

# Deep Learning-based Framework for Accurate Clothing Attribute Recognition and Style Navigation for Gait Recognition

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**Abstract**—Recognizing clothing refers to the process of identifying and classifying various attributes of clothing, such as pattern, color, texture, style, length, sleeves, collars, buttons, and waists, from images using computer vision and machine learning techniques, which can be later used in gait recognition. This paper presents a method for recognizing various attributes of clothing, such as waists, collars, front buttons, lengths, and sleeves, using a modified selective search algorithm and a classifier based on L-softmax loss and sparse CNN. The proposed framework has applications in retrieving and navigating based on style, as well as labeling clothing pieces according to personalized style. The paper reviews previous work in image recognition and clothing, discusses the proposed method and framework, presents modified analysis and experiments, and concludes with the contributions of the paper. As the paper focuses on presenting a new method, the results obtained are related to the performance of the proposed framework. According to the experimental results, the proposed method achieves a higher accuracy rate in recognizing clothing attributes compared to previous methods. The framework also shows potential in applications such as personalized style labeling and style-based retrieval and navigation.

**Index Terms**—Clothing attribute recognition, Selective search algorithm, sparse CNN, Deep Learning, Image recognition, Gait recognition.

## I. INTRODUCTION

Extraction of information has become more constant due to availability of large amounts of image data and e-commerce. The clothing industry-being the biggest group in e-commerce, is insisting more use of this technology. Fashion trends preferred to buy the consumers can be predicted by analysing the style of attributes trending at the time. The model can be built by incorporating reviews of customers, volume of sales, and the price of the goods. The results can jointly help designers and sellers of the goods alike. Recognising

attributes in an image is gaining recognition to forecast tasks. Our paper mainly focuses on recognising attributes related to clothing which are built using Deep CNN [1]-[7]. Visual object recognition is a subset of clothing attribute recognition. Due to differences in feature design and expensive elements of clothing, recognition becomes difficult. Studies prior to our paper were mainly concerned with textures and their distribution in pattern, color of the theme in low features which were based on pixels to search for connection. They were unable to apprehend the characteristics of visual aspect to identify the attributes of clothing. On order to resolve these issues, we are presenting a method based on RCNN [8] to identify various clothing attributes like waists, collars, front buttons, lengths, and sleeves.

Clothing style is also a notable feature apart from patterns and colors. Nevertheless, local attributes like sleeves of the item and collar decide the clothing style. Women's shirt and overcoats are the focal point of this paper. The categorization of this domain differs based on attributes. To identify the clothing attributes, we have used a new technique for recognizing the style of clothing in this paper. Our system consists of three sections. The first step is the application of modified algorithm [9] to produce regions which are independent from categories. Sparse Deep convolutional neural network is the second section [7] along with the use of L-softmax loss [10] to extract feature vector of predetermined length from every region and sort them in different groups. The last section consists of boundary correction for regions of candidates.

We can summarize the contributions of this paper with two approaches. Firstly, to make the selective search algorithm more efficient in extracting main parts of clothing, we make changes to improve the methods for calculating texture and color similarity. Secondly, to classify features from region

of candidates using a classifier which works on L-softmax loss, sparse CNN was used [10]. Our framework has a lot of applications like retrieving and navigating on basis of style, labeling of clothing pieces according to personalized style.

Structure of the rest of the paper is as follows. Image recognition and clothing related work is reviewed in section 2. Steps of the method proposed, and framework are discussed in section 3. Section 4 consists of modified analysis and experiments. And conclusion is presented in 5th section.

#### A. Literature review

There has been a lot of research on the topic of clothing identification as there is a lot of regard for automatic analysis of the images due to increase of online shopping. To solve regions of clothing in the images, most of the work is focused on segmentation of clothing. One of the methods of feature extraction is subtracting background from the foreground. A method based on CDT (Constrained Delaunay Triangulation) based on segmentation of clothing was presented by Hu et al. [11] to remove background from the images. An automatic algorithm for extracting pieces of clothing with the use of image-based segmentation to estimate the background and foreground of images was proposed by Wu et al. [12]. A segmentation approach was made by Weber and Bauml et al. [13] to segment a lower and upper region of clothing. Markov network layout was formed by Wang and Ai [14] for optimal layout of clothing.

To address the work of finding same questions of image clothing were presented by images of retrieval. Shopping to street was explored to replicate the difference between images of clothing pieces and photographs of users. In [15] proposed an attribute subordinate descriptor for color, texture, and shape to survey a similarity in outfit for settings of the real world. To calculate the resemblance of pieces, works [15]-[19] were based on measuring same nature of images despite the instances of features of clothing attributes. To retrieve the clothing, framework for multi-task learning was applied [20]. A deep learning method was produced to retrieve and classify the images [21]. Great presentation on the database built on deep-learning mechanism were yielded by the two methods demonstrate supremacy on dataset of big scale which are based on deep-learning method. To present and categories different parts of clothing, study of image identification was conducted. A framework built on ELM NN and origin of multiple attributes was produced [22]. To generate genres on style sections, a new method was generated for classifying clothing [23]. An analyzing framework was made [24] to recognize clothing category. A method of automatic visual recognition for seasonal trend representation was proposed [25].

Local features of clothing like recognition of collar position and hem of overcoat are worked upon in this paper. For local identification of clothing, maximum methods are bounded to super pixel. CRF (Conditional Random Field) was produced [26] to fragment distinct clothing pieces used by a person. A lot of clothing items were produced [27] and [28] to make

style model that described upper wear. They took specified regions for identification to estimate the pose of a person in an image. The method was bounded to straight frontal pose as variation in pose was the focal point of their research. One of the limitations of the above methods is that they deeply rely on extraction of features.

Lately, some advancement has been achieved to move towards high level features for processes related to deep learning in clothing probe instead of the low-level feature dependency. [1], [3]-[7] used various visual image categorization tasks. Detection based on objects [8], [29], [30], image based segmentation [31]- [34] labeling of the images on the basis of pixels [32], [35] and the analysis centered around humans [36], [37]. Procedures on faster R-CNN and multiple task learning for feature identification were produced [3]. Based upon the previous gained knowledge about human beings and the type of clothing [4] produced a viewpoint for localization of the key points. For small targets, the faster R-CNN and Mask-RCNN were used to get faulty identification effect. Categorization and positioning of regional pieces are the key parts of detecting objects; our study considers the features of clothing identification as a method for the same. Our model regards a practical constraint by training model poses and extract regional attributes by describing features of clothing pieces.

## II. PROPOSED METHODOLOGY

The framework produced by us for identifying features of clothing pieces and then gait recognition is overviewed in figure 1. The model comprises of extracting attributes; predicting features for classification. SAR dataset containing shirt and coat images was built which accommodates about 100,000 images from online stores. Then CASIA B dataset is used to remove coat effects. First, a search algorithm was used for proposal region extraction and building a model with the help of notation data. After that, a framework consisting of a sparse deep CNN was recruited for attribute extraction. L- Softmax was used later to foresee the different parts of attribute extraction. The task of identifying has a lot of contents like recognizing them of short or a coat, sleeves, number of pockets in the piece, color, height, waist length, etc. Dimensions of a classification are identified by combining clothing features with images in the dataset.

#### A. Feature extraction

To represent LBP descriptors and attributes of images colour moment is recruited in our algorithm of selective search. We optimize the threshold and scale to run the effect of extracting. Distinct scales and thresholds are mentioned in figure 9. The figure also depicts the co-relation between region boxes extraction and small scale and threshold, they are related to each other directly. Nevertheless, score has no effect with the count of boxes. In fact, having more boxes increases computational scrap. The proposed model shows good effects when threshold is near 250 to 380 and when scale value is from

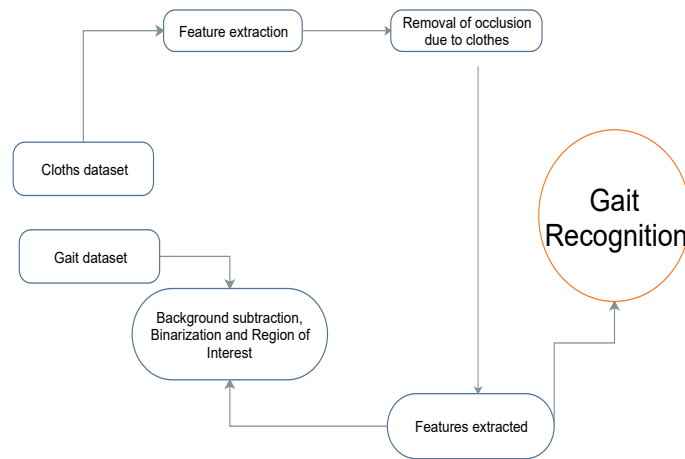


Fig. 1. Example of a figure caption.

85 to 130. The scale and threshold of this paper has been set to 130 and 380 respectively to reduce the computational cost.

To check the effect on the accuracy for identification our produced framework was directly regional scheme effect. Our study makes the use of algorithm for selective search for extracting regions for candidate just like recurrent convolutional neural network [8]. Uijlings et al. [9] produced the algorithm for selective search for identifying objects. The images are divided into a lot of parts with segmentation procedure built on graphs. Later, merging of similar regions is done for extracting the said regions with objects. For image inputs, algorithm of selective search is used.

1) *Algorithm:* Steps for input of images are as follows,

1.  $R = r_1, r_2 \dots r_n$  is the set which is used to acquire the initial region with the use of segmentation procedures built on graphs.

2. size, color and texture resemblance are stored in a set  $S$  are used for similarity calculation.

3.  $R_q$  and  $r_p$  are combined inn set  $R$  to produce  $r_t$  and similarity between  $r_q$  and  $r_p$  is deleted.

4.  $R_t$  was stored in  $R$  set to calculate resemblance between regions adjacent and  $r_t$ .

5. The last two steps are iterated till set  $S$  is empty.

6. Candidate packs are filtered according to size.

## B. Classification

Four similarities namely fit, texture, color and size are considered to calculate the resemblance of regions is shown in step 2. Color resemblance is measured in this paper by making use of resemblance. Moments of color are collected to intensify the educement of attributes. Weighted gray value,  $H, S, V, R, G, B,$  and  $L, a, b$  color space are denoted by  $I$ . Slope which is central moment of third order, moment of color which is mean is of the first order and variance is second order. Segments of ResNet are depicted in figure 3. The ResNet is a  $35 \times 35$  schema having 256-dimension outputs. Reduction-A is applied to minimize the size of segment to  $17 \times 17 \times 896$  from  $35 \times 35 \times 256$  as depicted in figure 1, 2. To extract attributes

from  $17 \times 17$  grid ResNet-B inception segments are depicted in 3(b) figures. A replica map called Reduction-B is made to shrink grid size to  $8 \times 8 \times 1792$  from  $17 \times 17 \times 896$ . To extract features from  $8 \times 8$  grid, ResNet-C section is used which is depicted in figure 1. at last, theme features are extracted with the help of average layer of pooling.

The model produced has been separated by two parts one being extracted region of algorithm of selective-search and the second part is labelled manually in order to intensify data generalization in model of classification. Our model sets IOU-thresholds to distinguish between samples that are negative and positive. Positive samples are detected by checking their thresholds and IOU scores. If IOU score is larger than the T1 threshold are deemed as positive while the rest whose score is less than T2 threshold are termed to be negative and are categorised asa background. The values of T1 and T2 are 0.7 and 0.3 respectively.

Measurements of regions obtained are normalised as input required by the model requires input to be of same size.  $299 \times 299 \times 3$  is the size of input of the ResNet V1 inception model selected by us. Longer edge of a rectangle is used for scaling factor bilinear-interpolation is used for scaling an image. Convergence of loss goes up to 0.4 for the training model. Mean accuracy reaches to 82.32 % when training reaches 16 epochs. A test set was formed for testing effectiveness of the model. Distribution of identification set is depicted by figure 11S. Results of classification are found to be satisfactory.

## C. Results and Analysis

Scores of extracted regions are acquired after the process of categorization is over. With the help of acquired score, soft NMS is applied on categorised result. Figure 2 constitutes of all the labels needed for identification result. Tests are conducted on 10,000 images of the testing set. Recall, precision and rate of labelling are three indicators used to evaluate the model of identification. Rate of recoil and thorough precision are 83.84% and 73.59%. Rank and confusion matrix can be seen in figure 3 and 4.

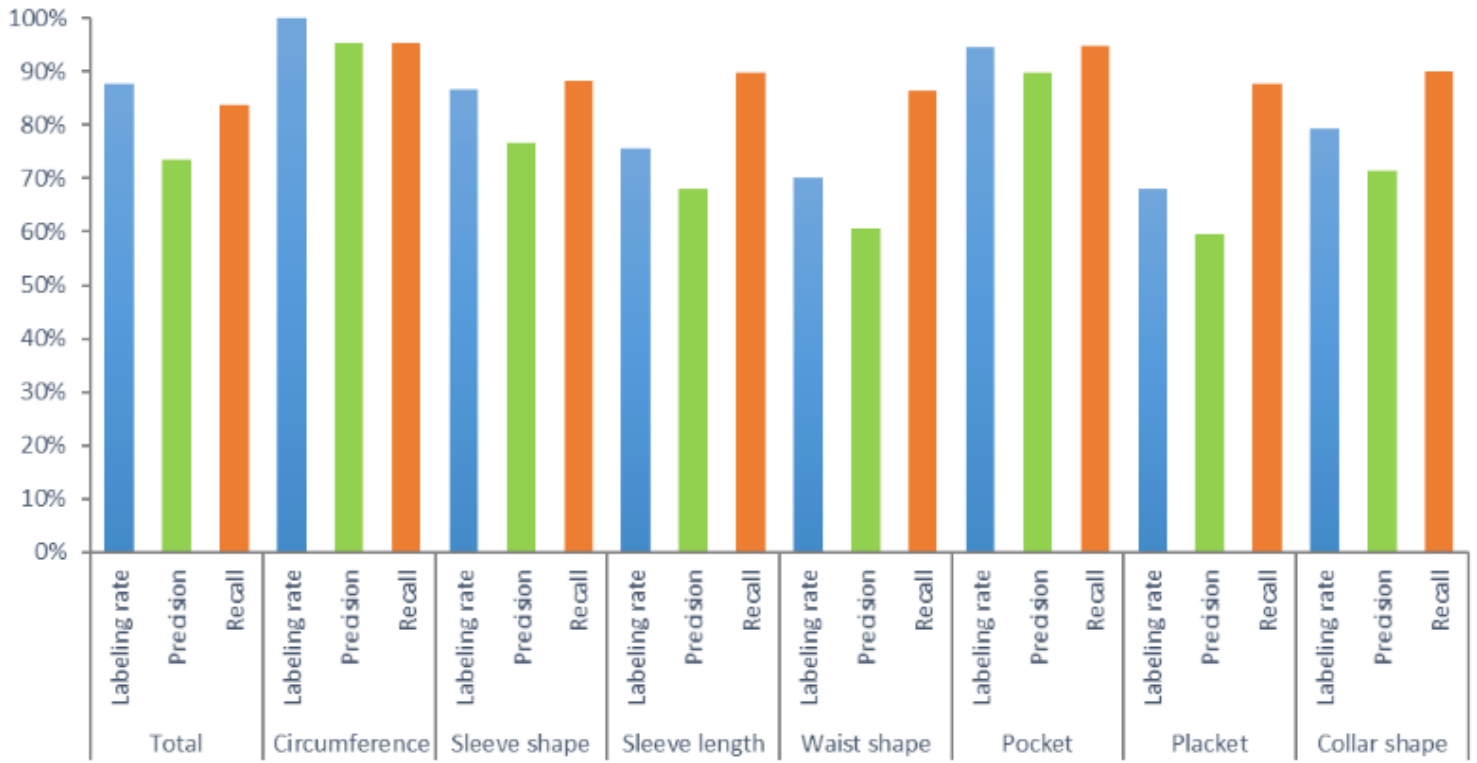


Fig. 2. Accuracies for different models or algorithms that were evaluated on the dataset.

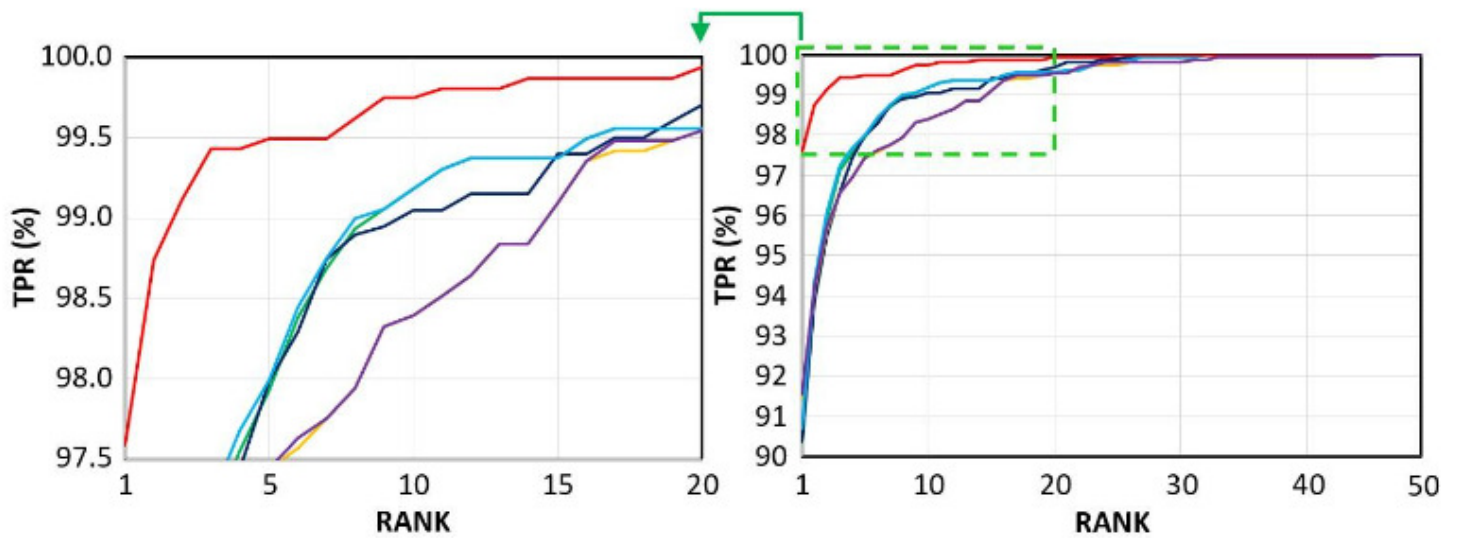


Fig. 3. Rank obtain of different models based on their performance on the dataset.

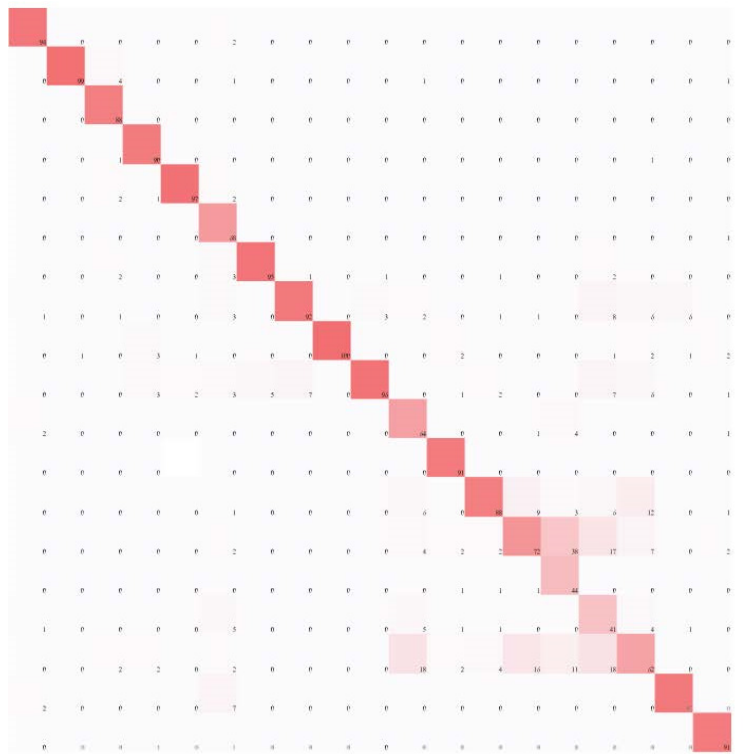


Fig. 4. Confusion matrix to evaluate the performance of classification algorithm

Due to visual attributes being more prominent the model presents good results in identification and positioning. There are three main aims of wrong and overlooked detection (1) it is problematic to label the region of feature for plain pieces making the results of shape of waist and length of sleeves very poor. (2) we cannot reduce the effect of posture in the images. (3) extraction of applicable region is not always apt by algorithm of selective-search. Correctness of the algorithm has reached to 79.65% when the model is applied on dataset containing anything but people.

### III. CONCLUSION

The framework is produced in this paper for the task of identification and categorization. We have produced a new framework to extract the regions of attribute and clothing features by keeping precision and time of training in mind. First and foremost, algorithm of selective search is used for extracting target regions. After that L-softmax and ResNet-V1 are utilised for extracting attribute region and speculating the classification. Then region with highest score is selected with the help of NMS-soft. In the end, corrections are made in the region containing boundaries by applying NN. Our plan is to upgrade execution and the framework used for future projects. For one, our framework demands a lot of plain regions. We also wish to resolve speed problems in regions containing candidates by implementing faster-RCNN. Our second goal is to extend our framework to retrieve clothing pieces. The main focus is attributes of coding and reducing the dimensionality.

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