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PIXELSEGNET-CNN: A HYBRID DEEP LEARNING FRAMEWORK WITH OPTIMIZED PRE-PROCESSING FOR HIGH-PRECISION TEXTILE DEFECT SEGMENTATION

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Abstract

Automated textile defect detection is essential for quality control in manufacturing; however, it presents challenges due to variability in defects, intricate textures, and the need for real-time processing. This research presents PixelSegNet-CNN, an innovative deep learning framework that combines advanced pre-processing techniques (Gaussian Blur, Gabor filters, Local Binary Pattern) with lightweight encoder-decoder architecture for pixel-wise defect segmentation. The model was assessed using three benchmark datasets such as TILDA 400, FABRIC STAIN, and AITEX and demonstrated state-of-the-art performance, exceeding established methods (U-Net, ResNet, CNN, Mask R-CNN) in terms of accuracy (91.0%), precision (83.0%), recall (85.0%), F1-score (84.0%), IoU (80.0%), and Dice coefficient (88.0%). Pre-processing techniques improve defect visibility and reduce noise, while the efficient design of PixelSegNet-CNN allows for accurate localisation of defects such as holes, stains, and weave irregularities. The framework exhibits robustness across various fabric types and defect categories, providing a scalable solution for industrial automated inspection systems.

Keywords: Pre-processing techniques, Segmentation, Gabor filter, Gaussian Blur, Local Binary Pattern, PixelSegNet-CNN .

1. Introduction

Textile manufacturing relies heavily on defect detection to maintain product quality, yet manual inspection is labor-intensive, subjective, and error-prone [1]. Automated vision-based

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systems, particularly deep learning (DL) approaches, have emerged as promising solutions. Recent studies leverage convolutional neural networks (CNNs), U-Net, Mask R-CNN, and Swin-Unet variants to address challenges like defect heterogeneity and intricate fabric textures [2–9]. Hybrid methods incorporating traditional techniques (e.g., Gabor filters, fuzzy logic) further improve robustness [3,6,9]. Despite advances, limitations persist: high computational demands [2,7], limited generalization across pattern types [4], coarse segmentation [5], and scalability issues [6,8].

This paper proposes PixelSegNet-CNN, an end-to-end DL framework optimized for textile defect segmentation. Our contributions are:

- A novel segmentation architecture combining a streamlined encoder-decoder with skip connections and sigmoid activation for pixel-wise defect mapping.
- Integration of pre-processing techniques (Gaussian Blur, Gabor filters, LBP) to enhance defect visibility and suppress noise.
- Comprehensive evaluation across three datasets (TILDA 400, FABRIC STAIN, AITEX) featuring diverse defects and fabric types.
- State-of-the-art performance in accuracy, IoU, and computational efficiency, validated against U-Net [10], ResNet [11], CNN [12], and Mask R-CNN [13].

The paper is structured as follows: Section 2 reviews related work; Section 3 details methods and datasets; Section 4 presents results; Section 5 concludes with implications and future work.

2. Literature review

The literature review emphasises contemporary deep learning (DL) methodologies for the detection and segmentation of textile defects. Diverse models, including CNNs, U-Net, Mask R-CNN, Swin-Unet, and their enhanced iterations, have been utilised to address issues such as defect variability and intricate fabric textures. Numerous researches incorporate conventional methods such as Gabor filtering and fuzzy logic to improve precision and resilience. The approaches were assessed using datasets such as TILDA, TEXFED, and HKBU, exhibiting good accuracy, enhanced IoU, and dependable defect localisation. The table below delineates the principal methodology, utilised datasets, and performance indicators of each study.

Table.1. Overview of DL Techniques for Textile Defect Segmentation

Author & Year	**Dataset Used**	**Segmentation Method**	**Limitation**
Y. P. et al. (2024) [2]	Textile Fabric Defect Dataset	U-Net, ResNet, Mask R-CNN	High data and compute requirements.

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Xu et al. (2023) [3]	TILDA, SDCFD, Custom Complex Background Dataset	Improved Swin-Unet	Low IoU; complex transformer design.
Koulali and Eskil (2023) [4]	Patterned Fabrics Benchmark Dataset	Motif based anomaly segmentation (unsupervised CNN)	Limited to periodic textures; lacks flexibility.
H. V and S. K (2023) [5]	TEXFED Dataset	Patch-level segmentation using CNN	Coarse localization; lacks pixel precision.
Ren et al. (2024) [6]	TILDA Textile Defect Dataset	Fuzzy-UNet	Rule-dependence limits scalability.
Xiang (2024) [7]	Custom Fabric Pattern Dataset	Mask R-CNN (ResNet-50)	Slower for real-time inspection.
Revathy and Kalaivani (2023) [8]	HKBU Fabric Defect Dataset	Improved Mask R-CNN (IM-RCNN)	Risk of over fitting; heavy pre-processing.
Huang and Xiang (2022) [9]	FID-RPD	DeepLabV3+ (RPDNet)	Weak on non-repetitive patterns.

3. Methods and Materials

The proposed framework for textile defect detection integrates advanced pre-processing techniques with a novel segmentation model, PixelSegNet-CNN. It is assessed in comparison to established deep learning methods such as U-Net [10], ResNet [11], CNN [12], and Mask R-CNN [13]. Pre-processing techniques such as Gaussian Blur, Gabor Filters, and Local Binary Pattern (LBP) are utilised to improve defect visibility and reduce noise interference. The system underwent testing using three benchmark datasets: TILDA 400, FABRIC STAIN DATASET, and AITEX Fabric Database. Each dataset comprises a variety of fabric types and defect categories. PixelSegNet-CNN utilises a streamlined encoder-decoder framework featuring skip connections and sigmoid activation to generate accurate pixel-wise defect maps. The experimental results indicate a notable enhancement in segmentation accuracy and robustness when compared to current methodologies.

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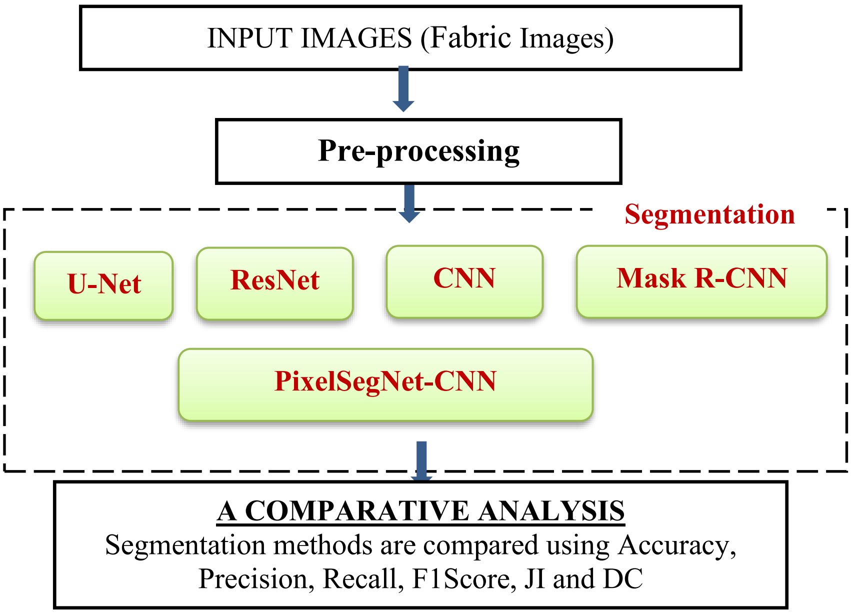

Fig.1. System Overview

3.1 Dataset Overview

The suggested segmentation model for textile defect identification is constructed utilising three benchmark datasets: TILDA 400, FABRIC STAIN DATASET, and AITEX Fabric Image Database. These datasets include a varied array of fault kinds and fabric textures, facilitating thorough evaluation and enhancing the model's adaptability for automated textile inspection.

- **TILDA 400** consists of 12,838 image patches (64×64 pixels) categorised into five defect classes: *Good, Hole, Object, Oil Spot, and Thread Error.*
- **FABRIC STAIN DATASET:** Comprises photos exhibiting staining faults of diverse shapes, sizes, and intensities, recorded under variable lighting conditions and backgrounds.
- **AITEX Fabric Image Database:** Comprises high-resolution photographs depicting prevalent textile faults, including *Broken Ends, Missing Yarns, Thick Places, and Holes.*

Table.2. Textile Defect Datasets and Image Distribution

Dataset	**Defect Categories**	**Total Images**
TILDA 400	Good, Hole, Object, Oil Spot, Thread Error	12,838
FABRIC STAIN DATASET	Light, Medium, Heavy Stains, Background	3,500
AITEX Fabric Database	Broken Ends, Missing Yarns, Thick Places, Holes	800

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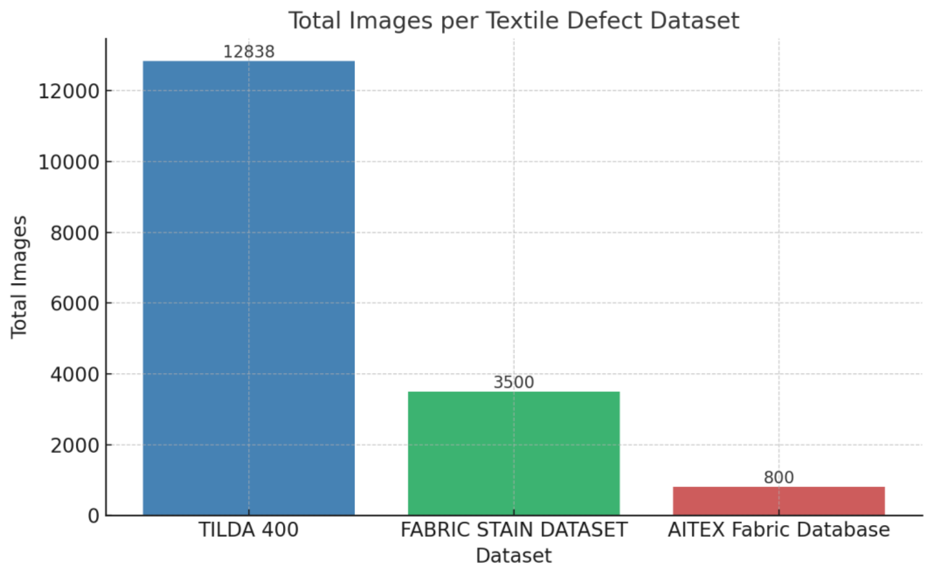

Fig.2. Data Set Defect Classifications Total Number of Images

The above bar chart illustrates the aggregate number of images across the three datasets utilised for textile fault segmentation. The TILDA 400 comprises 12,838 photos, succeeded by the FABRIC STAIN DATASET containing 3,500 images, and the AITEX Fabric Database with 800 images. The graphic illustrates the variation in dataset sizes employed for training and evaluating the segmentation model.

3.2 Data Pre-processing

Gaussian Blur, Gabor filters, and Local Binary Pattern (LBP) are employed in textile defect identification to improve defect visibility. Gaussian Blur diminishes noise and refines fabric textures. Gabor filters emphasise structural anomalies by detecting directional characteristics. LBP transforms local texture variations into binary patterns, identifying tiny anomalies. Collectively, these techniques enhance the efficacy of fault identification.

i. Gaussian Blur: Gaussian Blur is a commonly utilised pre-processing method in textile defect detection, employed to mitigate high-frequency noise and smooth repeated fabric textures that may conceal structural flaws. Let the input greyscale fabric image be represented as $I: \mathbb{Z}^2 \rightarrow [0,255]$, where $I(x, y)$ is the pixel intensity at the position(x, y). The Gaussian filter $G_\sigma\ (x, y)$ is defined as

$$G_\sigma\ (x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(x - \mu_x)^2 + \left(y - \mu_y\right)^2}{2\sigma^2}\right)$$

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It is a symmetric, isotropic kernel where $\sigma \epsilon \mathbb{R}^{+}$ regulates the blur radius, and $(\mu_x,\ \mu_y)$ denotes the kernel centre, commonly positioned at (0, 0). The convolution of the input picture with this kernel produces the blurred image

$$I_\sigma\,(x,y) = \ (I\ *\ G_\sigma)(x,y) = \sum_{i=-k}^{k}\sum_{j=-k}^{k} G_\sigma(i,j)\,.\ I(x\ -\ i, y\ -\ j)$$

Where $k\ =\ [3\sigma]$ specifies the kernel size. This method efficiently eliminates unwanted components $T(x,y) \subset I(x,y)$ including illumination variations and texture-induced gradients, while maintaining essential defect structures $\delta(x,y) \subset\ I(x,y)$. The smoothed image I_σ is subsequently input into a segmentation model S, which produces a binary defect map $D\ :\ \mathbb{Z}^2\ \rightarrow\ \{0,1\}$, defined as

$$D(x,y)\ =\ S(I_\sigma(x,y))$$

Where, $D(x,y) =\ 1$ signifies a defect at pixel (x,y). Gaussian Blur operates as a pre-processing operator $\mathcal{F}_\sigma : I\ \rightarrow\ I_\sigma$ that enhances the signal-to-noise ratio (SNR) of the defect region, represented as

$$SNR_{Post} = \frac{\mathbb{E}[\delta(x,y)]}{Var[T(x,y) -\ I_\sigma(x,y)]}$$

By choosing an ideal σ, the pre-processing guarantees that $SNR_{Post}\ >\ SNR_{raw}$, thus improving segmentation precision and facilitating reliable defect localisation in DL based textile inspection systems [14].

ii. Gabor filters: Gabor filters are efficient pre-processing methods for textile defect detection intended to extract localised texture features from fabric photographs displaying periodic and directional patterns. A Gabor filter $G_{\lambda,\theta,\phi,\sigma,\gamma}\,(x,y)$ is characterised as a sinusoidal plane wave modulated by a Gaussian envelope, facilitating concurrent localisation in spatial and frequency domains. The mathematical concept is expressed as:

$$G_{\lambda,\theta,\phi,\sigma,\gamma}\,(x,y) = \exp\left(-\frac{x'^2\ +\ \gamma^2 y'^2}{2\sigma^2}\right)\ .\ exp\left(i\left(2\pi\frac{x'}{\lambda} +\ \ \phi\right)\right)$$

The equations $x' =\ x\cos\theta +\ y\sin\theta$ and $y' =\ -x\ sin\,\theta +\ y\cos\theta$ represent the rotated coordinates. Essential parameters comprise: $\lambda\,\epsilon\,\mathbb{R}^{+}$ (wavelength governing frequency),), $\theta\ \epsilon\ [0,\ \pi)$ (orientation), $\phi\,\epsilon\,[-\pi,\ \pi]$ (phase offset), $\sigma\,\epsilon\,\mathbb{R}^{+}$ (standard deviation of the

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Gaussian envelope), and $\gamma \epsilon \mathbb{R}^+$ (aspect ratio regulating ellipticity). These parameters allow for the filter to be calibrated identifying texture differences across various orientations and scales, rendering it particularly effective for emphasising local anomalies such as broken threads, holes, or misaligned weaves. The convolution of a greyscale fabric image $I(x, y): \mathbb{Z}^2 \rightarrow [0,255]$ with a Gabor filter produces an output with increased features:

$$I_G(x, y) = I(x, y) * G_{\lambda,\theta,\phi,\sigma,\gamma}(x, y)$$

A filter bank $G = \left\{ G_{\lambda_i, \ \theta_j} \right\}$ is commonly employed to capture differences across diverse orientations and scales. This amplifies the contrast between standard fabric textures and localised imperfections, hence enhancing defect visibility. In contrast to smoothing approaches, Gabor filtering retains intricate directional features, rendering it ideal for emphasising faults such as misplaced threads, broken weaves, and holes. The resultant feature enhanced image offers a strong input for subsequent models, facilitating precise segmentation and classification of textile faults [15].

iii. Local Binary Pattern (LBP): LBP is a prevalent local texture descriptor that encodes micro-patterns by thresholding each pixel against its neighbours. For a greyscale image $I: \Omega \subset \mathbb{Z}^2 \rightarrow [0,255]$, where Ω denotes the image domain, LBP functions on each pixel $c = (x, y)$ by assessing its P neighbours $\{p_i\}_{i=1}^{P}$ arranged in a circular formation with radius R. In the typical scenario, P equals 8, R equals 1, and a 3×3 neighbourhood is employed. The comparison function $S(p_i, c)$ is defined as follows:

$$S(p_i, c) = \begin{cases} 1, & if\ g(p_i) \geq g(c) \\ 0, & if\ g(p_i) \geq g(c) \end{cases} \text{For } i = 1, \ldots.., P$$

Where $g(p_i)$ and $g(c)$ are the grey intensities of the neighbouring and central pixels, respectively. The binary string is represented as a decimal value:

$$LBP_{P,R}(c) = \sum_{i=1}^{P} 2^{i-1} . \ S(p_i, c)$$

Which produces an integer inside the range $\in [0, \ 2^P - 1]$. This local code records intensity transitions that signify textural irregularities, like thread breakage or surface flaws. To construct a global descriptor, the picture is partitioned into N non-overlapping regions $\{R_k\}_{k=1}^{N}$, and for each region, a histogram $H_k = [h_0, \ h_1, \ldots., h_{L-1}]$ is calculated, where h_j enumerates the occurrences of LBP code j and $L \leq 2^P$ is the quantity of permissible patterns, frequently condensed to 8 or 16 using uniform LBP encoding. The complete texture representation is created by concatenating all regional histograms.

$$F = [H_1, H_2, \ldots \ldots, H_N] \in \mathbb{R}^{N \ X \ L}$$

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The feature vector F functions as input for subsequent segmentation or classification models. LBP is intrinsically invariant to illumination and computationally economical, rendering it optimal for pre-processing in fabric defect detection systems that necessitate swift and dependable identification of localised texture anomalies [16].

3.3 Segmentation Process

PixelSegNet-CNN is introduced for the segmentation of textile defects, providing accurate identification of flaws at the pixel level. The model utilises an encoder to capture multi-scale features and a decoder with skip connections to reconstruct spatial details. The sigmoid activation function produces pixel-wise probability maps that identify defects, including holes, stains, and weave irregularities. This method facilitates precise and effective automated Inspection of textiles.

Algorithm: PixelSegNet-CNN

The PixelSegNet CNN algorithm accepts an RGB image $I \in \mathbb{R}^{\mathrm{H}\times\mathrm{W}\times 3}$ as input and utilises lightweight encoder-decoder architecture. The encoder employs strided residual blocks to extract multi-scale features, while the decoder produces a single channel ROI probability map $P \in \mathbb{R}^{\mathrm{H}\times\mathrm{W}}$ (values within [0, 1]) through convolutions activated by the sigmoid function. The map P is thresholded (e.g., at τ = 0.7) to generate a binary mask, which is subsequently subjected to morphological cleaning to eliminate noise, followed by contour detection and bounding box extraction. Ultimately, the technique generates a list of cropped regions of interest (ROI) $\{I_{ROI_1},\ I_{ROI_1}, \dots \dots .\}$ by extracting segments from the original image *I* based on the calculated bounding box coordinates, facilitating immediate application in subsequent tasks such as item categorisation or detection. The complete pipeline is efficient, scalable, and adaptable for real-time applications.

Algorithm: PixelSegNet-CNN
Input: RGB image $I \in \mathbb{R}^{\mathrm{H}\times\mathrm{W}\times 3}$
Final Output: ROI probability map $P \in \mathbb{R}^{\mathrm{H}\times\mathrm{W}}$ (values in [0, 1]) List of cropped ROI regions $\{I_{ROI_1},\ I_{ROI_1}, \dots \dots .\}$ extracted from *I*
Feature Encoding (Encoder)

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$X \leftarrow Conv2D(I, 32, kernel = 3, stride = 1, padding = 1)$

$X \leftarrow ReLU(BatchNorm(X))$

for $n \in \{1,2,3\}$ do

$F_n \leftarrow 32\ X\ 2^n$

$X \leftarrow ResBlock(X, F_n, downsample = True)$

ROI Probability Map (Decoder)

$X \leftarrow Conv2D(X, 256, kernel = 3, padding = 1)$

$X \leftarrow ReLU(BatchNorm(X))$

$P \leftarrow Conv2D(X, 1, kernel = 1)$

$P \leftarrow Sigmoid(P)$

Post-Processing

$\mathcal{B} \leftarrow Threshold(P, \tau)\ (Binary\ mask, e.g., \tau = 0.7)$

$\mathcal{B} \leftarrow MorphClean(B)\ (Remove\ noise)$

$\mathcal{C} \leftarrow FindContours(B)\ (Contour\ coordinates)$

$\mathcal{R} \leftarrow BoundingBoxes(C)\ (ROI\ boxes)$

ROI Extraction

for each box $(x_1, y_1, x_2, y_2 \in \mathcal{R}$ do

$I_{ROI} \leftarrow I[y_1 : y_2, x_1 : x_2, :]$

end for

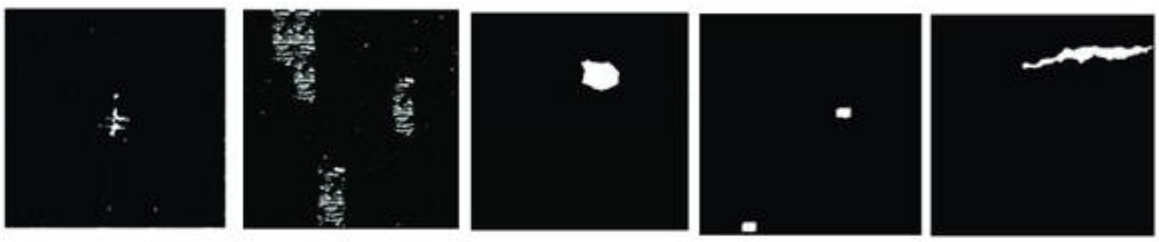

Fig.3. Segmented images

Segmented image regions highlight defective areas with high precision, isolating faults such as holes, stains, and weave irregularities for targeted analysis.

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4. Result and Discussion

The proposed DL based segmentation framework for textile defect detection aims to provide precise localisation of faults utilising the TILDA 400 dataset. The design proficiently captures complex fabric patterns and fault structures using an efficient segmentation pipeline. The model regularly exhibits strong performance in distinguishing various fault types, as assessed by rigorous measures including Accuracy, Sensitivity (Recall), Specificity, Dice Coefficient, and Jaccard Index. This approach guarantees dependable, scalable, and automated flaw identification, rendering it exceptionally appropriate for real-time industrial textile evaluation.

4.1 Evaluation Metrics

The proposed model's segmentation performance for textile defect identification is assessed using five principal metrics: Accuracy, Sensitivity (Recall), Specificity, Dice Coefficient, and Jaccard Index. These metrics jointly evaluate the model's ability to precisely localise and segment faulty areas within fabric images.

Table.3. Performance Metrics

Metric	Formula
Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\text{Precision} = \frac{TP}{TP+\ FP}$
Recall	$\text{Recall} = \frac{TP}{TP+\ FN}$
F1-Score	$\text{F1} - \text{Score} = \frac{2\ X\ Precision\ X\ Recall}{Precision + Recall}$

In textile defect segmentation, each pixel is categorised as True Positive (TP), False Positive (FP), False Negative (FN), or True Negative (TN). TP signifies accurately recognised defect pixels, FP indicates non-faulty pixels erroneously classified as defective, FN suggests defect pixels overlooked by the model, and TN represents correctly identified non-defective pixels. These classifications establish the foundation for assessing the model's efficacy in defect identification and segmentation.

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Table.4. Performance Comparison of Segmentation Models on TILDA 400 Dataset

Segmentation Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**IoU (JI) (%)**	**Dice Coefficient (DC) (%)**
U-Net	87.2	74.0	77.0	75.0	71.0	79.0
ResNet	88.6	76.0	79.0	77.0	73.0	81.0
CNN	89.4	78.0	81.0	79.0	75.0	83.0
Mask R-CNN	90.1	80.0	83.0	81.0	77.0	85.0
PixelSegNet-CNN (Proposed)	**91.0**	**83.0**	**85.0**	**84.0**	**80.0**	**88.0**

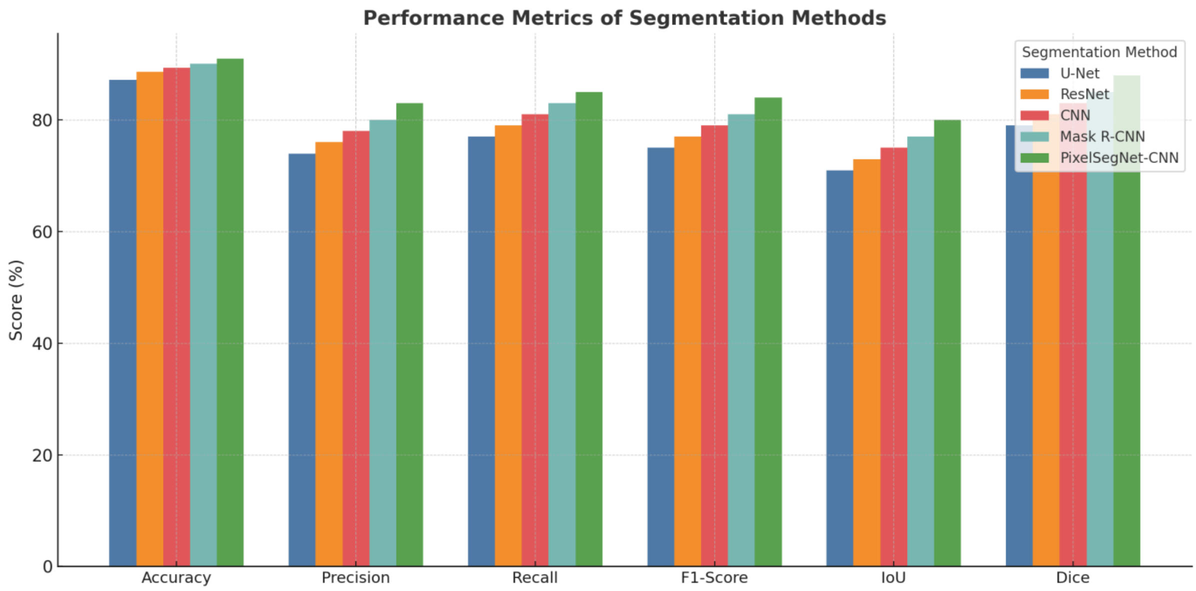

Fig.4. Segmentation Metrics of Models on TILDA 400 Dataset

The above table and graph illustrate a performance comparison of five segmentation methods: U-Net, ResNet, CNN, Mask R-CNN, and the proposed PixelSegNet-CNN, evaluated on the TILDA 400 dataset using metrics including Accuracy, Precision, Recall, F1-Score, IoU, and Dice Coefficient. The suggested PixelSegNet-CNN surpasses all alternative approaches, attaining the greatest metrics: 91.0% accuracy, 83.0% precision, 85.0% recall, 84.0% F1-score, 80.0% IoU, and 88.0% DC, thereby illustrating its efficacy in fabric defect segmentation.

Table.5. Performance Comparison of Segmentation Models on Fabric Stain Dataset

Segmentation Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**IoU (JI) (%)**	**Dice Coefficient (DC) (%)**

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U-Net	84.2	40.0	66.0	41.0	32.0	41.0
ResNet	85.6	47.0	69.0	46.0	34.0	46.0
CNN	86.3	45.0	68.0	45.0	35.0	45.0
Mask R-CNN	83.0	30.0	59.0	31.0	21.0	31.0
PixelSegNet-CNN (Proposed)	**87.1**	**50.0**	**69.0**	**52.0**	**39.0**	**52.0**

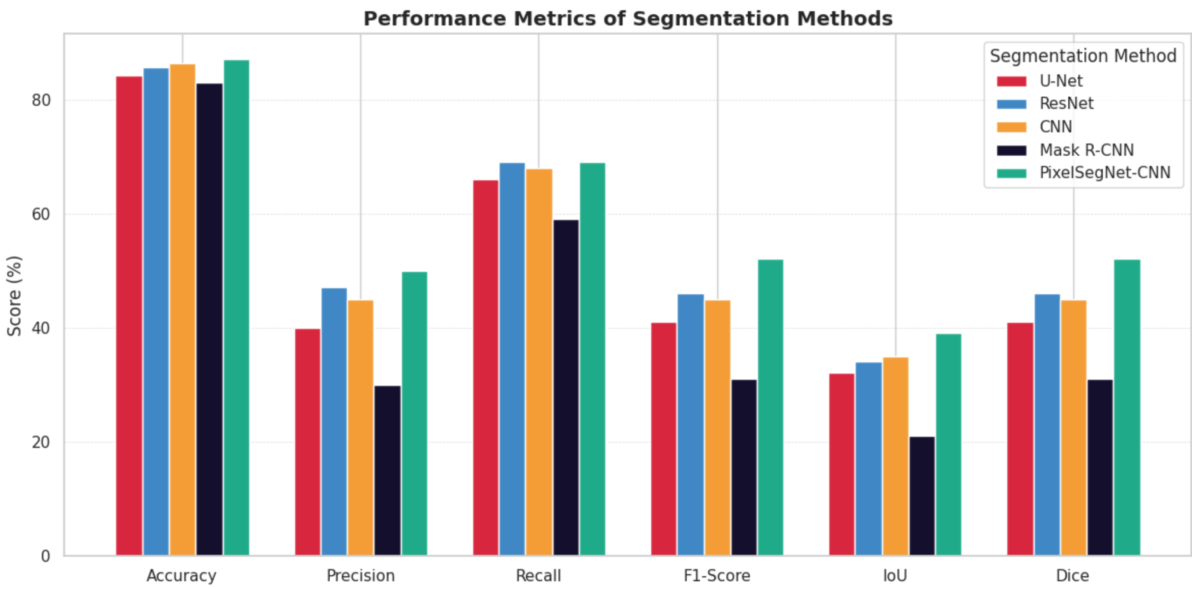

Fig.5. Performance Comparison of Segmentation Methods on Fabric Stain Dataset

The above table and graph illustrate a performance comparison of segmentation methodologies on the Fabric Stain Dataset, utilising Accuracy, Precision, Recall, F1-Score, IoU, and Dice Coefficient as metrics. PixelSegNet-CNN (Proposed) attains superior performance, exhibiting an accuracy of 87.1%, precision of 50.0%, recall of 69.0%, F1-score of 52.0%, IoU of 39.0%, and a Dice Coefficient of 52.0%. ResNet and CNN exhibit moderate efficacy, although U-Net demonstrates marginally inferior performance. Mask R-CNN exhibits the poorest performance across all metrics. The results underscore the efficacy of the suggested methodology in segmenting cloth stain problems.

Table.6. Performance Comparison of Segmentation Models on AITEX Fabric Database

Segmentation Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**IoU (JI) (%)**	**Dice Coefficient (DC) (%)**
U-Net	89.7	60.0	74.0	61.0	50.0	61.0

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ResNet	90.5	64.0	76.0	66.0	54.0	66.0
CNN	90.7	60.0	74.0	63.0	51.0	63.0
Mask R-CNN	91.1	62.0	75.0	65.0	52.0	65.0
PixelSegNet-CNN (Proposed)	**91.9**	**69.0**	**79.0**	**73.0**	**59.0**	**73.0**

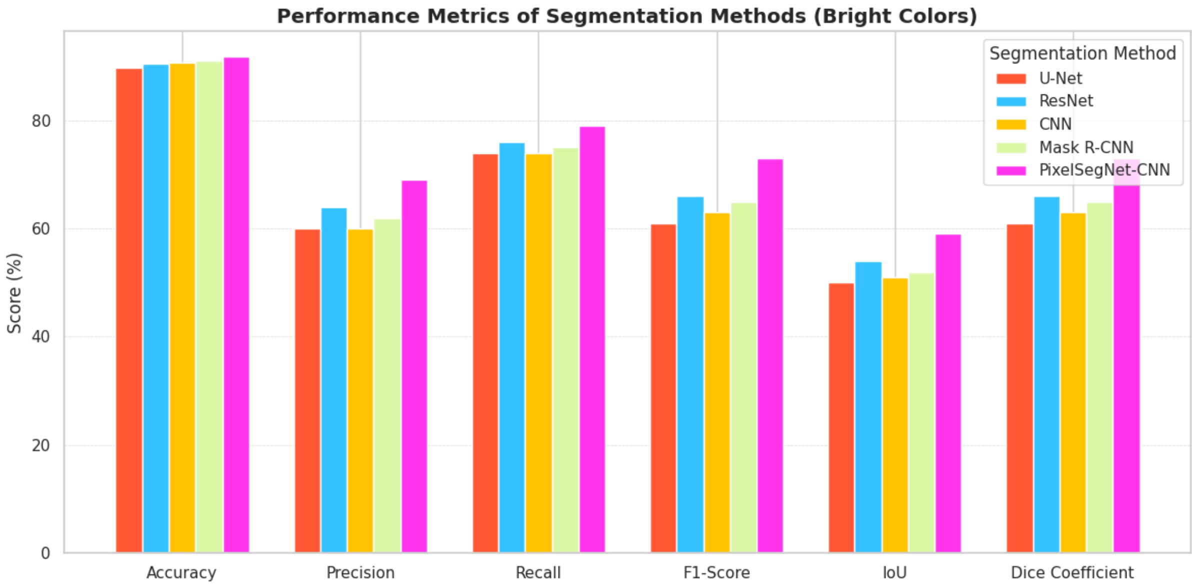

Fig.6. Performance Metrics Comparison of Segmentation Models on AITEX Fabric Database

The above table and graph compare segmentation performance on the AITEX Fabric Database across five models. PixelSegNet-CNN (Proposed) attains the highest metrics, with 91.9% accuracy, 69.0% precision, 79.0% recall, 73.0% F1-Score, 59.0% IoU, and 73.0% Dice Coefficient, surpassing U-Net, ResNet, CNN, and Mask R-CNN across all parameters. This illustrates its enhanced efficacy in fabric fault segmentation.

Table.7. PixelSegNet-CNN Performance with Pre-processing on Fabric Defect Datasets

Dataset	Pre-processing Technique	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	IoU (JI) (%)	Dice Coefficient (DC) (%)
TILDA 400	Before Pre-processing	88.2	80.0	83.0	81.0	76.0	81.0
	Gaussian Blur	89.1	81.0	84.0	82.0	77.0	82.0
	Gabor Filters	89.6	82.0	84.0	83.0	78.0	83.0

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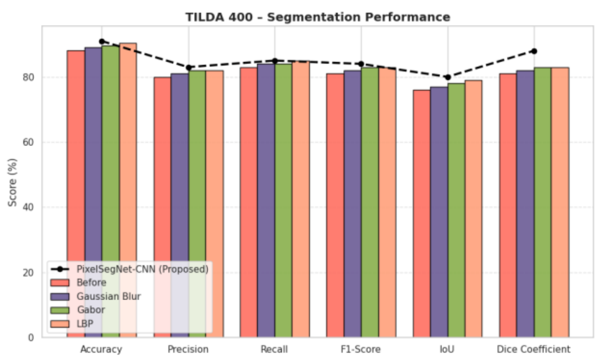
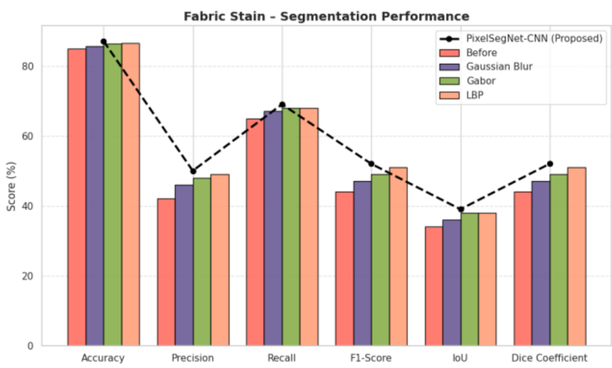
	Local Binary Pattern (LBP)	90.3	82.0	85.0	83.0	79.0	83.0
	PixelSegNet-CNN (Proposed)	**91.0**	**83.0**	**85.0**	**84.0**	**80.0**	**88.0**
Fabric Stain	Before Pre-processing	84.9	42.0	65.0	44.0	34.0	44.0
	Gaussian Blur	85.7	46.0	67.0	47.0	36.0	47.0
	Gabor Filters	86.3	48.0	68.0	49.0	38.0	49.0
	Local Binary Pattern (LBP)	86.6	49.0	68.0	51.0	38.0	51.0
	PixelSegNet-CNN(Proposed)	**87.1**	**50.0**	**69.0**	**52.0**	**39.0**	**52.0**
AITEX Fabric DB	Before Pre-processing	89.4	62.0	73.0	60.0	48.0	60.0
	Gaussian Blur	90.1	65.0	75.0	64.0	52.0	64.0
	Gabor Filters	90.9	67.0	77.0	69.0	56.0	69.0
	Local Binary Pattern (LBP)	91.2	68.0	78.0	71.0	57.0	71.0
	PixelSegNet-CNN(Proposed)	**91.9**	**69.0**	**79.0**	**73.0**	**59.0**	**73.0**





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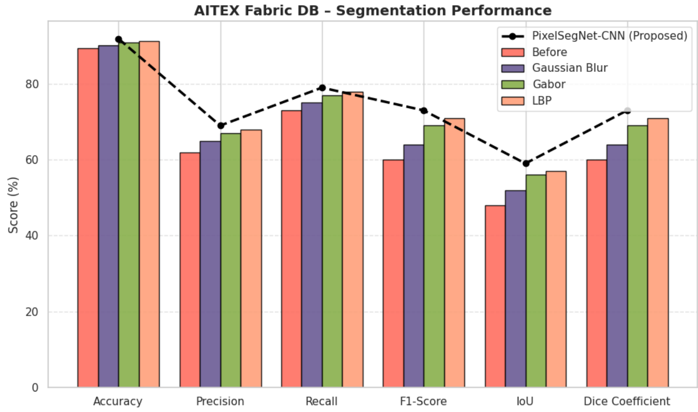

Fig.7. Impact of Pre-processing Techniques on Segmentation Performance across Fabric Datasets

The above table and graph illustrate the influence of diverse pre-processing strategies on segmentation efficacy across three datasets: TILDA 400, Fabric Stain, and AITEX Fabric DB. Metrics such as Accuracy, Precision, Recall, F1-Score, IoU, and Dice Coefficient were assessed. In all three datasets, performance consistently enhanced with Gaussian Blur, Gabor Filters, and LBP, attaining peak values with the PixelSegNet-CNN (Proposed) technique. PixelSegNet-CNN attained accuracies of 91.0%, 87.1%, and 91.9% on TILDA 400, Fabric Stain, and AITEX, respectively, with concomitant enhancements in F1-Score, IoU, and Dice Coefficient, illustrating its exceptional segmentation proficiency.

5. Conclusion

PixelSegNet-CNN is a DL framework designed for textile defect segmentation. It integrates advanced pre-processing techniques, including Gaussian Blur, Gabor filters, and LBP, with a robust encoder-decoder architecture to attain accurate pixel-level localisation of defects. The model consistently surpassed traditional architectures such as U-Net, ResNet, and Mask R-CNN on benchmarks like TILDA 400, attaining peak performance with 91.0% accuracy, 80.0% IoU, and 88.0% Dice coefficient. Pre-processing markedly improved defect visibility and reduced noise, resulting in quantifiable enhancements in segmentation results. The framework exhibited robust generalisation across various defect types, accurately detecting stains, holes, and thread irregularities, thus confirming its appropriateness for industrial-scale applications. Challenges persist regarding parameter sensitivity and the segmentation of highly irregular patterns. Future advancements will focus on real-time processing, few-shot learning for new defect types, and deployment on edge devices for in-situ quality control. PixelSegNet-CNN offers a scalable and precise approach for automated textile inspection, facilitating enhanced quality assurance and minimising waste.

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