Convolutional Neural Networks for the Binary Classification of Textile Materials

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Abstract **– This study aims to improve the binary classification of textile materials-specifically distinguishing between acceptable items and those with defects using convolutional neural networks (CNNs). A quantitative, applied approach with a pure experimental design was employed, incorporating the Mobile-D methodology. Data collection was conducted through direct observation, and two groups were compared: The experimental group (EG), used the mobile application, and the control group (CG), did not. Results, validated through the Mann–Whitney U test, showed that the EG outperformed the CG with a 35-second reduction in classification time, a 10% increase in accuracy, and a 17% improvement in the timely detection of non-conformities. In conclusion, the use of convolutional neural networks enhances the effectiveness and efficiency of binary classification in textile inspection processes.**

Keywords **– Convolutional neural networks, deep learning, binary classification, textile inspection.**

DOI: 10.18421/TEM153-19
https://doi.org/10.18421/TEM153-19

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Received: 12 August 2025.
Revised: 16 February 2026.
Accepted: 04 March 2026.
Published: 27 August 2026.

1. Introduction

The textile industry is a key driver of the global economy, producing fibers, yarns, fabrics, and garments. This sector not only generates employment but also shapes the culture and lifestyles of societies. It plays a strategic role in the fashion industry by providing the material foundation upon which new trends are built. Over time, the textile sector has evolved from manual techniques to increasing automation and digitalization, improving both operational performance and efficiency [1].

In 2024, it was projected that by 2025 the global textile industry would reach a value of approximately USD 2.25 trillion, driven by growing demand for clothing, particularly in developing nations such as China and India [2].

Peru is recognized for its robust textile sector and stands out as one of the largest producers of natural materials such as alpaca and vicuna fibers. This sector comprises around 50,000 companies employing more than 400,000 workers, and it is distinguished by its adaptability to various market conditions. Nevertheless, it continues to face major challenges in terms of technological innovation and the need to update processes to remain competitive in the global market [3].

In Trujillo, within the textile manufacturing field, it has been observed that defective fabric segments can appear at the beginning of the production process, especially when manufacturing sportswear. According to an interview with a local textile entrepreneur, fabric defects, if detected early, can result in both material and time savings [4].

Based on this, the study formulated the following general research problem: How does the use of neural networks improve the binary classification of textile materials? The specific research questions were:

RQ1: *How does the use of CNNs reduce classification time?*

RQ2: *How does the use of CNNs improve classification accuracy?*

RQ3: *How does the use of CNNs increase the number of detected non-conformities in textile materials?*

The general objective was to determine how the use of CNNs improves the binary classification of textile materials. The specific objectives were to reduce classification time, increase accuracy, and raise the number of non-conformities detected in a timely manner.

Finally, the general research hypothesis established that the use of CNNs improves the binary classification of textile materials. **General hypothesis (GH)**: *CNNs reduce classification time; convolutional neural networks increase classification accuracy; and convolutional neural networks increase the timely detection of non-conformities in textile materials.*

2. Theoretical Framework

The following theoretical foundations were used in this research, corresponding to the independent variable (convolutional neural networks) and the dependent variable (binary classification of textile materials).

a. Mobile Application

A mobile application is a type of software specifically designed for deployment on mobile devices such as smartphones and tablets. Unlike desktop applications, mobile apps are optimized for mobile environments, allowing users to perform specific tasks by leveraging the features of the device [5].

b. Image Processing

Image processing is a discipline focused on the analysis or manipulation of image data with the goal of enhancing visual quality or facilitating information extraction through computational techniques. The process begins with an input image and produces a new output, which may be another image, data, or decisions [6].

c. Binary Classification

Binary classification, within the field of machine learning, assigns each observation to one of two mutually exclusive categories. In the context of the textile industry, this technique is particularly useful for automating quality control processes, enabling fabrics to be classified as either “pass” or “with defects” according to pre-established criteria. For example, using computer vision algorithms trained on labeled images, it is possible to detect fabric defects such as stains, tears, or irregularities, and distinguish them from those that meet quality standards. This ability to make binary decisions automatically enhances visual inspection, reduces human error, and improves efficiency on the production line [7].

d. Convolutional Neural Networks

Convolutional neural networks (CNNs) are a subfield of machine learning and form the foundation of deep learning algorithms. Any neural network is layer-structured with an input layer, one or more hidden layers, and an output layer. The focus of this study was on predictive networks. There are various architectures designed for different applications for instance, recurrent neural networks for natural language processing and this model for image classification. CNNs, widely used in computer vision systems, have replaced manual feature extraction methods by offering a more effective alternative to identify visual patterns through mathematical operations, specifically matrix multiplication [8].

e. TensorFlow

TensorFlow is an open-source library for image processing and visual computing using Python. This high-level, object-oriented programming language with dynamic semantics is primarily used to develop web and software applications. The library offers functions for tasks such as filtering, edge detection, attribute identification, and object tracking, among others [9].

f. Mobile-D

Mobile-D is a mobile development methodology based on agile practices, structured into five phases: Exploration, initiation, production, stabilization, and system testing. Each phase includes distinct activities designed to guide the development process effectively [10].

3. Related Works

The following are some similar studies on the use of predictive models in the context of textile defect detection. These investigations were sourced from various digital databases such as Scopus and Web of Science.

One study mentions that the integration of computer vision and graphical image recognition into the design, production, and consumption of textiles and garments has become a growing trend in the sector. Artificial Intelligence (AI) applied to the textile and apparel industry has reached unprecedented levels. In the production and fabric identification stages, computer vision has gradually replaced manual tasks, driving the development of more automated and precise production lines. Moreover, in areas such as design, manufacturing, and consumer use, image recognition has played a key role in transforming traditional processes [11].

As described in [12], techniques for unsupervised computer vision were developed to enable the initial detection and segmentation of stains on textile materials. The study focused on two methods Otsu's thresholding and K-means clustering which do not require large training datasets or deep learning models. Results showed that the proposed system, tested on a preselected set of textiles, achieved an accuracy of 88.3% with an average computation time of 0.77 seconds per textile. Although a fixed-area sampling method achieved 74.0% accuracy, the proposed system outperformed it, especially for multicolored textiles.

According to [13], a web-based solution using neural networks was developed to improve attendance tracking in an educational institution. A sample of 30 randomly selected records was used, and the XP methodology was applied. Time and accuracy indicators were evaluated, showing that the experimental group reduced attendance recording time by 53.33% and report generation time by 60%. Furthermore, 80% of cases exceeded the control group's average accuracy, and 96.67% achieved higher precision. To validate the results, Mann-Whitney U and Student's t-tests were applied, concluding that the digital tool significantly enhanced the efficiency and reliability of the attendance tracking process.

As explained in [14], a deep learning algorithm using a CNNs was designed to extract depth features from textile images and classify defects. Experimental results showed that the optimized AlexNet-SVM model achieved 99% accuracy in defect categorization using the TILDA dataset. This performance was 5% higher than that of standard AlexNet and GoogleNet models.

According to [15], a deep learning model trained to facilitate fabric inspection and defect detection. The study used a dataset from Chenab Textiles to train a YOLOv8 model and compared it with YOLOv5 and MobileNetV2-SSD. The results showed a precision of 0.818 and a recall of 0.839 across seven types of defects. The YOLOv8 model achieved a performance with a mean average precision (mAP) of 84.8%.

In a study focused on the application of image processing based on visual features, the main objective was to analyze the use of the ROC curve as an evaluation approach on mobile devices. The research was conducted in the agricultural domain, specifically for the detection of pests and diseases in cocoa fruits and chili leaves. The results showed that, in the analysis of chili leaves, an accuracy of 60%, a sensitivity of 60%, and a precision of 100% were achieved. On the other hand, in the evaluation of cocoa fruits, an accuracy of 66.7%, a sensitivity of 67%, and a precision of 100% were obtained [15].

Previous research has addressed the automatic detection of defects in textile fabrics by developing systems aimed at improving product quality through high-speed inspection processes. In this context, image preprocessing techniques were employed to decompose the original images into smaller fragments, complemented by data augmentation and labeling strategies to enhance model robustness. The system was implemented within a hardware environment specifically designed for detection, achieving an accuracy of 95.3%. Furthermore, efficient real-time performance was demonstrated, with a detection speed of 34 frames per second, enabling reliable and automatic localization of defects in textile fabrics [16].

As shown by [17], an intelligent decision support system has been developed for the design and evaluation of new textile fabrics, based on Machine Learning techniques. Using a large-scale dataset obtained from a textile company, predictive approaches based on single-target regression and multi-objective regression were compared using deep neural networks. The results demonstrated a high level of accuracy, reaching up to 87%, with reduced prediction errors in the physical properties of the material, such as elasticity. This approach improved the precision of technical estimations and optimized decision-making time, highlighting the positive impact of machine learning in the textile industry.

Finally, [18] describes a pilot prediction system based on Machine Learning has been implemented to anticipate the need for hemorrhage resuscitation following trauma, with the aim of strengthening decision-making through the use of predictive variables collected in real time from mobile devices. For model training, the dataset was randomly divided into training and validation subsets, allowing the evaluation of its predictive performance. The main contribution of this approach lies in the fact that Machine Learning can serve as an objective decision-support reference against which human judgment can be contrasted, a principle that is applicable to the present study in the automation of evaluation and classification of textile materials.

4. Methodology

This study was applied in nature, as it focused on addressing specific questions to solve a particular problem. It relied on the practical application of previously developed theoretical knowledge and was especially relevant in contexts where challenges had cultural or organizational dimensions. For this research, an application was developed that employed CNNs to perform binary classification of textile materials in Trujillo [19].

A pure experimental design was adopted, incorporating two groups: Control Group (CG): Manual and visual inspection of fabric. Experimental Group (EG): Use of the CNNs-based software solution, supported by a conveyor belt and tripod system to automate the classification process. This design is characterized by the manipulation of one or more independent variables, whose effects are measured through a dependent variable. Its main strength lies in its control of internal validity, which reinforces the rigor of the study [20].

The independent variable was the use of CNNs for image classification through a mobile application. It was measured using a presence–absence indicator, initially assigned a value of "No" and subsequently "Yes" after implementation, and evaluated on a nominal scale.

The dependent variable was the binary classification of textile materials, defined as the process of determining whether a fabric meets quality standards ("pass") or contains defects ("with defects"), either manually or through an automated inspection system. Data collection was conducted using an observation form that measured three indicators: Identification time (IT), identification precision (IP), and number of non-conformities identified (NCI), all assessed using a ratio measurement scale.

The study population consisted of 30 textile material evaluations. Inclusion criteria: Items falling under the category of textile material. Exclusion criteria: Non-textile material. A non-probabilistic convenience sample was used, composed of 30 textile material evaluations for each group, both the Control Group (CG) and the Experimental Group (EG).

The techniques and instruments used for data and information collection included interviews and observation forms. Interviews were employed to gain detailed and comprehensive insights directly from individuals, making them particularly effective for exploring perspectives, experiences, and perceptions related to the research problem. Meanwhile, the observation form facilitated systematic data collection by guiding the observer on the specific elements to assess, who then simply recorded the relevant data or comments accordingly [21].

5. Software Development

The software solution for textile material classification was developed following the Mobile-D methodology, structured into five sequential stages: Exploration, Initiation, Production, Stabilization, and Deployment. Each stage incorporated agile practices tailored to mobile application development.

The following section outlines how these phases were executed in building the CNN-based application.

a. Phase 1: Exploration

In this initial phase, the application's core requirements were defined, along with the identification of key stakeholders. The development team included a software architect responsible for building the application and the end users, who were sportswear manufacturers.

The goal was to design a mobile app capable of performing binary classification of textile materials using a CNNS model, specifically the pre-trained MobileNetV2. Based on this objective, the functional requirements shown in Table 1 were established.

For the technical environment, Android Studio was selected as the integrated development environment (IDE) to build both the front-end and back-end components. PostgreSQL was used as the database management system, supported by Supabase Storage for managing media files. Dart served as the main programming language, chosen for its performance and compatibility with mobile platforms.

Table 1. Functional requirements

No	Requirement	Description
FR1	Automatic inspection	The system allows users to start an inspection that automatically captures a photo of the textile material every 10 seconds.
FR2	Inspection timer	The system records and stores the total time elapsed during each inspection.
FR3	Inspection result	The system assigns a result generated by the model, classifying the material as either "Pass" or "With defects."
FR4	Inspection records by date	The system enables users to view a list of all completed inspections, displaying the date, detection time, and result for each.

b. Phase 2: Initiation

In this phase, the focus shifted to configuring the tools and technologies needed for development. Android Studio was again used to implement both the interface and the application logic. PostgreSQL was employed for data handling, with Supabase Storage supporting image and file storage. Dart continued to be the primary language due to its suitability for cross-platform mobile development. The application was built using convolutional neural networks for image processing, and it adopted a model-view-controller (MVC) architecture can be seen in (Figure 1).

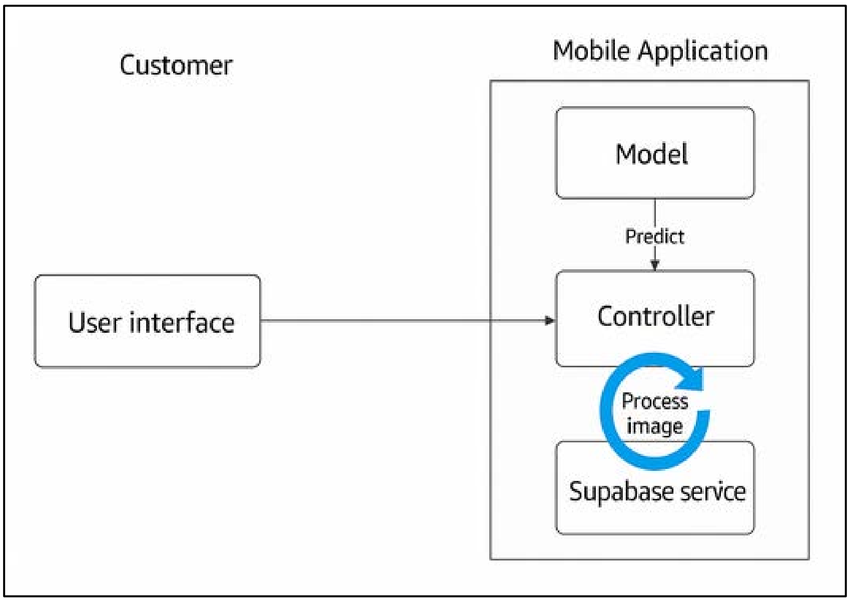

Figure 1. System architecture

c. Phase 3: Production

This phase marked the implementation of the mobile application's core functionalities. All requirements gathered during the earlier stages were consolidated and translated into a working product, ensuring the solution aligned with the predefined quality standards.

Once logged in, users are presented with a navigation interface offering two main options: (Start Inspection): Launches a new automatic inspection of textile materials and (Inspection History): Displays a record of all past inspections with access to detailed results can be seen in (Figure 2).

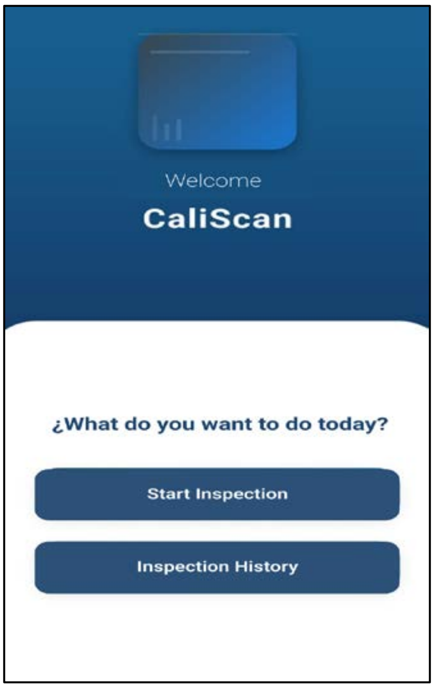

Figure 2. Main interface

Automatic inspection: The inspection interface allows users to initiate an automated image-capture process by pressing the "Start" button. The system takes one image every 10 seconds for analysis. Users can stop the process with the "Stop" button and review captured images through the "View Photos" option, which displays corresponding data such as date, elapsed time, and results can be seen in (Figure 3).

Figure 3. Automatic inspection user interface

Inspection history: The history screen enables users to view a list of all past inspections, with the ability to search by date. By selecting a specific record, the user can access full inspection details can be seen in (Figure 4).

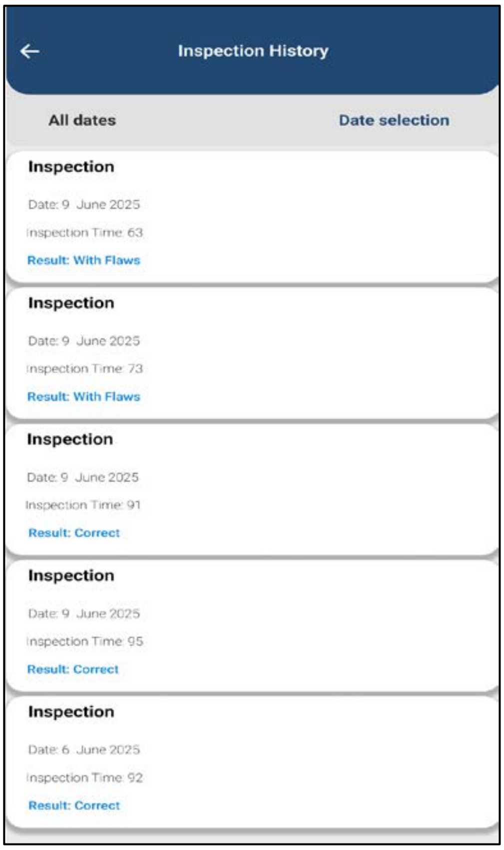

Figure 4. Inspection history user interface

Inspection results: When viewing the result of an inspection, the interface displays key details including the date of inspection, duration, and individual results for each captured photo can be seen in (Figure 5).

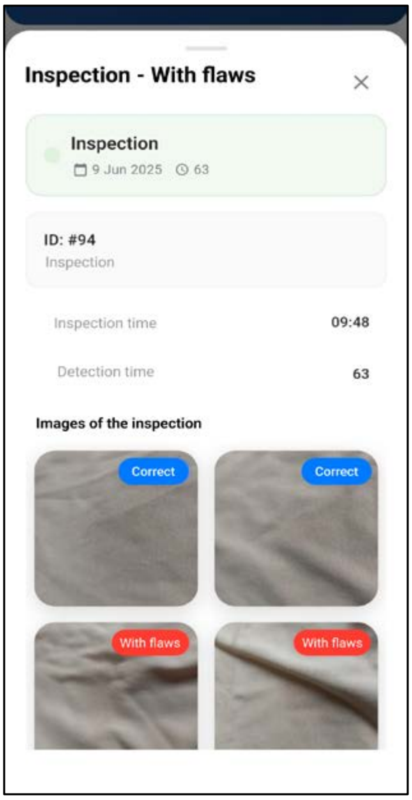

Figure 5. Inspection result user interface

d. Phase 4: Stabilization

In the stabilization phase, the system underwent a series of functional, integration, and performance tests to ensure reliable operation under real-world conditions. The objective was to validate system integrity, resolve any bugs identified during development, and fine-tune performance across all modules. Key integrations such as image processing, TensorFlow-based predictions, and result storage were thoroughly verified. Technical adjustments and optimizations were applied based on test outcomes, enhancing the application's operational stability prior to final deployment.

e. Phase 5: System Deployment

During the final phase, the mobile application was deployed for field use. Compatibility and performance were validated across various Android devices, including emulators and physical smartphones. Particular attention was given to evaluating the accuracy of the TensorFlow Lite model in performing binary classification of textile materials. Additionally, successful integration with the Supabase database was confirmed, ensuring smooth storage and retrieval of inspection records.

6. Results

This section presents the descriptive and inferential analysis of the results obtained from the study on the use of a processing application for the binary classification of textile materials during the first semester of 2025.

a. Descriptive Analysis

The following tables present the post-test results for the control group and experimental group across the research indicators: Identification time, classification precision, and the number of non-conformities timely identified.

Table 2. Post-Test results for the IDT indicator for both control and experimental groups

Research Indicator	Average		% Below Average	
	Control Group	Experimental Group	CG	EG
IDT	115	80	40	100

As shown in Table 2, the control group recorded an average identification time of 115 seconds, while the experimental group achieved 80 seconds, indicating a 35 seconds reduction.

Table 3. Post-test results for the CP indicator for both control and experimental groups

Research Indicator	Average		% Above Average	
	Control Group	Experimental Group	CG	EG
CP	77	87	57	93

As shown in Table 3, the control group reached 77% classification precision, whereas the experimental group achieved 87%, reflecting a 10% improvement.

Table 4. Post-test results for the NCI indicator for both control and experimental groups

Research Indicator	Average		% Above Average	
	Control Group	Experimental Group	CG	EG
NCI	66	83	70	100

As shown in Table 4, the control group reported 66% in the timely identified number of non-conformities, while the experimental group reached 83%, reflecting a 17% increase.

b. *Inferential Analysis*

For the inferential analysis, normality tests and hypothesis testing were conducted using the post-test data from both the CG and EG groups for the indicators: IDT, CP, and NCI. The decision criteria were as follows: **H0 (null hypothesis)**: *the post-test data follow a normal distribution*; **Ha (alternative hypothesis)**: *The post-test data do not follow a normal distribution*. If $p < 0.05$, the null hypothesis (H0) is rejected in favor of the alternative (Ha); if $p \geq 0.05$, the null hypothesis is accepted.

Given that the number of entries in each indicator was lesser than 50 the Shapiro-Wilk test was used for normality assessment.

Table 5. Shapiro–Wilk normality test for each indicator

N°	Indicator	p (GC)	p (GE)
1	IDT	0.016	0.049
2	CP	<.001	0.005
3	NCI	<.001	< .001

According to Table 5, the p-values for at least one group in each indicator are below 0.05, indicating that the data do not follow a normal distribution.

Therefore, the non-parametric Mann–Whitney U test is applied to evaluate differences between the independent groups. In the hypothesis tests, µ1 refers to the control group and µ2 to the experimental group.

Table 6. Mann–Whitney U test for each indicator

N°	Indicator	H0	Ha	p
1	IDT	$\mu1 <= \mu2$	$\mu1 > \mu2$	<.001
2	CP	$\mu1 <= \mu2$	$\mu1 < \mu2$	0.034
3	NCI	$\mu1 >= \mu2$	$\mu1 < \mu2$	0.125

Based on the results in Table 6, the p-values for the IDT and CP indicators are below 0.05, allowing the rejection of the null hypotheses and confirming statistically significant differences in favor of the experimental group regarding identification time and classification precision. However, for the NCI indicator, the p-value of 0.125 exceeds the 0.05 threshold, indicating no statistically significant difference between the groups for this measurement.

7. Discussion

Regarding identification time, post-test findings indicated that the control group required 115 seconds on average, whereas the experimental group completed the task in 80 seconds, resulting in a 35-second reduction. Comparable outcomes have been reported in industrial applications of neural networks, where processing efficiency improved substantially, reducing attendance registration time by 53.3% and report generation by 60% [11].

With respect to classification precision, manual inspection yielded 77%, while the automated approach reached 87%, representing a 10-percentage-point gain. These results are in agreement with [12], who evaluated CNN-based models for textile defect detection and documented accuracy rates above 85%, supporting the effectiveness of deep learning techniques in quality assessment tasks.

Concerning the number of non-conformities identified in a timely manner, the control condition detected 63% of defective cases, compared to 83% under the CNN-based system, reflecting a 20-percentage-point increase. Similar evidence was presented in [13], where a deep learning model implemented in real manufacturing environments achieved a recall of 83.9%, confirming the practical viability of intelligent inspection systems in production settings.

8. Conclusion

The post-test results revealed that the control group required an average of 115 seconds to classify textile material, whereas the experimental group completed the same task in 80 seconds. This 35-second reduction demonstrates that the implementation of convolutional neural networks, combined with a conveyor-belt prototype, significantly streamlines the inspection procedure. Classification precision increased from 76.6% in the control group to 86.6% in the experimental group, representing a 10% improvement.

These findings suggest that the proposed model not only raises predictive performance but also provides more stable automated outcomes compared to manual evaluation.

Regarding the timely identification of non-conformities, the experimental group achieved a detection rate of 83.3%, compared to 66.3% in the control group, reflecting a 17% enhancement. This evidence indicates that the deep learning approach enables more reliable defect recognition, thereby reinforcing quality control practices within inspection workflows.

The findings further indicate that the developed system is adaptable and appropriate for small and medium-sized textile enterprises, particularly in environments with restricted access to advanced industrial infrastructure. Its cost-effective design highlights the practicality of incorporating Artificial Intelligence into quality assurance processes without the need for sophisticated technological setups. However, certain constraints associated with the binary classification scheme and its sensitivity to environmental and material variability may limit broader applicability. Future research should therefore explore multiclass models, integrate more sophisticated deep learning architectures, and evaluate real-time or mobile-based implementations to strengthen system resilience and expand operational scope.

Overall, the results validate the effectiveness of this CNN-driven solution in enhancing textile material assessment and support its potential adoption in manufacturing workshops seeking to optimize inspection efficiency.

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