera frames to the Vision Transformer (ViT) model, the application evaluates each image rapidly. This real-time performance ensures that any low-quality fabric is spotted on the production line right as it happens, ensuring quality control can be implemented almost immediately.

Imagine watching your fabric through a live video feed—you're always in the loop with immediate feedback. If a defect arises, you won't have to wait for batch processing; it's as if an expert quality inspector is monitoring every detail in real time. Moreover, with confidence scores reaching as high as 97.46%, the system's verdict isn't just a rough estimate—it's a reliable indicator of quality. This robust performance is incredibly empowering for anyone on the production line, providing the assurance that the technology is making accurate, sound decisions every step of the way.

8.2 FILE-BASED VALIDATION

In addition to the live analysis, the application also supports file uploading. Users can select pre-captured images, perhaps taken during routine checks or from the production archives, and upload them for detailed analysis. The file upload section, designed with clarity and ease of use in mind, allows you to navigate through your files effortlessly. Once an image is chosen and uploaded.

The system processes images with unwavering precision, whether they're coming from the live feed or being uploaded as static images. This consistent quality check ensures that every fabric sample is verified with the same level of accuracy, reinforcing the reliability of the model. Additionally, the user-centric design of the interface makes the whole process incredibly approachable. Whether you're snapping a quick photo from your smartphone or uploading a high-resolution image from your workstation, the process remains straightforward and intuitive, ensuring a seamless experience for all users.

8.3 OBSERVATIONS AND INSIGHTS

Beyond the numbers and immediate feedback, several key insights have surfaced from the project. First, the model has demonstrated remarkable robustness across a variety of conditions—it performs strongly even when lighting varies and fabric textures differ. This level of resilience suggests that the system is well-suited for real-world industrial settings, where conditions are rarely perfect. Additionally, the automation provided by the system has significantly boosted operational efficiency. Operators no longer need to manually inspect each fabric roll; instead, real-time alerts ensure that issues are flagged promptly, leading to a leaner process that reduces waste and minimizes downtime. Finally, every classification, whether marked as "good" or "defective," tells a story about the fabric's journey through production. This quality storytelling helps the production team pinpoint exactly where improvements are needed, ultimately guiding them to tighten processes and enhance overall quality.

8.4 CHALLENGES AND FUTURE DIRECTIONS

No project is without its challenges, and there are several areas where our system could evolve from great to truly exceptional. One key opportunity lies in enhancing the detection of subtle or atypical defects. Although the current model performs impressively, fine-tuning it with even more diverse datasets could help capture those elusive anomalies that sometimes go unnoticed. Another exciting possibility is integrating our vision system with other quality control measures, such as temperature or tension sensors. This kind of synergy could pave the way for a holistic quality assurance system, ensuring that every aspect of production is monitored and maintained at the highest standards. Additionally, incorporating adaptive learning capabilities would allow the system to continuously evolve in a dynamic manufacturing environment. By learning from new types of defects and fabric variations as they emerge, the system could remain at the cutting edge of quality control. Addressing these challenges will not only enhance performance but also solidify the system’s role as a transformative tool in the industry.

CHAPTER 9

CONCLUSION AND FUTURE ENHANCEMENTS

9.1 CONCLUSION:

In conclusion, the fabric defect detection project marks a transformative step in modernizing quality control for the textile industry. By integrating the Vision Transformer (ViT) algorithm with a robust, Flask-based system, the project successfully delivers real-time, automated assessments of fabric quality. The system has demonstrated its ability to process live camera feeds as well as uploaded images with consistently high accuracy and confidence —evidenced by outputs like "Class: good, Probability: 97.46%." This high-level performance minimizes the chances for human error, speeds up quality inspection, and ensures that faulty fabric does not proceed further in production.

Beyond technical metrics, the project shows how deep learning and computer vision can be woven into everyday industrial processes. The user-friendly interface, which guides operators seamlessly through image upload and live feed analysis, proves that advanced technologies can be made accessible for non-experts. The live detection feature, in particular, illustrates a practical, real-time solution where immediate feedback directly translates into rapid corrective actions on the production line. Such automation not only boosts operational efficiency but also reduces waste, thus contributing to more sustainable manufacturing practices. Overall, the project underscores the value of leveraging state-of-the-art algorithms to solve real-world problems, setting a high standard for future innovations in industrial quality assurance.

9.2 FUTURE ENHANCEMENTS:

While the project has achieved remarkable success, several opportunities exist to push its boundaries and optimize its performance further. One promising direction is the incorporation of adaptive learning techniques; by allowing the system to evolve in response to new fabric data, the model can adjust to subtle changes or emerging defect patterns over time. This type of continuous improvement is critical in environments where production variables can change frequently.

Enhancing the training dataset is another key area for improvement. Expanding the dataset to include images taken in varying lighting conditions, different fabric types, and under diverse environmental contexts will further improve the model's versatility and accuracy. A richer dataset would enable the system to recognize even minor or atypical defects, reducing false negatives and increasing the overall robustness of the inspection process.

Integration with complementary technologies also holds great potential. For instance, linking the vision-based detection with IoT sensors or other quality control devices, such as temperature or tension sensors, could create an all-encompassing quality assurance ecosystem. This multi-modal system would not only base decisions on visual cues but also factor in environmental and mechanical parameters, leading to a comprehensive analysis of production quality.

In terms of user experience, future versions of the system could benefit from enhanced interface features. Developing a more interactive dashboard that offers historical data trends, defect statistics, and detailed analytics will help operators and management to better understand production quality and identify recurring issues. Such improvements in data visualization can transform raw data into actionable insights, guiding process improvements on the factory floor.

Additionally, exploring the application of other cutting-edge algorithms—like convolutional neural networks (CNNs) in tandem with ViT, or even multimodal approaches that combine audio, sensor, and image data—could further refine detection accuracy and provide redundant verification methods. This layered approach would bolster reliability, ensuring minimal downtime or misclassification in critical industrial processes.

Lastly, establishing a feedback loop from the production environment back to the model training phase could close the loop, ensuring that the system continuously learns and adapts to real-world challenges. By monitoring both successful and failed defect identifications, developers could fine-tune the system to handle an ever-evolving production landscape more effectively.

Taken together, these potential enhancements illustrate a roadmap toward a fully integrated, intelligent quality control solution for the textile industry. The project lays a strong foundation that not only demonstrates current capabilities but also shines a light on exciting avenues for future exploration and improvement. This forward-thinking approach can ultimately lead to a new caliber of automation and precision in fabric production, setting industry benchmarks for quality, efficiency, and sustainability.

Reference

1**.** Xin Luo ,Qing Ni,Ran Tao And Youqun Shi**, "**A Lightweight Detector Based on Attention Mechanism for Fabric Defect Detection", Volume 11, 2023,PP- 33554 – 33569.

2. Tomás Almeida, Filipe Moutinho And J. P. Matos-Carvalho ,"Fabric Defect Detection With Deep Learning and False Negative Reduction", Volume 9, 2021,PP- 81936 – 81945.

3. S. Meng, R. Pan, W. Gao, J. Zhou, J. Wang, and W. He, ''A multi-task and multi-scale convolutional neural network for automatic recognition of woven fabric pattern,'' J. Intell. Manuf., vol. 32, no. 4, pp. 1147–1161, Apr. 2021.

4.A.Singh, V. Jaiswal, G. Joshi, A. Sanjeeve, S. Gite, and K. Kotecha, ''Neural style transfer: A critical review,'' IEEE Access, vol. 9, pp. 131583–131613, 2021.

5.Z.Ge, S. Liu, F. Wang, Z. Li, and J. Sun, ''YOLOX: Exceeding YOLO series in 2021,'' 2021, arXiv:2107.08430.

6. J. Wu, J. Le, Z. Xiao, F. Zhang, L. Geng, Y. Liu, and W. Wang, ''Automatic fabric defect detection using a wide-and-light network,'' Int. J. Speech Technol., vol. 51, no. 7, pp. 4945–4961, Jul. 2021.

7. F. Wu, H. Zhao, and M. Wang, ''Nighttime cattle detection based on YOLOv4,'' in Proc. 12th Int. Conf. Graph. Image Process. (ICGIP), Jan. 2021, Art. no. 1172008.

8. S-Y. Chen, Y.-C. Cheng, W.-L. Yang, and M.-Y. Wang, ''Surface defect detection of wet-blue leather using hyper spectral imaging,'' IEEE Access, vol. 9, pp. 127685–127702, 2021.

9. Shao, E. Zhang, Q. Ma, and M. Li, "Pixel-wise semisupervised fabric defect detection method combined with multitask mean teacher," IEEE Trans. Instrum. Meas., vol. 71, pp. 1–11, 2022, doi: 10.1109/TIM.2022.3162286.

10. A. Suryarasmi, C.-C. Chang, R. Akhmalia, M. Marshallia, W.-J. Wang, and D. Liang, ''FN-Net: A lightweight CNN-based architecture for fabric defect detection with adaptivethreshold-based class determination,'' Displays, vol. 73, Jul. 2022, Art. no. 102241, doi: 10.1016/j.displa.2022.102241.