# Application of Deep Learning for Fabric Structure Recognition in Computer-Aided Sweater Design

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**Abstract.** With the widespread adoption of Computer-Aided Design (CAD) in the textile industry, there is an urgent need for efficient and automated design methods in sweater design to meet the rapidly changing market demands. This study explores the application of deep learning technology and computer-aided techniques in sweater product design. This paper proposes an improved model based on Yolov5s-SimAM for texture structure recognition and classification in sweater design, which effectively realizes digital design and production processes. By incorporating the SimAM attention mechanism, the deep learning network structure is improved, and related loss functions are designed. Experimental results show that the model is highly efficient and accurate in recognizing sweater texture structures, significantly outperforming traditional design methods. Moreover, with the current development of artificial intelligence, the application of deep learning technology has shortened the development cycle of sweater products, further promoting the rapid development of digital and intelligent design in knitwear.

**Keywords:** Deep Learning; Texture Structure Recognition; Sweater Design; Yolov5s-SimAM; Intelligent Design.
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## 1 INTRODUCTION

As the fashion industry rapidly develops and computer technology becomes increasingly widespread, more and more apparel companies are adopting corresponding CAD systems for garment design based on different product types. Among them, the CAD system for sweater products can help designers quickly create and modify the fabric structure of knitting patterns, accurately calculate the knitting process, achieve the digital design and production process, improve production efficiency, and reduce errors. Sweater products with a unique molding method, that is, the yarn through the knitting equipment directly processed into clothing or clothing pieces—the main production equipment includes, the main production equipment includes computerized flat knitting machines and full-form computerized flat knitting machines. Sweater garment CAD systems primarily comprise computerized flat knitting machine CAD design systems and full-form CAD design systems. During the knitting process of a sweater, changes in the pattern and knitted structure of the fabric not only affect the appearance and functionality of the garment but also its comfort and aesthetic appeal.

The style effect of sweater garments is mainly composed of changes in yarn and fabric structure that constitute the external characteristics of sweater fabrics, and the design process not only demands creativity but also tests designers' time and energy. Designers need to have an in-depth understanding of the characteristics of various knitted structures and the properties of yarns and flexibly use different knitting techniques and color matching to achieve the desired style effect. Traditionally, designers have had to create every structural pattern based on the desired garment effect. For garments that are sample-processed, this often involves manually dismantling them to analyze and design the structure, a process that is not only labor-intensive and time-consuming but also lacks automation. Such methods no longer suffice due to rapidly changing market demands and the need for quick production cycles.

With the development and application of deep learning technology, deep learning-based textile and apparel design has shown great potential and value, providing new possibilities for improving design quality and efficiency [1]. The integration of artificial intelligence and augmented reality can analyze and diagnose textile defects without human intervention. Hu et al. [2] proposed a lightweight convolutional neural network-based method for identifying and classifying weft-knitted fabric structures, which can efficiently extract double-sided features of knitted fabrics. Malaca et al. [3] addressed the issue of online monitoring of fabric texture in industrial scenarios by using histogram, Laws, and Sobel filters, as well as image pyramid analysis methods to obtain feature vectors. [4] proposed a method for woven fabric pattern recognition and classification based on deep convolutional neural networks, which is an important factor for improving the design and production of high-quality fabrics. Therefore, adopting deep learning technology can automatically identify sweater fabric structures, improving design efficiency during the computer-aided design stage. For instance, this can be used to construct a database of sweater patterns. Furthermore, this method can directly generate knitting instructions for the corresponding structures, saving a significant amount of design time and labor costs. The application of deep learning technology shortens the product development cycle, accelerates the sweater industry's move towards high efficiency and intelligence, and brings unprecedented design freedom and market responsiveness to the industry.

At present, target detection algorithms based on deep learning technology can be roughly divided into two kinds: one is based on region proposal, mainly using a region proposal network to generate candidate regions for classification and regression; the other is based on end-to-end methods, such as Yolo series algorithms. Yolo series algorithms excel in target detection by treating it as a single regression problem. These algorithms simultaneously predict the categories and locations of multiple targets using convolutional neural networks, making them highly effective for detecting small targets and widely used in real-time object detection systems. The Yolo series algorithms are widely used. [5] proposed a lightweight garment object detection method based on an improved YOLOv5 network. [6] proposed an improved YOLOv5s algorithm for object detection with an attention mechanism.

Therefore, this study addresses the problem of fabric structure design in computer-aided sweater design and proposes automatic detection and identification of fabric structure using convolutional neural network (CNN), and in this way, constructs a knitted structure database to assist designers in optimizing the overall design process of sweaters. The innovations of this study are as follows:

(1) Addressing the challenge of identifying tiny and numerous fabric structures, we've introduced the SimAM attention mechanism to the Yolov5s model, enhancing the accuracy of structure detection while maintaining high efficiency.

(2) Study and design the relevant loss function for organizational structures with inconspicuous contour boundaries as well as organizational structures of different sizes.

(3) The improved model is applied to different datasets and compared with other models, and the experimental results show that the proposed improved model has better generalization ability.

In this paper, we first explore the necessity of employing deep learning to assist in fabric structure recognition within sweater CAD for swift design implementation. We then outline the advancements in deep learning for knitted structure recognition and related research in CAD. Next, we discuss optimization methods and how to construct a classification model using the Yolov5s-SimAM algorithm. Finally, we evaluate the effectiveness of this algorithm in optimizing fabric structure designs in CAD systems, summarizing the research work and findings.

## 2 RELATED WORK

### 2.1 Literature Review

Currently, deep learning techniques have made some progress in the research field of knitted structure recognition applications. Xiao et al. [7] proposed an automated recognition method that significantly boosts production efficiency. This approach involves constructing a knitted structure database and leveraging a deep convolutional neural network (CNN) with transfer learning. The method automatically extracts texture features and performs classification using a pre-trained AlexNet model, originally trained on ImageNet but adapted through transfer learning to recognize knitted fabric structures. Experimental results demonstrate the method's robustness, effectively handling challenges such as fabric rotation, fuzziness, and uneven lighting and achieving high recognition accuracy. Tang et al. [8] developed a diverse dataset of weft-knitted fabrics and introduced a lightweight dual-branch classification network. This network addresses the issue of superficial similarity among weft-knitted fabrics and boosts feature recognition through an attention mechanism. Additionally, they employed an enhanced encoder-decoder network for fabric segmentation and MobileNetV2 with depthwise separable convolution to optimize multi-scale feature extraction and resolution enhancement. Xiang et al. [9] devised an image retrieval method for wool fabrics that enhances accuracy through soft similarity and listwise learning. They established a soft similarity metric for image pairs, created a compact CNN architecture with cross-domain connectivity, and implemented listwise learning for model training. Testing on a wool fabric dataset indicated a significant improvement over previous methods, especially in handling the high variability and complexity of fabric appearances while achieving stringent retrieval accuracy. Giri et al. [10] introduced a novel forecasting model that combines image feature attributes of garments with sales data to predict future demand. Utilizing data from European fashion retailers, they extracted key features of product images using deep learning techniques. Machine learning clustering based on product sales profiles and image similarities was then performed to predict weekly sales of new fashion garments. This model not only showed strong prediction performance but also provided an effective solution for fashion product demand forecasting. Chang et al. [11] explored a deep learning approach for clothing style recognition using Yolov5. Their research focused on developing lightweight learning algorithms to increase recognition speed and reduce model size. They used image samples from fashion apparel datasets and online stores to classify images into five categories: plaid, solid color, block, horizontal stripes, and vertical stripes. Experimental results demonstrated that Yolov5 surpasses other learning algorithms in recognition accuracy and detection speed. [12] utilized principal component analysis to obtain the minimum redundancy and maximum principal component feature vectors and used a probabilistic neural network (PNN) to classify the fabrics. [13] used wavelet decomposition for multi-resolution decomposition and feature extraction of fabric images. They constructed a hybrid classifier using the BP network and Bayesian methods, achieving a classification accuracy of up to 96.67% for colored woven fabric structures.

In the field of computer-aided garment knit design, Trunz et al. [14] demonstrated a system that recognizes and localizes different knit types from a single image specified by the user. This rough localization information is then used to derive the underlying mesh structure and further extract knitting instructions. The framework employs an integer linear programming approach to optimize the mesh structure to extract the repeated knitting fabric structures and correct the errors according to the visual perception theory to determine the fabric structures' starting position. This approach provides a new way to derive knitting fabric structures from images not only automatically but also successfully demonstrates how the knitted structure can be transformed into actual knitting instructions through computer-aided design [15] deI designed and developed a weft knitting CAD/CAM system with a simulation interface that translates pattern structure diagrams into executable instructions and generatesachine files for weft knitting machines. Kaspar et al. [16] built a dataset of real and synthetic images and proposed a learning framework that blends real and synthetic data to improve the accuracy of mapping from images to knitting programs. The deep learning model used in the study inferred weaving instructions directly from fabric images, effectively bridging the gap between image recognition and manufacturing instruction generation. Kaspar et al. [17] developed an interactive computer-aided design tool for shaping and preparing knitted garments. The tool simplifies the design process for machine-knit garments by allowing the user to customize the shape and surface fabric structures of the garment. By integrating parametric knitting primitives and multi-layered knitting fabric structures, the system not only supports continuous user customization but also enhances interactivity through automatic layout and real-time fabric structure feedback. [18] provided a large and diverse dataset of knitted textures and their attributes, which, using a heuristic optimization algorithm, can be converted into knitting patterns that can be output as instructions for machine or hand knitting. [19] proposed a deep learning model based on LSTM that can generate low-level code for novel knitting patterns from high-level knitting design sketches and describe the knitting instructions as a one-dimensional sequence of tokens.

## 2.2 Sweater Design Method

The sweater design process is a systematic and intricate process that begins with market research and trend analysis to capture consumer demand and market trends. Extensive market research is needed to focus on popular colors, fabric structure, yarn selection, and consumer preferences. Subsequently, it enters the design stage, including garment style design and fabric structure design. Style structure is the foundation of garment modeling. In sweater design, it is necessary to convert the style structure into knitting technology and set up the silhouette modeling of the sweater through the CAD design system. The fabric structure is fundamental to sweater clothing, as shown in Figure 1, encompassing basic, modified, and color organization. Common structures include ' Rib stitch 1+1', ' Rib stitch 2+2', 'Purl stitch,' 'Loop transfer stitch,' 'Float stitch,' 'Tuck stitch,' 'Cable stitch,' 'Plain stitch, and so on. Through the CAD design system, the fabric structure can be designed and set by the process instruction to generate the file that can be knitted on the machine. In the traditional method, when designing the fabric structure, the designer usually needs to continuously work on the design in the CAD system and then transfer the design result to the machine for experimental weaving. This cumbersome process is both time-consuming and prone to lead to deviations between design and actual production, thus hindering the process of intelligent development of sweater CAD design systems. With the development of science and technology, as shown in Figure 2, the use of deep learning technology to identify and reconstruct the fabric structure on a large number of sweaters for application in sweater auxiliary design has become a research hotspot for the digital intelligent design of sweaters. This method aims to establish a knowledge base of the fabric structure, improve the design efficiency by directly displaying the effect of the acquired fabric structure, and complete the design of the new structure by quickly modifying it using process instructions. The application of this technology can not only reduce the time and labor cost in the design process but also improve the rapid adaptability of apparel enterprises so that they can adapt to market demand and trend changes more flexibly. The research is mainly divided into the following stages:

(1) Using SimAM attention mechanism and Yolov5 model to achieve accurate recognition and labeling of the basic structure of knitting fabric structures.

(2) By collecting knitted fabric image data, a knitted structure recognition network fused with SimAM was constructed to improve the recognition of knitted features.

(3) Comparison of different configurations of Yolov5 was performed to optimize the loss function, and precision, recall and average accuracy were used as performance evaluation criteria.

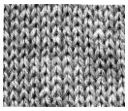
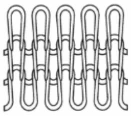
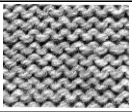
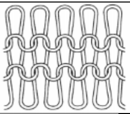
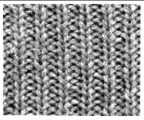
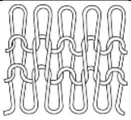
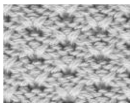
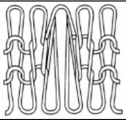
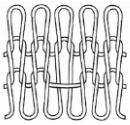
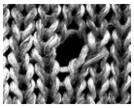
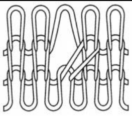
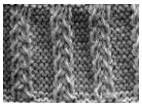
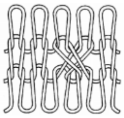
| StructureName | Real Structure Diagram | Coil Structure Diagram | Simple Weaving Instructions |
|---|---|---|---|
| Plain stitch |  |  | Both the front and back needle beds can be used for weaving. |
| Purl stitch |  |  | Both the front and back needle beds can be used for weaving. |
| Rib stitch |  |  | The needle slots of the two beds are aligned, with needles arranged alternately. |
| Tuck stitch |  |  | During knitting, the loops are collected. |
| Float stitch |  |  | The floating thread position is moved to the back needle bed, and after knitting one row, it is moved back to the front needle bed. |
| Loop transfer stitch |  |  | Single-needle loop transfer. |
| Cable stitch |  |  | During knitting, first drop the loop on the right onto the needle bed's needle and then place the loop on the left onto the needle. |

**Figure 1:** Common representation methods of sweater structures.

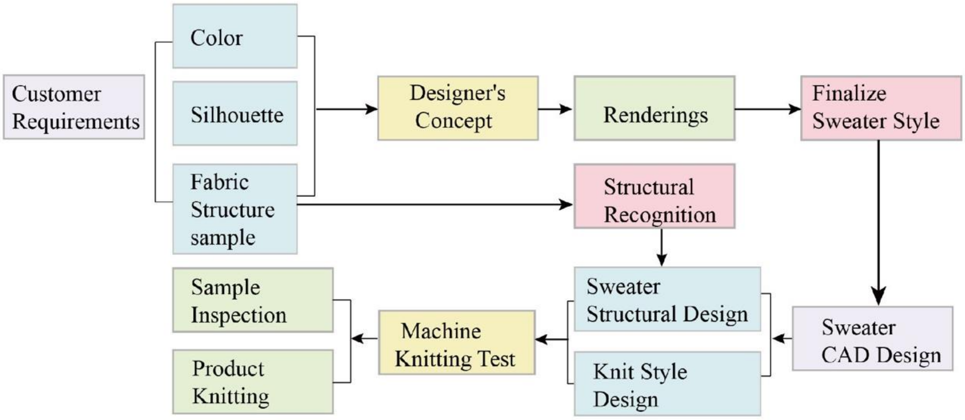



**Figure 2:** Sweater design process.

## 3 EXPERIMENTAL STUDY

### 3.1 Recognition Network Construction Based on SimAM Attention Mechanism

In this study, the continuity and density of the fabric structure lend significant spatial correlation to sweaters. At the same time, the similarity in features between different fabric structures necessitates careful consideration of the correlation and continuity between these structures during the recognition process. To address this, the SimAM attention mechanism is integrated after the CSP layer in the Yolov5s recognition model. This modification aims to enhance the model's performance on cross-knit garments by improving the accuracy and efficiency of recognizing structural features.

The network model developed in this study comprises four main components: the input layer, the backbone network, the neck network, and the output detection layer [20]. Notably, a SimAM attention layer is appended after the last CSP layer in the neck network to boost the model's capability in identifying knitted structural features. The model's structure is diagrammatically represented in Figure 3. In the task of recognizing basic knit structures, the model is required to handle eight different labels. Given that the captured images vary in size and the shapes and sizes of the labels are influenced by design and aesthetic considerations, the Yolov5s-SimAM network is specifically designed to meet these challenges. The input layer addresses various preprocessing operations such as data augmentation, adaptive anchor frames, and image scaling. These measures not only tackle issues related to sample and size imbalance but also enhance data diversity, thereby improving the network's detection accuracy for knitted structure targets.

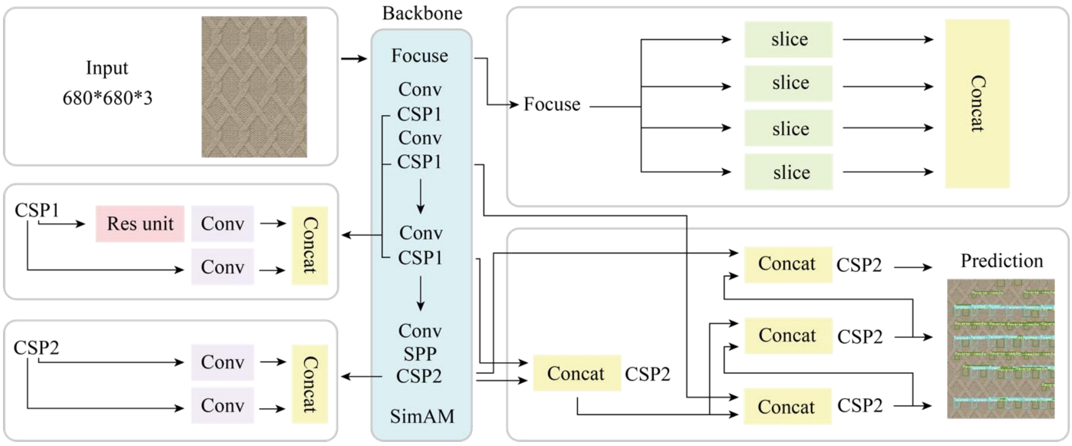



Figure 3: Mapping the network structure of the Yolov5 attention mechanism.

In order to effectively deal with the problem of inconspicuous and blurred feature contours in knit structure datasets, this study employs the CSPDarknet53 network, an improved network based on the Darknet architecture. This network introduces Cross Stage Partial (CSP) connections, aiming to enhance the efficiency of information flow and thus more accurately capture and represent the input image. The CSPDarknet53 comprehensively processes the image through a convolutional neural network architecture, where the backbone network is responsible for extracting features of the sweater's fabric structure, the neck network achieves the fusion of multi-scale features, and the head network is responsible for performing the final regression prediction.

Moreover, each neuron within the network is associated with a set of weights. As input signals pass through a neuron, each input value is multiplied by its corresponding weight, summed up, and then activated by an activation function, such as the Sigmoid function. This function compresses the input values into a range between 0 and 1, mimicking the stimulus-response of the neuron. This activated output is then forwarded to the next layer of neurons, thereby perpetuating the forward propagation process throughout the network. This process continues until the output layer is reached, as depicted in Figure 4.

Additionally, the study introduces the Adaptively Spatial Feature Fusion (ASFF) technique to refine the feature fusion process further. This technique enables the network to perform effective spatial filtering of features across different layers while retaining useful information for integration. Such enhancements significantly bolster the model's ability to distinguish between eight distinct organizational features, markedly improving its performance.

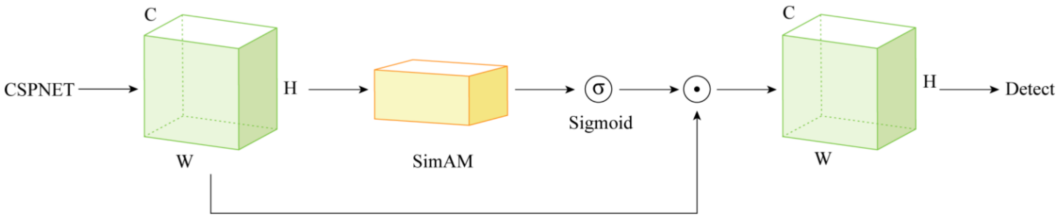



**Figure 4:** SimAM attention mechanism.

For similar structures, the SimAM module uses an adaptive learning process to identify and adjust the similarity information between labels, thus optimizing the importance of features. This process requires no additional parameters, allowing the network to focus on key neurons while remaining structurally stable. Quantitative evaluations for various visual tasks show that the SimAM module demonstrates flexibility and effectiveness for a wide range of visual tasks, significantly improving the feature characterization capabilities of a variety of convolutional neural networks (ConvNets), as shown in Equation (3.1):

$$e_t(w_t, b_t, y, w_i) = (y_t - t^{\lambda})^2 + \frac{1}{M-1}\sum_{i=1}^{M-1}(y_0 - x_i^{\lambda})^2 \tag{3.1}$$

Where $t^{\lambda}$ and $x_i^{\lambda}$ denote the linear transformations of two different neurons in the input feature and $M$ denotes the number of neurons. Where a smaller value of $e_t$ indicates that the neuron is more important.

### 3.2 Loss Function

In order to solve the above problems of subtle differences in the characteristics of fabric structures and inconspicuous contour boundaries, as well as to effectively recognize fabric structures of different sizes, a loss function consisting of three parts, lbox, lobj, and lcls, is designed in this study. lbox represents the rectangular box loss, which is evaluated by calculating the intersection and concatenation ratio ( $I_{oU}$ ) between the predicted bounding box and the target bounding box, and focuses on evaluating the performance of the model in terms of target localization accuracy. lobj is the confidence loss, while lcls is the classification loss, both of which are computed using the cross-entropy loss function so as to measure the performance of the model in terms of target detection confidence and classification accuracy. The cross-entropy loss function formula for the multi-classification problem is shown in Equation (3.2):

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log(p_{ij}) \tag{3.2}$$

In Equation, $N$ is the total number of training samples, while $C$ denotes the number of categories, which for this study is 8 different organisational units. Here, $y_{ij}$ indicates whether the $i$ sample belongs to category $j$ or not, while $p_{ij}$ represents the probability that the model predicts that the ith sample belongs to category $j$. The category labels of these 8 knitted structures include:' Rib stitch 1+1', ' Rib stitch 2+2', 'Purl stitch,' 'Loop transfer stitch,' 'Float stitch,' 'Tuck stitch,' 'Cable stitch,' 'Plain stitch.' Considering the balanced number of samples in these categories, this study uses a multiclassification cross-entropy loss function to accommodate this diverse classification task.

The intersection and union ratio ( $I_{oU}$ ) is a metric that assesses the degree of overlap between two bounding boxes or regions, with a value between 0 and 1, where 0 indicates no overlap and 1 indicates complete overlap. In organisational structure recognition tasks, $I_{oU}$ serves as a key metric for measuring the accuracy of model positioning. When the $I_{oU}$ exceeds a specific threshold, commonly used thresholds include 0.5 or 0.95, the model's prediction can be considered accurate. Specifically for the knitted structure recognition task, the model accuracy can be up to 86.7% when the $I_{oU}$ threshold is 0.5, while the accuracy drops to 65% when the $I_{oU}$ threshold is increased to 0.95. The $I_{oU}$ calculation formula is shown in Equation (3.3):

$$IOU(A,B) = \frac{Area(A \cap B)}{Area(AUB)} \tag{3.3}$$

In Equation (3.3), A is the position of the predicted frame and B is the position of the real frame, and the $I_{oU}$ loss calculation formula is shown in Equation (3.4):

$$LoU_{Loss} = (1 - IoU) \tag{3.4}$$

The overall loss function formula is shown in Equation (3.5):

$$Loss = lbox + lobj + lcls \tag{3.5}$$

## 4 EXPERIMENTS AND ANALYSIS

In this study, the experimental manipulation environment is set to Windows 10x64 operating system with RTX 3,060 graphics card (12G memory) and Intel Xeon E3-1245 V3 CPU. The project is constructed using Python programming language and Darknet deep learning framework.

After screening and excluding obviously defective images, a total of 1,021 image samples were obtained for the experiments. In the model training stage, the Yolov5s model improved by SimAM was selected. Considering the balance between computational resources and performance, the batch size was set to 6, and 2,000 iterations were executed, with the learning rate set at 0.0001. The overall experimental design and configuration aim to maximize the efficiency of hardware resource usage and to ensure that the deep learning model demonstrates excellent performance and generalization ability in image processing.

### 4.1 Data Preparation

Before recognizing the basic structures in sweaters, it is essential to acquire images representing various fabric structures. A total of 1,021 image datasets were collected and labeled, containing information about the structures on different garments. Each image includes one to three different fabric structure categories, with each category represented in approximately 600 to 1,200 samples. Notably, these fabric structures are not isolated in separate images but may coexist with other categories within the same image.During data annotation, <object> tags are utilized to mark each target border, where the number of tags corresponds to the number of labeled boxes in each image. The positions of these boxes are defined by the coordinates of two diagonal corners, specifically the upper left (xmin, ymin) and the lower right (xmax, ymax), ensuring precise identification and localization of each fabric structure.

A text file containing paths to the training and validation set images is automatically generated in the project's root directory. Care is taken during annotation to ensure that each labeled box contains only a single class of structure, avoiding nested labels or only labeling the interior of nested structures, as depicted in Figure 5.Prior to training, the dataset is divided into a training set and a validation set, with 80% of the data allocated for training and 20% for validation. Additionally, new images equivalent to the number of those in the validation set are selected for testing to assess the model's generalization capabilities.

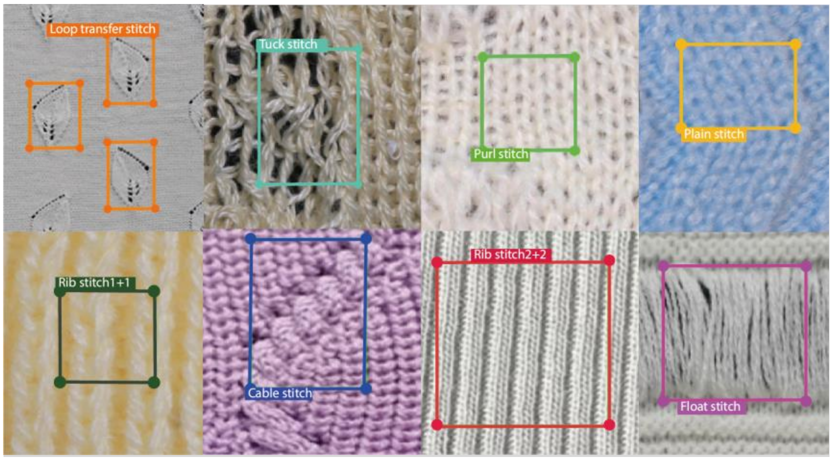



**Figure 5:** Example of labelling.

### 4.2 Evaluation Indicators

In target detection tasks, especially the classification and recognition of fabric structures, the evaluation of model performance usually relies on two core metrics, Precision and Recall. Here, TP (True Positive) indicates that the model correctly recognizes positive samples as positive, TN (True Negative) indicates that the model correctly recognizes negative samples as negative, FP (False Positive) indicates that the model incorrectly recognizes negative samples as positive, and FN (False Negative) indicates that the model incorrectly recognizes positive class samples as negative classes. Precision, which is the proportion of positive classes that are actually positive among those predicted by the model to be positive, and Recall, which is the proportion of all actual positive class samples that are correctly recognized by the model, are calculated according to Equations(4.1) and (4.2). In order to comprehensively evaluate the effectiveness of the algorithm, the F1 score is used as a comprehensive evaluation index, as shown in Equation (4.3):

$$P = \frac{TP}{TP + FP} \tag{4.1}$$

$$R = \frac{TP}{FN + TN} \tag{4.2}$$

$$F1 = \frac{2\ \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4.3}$$

Specifically, the intersection and merger ratio $I_{oU}$ is the ratio of intersection and merger between the predicted and real frames, which is used to measure the precision of the predicted frames and judge the accuracy of the predictions. In model evaluation, the mean average precision (mAP) is used as the main evaluation metric, according to Equations (4.4) and (4.5):

$$I_{\mathrm{oU}} = \frac{B \cap G}{B \cup G} \tag{4.4}$$

$$mAP = \frac{TP + TN}{TP + FN + FP + TN} \tag{4.5}$$

### 4.3 Experimental Process and Result Analysis

To verify the effectiveness of the proposed model, a series of comparative experiments were conducted against a range of commonly used deep learning networks in target detection, classification, and recognition. In the horizontal comparison experiments, the Yolov5s model was assessed both with and without the addition of the SimAM attention mechanism. For vertical comparisons, the model was juxtaposed against the Fastrcnn network model. These comparisons allow for a thorough evaluation of performance differences among the models specifically for the task of detecting sweater fabric structures, aiding in the selection and optimization of the most suitable model for this application. The experiments used a consistent set of training parameters across all tests on the sweater fabric structure dataset. The comprehensive training process included key phases such as data preparation, model selection, model initialization, defining the loss function, model training, tuning, and evaluation.

As can be seen from Table 1, on the dataset, the proposed Yolov5s-SimAM model has a precision rate of 72%, reflecting the model's performance in recognizing correctness; the recall rate (R) reaches 80%, indicating that the model is able to accurately capture all the positive instances to a greater extent, ensuring that fewer positive instances are missed. In the sweater fabric structure recognition project, it is limited by the large number of unlabeled features in the background, resulting in relatively high recall and slightly lower precision, which is consistent with the training results. When the value of $I_{\mathrm{oU}}$ is 0.5, the model's accuracy mAP is up to 90%, and when $I_{\mathrm{oU}}$ is 0.95 it corresponds to a more stringent localization requirement, so the accuracy is reduced. The model that introduces the SimAM attention mechanism performs better in handling data with insignificant background and feature differences and smaller target sizes. In contrast, Fastrcnn has not yet reached convergence on this dataset. As we know from the above, the Yolov5s-SimAM model not only recognizes only one category of diagrams but also supports the recognition of multiple fabric structures for a single sample. In addition to this, the model generates a txt file of predicted coordinate frame information for each image, which is represented by the file format classname, xmin, ymin, xmax, ymax, giving all the predicted categories in the diagram and the corresponding coordinates, respectively.

| | *Precision(%)* | *Recall(%)* | *mAP0.5* | *mAP0.95* | *F1score* |
|---|---|---|---|---|---|
| Yolov5sSimAM | 0.72 | 0.8 | 0.9 | 0.6 | 0.758 |
| Yolov5s | 0.06 | 0.07 | 0.09 | 0.06 | 0.065 |
| Fastrcnn | 0.03 | 0.06 | 0.06 | 0.06 | 0.04 |

**Table 1:** Identification and comparison of horizontal knitting organisation structure of different network models.

All models are initialized with pre-training weights, and experiments show that better training results can be obtained when batch size is set to 4, the learning rate is set to 0.0001, and the momentum value is set to 0.9. As shown in Figure 6, the loss function comparison curves of each model are plotted, and usually, the lower the loss value implies that the model's prediction accuracy is higher, and the difference between its predicted value and the real value the smaller the difference between its predicted value and the true value. By visualizing the analysis of each parameter during the training process, it is observed that the Yolov5s-SimAM model has the lowest loss value of 0.03 in each round of iteration. Meanwhile, compared to the other models, as shown in Figure 7, the model exhibits higher accuracy. Figure 8 shows the comparison of F1 test result curves of different models. The F1 parameter is a commonly used model performance metric that integrates the accuracy and recall of the model. The highest F1 parameter of Yolov5s-SimAM indicates a higher performance of the model in the classification task.

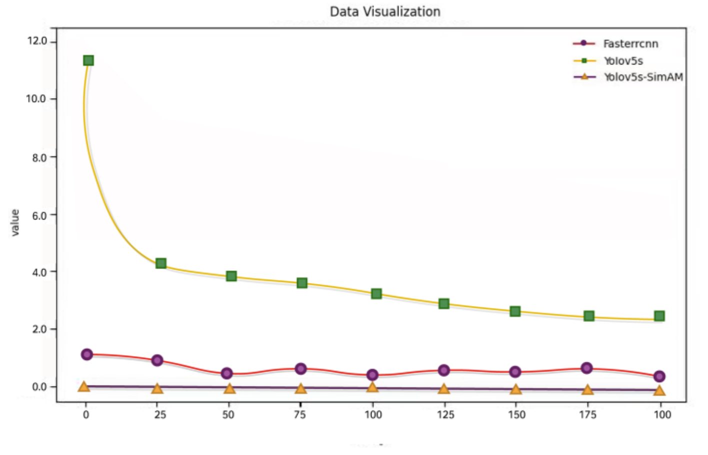



**Figure 6:** Comparison curve of loss function for different model training processes.

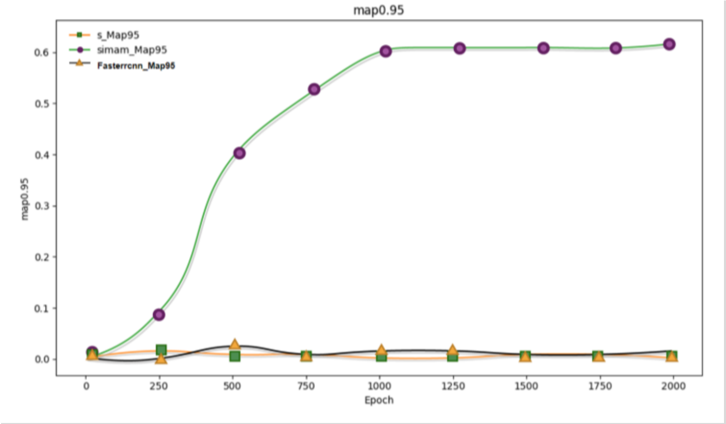



**Figure 7:** Training model accuracy comparison curve mAP.

### 4.4 Design Applications

In the CAD design stage of sweater production, designers traditionally need to create both the styles and fabric structures based on specific demands. However, the method described in this paper can significantly accelerate the design and development process, enhancing overall efficiency.

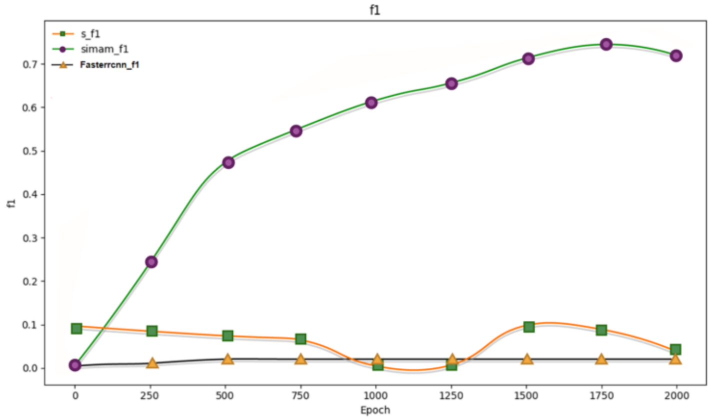
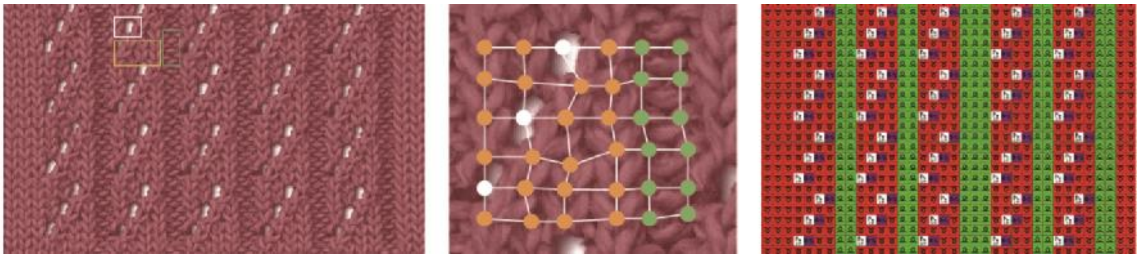



**Figure 8:** F1 test results for different models.

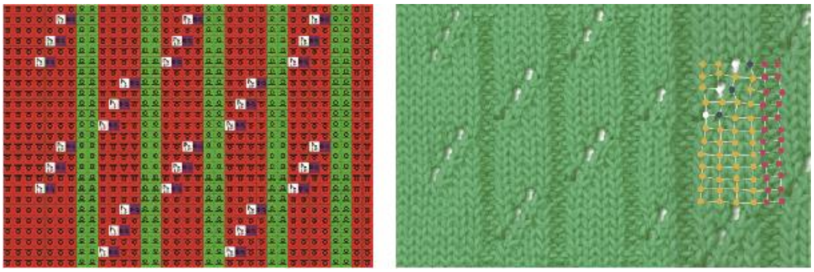
As outlined earlier, sweater design companies typically compile and sell detailed information on sweater processes and structures, along with corresponding process instructions, and build databases to support this activity. For this study, we have accessed a sweater database and utilized deep learning technology to identify the fabric structures on the sweaters. This research focuses on a common set of eight fabric structures to explore the structure identification algorithm. The identification of fabric structures from the knowledge base allows for the immediate determination of structure types, which then serve as a foundation for linking each structure's process instructions to specific color codes used in designs. This method enables designers to access a database of existing fabric images and use the process instructions to swiftly modify designs for new structures. As illustrated in Figure 9, this method aids in the rapid design of sweater structures: Figure a and Figure b show the identified fabric structures; Figure c displays the process instructions associated with each structure's color code; Figure d demonstrates the rapid adjustment of process instructions; and Figure e shows the new fabric structure ready to be knitted directly on the machine. This innovative approach eliminates the traditional need for constant redesigning in CAD and repetitive sampling on machinery, thereby significantly enhancing the rapid adaptability of apparel enterprises. Integrating deep learning technology with existing database systems not only speeds up the design process but also reduces the time and effort involved in bringing new sweater designs to market.

## 5 CONCLUSIONS

The rapid advancement of computer-aided manufacturing technology has significantly enhanced the capabilities of computer-aided sweater design. Utilizing existing sweater fabric structures to develop new designs quickly is becoming an integral part of product development for apparel enterprises. This research focuses on the application of sweater-aided design, aiming to harness digital intelligent design tools to visualize and swiftly realize new fabric structures using a dedicated knowledge base. This approach is aimed at boosting design efficiency, enabling apparel companies to respond more quickly to market demands, and fostering innovation and development in products. In this study, we leverage the fabric structure of sweaters as a pivotal point, employing an enhanced Yolov5s model integrated with the SimAM attention mechanism to detect and recognize common sweater fabric structures. This methodology circumvents the time-intensive processes traditionally associated with the design and development of sweater fabric structures, facilitating computer-aided design capabilities. Experimental results indicate that this method effectively mitigates issues related to fabric rotation, variations in fabric thickness and diameter, fabric hairiness, and uneven lighting during image acquisition while maintaining a high recognition rate.



(a) Identification of structure, (b) Definition of structure, (c) Process instruction correlation,



(d) Modification of process instructions, (e) The new structure is woven.

**Figure 9:** Sweater CAD design.

The proposed enhanced model not only improves recognition accuracy but also maintains high detection efficiency without the addition of extra learnable parameters compared to other models. In the sweater development stage, it is crucial to adhere to a design principle of high efficiency, selecting the most suitable methods to quickly realize fabric structure designs that meet the needs of apparel design.Looking forward, it is anticipated that the rapid design of fusion combination structures will become a key trend in knitwear design, significantly enhancing both design efficiency and accuracy.

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