age estimation

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1 Problem statement

Age estimation from facial features is a practical challenge in today's modern world that helps us accelerate the access of different individuals to their needs based on their age. Nowadays, using deep learning, we attempt to extract facial image features from photographs and estimate the age of the person.

1.1 Challenges

1.1.1 Individual differences

Each person may have different facial changes during similar age ranges, making facial age estimation potentially inaccurate.

1.1.2 Makeup and decorations

1.1.3 Genetic Changes

Genetic changes can have a significant impact on age estimation based on facial features. These changes can alter characteristics such as skin color and density, facial shape, and hair and eye conditions, all of which are influential in age determination.

1.1.4 Non-age related changes and correlations

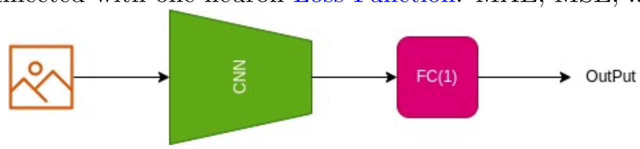
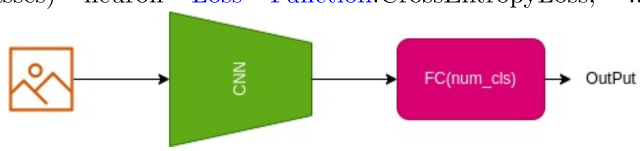
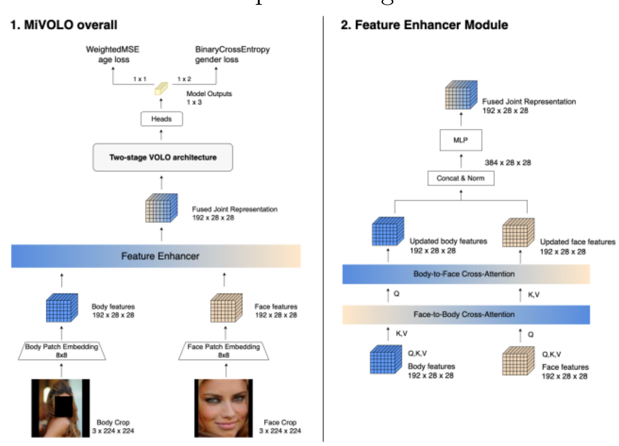
Age may be assessed based on specific areas of the face that are influenced by other factors, such as lighting conditions, background in the image, and light conditions.

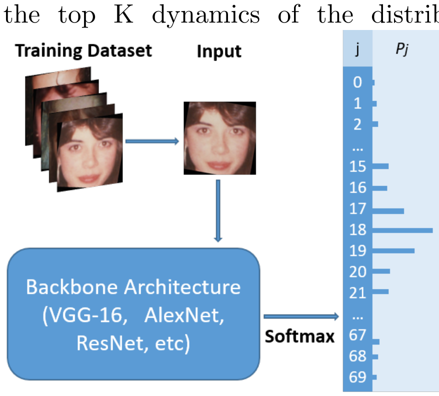
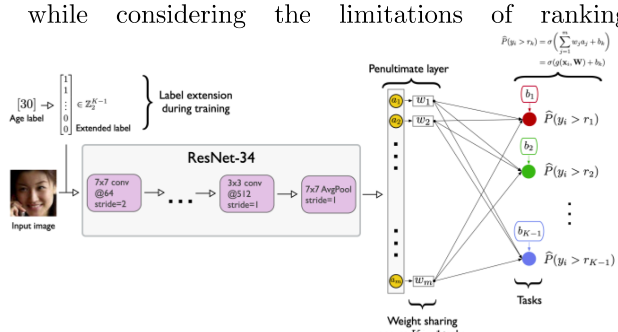
1.2 Goals:

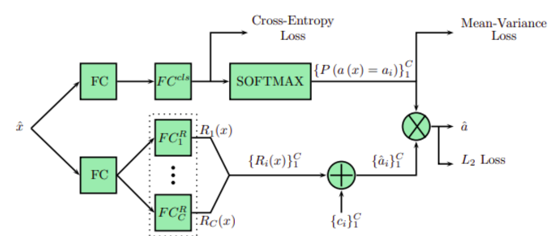
Optimal speed, **Optimal accuracy**, **Optimal parameters**, **Resistant to the mentioned challenges**

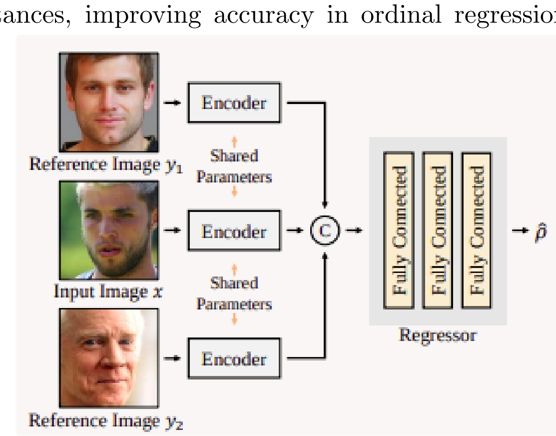
The goal is to adjust these high-quality features in a way that all of them are in their optimal state together.

2 Investigation of available methods

Method	Summary	Article	Code
Regression	Backbone: CNN layer like ResNet,MobileNet, ... FC: fully connected with one neuron Loss Function: MAE, MSE, ... 	-	link
Classification	Backbone: CNN layer like ResNet,MobileNet, ... FC: fully connected with n(number of classes) neuron Loss Function:CrossEntropyLoss, ... 	-	link
MiVOLO	In this article, we introduce MiVOLO (Multi Input VOLO), a simple approach for age and gender estimation using a newer visual transformer. Our method combines age and gender tasks into a unified input/output model and utilizes both face information and person image data for estimation 	link	link

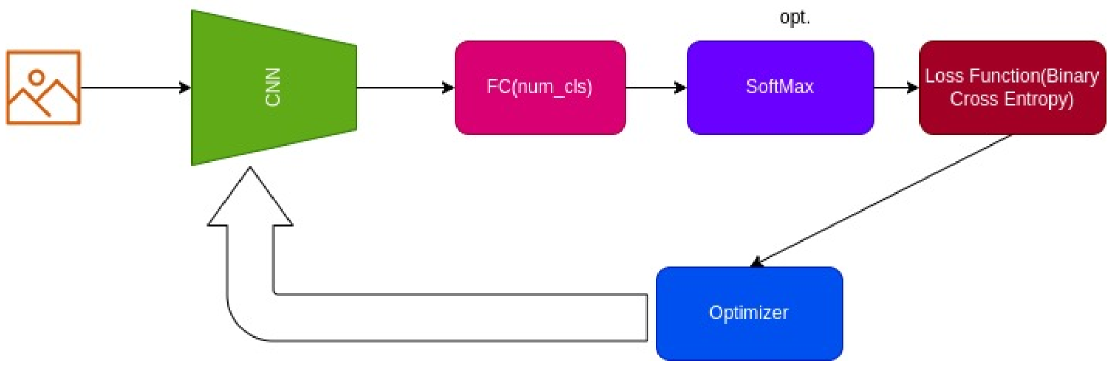
Method	Summary	Article	Code
Adaptive Mean-Residue Loss	In this work, we propose a simple but effective error function for strong age estimation via distribution learning, namely the approximate mean deviation function, where a combination of loss between estimated distribution mean age and ground truth age is present, while a combination of loss in age score magnitude in the top K dynamics of the distribution is present 	link	link
CORAL	The proposed method in this article addresses the limitations of previous ranking methods such as heteroscedasticity and uncertainty. The proposed method first combines training samples in pairs with different rankings. Then, a neural network is trained to simultaneously estimate the rankings. The proposed method evaluates itself using the Singapore dataset, which includes facial images of individuals at different ages. The results show that the proposed method achieves better results in age estimation compared to other existing methods. Therefore, this article presents a new proposed method for age estimation using neural networks, which provides better results compared to other existing methods, while considering the limitations of ranking 	link	link

Method	Summary	Article	Code
Hierarchical Attention-based	The embeddings are then aggregated by a Transformer Encoder, resulting in a single aggregated embedding ˆx. In the hierarchical regression phase, described in Section 3.2, the aggregated embedding ˆx is fed into a classification branch and a local regression branch. The classification branch estimates the probability distribution over discrete age labels P(a(x) = ac) for each age category ac. The local regression branch consists of a set of regressors Rc(ˆx), each trained to refine the age estimation within a specific age range. The final age estimation aˆ is obtained by combining the classification probabilities and the results of the local regressors. Our proposed scheme is evaluated on the MORPH II dataset for age estimation, achieving state-of-the-art accuracy. Additionally, we conduct a bias analysis to investigate the impact of gender and ethnicity on the age estimation results. This analysis is the first of its kind in face-based age estimation, using a scheme that achieves state-of-the-art accuracy. Overall, our contributions include the novel image embedding architecture based on attention, the hierarchical regression framework, and the bias analysis of age estimation results. Our approach can be applied to any high-dimensional regression problem, either as a whole or in separate components 	link	-

Method	Summary	Article	Code
Moving Window Regression	This can be done using a simple method such as nearest neighbor (NN) classification, where we find the reference instances that are closest to x and use their ranks as the initial estimate. Next, we select two reference instances, y1 and y2, to form a search window [(y1), (y2)]. The window is centered around the previous estimate, ˆ k1 (x), obtained from the (k-1)th iteration. Using the selected references, we predict the -rank ˆ(x, y1, y2) of x using the -regressor. Then, we update the estimate of the absolute rank using Equation (2): ˆ k (x) = ˆ(x, y1, y2) · (y1, y2) + µ(y1, y2) where k is the current iteration. This process is repeated iteratively until convergence, i.e., until the difference between the current estimate and the previous estimate is below a certain threshold. During the MWR process, the search window is updated in each iteration to refine the rank estimate. The window is bounded by the known ranks of the two reference instances, ensuring that the estimate remains within their range. In addition to the global -regressor, which is used for the entire rank range, we also develop local -regressors for specific rank groups. This is because different rank groups may have different characteristics, and using separate regressors for each group can improve accuracy. Overall, the MWR algorithm iteratively refines the initial rank estimate by estimating the -rank within a moving search window. This process takes into account the relative relations between the input instance and reference instances, improving accuracy in ordinal regression tasks 	link	link

3 Block diagram (Method 2)

3.1 Train:



3.2 Inference: