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Detection of partially occluded area in face image using U-Net model

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ABSTRACT

Occluded face recognition is important task in computer vision. To complete the occluded face recognition efficiently, first we need to identify the occluded region in face. Identifying the occluded region in face is a challenging task in computer vision. One case of face occlusion is nothing but wearing masks, sunglasses, and scarves. Another case of face occlusion is face is hiding the other objects like books, things, or other faces. In our research, identifying the occluded area which is corona virus disease of 2019 (COVID-19) masked area in face and generate segmentation map. In semantic segmentation, deep learning-based techniques have demonstrated promising outcomes. We have employed one of the deep learning-based U-Net models to generate a binary segmentation map on masked region of a human face. It achieves reliable performance and reducing network complexity. We train our model on MaskedFace-CelebA dataset and accuracy is 97.7%. Results from experiments demonstrate that, in comparison to the most advanced semantic segmentation models, our approach achieves a promising compromise between segmentation accuracy and computing efficiency.

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1. INTRODUCTION

When it comes to detecting occluded areas in face images, deep learning-based techniques have shown excellent results. The COVID-19 masked area in facial images is the occluded area in our research. Nowadays masks are used for different purposes such as COVID-19 pandemic widespread use of face masks to prevent spread of disease, escape from crimes, save our health from pollution. These are the cases to wear face masks. In such cases very difficult to identify faces while wearing masks. Face recognition technology is commonly used to identify people based on their facial features, and studies have shown that it performs extremely well. Many real time applications based on face recognition system such as face authentication-based payment systems, face access control failed to effectively recognize the masked faces.

In our research, main objective is to identify occluded area in face images which is first step in occluded face recognition. Occluded face recognition is challenging task in computer vision. This research topic comes under computer vision which is the subarea of artificial intelligence. Computer vision is used to interpret and understand visual world. To train our model using deep learning-based computer vision technique called segmentation technique which is U-Net semantic segmentation model. By dividing the images into semantically significant objects, semantic segmentation aims to interpret the images. It can be used extensively in a variety of applications such as medical image analysis, agriculture, and remote sensing images. The main aim of this research is to detect occluded area in face image using U-Net segmentation model. Segmentation is the process of categorizing an image at the pixel level in order to identify the precise area of occlusion. When one object hides a portion of another, this is known as occlusion in an image. Some of the occluded face images as shown in Figure 1.

Figure 1. Occluded face images

Figure 1 shows the face images contains face with objects such as mask, sunglass, beard, and scarf. When occurred these occluded face images in face recognition, very difficult to identify faces. In such cases need to remove occlusion and identify faces in face recognition technology. For that purpose, first we need to identify occluded area in faces and then remove occlusion in face images using deep learning-based models. In our research focus on occluded area which is COVID-19 masked area detection in face images using segmentation model called U-Net.

Semantic segmentation task challenging owning to detect objects in images. Several studies extract the meaningful information from the images using segmentation task. According to Pan *et al.* [1], the EG-TransUNet technique can significantly enhance the segmentation quality of biological pictures by concurrently implementing the perdekamp emotional method (PEM), the feature fusion module based on semantic guided attention, and the channel spatial attention (CSA_1) module into U-Net. On two well-known colonoscopy datasets (CVC-ClinicDB and Vasir-SEG) by attaining 95.44 and 95.26% on mDice, respectively. A better U-Net that achieves higher performance with less capacity by using a sparsely linked block with multiscale filters [2]. A sinkhole dataset was manually gathered from various sources, considered, then automatically marked with the suggested autoencoder, which shortened the time used for annotation while creating accurate masks, in order to evaluate our approach. The performance and dependability of the model were then further assessed using a benchmark nuclei dataset 94% of the time. Research by Dong *et al.* [3] to tackle the scale variance issue and improve the segmentation outcomes, an superpixel segmentation pooling (SSP) layer is integrated into the enhanced lightweight end-to-end semantic segmentation (ELES2) architecture to accomplish end-to-end efficient semantic segmentation of high-resolution remote sensing (HRRS) images. ELES2 can retain great computing efficiency while achieving promising segmentation accuracy. With just 12.62 M1 parameters and 13.09 floating-point operations per second (FLOPs), ion ELES2 obtains mIoU of 80.16 and 73.20% on the IPSRS Potsdam and Vaihingen_1 dataset, respectively. According to Gao *et al.* [4], a unique Swin-Unet network to enhance multi-scale lesion segmentation precision in COVID-19 CT scans. Research by Chen *et al.* [5] to improve the segmentation quality of biological pictures, a new transformer-based attention-directed U-Net called TransAttUnet simultaneously integrates multi-level guided attention and multi-scale skip connections into U-Net. Zuo *et al.* [6] suggests in order to accurately segment crop seedlings in their natural habitat and accomplish autonomous assessment of seedling location and phenotype. Gite *et al.* [7] use U-Net architecture used in lung segmentation using x-ray. Half-UNet, TransUNet, DS-TransUNet dual swin transformer [8]–[11] used for medical image processing. Research by Shelhamer *et al.* [12] fully convolutional network (FCN) on semantic segmentation and scene parsing, exploring PASCAL visual object classes (VOC)1, NYU-Depth v2 dataset (NYUDv2), and scale-invariant feature transform (SIFT) flow. Despite the fact that these activities have traditionally made a distinction between areas and objects. Research by Li *et al.* [13] to parallelize the semantic segmentation of target detection, a fast instance segmentation method based on metric learning is suggested for both log end face detection and semantic segmentation. Literate survey on different image segmentation techniques [14]–[19]. Object detection of aerial images, face detection and segmentation, detection of grape clusters using mask region-based convolutional neural networks (R-CNN) [20]–[23]. The Deeplabv3+ model's architecture with attention mechanisms for segmenting ocular images [24]. Different evaluations metrics used for semantic segmentation techniques [25].

The inference from literature review is that semantic segmentation is used in many different real-time applications such as medical image segmentation, agriculture, object detection in aerial images, and face detection. By inspiring existing work, we apply this semantic technique to occlusion area detection in face images which is masked area in face image. The main significant of this research work is to guide to remove the occlusion in face images and recognizes the faces in real-time. Without identifying occlusion in face images very difficult to remove occlusion.

The majority of existing approaches have focused on enhancing the network capacity to enhance the model's functionality. This will result in significant disadvantages: i) it makes there more layers, ii) it increases the likelihood of overfitting in the neural network, and iii) more training samples are needed. Summary of our primary contributions as follows:

- A U-Net Model that effectively identify the occluded area in the face images in-terms of the binary segmentation mask. The main advantage of this model is to identify occluded area in limited data sources.
- Providing a comprehensive review of the performance of segmentation models.
- The superiority and generalizability of the suggested U-Net for automatic occluded area segmentation are demonstrated by extensive experimental findings on datasets of occluded face images.
- Conducting a comparative study of three state-of-the-art (SOTA) segmentation models, namely FCN, DeepLabv3+, and Pyramid scene parsing network (PSPNET).

2. METHOD

In this section, in order to detect the occluded area in face images-in this case, the masked area in faces-we describe our novel network architecture. Mask covered by nose, mouth, chin areas. Detecting occluded area in face image is challenging task in computer vision. This is very important tasks for occlusion removal. The goal of our research is to generate a binary segmentation map of the masked object in the face image input.

2.1. Understanding the U-Net basic architecture

U-Net is a deep learning-based computer vision framework. U-Net architecture is look like a U-shaped architecture. The main purpose of U-Net architecture is used to segments images accurately. There are contracting and extending paths in the U-Net design. The contracting path consists of encoder layers. This encoder layers receives contextual information and decrease the spatial resolution of the input. The expanding path includes decoder layers that decoded the already encoded data and use the information from the contracting path via skip connections to generate the binary segmentation map. Finding the appropriate features in the input image is the primary goal of the contracting path. The contracting path is same as the convolutional neural network. The operation of convolutional neural network is to convolutional operation followed by rectified linear unit (ReLU). Every block comprises of two consecutive 3×3 convolutional layers, succeeded by an activation function of ReLU. Following the convolution operation, max pooling 2×2 operations with stride 2 is used. The next convolutional layer doubles the number of filters employed after each max pooling step. A layer that begins with 64 feature channels, for instance, will have 128 channels following the subsequent pooling and convolution processes. On the other hand, expansive path which takes the extracted input features and generate segmentation mask. Each block is followed by up sampling layer. The decoder layers in the expansive path upsampling the feature maps. The decoder layers can detect the features more precisely by using the skip connections from the contracting path to the expansive path, which helps to preserve lost spatial information.

Figure 2 illustrates how the U-Net network converts a gray scale input image of size 572×572×1 into a binary segmented output map of size 388×388×2. Since no padding has been used, the output size is smaller than the input size, which can be observed. We have to keep the input size the same if we can use the padding. The input image rapidly decreases width and height as the number of channels grows along the contracting path. If more channels exist, the network may gather higher-level data. A last convolution operation at the bottleneck produces a feature map with 30×30×1024 pixels. After removing the feature map from the bottleneck, the expansive path resizes it to fit the initial input size upsampling layers, which decrease the number of channels in the feature map while improving its spatial resolution, are used to achieve this. The decoder layers use the skip connections from the contraction path to locate and refine the image's features. In the end, each pixel in the output image corresponds to a label in the input image that is connected to a particular object or class. Each pixel in this output map shows either the background or the foreground because it is a binary segmentation map. Basic steps in proposed methodology:

- The input image is delivered to the contracting path, which seeks to capture relevant details about the input image while reducing the spatial dimensions of the image.
- After extracting complex characteristics and patterns, the feature map proceeds to the expanding path.

– The expanding path upsamples the input feature map and combines learned features using both convolution and up-convolution processes to produce a segmentation map.
– Skip connections are used to double the feature channels and concatenate the relevant feature map from the contracting path.
– Each pixel in the feature map should be classified separately in a segmentation map that is produced after upsampling it in the expanding path.

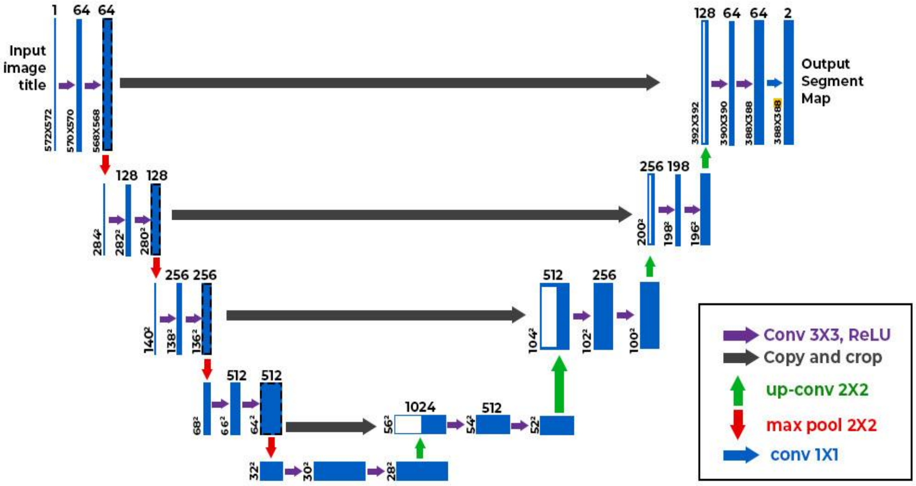


Figure 2. Proposed system architecture

3. RESULTS AND DISCUSSION

In this section, we present the experimental setup and outcomes of our method. We begin by describing the dataset used for training and evaluation purposes. The training process is then described, together with the particulars and configurations that were used. We develop appropriate evaluation metrics and apply them to our network to evaluate its performance. Carried out a few tests to evaluate our suggested model against SOTA techniques.

3.1. Dataset

The MaskedFace-CelebA dataset is available to the public. This dataset is constructed from CelebA dataset using the MaskTheFace tool. This dataset is used in the field of computer vision, especially for face analysis tasks. We assess the models mentioned previously using the masked-face datasets. This dataset contains 21,844 masked face images and corresponding target or ground truth images on occluded area. Images of size are 256×256 pixels. These images are randomly divided into 17,476 (80%) images for training, 2,184 (10%) images for validation, and 2,184 (10%) images for testing from the MaskedFace-CelebA dataset.

3.2. Evaluation metric

In our experiment, we use accuracy as the main parameter to determine how closely the predicted mask and ground truth match. This metric is associated with four values i.e., true-positive (TP), true-negative (TN), false-positive (FP), and false-negative (FN). The formula for accuracy is shown in (1).

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \quad (1)$$

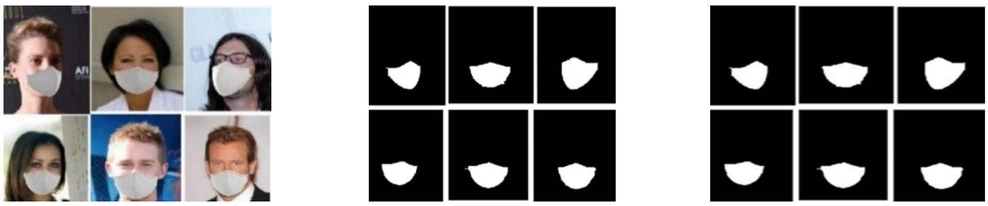
The number of occluded area pixels, or masked area pixels that have been correctly identified, is represented by TP. The number of background pixels that are incorrectly classified as background is known as FP. The number of occluded area pixels that are incorrectly classified as background is known as FP. The number of background pixels that are correctly classified as background is known as TN.

3.3. Experimental settings

The network is trained using the input images and the segmentation maps that correspond to them. All the experiments are implemented with Tensorflow which is Python framework. An 8-core 32G+1 V100 GPU PC and a 3.8 GHz CPU are used in the experiment to train the network. Adam is employed as an optimizer to adjust the occluded face image segmentation network's parameters. This work employed the following super parameters: batch size of 16, image resolution of 256, epochs of 100, and starting learning rate η of 0.05. In this manuscript, 100 was utilized for epochs, which are the number of experimental training rounds. The images used for experimental training and testing were converted into 256×256 resolution. Batch_Size is the number of samples selected for one training.

3.4. Experimental results

To evaluate the efficacy of the proposed U-Net we first conduct the experiments on the MaskedFace-CelebA dataset for the task of masked area segmentation. The results of our proposed model as shown in Figure 3. The image as shown in Figure 3(a) is the masked face image which is input to our proposed model. The image as shown in Figure 3(b) is the mask which is the ground truth label. This is what our model must predicted for the given masked face image. The image as shown in Figure 3(c) predicted occluded region. The white region denotes the masked area which is occlude area and the black region denotes the no occluded area. Notice that if the mask is entirely black this means there are no occluded area deposits in the given masked face image.



(a) (b) (c)

Figure 3. Experimental result for U-Net model on MaskedFace-CelebA dataset of (a) the original occludes face image, (b) ground truth, and (c) predicted occluded area

3.5. Comparative study

We have contrasted the obtained experimental results with those of other semantic segmentation approaches in order to assess the effectiveness of our suggested method further. The Table 1 shows the comparative analysis of various existing semantic segmentation models. This comparative analysis says that superiority of our proposed model for detection of occluded region in human face images. We noticed that our model performs 97.7% accuracy with other three methods as shown in Table 1. From the comparative study as shown in Figure 4, it is observed that proposed system provides appreciable accuracy of 97.7%. It outperforms compared to existing image segmentation algorithms.

Table 1. Comparative analysis of various image segmentation techniques

S. no	Method	Accuracy (%)
1	FCN [12]	90.3
	DeepLabv3+ [24]	93.4
3	PSPNet [25]	94.2
4	The proposed model	97.7

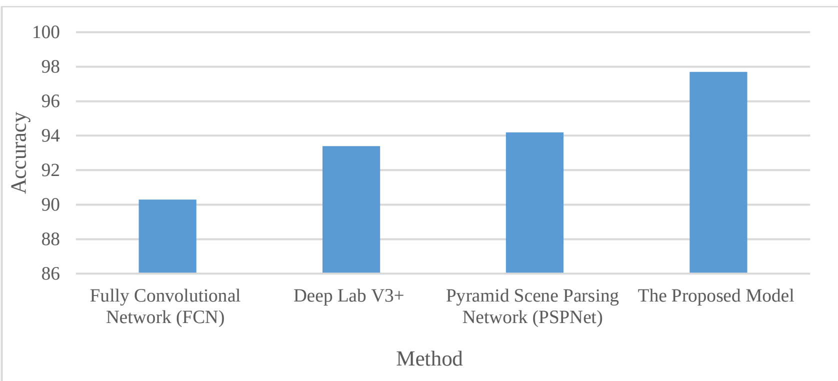


Figure 4. Graphical representation of comparative study between proposed system and existing system approaches with reference to accuracy

3.6. Ablation study

Role of using skip connections: we investigate the effectiveness of using skip connections. Assume that a U-Net without skip connections would produce a blurry mess. If you would be interested, it could be interesting to try disabling the skip connection and see what happens. By gradually adding more features to a convolutions-based vision model, they transform it from an unstable and inaccurate model into a SOTA one. By avoiding the bottleneck and giving the model access to the encoder's intermediate activations-which include these fine-grained, high-resolution details-skip connections help solve this issue. That is what is meant by recover fine grained details in the prediction.

4. CONCLUSION AND FUTURE WORK

This paper proposed a novel method for binary segmentation map on occluded area detection in face images called U-Net model. This proposed model is improved version of fully convolutional network. The experimental results show that our model efficiently segmenting occluded area in human face image, in our case occluded area is masked area. Despite the promising results on dataset. Experiments on publicly available dataset which is MaskedFace-CelebA dataset shows 97.7% segmentation accuracy. It produces high perpetual quality results compared to other SOTA image segmentation methods. The main advantage of our model has fewer parameters, limited dataset and faster in speed. This work is useful for masked face recognition in real-time. There are promising areas for further study and advancements in face mask identification, such as improving our model's performance in difficult situations like high occlusion or complex mask patterns. Enhancing the dataset for different sizes of masks and shapes. We also think that merging with facial recognition research has a lot of potential. We can increase the precision and dependability of facial recognition systems by eliminating masks as a preprocessing step.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available at https://drive.google.com/drive/folders/1EJbxfgTVHDBNvfe7KzESwJoWc8e4J2HJ?usp=share_link.

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