Knowledge Distillation from Ensemble of Offsets for Head Pose Estimation
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Abstract—This paper proposes a method for estimating the head pose from a single image. This estimation uses a neural network (NN) obtained in two stages. In the first stage, we trained the base NN, which has one regression head and four regression via classification (RvC) heads. We build the ensemble of offsets using small offsets of face bounding boxes. In the second stage, we perform knowledge distillation (KD) from the ensemble of offsets of the base NN into the final NN with one RvC head. On the main test protocol, the use of the offset ensemble improves the results of the base NN, and the KD improves the results from the offset ensemble. The KD improves the results by an average of 7.7% compared to the non-ensemble version. The proposed NN on the main test protocol improves the state-of-the-art result on AFLW2000 and approaches, with only a minimal gap, the state-of-the-art result on BIWI. Our NN uses only head pose data, but the previous state-of-the-art model also uses facial landmarks during training. We have made publicly available trained NNs and face bounding boxes for the 300W-LP, AFLW, AFLW2000, and BIWI datasets. KD-ResNet152 has the best results, and KD-ResNet18 has a better result on the AFLW2000 dataset than any previous method.

Index Terms—head pose estimation, knowledge distillation, offset ensemble, regression via classification, deep learning, computer vision, neural networks.

1 INTRODUCTION

FACIAL analysis is one of the most important tasks of computer vision. This includes such tasks as face detection [1], facial landmarks detection [2], facial age estimation [3], head pose estimation (HPE) [4], and others [5]. In this paper, we focus on HPE. Many practical applications, such as analysing facial expressions [6], gaze estimation [7], driver monitoring systems [8, 9], and others [10, 11], require fairly accurate HPE.

The head pose is usually a vector containing the pitch, yaw, and roll angles. This vector is visualized using three axes, as shown in Fig. 1. The HPE problem is to find these angles from the image of the face.

Fig. 1: Visualization of head pose.

Many approaches have been proposed to solve the HPE problem. One of the first approaches was to use appearance template methods [12], deformable models [13], manifest embeddings methods [14], facial landmarks [15, 16], and others [17, 18]. An overview of these methods is given in [4, 19]. Recently, convolutional neural networks (NNs) have been widely used to solve many computer vision problems. Applying this approach to the HPE problem yields good results [19].

One way to improve prediction accuracy is to train several NNs and then use an ensemble of their predictions [20, 21, 22]. The disadvantage of this approach is the increase in the computational complexity of the prediction since it is necessary to get predictions from all the NNs. The KD method was proposed [23, 24] to solve this problem. The essence of this method is to train a new NN using the trained NNs. This method has been used in a number of studies and has yielded good results [25]. The paper [26] shows that KD can improve the accuracy of an ensemble prediction.

In [27] it is shown that the bounding box significantly affects the quality of the trained NN for the HPE problem. In [28] there is proposed an approach in which the bounding box is first corrected, and then the angles are predicted using the NN presented in the previous paper [29]. This feature of bounding boxes allows one to build an ensemble which uses many predictions of a single NN but with different offsets for the bounding box. We call such an ensemble the offset ensemble. The KD approach has not yet been used for HPE.

This paper makes the following contributions.

- We show that averaged results of predictions of the same NN, but with various bounding box offsets, increases the accuracy of predicting the head position. We call this ensemble the offset ensemble.
- We apply the KD approach to train a new NN using the offset ensemble. In some cases, the new NN improves the results of the offset ensemble.
2 RELATED WORK

This section gives an overview of the approaches used to solve the HPE problem. Subsection 2.1 provides an overview of methods based on facial landmarks. Subsection 2.2 provides an overview of landmark-free methods.

2.1 Landmark-based methods

Initially, facial landmark approaches were used for HPE. Such methods first find facial landmarks in the image, using, for example, the algorithm from [2]. Then the head pose is estimated using the average 3D head model and some algorithm [30, 31]. Some methods, such as [32], use a depth map as additional information. The applicability of these methods is limited by the need to use special devices to obtain RGB-D images.

However, these methods significantly depend on finding facial landmarks. In some cases, facial landmarks are difficult to find accurately. For example, when part of the face is hidden. One way to solve this problem could be to use heat maps of facial landmarks [33]. Also, the RANSAC [34] algorithm can be used, or an incomplete set [35] of facial landmarks can be used. Another problem with these methods is the use of an averaged 3D head model. The difference between the actual 3D head model and the average 3D head model introduces an additional error in the estimation. The paper [36] suggests a way to solve this problem. However, close to state-of-the-art results are obtained when only using depth information.

2.2 Landmark-free methods

In [37, 38, 39] the possibility of solving the HPE problem using convolutional NNs without using key points is demonstrated. These approaches yield better results than approaches based on facial landmarks. Also, these methods are less susceptible to the problems associated with overlapping parts of the face, and they do not depend on the accuracy of finding facial landmarks.

HopeNet [40] is one of the first methods to yield good results. The final prediction of the angles was calculated using RvC [41] with a bin size of 3. The loss function in this method combined classification and regression loss functions. Subsequently, this approach received several improvements. The paper [42] presents a modification of this method, in which the final prediction used an RvC head with a bin size of 1, and other RvC heads with bigger bin sizes were used as regularizers during the training. The paper [43] presented another modification of the method. This modification also uses an RvC head, but the top 40 classes were used for the HPE. Some papers [44, 45] use depth maps as additional information. Although these studies have obtained good results, the practical applicability of these methods is also limited by the availability of special cameras.

The paper [46] is one of the latest papers to surpass all previous results. However, in that paper, when training an NN, information about facial landmarks is used, which is a regularizer for the HPE problem. They implicitly extended the training dataset with head poses by using datasets with facial landmarks, which could be the reason for their improvement of the accuracy of the HPE.

3 METHOD

The approach proposed in the present paper aims to build an offset ensemble that uses the KD method to train an NN to then perform the HPE. First, we formulate the HPE problem in subsection 3.1. Then, we describe the architectures of the trained NN in subsection 3.2.

Getting the final NN is done in two stages. In the first stage, we train an NN to perform the HPE. We construct an ensemble of offsets based on the trained NN model and offsets of the bounding box. The algorithm is given in subsection 3.3. In the second stage, we train the final NN. The training uses the results of the prediction of the constructed offset ensemble. A detailed description of the KD is given in subsection 3.4.

3.1 Problem formulation

The HPE problem is to use an image of a face to predict the pitch, yaw and roll angles of that face. Consider the images $X = \{X_1, \ldots, X_N\}$ and the pose vector $\vec{y}_i = (\alpha_k, \beta_k, \gamma_k)$ for each image $X_i$, where $N$ is the number of images, while $\alpha_k, \beta_k, \gamma_k \in [-\theta, \theta]$ represent the pitch, yaw, and roll angles, respectively. The goal is to find a function $F$ which estimates the head pose for the image $X$, minimizing the mean average error $E$:

$$E(X) = \frac{1}{N} \sum_{i=1}^{N} \|F(X_i) - \vec{y}_i\|_1$$  \hspace{1cm} (1)

3.2 Architecture of the neural network

We use the RvC [41] method to estimate head pose. This method is used in many papers devoted to the HPE problem [40, 42, 43].

The architecture of the NN is shown in Fig. 2. This architecture contains a backbone and several head branches. In the first stage, the NN contains several head branches: $M$ fully connected layers that perform the classification with bin sizes $B = \{b_1, \ldots, b_M\}$, number of bins $Q = \{q_1, \ldots, q_M\}$, and a fully connected layer performing a regression. In the second stage, the NN contains only one head branch: a fully connected layer that performs a classification with the bin size $b_k \in B$.

The architecture used in the ImageNet challenge [47] can be used as a backbone. ResNet50 was used earlier for the head estimation problem [27, 30, 42, 43].

We will now describe the method for making the NN predictions during the training for the proposed architecture. For a classification head with bin size $b_k$ and number of bins $q_k$, the angles are calculated using the formula (2), where $\vec{c} = (c_1, \ldots, c_{q_k}) \in [-\theta; \theta]^3$ is the bin center vector, and $\vec{y}_{\text{out}} = (\vec{\alpha}_{\text{out}}^{(k)}, \vec{\beta}_{\text{out}}^{(k)}, \vec{\gamma}_{\text{out}}^{(k)}) \in \mathbb{R}^{q_k \times 3}$ is the output of the $k$th classification head. For a regression head, the angles are calculated using the formula (3), where $\vec{y}_{\text{out}} = (\vec{\alpha}_{\text{reg}}^{(k)}, \vec{\beta}_{\text{reg}}^{(k)}, \vec{\gamma}_{\text{reg}}^{(k)}) \in \mathbb{R}^3$ is the output of the regression head.

$$\vec{\xi}_{\text{pred}}^{(k)} = \langle \vec{c}, \text{softmax} \left(\vec{\xi}_{\text{out}}^{(k)}\right) \rangle \text{ where } \xi \in \{\alpha, \beta, \gamma\}$$  \hspace{1cm} (2)

$$\xi_{\text{reg}}^{(k)} = \theta \tanh (\vec{z}_{\text{out}}^{(k)}) \text{ where } \xi \in \{\alpha, \beta, \gamma\}$$  \hspace{1cm} (3)
The average of the values of the loss functions for the $M$ classification heads and the regression head is used as the loss function. The resulting loss function $L$ is calculated using the formulas (4), where for some image $\hat{y}_{gt} = (\alpha_{gt}, \beta_{gt}, \gamma_{gt})$ is the ground truth pose vector, $\hat{y}^{(i)} = (\alpha^{(i)}_{out}, \beta^{(i)}_{out}, \gamma^{(i)}_{out})$ is the output of the $i$th classification head, and $\hat{y}^{\text{reg}} = (\alpha^{\text{reg}}_{pred}, \beta^{\text{reg}}_{pred}, \gamma^{\text{reg}}_{pred})$ is the output of the regression head.

$$L^{(i)} (\hat{y}_{gt}, \hat{y}^{(i)}_{out}) = \sum_{\xi \in \{\alpha, \beta, \gamma\}} \text{CrossEntropy} (\hat{y}_{gt}, \hat{y}^{(i)}_{out})$$

$$L^{\text{reg}} (\hat{y}_{gt}, \hat{y}^{\text{reg}}_{pred}) = \text{MAE} (\hat{y}_{gt}, \hat{y}^{\text{reg}}_{pred})$$

$$L = \frac{L^{(1)} (\hat{y}_{gt}, \hat{y}^{(1)}_{out}) + \sum_{j=1}^{M} L^{(j)} (\hat{y}_{gt}, \hat{y}^{(j)}_{out}) + L^{\text{reg}} (\hat{y}_{gt}, \hat{y}^{\text{reg}}_{pred})}{M + 1}$$

The output of a fully connected classification layer with a minimum bin size $b_k$ is used to calculate the NN prediction in test mode. The remaining heads are used as regularizers during training.

### 3.3 Offset ensemble

The paper [27, 28] shows that one of the easiest ways to improve the accuracy of machine learning algorithms is to use an ensemble. This method consists of training several models and then averaging their predictions. The papers [27, 28] demonstrate that the choice of bounding box affects the prediction result. We propose to perform small bounding box offsets and use a single prediction network to construct the ensemble. Using bounding box offsets avoids training multiple NNs for an ensemble.

Constructing an ensemble of offsets for the HPE consists of training the base NN and constructing a data flow for the image offsets used for prediction. The offset ensemble is shown in Fig. 3.

![Offset ensemble](image)

Fig. 3: Offset ensemble.

The basic NN uses the NN architecture described in 3.2 and contains several head branches: $M$ classification heads with bin sizes $B = \{b_1, \ldots, b_M\}$ and a regression head. The $k$th classification head with the bin size $b_k$ is used for the prediction. The loss function (4) is used during training the basic NN.

We will now consider the data flow for constructing the image offsets. Let there be an image $X \in \mathbb{R}^{C \times H \times W}$, bounding box $b = (x_1, y_1, x_2, y_2)$ and let the input size of the NN be $C \times h \times w$. The image is cropped by the bounding box and scaled to the required size of the NN to estimate the head pose.

Let $x_s = \frac{x_2 - x_1}{w}$ and $y_s = \frac{y_2 - y_1}{h}$. We will now construct the set $B_{K,d} (b)$ of offsets of the original bounding box $b$ by (5), where $K \in \mathbb{N}_0$ and $d \in \mathbb{N}$.

The set of offsets is shown in Fig. 4.

$$R_{i,j}^{(d)} (b) = (x_1 + ids, y_1 + jds, x_2 + ids, y_2 + jds)$$

$$B_{K,d} (b) = \left\{ R_{i,j}^{(d)} (b) : -K \leq id, jd \leq K \land i, j \in \mathbb{Z} \right\}$$

(5)

We crop the original image and scale it with the coefficients $(\frac{1}{x_s}, \frac{1}{y_s})$ for each bounding box $b' \in B_{K,d} (b)$. As a result, we get a set $C_{K,d} (X, b) = \{ X_1^{(1)}, \ldots, X_1^{(S)} \}$ of images of size $C \times h \times w$, where $S = |B_{K,d} (b)|$. For each $x \in C_{K,d} (X, b)$, we use the base NN to find the predictions $\mathcal{Y} = \{ \hat{y}^{(1)}_{out}, \ldots, \hat{y}^{(T)}_{out} \}$, where $\hat{y}^{(i)}_{out} = (\alpha^{(i)}_{out}, \beta^{(i)}_{out}, \gamma^{(i)}_{out}) \in \mathbb{R}^{3 \times 3}$.

The offset ensemble prediction uses (6). Note that the probabilities are the result of this formula.

$$\xi^{(j)}_{\text{ens}} = \frac{1}{T} \sum_{i=1}^{T} (\text{softmax} (\hat{\xi}^{(i)}_{out}))_j , \quad \xi \in \{\alpha, \beta, \gamma\}$$

$$\hat{\xi}^{(i)}_{\text{ens}} = (\hat{\xi}^{(i)}_{\text{ens}}^{(1)}, \ldots, \hat{\xi}^{(i)}_{\text{ens}}^{(q)}) , \quad \xi \in \{\alpha, \beta, \gamma\}$$

(6)
4.2 Preprocessing

Following [29], [40], [42], [43], [56], we reduced the datasets, leaving only images with head rotation angles in the range \([-99°; +99°]\).

The images from the datasets contain a face and some background. The main object of analysis in the HPE problem is the face. Therefore, it is necessary to draw the attention of the NN to it. The attention mechanism is performed by cropping the image on the bounding box containing the face and further resizing it to the size of the NN.

The bounding boxes of 300W-LP [15], AFLW2000 [15], and AFLW [50] datasets are obtained by constructing a bounding rectangle around the facial landmarks and then slightly enlarging them. The BIWI dataset does not contain bounding boxes. In the literature on HPE, bounding boxes are obtained in different ways. For example, the Faster R-CNN [57] detector was used in [40], the MTCNN [58] detector was used in [29], the Dlib [59] detector was used in [43], [56], and the depth maps were used in [46].

Since bounding boxes affect the result [27], [28], the differences in the ways of getting the bounding boxes do not allow for a valid comparison of the methods for HPE. To solve this problem, we trained the YOLOv5 [60] detector on the WIDER [61] dataset. We redefined the bounding boxes using this detector for all four datasets: 300W-LP [15], AFLW2000 [15], AFLW [50] and BIWI [51]. The new bounding boxes for these datasets are publicly available in [62], which will allow performing an objective comparison of methods for the HPE problem without depending on the bounding boxes.

4.3 Augmentations

Data augmentation is an integral part of NN training. Augmentation can significantly expand the training set and increase the representativeness of the data. Due to augmentation, it is possible to improve the quality of the trained NN significantly [63], [64].

Concerning the HPE problem, augmentation can be divided into two types: those that affect the head pose and those that do not affect the head pose. In our workflow, augmentations that affect the head pose are applied first, and then augmentations that do not affect the head pose.

We use a horizontal flip with a probability of 0.5 and rotate by a random angle in the range \([-15°; +15°]\) from the augmentations affecting the head pose. In the process of applying these augmentations, the head poses are corrected, as described in [65].

The augmentations that do not affect the head pose were taken from the Albumentations library [66]. First, with a probability of 0.5, no augmentation is applied, or
with a probability of 0.5, one randomly selected augmentation from the list is applied: HueSaturationValue, CLAHE, Equalize, or Solarize. Then, with a probability of 0.5, no augmentation is applied, or with a probability of 0.5, one randomly selected augmentation from the list is applied: ChannelShuffle or ChannelDropout. Then MedianBlur is applied with a probability of 0.5. Then, with a probability of 0.5, no augmentation is applied, or with a probability of 0.5, one randomly selected augmentation from the list is applied: RandomShadow or ISONoise.

Lastly, CoarseDropout is applied with a probability of 0.5.

4.4 Testing protocols
In accordance with previous papers, we use the following test protocols, shown in Table 1. The test protocols are described in more detail below.

| TABLE 1: Test protocols |
|-------------------------|
| Protocol #1 | Train Dataset # of Faces | Test Dataset # of Faces |
| 300W-LP | 122415 | AFLW2000 | 1969 |
| BIWI | 15677 | BIWI | 5065 |
| Protocol #2 | AFLW | 22079 | AFLW | 1969 |
| Protocol #3 | BIWI | 10612 | BIWI | 5065 |

**Test protocol 1.** 300W-LP is used for training. AFLW2000 and BIWI are used for testing. Only images from datasets with head rotation angles in the range $[-99^\circ; +99^\circ]$ were used.

**Test protocol 2.** The AFLW dataset is used for training and testing. In [67], it was pointed out that there is no standard test protocol for the AFLW dataset. In addition, some papers [16], [42] use a random division of the dataset into training and testing. This does not allow for a valid comparison of methods. For these reasons, we decided to use the first 2000 jpg images that make up the AFLW2000 dataset for testing and use the rest for training. Similarly, only images from datasets with head rotation angles in the range $[-99^\circ; +99^\circ]$ were used.

**Test protocol 3.** Images corresponding to 70% of the video from the BIWI dataset are used for training. The remaining images are used for testing. The division of the
dataset into training and testing is performed in accordance with the method of [29]. Similarly, only images from datasets with head rotation angles in the range $[-99^\circ; +99^\circ]$ were used.

## 5 Experiments

In this section, we describe the experiments. Subsection 5.1 describes the environment in which the experiments were conducted. Subsection 5.2 contains the results of the experiments for the first stage. Subsection 5.3 contains the results of the experiments for the second stage.

### 5.1 Implementation details

Python [68] was used to implement these computational experiments. The NNs were implemented in the Pytorch [69] library. The data augmentation was performed using the Alburnetions [66] library.

Our research was performed using “Uran” supercomputer of the IMM UB RAS. The NNs were trained on 8 Tesla v100 GPUs with 32GB of memory.

### 5.2 First stage

In the first stage, we used ResNet50 as a backbone, pre-trained on ImageNet [47]. The NN contained 5 head branches: 4 classification heads with bin sizes $B = \{1, 2, 3, 4\}$ and a regression head.

The NN was trained using the Adam [70] optimizer with a learning rate of $10^{-4}$ for 100 epochs. The batch size was 128.

To construct the offset ensemble, the parameters $K$ and $d$ were taken from the range $[0; 15]$. Note that for $K < d$, the size of the ensemble is 1, i.e. it is not actually used.

Tables 2, 3, and 4 for each test protocol show the corresponding values of the MAE metric for some parameters $K$ and $d$. $S$ is the size of the ensemble. Fig. 7 shows the MAE heat map for different values of the parameters $K, d$ for all three test protocols. The best results are highlighted in bold. The best parameters of the ensemble are also highlighted in bold.

### 5.3 Second stage

Based on the results of the first stage, the best parameters of the offset ensemble were determined. The maximum improvement is achieved on the first test protocol with the values $K = 15$ and $d = 5$. Other protocols have results comparable to the optimal one with these parameters.

In the second stage, various architectures of the ResNet family were used as the backbone: ResNet18, ResNet34, ResNet50, ResNet101 and ResNet152. All backbones were pre-trained on ImageNet [47]. A single head branch was also used: a classification head with a bin size of 1.

The NN was trained using the Adam [70] optimizer with a learning rate of $3 \times 10^{-4}$ for 100 epochs. The batch size was 128.

Table 5 shows a summary of the results of the experiments for each test protocol and their comparison with the state-of-the-art results. The best results in the table are highlighted in bold.

Fig. 8 shows examples of predictions of a trained NN with ResNet152 backbone for all test protocols.

## 6 Discussion

In this section, we discuss the results obtained for each test protocol.

### 6.1 Test protocol 1

In the first test protocol, the use of the offset ensemble gives an increase in the quality of the prediction from 3.74 to 3.67 (1.9%) for the AFLW2000 dataset and from 4.14 to 4.04 (2.4%) for the BIWI dataset. The KD further improves the results. The improvement is achieved on all variants of the backbone. For the AFLW2000 dataset, there is an improvement in the results with an increase in the depth of the backbone. The best result is achieved with the ResNet152 backbone. The KD increases the quality of the prediction compared to the non-ensemble version from 3.74 to 3.48 (7.0%) for the AFLW2000 dataset and from 4.14 to 3.70 (10.6%) for the BIWI dataset.

The best result shown is superior to the state-of-the-art results for the AFLW2000 dataset. In particular, the increase is 9.1%: 3.48 versus 3.83. The result comparable to state-of-the-art result is obtained for the BIWI dataset: 3.70 versus 3.66 respectively. The difference is 1.0%.
The result obtained on the BIWI dataset can be explained by the previous state-of-the-art result obtained with the implicit use of additional data about facial landmarks. We conducted pure experiments according to the test protocol without using additional data. We also used the YOLOv5 detector, which normalizes the positions of the bounding boxes relative to the face in all datasets. Some publications do not contain a clear description of how the bounding boxes were obtained for the datasets. As we mentioned earlier, choosing the bounding boxes can significantly improve the result without changing the method [27, 28].

### 6.2 Test protocol 2

Different papers use a different division of the AFLW dataset into training and testing parts for the second test protocol. This does not allow us to compare the results of different methods objectively.

The offset ensemble for this protocol increases the prediction quality from 5.40 to 5.32 (1.5%). The KD allows one to increase the quality of the prediction compared to the non-ensemble variant from 5.40 to 5.10 (5.6%). Also, note that KD improves the quality of the offset ensemble on all the backbone options considered.

### 6.3 Test protocol 3

The offset ensemble for third protocol increases slightly the prediction quality from 2.54 to 2.52 (0.8%). The KD decreases the quality of the prediction compared to ensemble and non-ensemble variants. The best result shown increases the state-of-the-art result from 2.80 to 2.52 (10%).

Note that the BIWI dataset has a high representativeness in terms of head poses but a low representativeness in terms of shooting conditions and people, since it was obtained in the laboratory, and it contains only 20 people. Apparently, the low representativeness in terms of shooting conditions and people does not allow showing the strengths of the offset ensemble and the KD.

### 7 Conclusion

We showed that the offset ensemble allows increasing the accuracy of head pose estimation. We demonstrated that knowledge distillation (KD) allows increasing the accuracy of the offset ensemble. KD improves the results by an average of 7.7% compared to the non-ensemble version. The best result shown increases the state-of-the-art result from 2.80 to 2.52 (10%).

We have made the trained NNs publicly available. ResNet152 obtains the best results in terms of accuracy. ResNet18 obtains a better result on the AFLW2000 dataset.

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**TABLE 5: Comparison of head pose estimations**

| Method    | Use extra data | Protocol 1 | Protocol 2 | Protocol 3 |
|-----------|----------------|------------|------------|------------|
|           |                | AFLW2000   | BIWI       |             |
|           |                | pitch | yaw | roll | avg. | pitch | yaw | roll | avg. | pitch | yaw | roll | avg. |
| HopeNet [40] | ✓              | 6.55  | 5.47 | 5.34 | 5.15 | 6.60 | 4.81 | 3.26 | 4.89 | 5.89 | 6.26 | 3.82 | 5.32 |
| FSA-Net [27] |                | 6.08  | 4.50 | 4.64 | 5.07 | 4.96 | 4.27 | 2.76 | 4.00 | 4.31 | 3.93 | 2.59 | 3.61 |
| QuadNet [21] |                | 5.61  | 3.97 | 3.92 | 4.50 | 5.49 | 4.01 | 2.93 | 4.14 | 4.31 | 3.93 | 2.59 | 3.61 |
| Hybrid [27]  |                | 6.28  | 4.82 | 5.14 | 5.40 | 6.37 | 5.07 | 4.99 | 5.48 | 7.25 | 4.59 | 6.15 | 6.00 |
| BBox Margin [27] |            | 5.61  | 3.78 | 3.88 | 4.42 | 4.70 | 4.52 | 2.56 | 3.93 | 4.43 | 5.22 | 2.53 | 4.06 |
| CNN + Heatsmaps [53] |        | 4.69  | 3.34 | 3.48 | 3.83 | 4.61 | 3.98 | **2.39** | **3.66** | 3.07 | 4.16 | **2.43** | **3.22** |
| FDN [56]     |                | 6.18  | 4.87 | 4.80 | 5.28 | 5.18 | 4.57 | 3.12 | 4.29 | 3.07 | 2.44 | 2.93 | 2.80 |
| MNN [46]     |                | 5.77  | 4.20 | 4.04 | 4.67 | 4.76 | 3.05 | 4.11 | 3.97 | 3.04 | 2.44 | 2.93 | 2.80 |
| Base ResNet50 |                | 4.86  | 3.06 | 3.30 | 3.74 | 5.18 | 4.12 | 3.11 | 4.14 | 6.42 | 5.38 | 4.42 | 5.40 |
| Ensemble     |                | 4.82  | 2.96 | 3.22 | 3.67 | 5.23 | 3.89 | 3.01 | 4.04 | 6.34 | 5.29 | 4.32 | 5.32 |
| ResNet18     |                | 4.69  | 3.00 | 3.22 | 3.64 | 5.07 | 3.96 | 3.06 | 4.04 | 6.02 | 5.45 | 4.16 | 5.21 |
| ResNet34     |                | 4.74  | 3.00 | 3.21 | 3.65 | **4.49** | 4.06 | 2.96 | 3.83 | 6.10 | 5.39 | 4.24 | 5.24 |
| ResNet50     |                | 4.68  | 2.92 | 3.11 | 3.57 | 4.80 | 4.05 | 2.94 | 3.93 | 6.04 | 5.38 | 4.28 | 5.24 |
| ResNet101    |                | 4.65  | 2.96 | 3.02 | 3.54 | 5.31 | 3.76 | 2.76 | 3.94 | 5.96 | 5.36 | 3.98 | 5.10 |
| ResNet152    |                | **4.52** | 2.97 | **2.96** | **3.48** | 4.73 | 3.50 | 2.87 | 3.70 | 5.93 | 5.41 | 4.07 | 5.14 |

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Fig. 7: MAE heat map of ensemble results.
than any previous method. ResNet18 may be of interest for application tasks where maximum performance is important.

We have made publicly available the face bounding boxes for the 300W-LP, AFLW, AFLW2000, and BIWI datasets. This labeling allows one to perform a more objective comparison of methods and to level out the errors associated with the choice of the bounding boxes.

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