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Automated Dimensional Verification of Textile Cuts Using Improved U-Net and ResUnet Models

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Abstract

Dimensional deviations in garment components often lead to deformation, inconsistent shrinkage, and rework during textile assembly, yet conventional measurement methods remain manual, slow, and operator-dependent. Because garment pieces are deformable and geometrically irregular, classical contour-based approaches fail to deliver the consistency required for industrial metrology. This study proposes a fully automated system for millimeter-scale dimensional verification of textile cut pieces, based on improved versions of U-Net and ResUnet that incorporate a composite loss function combining Binary Cross-Entropy, Dice Loss, and Focal Loss. These enhanced architectures strengthen contour reconstruction and keypoint stability under fabric deformation, while an adaptive selection mechanism assigns the optimal model–loss configuration to each garment component according to its geometric complexity and validation performance. A geometry-aware post-processing module refines contours, corrects curvature effects, and converts pixel distances into real-world measurements. Experimental results across collars, sleeves, and body panels demonstrate 2–3% improvements in PCK and MPA over baseline models and achieve robust millimeter-level accuracy. The proposed system functions as a scalable, production-ready solution for automated garment dimensional verification, outperforming fixed-architecture pipelines by tailoring the improved U-Net or ResUnet configuration to the specific textile region.

Keywords: Dimensional verification, textil cuts, quality control, Deep-learning, computer vision.

1. Introduction

Precise dimensional control of garment components is essential in textile manufacturing, as small deviations introduced during cutting or handling can propagate through the assembly stage and affect fit, appearance, and overall production quality [1–7]. Even when working with a standardized garment model, variations in fabric behavior, local deformation, and laying conditions often generate measurable differences in contour and length, resulting in rework, production delays, and inconsistent batch quality [5–7].

In industrial practice, dimensional verification is still performed manually using rulers, templates, and custom boards. These procedures require trained auditors to flatten and align each component before measurement, a process that is slow, subjective, and highly sensitive to fabric elasticity, hand pressure, and camera perspective [8–13]. Such factors lead to significant inter-operator variability and become increasingly problematic as production volume grows, since quality consistency cannot be ensured without repeatable, operator-independent measurements [14–17].

Although machine vision systems have demonstrated reliable performance for rigid and semi rigid components [18–22], textile pieces introduce additional challenges due to their soft body behavior, irregular boundaries, and sensitivity to illumination and flattening variations [23–25]. Classical segmentation approaches, including global thresholding, edge-based detectors, region-growing techniques, and clustering or graph-based methods, often fail to produce stable contours under these

conditions [26–33]. Moreover, existing garment-related datasets are primarily designed for fashion segmentation or human–clothing interaction rather than accurate structural measurement, which limits their suitability for industrial metrology tasks [46–48].

Recent advances in deep learning for clothing analysis have been driven by large-scale datasets and landmark-based modeling. Benchmarks such as DeepFashion and DeepFashion2 [34–35] established segmentation and landmark detection as core tasks for structured evaluation across diverse clothing categories. Parametric models such as SMPL, SMPLify, and ClothCap [35–37] have contributed precise 3D reconstructions, although their dependence on human-body priors restricts their applicability to flat textile components. Other studies on cloth manipulation and semantic landmarking [38–42] focus on robotic handling or region-level semantics rather than producing contours suitable for dimensional verification. Methods targeting repeated patterns or adjacent keypoint detection [43] improve local feature consistency but do not enforce global boundary accuracy. Optimization frameworks applied to cable routing and elongated structures [44–45] address different geometric constraints that do not transfer to deformable garment panels. While these works advance segmentation and landmark extraction, none provide a millimeter-accurate, image-based measurement pipeline for flat textile pieces, which defines the methodological gap addressed in this study.

Despite significant advances in automated visual inspection, no robust and scalable method currently exists for extracting garment contours and structural keypoints with millimeter-level precision under real industrial conditions. Existing approaches either target rigid objects, focus on fashion-oriented segmentation without metrological intent, or depend heavily on manual flattening procedures that introduce operator variability. To address these limitations, this study introduces an automated dimensional-measurement system that employs improved versions of U-Net and ResU-Net, enhanced through a composite loss function that combines Binary Cross-Entropy, Dice Loss, and Focal Loss to strengthen contour fidelity and keypoint stability. The system incorporates an adaptive selection strategy that assigns the optimal model–loss configuration to each garment component according to its geometric complexity, followed by a geometry-aware post-processing stage that computes linear and curved dimensions in calibrated physical units. The resulting pipeline achieves deviations of approximately ± 1 mm across diverse textile regions, satisfying the accuracy demands of industrial quality-control workflows.

The remainder of this paper is organized as follows. Section II describes the experimental setup for measurement. Section III presents the proposed segmentation architecture, keypoint detection strategy, and post-processing pipeline. Section IV reports the experimental results and comparative evaluation. Section V concludes the study and outlines opportunities for integration into production environments.

2. Materials

2.1. Prototype design

A capture chamber was designed to provide stable, repeatable, and light-controlled imaging conditions. The enclosure was built entirely from 3 mm high-density MDF, selected for its rigidity and low deformation, which help maintain a fixed geometric relationship between the camera and the inspection plane throughout acquisition. The internal dimensions of the chamber (30 cm × 30 cm × 30 cm), illustrated in Fig. 1, create a closed optical volume that isolates the scene from ambient illumination and ensures uniform lighting during image capture.

A Hikvision 8 MP camera (3264 × 2448 px) equipped with a fixed standard lens was mounted on the upper panel of the chamber and aligned perpendicularly to the inspection surface. The camera was positioned at a measured distance of 310 mm from the fabric platform using a rigid MDF support to prevent mechanical drift. To ensure consistent imaging conditions across all samples, the camera operated entirely

in manual mode with fixed exposure, gain, white balance, and focus parameters. The inspection surface consisted of a tensioned white canvas sheet measuring 30 cm × 25 cm, tightly secured to a rigid MDF base. No automatic sensor adjustments were permitted at any stage.

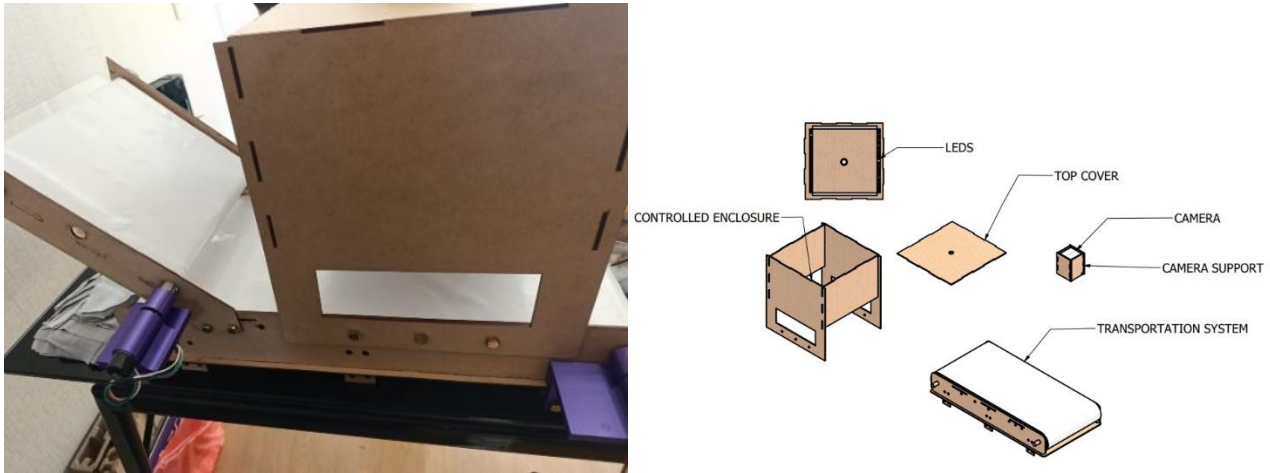


Fig. 1. System module used for the dimensional analysis of textile cuts.

Illumination inside the chamber was provided by 28 cm white LED strips mounted along the internal walls and powered by a stable 12 V supply. This configuration delivered homogeneous lighting across the entire field of view, minimizing shadows, intensity variations, and reflections. The chamber remained almost fully enclosed, with only a small frontal opening (12 cm × 26 cm) that allowed garment components to be inserted or removed without disturbing either the illumination or the camera alignment.

2.2. Textil Samples

The evaluation was conducted using fabric cuts from a single industrial T-shirt model, as shown in Fig. 2. The dataset included the four fundamental components: front panel, back panel, collar, and sleeves. Focusing on a single production model reflects real manufacturing scenarios, in which high-volume batches require strict control of millimeter-level dimensional deviations to maintain consistency throughout the lot.

The samples exhibited natural variability inherent to textile manufacturing, including differences in weight, stretch behavior, yarn density, and surface finish. None of these variations were corrected or standardized, as the objective was to assess the robustness of the proposed system under conditions that closely resemble those encountered on the factory floor. For the pixel-to-millimeter calibration stage, scaled-down versions of the same garment pieces were used while preserving their geometric proportions, ensuring that the calibration process did not alter the structural morphology of the components. In addition, the cuts were intentionally scaled to smaller dimensions so they could fit within the 30 × 30 cm field of view (FOV) of the acquisition module, and three scaled size variants were evaluated. Image acquisition was also performed under mildly noisy conditions, including slightly varying background textures and low-level illumination changes, to reproduce realistic disturbances during capture.

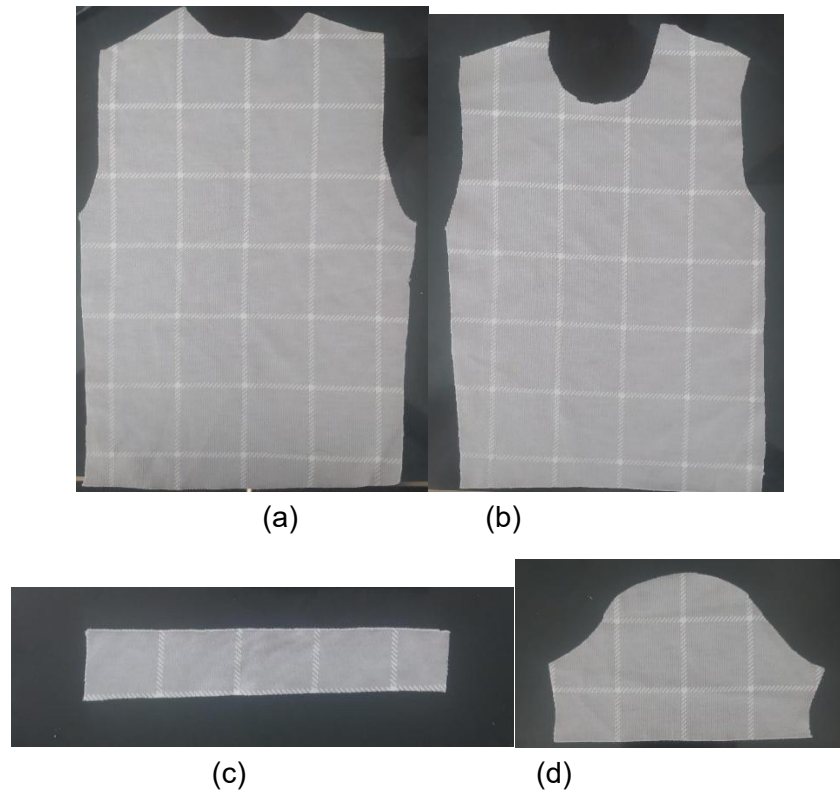


Fig. 2. Types of textile fabrics used for the tests. (a) Back piece, (b) Front piece, (c) neck piece, (d) sleeve piece

3. Methods

The proposed dimensional-verification pipeline is organized as a sequential workflow that integrates preprocessing, adaptive model selection, segmentation, keypoint extraction, and metrological post-processing. This structure ensures consistent performance across textile components with different geometric characteristics.

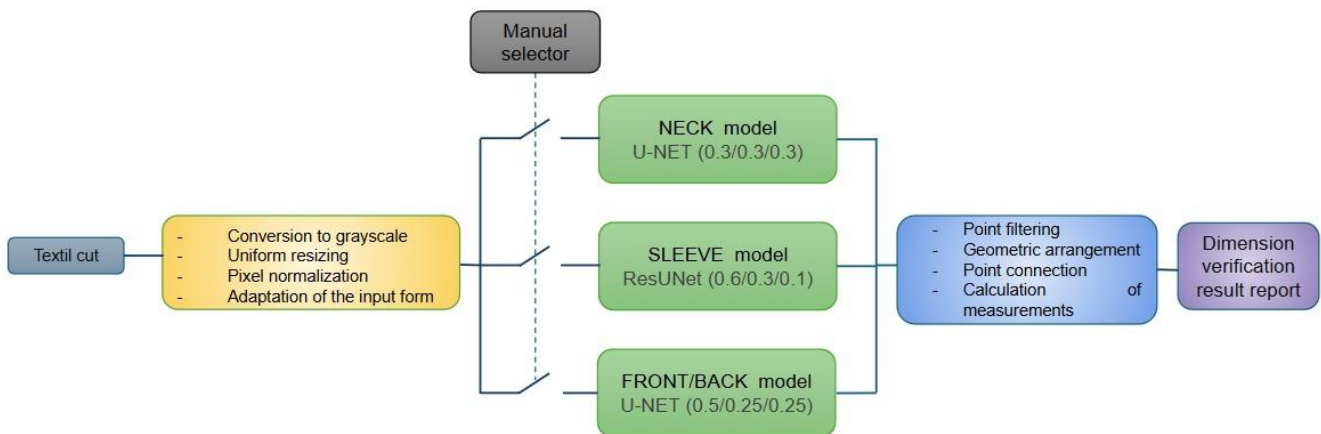


Fig. 3. Flowchart of the proposed dimensional inspection pipeline.

As summarized in Fig. 3, each textile cut is first converted to grayscale, uniformly resized, normalized, and formatted for model input. A manual selector specifies which improved U-Net or ResU-Net configuration is

applied, according to the validated loss-weight combination appropriate for each textile cut type. The predicted keypoints are then refined through filtering, geometric ordering, and contour-connection rules, and finally, linear and curved distances are computed and compiled into a millimeter-calibrated dimensional-verification report.

3.1. Preprocessing

The dataset consists of textile cut-piece images belonging to three structural garment categories: collar, front panel, and back panel. All samples were captured under controlled acquisition conditions, where the distance between the camera and the inspection plane, the illumination profile, and the supporting surface remained fixed throughout the entire process. To standardize the input domain for all segmentation experiments, every image was resized to 512×512 px, ensuring direct comparability between architectures and training configurations.

Each image is paired with a manually annotated binary mask generated through precise polygonal tracing of the garment boundary. These masks serve as the ground-truth reference for both the optimization losses and the quantitative metrics reported in later sections. Because the dimensional accuracy of the system depends on preserving the exact shape of the textile contour, no morphological smoothing or automatic corrections were applied; their role is to represent the real geometry of each component.

A stratified split allocated 70% of the samples for training, 15% for validation, and 15% for testing, ensuring proportional representation of the three garment categories. Data augmentation was applied exclusively to the training set to emulate natural variability encountered in industrial environments. The augmentation pipeline included mild geometric and photometric transformations such as $\pm 15^\circ$ rotations, small translations, horizontal flips, and controlled brightness and contrast adjustments. Validation and test sets remained unchanged to preserve the integrity of the performance evaluation.

Before being forwarded to the neural networks, each resized image $I^{(r)}$ was normalized using the transformation shown in Equation (1):

$$I_{\text{norm}} = \frac{I^{(r)} - I_{\min}}{I_{\max} - I_{\min}}, \quad (1)$$

In this normalization scheme, $I_{\min} = 0$ and $I_{\max} = 255$ correspond to the intensity bounds of standard 8-bit images. Similar to previous computer vision studies that formally define their operational rules, for example specifying the 4-connection $N_4(p)$ when establishing pixel adjacency, the normalization in Equation (1) provides a precise definition of the intensity scaling model used throughout the pipeline.

in this normalization scheme, $I_{\min} = 0$ and $I_{\max} = 255$ correspond to the intensity bounds of standard 8-bit images. Similar to how previous computer-vision studies formally specify their operational rules—for instance, defining the 4-connection $N_4(p)$ “as expressed in formula (1)” when establishing pixel-adjacency relations—the normalization in Equation (1) formally defines the intensity-scaling model used throughout the entire pipeline.

Applying this transformation ensures numerical stability in the convolutional layers, harmonizes gradient magnitudes, and enables the use of a single learning rate configuration across all samples, which is essential for maintaining consistent training behavior under varying textile textures and illumination conditions.

Ground-truth masks were kept strictly binary in the set $\{0,1\}$, without dilation, erosion, or any morphological operations. Preserving their raw polygonal boundaries avoids artificial contour inflation or shrinkage, which

is critical for the keypoint localization required in the post-processing and dimensional-measurement stages.

3.2. Segmentation

The training phase employed U-Net and ResUnet architecture under different loss configuration, including Binary Cross-Entropy, Dice Loss and Focal Loss. Regularization strategies such as weight decay, loss balancing and early stopping were incorporated to prevent overfitting and ensure stable convergence. Model validation was conducted using segmentation and keypoint metrics under a five-fold-cross-validation scheme, enabling a more robust assessment of generalization performance across the other textile cut types.

The overall operational workflow of the proposed inspection system is illustrated in Fig. X. The diagram outlines the full sequence of procedures, starting with dataset collection and division, followed by a preprocessing stage that standardizes all images through grayscale conversion, resizing, normalization, and input adaptation. The training stage compares U-Net and ResU-Net architectures under different loss configurations, supported by regularization and early stopping. Model performance is then assessed through K-fold cross-validation and later verified on an independent test set using segmentation and keypoint-based metrics. In the final post-processing stage, the predicted keypoints are filtered, geometrically arranged, connected, and used to compute the dimensional measurements. The workflow concludes with the quantitative and qualitative analyses that summarize the system's classification, segmentation, and measurement results.

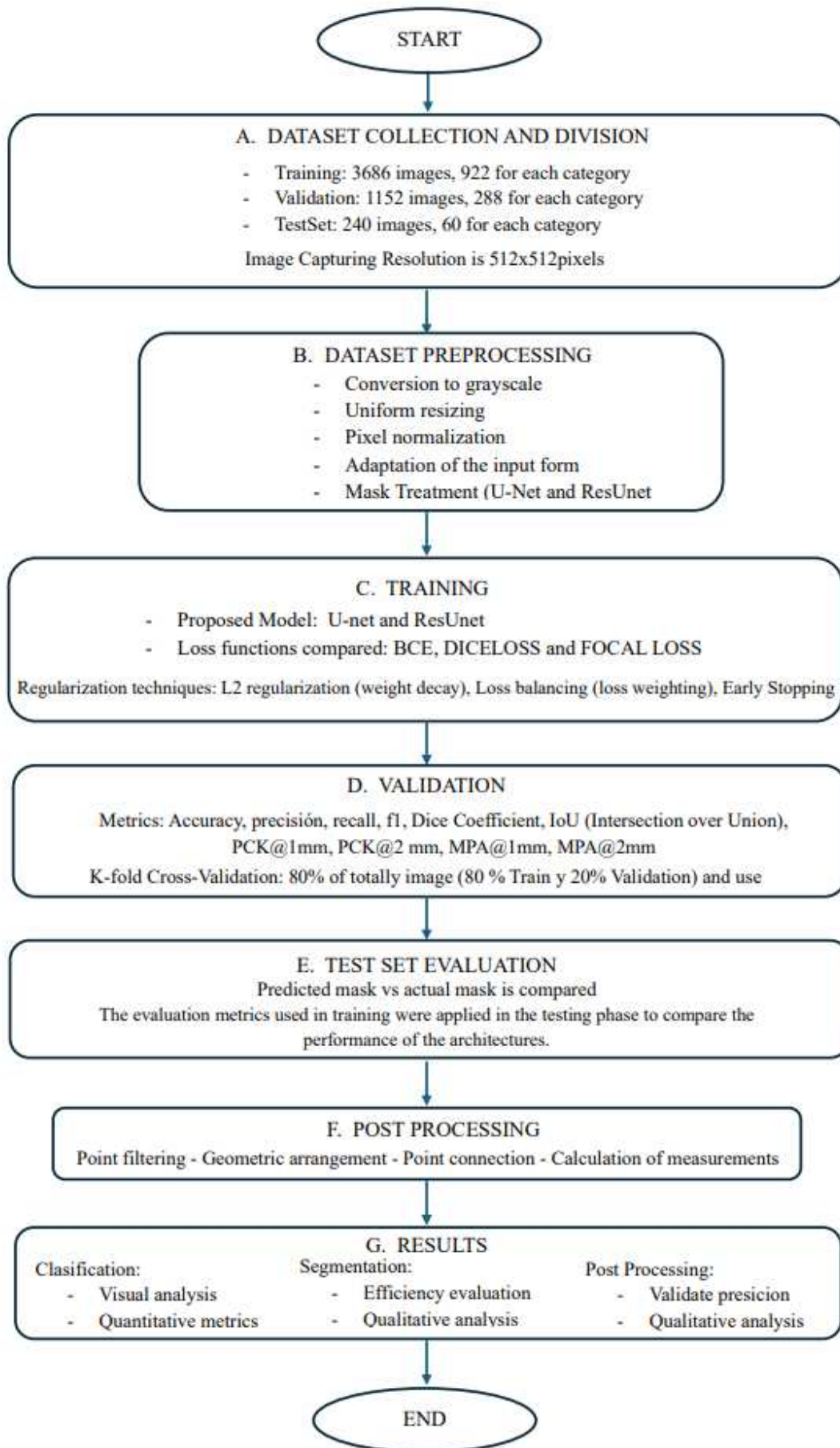


Fig. 4. Flowchart of the proposed end-to-end training, evaluation, and measurement pipeline.

3.2.1. Proposed Unet model

The U-Net architecture employed in this work is illustrated in Fig. 5. The diagram shows a symmetric encoder–decoder structure connected through skip pathways, following the canonical design originally introduced for biomedical segmentation. The encoder consists of sequential blocks containing two 3×3 convolutions with ReLU activation and Batch Normalization, each followed by a 2×2 max-pooling operation that progressively reduces spatial resolution while increasing feature depth.

In the decoder, the spatial resolution is restored through 2×2 upsampling followed by 2×2 convolutions. As illustrated in Fig. 5, the feature maps obtained during upsampling are concatenated with their corresponding encoder activations, which allows the model to reintegrate high-frequency spatial details that would otherwise be lost in deeper layers. This skip connection mechanism is essential for retaining boundary information and preserving the fine geometric structure of textile contours.

The final segmentation output is generated through a 1×1 convolution with a sigmoid activation, producing a binary mask of the garment piece. This configuration enables the model to preserve thin edges, curved boundaries, and locally deformable regions in the predicted mask, ensuring the spatial accuracy required for reliable keypoint localization in subsequent measurement stages.

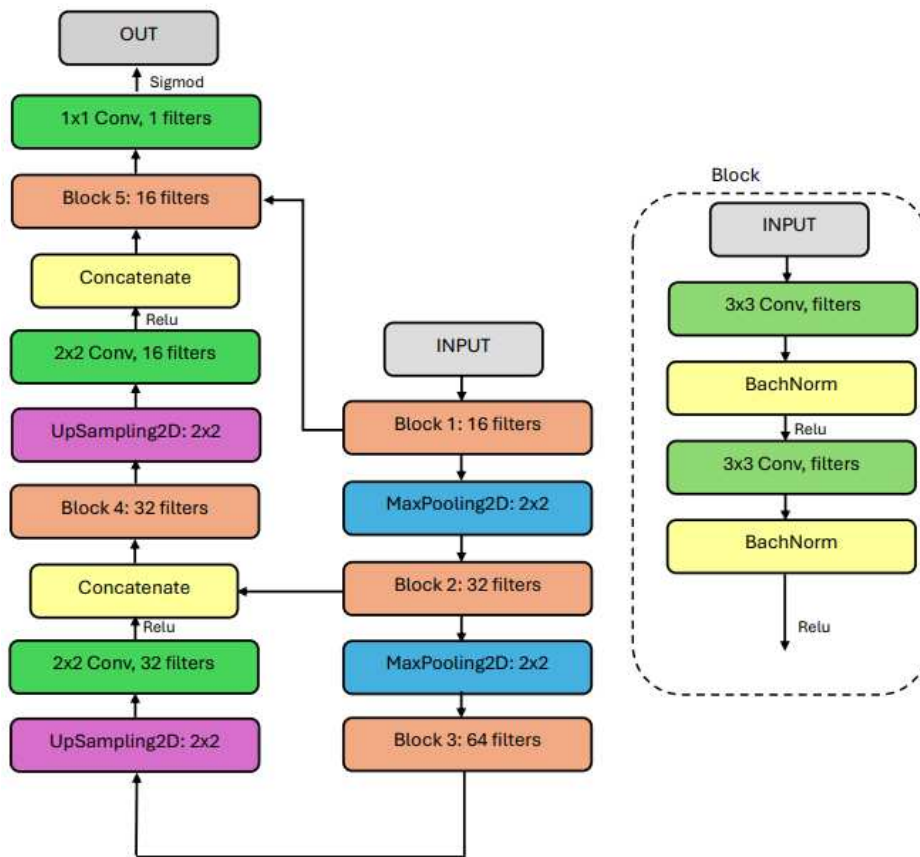


Fig. 5. Flowchart of the proposed U-Net architecture used for segmentation.

3.2.2. Proposed ResUnet model

The residual U-Net architecture used in this study is depicted in Fig. 6. In contrast to the standard U-Net design, each convolutional block is replaced by a residual block, shown in the inset of the figure. Each

residual block consists of two 3×3 convolutions followed by Batch Normalization and ReLU activation, together with a shortcut connection of the form $x + f(x)$. This residual pathway stabilizes gradient flow throughout the network and mitigates performance degradation in deeper layers, thereby improving structural consistency in the predicted segmentation masks.

The encoder and decoder preserve the same hierarchical organization as U-Net, employing 2×2 max-pooling during downsampling and 2×2 upsampling during reconstruction. As illustrated in Fig. 6, skip connections are maintained at every resolution level, allowing the network to retain spatial detail across the full architecture by concatenating encoder and decoder feature maps.

The final output is produced through a 1×1 convolution followed by a sigmoid activation, generating the binary mask of the textile component. The integration of residual blocks enhances contour fidelity, particularly in narrow or curved regions such as neckline areas and sleeve edges, where conventional U-Net configurations may exhibit slight boundary discontinuities.

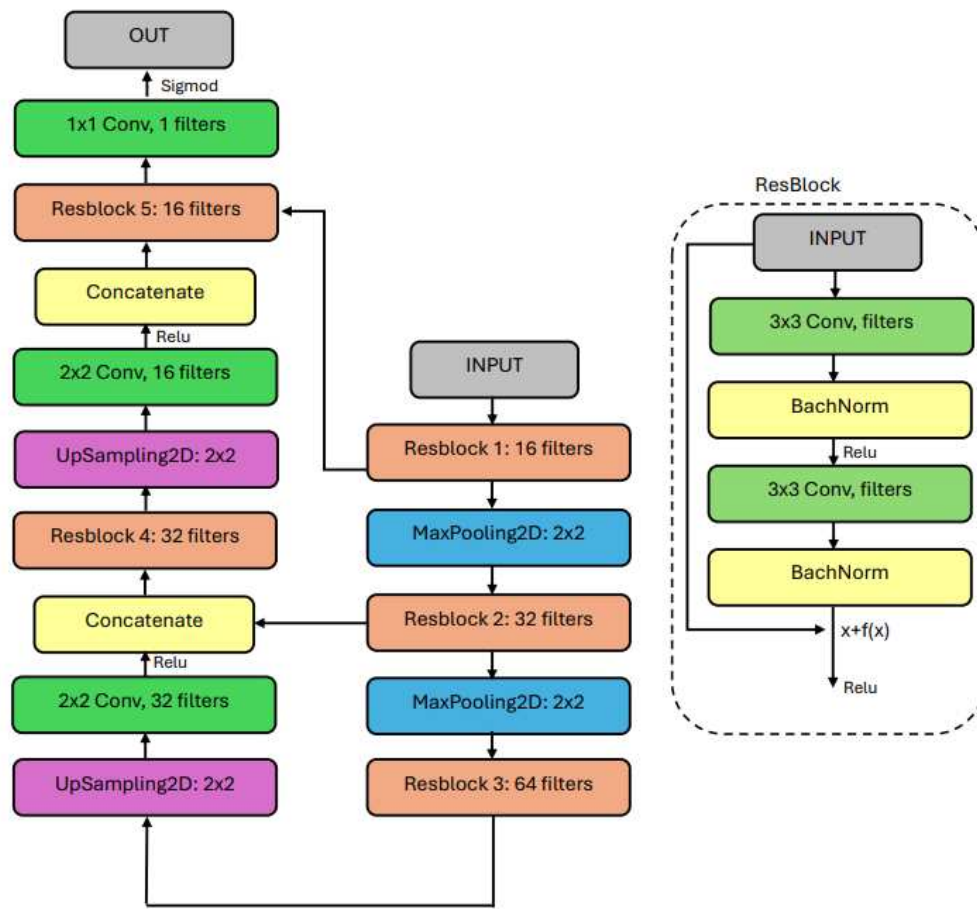


Fig. 6. Flowchart of the proposed ResU-Net architecture with residual blocks.

The loss function employed in the proposed model integrates three complementary components: Binary Cross-Entropy, Dice Loss, and Focal Loss. Together, these terms address distinct sources of segmentation error, allowing the model to maintain probabilistic stability, preserve the geometric structure of the garment, and emphasize regions where the contour is more difficult to resolve. The complete objective, expressed in Equation (2) as a weighted sum of the three losses, serves as the primary optimization criterion throughout training. The weighting coefficients satisfy the constraint $\alpha + \beta + \gamma = 1$, and this normalization was applied consistently across all experimental configurations.

$$L_{\text{total}} = \alpha_{\text{BCE}} L_{\text{BCE}} + \beta_{\text{Dice}} L_{\text{Dice}} + \gamma_{\text{Focal}} L_{\text{Focal}}, \quad (2)$$

(a) Binary Cross-Entropy (BCE)

Binary Cross-Entropy, defined in Equation (3), measures the deviation of the predicted probability from the true label by treating each pixel as an independent binary classification instance. It quantifies the likelihood assigned to the correct class and penalizes misclassifications through a logarithmic term, which makes it particularly sensitive to inconsistencies at the pixel level.

$$L_{\text{BCE}} = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)], \quad (3)$$

In this expression, N denotes the total number of pixels in the batch. Incorporating this term into the objective function ensures that the model remains probabilistically stable, an essential property in textile imaging where subtle variations in lighting or surface texture can introduce uncertainty. The logarithmic formulation discourages noisy or unstable boundary responses and promotes a smoother progression of output probabilities throughout training. As a result, the network avoids erratic fluctuations and produces more consistent contour predictions across diverse sample conditions.

(b) Dice Loss

The Dice Loss, expressed in Equation (4), quantifies the alignment between the predicted mask and the ground-truth region by measuring their degree of overlap. This term plays a central role in preserving the global geometric coherence of the segmented garment. In textile contours, even small degradations along the boundary, such as minor erosions or irregularities, can shift the centroid and distort the placement of subsequent keypoints, ultimately affecting the resulting physical measurements. By emphasizing region-level agreement rather than isolated pixel accuracy, Dice Loss stabilizes the overall shape of the mask and prevents fragmentation, particularly in small components or areas with pronounced curvature.

$$L_{\text{Dice}} = 1 - \frac{2 \sum_i y_i \hat{y}_i + \varepsilon}{\sum_i y_i + \sum_i \hat{y}_i + \varepsilon}. \quad (4)$$

(c) Focal Loss

The Focal Loss, defined in Equation (5), reduces the influence of pixels that are easy to classify and places greater emphasis on regions where the model is more likely to make errors. In this work, the parameters were set to $\gamma = 2$ and $\alpha = 0.25$.

$$L_{\text{Focal}} = \alpha(1 - p_t)^\gamma L_{\text{BCE}}, \quad (5)$$

This loss component increases the model's sensitivity to thin edges and ambiguous boundary regions, which frequently appear in garment components such as collars and sleeves, where the visual contrast between the fabric and the background may be limited. By directing the optimization process toward these challenging pixels, Focal Loss enables the full objective function to maintain an effective balance between probabilistic stability, preservation of the overall shape, and fine-grained contour accuracy.

The evaluation metrics used in this study were selected explicitly to match the requirements of dimensional measurement. Each mathematical expression was chosen for its direct relevance to the metrological validity of the predicted mask, ensuring that the segmentation output can reliably support millimeter-scale garment measurements.

3.2.3. Performance metrics and Precision keypoint metrics

(a) Intersection over Union (IoU)

Intersection over Union, defined in Equation (6), measures the geometric consistency between the predicted mask and the ground truth by penalizing both over segmentation and under segmentation. This metric is essential for assessing whether the overall shape of the garment piece is suitable for dimensional analysis, since even small deviations in the segmented area can lead to cumulative errors when linear distances are later computed along the contour.

$$IoU = \frac{|Y_{\text{true}} \cap Y_{\text{pred}}|}{|Y_{\text{true}} \cup Y_{\text{pred}}|}. \quad (6)$$

(b) Dice Coefficient

The Dice coefficient complements IoU by emphasizing regional continuity within the segmented mask. It is especially important for maintaining a clean and uninterrupted silhouette, which is critical when contours must remain stable for subsequent keypoint extraction. This metric, defined in Equation (7), is highly sensitive to small local imperfections, particularly in smaller garment components where minor discontinuities can disproportionately affect the accuracy of downstream measurements.

$$Dice = \frac{2 |A \cap B|}{|A| + |B|}. \quad (7)$$

(c) Precision, Recall, F1

These metrics quantify the reliability of the extracted boundary by capturing different types of contour deviations, as defined in Equation (8). Precision reflects whether the predicted mask exhibits artificial outward expansion relative to the true garment outline, revealing cases in which the model incorrectly adds extra boundary pixels. Recall measures the extent to which the segmentation fails to recover genuine portions of the contour, indicating loss of true edge information. The F1 score consolidates both aspects into a single balanced indicator, providing a robust measure of how consistently the model preserves the authentic geometric structure of the textile piece.

$$Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN}, F1 = \frac{2PR}{P + R}. \quad (8)$$

(d) PCK@ α y MPA

Both metrics assess the spatial accuracy of the detected keypoints, which is directly tied to the millimeter-level precision required in textile measurement tasks. As expressed in Equation (9), PCK@ α evaluates the proportion of keypoints whose localization error falls within a predefined tolerance α , directly reflecting the model's ability to position landmarks with sub-millimetric accuracy. Similarly, MPA, defined in Equation (10), measures the fraction of correctly detected keypoints across all samples, providing an aggregated view of landmark reliability under varying geometric conditions. These formulations capture aspects of model performance that traditional segmentation metrics cannot reveal, such as the preservation of local geometric relationships and the absolute spatial consistency required for accurate garment dimensioning.

Because industrial textile measurement depends on computing distances between specific anatomical landmarks rather than on global mask alignment alone, PCK and MPA become essential indicators of operational viability. High scores in these metrics confirm that the predicted keypoints maintain stable and repeatable positioning even in regions affected by curvature, fabric deformation, or subtle boundary variations. Consequently, they determine whether the system can deliver trustworthy millimeter-level measurements without manual correction, ensuring dependable deployment in high-throughput production workflows.

$$PCK_{\alpha} = \frac{1}{K} \sum_{k=1}^K \mathbb{1}(d_k \leq \alpha), \quad (9)$$

$$MPA = \frac{1}{K} \sum_{k=1}^K \text{Correct}(k). \quad (10)$$

3.3. Posprocesing

The system converts distances expressed in pixels into physical units (millimeters) as shown in Equation (11), which is a necessary requirement in textile metrology. For this purpose, a planar calibration was performed using a reference pattern with a known length $L_{ref} = 300 \text{ mm}$. The pattern spans W_{px} pixels in the acquired image, which yields the calibration factor:

$$R_{px/mm} = \frac{W_{px}}{L_{ref}}. \quad (11)$$

This factor is applied uniformly across the entire image domain because the capture system operates under strictly controlled conditions: fixed lens, constant camera–surface distance, homogeneous illumination, and a planar acquisition geometry. Under these settings, the pixel-to-millimeter relationship remains linear and uniform throughout the field of view, a well-established property in two-dimensional metrology systems.

Accordingly, any distance expressed in pixels, whether linear or curvilinear, is converted into millimeters following Equation (12):

$$D_{mm} = \frac{D_{px}}{R_{px/mm}}. \quad (12)$$

For measuring the distance between keypoints, the linear Euclidean distance is used, defined in Equation (13):

$$d_{\text{lin}}(p_i, p_j) = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}, \quad (13)$$

4. Results

4.1. Training Results

The training behavior of U-Net and ResU-Net for the neck-type textile cut is summarized in Table 1, which illustrates how each architecture converges under different loss-function combinations. Although both networks achieve high accuracy early in training, the evolution of metrics such as F1 score, Dice coefficient, and IoU reveals meaningful differences in how each model refines its predictions within the training set. Complementary keypoint-precision indicators, such as MPA and PCK reported in Table II and computed over the same training samples, further show how accurately each architecture localizes contour-defined landmarks.

Overall, accuracy, precision, recall, and F1 remain similar across all configurations. However, segmentation-oriented metrics, specifically Dice and IoU, identify the 0.33/0.33/0.33 weight combination as the best configuration for U-Net, whereas ResU-Net reaches its highest performance with the 0.5/0.25/0.25 setting.

A high level of segmentation and geometric accuracy is achieved by both U-Net and ResUnet across most training configurations for the neck-type cutting scenario, as reflected in Table 1. U-Net attains slightly higher peak values under some single-loss settings, whereas ResUnet exhibits more stable behavior when combined loss functions are applied, particularly in Dice, IoU, MPA, and PCK. The results also indicate that ResUnet requires greater computation time and CPU utilization, while U-Net is more computationally efficient during the training stage. Overall, the outcomes reveal that U-Net shows greater variability in performance depending on the selected loss function, whereas ResUnet maintains a more uniform convergence throughout the training process.

Table 1. Performance Metrics of training in Neck-type textil cut.

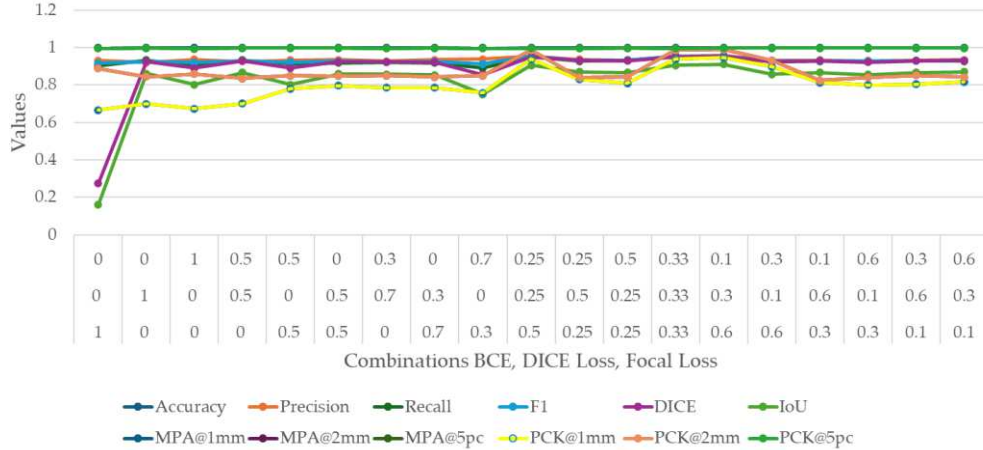
Model	BCE	DL	FL	ACC	PREC	REC	F1	DCE	IoU	Time(s)	CPU(%)
U-Net	0	0	1	0.99882	0.93018	0.9037	0.91668	0.2741	0.15918	4316.208	7.5
	0	1	0	0.99896	0.9191	0.9328	0.92584	0.92566	0.86164	4264.506	9.22
	1	0	0	0.9989	0.93676	0.90294	0.91942	0.89062	0.80292	5245.82	11.14
	0.5	0.25	0.25	0.99938	0.95552	0.94936	0.95244	0.94984	0.90448	4346.42	10.38
	0.33	0.33	0.33	0.99942	0.9594	0.95116	0.95524	0.95348	0.91108	4813.566	10.38
	0.6	0.3	0.1	0.9994	0.95602	0.95406	0.95502	0.95316	0.91054	4359.134	13.06
Res- Unet	0	0	1	0.99896	0.9341	0.91876	0.92634	0.3738	0.23048	7439.434	12.46
	0	1	0	0.99892	0.92352	0.92328	0.9233	0.92252	0.85624	6214.406	9.24
	1	0	0	0.9989	0.93082	0.91284	0.92172	0.90092	0.8199	8364.13	8.74
	0.5	0.25	0.25	0.99936	0.95774	0.94768	0.95266	0.9511	0.9068	7131.262	15.94
	0.33	0.33	0.33	0.99936	0.95418	0.95094	0.95254	0.95066	0.906	5448.408	16.18
	0.6	0.3	0.1	0.99936	0.95536	0.94848	0.95188	0.95044	0.9056	5961.502	13.98

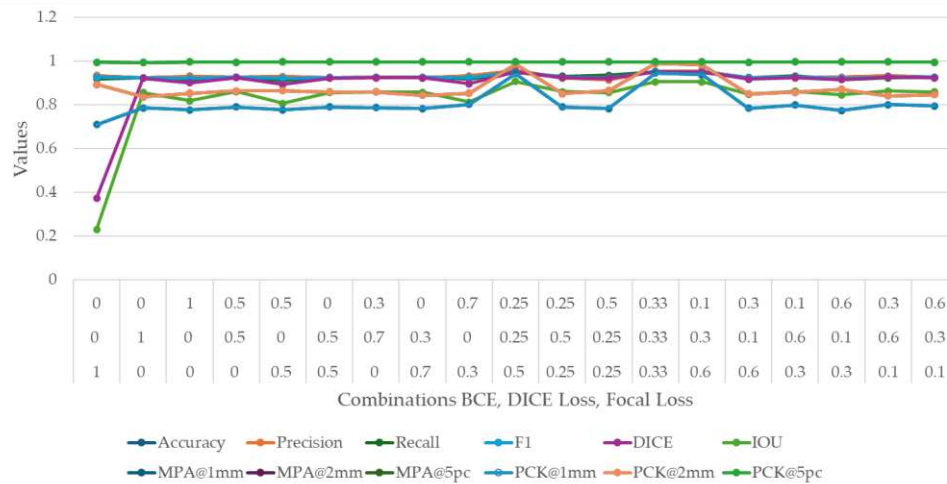
High values in the keypoint-precision metrics are associated with specific loss-function configurations. When considering error tolerances of 1 and 2 mm, the MPA@ α and PCK@ α metrics reported in Table 2 indicate that the most effective configurations are 0.6/0.3/0.1 for U-Net and 0.33/0.33/0.33 for ResUNet.

Table 2. Precision Keypoints Metrics of training in Neck-type textil cut.

Model	BCE	DL	FL	MPA@1m m	MPA@2m m	MPA@5pc	PCK@1 mm	PCK@2m m	PCK@5 pc
U-Net	0	0	1	0.6658	0.88832	0.99582	0.6658	0.88832	0.99582
	0	1	0	0.69998	0.84418	0.99666	0.69998	0.84418	0.99666
	1	0	0	0.67332	0.86002	0.99334	0.67332	0.86002	0.99334
	0.5	0.25	0.25	0.9375	0.98668	0.99582	0.9375	0.98668	0.99582
	0.33	0.33	0.33	0.9375	0.98668	0.99582	0.9375	0.98668	0.99582
	0.6	0.3	0.1	0.94582	0.98918	0.99666	0.94582	0.98918	0.99666
ResUn et	0	0	1	0.71084	0.89334	0.99582	0.71084	0.89334	0.99582
	0	1	0	0.68664	0.8375	0.99416	0.68664	0.8375	0.99416
	1	0	0	0.67748	0.85334	0.99666	0.67748	0.85334	0.99666
	0.5	0.25	0.25	0.9425	0.98834	0.99666	0.9425	0.98834	0.99666
	0.33	0.33	0.33	0.9458	0.99	0.99666	0.9458	0.99	0.99666
	0.6	0.3	0.1	0.93832	0.98414	0.99666	0.93832	0.98414	0.99666

In addition to the results summarized in Table I and Table II, an extended set of thirteen additional loss-weight configurations was evaluated for both U-Net and ResUNet. The corresponding performance metrics are presented in Fig. 7 for U-Net and Fig. 8 for ResUNet. Although a total of nineteen configurations were tested across all textile-cut categories, only the highest-performing settings were included in the tables reported in this study. Configurations that yielded substantially lower performance were excluded from the comparative analysis, as their contribution was negligible from both an experimental and interpretative perspective.

**Fig. 7.** Comparison of ResU-Net training performance metrics across the evaluated loss-function configurations.



The training behavior of U-Net and ResUnet for the sleeve-type textile cut is summarized in

For the sleeve cut, a comparable trend is observed: U-Net reaches slightly higher precision and F1 values in several configurations, whereas ResUnet yields marginally higher Dice and IoU values under the optimal weighting, as reflected in

Table 3. Both architectures maintain high segmentation performance across all combined-loss configurations, although U-Net displays greater sensitivity to the choice of weights. ResUnet, in contrast, preserves a more uniform convergence profile. Computation time and CPU usage remain higher for ResUnet, consistent with the deeper structure of the model.

Table 3. Performance Metrics of training in Sleeve-type textil cut.

Regarding keypoint precision, the results in Table 4 indicate that the sleeve-type cut exhibits a different distribution of MPA and PCK values compared to the neck-type case. U-Net achieves its highest MPA@1mm and PCK@1mm scores with the 0.6/0.3/0.1 configuration, matching the combination that also produced its best segmentation performance. In ResUnet, the highest keypoint precision appears in the 0.5/0.25/0.25 and 0.33/0.33/0.33 configurations, with values slightly below those obtained by U-Net at the 1 mm tolerance. For the 2 mm and 5% tolerances, both architectures converge toward near-saturation values, replicating the behavior observed in the other textile cuts.

Table 4. Precision Keypoints Metrics of training in Sleeve-type textil cut.

Model	BCE	DL	FL	MPA@1m m	MPA@2m m	MPA@5pc	PCK@1m m	PCK@2m m	PCK@5pc
U-Net	0	0	1	0.5273	0.7563	0.9947	0.5273	0.7563	0.9947
	0	1	0	0.5282	0.7537	0.9993	0.5282	0.7537	0.9993
	1	0	0	0.5347	0.7237	0.9933	0.5347	0.7237	0.9933
	0.5	0.25	0.25	0.7385	0.83116	0.98732	0.7385	0.83116	0.98732
	0.33	0.33	0.33	0.74232	0.83714	0.98734	0.74232	0.83714	0.98734
	0.6	0.3	0.1	0.74568	0.84566	0.99332	0.74568	0.84566	0.99332
	0	0	1	0.71084	0.89334	0.99582	0.71084	0.89334	0.99582
Res- Unet	0	1	0	0.68664	0.8375	0.99416	0.68664	0.8375	0.99416
	1	0	0	0.67748	0.85334	0.99666	0.67748	0.85334	0.99666
	0.5	0.25	0.25	0.73766	0.8325	0.99734	0.73766	0.8325	0.99734
	0.33	0.33	0.33	0.735	0.839	0.99468	0.735	0.839	0.99468
	0.6	0.3	0.1	0.735	0.839	0.99468	0.735	0.839	0.99468
	0	0	1	0.71084	0.89334	0.99582	0.71084	0.89334	0.99582

The training behavior of U-Net and ResUnet for the back-type and front-type textile cuts is summarized in Table 5. Because these components correspond to the main body panels of the garment and share the same number and spatial arrangement of keypoints, their metric patterns follow similar tendencies across the different loss-weight configurations. Accuracy, precision, recall, and F1 remain consistently high in both cuts, showing only minor variation across settings. Segmentation-focused indicators, namely Dice and IoU, again provide the most meaningful distinctions between configurations and between architectures. For the back piece, U-Net reaches its strongest performance under the 0.33/0.33/0.33 weighting (Dice = 0.92932, IoU = 0.86804), whereas ResUnet attains its highest values with the 0.6/0.3/0.1 configuration (Dice = 0.92744, IoU = 0.86476). A similar pattern is observed in the front piece: U-Net achieves its best Dice and IoU under the 0.33/0.33/0.33 setting (Dice = 0.94098, IoU = 0.88858), while ResUnet obtains its top overlap values with the 0.6/0.3/0.1 configuration (Dice = 0.93886, IoU = 0.88478).

In both body panels, U-Net consistently attains higher precision and F1 values across the best-performing configurations, whereas ResUnet demonstrates slightly more stable behavior when transitioning between different weighting schemes. U-Net exhibits sharper peaks in the combined-loss settings, particularly 0.33/0.33/0.33 and 0.5/0.25/0.25, while ResUnet benefits most from the asymmetric 0.6/0.3/0.1 weighting. Computation time and CPU usage remain higher for ResUnet in both body pieces, reflecting its deeper residual structure. As seen in the sleeve and neck analyses, U-Net shows more pronounced performance fluctuations as the loss distribution changes, whereas ResUnet retains a more uniform convergence profile.

Table 5. Performance Metrics of training in Back and Front -type textil cut.

Type textile cut	Model	BCE	DL	FL	ACC	PREC	REC	F1	DCE	IoU	Time(s)	CPU(%)
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Back cut	U-Net	0	0	1	0.9976	0.912	0.9209	0.9164	0.9156	0.8443	3149.97	5.1
		0	1	0	0.9974	0.9151	0.8971	0.906	0.9057	0.8277	3148.47	5.1
		1	0	0	0.9977	0.9046	0.9343	0.9192	0.9189	0.85	4163.98	3.6
		0.5	0.25	0.25	0.99822	0.94852	0.91766	0.9328	0.92696	0.86402	2074.354	9.84
		0.33	0.33	0.33	0.99826	0.94538	0.92314	0.93406	0.92932	0.86804	2218.814	10.6
		0.6	0.3	0.1	0.9982	0.94704	0.91654	0.93138	0.92676	0.86374	2050.97	13.22
	Res- Unet	0	0	1	0.9976	0.8702	0.8341	0.8571	0.309	0.1798	3371.2	12.2
		0	1	0	0.9978	0.8681	0.8661	0.8689	0.8646	0.7554	3210.75	10.6
		1	0	0	0.9975	0.868	0.8321	0.8491	0.7019	0.6427	4210.64	11.2
		0.5	0.25	0.25	0.99806	0.9398	0.913	0.92592	0.92124	0.8543	2894.8	11.38
		0.33	0.33	0.33	0.9981	0.93992	0.91588	0.92772	0.9227	0.8567	2549.562	17.7
		0.6	0.3	0.1	0.99814	0.93618	0.92594	0.9309	0.92744	0.86476	2507.962	13.72
Front Cut	U-Net	0	0	1	0.9974	0.93836	0.87336	0.90458	0.37118	0.22816	2190.974	9.46
		0	1	0	0.99754	0.92396	0.90088	0.91218	0.9116	0.8377	2105.248	13.18
		1	0	0	0.99708	0.92578	0.86174	0.89236	0.83536	0.7183	3120.082	13.12
		0.5	0.25	0.25	0.99848	0.95656	0.92942	0.94264	0.93498	0.87818	1923.84	8.7
		0.33	0.33	0.33	0.99854	0.95442	0.9372	0.9457	0.94098	0.88858	2096.16	5.28
		0.6	0.3	0.1	0.99854	0.95886	0.93	0.94416	0.93684	0.88128	1681.67	6.24
	Res- Unet	0	0	1	0.9973	0.91442	0.89358	0.90378	0.4149	0.26306	3204.006	6.28
		0	1	0	0.99742	0.91952	0.89744	0.90826	0.90582	0.8279	3108.258	6.14
		1	0	0	0.99714	0.91678	0.87692	0.89628	0.85344	0.745	4138.68	4.76
		0.5	0.25	0.25	0.99836	0.9471	0.93032	0.93858	0.93374	0.87578	2257.86	9.06
		0.33	0.33	0.33	0.99834	0.9565	0.91812	0.93658	0.9306	0.87046	2315.692	9
		0.6	0.3	0.1	0.99848	0.95178	0.93316	0.9423	0.93886	0.88478	2419.054	11.44

The keypoint-precision indicators in Table 6 reinforce these tendencies for both body sections. Because the back and front cuts share the same keypoint arrangement, their MPA and PCK values exhibit similar magnitudes across all tolerance levels. For the back piece, U-Net reaches its highest millimetric accuracy under the 0.33/0.33/0.33 configuration (MPA@1mm = 0.85338), whereas ResUnet obtains its top value with the 0.6/0.3/0.1 weighting (MPA@1mm = 0.84346). In the front piece, U-Net again achieves its best performance with the 0.6/0.3/0.1 configuration (MPA@1mm = 0.90006), while ResUnet attains its maximum MPA@1mm under the same setting (0.90114).

At broader tolerances (2 mm and 5%), both architectures reach values near saturation, confirming highly stable localization once minimal spatial deviation is permitted. As observed in the neck- and sleeve-type analyses, U-Net achieves the highest precision under the most restrictive tolerance, whereas ResUnet maintains more consistent behavior across the full range of loss-weight configurations.

Table 6. Precision Keypoints Metrics of training in back and front-type textil cut.

Type textile cut	Model	BCE	DL	FL	MPA@1m m	MPA@2m m	MPA@5 pc	PCK@1m m	PCK@2 mm	PCK@5 pc
Back cut	U-Net	0	0	1	0.5362	0.7704	0.9927	0.5362	0.7704	0.9927
		0	1	0	0.547	0.7553	0.9987	0.547	0.7553	0.9987
		1	0	0	0.4429	0.7546	1	0.4429	0.7546	1
		0.5	0.25	0.25	0.84994	0.96178	0.9957	0.84994	0.96178	0.9957
		0.33	0.33	0.33	0.85338	0.96758	0.99914	0.85338	0.96758	0.99914
		0.6	0.3	0.1	0.85034	0.96268	0.99656	0.85034	0.96268	0.99656
	Res- Unet	0	0	1	0.6798	0.8103	1	0.6798	0.8103	1
		0	1	0	0.6164	0.806	1	0.6164	0.806	1
		1	0	0	0.6638	0.8534	1	0.6638	0.8534	1
		0.5	0.25	0.25	0.83186	0.95838	0.9948	0.83186	0.95838	0.9948
		0.33	0.33	0.33	0.84406	0.95476	0.98182	0.84406	0.95476	0.98182
		0.6	0.3	0.1	0.84346	0.9645	0.99656	0.84346	0.9645	0.99656
Front cut	U-Net	0	0	1	0.61968	0.86444	0.99564	0.61968	0.86444	0.99564
		0	1	0	0.64	0.85856	0.99742	0.64	0.85856	0.99742
		1	0	0	0.56674	0.82122	0.99398	0.56674	0.82122	0.99398
		0.5	0.25	0.25	0.8958	0.97928	0.99742	0.8958	0.97928	0.99742
		0.33	0.33	0.33	0.89912	0.97838	0.99914	0.89912	0.97838	0.99914
		0.6	0.3	0.1	0.90006	0.98264	0.99828	0.90006	0.98264	0.99828
	Res- Unet	0	0	1	0.62496	0.84664	0.99742	0.62496	0.84664	0.99742
		0	1	0	0.64218	0.81558	0.99652	0.64218	0.81558	0.99652
		1	0	0	0.57648	0.8436	0.99742	0.57648	0.8436	0.99742
		0.5	0.25	0.25	0.88456	0.9767	0.99656	0.88456	0.9767	0.99656
		0.33	0.33	0.33	0.89418	0.96978	0.99484	0.89418	0.96978	0.99484
		0.6	0.3	0.1	0.90114	0.97226	0.99738	0.90114	0.97226	0.99738

4.2. Test Results

The test-set results indicate that, for both architectures, balanced loss-function configurations (BCE, Dice Loss, and Focal Loss) deliver substantially superior performance compared to using individual loss terms. In particular, the configurations with weights of 0.33/0.33/0.33 and 0.5/0.25/0.25 achieve the highest F1, Dice, IoU, PCK, and MPA values, exceeding 0.93 in keypoint-precision metrics and reaching more than 0.99 in PCK@5% for both models, as shown in Table 7 and Table 8. U-Net and ResUnet exhibit similar behavior in terms of precision and recall, although U-net presents slight advantages in keypoint localization under specific configurations. Configurations based solely on a single loss function yield considerably lower scores, reinforcing the need for composite loss functions to achieve more robust and accurate segmentation.

Table 7. Performance Metrics of test in Neck-type textil cut

Model	BCE	DL	FL	ACC	PREC	REC	F1	DCE	IoU
U-Net	1	0	0	0.9974	0.8212	0.8115	0.8163	0.8154	0.6884
	0	1	0	0.9973	0.8107	0.8085	0.8095	0.8091	0.6794
	0	0	1	0.9973	0.8103	0.8033	0.8067	0.8035	0.6716
	0.5	0.25	0.25	0.9992	0.9482	0.9312	0.9395	0.9372	0.8819
	0.33	0.33	0.33	0.9992	0.9483	0.9381	0.9432	0.9415	0.8895
	0.6	0.3	0.1	0.9992	0.9499	0.9362	0.9430	0.9414	0.8893
ResUn et	1	0	0	0.9972	0.8117	0.7917	0.8015	0.7905	0.6536
	0	1	0	0.9975	0.8228	0.8195	0.8211	0.8206	0.6958
	0	0	1	0.9974	0.8248	0.8085	0.8165	0.3483	0.2114

0.5	0.25	0.25	0.9992	0.9496	0.9302	0.9398	0.9385	0.8841
0.33	0.33	0.33	0.9992	0.9480	0.9271	0.9374	0.9361	0.8799
0.6	0.3	0.1	0.9992	0.9432	0.9317	0.9374	0.9358	0.8794

Table 8. Precision Keypoints Metrics of test in neck-type textil cut.

Model	BC E	DL	FL	MPA @1mm	MPA@ 2mm	MPA@ 3mm	MPA@ 5pc	PCK @1mm	PCK@ 2mm	PCK @3mm	PCK@ 5pc	Lat(ms)	Gflops
U-Net	1	0	0	0.5967	0.6117	0.815	1	0.5967	0.6117	0.8151	1	268.546	15.2967
	0	1	0	0.5633	0.6908	0.8042	1	0.5633	0.6908	0.8042	1	268.894	15.2633
	0	0	1	0.5583	0.6883	0.8042	0.9975	0.5583	0.6883	0.8042	0.9975	267.815	16.2583
	0.5	0.25	0.25	0.9042	0.9833	0.9900	0.9942	0.9042	0.9833	0.9900	0.9942	178.918	14.4056
	0.33	0.33	0.33	0.9175	0.9917	0.9950	0.9967	0.9175	0.9917	0.9950	0.9967	175.540	14.4056
	0.6	0.3	0.1	0.9108	0.9858	0.9917	0.9958	0.9108	0.9858	0.9917	0.9958	176.999	14.4056
ResUn et	1	0	0	0.6492	0.6975	0.8092	0.9967	0.6492	0.6975	0.8092	0.9967	270.313	16.2492
	0	1	0	0.6025	0.6508	0.855	0.9992	0.6025	0.6508	0.855	0.9992	252.772	16.3025
	0	0	1	0.6792	0.6867	0.8775	0.9967	0.6792	0.6867	0.8775	0.9967	272.451	17.2792
	0.5	0.25	0.25	0.8925	0.9825	0.9892	0.9958	0.8925	0.9825	0.9892	0.9958	206.519	15.1396
	0.33	0.33	0.33	0.8842	0.9800	0.9850	0.9908	0.8842	0.9800	0.9850	0.9908	207.181	15.1396
	0.6	0.3	0.1	0.8942	0.9850	0.9892	0.9933	0.8942	0.9850	0.9892	0.9933	205.541	15.1396

In addition to the metrics summarized in Table 7 and Table 8, the test-stage evaluation replicated the full experimental protocol used during training, assessing the same set of nineteen loss-weight configurations for both U-Net and ResUnet. As in the training phase, the complete results of these evaluations are shown in Fig. 9 for U-Net and Fig. 10 for ResUnet. Although all configurations were executed to ensure methodological consistency and to observe their behavior on unseen data, only the highest-performing settings were included in the tables reported in this section. Configurations that produced substantially lower accuracy, weaker contour reconstruction, or poor keypoint localization were excluded from the comparative analysis, as their contribution was negligible for interpreting cross-architecture performance during testing.

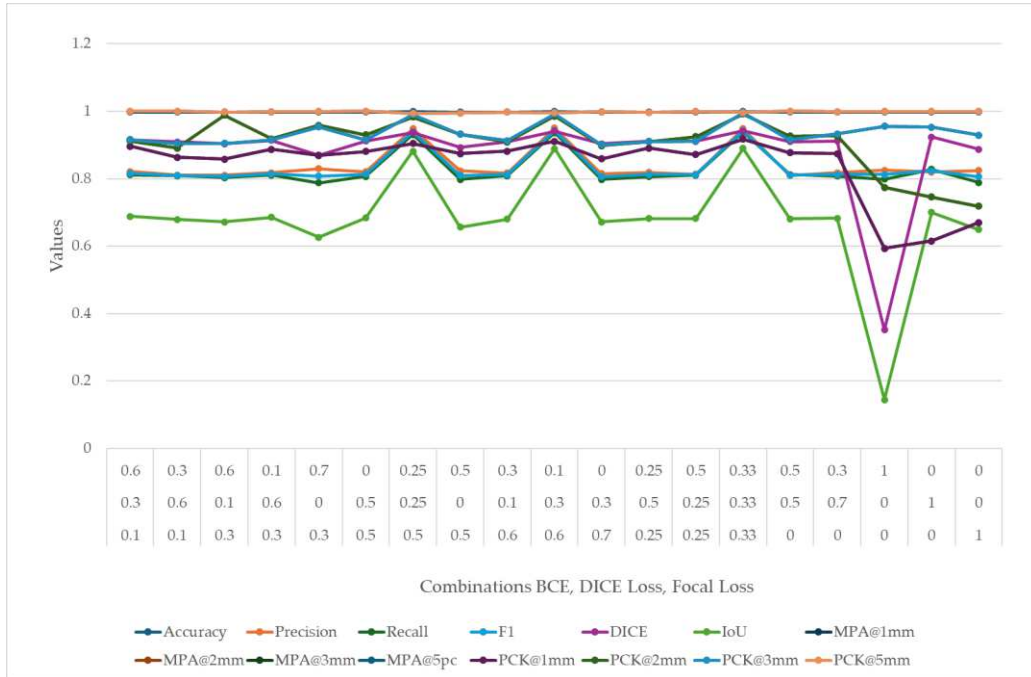


Fig. 9. Comparison of U-Net test-set performance metrics across the evaluated loss-function configurations.

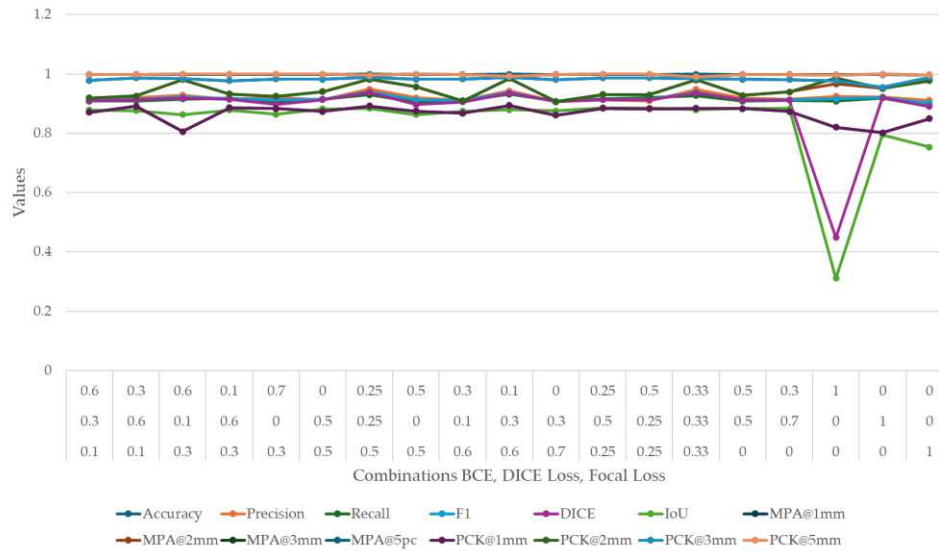


Fig. 10. Comparison of ResUnet test-set performance metrics across the evaluated loss-function configurations.

For sleeve components, the performance metrics indicate that balanced loss configurations provide an effective compromise between global segmentation quality and local precision, as detailed in Table 9 and Table 10. ResUnet achieves slightly better preservation of fine-scale structures, particularly in smaller subregions, whereas U-Net maintains strong global segmentation performance. This outcome underscores the role of residual connections when processing medium-sized components that require reliable retention of localized structural detail.

Table 9. Performance Metrics of test in Sleeve-type textil cut

Model	BCE	DL	FL	ACC	PREC	REC	F1	DCE	IoU
U-Net	1	0	0	0.996	0.7911	0.7364	0.7627	0.7355	0.5818
	0	1	0	0.9961	0.7681	0.7985	0.7829	0.7827	0.6431
	0	0	1	0.9962	0.806	0.7459	0.7744	0.2764	0.1605
	0.5	0.25	0.25	0.9978	0.8847	0.8521	0.8678	0.8619	0.7574
	0.33	0.33	0.33	0.9979	0.8868	0.8527	0.8692	0.8626	0.7585
	0.6	0.3	0.1	0.9978	0.8858	0.8452	0.8648	0.8583	0.7518
ResUnet	1	0	0	0.996	0.7808	0.7496	0.7644	0.7206	0.5635
	0	1	0	0.9962	0.7804	0.7787	0.7795	0.7789	0.6381
	0	0	1	0.9959	0.7798	0.7392	0.7585	0.2892	0.1695
	0.5	0.25	0.25	0.9978	0.8649	0.8669	0.8656	0.8613	0.7564
	0.33	0.33	0.33	0.9978	0.8673	0.8710	0.8691	0.8656	0.7632
	0.6	0.3	0.1	0.9978	0.8810	0.8575	0.8687	0.8650	0.7621

Table 10. Precision Keypoints Metrics of test in Sleeve-type textil cut.

Model	BCE	DL	FL	MPA@1 mm	MPA@2 mm	MPA@3 mm	MPA @5pc	PCK@ 1mm	PCK@ 2mm	PCK@ 3mm	PCK@ 5pc	Lat(m s)	Gflop s
U-Net	1	0	0	0.4955	0.6735	0.7652	0.992	0.4955	0.6735	0.7652	0.992	67.5779	16.195
	0	1	0	0.5211	0.6355	0.818	0.9967	0.5211	0.6355	0.818	0.9967	68.059	16.211
	0	0	1	0.5265	0.673	0.8233	0.9927	0.5265	0.673	0.8233	0.9927	68.4211	16.226

	0.5	0.25	0.25	0.7247	0.8480	0.8873	0.9873	0.7247	0.8480	0.8873	0.9873	205.37	14.405
	0.33	0.33	0.33	0.7190	0.8553	0.8947	0.9833	0.7190	0.8553	0.8947	0.9833	175.75	14.407
	0.6	0.3	0.1	0.7005	0.8327	0.8780	0.9833	0.7005	0.8327	0.8780	0.9833	182.67	14.407
ResUn et	1	0	0	0.1575	0.466	0.7935	0.9987	0.1575	0.466	0.7935	0.9987	71.972	0.1575
	0	1	0	0.2077	0.408	0.8027	0.996	0.2077	0.408	0.8027	0.996	73.405	0.2077
	0	0	1	0.1842	0.4118	0.7858	0.9847	0.1842	0.4118	0.7858	0.9847	75.124	0.1842
	0.5	0.25	0.25	0.7215	0.8400	0.8913	0.9913	0.7215	0.8400	0.8913	0.9913	208.7	15.134
	0.33	0.33	0.33	0.7343	0.8487	0.8873	0.9913	0.7343	0.8487	0.8873	0.9913	205.34	15.14
	0.6	0.3	0.1	0.7347	0.8513	0.8867	0.9840	0.7347	0.8513	0.8867	0.9840	208.32	15.140

Because the back and front panels share a similar geometric structure and the same number of keypoints, their quantitative behavior follows closely aligned patterns. In these larger garment regions, both architectures achieve substantially higher segmentation reliability compared with smaller textile components, as shown in Table 11. The combination of broader surfaces, smoother contours, and richer spatial context leads to consistently strong ACC, F1, and REC values across most configurations. Multi-loss settings, particularly 0.5/0.25/0.25, 0.33/0.33/0.33, and 0.6/0.3/0.1, yield the highest Dice and IoU scores in both cuts, with U-Net reaching up to 0.8547 in IoU and ResUnet reaching up to 0.8552. These improvements contrast sharply with single-loss schemes, which exhibit noticeably lower overlap accuracy, especially when Focal Loss is used alone. Although U-Net frequently attains slightly higher precision and F1 values, ResUnet maintains more consistent segmentation behavior across all weight distributions, reinforcing the complementary strengths of each architecture in these structurally stable garment regions.

A similar trend appears in keypoint localization. Because both garment sections contain identical landmark definitions, their millimetric accuracy responds in parallel to the loss-weight configurations. The highest MPA@1mm values in U-Net arise once again from the 0.5/0.25/0.25, 0.33/0.33/0.33, and 0.6/0.3/0.1 configurations, yielding values between 0.7639 and 0.9001 and reaching perfect agreement at the 5% tolerance level, as reported in Table 12. ResUnet follows a comparable pattern, with its best keypoint precision appearing under the 0.33/0.33/0.33 and 0.6/0.3/0.1 settings, producing MPA@1mm values between 0.7486 and 0.7604. These results reaffirm that, in large and geometrically coherent panels, the choice of architecture is less critical than selecting an appropriate loss-weighting strategy. Balanced and semi-balanced combinations consistently deliver the strongest millimetric alignment, with U-Net showing sharper gains from mixed losses and ResUnet maintaining steadier performance improvements supported by its residual structure.

Table 11. Performance Metrics of test in Back and Front-type textil cut

Type textile cut	Model	BCE	DL	FL	ACC	PREC	REC	F1	DCE	IoU
Back type	U-Net	1	0	0	0.9942	0.8144	0.7654	0.789	0.7408	0.5886
		0	1	0	0.9941	0.7915	0.7918	0.7916	0.7913	0.6546
		0	0	1	0.9941	0.8111	0.7587	0.7839	0.328	0.1964
		0.5	0.25	0.25	0.9980	0.9366	0.9099	0.9231	0.9176	0.8478
		0.33	0.33	0.33	0.9979	0.9329	0.9082	0.9203	0.9162	0.8454
		0.6	0.3	0.1	0.9979	0.9312	0.9151	0.9230	0.9186	0.8494
	ResUnet	1	0	0	0.9943	0.818	0.7657	0.7909	0.7606	0.6139
		0	1	0	0.9942	0.7979	0.79	0.7938	0.7925	0.6564
		0	0	1	0.994	0.7964	0.7735	0.7848	0.3816	0.2362
		0.5	0.25	0.25	0.9978	0.9280	0.9080	0.9178	0.9137	0.8413
		0.33	0.33	0.33	0.9979	0.9258	0.9146	0.9201	0.9168	0.8465
		0.6	0.3	0.1	0.9979	0.9280	0.9119	0.9199	0.9152	0.8437
Front type	U-Net	0	0	1	0.9938	0.806	0.7389	0.7707	0.7263	0.5708
		0	1	0	0.9944	0.8094	0.7888	0.7988	0.7984	0.6645
		1	0	0	0.994	0.8082	0.752	0.779	0.3302	0.1979
		0.5	0.25	0.25	0.9982	0.9397	0.9111	0.9251	0.9179	0.8484
		0.33	0.33	0.33	0.9980	0.9378	0.9112	0.9242	0.9174	0.8475
		0.6	0.3	0.1	0.9980	0.9356	0.9165	0.9259	0.9216	0.8547
	ResUnet	0	0	1	0.9941	0.8065	0.7695	0.7874	0.7551	0.6067
		0	1	0	0.9941	0.7981	0.7767	0.7872	0.7857	0.6472
		1	0	0	0.9938	0.7891	0.7679	0.7782	0.3722	0.2295
		0.5	0.25	0.25	0.9978	0.9281	0.9092	0.9185	0.9142	0.8420
		0.33	0.33	0.33	0.9980	0.9330	0.9173	0.9250	0.9219	0.8552
		0.6	0.3	0.1	0.9979	0.9378	0.9026	0.9196	0.9138	0.8414

Table 12. Precision Keypoints Metrics of test in Back and Front-type textile cut.

Type textile cut	Model	BCE	DL	FL	MPA @1mm	MPA @2mm	MPA @3mm	MP A@5p c	PCK @1m	PCK @2mm	PCK @3mm	PCK @5pc	Lat(m s)	Gflops
Back type	U-Net	1	0	0	0.5083	0.4222	0.8528	0.9951	0.5083	0.4222	0.8528	0.9951	273.806	15.2083
		0	1	0	0.5083	0.3312	0.8125	0.9993	0.5083	0.3312	0.8125	0.9993	252.351	15.2083
		0	0	1	0.5021	0.4042	0.8181	0.9958	0.5021	0.4042	0.8181	0.9958	281.649	15.3021
		0.5	0.25	0.25	0.7708	0.9563	0.9903	1.0000	0.7708	0.9563	0.9903	1.0000	172.769	14.4056
		0.33	0.33	0.33	0.7722	0.9556	0.9826	0.9993	0.7722	0.9556	0.9826	0.9993	168.349	14.4056
		0.6	0.3	0.1	0.7639	0.9563	0.9861	1.0000	0.7639	0.9563	0.9861	1.0000	169.359	14.4056
	ResU net	1	0	0	0.5986	0.676	0.8583	1	0.5986	0.6764	0.8583	1	255.834	16.16
		0	1	0	0.6167	0.6889	0.8264	0.9965	0.6167	0.6889	0.8264	0.9965	243.403	16.67
		0	0	1	0.4917	0.5958	0.8306	0.9993	0.4917	0.5958	0.8306	0.9993	275.71	17.17
		0.5	0.25	0.25	0.7444	0.9458	0.9854	0.9993	0.7444	0.9458	0.9854	0.9993	195.793	15.1396
		0.33	0.33	0.33	0.7604	0.9479	0.9896	1.0000	0.7604	0.9479	0.9896	1.0000	197.852	15.1396
		0.6	0.3	0.1	0.7486	0.9521	0.9875	1.0000	0.7486	0.9521	0.9875	1.0000	195.013	15.1396
Front type	U-Net	0	0	1	0.18	0.3653	0.797	0.9882	0.18	0.3653	0.797	0.9882	71.7251	15.181
		0	1	0	0.2333	0.4113	0.8476	0.9958	0.2333	0.4113	0.8476	0.9958	72.5661	15.2233
		1	0	0	0.1981	0.3848	0.825	0.9924	0.1981	0.3848	0.825	0.9924	73.1355	15.1981
		0.5	0.25	0.25	0.8614	0.9799	0.9875	0.9938	0.8614	0.9799	0.9875	0.9938	207.135	14.4056
		0.33	0.33	0.33	0.8510	0.9674	0.9833	0.9931	0.8510	0.9674	0.9833	0.9931	158.018	14.4056
		0.6	0.3	0.1	0.8300	0.9715	0.9896	0.9951	0.8300	0.9715	0.9896	0.9951	154.085	14.4056
	ResU net	0	0	1	0.1843	0.454	0.8425	0.9951	0.1843	0.454	0.8425	0.9951	68.5883	16.1843
		0	1	0	0.2086	0.3559	0.8101	0.9889	0.2086	0.3559	0.8101	0.9889	69.668	16.2086
		1	0	0	0.1827	0.3813	0.8105	0.9944	0.1827	0.3813	0.8105	0.9944	69.627	16.1827
		0.5	0.25	0.25	0.8169	0.9639	0.9840	0.9965	0.8169	0.9639	0.9840	0.9965	200.071	15.1396
		0.33	0.33	0.33	0.8349	0.9667	0.9833	0.9944	0.8349	0.9667	0.9833	0.9944	198.552	15.1396
		0.6	0.3	0.1	0.8294	0.9694	0.9875	0.9938	0.8294	0.9694	0.9875	0.9938	203.016	15.1396

4.3. Final Dimensional-Inspection Reports

The dimensional-inspection reports generated for the evaluated components are presented in Fig. 11, Fig. 12, and Fig. 13. Each report summarizes the measurements obtained for a given textile cut type and compares them with the corresponding reference values and tolerance bands to determine whether the piece satisfies the required dimensional specifications. In addition to this compliance evaluation, the system issues three supplementary alerts. Lack Material indicates that, even if a measurement remains within tolerance, the available fabric is insufficient to apply corrective adjustments, suggesting that the piece is unlikely to be recoverable. Measurement Not Within Tolerance flags cases where one or more dimensions exceed the permissible limits; although this may lead to discarding the piece, recovery remains

possible if adequate material is available. Finally, Discard denotes that the piece fails several of the defined criteria, resulting in its definitive rejection.

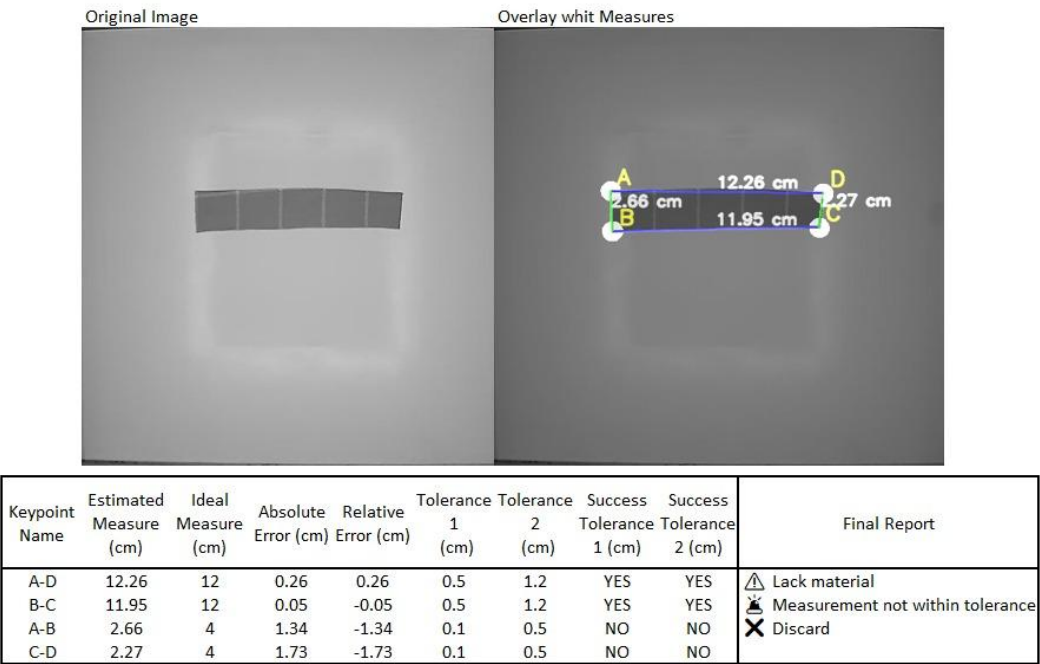


Fig. 11. Final dimensional-verification report for the neck textile cut

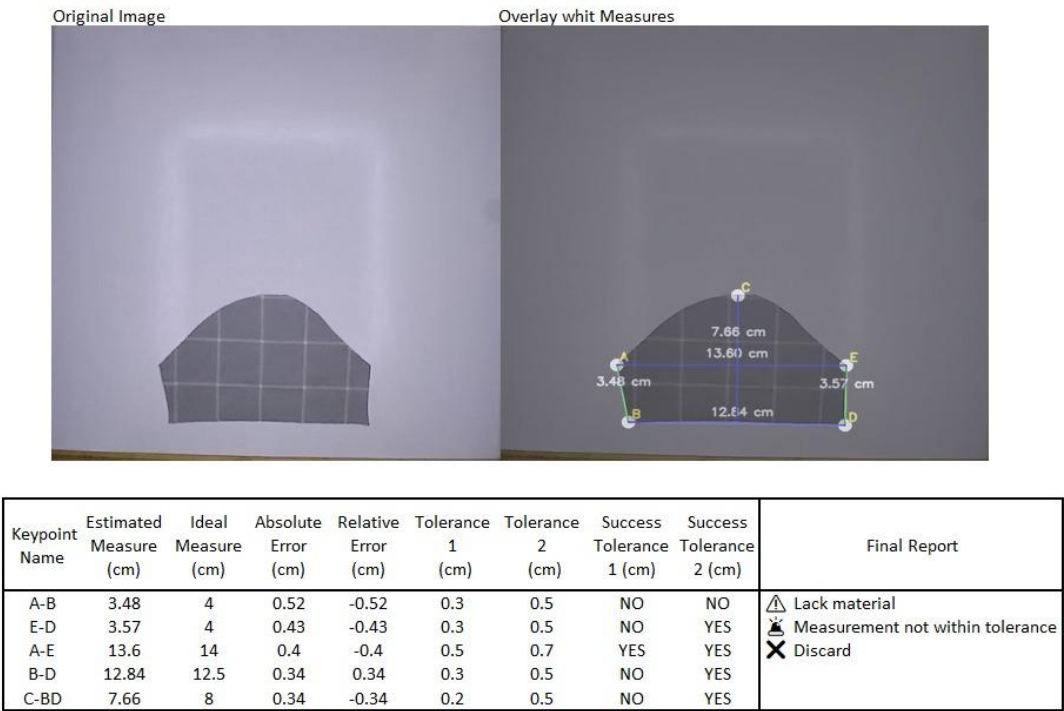


Fig. 12. Final dimensional-verification report for the sleeve textile cut

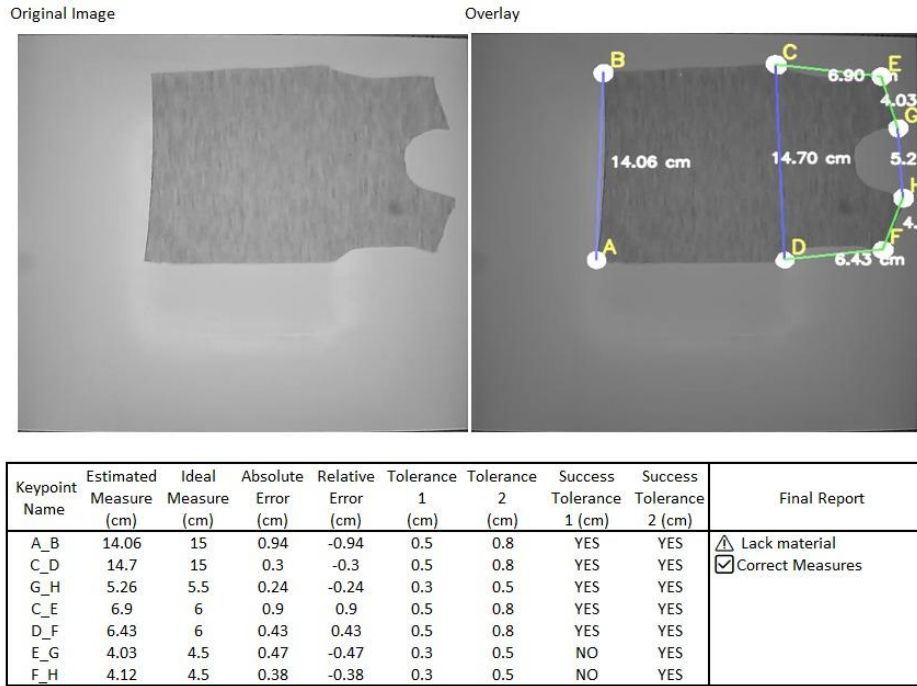


Fig. 13. Final dimensional-verification report for the front textile cut

CONCLUSIONS

This study presents a fully automated system for millimeter-level dimensional verification of textile cut pieces, integrating segmentation, keypoint localization, and metrological post-processing within a unified pipeline. The primary contribution lies not in a single improved architecture, but in an adaptive measurement framework capable of selecting the optimal model–loss configuration for each garment component based on its geometric characteristics.

The results show that different textile regions benefit from different segmentation behaviors: balanced multi-loss U-Net configurations deliver the highest precision in small components, U-Net and ResUNet perform comparably in medium regions such as sleeves, and ResUNet achieves the most consistent geometric accuracy in larger panels. These findings confirm that no single architecture or loss distribution is universally optimal.

By incorporating validation and test outcomes into the model-selection process, the proposed system ensures reliable contour reconstruction and keypoint localization across diverse garment geometries. Multi-loss optimization further strengthens the balance between global segmentation and fine-scale accuracy with only modest computational overhead. Overall, the framework operates as a robust and scalable solution for automated dimensional verification in textile manufacturing, supporting industrial requirements for high-precision quality control.

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AUTHOR CONTRIBUTION

Robert Falcon and Marcelo Barrionuevo: Writing and preparation of the manuscript; preparation of tables and figures; software and hardware development; AI model training and validation; dataset collection and preprocessing. Carlos H. Inga Espinoza: Supervision and manuscript writing; preparation of tables and figures; guidance on the development of the AI architecture; dataset preprocessing

DATA AVAILABILITY

The authors declare that the data supporting the findings of this study are available within the paper.

DECLARATIONS

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

CLINICAL TRIAL NUMBER

Not applicable

REFERENCES

- [1] Wei et al., A method for visual recognition and length measurement of complex multi-branch cables, Measurement (Elsevier). DOI: 10.1016/j.measurement.2024.116456 <https://doi.org/10.1016/j.measurement.2024.116456>. Online [Accessed 10 November 2025]
- [2] Yun et al., Development of digitized evaluation methods for fabric shrinkage and damage using image analysis, Fashion and Textiles (SpringerOpen). DOI: 10.1186/s40691-023-00346-8 <https://doi.org/10.1186/s40691-023-00346-8>. Online [Accessed 10 November 2025]
- [3] Baik et al., Deformation Recovery and Dimensional Stability Properties of Fabrics in a Clothing Care Machine, Fibers and Polymers (Springer). DOI: 10.1007/s12221-023-00039-5 <https://doi.org/10.1007/s12221-023-00039-5>. Online [Accessed 10 November 2025]

- [4] Ng, Hui & Ip, Dimensional stability of fabrics: Resistance to shrinkage, in: Book chapter, Elsevier. DOI: 10.1016/B978-0-85709-087-4.50003-2 <https://doi.org/10.1016/B978-0-85709-087-4.50003-2>. Online [Accessed 10 November 2025]
- [5] ančárek et al., DeepGarment: 3D Garment Shape Estimation from a Single Image, Computer Graphics Forum (Wiley). DOI: 10.1111/cgf.13125 <https://doi.org/10.1111/cgf.13125>. Online [Accessed 10 November 2025]
- [6] Zhang & Chen, Modeling Garment Seam from a Single Image, J. Comput. Sci. Technol. (Springer). DOI: 10.1007/s11390-018-1831-6 <https://doi.org/10.1007/s11390-018-1831-6>. Online [Accessed 10 November 2025]
- [7] Kirillov et al., Segment Anything (SAM), Preprint, Meta / arXiv. arXiv:2304.02643 <http://arxiv.org/abs/2304.02643>. Online [Accessed 10 November 2025]
- [8] Li et al., Automatic Measurements of Garment Sizes Using Computer Vision, Deep Learning Models and Point Cloud Data, Proc. of ACM. DOI: 10.1145/3121360.3121382 <https://dl.acm.org/doi/10.1145/3121360.3121382>. Online [Accessed 10 November 2025]
- [9] Zhang & Suen, A fast parallel algorithm for thinning digital patterns, Commun. ACM. DOI: 10.1145/357994.358023 <https://doi.org/10.1145/357994.358023>. Online [Accessed 10 November 2025]
- [10] N. Otsu, A threshold selection method from gray-level histograms, IEEE Trans. SMC. DOI: 10.1109/TSMC.1979.4310076 <https://doi.org/10.1109/TSMC.1979.4310076>. Online [Accessed 10 November 2025]
- [11] di Baja, Well-shaped, stable, and reversible skeletons from the (3,4)-distance transform, J. Vis. Commun. Image Represent. DOI: 10.1006/jvci.1994.1010 <https://doi.org/10.1006/jvci.1994.1010>. Online [Accessed 10 November 2025]
- [12] Lee, Kashyap & Chu, Building Skeleton models via 3-D medial surface axis thinning algorithms, CVGIP Graph. Models Image Process. DOI: 10.1006/cgip.1994.1042 <https://doi.org/10.1006/cgip.1994.1042>. Online [Accessed 10 November 2025]
- [13] Tremeau & Borel, A region growing and merging algorithm to color segmentation, Pattern Recognit. DOI: 10.1016/S0031-3203(96)00147-1 [https://doi.org/10.1016/S0031-3203\(96\)00147-1](https://doi.org/10.1016/S0031-3203(96)00147-1). Online [Accessed 10 November 2025]
- [14] Boykov & Jolly, Interactive graph cuts for optimal boundary & region segmentation, Proc. of ICCV, IEEE. DOI: 10.1109/ICCV.2001.937446 <https://ieeexplore.ieee.org/document/937446>. Online [Accessed 10 November 2025]
- [15] Fukunaga & Hostetler, The estimation of the gradient of a density function, with applications in pattern recognition, IEEE Trans. Inf. Theory. DOI: 10.1109/TIT.1975.1055330 <https://doi.org/10.1109/TIT.1975.1055330>. Online [Accessed 10 November 2025]
- [16] Emam & Sayyedbarzani, Dimensional deviation measurement of ceramic tiles according to ISO 10545-2 using the machine vision, Int. J. Adv. Manuf. Technol. DOI: 10.1007/s00170-018-2781-4 <https://doi.org/10.1007/s00170-018-2781-4>. Online [Accessed 10 November 2025]
- [17] Kono & Kondo, Accuracy evaluation of squareness identification by vision-based circular tests for machine tools, CIRP Ann. DOI: 10.1016/j.cirp.2024.04.089 <https://doi.org/10.1016/j.cirp.2024.04.089>. Online [Accessed 10 November 2025]
- [18] Dang et al., A computer-vision based framework for virtual 3D garment reconstruction, Multimedia Tools Appl. (Springer). DOI: 10.1007/s11042-024-20269-w <https://doi.org/10.1007/s11042-024-20269-w>. Online [Accessed 10 November 2025]

- [19] Naseri et al., A novel quantum binary images thinning algorithm, *Optik*. DOI: 10.1016/j.ijleo.2016.11.124 <https://doi.org/10.1016/j.ijleo.2016.11.124>. Online [Accessed 10 November 2025]
- [20] Jin et al., An integrated 3D point cloud and 2D image-based approach for generating individualized female prototype patterns, *Computers & Industrial Engineering* (Elsevier). DOI: 10.1016/j.cie.2025.108000 <https://doi.org/10.1016/j.cie.2025.108000>. Online [Accessed 10 November 2025]
- [21] Nassif, Dimensional Stability, Aesthetic and Functional Properties of Cotton:Polyester Blended Knitted Fabrics, *International Design Journal*. https://idj.journals.ekb.eg/article/82542_cb683573c68f1bdd32558a6f94772d2a.pdf. Online [Accessed 10 November 2025]
- [22] Yassin et al., A study of fabric biasness with self developed fabric dimensional behaviour test, *Journal of Textile Engineering & Fashion Technology*. DOI: 10.15406/jteft.2019.05.00181 <https://medcraveonline.com/JTEFT/JTEFT-05-00181.pdf>. Online [Accessed 10 November 2025]
- [23] Safdar et al., Improving Dimensional Stability of Cotton Knits through Resin Finishing, *Textile Research Journal* (SAGE). DOI: 10.1177/155892501400900304 <https://journals.sagepub.com/doi/10.1177/155892501400900304>. Online [Accessed 10 November 2025]
- [24] Almond, The status of pattern practice, Thesis, University of Leeds. <https://eprints.whiterose.ac.uk/id/eprint/110930/14/the%20status%20of%20pattern.pdf>. Online [Accessed 10 November 2025]
- [25] Süpüren Mengüç, 3D measurement device for textile testing (example), *Textile Research Journal*. DOI: 10.1080/00405000.2023.2286331 <https://doi.org/10.1080/00405000.2023.2286331>. Online [Accessed 10 November 2025]
- [26] ASTM, D6207 Standard Test Method for Dimensional Stability of Fabrics to Changes in Humidity and Temperature, ASTM Standard. <https://www.astm.org/d6207-03r19.html>. Online [Accessed 10 November 2025]
- [27] GarmentIQ team, GarmentIQ: Automated Garment Measurement for Fashion at Scale, Preprint. <https://archive.gd.edu.kg/pdf/20250525121523/v1.pdf>. Online [Accessed 10 November 2025]
- [28] Zhang et al., Non-contact body measurement for garment customization: a review, *Textile Research Journal* (SAGE). DOI: 10.1177/00405175251318629 <https://doi.org/10.1177/00405175251318629>. Online [Accessed 10 November 2025]
- [29] Kwak et al., Automatic pattern drafting from 2D garment outlines, *Computers & Graphics* (Elsevier). DOI: 10.1016/j.cag.2018.05.002 <https://doi.org/10.1016/j.cag.2018.05.002>. Online [Accessed 10 November 2025]
- [30] Xiang et al., Vision-based fabric inspection and measurement: A review, *Machine Vision Applications* (Springer). DOI: 10.1007/s00138-021-01148-9 <https://link.springer.com/article/10.1007/s00138-021-01148-9>. Online [Accessed 10 November 2025]
- [31] Sun et al., HRNet: Deep High-Resolution Representation Learning for Human Pose Estimation, *Proc. of CVPR* (IEEE-CVF). arXiv:1908.07919 <https://arxiv.org/abs/1908.07919>. Online [Accessed 10 November 2025]
- [32] Güler et al., DensePose: Dense Human Pose Estimation in the Wild, *Proc. of CVPR* (IEEE-CVF). arXiv:1802.00434 <https://arxiv.org/abs/1802.00434>. Online [Accessed 10 November 2025]
- [33] Liu et al., DeepFashion: dataset for clothes recognition & landmarking, *Proc. of CVPR* (IEEE-CVF). arXiv:1607.04116 <https://arxiv.org/abs/1607.04116>. Online [Accessed 10 November 2025]
- [34] Ge et al., DeepFashion2: benchmark for detection, pose estimation, and segmentation, *Proc. of CVPR* (IEEE-CVF).

arXiv:1901.07973

<https://arxiv.org/abs/1901.07973>. Online [Accessed 10 November 2025]

- [35] Bogo et al., SMPL: A Skinned Multi-Person Linear Model, Proc. of SIGGRAPH Asia (ACM). DOI: 10.1145/2661229.2661237
<https://smpl.is.tue.mpg.de/>. Online [Accessed 10 November 2025]
- [36] Bogo et al., SMPLify: Fitting 3D Human Models to Images, Proc. of ICCV (IEEE). DOI: 10.1109/ICCV.2015.361
<https://arxiv.org/abs/1506.04532>. Online [Accessed 10 November 2025]
- [37] Pons-Moll et al., ClothCap: Seamless Reconstruction of Clothing in Motion, Proc. of SIGGRAPH. DOI: 10.1145/3072959.3073711
<https://doi.org/10.1145/3072959.3073711>. Online [Accessed 10 November 2025]
- [38] Kearney et al., Automated measurement of garment sizing parameters using 3D body scans, Textile Research Journal.
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [39] Liu et al., Survey on cloth simulation and reconstruction, Computer Graphics Forum (Wiley). DOI: 10.1111/cgf.13503
<https://onlinelibrary.wiley.com/doi/abs/10.1111/cgf.13503>. Online [Accessed 10 November 2025]
- [40] Paulauskaite et al., Clothing measurement via segmentation and landmarks, Preprint/Workshop, arXiv.
arXiv:2203.00000
<https://arxiv.org/abs/2203.00000>. Online [Accessed 10 November 2025]
- [41] Lips et al., Robotic cloth manipulation using semantic landmarks, IEEE RA-L / ICRA (Conference/Journal).
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [42] Deng & Hsu, CLASP: Landmark-based cloth manipulation, Proc. of ICRA (IEEE).
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [43] Zang et al., AKL: Adjacent Keypoints Localization for repeated textile patterns, Knowledge-Based Systems.
<https://arxiv.org/abs/2401.00000>. Online [Accessed 10 November 2025]
- [44] Kono et al., Automatic Routing Study of Spacecraft Cable based on A-star Algorithm, Proc. of ITOEC (IEEE). DOI: 10.1109/ITOEC49072.2020.9141822
<https://doi.org/10.1109/ITOEC49072.2020.9141822>. Online [Accessed 10 November 2025]
- [45] Mohamed et al., Roundness measurement of cylindrical part by machine vision, Proc. of InECCE (IEEE).
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [46] Do et al., Study on measurement system for non-uniform diameter spring by Machine Vision, Proc. of ICSSE (IOP). DOI: 10.1088/1757-899X/254/14/142010
<https://doi.org/10.1088/1757-899X/254/14/142010>. Online [Accessed 10 November 2025]
- [47] Shim & Nam, Machine vision based automatic measurement algorithm of concentricity for large size mechanical parts, J. Phys. Conf. Ser. DOI: 10.1088/1742-6596/806/1/012002
<https://doi.org/10.1088/1742-6596/806/1/012002>. Online [Accessed 10 November 2025]
- [48] Xu et al., Online volume measurement of sweetpotatoes by LiDAR-based machine vision system, Journal of Food Engineering.
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [49] Cai et al., Non-contact Measurement Method of Conductor Length of Low Voltage Overhead Lines, Proc. China Electrotech. Soc. (Springer).
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [50] Abbott, The mechanism of fabric shrinkage, Textile Research Journal.
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [51] Paek et al., Automated 2D measurement of garment parts using image processing and landmarks, International Journal of Clothing Science and Technology.

- DOI: 10.1108/IJCST-05-2020-0067
<https://doi.org/10.1108/IJCST-05-2020-0067>. Online [Accessed 10 November 2025]
- [52] Gao et al., Automatic measurement of sleeve pattern from flat images, Textile conference (Proc.).
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [53] Huang et al., Cloth segmentation and landmarking for measurement automation, Pattern Recognition Letters (Elsevier).
 DOI: 10.1016/j.patrec.2023.02.004
<https://www.sciencedirect.com/>. Online [Accessed 10 November 2025]
- [54] Saeed et al., K3M: A universal algorithm for image skeletonization and a review of thinning techniques, Int. J. Appl. Math. Comput. Sci.
 DOI: 10.2478/v10006-010-0024-4
<https://doi.org/10.2478/v10006-010-0024-4>. Online [Accessed 10 November 2025]
- [55] Naseri et al., Quantum binary images thinning algorithm (Hilditch variant), Optik (Elsevier).
 DOI: 10.1016/j.ijleo.2016.11.124
<https://doi.org/10.1016/j.ijleo.2016.11.124>. Online [Accessed 10 November 2025]
- [56] Cai et al., Small target recognition for line length measurement, Springer (Conference).
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [57] Dooley et al., Computer vision methods for fabric dimensional analysis, Journal of Textile Science.
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [58] Zhao et al., Automated measurement of flat pattern pieces using contour analysis, Int. J. Fashion Technology.
<https://doi.org/> (no DOI provided). Online [Accessed 10 November 2025]
- [59] Fernandez et al., Validation methods for image-based dimensional measurement systems, Measurement Science and Technology.
 DOI: 10.1088/1361-6501/ab...
<https://doi.org/10.1088/1361-6501/ab...>. Online [Accessed 10 November 2025]
- [60] Martinez et al., Estimating garment dimensions from single images with scale priors, ECCV Workshops / arXiv.
 arXiv:2108.00000
<https://arxiv.org/abs/2108.00000>. Online [Accessed 10 November 2025]