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# A Unified Learning Approach for Hand Gesture Recognition and Fingertip Detection

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## Abstract

In human-computer interaction or sign language interpretation, recognizing hand gestures and detecting fingertips become ubiquitous in computer vision research. In this paper, a unified approach of convolutional neural network for both hand gesture recognition and fingertip detection is introduced. The proposed algorithm uses a single network to predict the probabilities of finger class and positions of fingertips in one forward propagation of the network. Instead of directly regressing the positions of fingertips from the fully connected layer, the ensemble of the position of fingertips is regressed from the fully convolutional network. Subsequently, the ensemble average is taken to regress the final position of fingertips. Since the whole pipeline uses a single network, it is significantly fast in computation. The proposed method results in remarkably less pixel error as compared to that in the direct regression approach and it outperforms the existing fingertip detection approaches including the Heatmap-based framework.

*Keywords:* Convolutional neural network, Fingertip detection, Gesture recognition, Human-computer interaction, Unified detection

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## 1. Introduction

In human-computer interaction (HCI), hand plays an instrumental role as a medium of interaction [1, 2, 3, 4]. The gesture of a hand and the location of its fingertips are essential information for a computer to understand the state of the interaction medium. Recognizing hand gestures is equally important to interpret sign language [5, 6, 7, 8, 9]. Moreover, in virtual reality (VR) and mixed reality (MR) environments, the recognition of hand gestures, and detection of fingertips are essential to interact with the virtual environment [10, 11, 12, 13, 14]. Existing hand gesture recognition and fingertip detection approaches can be broadly classified into two categories - image processing and deep learning-based approaches. The image processing approach relies mostly

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on the background segmentation, and the shape and color of hand [15, 16, 17, 18, 19]. Due to these dependencies, these methods often tend to fail in the presence of complex background, illumination effects, and in the variation of size and color of a person. On the contrary, the deep learning approach works much better in these scenarios due to its significant level of learning capability [20, 21, 22, 23, 24]. Since a given hand gesture has a given number of visible fingertips, traditional direct regression-based deep learning algorithms need to recognize hand gestures first, and afterward, they use corresponding trained fingertip detection model to detect the position of the fingertips. The problem arises since the number of visible fingers in a gesture can be variable but the number of outputs of a convolutional neural network (CNN) must be fixed. Therefore, these algorithms require to train different fingertip detection models for different hand gestures. In this paper, we address this issue by proposing a unified approach to predict both the probabilistic output of the gesture of fingers and the positional output of all the fingertips using one forward propagation of a single network. In the probabilistic output of gesture, the high probability indicates the existence of a visible finger while the low probability indicates the hidden finger. In general, the visible and hidden fingers are represented as ‘1’ and ‘0’, respectively. Hence, each gesture of hand can be recognized by the unique sequence of binary numbers by taking into account the probabilistic information of the fingers. Moreover, the proposed method estimates the coordinate position of fingertips by averaging the regressed ensemble of fingertip coordinates using a fully convolutional network (FCN), instead of using conventional direct regression using a fully connected (FC) layer. Thus, the estimation of the probability of fingers in a gesture and their relative sequence, and accurate positional information of fingertips make the overall hand gesture recognition and fingertip detection algorithm highly robust and reliable. Also, it is less likely to predict false positive and false negative as compared to the existing direct regression [25] and Heatmap-based [26] frameworks. In particular, the proposed detection method results in significantly less pixel error as compared to the direct regression approach where pixel coordinates are directly regressed from an FC layer of a learning model. Besides, the proposed approach provides less localization error when comparing with the Heatmap-based framework. In the following subsections, a literature review of previous works is presented and then the scope of analysis is given. Finally, specific contributions made in this paper are listed.

### 1.1. Related Works

Related works can be categorized into three different groups. The first group of works is concerned about gesture recognition. The second group of works is concerned with the detection of fingertips and the third one deals with both of the gesture recognition and fingertip detection. The works on these groups are discussed in the following subsections.

#### 1.1.1. Gesture Recognition

Hand gestures are mainly different combinations of fingers producing different shapes of a hand. Thus, the primary focus of gesture recognition methods that use image processing is shape matching or measuring dissimilarity among hand shapes. For instance, Ren *et al.* [27] presented a part-based gesture recognition system that uses dissimilarity measure and template matching for an HCI application of arithmetic computation by gesture command. Similarly, Alon *et al.* [28] use spatiotemporal matching and pruning classifier for gesture learning to recognize the American

sign language (ASL). In [8], the ASL is retrieved by applying a transfer learning algorithm for gesture recognition in GoogleNet architecture. Ravikiran *et al.* [29] employ edge detection, clipping, boundary tracing, and fingertip detection for ASL recognition. Discriminative 2D Zernike moments are also used for the recognition of static hand gestures of the ASL [30]. In [3], CNN is used for hand gesture recognition in an HCI system, wherein the gesture is utilized to trigger mouse and keyboard events and to control a simulated robot. Lin *et al.* [31] proposed that the background of a hand can be segmented first by using the Gaussian mixture model (GMM) and then the binarized image can be feed to a CNN classifier for learning instead of directly using the captured RGB image for hand gesture recognition. Different architectures of CNN such as those in [23] and [32] are applied for hand gesture recognition. Koller *et al.* [23] embedded a CNN within an iterative expectation-maximization (EM) algorithm for the classification of hand shapes particularly in the case of continuous and weakly labeled data. Nunez *et al.* [33] reported a method that combines the CNN and the long short term memory (LSTM) network for skeleton-based temporal 3D hand gesture recognition.

### 1.1.2. Fingertip Detection

Image processing-based fingertip detection algorithms generally use background segmentation, contour analysis, and convex envelope techniques. Such a system is presented by Nguyen *et al.* [34] where they first use a CNN-based hand detector, and then apply thresholding for hand segmentation in the detected region, and finally use the convex hull technique for fingertip detection. Deep learning-based fingertip detection mostly uses direct regression to predict the coordinate position of fingertips from the final FC layer of the CNN. However, Alamsyah *et al.* [35] use an object detection algorithm by employing the region-based CNN (R-CNN) for predicting fingertips with an assumption that each fingertip is a class independent object. Huang *et al.* [20] report a two-stage cascaded CNN-based direct regression for joint detection of fingertip and finger for a given hand gesture in egocentric vision. Similarly, Liu *et al.* [24] use a bi-level cascaded CNN for detection of fingertips in a predetermined gesture in the egocentric videos. In the same vein, Huang *et al.* [21] use two-stage CNN to detect fingertips from a hand image for an application of air writing wherein a fingertip acts like a pen. Jain *et al.* [22] report the detection of only the index fingertip using a direct regression approach for an MR application in which the fingertip functions as a gestural interface for smart-phones or head-mounted devices. Wetzler *et al.* [36] mainly focus on CNN-based fingertip detection using a Kinect camera. This method uses a computationally extensive global orientation regression approach and an in-plane derotation scheme of depth images to predict the coordinate of fingertips.

### 1.1.3. Gesture Recognition and Fingertip Detection

An algorithm that detects a variable number of visible fingertips in a gesture implicitly recognizes the gesture too. For example, Prakash *et al.* [37] use a convex hull-based algorithm for detecting a variable number of visible fingertips, and hence, recognizing gesture concurrently for an HCI application. In contrast, Lai *et al.* [38] use two-step method for gesture recognition. First, fingertips are detected using discrete curve evolution and then the gesture is recognized by partitioning the evolved curves detected from fingertips. Similarly, Meng *et al.* [39] approximates the contours and convexity defect to find the coordinate positions of fingertips and then the gesture is

recognized by using features such as the number of fingers, the Hu moments of a region bounded by the contour, and the compactness and the convexity of detected contour. Lee *et al.* [40] estimates the scale-invariant angle between the fingers to determine the different number of visible fingertips. Afterward, fingertip gestures are recognized using a contour analysis of the fingers. Nguyen *et al.* [41] use a deep learning-based approach where a modified multi-task segmentation network is employed for both segmentation of hand and detection of a variable number of fingertips. Wu *et al.* [26] represent the pixels of each fingertip as samples of 2D Gaussian distribution in the output tensor of Heatmap-based FCN. By applying a suitable threshold, only the visible fingertips are detected that determines the gesture at the same time.

### 1.2. Scope of Analysis

Existing literature on gesture recognition and fingertip detection uses both image processing and deep learning-based approaches to confront the challenges. However, the image processing-based approaches have the dependency on background, hand shape and color thus tend to fail in complex and diverse scenarios. Moreover, the approaches that use the convex hull technique for gesture recognition and fingertip detection [39, 34, 37] have their instinctive disadvantage. For instance, although they can recognize the gesture and detect fingertips, they cannot classify fingers and thus cannot apprise which fingertips have been detected. Consequently, we argue that deep learning-based detection will be more robust in diverse environments and finger classification. Nevertheless, deep learning-based direct regression approaches [20, 21, 24] directly regress the fingertips in a predetermined gesture. So, there remains a scope of work in identifying hand gestures and finding fingertips concurrently. The direct regression approaches are simple, easy to implement, and requires no post-processing. However, the CNN-based standard direct regression approach makes more pixel error compared to the Heatmap-based methods. So, it is worthwhile to figure out a new way of direct regression approach that will result in less pixel error than the Heatmap-based solution with a slightly increased post-processing cost. Besides, Heatmap- [26] and segmentation network-based [41] approaches use a higher-order (3<sup>rd</sup>) tensor representation which possesses complexity during post-processing. Hence, a unified gesture recognition and fingertip detection algorithm with a lower order (1<sup>st</sup> and 2<sup>nd</sup>) tensor representation will reduce the post-processing complexity. Therefore, based on the motivations stated above, the development of CNN-based unified gesture recognition and fingertip detection algorithm is worth investigating.

### 1.3. Specific Contributions

In this paper, a CNN-based unified gesture recognition and fingertip detection algorithm is proposed for many potential applications in HCI. The specific contributions of the paper are as follows:

- A unified gesture recognition and fingertip detection algorithm using a lower order representation with a lower level of post-processing complexity is proposed
- A new direct regression approach is introduced where an ensemble of fingertips position is directly regressed from FCN and later ensemble average is taken for the final position of fingertips

- A higher level of accuracy in classification and a lower level of localization error in regression as compared to the well known direct regression and Heatmap-based framework is achieved through experimentations

The rest of the paper is organized in the following order. In Section 2, the proposed method is presented in detail. Section 3 includes the experiments and results along with a comparison with the existing methods. Section 4 shows the performance of the algorithm in the real-life images. Finally, Section 5 provides a conclusive remark.

## 2. Proposed Method

The proposed method is a CNN-based unified gesture recognition and fingertip detection algorithm that combines the classification of gestures and regression of fingertips together. Using a single CNN both the probabilistic output for each of the fingers is predicted and the positional output of fingertips is regressed in one forward propagation of the network. In the following subsections, first, the unified detection algorithm is proposed, then CNN architecture for implementing the algorithm is explained and finally, the training and optimization of the network is described.

### 2.1. Unified Detection

We unify the classification and regression into a single CNN using a lower-order binary representation. Hand gestures are the combination of different visible fingers where the total number of fingers in hand  $N$  ( $N = 5$ ) is fixed. However, in a specific gesture, the number of visible fingers  $l$  ( $l \in 0, 1, 2, \dots, N$ ) is variable. Thus, for a specific gesture to locate the fingertips, the number of  $x$ -, and  $y$ -coordinates to be regressed from a CNN is  $2l$ . As the number of outputs of a CNN must be fixed and  $l$  is variable here, we have addressed this issue by predicting the probabilistic output of length  $N$  and regressing the positional output of length  $2N$  from a single CNN. The probabilistic output is the binary representation of each finger, where ‘1’ corresponds to the visible finger, and ‘0’ corresponds to the finger being hidden. Consequently, each gesture will generate a unique sequence of binary numbers and from this sequence, the gesture can be recognized. Concurrently, as the binary sequence represents the visibility of fingers in a gesture, the positional output of fingertips of the hidden finger can be set as *don’t care* and ignored. Suppose, the probabilistic output of the CNN of length  $N$  is  $(p_1, p_2, \dots, p_N)$  and the positional coordinate output of the CNN of length  $2N$  is  $((x_1, y_1), (x_2, y_2), \dots, (x_N, y_N))$  then the final output will be  $(p_1 \times (x_1, y_1), p_2 \times (x_2, y_2), \dots, p_N \times (x_N, y_N))$ . From the final output, any  $(0, 0)$  coordinate will be considered as a hidden finger and ignored. If  $(0, 0)$  coordinate is considered as probable fingertip positional output, the probabilistic output can be further processed as  $(2p_n - 1)$  where  $n$  ( $n \in 1, 2, \dots, N$ ) to change the output range from  $(0, 1)$  to  $(-1, 1)$ , and then only negative coordinates will be ignored.

Fig. 1 shows two example images of hand gestures wherein Example-1 only thumb, index, and pinky fingers are visible and the middle and the ring fingers are hidden. So, the ground truth (GT) probabilistic binary output sequence for Example-1 will be  $[1 \ 1 \ 0 \ 0 \ 1]$ . Likewise, for Example-2 the GT probabilistic binary output sequence will be  $[0 \ 1 \ 1 \ 1 \ 1]$ . These are not only unique

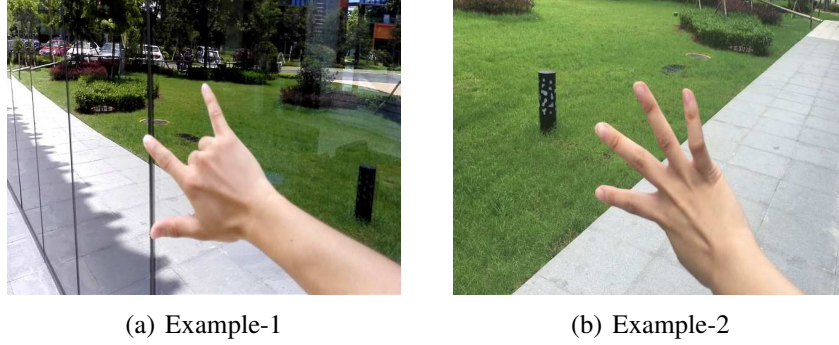


Figure 1: Illustrative images of the two different hand gestures are shown in (a) and (b).

sequences for specific gestures but also apprise the visibility of the finger in a particular gesture which helps to determine which fingertip coordinates to ignore from the positional coordinates output of the CNN.

During prediction, the probabilistic output will predict the visibility of fingers in a gesture. For a visible finger, it will give a higher confidence value and for a hidden finger, it will give a lower confidence value. So, a confidence threshold  $\tau$  ( $0 < \tau < 1$ ) needs to be set above which the finger is visible and below which is hidden. Therefore, the criteria of detecting the visibility  $p'_n$  of fingers in a gesture from confidence value  $p_n$  where  $n$  ( $n \in 1, 2, \dots, N$ ) is given by

$$p'_n = \begin{cases} 1, & p_n > \tau \\ 0, & p_n < \tau \end{cases} \quad (1)$$

For positional output, we propose an ensemble of direct regression from FCN where an ensemble of fingertips coordinates is regressed at first, and then the ensemble average is taken for final positional output of length  $2N$  (both  $x$ -, and  $y$ -coordinates of  $N$  fingers). Here, the ground truth ensemble of positional output is generated by stacking the same ground truth positional output  $2N$  times for training purposes. The idea behind the stacking of the same output and creating an ensemble of positional output is that each output of the regression from the FCN will correspond to the different input features of the previous layer. Whereas, each output of the FC layer corresponds to all the input features of the previous layer. As a result, the output from the FCN will be more independent of a particular feature, and it is expected that even if few outputs may deviate from the ground-truth value which will be mitigated after taking the ensemble average. Therefore, a matrix  $\mathbb{X}$  of size  $2N \times 2N$  is regressed at first from  $\underline{\underline{\mathbb{X}}}$  FCN, and then column-wise ensemble average is taken as the final output of fingertips position  $\tilde{\mathbb{X}}$  given by

$$\tilde{\mathbb{X}} = \frac{1}{2N} \sum_{i=1}^{2N} \mathbb{X}(:, i) \quad (2)$$

## 2.2. CNN Architecture Design

For gesture recognition and fingertip detection, the relevant portion of the hand is cropped from the input image using a bounding box and resized to  $(128 \times 128)$ . The resized image is used

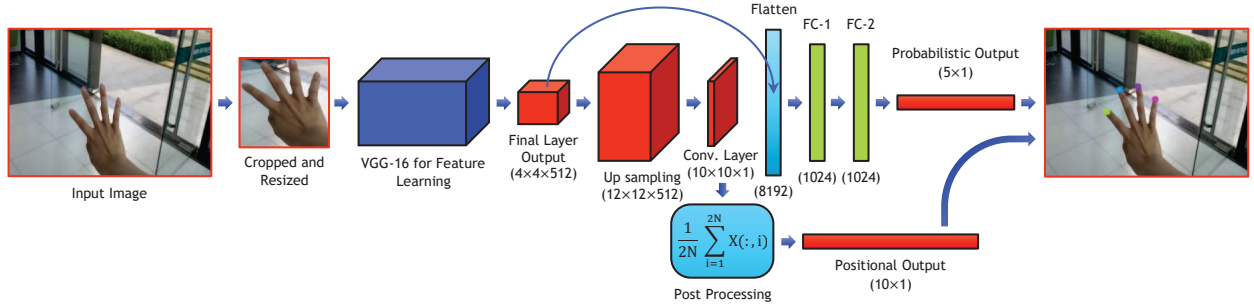


Figure 2: A block diagram of the unified gesture recognition and fingertip detection algorithm depicting the CNN architecture with input and output.

as the input to the proposed network for learning. During detection, the real-time object detection algorithm ‘you only look once’ (YOLO) [42] is used for hand recognition in the first stage. Later, that hand portion can be cropped and resized to feed to the proposed framework. For feature learning, 16-layers visual geometry group (VGG) configuration given in [43] is employed. This output is utilized to generate both the probabilistic output and positional output. First, the output of the feature learning stage is flattened and two FC layer is used back-to-back for better classification. Each of the FC layers is followed by a rectified linear unit (ReLU) activation function and a dropout layer. Finally, an FC layer is appended at the end to reduce the feature vector size to the same as that of the desired probabilistic output  $\mathbb{P}$  of length  $N$  given by

$$\mathbb{P} = [p_t \ p_i \ p_m \ p_r \ p_p]^T \quad (3)$$

where from  $p_t$  to  $p_p$  are the probability of thumb ( $t$ ), index ( $i$ ), middle ( $m$ ), ring ( $r$ ), and pinky ( $p$ ) finger, respectively. A sigmoid activation function is applied to the output of the final FC layer to normalize the probabilistic output. Moreover, the output of the feature learning stage is up-sampled followed by a ReLU activation function. Next, a convolution operation with a single filter is performed to further reduce the size of the feature vector to the same as that of the desired ensemble of positional output  $\mathbb{X}$  of size  $2N \times 2N$  given by

$$\mathbb{X} = \begin{bmatrix} x_t & y_t & x_i & y_i & x_m & y_m & x_r & y_r & x_p & y_p \\ x_t & y_t & x_i & y_i & x_m & y_m & x_r & y_r & x_p & y_p \\ x_t & \cdots & & & & & & & \cdots & y_p \\ \vdots & \ddots & & & & & & & \ddots & \vdots \\ x_t & \cdots & & & & & & & \cdots & y_p \end{bmatrix} \quad (4)$$

where  $x_f$  and  $y_f$  ( $f \in t, i, m, r, p$ ) stand for the coordinate position of the fingertips from thumb to pinky finger successively. In the final convolution operation, a linear activation function is applied. Finally, the column-wise ensemble average is taken as the final output of the fingertip positions. The overall system with CNN architecture is presented in Fig. 2. The activation functions and dropout layers are not shown in the figure for brevity.



### 2.3. Training and Optimization

In the proposed framework, the probabilistic output and the positional output need to be optimized independently at the same time and thus two loss functions are defined. The probabilistic output predicts the binary sequence of ‘1’ and ‘0’ considering the visibility of the finger, and therefore, the following binary cross-entropy loss function is proposed to optimize the probabilistic output given by

$$\mathcal{L}_1 = \frac{1}{NM} \sum_{j=1}^M \sum_{k=1}^N - \{ \mathbb{P}_{(jk)} \log_e \hat{\mathbb{P}}_{(jk)} + (1 - \mathbb{P}_{(jk)}) \times \log_e (1 - \hat{\mathbb{P}}_{(jk)}) \} \quad (5)$$

where  $N$  and  $M$  represent the length of the probabilistic output and batch size, respectively. This loss function is the average of the loss over the batch.

The positional output regresses the ensemble of fingertips coordinate position which is a matrix of size  $(2N \times 2N)$ . To optimize the positional output, the following mean squared error (MSE) loss function is proposed given by

$$\mathcal{L}_2 = \frac{1}{4N^2M} \sum_{j=1}^M \sum_{k=1}^{2N} \sum_{l=1}^{2N} \mathbb{1}^{finger} \{ \mathbb{X}_{(jkl)} - \hat{\mathbb{X}}_{(jkl)} \}^2 \quad (6)$$

where  $\mathbb{1}^{finger}$  denotes the visibility of the finger which is used for masking. If any finger is hidden in the gesture, the network should not be penalized for that fingertip regression. Hence, using the masking, fingertip detection loss for the hidden finger is eliminated. Finally, the total loss is the sum of the probabilistic and positional losses given by

$$\mathcal{L} = \mathcal{L}_1 + \mathcal{L}_2 \quad (7)$$

To optimize both of the loss functions  $\mathcal{L}_1$  and  $\mathcal{L}_2$ , the commonly referred adaptive moment estimation (ADAM) optimizer is employed. This optimizer utilized the moving averages of both the first moment  $m_k$  and second moment  $v_k$  of the gradient of the loss functions that are given by [44]

$$m_k = \beta_1 \times m_{k-1} + (1 - \beta_1) \times \left\{ \frac{d(\mathcal{L}_q)_k}{dw_k} \right\} \quad (8)$$

$$v_k = \beta_2 \times v_{k-1} + (1 - \beta_2) \times \left\{ \frac{d(\mathcal{L}_q)_k}{dw_k} \right\}^2 \quad (9)$$

where  $q$  ( $q \in 1, 2$ ),  $\beta_1$  and  $\beta_2$  ( $0 < \beta_1, \beta_2 < 1$ ) are the two hyper-parameters that control the decay rate of the moving averages, and  $k$  stands for a particular iteration. Finally, the update of the weights of the model is given by

$$w_k = w_{k-1} - \frac{\eta m_k}{\sqrt{v_k} + \epsilon} \quad (10)$$

where  $\eta$  ( $\eta > 0$ ) is the learning rate and  $\epsilon$  ( $\epsilon > 0$ ) is a infinitesimal number used for avoiding zero division error.

### 3. Experiments and Results

Experiments are performed based on the proposed method to validate the unified gesture recognition and fingertip detection algorithm. This section first presents the characteristics of the dataset on which experiments are carried out and a short description of data augmentation which is applied during the training period of the network. Afterward, the training and detection procedure of the gesture recognition and fingertip detection are explained. Next, a short description of the comparing methods and performance metrics are provided. Finally, the results of the performance of the proposed approach are reported and compared with the existing methods which are presented both in terms of classification of hand gesture and regression of fingertips. All the training and testing code concerning the experimentations and results along with the pre-trained weights of the model are publicly available to download.<sup>1</sup>

#### 3.1. Dataset

In this experiment, the SCUT-Ego-Gesture database [26] is employed for experimentation that contains eleven different datasets of single hand gesture. Among these gesture datasets, eight are considered in the experimentation as they represent digit-type hand gestures. The eight datasets include 29,337 RGB hand images in the egocentric vision each having a resolution of  $640 \times 480$ . Each of the datasets is partitioned into the test, validation, and training sets. First, for the test set 10% images of each of the datasets are taken by randomly sampling one every ten images. Next, for the validation set 5% images of the remaining images of the datasets are used by randomly sampling one every twenty images. Finally, the rest of the images of the datasets are employed for the training set. The number of images utilized in the test, validation, and training sets of different gesture classes are provided in Table 1. Fig. 3 shows visual examples of hand gesture images of different classes where each gesture is constituted by a variable number of fingers. The list of names of the images used for the test, validation, and the training sets is made publicly available.<sup>2</sup>

#### 3.2. Data Augmentation

To reduce the risk of overfitting, data augmentation is applied during training by including new training images artificially generated from the existing images of the datasets. In particular, the on-the-fly data augmentation process is used that generates new training images by applying random rotation, translation, shear transformation, illumination variation, scaling, cropping, additive Gaussian noise, and salt noise. The augmented images are generated randomly in each batch. As a result, the trained gesture recognition and fingertip detection model is learned from a large dataset. Hence, the trained model is expected to be generalized.

#### 3.3. Training

To train the proposed gesture recognition and fingertip detection model, the relevant ground truth portion of the hand from the input image is cropped and resized to  $(128 \times 128)$  using bilinear

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<sup>1</sup> Project: <https://github.com/MahmudulAlam/Unified-Gesture-and-Fingertip-Detection>

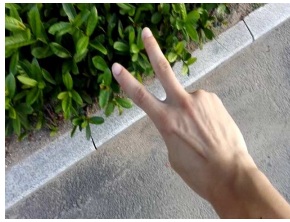
<sup>2</sup> Dataset: <https://github.com/MahmudulAlam/Unified-Gesture-and-Fingertip-Detection/tree/master/dataset>

Table 1: The list of the number of images used in the test, validation, and the training sets of the generic database

Gesture Class	Test Set	Validation Set	Training Set	Total
SingleOne	337	151	2886	3374
SingleTwo	376	169	3218	3763
SingleThree	376	169	3223	3768
SingleFour	376	169	3222	3767
SingleFive	375	169	3211	3755
SingleSix	375	169	3213	3757
SingleSeven	377	169	3227	3773
SingleEight	338	152	2890	3380
Total	2930	1317	25090	29337



(a) SingleOne



(b) SingleTwo



(c) SingleThree



(d) SingleFour



(e) SingleFive



(f) SingleSix



(g) SingleSeven



(h) SingleEight

Figure 3: Visual examples of each of the eight gestures in the database are shown from (a) to (h).

interpolation which is the input of the CNN. The model predicts a probabilistic output vector  $\mathbb{P}$  of length 5 and regresses an ensemble of positional output matrix  $\mathbb{X}$  of size  $(10 \times 10 \times 1)$ . To generate the outputs of the desired size, the output tensor of the VGG-16 feature learning stage of size  $(4 \times 4 \times 512)$  is flattened to a vector of length 8192. The output vector length of the FC layers is chosen to be 1024 and the dropout rate to be 0.5. The final FC layer having an output length of 5 is used to generate the probabilistic output. To produce the ensemble of the positional output of fingertips, the output tensor of the feature learning stage is three times up-sampled to  $(12 \times 12 \times 512)$ . Next, this output is convolved with a single filter of size  $(3 \times 3)$  that results in a matrix of desired output size  $(10 \times 10 \times 1)$ . The proposed network is trained

for a total of 300 epochs where the learning rate is lowered from  $10^{-5}$  to  $10^{-7}$  in a step by step process for better convergence. The parameter of the ADAM optimizer  $\beta_1, \beta_2$ , and  $\epsilon$  is chosen to be 0.9, 0.999, and  $10^{-10}$ , respectively, with a batch size of 64. Fig. 4 shows the learning curves of the unified gesture recognition and fingertip detection model in terms of loss function both in the training and validation stages. Specifically, Fig. 4(a) shows the convergence of probabilistic loss function  $\mathcal{L}_1$  and Fig. 4(b) shows the convergence of positional loss function  $\mathcal{L}_2$ . Fig. 4(c) shows the learning curves in terms of the total loss  $\mathcal{L}$  where the probabilistic and positional loss functions are combined. It can be seen from the learning curves that the proposed model is free from overfitting.

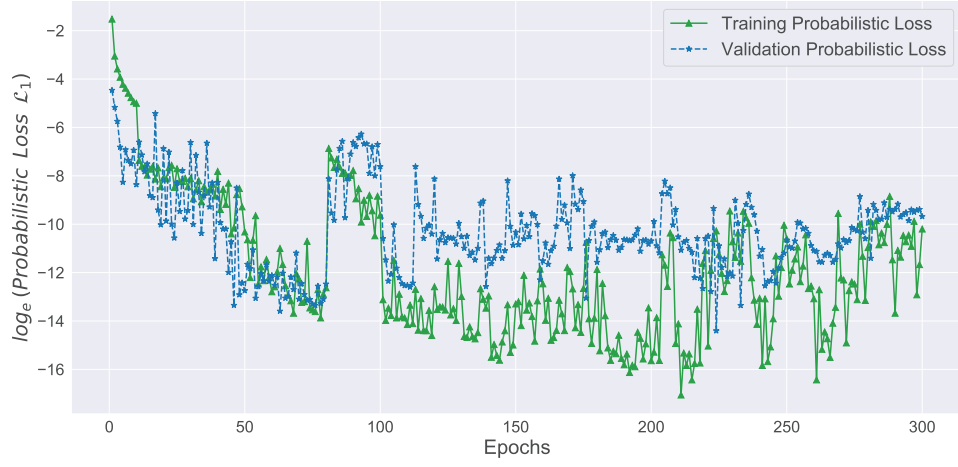
### 3.4. Detection

During detection, in the first stage, the hand is detected using the YOLO object detection algorithm. Afterward, the detected hand portion from the image is cropped and resized to feed to the proposed network. The network predicts the probabilistic output of fingers and regresses the ensemble of fingertip positions. The probabilistic output of the network predicts a higher confidence value if the finger is visible and a lower confidence value if the finger is hidden in a gesture. To estimate a binary output sequence representing the array of visible fingers in hand, a confidence threshold  $\tau$  is set. Due to the equal probability of the visibility or invisibility of the fingers, the confidence threshold  $\tau$  is set to be 50%. As the proposed network directly regresses the ensemble of fingertip positional output  $\mathbb{X}$ , a column-wise ensemble average is estimated as the final fingertip positional output  $\bar{\mathbb{X}}$ .

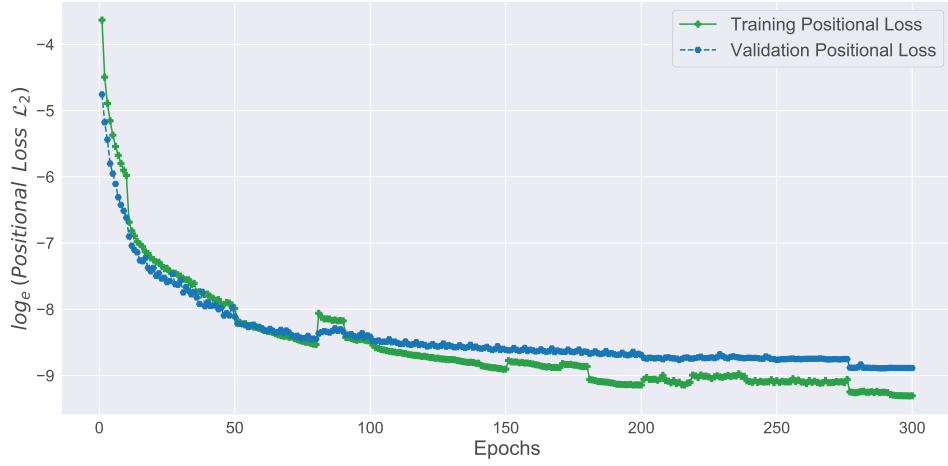
### 3.5. Comparing Methods

The proposed method is compared with the existing direct regression approach [25] and the Heatmap-based gesture recognition and fingertip detection algorithm called ‘you only look what you should see’ (YOLSE) [26]. Before comparing to the proposed method, a brief description of these algorithms is provided here.

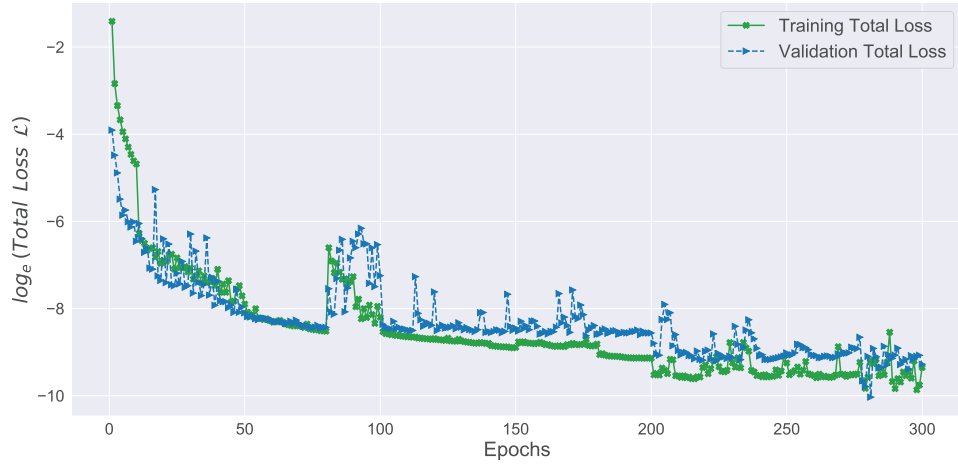
- **Direct Regression Approach:** Mishra *et al.* [25] proposed the direct regression-based hand gesture and fingertip detection algorithm in 2019. They employed MobileNetV2 [45] architecture as a backbone model and later produced a linear output using global average pooling. Afterward, from the same linear output, they used three fully connected (FC) layers for gesture classification, finger identification, and estimation of finger position. This algorithm is referred to as the Direct Regression approach as the final positional output of the fingertips are directly regressed from the FC layers.
- **YOLSE Approach:** The YOLSE method of hand gesture recognition and fingertip detection algorithm is proposed by Wu *et al.* [26] in 2017. They proposed a Heatmap-based approach using a fully convolutional network by representing each fingertip as a 2D Gaussian distribution in the output tensor. Each layer of the tensor represents a specific finger. The algorithm predicts a tensor and later from each layer of the tensor, the peak value is calculated. If the peak value exceeds a given threshold then the peak location is considered as the position of a visible fingertip. If the peak value falls below the threshold then that fingertip is considered hidden.



(a) Convergence of probabilistic loss function  $\mathcal{L}_1$



(b) Convergence of positional loss function  $\mathcal{L}_2$



(c) Learning curves in terms of the total loss  $\mathcal{L}$

Figure 4: The learning curves of the proposed unified gesture recognition and fingertip detection model. The convergence of the probabilistic, positional, and total loss functions are shown from (a) to (c), respectively.

### 3.6. Performance Metrics

The performance of the classification of hand gestures and that of estimation of the fingertips position are evaluated separately. The performance of the classification is assessed in terms of four measures, namely, accuracy, precision, recall, and F1 score. The higher the value of accuracy or F1 score, and the closer the value of precision or recall to unity, the better is the performance of the classification algorithm. In all of these evaluation metrics, unless otherwise stated, the confidence threshold is set to 50%. To evaluate the performance of estimation of fingertip position, the error in terms of mean Euclidean distance between ground truth pixel coordinate and regressed pixel coordinate is calculated as

$$\overline{D_f - \hat{D}_f} = \frac{1}{S \langle \mathbb{P}, \mathbf{1} \rangle} \sum_{k=1}^S \sum_{j=1}^{\langle \mathbb{P}, \mathbf{1} \rangle} (p'_f)_{jk} \sqrt{\{(x_f)_{jk} - (\hat{x}_f)_{jk}\}^2 + \{(y_f)_{jk} - (\hat{y}_f)_{jk}\}^2} \quad (11)$$

where  $f$  ( $f \in t, i, m, r, p$ ),  $S$  stands for the total number of correctly recognized gestures in the test set in a particular class, and  $\langle \mathbb{P}, \mathbf{1} \rangle$  is the number of total fingers in the gesture.

### 3.7. Results

Table 2 shows the results of gesture recognition in terms of the accuracy, precision, recall, and F1 score of the comparing methods. The overall performance in terms of the mean value of these metrics is also shown in this table. The name of the methods is prefixed by GT as no hand detector is included as preprocessing rather ground truth bounding box is used to directly crop the relevant hand portion from an input image. The results of each method are also presented by including the YOLO hand detector in the first stage, and in this case, the name of the methods is prefixed by YOLO. It can be observed from Table 2 that the proposed method has outperformed the other gesture recognition methods and attained very high accuracy in all classes. In particular, the proposed method provides gesture recognition accuracy of at least 99.90% and an F1 score as high as 0.99.

In estimating the position of fingertips, the distance error between the ground truth coordinate, and the regressed coordinate among the different classes is calculated. Table 3 shows the results of the mean and standard deviation of the regression error in pixel (px) for different methods. It is seen from this table that, the proposed fingertip regression approach achieves a better result in terms of the mean and standard deviation of the pixel error as compared to the Direct Regression method, but a comparable performance with the YOLSE method. However, the superiority of the proposed method over the YOLSE method is clear when comparing it with the GT hand image. Nevertheless, the proposed method with the YOLO hand detector has achieved a mean pixel error of 4.84 px with a standard deviation of 3.59 px.

Fig. 5 shows the confusion matrices depicting the performance of the classification of gesture by the proposed method, the YOLSE approach, the Direct Regression approach where each row represents the actual class of gesture and each column represents the predicted class of gesture. The figure illustrates that the proposed model has very little confusion in classifying gestures. Fig. 6 shows examples of visual output of the proposed gesture recognition and fingertip detection algorithm of each gesture class where not only each fingertip position is detected but also the type of hand gesture is recognized by classifying each finger. The average forward propagation time of

Table 2: Performance of gesture classification of the comparing methods in terms of Accuracy, Precision, Recall, and F1 score

Method	Metric	Gesture								Mean
		SingleOne	SingleTwo	SingleThree	SingleFour	SingleFive	SingleSix	SingleSeven	SingleEight	
GT-Proposed Method	Accuracy (%)	99.97	100.00	100.00	99.97	99.93	99.93	99.93	99.93	<b>99.96</b>
	Precision (%)	99.70	100.00	100.00	99.73	100.00	100.00	99.47	99.70	<b>99.82</b>
	Recall (%)	100.00	100.00	100.00	100.00	99.47	99.47	100.00	99.70	<b>99.83</b>
	F1 Score	0.9985	1.0000	1.0000	0.9987	0.9973	0.9973	0.9974	0.9970	<b>0.9983</b>
YOLO-Proposed Method	Accuracy (%)	99.90	100.00	100.00	99.93	99.90	99.93	99.90	99.90	99.93
	Precision (%)	99.12	100.00	100.00	99.47	100.00	100.00	99.21	100.00	99.72
	Recall (%)	100.00	100.00	100.00	100.00	99.20	99.47	100.00	99.11	99.72
	F1 Score	0.9956	1.0000	1.0000	0.9973	0.9960	0.9973	0.9960	0.9955	0.9972
GT-YOLSE	Accuracy (%)	96.72	98.16	98.46	97.99	98.87	99.08	98.74	96.86	98.11
	Precision (%)	85.13	97.63	96.88	97.89	100.00	98.33	97.22	93.31	95.80
	Recall (%)	86.65	87.77	90.96	86.17	91.20	94.40	92.84	78.40	88.55
	F1 Score	0.8588	0.9244	0.9383	0.9165	0.9540	0.9633	0.9498	0.8521	0.9196
YOLO-YOLSE	Accuracy (%)	97.00	98.16	98.46	98.19	99.01	99.04	98.70	97.00	98.20
	Precision (%)	86.94	96.26	96.62	98.50	100.00	98.87	97.75	93.71	96.08
	Recall (%)	86.94	89.10	91.22	87.23	92.27	93.60	92.04	79.29	88.96
	F1 Score	0.8694	0.9254	0.9384	0.9252	0.9598	0.9616	0.9481	0.8590	0.9234
GT-Direct Regression	Accuracy (%)	99.97	99.90	99.86	99.86	99.76	99.62	99.52	99.73	99.78
	Precision (%)	100.00	99.73	99.47	99.47	99.46	98.66	98.40	97.60	99.10
	Recall (%)	99.70	99.47	99.47	99.47	98.67	98.40	97.88	100.00	99.13
	F1 Score	0.9985	0.9960	0.9947	0.9947	0.9906	0.9853	0.9814	0.9879	0.9911
YOLO-Direct Regression	Accuracy (%)	99.69	99.93	99.93	99.90	99.86	99.93	99.90	99.59	99.84
	Precision (%)	97.95	99.47	99.73	99.47	100.00	99.73	99.73	98.80	99.36
	Recall (%)	99.41	100.00	99.73	99.73	98.93	99.73	99.47	97.63	99.33
	F1 Score	0.9867	0.9973	0.9973	0.9960	0.9946	0.9973	0.9960	0.9821	0.9934

the proposed network is 13.10 ms or 76 frames per second. Thus, the proposed method satisfies the requirements of real-time implementation. The experiments are performed on a computer with Intel Core i5 4590 CPU with 8 GB memory and NVIDIA GTX1050 Ti GPU with 4 GB memory and some of the training portions are conducted using an NVIDIA Titan Xp GPU.

Table 3: Performance of fingertip positional accuracy of the comparing methods in terms of the mean pixel (px) error

Method	Gesture								Mean Error (px)
	SingleOne	SingleTwo	SingleThree	SingleFour	SingleFive	SingleSix	SingleSeven	SingleEight	
GT-Proposed Method	4.51 ± 3.14	3.89 ± 1.91	3.62 ± 1.80	3.79 ± 1.89	3.63 ± 1.46	3.4 ± 1.48	3.64 ± 1.51	5.68 ± 3.51	<b>4.02 ± 2.09</b>
YOLO-Proposed Method	6.78 ± 7.37	4.23 ± 3.00	3.87 ± 2.05	4.31 ± 2.43	3.81 ± 1.64	4.29 ± 3.54	4.04 ± 2.03	7.37 ± 6.67	4.84 ± 3.59
GT-YOLSE	5.71 ± 15.29	4.16 ± 3.89	3.51 ± 1.92	3.95 ± 4.76	3.74 ± 1.61	3.59 ± 1.56	3.89 ± 1.66	5.22 ± 2.48	4.22 ± 4.15
YOLO-YOLSE	5.06 ± 9.53	4.31 ± 4.56	3.56 ± 2.20	3.6 ± 2.46	3.76 ± 1.65	3.62 ± 1.51	3.98 ± 2.68	5.14 ± 2.66	4.13 ± 3.41
GT-Direct Regression	7.98 ± 5.57	7.23 ± 3.80	6.64 ± 3.36	7.04 ± 3.22	6.68 ± 2.45	6.71 ± 3.10	7.47 ± 2.91	9.04 ± 4.34	7.35 ± 3.59
YOLO-Direct Regression	11.20 ± 9.13	7.89 ± 4.51	7.10 ± 3.52	7.69 ± 3.51	6.97 ± 2.55	7.90 ± 4.04	8.26 ± 3.64	10.71 ± 6.63	8.47 ± 4.69

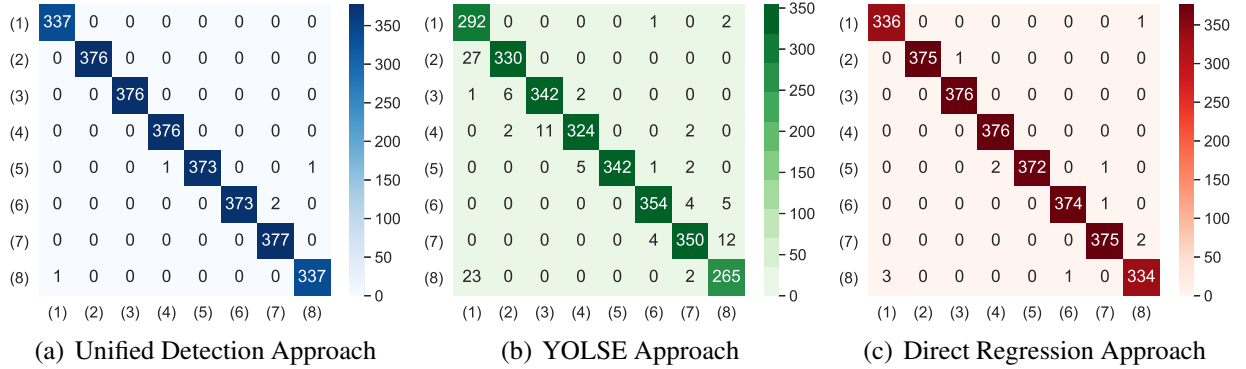


Figure 5: Confusion matrices depicting the performance of the gesture classification by the experimental methods shown in (a) to (c). Here (1) to (8) are representing SingleOne to SingleEight gestures.

#### 4. Detection In The Wild

To evaluate the performance of the proposed method in real-life scenarios, 25 publicly available hand gesture images are collected from the internet. The imaging conditions of this wild set of gesture images are quite different as compared to the SCUT-Ego-Gesture database. In particular, they are different in terms of background, illumination, resolution, and pose of the fingers. Fig. 7 shows the output images with the prediction of the proposed method. It is seen from the output images that the proposed method is capable of successfully predicting all the gestures and detects all the fingertips. Therefore, in real-life HCI, VR, and MR applications, the proposed method can play an indispensable role.



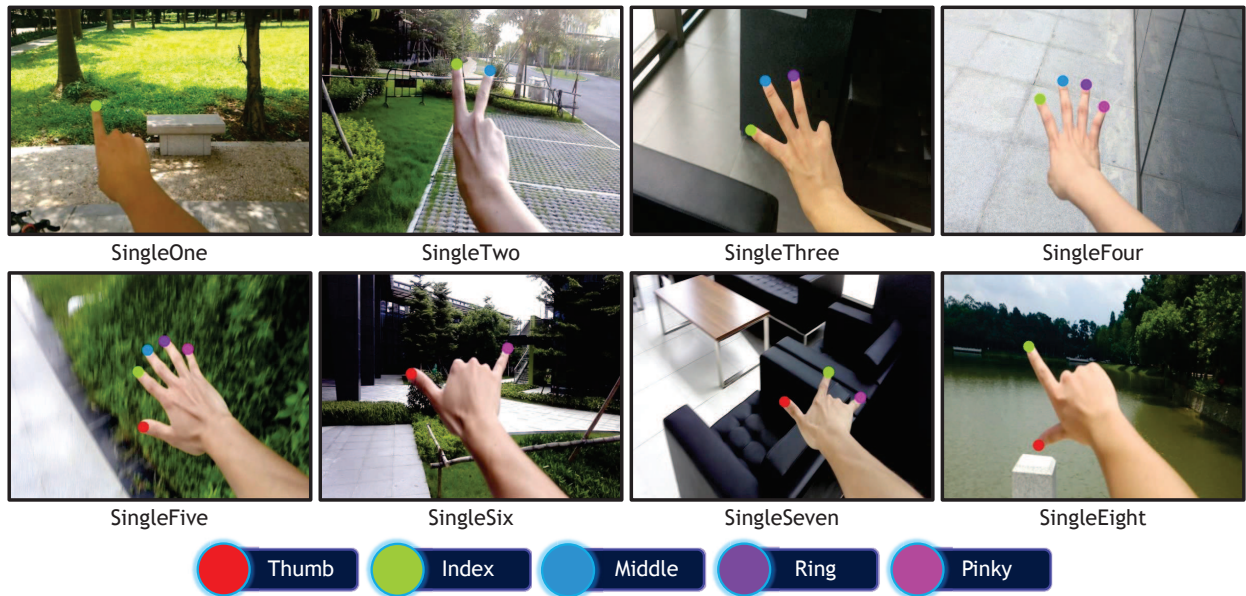


Figure 6: A visual representation of the outputs of the proposed gesture recognition and fingertip detection model where not only each fingertip is detected but also each finger is classified.

## 5. Conclusion

In this paper, a new CNN-based method is proposed that unifies the gesture recognition and prediction of fingertip position in a single step process. In particular, the proposed method regressed the ensemble of the position of fingertips using a fully convolutional network instead of directly regressing the positions of fingertips using the fully connected layer. The experiments have been carried out by employing a commonly referred SCUT-Ego-Gesture database. The accuracy of the automatic gesture recognition has been found to be at least 99.90%, and the minimum F1 score among the classes have been found to be at least 0.9955. The mean pixel error in fingertip detection among the classes has been found to be 4.84 px. As the proposed method uses a single network for both gesture recognition and fingertip detection, it is very fast and meets the requirements of real-time implementation. Moreover, the proposed method has achieved lower false positive and false negative rates in classification and made less localization error in regression as compared to the direct regression and Heatmap-based YOLSE methods. The performance of the proposed method is also ensured by experimentation using the hand gesture images available in the wild. In conclusion, with the speed of the detection, and accuracy in performance, the proposed algorithm can play a significant role in the HCI, VR, and MR applications.

## 6. CRediT Authorship Contribution Statement

**Mohammad Mahmudul Alam:** Conceptualization, Methodology, Software, Formal analysis, Data Curation, Writing - Original draft, Writing - Review & Editing. **Mohammad Tariqul**

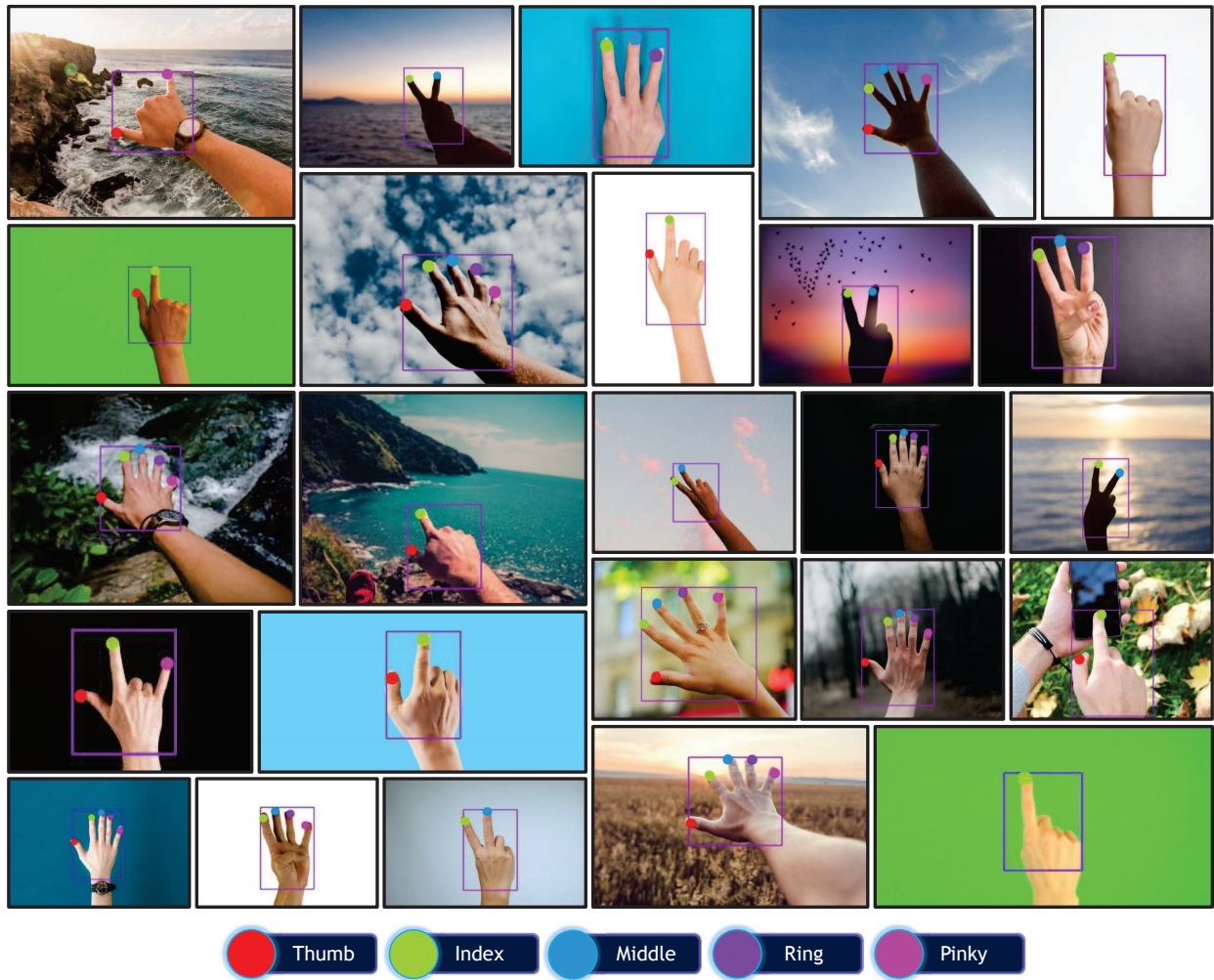


Figure 7: Prediction of the model using random images collected over the internet to show the real-life usability of the proposed method.

**Islam:** Validation, Formal analysis, Writing - Original Draft. **S. M. Mahbubur Rahman:** Formal analysis, Resources, Writing - Original Draft, Writing - Review & Editing, Supervision.

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