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ESTIMATING A PERSON'S AGE IS STRANGE TO HUMAN EYE

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Abstract- In recent years, biometrics has gotten much attention and has become the most reliable way to identify someone. This is because much research has gone into this field, and accurate technology is now available, while other identification systems aren't as good. Still, people are working on making a more user-friendly system that meets security system standards, gives more accurate results, protects assets, and keeps people's privacy safe. Estimating how older adults are an essential and challenging task. Researchers have examined different biomarkers and methods for determining a person's biological age. Each has its pros and cons. Age estimation based on face images is essential in many situations, such as security and security systems, border security, human interaction in advanced ambient analytics, and identification based on soft biometric data. Foreground age estimation is a complex and thorough way to determine how old someone is. Estimation accuracy is a meaningful way to judge algorithms and how well they can predict absolute ages by using deep learning, which started a revolution in the field of face systems. The technique was tested with data set as the foundation of the face estimation system in this field (UTKFace). The most important parts of the job are the eyes, cheeks, nose, lips, and forehead, which make up the front half of the face. Residual Network (ResNet -50) model can get the age up to 98% of the time.

Keywords: Estimation, Age, UTKFace, Deep Learning, IMDB, CNN.

1. INTRODUCTION

Age data is essential for many real-world uses, such as social understanding, biometrics, proof of identity, surveillance cameras, human-computer interaction, digital consumers, crowd analysis, online advertising, and product recommendations. Even though it has a wide range of uses, it is hard to figure out someone's age from a picture of their face. This is mainly because there are many intra-class differences in people's faces, making these models less useful in the real world [1]. Face analysis tasks have been a popular subject of study for a long time. Age recognition is a set of tasks that give essential information about a person's face [2]. This information can be helpful in many ways, such as self-monitoring [3]. Automatic age prediction from frontal photos of the face has recently gotten a lot of attention because it can be used in a wide range of face analysis problems [1]. Face analysis tasks have been a popular subject of study for a long time. Age recognition is one of those jobs that can be hard for software because of low resolution, intense lighting, and different human races, especially dark-skinned people like those of African descent or closely related forms. Information about a person's face is clear and essential.

This information can be helpful in many ways, such as self-monitoring [4]. Researchers have adopted standard machine learning (ML) approaches, and current methods show that deep learning (DL) methods have a lot of potential for use in age recognition applications [5]. Deep learning methods have also been used with great success in other areas. Convolutional neural network (CNN) is the best-known example of deep learning, and training data is critical. With more learning algorithms, the network's generalization will be broader. But it may be hard to get and hard to get enough separate data for face-based age and gender recognition. Overshooting is more likely when the training images aren't good enough. There are several ways to fix the problem of over-fitting [6]. Face recognition is a hot topic in image processing because most face recognition algorithms focus on frontal faces of people.

On the other hand, face recognition is a well-known area of computer vision. Visibility is essential for many practical uses, such as checking someone's identity, using intelligent video surveillance, and automating the immigration process [7], [8]. Also, it is a big problem for people's vision in several real-world applications, such as automated immigration clearance systems, intelligent visual surveillance, and verifying people's identities [9]. According to several application scenarios, face recognition systems are hard to use in the real world [10]. There are many ways to look at a face, such as from different angles, ages, facial expressions, and light levels. This is why some things, like being in the way or standing in a certain way, still make it hard to tell faces apart [11].

2. FACE SYSTEM TYPES

Visual pattern recognition includes face recognition as one of its many subcategories. Humans use their eyes to recognize patterns and gather visual data [12]. Because of this, the brain interprets this information as having some significance. A computer is just a grid of pixels displaying a picture or a video. Visual model recognition has a classification problem where the computer must decide what concept a particular piece of data represents. Data that all computers regard to be a face must identify who the face belongs to for facial recognition systems like this one to work [13]. Face recognition is a biometric technique that utilizes a person's unique facial characteristics. People take photos of their faces, and facial recognition software automatically analyzes the images. There are two modes of functioning [14]:

- Face-to-Face Validation (Or Authentication)
- Identification of a face (Or Recognition)
- Face estimated

Biometric methods and algorithms are not innovative approaches to Authentication [15]. Babylonian monarchs employed clay fingerprints many years ago to prove their legitimacy. Egyptians employed physical traits like forearm circumference and hand length for biometric identification. Algorithms for recognizing faces might be feature-based, holistic, or hybrid. Holistic face identification and recognition algorithms examine the entire structure of the photographs and relationships across shots [16].

3. AGE ESTIMATION

Grouping of people based on their ages. Before the 2002 introduction of the Face Recognition Vendor Test (FRVT), which focused on the effect of demographic variables on the ability to recognize faces, researchers concentrated on age groups and found conflicting results. Studies have consistently shown that older adults are more accessible to spot than younger ones [17]. According to some database studies, facial recognition technology (FERET) has a harder time recognizing younger faces than older ones. This is because it is assumed that younger faces have fewer distinguishing characteristics. Researchers have looked into the potential impact of sub-branch factors on facial recognition skills in several ways. They looked at three popular methods (Principal Component Analysis) and concluded that younger people, particularly children, are more challenging to recognize than older people. The use of demographics has led to a new point of view [18].

4. RELATED WORK

Many articles on human age estimation have been published in recent years, and this thesis highlights a few of them**.** In [19], A deep CNN-trained model on a face recognition database is used in the proposed approach for predicting age data from the audience database. This paper offers three significant contributions to the discipline. 1) This study demonstrates that a CNN-trained model for facial Recognition may be used to improve age estimation performance; 2) The issue of over-fitting may be avoided by using a CNN that has been pre-trained on an extensive database for facial Recognition and 3) The performance of the age estimation model is influenced not only by the number of training images and the number of individuals in the training database but also by the pre-training job of the VGG-CNN (Visual Geometry Group Convolutional Neural Network) employed, which impacts the performance mode. The result of the system is 59.90 in accuracy. In [20], they present the first investigation into how post processing techniques may be utilized to enhance the performance of pre-trained deep neural networks.

Several trained CNNs extracts features from the input facial image. Similar methods employ Feed-Forward Neural Networks to combine information, minimize the number of dimensions in features, and predict the age of individuals Feed-Forward Neural Network (FFNN). A publicly available dataset (Audience Benchmark of Unfiltered Faces for Recognition System) and a privately obtained dataset of non-ideal samples with controlled rotations were used to evaluate the performance of the approach. The age estimation method produced superior or equivalent results to state-of-the-art techniques and excellent performance in less-than-ideal situations. In addition, the results illustrate that CNNs trained on massive datasets may achieve acceptable accuracy on a range of validation images without the need for fine-tuning. Consequently, the MAE has fallen to 0.46.

In [21], suggest the CNN architecture known as Fusion Network (FusionNet) to solve the age estimate issue. Instead of using the whole face picture, FusionNet utilizes a series of age-specific facial patches as input to highlight the traits that are unique to each age group. Experiments demonstrate that the FusionNet performs better than other cutting-edge networks on the MORPH II benchmark. This involves implementing FusionNet to solve the problem of face-based age estimation. In addition to the face, the model uses numerous age-specific facial patches as inputs. The input face patches may be regarded as network shortcuts that improve the learning Efficiency for age-specific traits. Experiments reveal that our network outperforms existing CNN-based cutting-edge techniques on the MORPH II benchmark. For testing and training, 80% of the dataset is divided into two equal halves. Only one set of data is used for both the training and testing purposes. It was necessary to divide the data into 20 separate parts for statistical analysis (with the same ratio but different distribution). The system's performance was 96.37%.

In [22], a face-based age prediction article will employ convolutional neural networks and Support Vector Regression (SVR). Representation learning, metrics learning, and SVR are used to train a CNN to learn the learned features. Face recognition can help fill in the gaps left by the lack of large datasets with age-specific information. The proposed methodology performed well in MORPH-II and FG-Net datasets compared to current approaches. By retraining the SVR layer instead learning the CNN, the results of the system may be up to 84.28% more accurate for tiny datasets like the Face and Gesture Recognition Network (FG-Net). In [23], classification and regression methods are combined, and important characteristics are highlighted via preprocessing images and data augmentation approaches. These changes to the output layer are proposed. Reducing non-face-related noise vectors, such as ambient information that isn't connected to a person's appearance in a picture, improves the age estimate accuracy. Mean Absolute Error = 3.81 and Accuracy = 7.19 as a consequence.

In [24], develop a better loss function for neural net learning. The stochastic gradient descent-based optimization (SGD) approach will benefit from the loss function's smoothness. The recommended loss function has a smaller gradient than current loss functions, allowing SGD to reach a better optimum point and, as a result, more generalization. The proposed method beats current state-of-the-art algorithms in terms of accuracy and generalization, according to research conducted on a wide variety of datasets. The 81.57 percent of the system's performance was achieved. The following table summarized the related work.

Table 1. Summarized of related work

RF	Method	Ami	result
[19]	CNN VGG-CNN	Three contributions to the field This study shows that a CNN-trained model for facial Recognition can improve age estimation performance; 2) Over-fitting can be avoided by using a CNN that has been pre-trained on an extensive facial Recognition database; and 3) The performance of the age estimation model is influenced not only by the number of training images and the number of individuals in the training database, but also by the pre-training job of the VGG-CNN employed.	accuracy 59.90
[20]	CNN	Show how post-processing can improve pre-trained deep neural networks. Multiple trained CNNs extract facial features. Feed-Forward Neural Networks are used to combine information, reduce feature dimensions, and predict age.	MAE 0.46
[21]	CNN	CNN uses FusionNet to estimate ages. FusionNet uses age-specific facial patches instead of the complete face to highlight age-specific features. Experiments show FusionNet outperforms other cutting-edge networks on MORPH II. FusionNet is used to estimate a face's age. The model also uses age-specific facial patches. Input face patches are network shortcuts that facilitate age-specific learning.	accuracy 96.37%
[22]	CNN SVR	Face-based age prediction uses convolutional neural networks with SVR (SVR). CNNs learn features through representation learning, metrics learning, and SVR. Face recognition can help fill the gaps.	accuracy 84.28%
[23]	augmentation	Important characteristics are highlighted by preprocessing images and data augmentation.	Mean Absolute Error 3.81 Accuracy = 7.19 as
[24]	SGD	Improve neural net loss function. The smooth loss function helps SGD optimize.	Accuracy 81.57%

5. ESTIMATION OF AGE BASED ON FRONT SHOT

The suggested system offers a human age estimate technique based on a vast dataset of over 150.000 Internet Movie Database (IMDB) images; the availability of several human conditions distinguishes it. Using a multitasking convolutional neural network (CNN) algorithm, the suggested system takes as input the facial picture of a person required for age assessment. Figure (1) depicts a schematic of the suggested method for measuring the ages of humans:

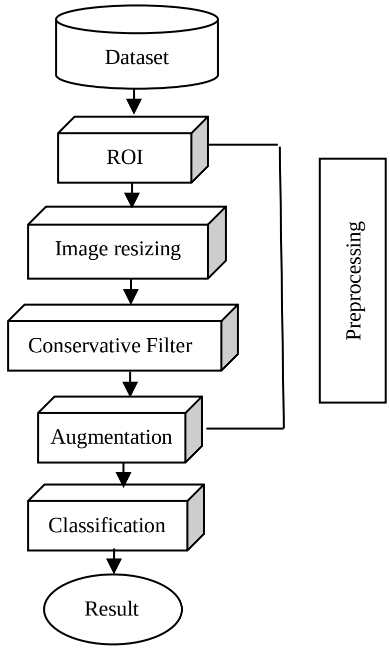

Figure 1. Block diagram of the system

5.1. Dataset Used in the Proposed System

Selecting a data set is one of the essential steps as a tool for training and evaluating the functioning and efficiency of algorithms. On this basis, the global datasets dedicated to face systems were selected, namely UTKFace [24]; the dataset is a large-scale face dataset with a long age span (ranging from 0 to 116 years old). The dataset consists of over 20,000 face images with age, gender, and ethnicity annotations.

Figure 2. Samples in the IMDB dataset

The images cover considerable variation in pose, facial expression, illumination, occlusion, resolution, etc. This dataset could be used on various tasks, e.g., face detection, age estimation, age progression/regression, and landmark localization. Figure 2 shows the sample image in the IMDB dataset. Below is a table detailing the data set.

Table 2. Data set description

Age	is an integer from 0 to 116, indicating the age
Gender	is either 0 (male) or 1 (female)
Face	is an integer from 0 to 4, denoting White, Black, Asian, Indian, and Others (like Hispanic, Latino, and Middle Eastern)
Date and Time	is in the format of yyyymmddHHMMSSFFF, showing the date and time an image was collected to UTKFace

5.2. Region of Interest (ROI)

This methodology or technology has the benefit of limiting the so-called ROI deduction zone to the middle of the face. One of the most widely-used facial recognition libraries, the Dlib library, is employed to make this possible. Max-margin object detection. According to this library, the ROI process is based on 68 points that locate and comprise prominent facial features (eyes, eyebrows, nose, mouth, jawline). The goal is to identify critical facial structures using shape prediction techniques to determine the center of the face based on these points.

5.3. Image Resizing

The resizing procedure is vital since it strives to bring together the image's dimensions. The data set in the proposed system is vast, and most importantly, it varies widely in size, ranging from (the most petite 70×70) to (300×300). Before the ROI process, the ROI output will be images of very different sizes, the image size was adjusted to 200×200, and this number was approved based on the experiment on different sizes and their impact on accuracy.

5.4. Conservative Filter

The salt and pepper sounds can be eliminated with the help of the conservative filter. Returns the minimum and highest intensity values for a pixel's surrounding area. The maximum value will be substituted for the central pixel if its intensity is higher than the maximum. When this value is less than the minimum value, the minimal value takes its place. A feature of the conservative filter is that it does not eliminate speckle noise but keeps edges intact.

5.5. Data Augmentation

The process of artificially increasing the data set so the software model can receive many additional states and image modes. Data augmentation was used in the system to train the model on many cases that may not be found in the data set. Any expansion notion is dummy training for many cases that do not exist to improve the system's efficiency in predicting age in various forms. The operations of data augmentation: Rotation, Construct, Brightness, and Flip.

5.6. Classification Using ResNet-50

The categorization of face photos or videos into preset age groups is a challenging process. Using a ResNet-50 to analyze pictures and videos of human faces have recently demonstrated impressive results. On the (UTKFace) dataset, the ResNet-50 model was trained and evaluated to perform a classification job for age groups. ResNet-50 model-based deep learning models were employed to create a 128-dimensional representation that quantifies the age group's face.

Due to better classification performance, ResNet-50 has tremendous success classifying people by age. The majority of earlier studies enhanced classification accuracy by modifying network architecture. However, the classification of age groups with an uneven data distribution has not yet been fully addressed. This work showed a ResNet-50 model capable of categorizing age groups with unequal data distribution.

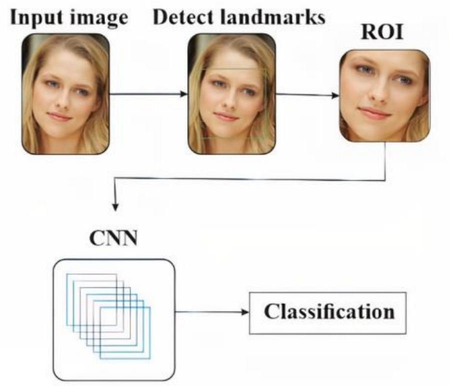

Figure 3. Structure of CNN of the proposed system

5.7. Network Architecture

Using the proposed network architecture, only 12 convolutional layers and two fully connected layers are needed to classify ages. It was decided to use a smaller network design rather than a much larger one to reduce the risk of overfitting. The age classification set requires differentiation between 91 classes (1 to 90 years old). Immediately all three-color channels are processed by the system. To feed images to the network, they must first be rescaled to 200×200. ResNet-50 is a convolutional neural network that is 50 layers deep. ResNet, is a classic neural network used as a backbone for many computer vision tasks. The fundamental breakthrough with ResNet allowed us to train intense neural networks with 150+layers. It is an innovative neural network introduced by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their 2015 computer vision research paper titled 'Deep Residual Learning for Image Recognition. The conception is Adding the original input to the output of the convolutional block. Figure 4 shows how it works.

Convolutional Neural Networks have a significant disadvantage, the 'Vanishing Gradient Problem'. During backpropagation, the value of the gradient decreases significantly; thus, hardly any change comes to weights. To overcome this, ResNet is used. It makes use of "SKIP CONNECTION".

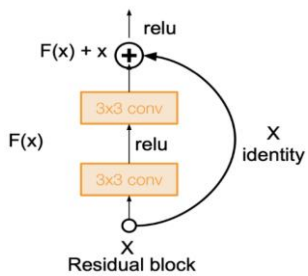

Figure 4. Structure of CNN of the proposed system

6. EVALUATION METRICS AND RESULT

The recommended evaluation approach will utilize the confusion matrix [25]. Classification models can either correctly estimate or wrongly forecast the number of occurrences.

• Precision: It is measured using the standard deviation of a data set, while bias is measured using the mean and standard deviation of the data set and the value of the item being measured. As described by the following precision equation, precision is the proportion of positive records in the group the classifier has designated as belonging to the positive class.

$$Precision(p) = \frac{TP}{TP+FP} \quad (1)$$

By applying Equation (1) for all images, the equation result is:

• Recall: Recall measures the percentage of correctly predicted positive cases, and its value is equivalent to the actual positive rate.

$$Recall(r) = \frac{TP}{TP+FN} \quad (2)$$

• F1: Precision and recall harmonic mean is indicated by F1 with a matching equation.

$$F1 = \frac{2rp}{r+p} = \frac{2TP}{2TP+FP+FN} \quad (3)$$

By applying Equation (3) to every image, the following result is obtained:

• Accuracy: The classification accuracy will be tested on the search data collection. It is assumed that each category of membership is described.

$$Accuracy = \frac{\text{number of correctly classified image}}{\text{total number of image}} \times 100\% \quad (4)$$

By applying Equation (4) for all images calculated by using the mean average, the result is:

$Accuracy = 0.99\%$

Figure 5 shows the result of the system work that shows the measurement results. Table 1 shows the result of the system.

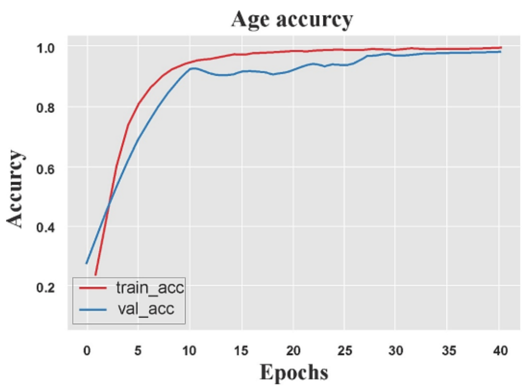

Figure 5. Age accuracy

Table 3. Result of the system

Precision	0.96
Recall	0.97
F1	0.95
Accuracy	0.98

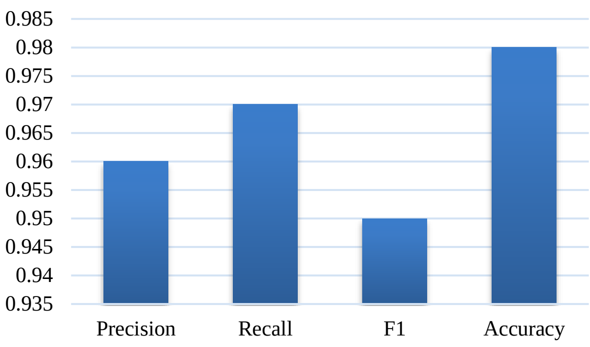

Figure 6. Result of the system

7. CONCLUSIONS

Face age estimation is a soft biometric that can be used with facial, fingerprint, or iris recognition to improve the accuracy of Recognition, verification, or Authentication. Faces that don't change much over time can be recognized by their ages. To improve the accuracy of the (central) solid biometric system, it can use iris recognition, hand geometry recognition, and fingerprint recognition. The goal of the method described was to get a more accurate estimate of a person's age by using the CNN algorithm for deep learning and photos of the foreground. A vital part of the (DA) process is creating fake cases, not in the data set. This makes the system more reliable. Its main idea is to create and deal with massive data sets to get a high-quality classification process that works well with face systems. Instead of the algorithm used, it would be better to use the "You only look once" (YOLO) algorithm in future work.

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