Gender Recognizer based on Human Face using CNN and Bottleneck Transformer Encoder

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2023 International Workshop on Intelligent Systems (IWIS) | 979-8-3503-0504-3/23/$31.00 ©2023 IEEE | DOI: 10.1109/IWIS58789.2023.10284684

***Abstract*—Several applications, such as Human-Robot interactions and offline advertising platforms, perform gender recognition based on a human face to profile their audience. These applications demand gender recognition that can operate in real-time on a low-cost or CPU device. This work proposes a gender recognizer based on a human face using a Convolutional Neural Network (CNN) and Bottleneck Transformer Encoder (BTE) that renders low parameters and operation. BTE is offered to support the primary CNN feature extractor in learning the global representation of the feature maps efficiently. This work uses three face gender datasets benchmark, namely UTKFace, Labeled Faces in the Wild (LFW), and Adience, to train and validate the proposed network. The CNN network consisted of the BTE achieves competitive accuracy compared to the state-of-the-art network. The recognizer can operate in real-time on a CPU with 150 frames per second.**

***Index Terms*—Bottleneck Transformer, Convolutional Neural Network (CNN), Efficient Architecture, Gender Recognition, Self-Attention**

I. Introduction

As a unique soft biometric property, gender is an essential part that can be used in profiling users. Several applications utilize gender by recognizing it based on a human face to support their purpose [1]. In Human-Robot interactions [2], [3], robots can use gender property to characterize their interlocutors to personalize and make conversations more pleasant. Foggia et al. [2] demonstrated that people prefer conversations with robots that can personalize their interlocutors according to gender by using appropriate pronouns and honorifics. In advertising applications such as digital signage, gender recognition is used as a basis to provide relevant advertising content in real-time [4]. This technology can analyze the gender of individuals facing the platform and adapting the displayed advertisements accordingly. By tailoring relevant advertising messages to the audience, businesses can enhance the effectiveness of their marketing efforts and provide a more personalized experience to potential customers.

Gender recognition through a human face is initiated by detecting the audience's face via a camera and then classifying it to the gender class. In robotics or digital signage applications utilizing a low-cost device, there is a need for the gender recognition operation to function effectively in real time when individuals are facing it. Therefore, an efficient gender recognition mechanism with low computation is required. Hence, robotics or digital signage platform that uses a low-cost device, or at least a CPU device, can operate it properly.

Convolutional Neural Networks (CNNs) have recently demonstrated substantial effectiveness in recognition tasks [5]. To construct a recognition system, particularly for gender recognition based on human faces, many researchers have created various CNN designs. Savchenko [6] proposed a CNN architecture modified from MobileNet to predict facial gender, gaining 91.95% based on accuracy on the UTKFace [7] dataset. HyperFace-ResNet [8], improved ResNet-101 [9] architecture by fusing the lower and deeper layers using an element-wise addition operation, is offered to predict facial gender. This presented architecture gained 94% based on accuracy on the LFW [10] datasets. Greco et al. [4] applied MobileNetV2 architecture to develop a gender recognizer system that supports a digital signage platform. Other works [11]–[13] designed more efficient CNN architectures for gender recognition based on human face generating fewer parameters and achieved great accuracy on Adience [14], UTKFace [7], and LFW [10] datasets. These architectures can perform fast in a CPU device. Employing CNN architecture with fewer parameters will improve efficiency and lead the recognizer to operate more quickly, especially on low-cost or CPU devices.

Considering the efficiency and computation, a lightweight

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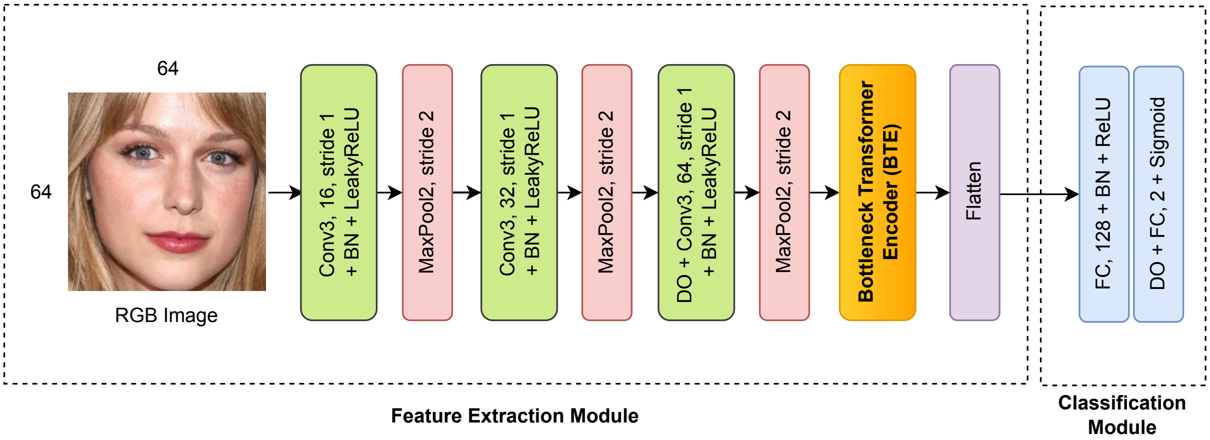
64
64
RGB Image
Conv3, 16, stride 1 + BN + LeakyReLU
MaxPool2, stride 2
Conv3, 32, stride 1 + BN + LeakyReLU
MaxPool2, stride 2
DO + Conv3, 64, stride 1 + BN + LeakyReLU
MaxPool2, stride 2
Bottleneck Transformer Encoder (BTE)
Flatten
FC, 128 + BN + ReLU
DO + FC, 2 + Sigmoid
Feature Extraction Module
Classification Module

Fig. 1. Overall view of the proposed CNN network with Bottleneck Transformer Encoder (BTE) for facial gender recognition based on human faces.

CNN network is proposed incorporated with Bottleneck Transformer Encoder (BTE) to perform gender recognition based on a human face. This architecture generates a few parameters and low operation, appropriate to implement on a CPU device. In this work, the contribution is outlined as follows:

1) A gender recognition based on a human face with only 555,770 parameters and 24.8 MFLOPs achieves very competitive accuracy and efficiency compared to other networks on three datasets, UTKFace [7], Adience [14], and LFW [10].
2) A Bottleneck Transformer Encoder (BTE) leads the architecture not only able to capture the local representation but also the global representation by efficiently calculating the relationship between each spatial information.
3) The proposed gender recognizer based on a human face can operate in real-time on a CPU with a speed of 131.85 frames per second, outperforming the other gender recognizer based on a human face.

II. Proposed Architecture

The proposed gender recognition architecture has a feature extraction and classification modules shown in Fig. 1. It produces only 555,770 parameters.

A. Feature Extraction Module

The feature extraction module serves as an instrument to grasp facial features from the input face area image, containing three of 3×3 convolution layers with a growing number of channels from 16 to 64. This mechanism is designed to capture additional details from the higher-level facial image features. This module utilizes Batch Normalization (BN) as well as Leaky Rectified Linear Unit (LeakyReLU) activation in each convolutional layer to address gradient-related issues [15]. Before the final convolutional layer, a dropout (DO) operation [16] is applied to mitigate the risk of overfitting. After each convolutional layer, a downsampling mechanism is employed, consisting of three times 2×2 max-pooling operations with a stride of two. Involving several convolution layers captures only the local representation of the facial feature. Therefore, we propose a Bottleneck Transformer Encoder (BTE) to grasp the global representation of the feature maps. In this architecture, BTE is positioned following the final max-pooling operation and just before the flattening operation.

B. Bottleneck Transformer Encoder (BTE)

Modern networks concentrate on improving the self-attention mechanism oriented to the success of the Vision Transformer (ViT) [17] technique. However, it brings high operations (multiplication and addition), leading to inadequate implementation for vision tasks on low-cost devices. This work proposes a Bottleneck Transformer Encoder (BTE) to alleviate the mentioned above problem. Similar to the general Transformer Encoder, this function will transform a tensor input $\mathbf{X}$ of shape $H \times W \times C$ into a query ($\mathbf{Q}$), key ($\mathbf{K}$), and value ($\mathbf{V}$) by applying a 1×1 convolution operation with Rectified Linear Unit (ReLU). However, a reduction channel r and multi-head mechanism with $NumHead$ are applied in this work to produce a slimmer tensor $H \times W \times ((\frac{C}{NumHead})/r)$, followed by reshaping operation to produce a $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$ matrix with shape $HW \times ((\frac{C}{NumHead})/r)$. After that, we compute these matrices using scaled dot-product attention shown in Fig. 2, which is described as follows:

$$SDPA\left(\mathbf{Q},\mathbf{K},\mathbf{V}\right) = softmax\left(\frac{\mathbf{QK}^T}{\sqrt{d_k}}\right)\mathbf{V}, \qquad (1)$$

where d_k is a scaling factor to control the softmax temperature and T is a transpose matrix operation. To reform the output matrix shape into $H \times W \times ((\frac{C}{NumHead})/r)$, the reshaping operation is also performed. Then, a concatenation operation is used to merge all output from all heads, followed by 1×1 convolution operation with a dropout (DO) and Rectified Linear Unit (ReLU) activation layers to restore the number of channels according to the input tensor $\mathbf{X}$ with shape $H \times W \times C$ that represents a bottleneck mechanism. Once again, a linear projection using 1×1 convolution operation

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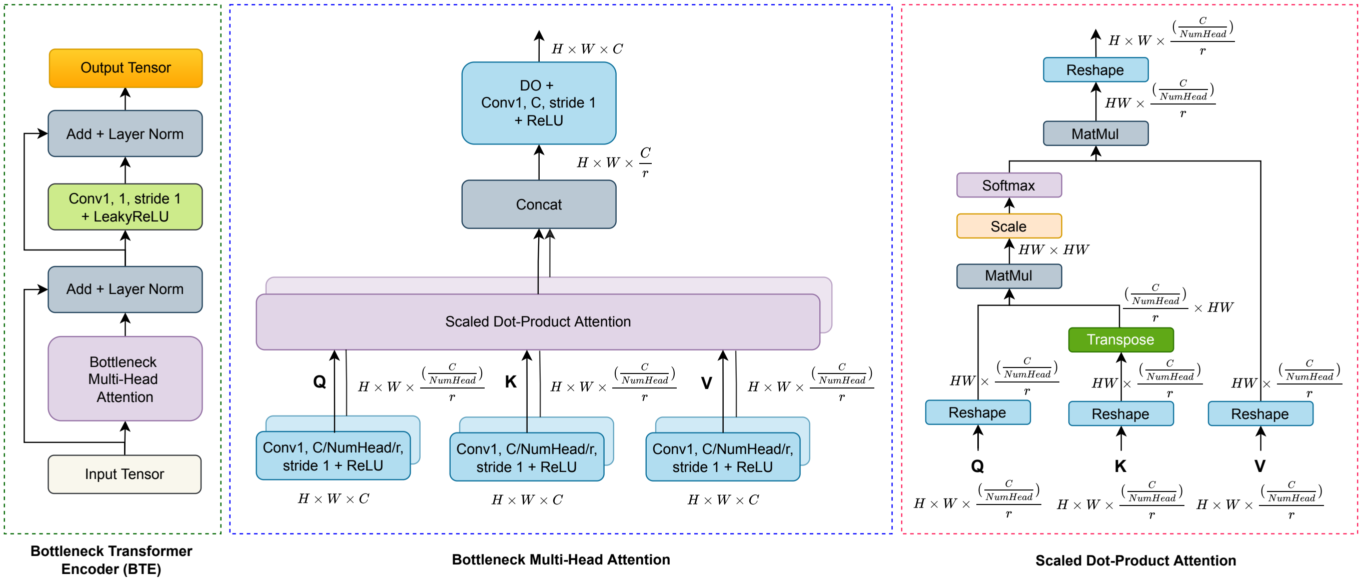
Output Tensor
Add + Layer Norm
Conv1, 1, stride 1 + LeakyReLU
Add + Layer Norm
Bottleneck Multi-Head Attention
Input Tensor
$H \times W \times C$
DO + Conv1, C, stride 1 + ReLU
$H \times W \times \frac{C}{r}$
Concat
Scaled Dot-Product Attention
Q
K
V
$H \times W \times \frac{(\frac{C}{NumHead})}{r}$
Conv1, C/NumHead/r, stride 1 + ReLU
$H \times W \times C$
Reshape
$HW \times \frac{(\frac{C}{NumHead})}{r}$
MatMul
Softmax
Scale
$HW \times HW$
Transpose
$\frac{(\frac{C}{NumHead})}{r} \times HW$

Bottleneck Transformer Encoder (BTE)

Bottleneck Multi-Head Attention

Scaled Dot-Product Attention

Fig. 2. The proposed Bottleneck Transformer Encoder (BTE).

with a LeakyReLU activation is performed, integrating with a residual connection [9] and Layer Normalization (LN) [18] around the multi-head attention and last convolution layer.

C. Classification Module

The second phase of the gender recognition architecture proposed here involves a classification module comprising two fully connected (FC) layers, one with 128 units and the other with 2 units. The first FC layer incorporates BN and ReLU (Rectified Linear Unit) activation to mitigate gradient-related challenges. The second FC layer employs a dropout mechanism [16] to prevent overfitting and utilizes Sigmoid activation to produce the input for the final prediction decision. This classification module is utilized to compute the probability associated with each gender class, aiding in the discrimination between male and female based on facial features.

III. Implementation Configuration

In this experiment, UTKFace, LFW, and Adience datasets are used to train the proposed architecture. The training process utilizes an initial learning rate of 10^{-2}, 512 batch size, and 300 epochs. Tensorflow and Keras are used as a framework, while an Nvidia GTX 1080Ti with 11GB of GPU is employed as the accelerator. The Binary Cross-Entropy loss and Adam optimizer are used for the training. To further enhance training, a learning rate reduction strategy is implemented, reducing the rate by 75% when accuracy fails to improve over 20 consecutive epochs. The computational speed of the proposed architecture is assessed on an Intel Core i7-9750H CPU clocked at 2.6 GHz, with 20GB of RAM.

TABLE I
Assessment outcomes on three datasets used in this work.

Networks	**Number of Parameters**	**Accuracy on Validation (%)**
UTKFace		
EfficientNetV2B1 [19]	77,54,679	90.31
VGG16 [20]	138,357,544	91.90
Shahzeb et al. [21]	14,715,201	91.94
Savchenko (Modified MobileNet) [6]	3,491,521	91.95
SufiaNet [12]	226,574	92.05
MPConvNet [11]	659,650	92.32
MudaNet [13]	674,760	92.66
Proposed	**555,770**	**92.78**
LFW		
Rouhsedaghat et al. [22]	16,900	94.63
SufiaNet [12]	226,574	95.66
MudaNet [13]	674,760	96.22
MPConvNet [11]	659,650	96.30
Greco et al. [23]	3,538,984	**98.73**
Proposed	**555,770**	**96.50**
Adience		
SufiaNet [12]	226,574	84.60
MudaNet [13]	674,760	84.85
Saha et al. [24]	3,190,913	84.94
MPConvNet [11]	659,650	85.67
Opu et al. [25]	210,050	85.77
Proposed	**555,770**	**85.86**

IV. Experimental Results

A. Assessment on Datasets for Face Gender Classification

1) UTKFace: There are more than 23,000 facial images on this dataset labeled in gender, age, and ethnicity, covering many variations such as expression, pose, age, illumination, etc. The proposed architecture is trained on 70% of this dataset, while the remains for testing sets. The proposed architecture attains a validation accuracy of 92.78% on this

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TABLE II
MODEL ANALYSIS OF THE PROPOSED MODEL BASED ON UTKFACE.

Settings	Number of Parameters	MFLOPs	Validation Accuracy (%)
The Backbone without BTE	549,218	23.92	92.46
The Backbone with BTE	555,770	24.80	92.78

TABLE III
CHANNEL REDUCTION ANALYSIS OF THE PROPOSED BTE ON UTKFACE DATASET

Value of Reduction r	Number of Parameters	MFLOPs	Validation Accuracy (%)
-	570,274	27.18	92.49
2	561,986	25.72	92.53
4	557,842	25.09	92.57
6	556,288	24.87	92.63
8	**555,770**	**24.80**	**92.78**
10	555,252	24.73	92.60

- indicates that the BTE is performed without channel reduction r

TABLE IV
EFFICIENCY IN TERMS OF RUNTIME ON A CPU SETUP

Networks	Number of Parameters	MFLOPs	GR (FPS)	FD + GR (FPS)
VGG16 with BN	39,782,722	2,290	42.42	36.35
ResNet50V2	23,568,898	571	57.15	46.67
MudaNet [13]	674,760	69	58.57	48.07
MobileNetV2	2,260,546	50	118.56	80.43
SufiaNet [12]	226,574	22	127.50	84.90
MPConvNet [11]	659,650	67	265.07	131.85
Proposed	**555,770**	**25**	**345.69**	**150.49**

GR indicates the Gender Recognition
FD + GR indicates the Gender Recognition integrated with Face Detection

dataset while utilizing only 555,770 parameters. Table I shows that the accuracy surpasses the other State-of-The-Art (SOTA) architectures, which differed by 0.12% from the second-best. The proposed architecture also generates fewer parameters compared to the second-best.

2) LFW: This dataset includes more than 13,000 face images, divided into testing (30%) and training (70%). This dataset has two labels, females and males, with a substantial disparity, with females accounting for 23% and males constituting 77%. Table I describes that the proposed architecture achieves competitive validation accuracy with 96,50% on this dataset. It becomes second-best compared to the other SOTA architectures. However, the proposed architecture generates far fewer parameters.

3) Adience: This dataset comprises over 26,000 facial images annotated with gender and age labels, encompassing a range of variations including age, pose, noise, lighting, appearance, and more. Some pre-processing is established on this dataset in this experiment, such as eradicating data with missing values and generating 17,492 face images. Following the two other datasets mentioned before, this data set is also split into 30% and 70% as a testing and training set, respectively. As a result, the proposed architecture gains a validation accuracy of 85.86%, shown in Table I. This result surpasses the other SOTA architectures, which differed by 0.09% from the second-best.

B. Ablation Study

1) Model Analysis: This analysis is established on the UTKFace dataset to investigate the impact of the proposed BTE on recognition accuracy in this work. Table II reveals that the proposed BTE can improve the validation accuracy by 0.32%. With this increased performance, the proposed BTE only generates 6,552 and 0.88 more additional parameters and MFLOPs, respectively.

2) Channel Reduction Analysis: This work arranges this analysis to examine the optimal channel reduction value on the proposed BTE concerning the recognition performance. Table III shows that using a channel reduction value of one does not enhance performance. The proposed BTE with a channel reduction value of eight produces the highest validation accuracy in this work.

C. Runtime Efficiency

The proposed architecture, with only 555,770 parameters and 24.8 MFLOPs, is principally developed to perform on a CPU device in real-time scenarios. Due to this, the proposed architecture can operate 345.69 FPS for gender recognition and 150.49 FPS when integrated with an efficient face detector, dubbed LWFCPU [26], as shown in Table IV. The proposed gender recognizer based on a human face outperforms the other public and light architecture used in this case. Fig. 3 demonstrates the gender recognition result of the proposed gender recognizer based on a human face on a CPU. The male and female faces are indicated with fuchsia and yellow bounding box, respectively.

D. Limitations

The UTKFace dataset used to train the proposed architecture for the gender recognizer in this work encompasses a range of pose variations. Nevertheless, it lacks face instances with extreme yaw and pitch pose, pushing to inaccurate predictions in certain cases involving faces in extreme yaw and pitch poses, as shown in the last row of Fig. 3. In this case, a female face is recognized as a male face.

V. CONCLUSION

This work proposes a gender recognizer based on a human face. It offers a light CNN as a feature extractor supported by a Bottleneck Transformer Encoder (BTE) to learn the global representation of the feature maps efficiently. This encoder will enhance the feature map quality generated by the feature extractor. The proposed network achieves rivalrous accuracy compared to the SOTA network on three face gender dataset benchmarks (UTKFace, LFW, and Adience). The proposed gender recognizer based on a human face consisting of the proposed gender recognition integrated with a face detector can operate in real-time on the CPU with 150.49 frames per

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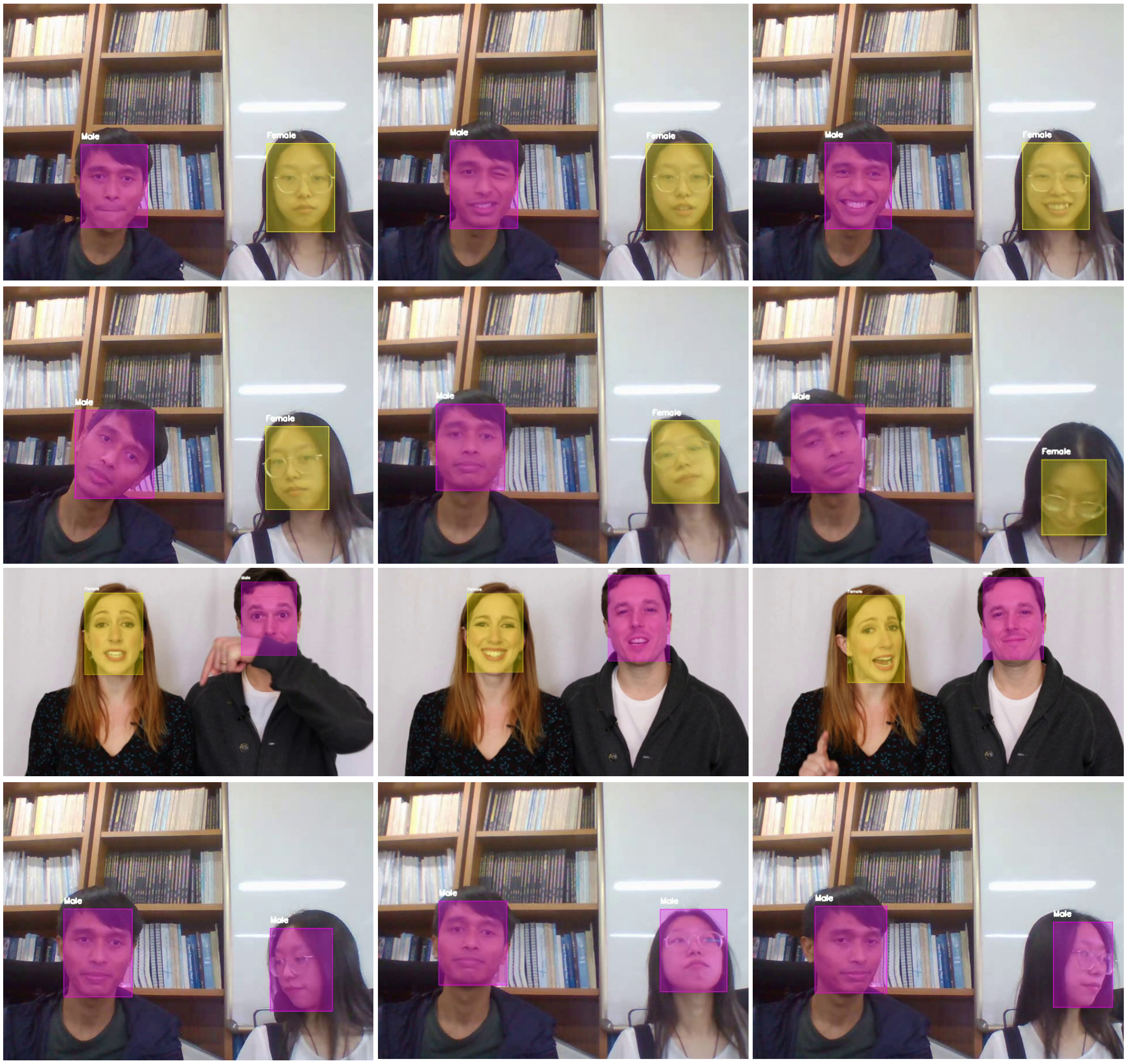

Fig. 3. The accurate recognition outcome (the three first rows) and the inaccurate recognition outcomes (the last row) generated by the proposed gender recognizer based on human faces.

second. In future research, we will investigate alternative approaches to address the limitations identified in this study and to enhance both the accuracy and speed of gender recognition through a human face.

Acknowledgment

This result was supported by ”Regional Innovation Strategy (RIS)” through the National Research Foundation of Korea(NRF) funded by the Ministry of Education(MOE)(2021RIS-003)

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