# Analysis and classification of footwear line drawings: research on fashion attributes using computer vision algorithms

**DOI: 10.35530/IT.075.06.2023127**

LI JINGJING
ZHAO YEBAO
KEYU HOU
ZHOU JIN

**ABSTRACT – REZUMAT**

**Analysis and classification of footwear line drawings: research on fashion attributes using computer vision algorithms**

*With the rapid evolution of fashion trends and consumer preferences, the imperative for agility in footwear design has become increasingly pronounced. Central to the design process was the criticality of shoe line drawings, the burgeoning advancements in computer vision and deep learning technologies have engendered a wealth of research in fashion element recognition. Regrettably, the application of such advancements to footwear remains relatively underexplored. This study introduces a novel computer vision system tailored to discern and categorise footwear line drawings. The methodology entails the preliminary training of Mask R-CNN for shoe body extraction from footwear imagery, followed by applying the PIDINet edge detection algorithm for line drawing delineation, culminating in utilising a classification model for line drawing. Encouragingly, our findings evince the system's adeptness in successful line drawing extraction and classification, particularly demonstrating heightened accuracy in differentiating distinct styles such as nude shoes, boots, and slippers characterized by salient outline features. This pioneering endeavour not only addresses a gap in footwear element recognition research but also circumvents the need for an extensive footwear database for algorithmic training. The anticipated automation of algorithmic footwear line drawing recognition holds promise for enhancing operational efficiency and innovation, fostering sustainable advancements in fashion research.*

***Keywords:*** *footwear, computer vision, line drawing, fashion attribute, classification*

**Analiza și clasificarea schițelor liniilor de încălțăminte: studiu asupra atributelor modei folosind algoritmi de viziune computerizată**

*Odată cu evoluția rapidă a tendințelor modei și a preferințelor consumatorilor, imperativul pentru agilitate în designul încălțămintei a devenit din ce în ce mai pronunțat. Pentru procesul de proiectare, necesitatea schițelor liniilor de încălțăminte a fost esențială, iar progresele în domeniul viziunii computerizate și tehnologiile de învățare profundă au generat o serie de cercetări în recunoașterea elementelor de modă. Din păcate, aplicarea unor astfel de progrese în domeniul încălțămintei rămâne un element relativ subexplorat. Ca răspuns, acest studiu introduce un nou sistem de viziune computerizată, adaptat pentru discernământul și clasificarea schițelor liniilor de încălțăminte. Metodologia presupune instruirea preliminară a modelului Mask R-CNN pentru extragerea formei pantofului din imaginile încălțămintei, urmată de aplicarea algoritmului de detectare a marginilor PIDINet pentru delimitarea schițelor de linii, culminând cu utilizarea unui model de clasificare pentru schița liniilor. În mod încurajator, rezultatele cercetării evidențiază eficiența sistemului în extracția și clasificarea cu succes a schițelor liniilor de încălțăminte, demonstrând în special o acuratețe sporită în diferențierea stilurilor distincte, cum ar fi pantofii decupați, cizmele și papucii, definiți prin caracteristici de contur proeminente. Acest efort de pionierat nu numai că abordează o lacună în cercetarea recunoașterii elementelor de încălțăminte, dar elimină și nevoia unei baze de date extinse pentru încălțăminte pentru instruirea algoritmică. Automatizarea anticipată a recunoașterii algoritmice a schițelor liniilor de încălțăminte este promițătoare pentru îmbunătățirea eficienței operaționale și a inovației, ducând la progrese durabile în cercetarea modei.*

***Cuvinte-cheie****: încălțăminte, viziune computerizată, schița liniei, atribut de modă, clasificare*

## INTRODUCTION

The current fashion cycle has suddenly become shorter [1], leading to intense competition. Designers need to quickly keep up with trends and create shoes that meet the diverse needs and preferences of consumers. Traditional fashion design work heavily relies on designers [2], as well as hand-line drawings were often the starting point and key to many creative and fashion workflows [3, 4]. For footwear designers, line drawing of shoes was crucial in determining their shape, size, and details [5]. The quality of line drawing directly impacts the shoe's appearance and comfort. Traditional shoe design requires a lot of manual drawing and sample making, which is time-consuming and labour-intensive. In addition, new designers often struggle to create line drawing styles that are accepted by the general public due to lack of experience. Hand-line drawings are subjective and vary from individual to individual, leading to differences in product understanding. Furthermore, shoe design also needs to consider ergonomics, materials, and processes, making the design process more complex and difficult. Currently, well-known fashion trend websites such as WGSN (the world's leading consumer trend forecaster: https://www.wgsn.com), POP (a fashion Trend Network: https://www.pop-fashion.com), and Diexun (global fashion consulting provider: https://www.diexun.com) provide line drawing design materials for footwear and apparel, allowing designers to quickly grasp design trends. However, most of these were manually drawn, resulting in low output efficiency, small quantity, and untimely updates. For different footwear designers, more efficient exploration of line drawing design trends can better grasp market demand, cater to consumer preferences, and introduce more competitive products.

Computer vision technologies have become indispensable tools for understanding and analysing large-scale cross-media fashion data semantics and studying the mechanisms of fashion trends. There is a growing interest in using computer systems to analyse collected images, automatically detect and identify objects, and extract valuable information in the fashion industry. Research on fashion style recognition has been extensive, with studies such as that of Al-Halah et al. [6] utilising supervised deep convolutional models and non-negative matrix factorization to discover the "vocabulary" of latent styles, and then train a predictive model to represent the trend of latent styles over a period, providing an overall view of the fashion visual style lifecycle. Ferreira et al. [7] proposed a unified model with structured output to classify categories, subcategories, and attributes of high-end fashion website images using an end-to-end architecture, thoroughly identifying visual information in fashion images to analyse potential key elements for trend forecasting. Bossard et al. [8] applied random forests to classify garment types and used multiple Support Vector Machines (SVMs) to train 78 attributes to identify garment styles. Shi et al. [9] modified the Faster Region-based Convolutional Neural Network (Faster R-CNN) and Mask Region-based Convolutional Neural Network (Mask R-CNN) for identifying attributes in images and videos to recognize texture, style, and design details. Zhao et al. [10] applied Mask R-CNN for garment segmentation and classification, analysing colour, style, and other attributes as well as fashion trends in garment combinations. While research on the application of computer vision in fashion design was extensive, existing studies and applications related to footwear were limited. Additionally, there was a lack of research on the classification and detection of popular elements related to shoes in fashion element recognition studies.

The aforementioned deep learning algorithms have demonstrated better performance than traditional methods. These algorithms can overcome the drawbacks of manual image interpretation, such as fatigue, low efficiency, and high subjectivity, and offer broad application prospects [11]. Mask R-CNN [12], as one of the most widely used instance segmentation networks in recent years, was capable of simultaneously performing object detection, classification, and semantic segmentation tasks. It excels in instance segmentation by first classifying objects through the detection of candidate regions and then achieving pixel-level instance segmentation (classification before segmentation). Edge detection, an important branch of image segmentation, was commonly used to evaluate object shapes by identifying positions where intensity levels change sharply [13]. The Pixel Difference Network (PidiNet) proposed by Su et al. [14] integrates traditional Canny and SE edge detection results as candidate points, for a convolutional network and extends the Local Binary Pattern to derive the Pixel Difference Convolutionvas the main convolutional kernel for building a lightweight network. Due to its integration of traditional edge detection operators into modern CNN, PidiNet possesses advantages such as a smaller memory footprint, high accuracy without pre-training, and faster inference speed [14].

This study aimed to analyse and classify shoe line drawings to improve shoe design efficiency and innovation capability through computer vision algorithms. The technical approach involved using the Mask R-CNN instance segmentation algorithm to extract shoes from complex backgrounds, utilising PidiNet edge detection for rapid extraction of line drawings, and then analysing footwear classification to output line templates. This would provide designers with a large number of professional footwear line drawing templates made to the correct proportions, enabling them to explore diverse design inspirations and possibilities more quickly.

## METHODOLOGY

This study proposed a computer vision-based analysis system to analyse and classify footwear line drawings. First, the original images were input into Mask-RCNN to extract the shoes from the background. Then, the PidiNet edge detection was used to recognize the contours of the extracted shoes and generate the lines. Finally, the line drawings were identified and classified based on a classification model. The classification model was empirically studied using footwear images collected from WGSN.

### Image segmentation and line extraction

Training and inference on the Microsoft Common Objects in Context Dataset (COCO dataset) using different backbone networks in Mask RCNN. 4744 shoe images were collected for testing the accuracy. After training, Mask RCNN was used to identify and segment the shoes from the background of the complete images. Subsequently, PidiNet was employed to extract the outlines of the shoes. PidiNet has an efficient backbone network consisting of four stages, with each stage using a pooling layer for downsampling. The first stage comprises an initial convolutional layer and three residual modules, while the second,

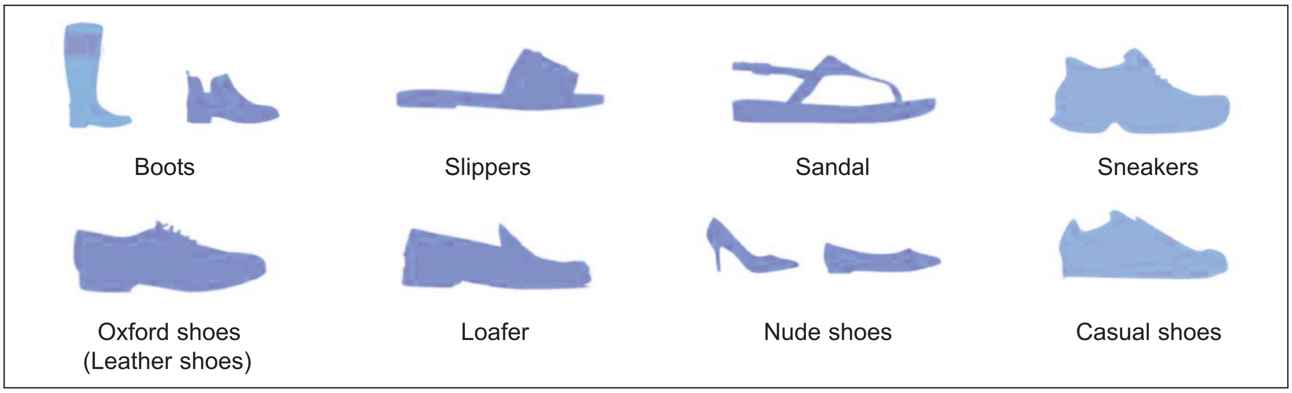


Fig. 1. Classification of shoes and description of shape features

third, and fourth stages each contain four residual modules. Each residual module includes Pixel Difference Convolution (PDC) depth convolutional layers, Rectified Linear Unit (ReLU) layers, and point convolutional layers. To ensure comprehensive learning of edge features, an edge feature map was generated from each stage and used to calculate the loss function with the Ground Truth, enabling deep supervised learning.

**Establishment of footwear line drawing classification model**

We chose to label the shoe images from the full side view to avoid recognition errors caused by angles. The classification of shoes was mainly based on their external contour characteristics, as shown in the following figure. For example, compared to slippers, boots have distinct features such as a boot shaft and a high top, whereas slippers lack back support.

As shown in figure 2, the modelling steps for marking the shoe line drawing were as follows:

a. Identified the toe cap point (T), heel midpoint (H), quarter bump (B) for the back of the shoe, quarter vertex (Q), and vamp front vertex (V).
b. Connected the five marked points in sequence to form a pentagon. Compared the heights of points B and V. If point B was lower than point V, connected points Q and H to form the quadrilateral 'THQV'. If point B was higher than point V, connected points Q and T to form the quadrilateral 'THBQ'.
c. The acute angle formed by the line HT and line l, passing through point H, was denoted as angle $\alpha$.
d. Draw a perpendicular line from point B to line l, intersecting at point A. The acute angle formed by the extension of line BQ and line AB was denoted as angle $\beta$.
e. Draw a perpendicular line from point Q to line l, intersecting at point P.
f. Connected TQ and HV in quadrilateral THQV to form $m_1$ and $n_1$. Connect TB and HQ in quadrilateral THBQ to form $m_2$ and $n_2$.
g. The angle formed by the intersection of $m_1$ and $n_1$ was denoted as $\gamma_1$, and the acute angle formed by the intersection of $m_2$ and $n_2$ was denoted as $\gamma$.

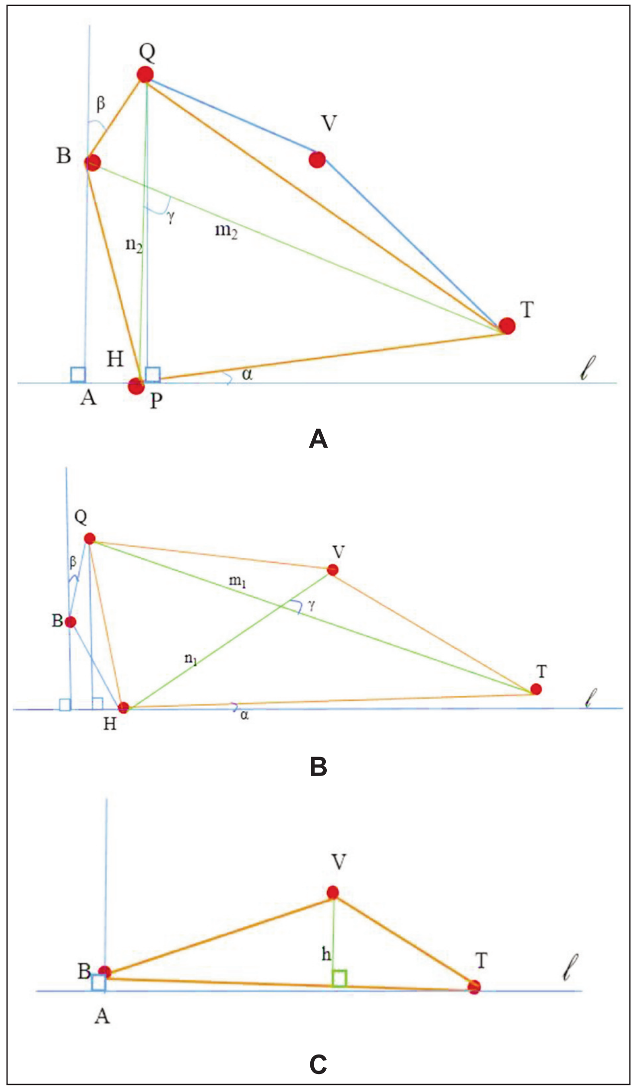


Fig. 2. Footwear line drawing classification model.
*A:* Modelling when point B was higher than point V;
*B:* Modelling when point B was lower than point V;
*C:* Triangle shoe modelling

For shoes without heels, such as flat shoes and loafers, point B was directly marked at the rear end of the sole, and point H could be disregarded. For shoes without a quarter or with open toes, such as sandals and flip-flops, point Q could be disregarded, and point T was marked at the front end of the sole. Therefore, besides forming a pentagon, some shoes could only be marked as a quadrilateral or a triangle. The modelling method for forming a quadrilateral was the same as described above.

The modelling method for shoes that could only form a triangle was as follows:

a. Identified the front end of the sole (T), the high point of the vamp (V), and the rear end of the sole (B).
b. Connected the three points in sequence to form a triangle.
c. Draw a horizontal line passing through point T, and draw a perpendicular line from point B intersecting with the horizontal line at point A.
d. Draw a perpendicular line from point V to line segment BT, and denote this line as h.

**Application of the classification model**

The quadrilateral or triangle formed by connecting points represents the area occupied by the shoe in the image. In the case of a fixed shoe length, the area of the shoe could be calculated through the formula which could be used for style classification later. At present, the area sizes are correlated with the corresponding shoe styles to establish a ranking.

(1) Area (S) Formula for Quadrilateral Shoe Styles

① Situation where point B was lower than point V (Part A of figure 3).

$$S = \frac{1}{2} m_1 n_1 \cdot \sin\gamma \qquad (1)$$

② Situation where point B was higher than point V (Part B of figure 3).

$$S = \frac{1}{2} m_2 n_2 \cdot \sin\gamma \qquad (2)$$

(2) Area Formula for Triangle Shoe Styles (Part C of figure 3).

$$S = \frac{1}{2} AB \cdot h \qquad (3)$$

(3) In general, the area size corresponds to the ranking of the shoe categories.

$$S_{Slippers} < S_{Sandal} < S_{Nude} < S_{Loafer} <$$
$$< S_{Oxford} < S_{Sneakers} \approx S_{Casual} < S_{BOOT}$$

The size of angle $\alpha$ depended on the distance of point T from the horizontal plane, representing the thickness of the waterproof platform or the forefoot part of the sole. A larger angle $\alpha$ indicated a greater distance of point T from the horizontal plane, therefore, a thicker waterproof platform or forefoot part of the sole. Conversely, a smaller angle α indicated a smaller distance of point T from the horizontal plane, hence, a thinner waterproof platform or forefoot part of the sole.

The size of angle $\beta$ was related to the height of the heel. A higher heel results in a larger angle $\beta$, while a lower heel results in a smaller angle $\beta$.

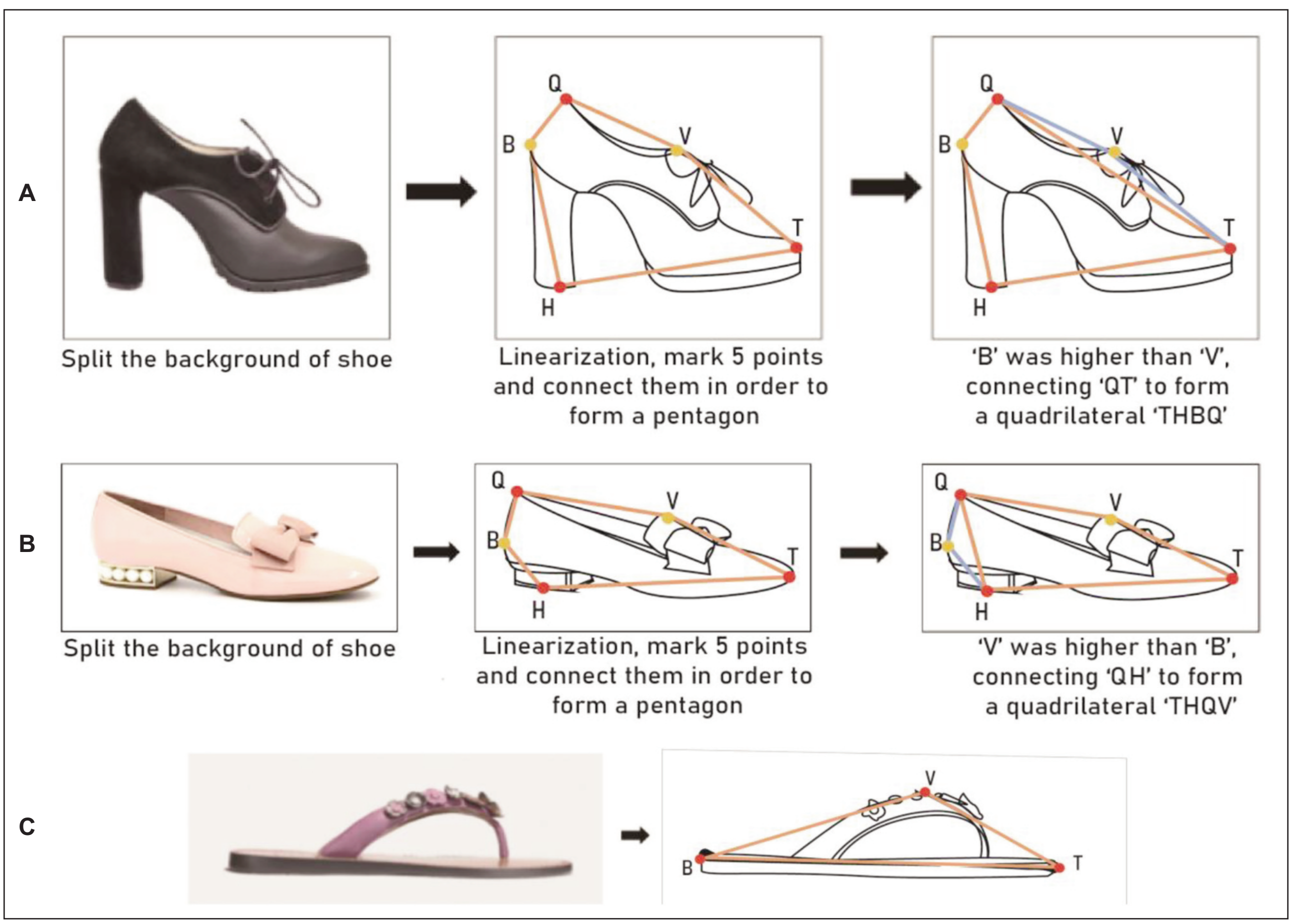


Fig. 3. Shoe modelling case. *A:* Modelling when point B was higher than point V; *B:* Modelling when point B was lower than point V; *C:* Triangle shoe modelling

The position and direction of line BH were directly related to the degree of heel inclination and the position relationship.

Point B was approximately located at one-third of the height of the shoe's heel. Line segment PQ represents the distance from the high point of the heel to the horizontal plane. Therefore, the height of the heel could be calculated using the lengths of line segment BA and line segment PQ. By deriving a simplified formula, the height of the heel ($h_{HEEL}$) could be calculated.

$$h_{HEEL} = \frac{3}{2} AB - \frac{1}{2} PQ \quad (4)$$

Finally, the feasibility of the shoe line drawing classification method was verified by shoe images of fashion trends from autumn/winter 2023 to spring/summer 2024 from the WGSN website.

## EXPERIMENTS AND RESULTS

### Shoe recognition and extraction

This study trained on the COCO dataset using Mask-RCNN with different Residual Network Backbone. Combining the efficiency and performance comparisons of various backbone networks, ResNet-101-FPN achieved the best balance between performance and consumption and was ultimately adopted. Figure 4 shows segmentation examples using Mask R-CNN and ResNet-101-FPN backbone. It could be seen that Mask-RCNN could effectively segment the shoe body from the background.

### Shoe body line drawing extraction

Based on the Python Torch framework, using the Adaptive Moment Estimation Optimizer, PidiNet was trained on the Berkeley Segmentation Dataset and


Fig. 4. The result of instance segmentation by removing shoes from the background of the image

Benchmark 500 (BSDS500) dataset. PidiNet's performance on the BSDS500 dataset was significantly better than some edge detection networks that have emerged in recent years. The following figure 5 shows the recognition effect of the Pixel Difference Network (PidiNet), Dense Extreme Inception Network for Edge Detection (DexiNed), Richer Convolutional Features (RCF), and Canny edge detection networks on typical sneakers, board shoes, and boots. The DexiNed focused too much on detailed edges and identified subtle edges such as fluff and mesh, which was not conducive to establishing a database of the line drawings of the shoe. RCF focused too much on the line drawings and ignored some details of the shoe body, which were likely to be special designs that attracted consumers. Compared to other networks, thanks to the simplified network architecture, PidiNet could effectively extract the line drawings of the shoe, it could also eliminate unimportant edge information caused by small mesh and fluff materials.

### Case study of model recognition

This article collects the shoe images released by brands from autumn and winter 2023 to spring and summer 2024 on WGSN as the analysis object. 476 valid images were crawled as the analysis dataset, including Berluti (https://www.berluti.cn),

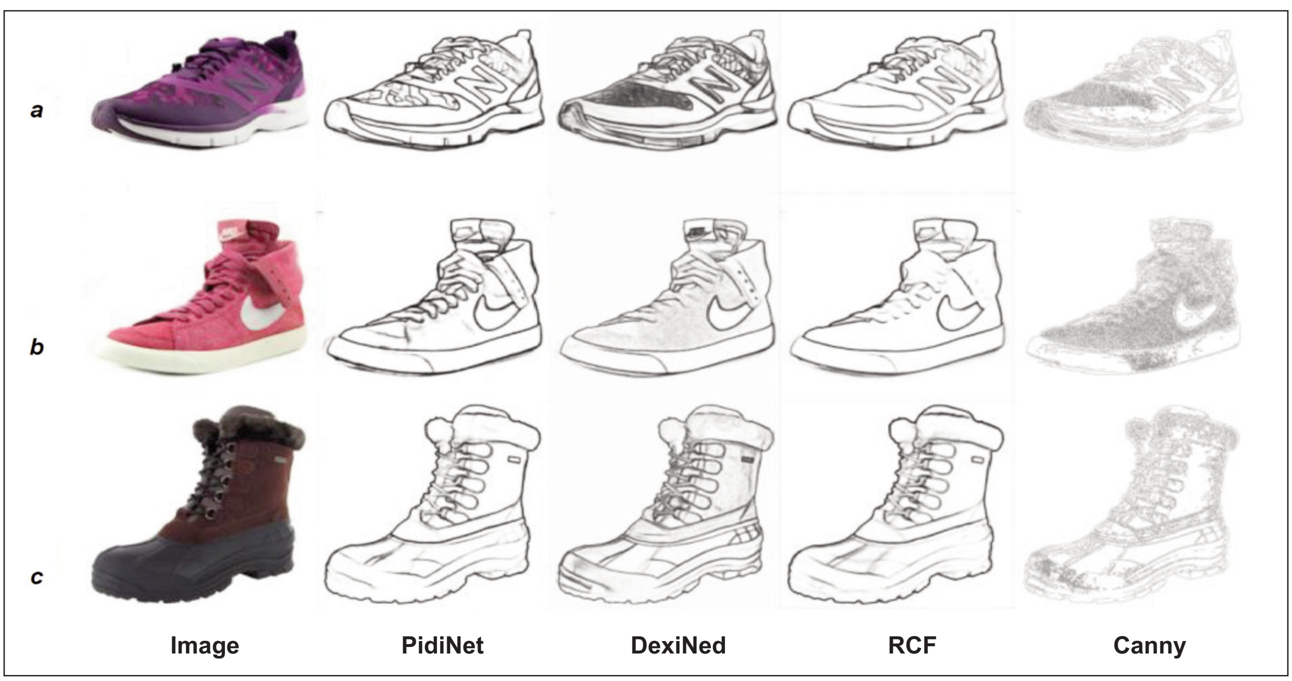


Fig. 5. Shoe Line drawing extraction results

Table 1

| THE CLASSIFICATION PERFORMANCE OF SHOE BODY LINE DRAWING | | | | | |
|---|---|---|---|---|---|
| **Category** | **Classification accuracy** | **Category** | **Classification accuracy** | **Category** | **Classification accuracy** |
| Boots | 0.97 | Sneakers | 0.92 | Nude shoes | 0.97 |
| Slippers | 0.93 | Oxford | 0.80 | Casual | 0.84 |
| Sandal | 0.92 | Loafer | 0.83 | - | - |

Homers (https://www.homers-shoes.com/), Maliparmi (https://www.maliparmi.com/), Urbanima (https://urbanima.com/) and other fashion brands. The performance of image classification was compared and calculated by manual and algorithmic.

It can be seen from table 1 that the classification detection performance of boots, nude shoes, and slippers was relatively good. This may be due to the large differences in the appearance and outline of these shoes, which were easy to distinguish.

Relatively speaking, the recognition performance of loafers and Oxford shoes was the worst, mainly due to these shoes having similar contour characteristics, making it difficult for even ordinary laypersons to distinguish them. Material also affected the classification result, for example, a pair of loafers or leather shoes had a similar outline to a nude shoe, but the algorithm still recognized the shoe as a nude shoe based on the outline characteristics. Of course, the small size of training images in our dataset also restricted the performance of the classification network to some extent.

## DISCUSSION

The results strongly verify that computer vision could achieve shoe line drawing extraction and classification. The instance segmentation training based on Mask-RCNN could effectively segment the shoe body. On this basis, we compared the performance and efficiency of various edge detection algorithms for line drawing style recognition, using the PidiNet edge detection network to detect different shoe line templates, and finally using the self-established classification model for classification. The classification results also had significant differences, which may be due to the size of the differences between styles, the influence of some unconventional and exaggerated design line drawings on the results, and the relatively small number of training sets that also restricted the performance of the classification network. Compared with traditional manual hand-drawn lines, this method conveniently improved the efficiency of shoe line drawing extraction and style classification.

This study designed a classification model for shoe line drawing styles. However, in the research on recognition methods based on digital image processing, various techniques mainly recommend and implement deep recognition and extraction classification for clothing fashion elements such as colour and material. Yang et al. [15] developed an effective colour segmentation method and proposed a complete real-time clothing category labelling system. Hidayati et al. [16] determined a set of style elements based on fashion design theory and proposed a new method for automatically classifying clothing genres based on visually distinguishable style elements. Di et al. [17] used Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), and Histogram of Oriented Gradients (HOG) features and used a Support Vector Machine Classifier (SVM) classifier to classify clothing into 12 categories. Chen et al. [18] used the same features and based on a sparse coding method to classify clothing into 10 fashion style categories. In this study, we innovatively designed a classification method for shoe line drawings, which complements the gap in the field of computer vision fashion research in the classification of shoe style elements.

Secondly, this study successfully extracted the line drawings of shoes with good effect using the edge detection PidiNet algorithm. In the current field of popular element recognition for line drawings, the main methods for feature extraction and classification of clothing line drawings were extreme learning machine classification based on wavelet Fourier descriptor and Euclidean distance classification based on fused features. Manikandan et al. [19] used digital image processing techniques such as image binary conversion, noise point removal, stripe edge smoothing, and stripe width measurement to obtain the image contour of clothes and measure the elongation of fabrics. Takahashi et al. [20] proposed an image processing system that extracts the outline of clothing in images using edge information for automatic inspection of T-shirts and other flat clothing, making the clothing detection process more effective. Wu et al. [21] proposed a classification method based on Fourier contour descriptor using SVM, which obtained the edge of images at various resolutions using an edge detection algorithm. The experiment results of various clothing styles show that the Fourier descriptor had a high recognition rate for each piece of clothing. However, at present, there is no effective method to extract the features of clothing and classify them. Moreover, in many applications, the extracted 2D data line extraction could be very challenging. Donati et al. [3] proposed an automatic vectorization system for fashion hand-drawn sketches based on the Pearson correlation coefficient and multiple Gaussian kernels to enhance and extract the curve structure in sketches. It used a dataset of hand-drawn sketches drawn by professional designers using different pens, different styles, and different backgrounds to train the extracted lines for more reliable vectorization. However, these studies on line drawings also focus more on clothing, and fewer relevant studies could be directly and effectively applied to the field of shoe design.

At the same time, the algorithm classification method in this study overcame one of the main challenges in learning the attributes of shoes, which was the lack of a training database. Nowadays, in the fashion field, most classification methods train algorithms through large-scale clothing databases, for the complex problem of feature extraction in image recognition and have people label the image attributes in the database, allowing deep learning algorithms such as convolutional neural networks to train and self-learn recognition and classification [15, 22, 23]. Elleuch et al. [24] verified on the popular ImageNet clothing dataset. They identify the clothing types based on deep learning and transfer learning in a given dataset from images [25]. ImageNet was the most commonly used dataset in this research field, as it was considered to be one of the largest datasets for image object recognition, with 1.2 million 256×256 RGB images [26]. Chen et al. [27] verified the optimization of convolutional neural network deep learning algorithm in clothing style classification and retrieval tasks in 3 large-scale clothing public databases. Yamaguchi et al. [28] created a dataset containing 158,235 images. Yan et al. [2] established a large-scale dataset consisting of 115,584 pairs of fashion item images for model performance evaluation. Lin et al. [29] applied transfer learning to a clothing retrieval system based on a hierarchical deep search framework on a dataset consisting of 161,234 images from Yahoo Shopping. In these studies, labelling clothing attributes in images required a lot of time, and extensive domain expertise. At the same time, these studies mainly focus on establishing a database for clothing. In contrast, this study did not rely on a large number of shoe images for training, achieving more efficient, fast, and low-cost automatic shoe fashion elements classification.

Overall, by automatically extracting effective and reasonable line drawings from shoe images through image segmentation and edge detection techniques, the efficiency of transforming design line drawings into vector design drawings could be further improved, while providing more design inspiration and possibilities. At the same time, this complements the gap in the specific research on shoe fashion elements in the AI fashion industry. In the future, it could even assist in automatically generating the line design of new shoes, adding direct modification editing and 3D effect transformation functions [30].

## CONCLUSION

Our study developed a footwear line drawing analysis and classification system based on computer vision technology. Initially, the study focused on the targeted classification of footwear line characteristics, and the algorithms were trained accordingly. Subsequently, an innovative approach for classifying footwear line drawings was developed, Finally, a high-precision extraction and classification of the lines drawing styles of footwear products from the 2023–2024 WGSN trend website was performed. The results demonstrated a good accuracy in footwear line drawing extraction and classification. The automation of footwear line drawing recognition and extraction was expected to enhance the efficiency and innovation capabilities of the fashion industry, thereby promoting sustainable development in the field of fashion research. This technological advancement not only accelerates product innovation and market entry but also reduces the environmental burden, ensuring the long-term healthy development of the fashion industry in line with social and environmental responsibilities. Furthermore, it provided robust support for the large-scale establishment of foundational datasets for popular footwear trends.


## ACKNOWLEDGMENTS

Supported by the National Market Supervision Administration Science and Technology Program (grant numbers 2023MK155 and 2024-YF05-01237-SN).


## REFERENCES


[1] Nobile, T.H., Noris, A., Kalbaska, N., Cantoni, L., *A review of digital fashion research: before and beyond communication and marketing*, In: Int. J. Fash. Des. Technol. Educ., 2021, 14, 293–301

[2] Yan, H., Zhang, H., Liu, L., et al., *Toward intelligent design: An ai-based fashion designer using generative adversarial networks aided by sketch and rendering generators,* In: IEEE Trans Multimed, 2022

[3] Donati, L., Cesano, S., Prati, A., *An Accurate System for Fashion Hand-Drawn Sketches Vectorization. In: 2017 IEEE International Conference on Computer Vision Workshops (ICCVW)*, In: IEEE, Venice, Italy, 2017, 2280–2286

[4] Robson, C.J., *Garment modeling from fashion drawings and sketches*, PhD Thesis, University of British Columbia, 2009

[5] Luximon, A., *Handbook of footwear design and manufacture*, Woodhead Publishing, 2021

[6] Al-Halah, Z., Stiefelhagen, R., Grauman, K., *Fashion forward: Forecasting visual style in fashion,* In: Proceedings of the IEEE International Conference on Computer Vision, 2017, 388–397

[7] Ferreira, B.Q., Baía, L., Faria, J., Sousa, R.G., *A unified model with structured output for fashion images classification*, 2018, ArXiv Prepr ArXiv180609445

[8] Bossard, L., Dantone, M., Leistner, C., et al., *Apparel classification with style*, In: Computer Vision–ACCV 2012: 11th Asian Conference on Computer Vision, Daejeon, Korea, November 5-9, 2012, Revised Selected Papers, 2013, IV 11, Springer, 321–335

[9] Shi, M., Chussid, C., Yang, P., et al., *The exploration of artificial intelligence application in fashion trend forecasting,* In: Text. Res. J., 2021, 91, 2357–2386
[10] Zhao, L., Li, M., Sun, P., *Neo-fashion: A data-driven fashion trend forecasting system using catwalk analysis*, In: Cloth. Text. Res. J., 2021, 0887302X211004299
[11] Marfo, E., Anderson, N.G., Butler, A.P., et al., *Assessment of material identification errors, image quality, and radiation doses using small animal spectral photon-counting CT*, In: IEEE Trans. Radiat. Plasma Med. Sci., 2020, 5, 578–587
[12] Dollár, K., Girshick, R., *Mask r-cnn*, In: Proceedings of the IEEE International Conference on Computer Vision, 2017, 2961–2969
[13] Katiyar, S.K., Arun, P., *Comparative analysis of common edge detection techniques in context of object extraction*, 2014, ArXiv Prepr ArXiv14056132
[14] Su, Z., Liu, W., Yu, Z., et al., *Pixel difference networks for efficient edge detection*, In: Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, 5117–5127
[15] Yang, M., Yu, K., *Real-time clothing recognition in surveillance videos*, In: 18th IEEE International Conference on Image Processing, 2011, 2937–2940
[16] Hidayati, S.C., You, C.-W., Cheng, W.-H., Hua, K.-L., *Learning and recognition of clothing genres from full-body images*, In: IEEE Trans. Cybern., 2017, 48, 1647–1659
[17] Di, W., Wah, C., Bhardwaj, A., et al., *Style finder: Fine-grained clothing style detection and retrieval*, In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshop, 2013, 8–13
[18] Chen, J., Xue, B., Lin Kawuu, W., *Dictionary learning for discovering visual elements of fashion styles*, CEC workshop, 2015
[19] Manikandan, G., Kavitha, K., *Analysis of heart vessel segmentation using ant colony optimization algorithm based on digital image processing*, In: Int. J. Comput. Sci. Eng., 2018, 6, 189–197
[20] Takahashi, K., Masuyama, G., Umeda, K., et al., *Measurement of planar clothes using level set method for automatic inspection*, In: 2018 International Workshop on Advanced Image Technology (IWAIT), IEEE, 2018, 1–4
[21] Wu, T., et al., *Clothing Style Recognition Method Based on Digital Image Processing*, In: Int. J. Front. Sociol., 2021, 3
[22] Lassner, C., Pons-Moll, G., Gehler, P.V., *A generative model of people in clothing*, In: Proceedings of the IEEE International Conference on Computer Vision, 2017, 853–862
[23] Wang, W., Xu, Y., Shen, J., Zhu, S.-C., *Attentive fashion grammar network for fashion landmark detection and clothing category classification*, In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, 4271–4280
[24] Elleuch, M., Mezghani, A., Khemakhem, M., Kherallah, M., *Clothing classification using deep CNN architecture based on transfer learning*, In: Hybrid Intelligent Systems: 19th International Conference on Hybrid Intelligent Systems (HIS 2019), Springer, 2021, 240–248
[25] Deng, J., Dong, W., Socher, R., et al., *Imagenet: A large-scale hierarchical image database*, In: 2009 IEEE Conference on Computer Vision and Pattern Recognition, 2009, 248–255
[26] Krizhevsky, A., Sutskever, I., Hinton, G.E., *ImageNet classification with deep convolutional neural networks*, In: Commun ACM, 2017, 60, 84–90
[27] Chen, J.-C., Liu, C.-F., *Visual-based deep learning for clothing from large database*, In: Proceedings of the ASE Big Data & Social Informatics, 2015, 1–10
[28] Yamaguchi, K., Kiapour, M.H., Ortiz, L.E., Berg, T.L., *Parsing clothing in fashion photographs*, In: 2012 IEEE Conference on Computer vision and pattern recognition, 2012, 3570–3577
[29] Lin, K., Yang, H.-F., Liu, K.-H., et al., *Rapid clothing retrieval via deep learning of binary codes and hierarchical search*, In: Proceedings of the 5th ACM on International Conference on Multimedia Retrieval, 2015, 499–502
[30] Bao, C., Miao, Y., Gu, B., et al., *3D interactive garment parametric pattern-making and linkage editing based on constrained contour lines*, In: Int. J. Cloth. Sci. Technol., 2021, 33, 696–723

**Authors:**

LI JINGJING[1], ZHAO YEBAO[2], KEYU HOU[3], ZHOU JIN[1]

[1]Sichuan University, College of Biomass Science and Engineering, National Engineering Laboratory for Clean Technology of Leather Manufacture, Section of Chengdu No. 24 Southern Yihuan, 610065, Chengdu, China

[2]Zhejiang Huafeng new material Co., LTD. Wenzhou Zhejiang Province, 325200, China
e-mail: zhao.yebao@huafeng.com

[3]Zhejiang Huilima Industrial Internet Co., Ltd, Wangjiawei Road, Dongou Industrial Zone, Oubei Street, Yongjia County, Wenzhou City, Zhejiang Province (within Zhejiang Red Dragonfly Shoes Co., Ltd.), China
e-mail: 625368881@qq.com

**Corresponding author:**

ZHOU JIN
e-mail: zj_scu@scu.edu.cn