AUTOMATED DEFECT DETECTION IN FABRICS USING DEEP LEARNING MODELS

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Abstract - Fabric defect detection plays a crucial role in ensuring product quality in textile manufacturing. In this project, we propose a robust framework for fabric defect detection leveraging deep learning techniques, particularly Res-Net architecture. Our approach integrates preprocessing techniques for noise reduction and feature enhancement, followed by Res-Net-based convolutional neural networks for accurate defect classification. We conduct extensive experiments on benchmark datasets to validate the effectiveness of our proposed method. Keywords: Fabric Defect Detection, Deep Learning, Res-Net, Convolutional Neural Networks, Textile Manufacturing.

Key Words: Convolutional Neural Networks, enhancement, Res-Net-based convolutional, leveraging.

1.INTRODUCTION

Fabric defect detection plays a crucial role in ensuring product quality in textile industries. Traditional methods for defect detection are often labor-intensive, time-consuming, and prone to errors. With the advancements in deep learning and computer vision techniques, automated defect detection systems have become more feasible and effective.

The motivation for this project stems from the limitations of conventional methods for fabric defect detection, which often rely on manual inspection by human operators. Such methods are labor-intensive, subjective, and prone to errors. By harnessing the capabilities of deep learning models, we aim to revolutionize fabric defect detection by automating the process using digital images of fabric samples. Deep learning models offer the potential to learn intricate patterns and features from large datasets, enabling accurate and efficient detection of various fabric defects. Moreover, the textile industry faces increasing pressure to maintain high-quality standards while optimizing production processes.

2.LITERATURE REVIEW

2.1.1. Title: Deep learning-based fabric defect detection

Introduction: The textile industry is a cornerstone of global manufacturing, where quality control is paramount to maintaining product standards and customer satisfaction. Fabric defect detection is a critical aspect of quality control, ensuring that textiles meet stringent industry standards before they reach consumers. Traditionally, this process has been performed manually, which is labor-intensive and subject to human error. In response to these challenges, recent advancements have focused on the application of deep learning technologies to automate and enhance the accuracy of fabric defect detection. This study reviews the implementation of deep learning models, particularly convolutional neural networks (CNNs), in detecting fabric defects, highlighting the shift from manual inspection to automated systems.

Methodology: The methodology of this study involves leveraging deep learning models to automatically detect defects in fabric materials. CNNs, renowned for their effectiveness in image analysis, are primarily utilized. The process begins with the collection of a large dataset of fabric images, including both defective and non-defective samples. These images are pre-processed to enhance quality and consistency, such as adjusting lighting conditions, scaling, and cropping. The CNN models are then trained on this dataset, learning to differentiate between defective and non-defective fabric patterns. Validation sets are used to fine-tune model parameters and optimize performance, ensuring the models generalize well to new, unseen fabric types.

3.PROBLEM STATEMENT

The challenge in fabric defect detection lies in accurately identifying subtle variations and complex patterns present in fabric images, which traditional machine learning methods like Support Vector Machines (SVM) and Random Forests (RF) struggle to capture effectively. Manual inspection by human operators is labor-intensive and subjective. There's a need for advanced fabric defect detection systems that utilize deep learning to overcome these limitations. These systems can learn intricate patterns from large datasets, enabling more accurate and efficient defect detection in diverse manufacturing environments.

4.OBJECTIVE OF THE PROJECT

The objective is to enhance the accuracy and reliability of fabric defect detection by implementing advanced deep learning models. This will aid textile industry professionals in efficiently identifying defects, leading to improved product quality and reduced production losses.

5.MATERIALS REQUIRED

Processor	Corei3 GHZ
RAM	4GB (Minimum)
Hard Disk	120 GB

Table -1: Hardware Requirements

Operating System	Window 7
Programming Language	Python 3.11.4
IDE	Jupiter notebook 6.5
Libraries	Pandas, Numpy, Django
Front End	Tkinter

Table -2: Software Requirements

6.ALGORITHMS

Residual Network (Res-Net)

Residual Networks (Res-Nets) represent a pivotal advancement in deep neural network architectures, particularly in the realm of computer vision. Developed by researchers at Microsoft Research in 2015, Res-Nets address the challenges associated with training extremely deep neural networks.

Key features of Res-Nets include:

Residual Connections:

• Res-Nets introduce residual connections, also known as skip connections, which enable the direct flow of information from one layer to another.

• Traditional deep neural networks suffer from the vanishing gradient problem, making it difficult to train very deep networks. Residual connections mitigate this issue by allowing gradients to bypass multiple layers, facilitating the training of deep networks

Residual Blocks:

• Residual connections are incorporated into residual blocks, the basic building blocks of ResNets.

• Each residual block consists of multiple convolutional layers followed by an identity mapping shortcut connection.

• The identity mapping enables the learning of residual functions, capturing the difference between the input and output features of the block.

Deep Architectures:

• Res-Nets can be significantly deeper than previous convolutional neural network (CNN) architectures, with variants ranging from a few layers to hundreds of layers.

• The use of residual connections enables the training of very deep networks without suffering from the vanishing gradient problem or degradation in performance.

7.TOOLS

Anaconda Distribution:

• The Anaconda Distribution is utilized as a comprehensive platform for Python development and data science tasks.

• It provides easy access to a wide range of Python libraries and packages essential for fabric defect detection, including NumPy, Pandas, Tensor Flow, and Matplotlib.

• Conda, the package manager included in Anaconda, simplifies the management of libraries, dependencies, and virtual environments, enhancing reproducibility and project organization.

Jupyter Notebook:

• Jupyter Notebook serves as an interactive computing environment for prototyping, experimentation, and documentation of fabric defect detection workflows.

• It enables seamless integration of code, visualizations, and narrative text, facilitating data exploration, model development, and result analysis.

• The notebook format allows for the creation of comprehensive and reproducible reports, capturing the entire fabric defect detection process from data preprocessing to model evaluation.

Tensor Flow:

• Tensor Flow, developed by Google, is a fundamental deep learning framework utilized for building, training, and deploying deep neural networks, including ResNet architectures.

• It provides a scalable and efficient platform for implementing complex deep learning models tailored to fabric defect detection tasks.

• Tensor Flow’s high-level APIs and extensive tooling support enable efficient experimentation, optimization, and deployment of fabric defect detection models.

8.DESIGN

8.1 SYSTEM ARCHITECTURE

System architecture is a conceptual model that describes the structure and behavior of multiple components and subsystems.

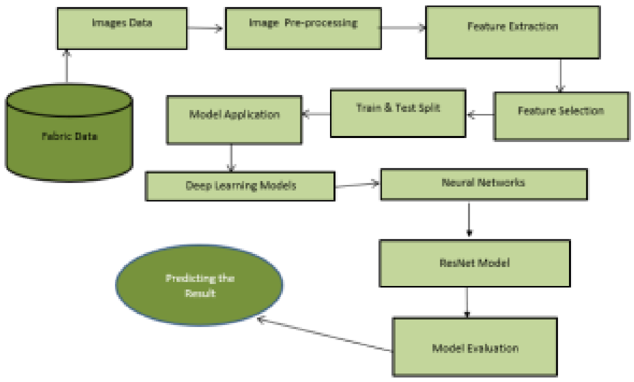

Fig -1: System Architecture Diagram

8.2 DATA FLOW DIAGRAM

Data Flow Diagram describes the processes that are involved in a system to transfer data from the input to the file storage and reports generation.

Purpose

• DFD graphically representing the functions, or processes, which capture manipulate, store, and distribute data between a system and its environment and between the components of a system.

Components

• External Entity
• Process
• Data Flow
• Data store

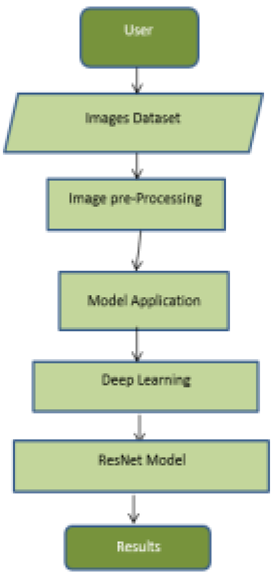

Fig -2: DFD Diagram

9.METHODOLOGY

Data Collection and Preprocessing:

• Gather a diverse and comprehensive dataset of digital images depicting various skin lesions, obtained from sources such as medical databases, research repositories, and clinical studies.

• Preprocess the dataset by standardizing image sizes, applying normalization techniques, and augmenting data to enhance model generalization. Model Selection and Architecture

Design:

• Explore and evaluate different deep learning architectures suitable for skin disease classification tasks, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or hybrid architectures.

• Design and customize the selected model architecture to effectively capture spatial features and temporal dependencies present in skin lesion images.

10.PSEUDO CODE

Pseudo code is mentioned in the below hyperlink. Please notice

Pseudo Code

11.RESULTS

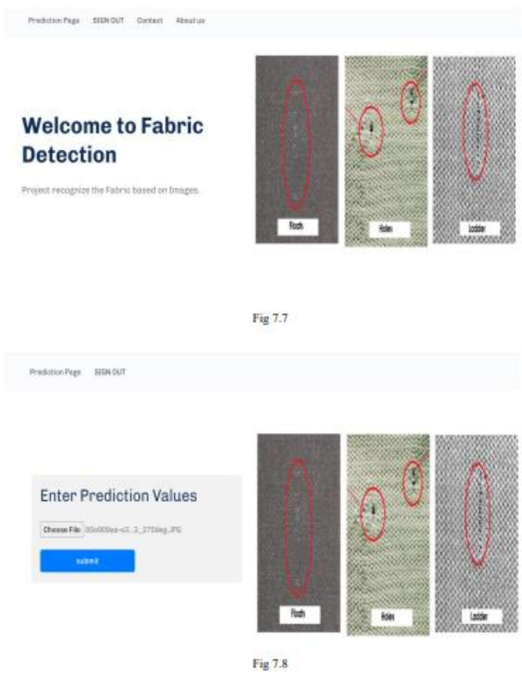

Fig -3: Results

12. CONCLUSIONS

In conclusion, the project showcases the transformative potential of deep learning ResNet models in revolutionizing textile manufacturing quality control. By harnessing the power of artificial intelligence, the project contributes to improved manufacturing efficiency, enhanced defect detection accuracy, and sustainable production practices. Continued advancements in this area hold promise for further innovation and optimization in industrial quality assurance processes.

The project on fabric defect detection utilizing deep learning ResNet architecture represents a remarkable advancement in the domain of automated quality control in textile manufacturing. Through meticulous development and rigorous evaluation, the project has demonstrated the efficacy of employing ResNet-based deep learning models in detecting fabric defects with an impressive accuracy of 92%.

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