NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY

(AN AUTONOMOUS INSTITUTION, AFFILIATED TO VISVESVARAYA TECHNOLOGICAL UNIVERSITY, BELGAUM, APPROVED BY AICTE & GOVT.OF KARNATAKA)

LA Report

on

AI Stylist

Submitted in partial fulfilment of the requirement for the Learning Assessment of Introduction to Machine Learning 18CSE751 Course of 7th Semester

Bachelor of Engineering

in

Computer Science and Engineering

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ABSTRACT

The idea is to utilize machine learning models for salient object detection, image segmentation and classifying a picture of clothing, according to a set of predetermined features (Example: tops, trouser, skirt, etc). We plan on building a ML model for automatic categorization of fashion apparels. In that process, Firstly we will be partitioning an image into multiple segments according to its features and properties so as to obtain a simplified image for image analysis, then removing the background of the obtained image . After that we intend to do object detection and in the end classify the detected instances into different clothing apparels and produce that as the result. In short ,we propose fashion apparel detection and feature tagging.

CONTENTS

INTRODUCTION

In Machine Learning (ML) and AI – Computer vision is used to train the model to recognize certain patterns and store the data into their artificial memory to utilize the same for predicting the results in real-life use[2].

MOTIVATION

Keeping track of fashion sense requires significant time and effort, which leads some people to seek help from a professional stylist. Personal stylists can be expensive though and cannot be with clients all the time.

AI stylist programs can also store descriptions of user's items and help users be more organized and efficient.An Artificial Intelligence based computer program could be the new fashion consultant.There are many benefits associated with using computer programs as future stylists. They could process large amounts of data faster when learning a user's style and memorizing users' feedback.

PROBLEM DOMAIN

Everyday people face this problem , where they are unable to decide which clothes to wear. So, they end up wasting a lot of time selecting clothes. Each day the average woman spends 17 minutes picking out what to wear and in their whole lifetime they spend almost 287 days deciding what to wear, that's nearly a year of their life. In fact, guys spent 13 minutes a day on their outfit selection, just four minutes shy of the ladies' totals.

People like Steve Jobs and Mark Zuckerberg wear the same outfit everyday so that they do not have to spend much time deciding on what to wear.

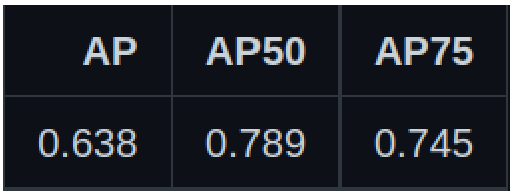
Being fashionable and trendy comes handy in your meetings and daily life. But, how can we achieve this within 10 mins or less in our busy life?

AIM AND OBJECTIVES

- We aim to build a system that utilizes machine learning models for detecting the features from the picture of a piece of clothing, then classifies it according to a set of predetermined features (Example: shirt, t-shirt, jeans, etc).
- We will be performing Image segmentation, Background removal and Object detection
- We propose a fashion apparel detection and feature tagging system.

DATA SOURCE AND DATA QUALITY

We are using the DeepFashion2[4] dataset, it has labels and annotations much larger than any other dataset. DeepFashion2 is a comprehensive fashion dataset. It contains 491K diverse images of 13 popular clothing categories from both commercial shopping stores and consumers.



AP	AP50	AP75
0.638	0.789	0.745

Clothes detection trained with released DeepFashion2 Dataset evaluated on validation set.

1. Attributes

It totally has 801K clothing items, where each image is attributed with : scale, occlusion, zoom-in, viewpoint, category, style, bounding box, dense landmarks and per-pixel mask.

Annotations are in this format -

- source: a string, where 'shop' indicates that the image is from a commercial store while 'user' indicates that the image is taken by users.
- pair_id: a number. Images from the same shop and their corresponding consumer-taken images have the same pair id.
- item 1
    - category_name
    - category_id
    - style
    - bounding_box
    - landmarks
    - segmentation
    - scale
    - occlusion
    - zoom_in
    - viewpoint
- item 2

  ...
- item n

2. Dataset Organization

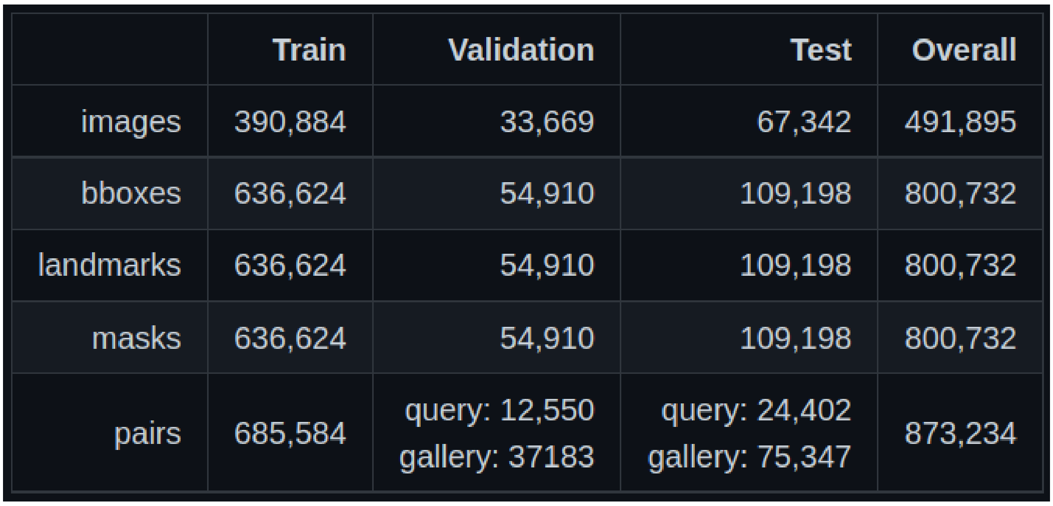
The dataset is split into a training set (391K images), a validation set (34k images), and a test set (67k images).

Training images: train/image Training annotations: train/annos

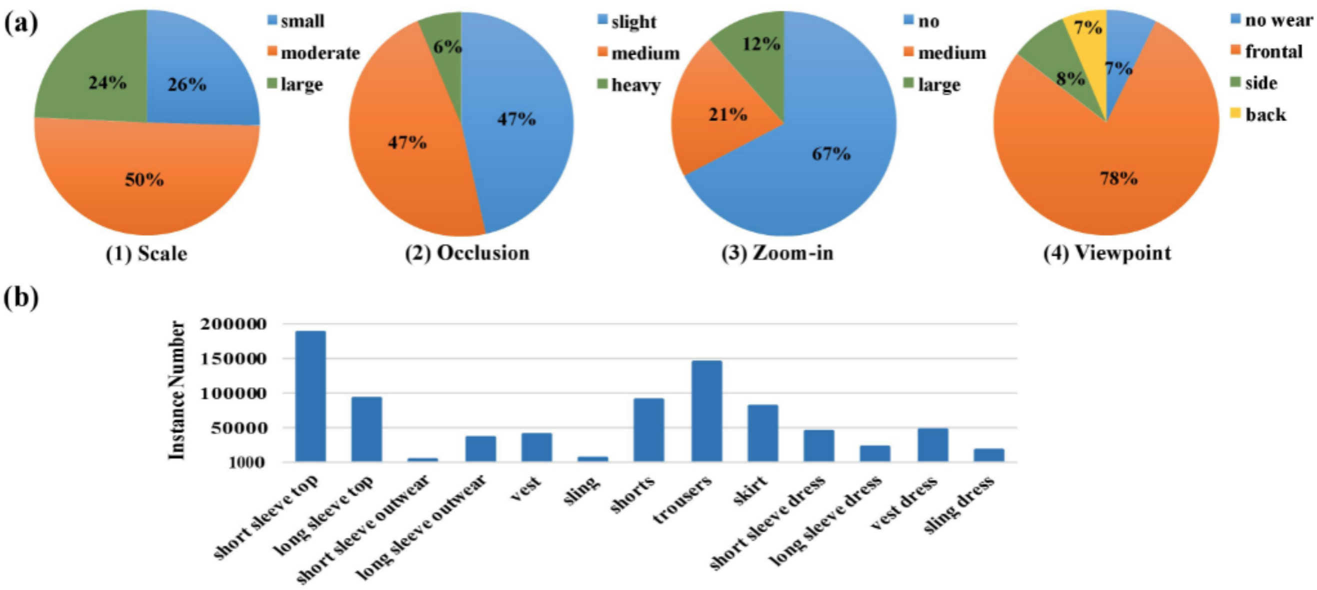
Validation images: validation/image Validation annotations: validation/annos
Test images: test/image

Each image in seperate image set has a unique six-digit number such as 000001.jpg. A corresponding annotation file in json format is provided in an annotation set such as 000001.json.

3. Dataset Statistics



	Train	Validation	Test	Overall
images	390,884	33,669	67,342	491,895
bboxes	636,624	54,910	109,198	800,732
landmarks	636,624	54,910	109,198	800,732
masks	636,624	54,910	109,198	800,732
pairs	685,584	query: 12,550 gallery: 37183	query: 24,402 gallery: 75,347	873,234



METHODS

Methods that we will be using to accomplish this task are -

1. Semantic Segmentation : The task of assigning a class to every pixel in a given image. Note here that this is significantly different from classification. Classification assigns a single class to the whole image whereas semantic segmentation classifies every pixel of the image to one of the classes.
   Why Semantic Segmentation?
   To detect the human body or the cloth in the input image.

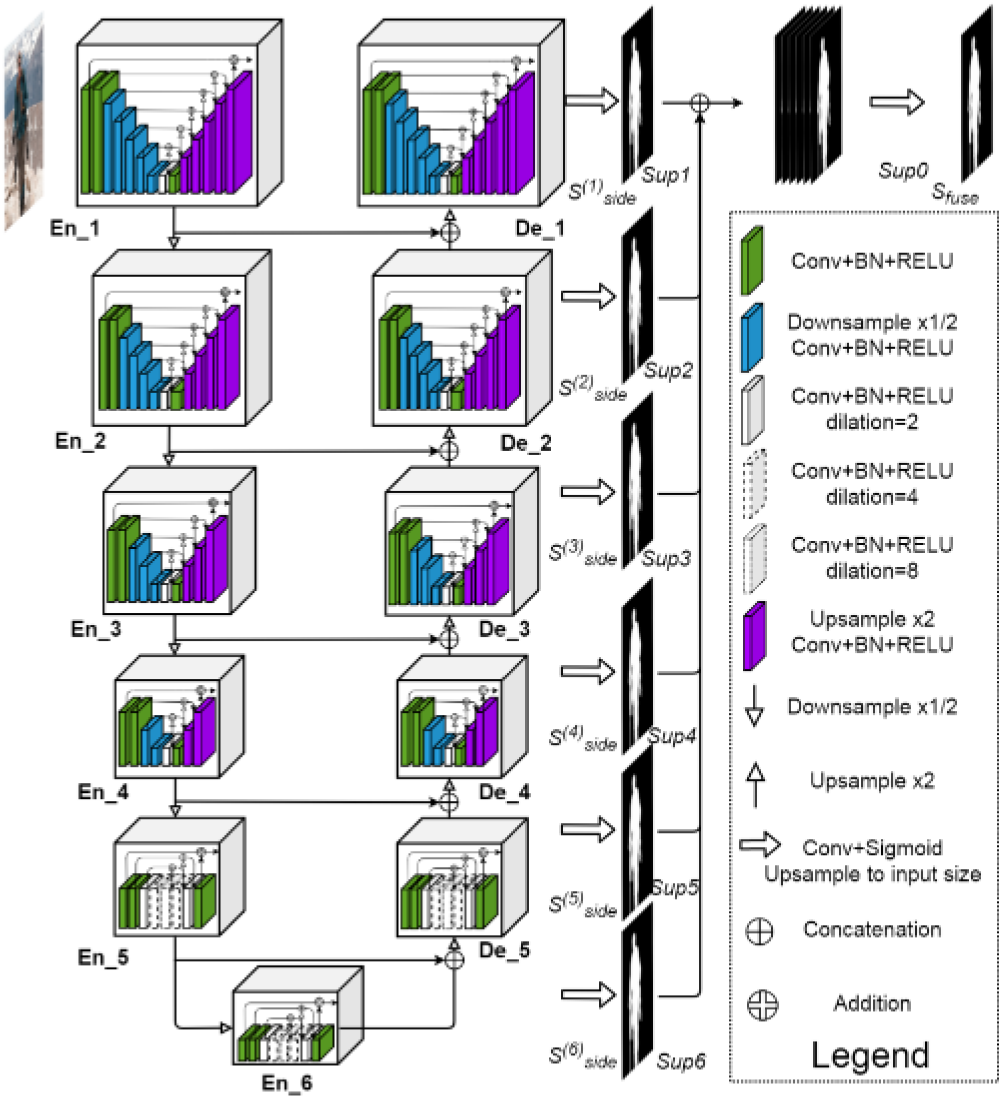
2. Background Segmentation : Background separation is a segmentation task, where the goal is to split the image into foreground and background. In semi-interactive settings, the user marks some pixels as “foreground”, a few others as “background”, and it’s up to the algorithm to classify the rest of the pixels.
   Why Background Segmentation?
   To remove the background noise which will disrupt the accuracy of the image classification model.

3. Image Classification : Image classification is where a computer can analyse an image and identify the 'class' the image falls under. (Or a probability of the image being part of a 'class'.) A class is essentially a label, for instance, 'car', 'animal', 'building' and so on.
   Why Image Classification?
   This method is the final step to predict the labels of the input image.

<u>MACHINE LEARNING MODELS</u>

Deep Learning Methods

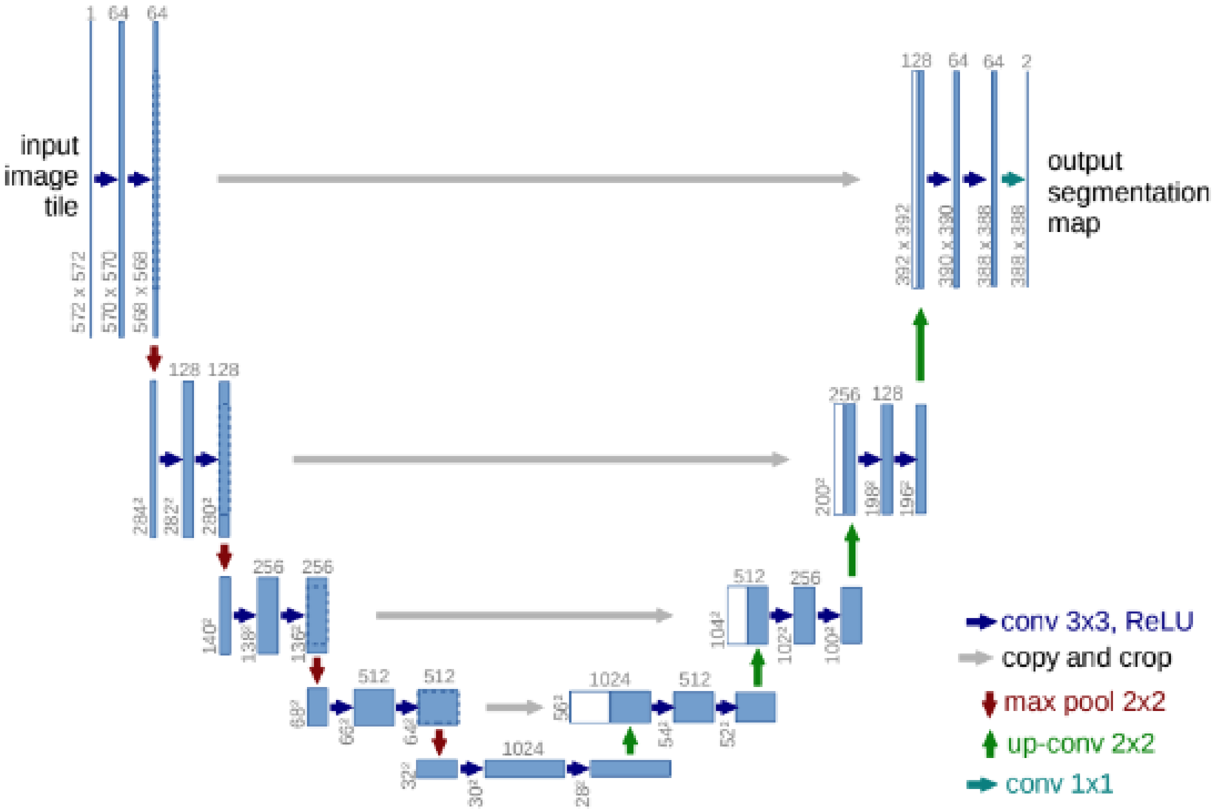
1. Semantic Segmentation[1]
   For Semantic Segmentation we are using the U^2NET[5] model. The model has been trained and tested on the DUTS and ECSSD dataset using tf v2.4.1 and keras v2.4.3.
   U^2NET : The architecture of the U2-Net is a two-level nested U-structure. The design has the following advantages: (1) it is able to capture more contextual information from different scales thanks to the mixture of receptive fields of different sizes in our proposed ReSidual U-blocks (RSU), (2) it increases the depth of the whole architecture without significantly increasing the computational cost because of the pooling operations used in these RSU blocks. This architecture enables you to train a deep network from scratch without using backbones from image classification tasks.



The authors of this paper have provided pre-trained models, and we are using that for semantic segmentation.

2. Background Segmentation
   For background segmentation we take the output of the U2-Net model which is a masked image and subtract that with the original image such that only the masked pixels are left in the image instance.
   To do so we use OpenCV’s subtract function “cv2.subtract(image1,image2)”.

3. Object Detection
   U-Net[6] is an architecture consisting of a contracting path and an expansive path.
   The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. At each downsampling step we double the number of feature channels. Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution (“up-convolution”) that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer a 1x1 convolution is used to map each 64-component feature vector to the desired number of classes. In total the network has 23 convolutional layers.

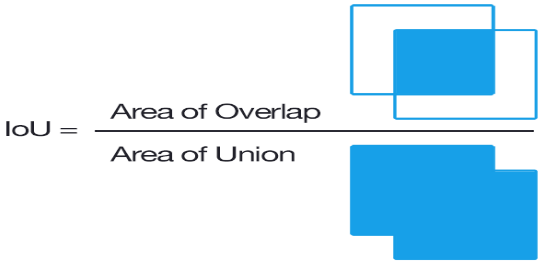


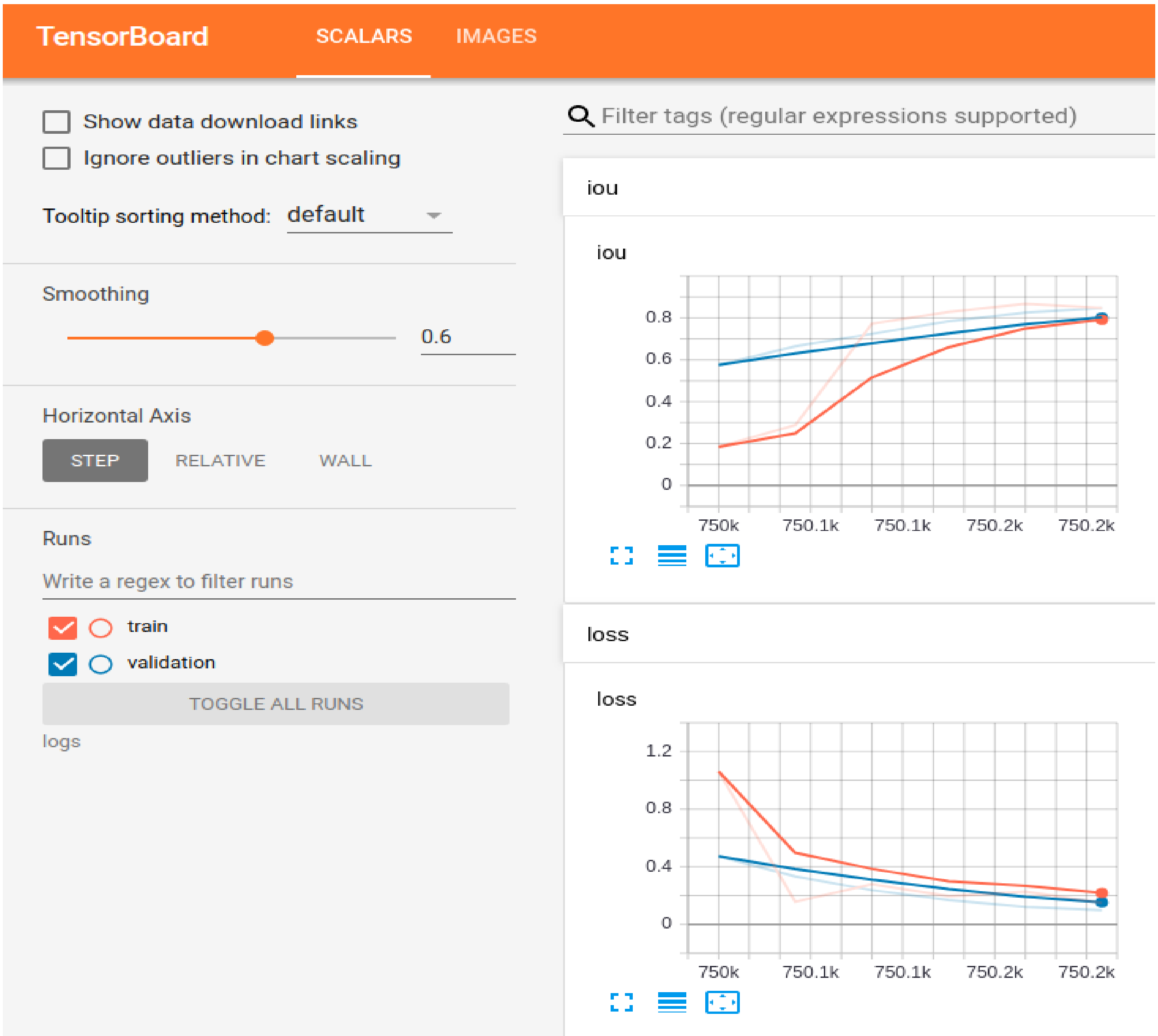
We trained the U-Net Model on DeepFashion2 dataset for object detection task for 6 classes for clothes: top, shorts, trousers, skirt, dress and outerwear.

RESULTS AND DISCUSSION

UNET Model:
To assess the unet model we used the IoU method.
IoU - Intersection over Union (IoU) is used when calculating mAP. It is a number from 0 to 1 that specifies the amount of overlap between the predicted and ground truth bounding box.

- an IoU of 0 means that there is no overlap between the boxes an IoU of 1 means that the union of the boxes is the same as their overlap indicating that they are completely overlapping





□ Show data download links
□ Ignore outliers in chart scaling
Tooltip sorting method: default

Smoothing 0.6

Horizontal Axis
STEP RELATIVE WALL

Runs
Write a regex to filter runs
☑ ○ train
☑ ○ validation
TOGGLE ALL RUNS
logs

Filter tags (regular expressions supported)

U2-NET Model:

Since we used a pre-trained model provided by the authors of U2-NET, we did not run any kind of assessment method.

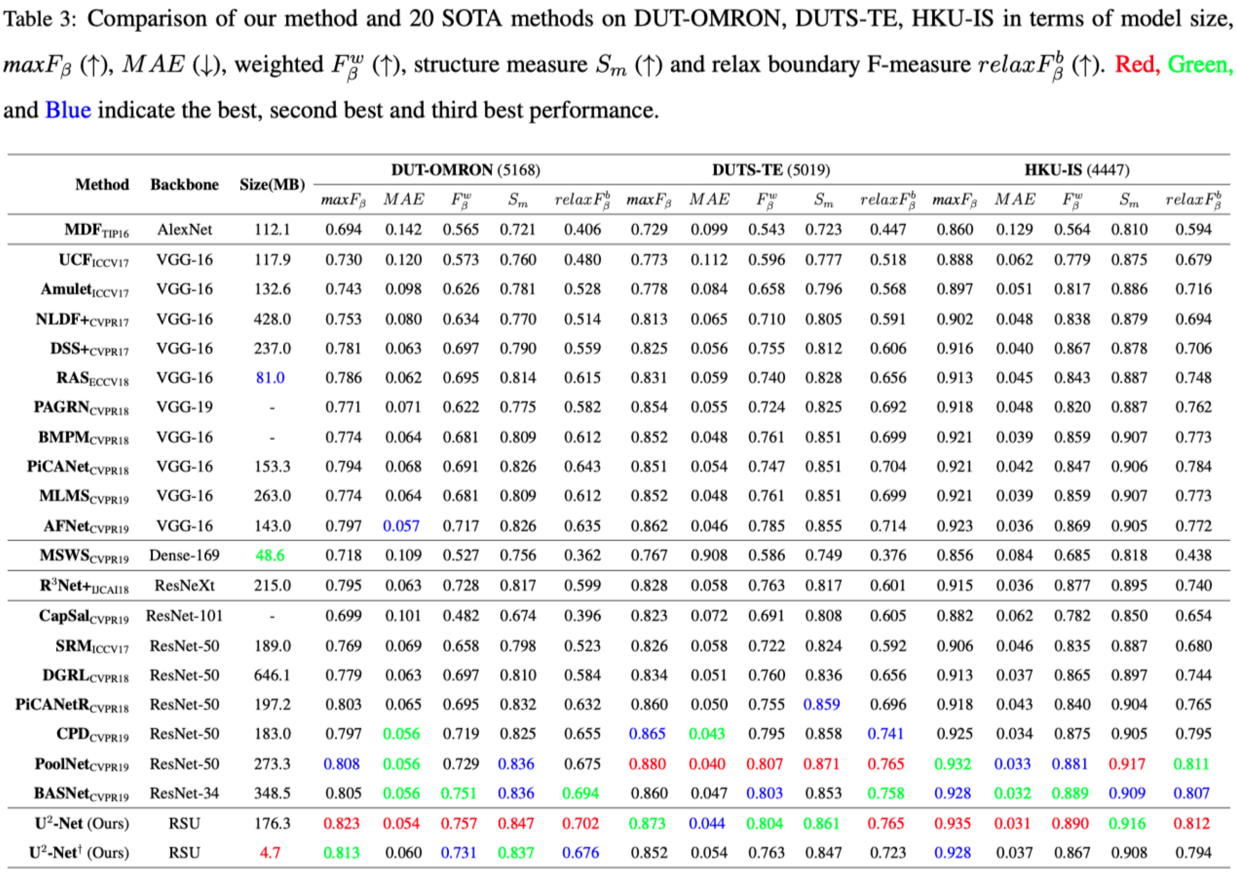


Table 3: Comparison of our method and 20 SOTA methods on DUT-OMRON, DUTS-TE, HKU-IS in terms of model size, $maxF_\beta$ (↑), MAE (↓), weighted F^w_β (↑), structure measure S_m (↑) and relax boundary F-measure $relaxF^b_\beta$ (↑). Red, Green, and Blue indicate the best, second best and third best performance.

Method	**Backbone**	**Size(MB)**	**DUT-OMRON** (5168)					**DUTS-TE** (5019)					**HKU-IS** (4447)				
			$maxF_\beta$	MAE	F^w_β	S_m	$relaxF^b_\beta$	$maxF_\beta$	MAE	F^w_β	S_m	$relaxF^b_\beta$	$maxF_\beta$	MAE	F^w_β	S_m	$relaxF^b_\beta$
MDF$_{\text{TIP16}}$	AlexNet	112.1	0.694	0.142	0.565	0.721	0.406	0.729	0.099	0.543	0.723	0.447	0.860	0.129	0.564	0.810	0.594
UCF$_{\text{ICCV17}}$	VGG-16	117.9	0.730	0.120	0.573	0.760	0.480	0.773	0.112	0.596	0.777	0.518	0.888	0.062	0.779	0.875	0.679
Amulet$_{\text{ICCV17}}$	VGG-16	132.6	0.743	0.098	0.626	0.781	0.528	0.778	0.084	0.658	0.796	0.568	0.897	0.051	0.817	0.886	0.716
NLDF+$_{\text{CVPR17}}$	VGG-16	428.0	0.753	0.080	0.634	0.770	0.514	0.813	0.065	0.710	0.805	0.591	0.902	0.048	0.838	0.879	0.694
DSS+$_{\text{CVPR17}}$	VGG-16	237.0	0.781	0.063	0.697	0.790	0.559	0.825	0.056	0.755	0.812	0.606	0.916	0.040	0.867	0.878	0.706
RAS$_{\text{ECCV18}}$	VGG-16	81.0	0.786	0.062	0.695	0.814	0.615	0.831	0.059	0.740	0.828	0.656	0.913	0.045	0.843	0.887	0.748
PAGRN$_{\text{CVPR18}}$	VGG-19	-	0.771	0.071	0.622	0.775	0.582	0.854	0.055	0.724	0.825	0.692	0.918	0.048	0.820	0.887	0.762
BMPM$_{\text{CVPR18}}$	VGG-16	-	0.774	0.064	0.681	0.809	0.612	0.852	0.048	0.761	0.851	0.699	0.921	0.039	0.859	0.907	0.773
PiCANet$_{\text{CVPR18}}$	VGG-16	153.3	0.794	0.068	0.691	0.826	0.643	0.851	0.054	0.747	0.851	0.704	0.921	0.042	0.847	0.906	0.784
MLMS$_{\text{CVPR19}}$	VGG-16	263.0	0.774	0.064	0.681	0.809	0.612	0.852	0.048	0.761	0.851	0.699	0.921	0.039	0.859	0.907	0.773
AFNet$_{\text{CVPR19}}$	VGG-16	143.0	0.797	0.057	0.717	0.826	0.635	0.862	0.046	0.785	0.855	0.714	0.923	0.036	0.869	0.905	0.772
MSWS$_{\text{CVPR19}}$	Dense-169	48.6	0.718	0.109	0.527	0.756	0.362	0.767	0.908	0.586	0.749	0.376	0.856	0.084	0.685	0.818	0.438
R^3**Net+**$_{\text{IJCAI18}}$	ResNeXt	215.0	0.795	0.063	0.728	0.817	0.599	0.828	0.058	0.763	0.817	0.601	0.915	0.036	0.877	0.895	0.740
CapSal$_{\text{CVPR19}}$	ResNet-101	-	0.699	0.101	0.482	0.674	0.396	0.823	0.072	0.691	0.808	0.605	0.882	0.062	0.782	0.850	0.654
SRM$_{\text{ICCV17}}$	ResNet-50	189.0	0.769	0.069	0.658	0.798	0.523	0.826	0.058	0.722	0.824	0.592	0.906	0.046	0.835	0.887	0.680
DGRL$_{\text{CVPR18}}$	ResNet-50	646.1	0.779	0.063	0.697	0.810	0.584	0.834	0.051	0.760	0.836	0.656	0.913	0.037	0.865	0.897	0.744
PiCANetR$_{\text{CVPR18}}$	ResNet-50	197.2	0.803	0.065	0.695	0.832	0.632	0.860	0.050	0.755	0.859	0.696	0.918	0.043	0.840	0.904	0.765
CPD$_{\text{CVPR19}}$	ResNet-50	183.0	0.797	0.056	0.719	0.825	0.655	0.865	0.043	0.795	0.858	0.741	0.925	0.034	0.875	0.905	0.795
PoolNet$_{\text{CVPR19}}$	ResNet-50	273.3	0.808	0.056	0.729	0.836	0.675	0.880	0.040	0.807	0.871	0.765	0.932	0.033	0.881	0.917	0.811
BASNet$_{\text{CVPR19}}$	ResNet-34	348.5	0.805	0.056	0.751	0.836	0.694	0.860	0.047	0.803	0.853	0.758	0.928	0.032	0.889	0.909	0.807
U^2**-Net** (Ours)	RSU	176.3	0.823	0.054	0.757	0.847	0.702	0.873	0.044	0.804	0.861	0.765	0.935	0.031	0.890	0.916	0.812
U^2**-Net**† (Ours)	RSU	4.7	0.813	0.060	0.731	0.837	0.676	0.852	0.054	0.763	0.847	0.723	0.928	0.037	0.867	0.908	0.794

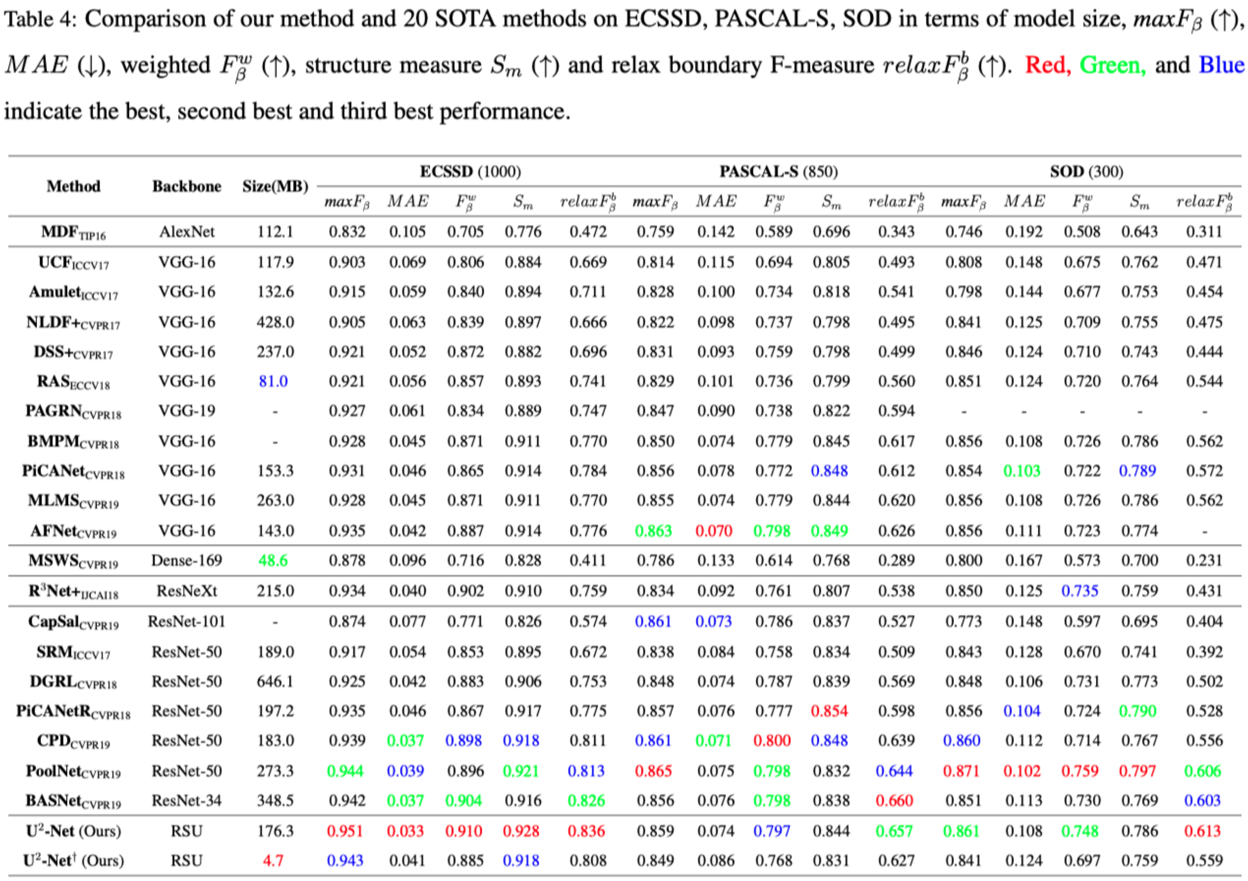
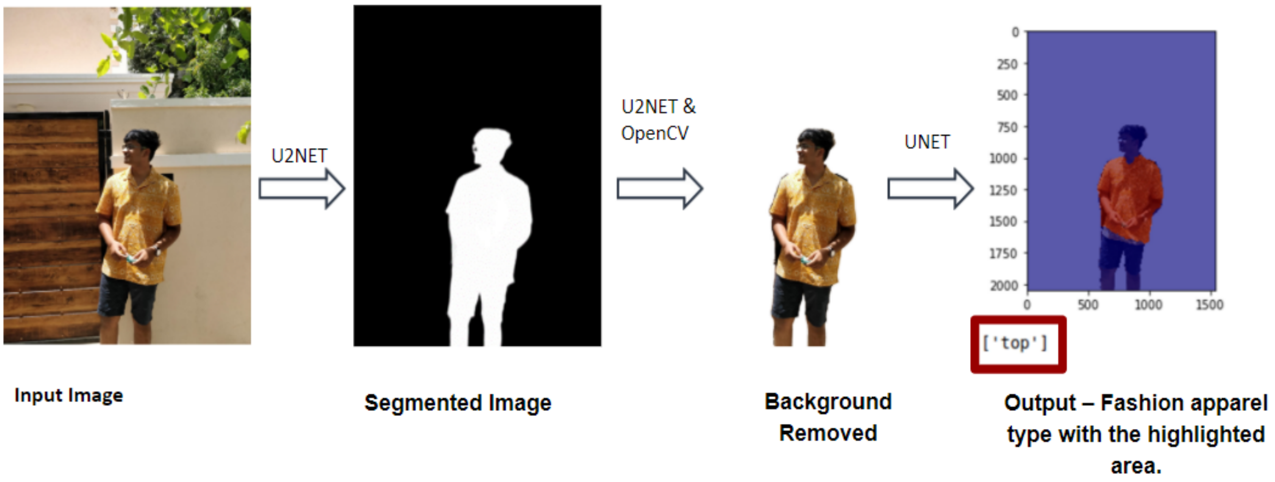


Table 4: Comparison of our method and 20 SOTA methods on ECSSD, PASCAL-S, SOD in terms of model size, $maxF_\beta$ (↑), MAE (↓), weighted F^w_β (↑), structure measure S_m (↑) and relax boundary F-measure $relaxF^b_\beta$ (↑). Red, Green, and Blue indicate the best, second best and third best performance.

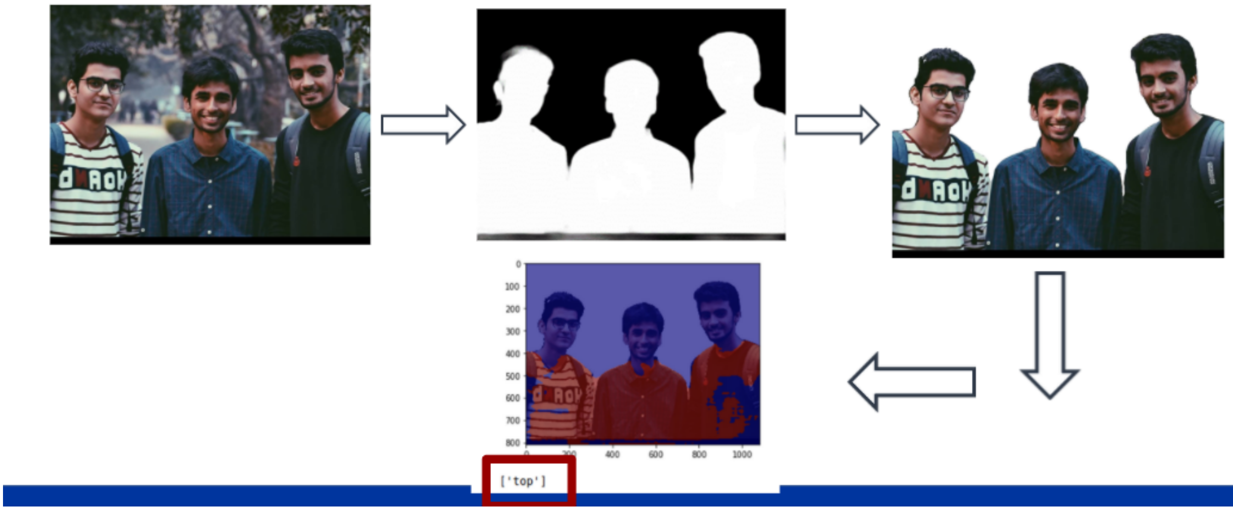
Method	Backbone	Size(MB)	ECSSD (1000)					PASCAL-S (850)					SOD (300)				
			$maxF_\beta$	MAE	F^w_β	S_m	$relaxF^b_\beta$	$maxF_\beta$	MAE	F^w_β	S_m	$relaxF^b_\beta$	$maxF_\beta$	MAE	F^w_β	S_m	$relaxF^b_\beta$
MDF$_{\text{TIP16}}$	AlexNet	112.1	0.832	0.105	0.705	0.776	0.472	0.759	0.142	0.589	0.696	0.343	0.746	0.192	0.508	0.643	0.311
UCF$_{\text{ICCV17}}$	VGG-16	117.9	0.903	0.069	0.806	0.884	0.669	0.814	0.115	0.694	0.805	0.493	0.808	0.148	0.675	0.762	0.471
Amulet$_{\text{ICCV17}}$	VGG-16	132.6	0.915	0.059	0.840	0.894	0.711	0.828	0.100	0.734	0.818	0.541	0.798	0.144	0.677	0.753	0.454
NLDF+$_{\text{CVPR17}}$	VGG-16	428.0	0.905	0.063	0.839	0.897	0.666	0.822	0.098	0.737	0.798	0.495	0.841	0.125	0.709	0.755	0.475
DSS+$_{\text{CVPR17}}$	VGG-16	237.0	0.921	0.052	0.872	0.882	0.696	0.831	0.093	0.759	0.798	0.499	0.846	0.124	0.710	0.743	0.444
RAS$_{\text{ECCV18}}$	VGG-16	81.0	0.921	0.056	0.857	0.893	0.741	0.829	0.101	0.736	0.799	0.560	0.851	0.124	0.720	0.764	0.544
PAGRN$_{\text{CVPR18}}$	VGG-19	-	0.927	0.061	0.834	0.889	0.747	0.847	0.090	0.738	0.822	0.594	-	-	-	-	-
BMPM$_{\text{CVPR18}}$	VGG-16	-	0.928	0.045	0.871	0.911	0.770	0.850	0.074	0.779	0.845	0.617	0.856	0.108	0.726	0.786	0.562
PiCANet$_{\text{CVPR18}}$	VGG-16	153.3	0.931	0.046	0.865	0.914	0.784	0.856	0.078	0.772	0.848	0.612	0.854	0.103	0.722	0.789	0.572
MLMS$_{\text{CVPR19}}$	VGG-16	263.0	0.928	0.045	0.871	0.911	0.770	0.855	0.074	0.779	0.844	0.620	0.856	0.108	0.726	0.786	0.562
AFNet$_{\text{CVPR19}}$	VGG-16	143.0	0.935	0.042	0.887	0.914	0.776	0.863	0.070	0.798	0.849	0.626	0.856	0.111	0.723	0.774	-
MSWS$_{\text{CVPR19}}$	Dense-169	48.6	0.878	0.096	0.716	0.828	0.411	0.786	0.133	0.614	0.768	0.289	0.800	0.167	0.573	0.700	0.231
R^{3}Net+$_{\text{IJCAI18}}$	ResNeXt	215.0	0.934	0.040	0.902	0.910	0.759	0.834	0.092	0.761	0.807	0.538	0.850	0.125	0.735	0.759	0.431
CapSal$_{\text{CVPR19}}$	ResNet-101	-	0.874	0.077	0.771	0.826	0.574	0.861	0.073	0.786	0.837	0.527	0.773	0.148	0.597	0.695	0.404
SRM$_{\text{ICCV17}}$	ResNet-50	189.0	0.917	0.054	0.853	0.895	0.672	0.838	0.084	0.758	0.834	0.509	0.843	0.128	0.670	0.741	0.392
DGRL$_{\text{CVPR18}}$	ResNet-50	646.1	0.925	0.042	0.883	0.906	0.753	0.848	0.074	0.787	0.839	0.569	0.848	0.106	0.731	0.773	0.502
PiCANetR$_{\text{CVPR18}}$	ResNet-50	197.2	0.935	0.046	0.867	0.917	0.775	0.857	0.076	0.777	0.854	0.598	0.856	0.104	0.724	0.790	0.528
CPD$_{\text{CVPR19}}$	ResNet-50	183.0	0.939	0.037	0.898	0.918	0.811	0.861	0.071	0.800	0.848	0.639	0.860	0.112	0.714	0.767	0.556
PoolNet$_{\text{CVPR19}}$	ResNet-50	273.3	0.944	0.039	0.896	0.921	0.813	0.865	0.075	0.798	0.832	0.644	0.871	0.102	0.759	0.797	0.606
BASNet$_{\text{CVPR19}}$	ResNet-34	348.5	0.942	0.037	0.904	0.916	0.826	0.856	0.076	0.798	0.838	0.660	0.851	0.113	0.730	0.769	0.603
U^2-Net (Ours)	RSU	176.3	0.951	0.033	0.910	0.928	0.836	0.859	0.074	0.797	0.844	0.657	0.861	0.108	0.748	0.786	0.613
U^2-Net† (Ours)	RSU	4.7	0.943	0.041	0.885	0.918	0.808	0.849	0.086	0.768	0.831	0.627	0.841	0.124	0.697	0.759	0.559

Presentation and visualization

The presentation and visualization will be done as shown below:



Another Example



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CONCLUSION AND FUTURE DIRECTIONS

The implementation presents a combination of U-net performing classification and object detection, U2-net performing Image Segmentation. Deep Fashion2 dataset is being used to train U-net model for classification of input image segments into top,bottom,dress etc on the segmented parts of the image. In conclusion, our model is able to detect and classify 6 different types of fashion apparels.

In future we plan to increase the number of labels that our model can predict, by training it on other datasets. Also, we plan to include fashion accessories in the label set.

LESSON LEARNT

This project helped us to gain an in-depth knowledge on the different machine learning algorithms that we used for implementation. We came across various models which were new to us. We learnt their uses and significance corresponding to salient object detection , image segmentation and classification. In Order to evaluate and compare the chosen machine learning models, we compared our models with a few state-of-the-art methods including some of the DenseNet, ResNeXt and ResNet based models. So, after keeping every observation in consideration U2-Net is able to produce error-free results on both small and large objects. This helped us to enhance our knowledge on their significance in machine learning and how they can be used efficiently to our advantage.

REFERENCES

[1]https://www.analyticsvidhya.com/blog/2019/02/tutorial-semantic-segmentation-google-deeplab/#:~:text=Semantic%20segmentation%20is%20the%20task,to%20one%20of%20the%20classes.

[2]https://www.cogitotech.com/blog/computer-vision-in-ai-and-machine-learning#:~:text=In%20Machine%20Learning%20(ML)%20and,results%20in%20real%2Dlife%20use.

[3] DeepFashion2 Code Repo https://github.com/switchablenorms/DeepFashion2

[4] DeepFashion2 https://arxiv.org/abs/1901.07973

[5] U2-Net: Going Deeper with Nested U-Structure for Salient Object Detection Xuebin Qin, Zichen Zhang, Chenyang Huang, Masood Dehghan, Osmar R. Zaiane and Martin Jagersand https://arxiv.org/pdf/2005.09007

[6] U-Net: Convolutional Networks for Biomedical Image Segmentation, Olaf Ronneberger and Philipp Fischer and Thomas Brox, 2015

[7] https://towardsdatascience.com/iou-a-better-detection-evaluation-metric-45a511185be1

APPENDIX

Link to dataset:
https://github.com/switchablenorms/DeepFashion2

Link to code:
https://colab.research.google.com/drive/1RTSKVCX_P94d7NsRcLA5ZYg-14V9qPuU?usp=sharing