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# Age Stage Prediction Using Light Convolution Neural Network

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**Abstract**

Age-stage prediction models based on facial images are essential for various applications, including forensic investigations, medical imaging, social media advertising, and compliance with age-related regulations. These models provide valuable insights and predictions, helping inform decision-making and improve outcomes. The proposed model estimates the human age stage by analyzing a face image, extracting various facial features and wrinkles, and then connecting these extracted feature patterns to determine the age stage. To address potential limitations in facial images, such as variations in lighting, pose, expression, and image quality, which can impact prediction performance, the proposed model utilizes a neural network architecture. On the other hand, the proposed CNN model has adopted a new light architecture to make it usable with reasonable computational capabilities. The practical results of this model resulted in an accuracy of 98.86% when implemented on the UTKFace dataset, which consists of over 20,000 face images.

**Keywords:** Age predictions, facial image, human life stage prediction, convolution neural network, facial features.

# التنبؤ بالمرحلة العمرية باستعمال الشبكة العصبية العميقة

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**الخلاصة**

تعد نماذج التنبؤ بالمرحلة العمرية المستندة إلى صور الوجه ضرورية لمختلف التطبيقات، بما في ذلك تحقيقات الطب الشرعي، والتصوير الطبي، وإعلانات وسائل التواصل الاجتماعي، والامتثال للوائح المتعلقة بالعمر . توفر هذه النماذج رؤى وتنبؤات قيمة، مما يساعد على إعلام عملية صنع القرار وتحسين النتائج. يقوم النموذج المقترح بتقدير مرحلة عمر الإنسان بناء على تحليل صورة الوجه لاستخراج ملامح الوجه المختلفة والتجاعيد المتوفرة في هذه الصورة ومن ثم ربط أنماط السمات المستخرجة لاتخاذ القرار وتحديد المرحلة العمرية. من أجل التغلب على القيود التي قد تعاني منها صور الوجه مثل الاختلاف في إضاءة الصورة، والوضعية، والتعبير، وجودة الصورة، والتي تؤثر على أداء التنبؤ، يستعمل النموذج المقترح نموذج CNN. ومن ناحية

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أخرى، ولجعل النموذج قابلاً للاستعمال بقدرات حسابية معقولة،تم تبني نموذج CNN المقترح ببنية خفيفة جديدة. أسفرت النتائج العملية لهذا النموذج عن دقة بلغت 98.86% تم تنفيذها على مجموعة بيانات UTK-Face التي تتكون من أكثر من 20000 صورة للوجه.

## 1. Introduction

Age group prediction is the technique of determining an individual's age range using information about their physical characteristics, behavioral habits, demographics, and other relevant information. Analysts and marketers frequently target particular age groups with specific goods, services, or marketing initiatives. The process of age estimation assigns an age or an age group to a facial signal. Depending on the labels assigned to the training data, this category's issues can be further subdivided into two subcategories: true age estimation and apparent age estimation, which refers to the age that people think from a person's appearance.
To overcome these problems, the age stage of the person is estimated and predicted. The human face holds the key to unlocking its secrets as it undergoes aging changes, including wrinkles and spots. Loss of the total volume of the facial bones can change the general shape of the face, leading to sagging.

Image classification can be used to classify facial images [1] or videos into predetermined age categories [2, 3]. The number of age groups used in image classification can vary depending on the purpose of the model and the available data. For example, one study used 7 age groups ranging from 1–10 to 61 and above [3], and another study used 8 age groups ranging [4, 5].

Different methods can be used for age group classification, such as convolutional neural networks [1], histograms of oriented gradients [5], rank-ordered features [3], and others that implement an improved architecture of CNN [6]. These methods use different features of the facial image to classify the age group. For example, oriented gradient histograms use the image's edge orientation to describe the face [5]. Gender prediction sometimes impedes age group estimation in an attempt to enhance face recognition [7].

Age group classification can be a complex task due to variations in facial features and expressions [4]. There are several stages in a person's life, each characterized by characteristics that differ in their totality from the characteristics that distinguish the other stages. Researchers differ in their division of the stages of life, and all divisions define the stages according to prominent aspects that characterize the stage under study and differentiate it from another stage. This is where the differences between the researchers' divisions arise. This paper employs the G. Stanley Hall division, a specialist's classification based on the stages a person experiences in their typical life. The common human life stages can be illustrated as follows:
Infants, from birth to 1 year of age, have a round face, soft facial features, large eyes, and tiny noses and lips.

1- Toddler: From 2 to 4 years old, children's faces become more angled, and the facial features at this stage become more familiar.
2- Child: from 5 to 12 years old, the cheekbones and jawline become more prominent.
3- Teenagers: From 13 to 19 years old, teenagers' facial features vary significantly as a result of hormonal changes. Acne, facial hair growth, and changes to the facial bone structure are all part of this period.
4- Young Adulthood: From 20 to 39 years old, the skeletal composition of the face eventually gets more symmetrical and distinct. Men have a leaner, more angular face, and more prominent facial hair.

5- Middle Age: From 40 to 59 years old, indications of aging, such as wrinkles, fine lines, and sagging skin, start to appear on the face. Patches, or sun spots, may also begin to appear on the skin.
6- Old Age: From 60 and above, the facial structures lose their suppleness and rigidity. Skin gets more delicate, and wrinkles are more obvious. Loss of bone density and muscle tone causes the face to become more rounded.
To determine if a picture belongs to any age group, the age prediction process entails detecting the distinctive facial characteristics of each of these life phases. These systems have gained wide resonance in scientific research across multiple industries and fields, making them a valuable tool for many applications. In medicine, an application adopted for the prediction of the age of patients is a useful tool to help doctors diagnose diseases related to age, and this can lead to the appropriate treatment [8].
Customer service is another important area. The age prediction system can be critical for providing businesses with personalized customer service based on various age categories. For example, such a system can detect people over the age of 60 and thus offer suitable products for this age group [3, 9, 10]. Surveillance systems detect threats or suspicious attitudes, and they are crucial in the field of security [9]. Forensic applications also pay considerable attention to such systems to help in the investigation and examination of cybercrime [10]. The ability to predict human age stages significantly aids forensic systems. Some of these benefits include:

- Estimation of Age Stage: The age stage estimation system can predict a person’s age via an image, which is an effective tool in forensic investigations, providing crucial details to identify the suspects, victims, or any missing persons [2, 3].
- Facial Recognition: Age stage estimation can be a potential tool to predict suspects by comparing their images with age-estimated images. This can be helpful for law enforcement agencies in completing the investigation of crimes [3, 11].
- Missing Person’s Cases: To allocate a missing person, the age-estimation system can provide an age-estimated image of the person at different life stages and thus provide posters for the missing person, which can lead to detecting them [3, 10].
- Cold case investigations: In cold case investigations, the system can be useful to estimate the age of an unidentified body and then recognize the victim [3, 10]. On the other hand, the system can provide age-estimated images of victims and witnesses in court proceedings, which can aid in the investigation of crimes and the prosecution of criminals [9].

In this research, we propose a light CNN architecture model to enhance the performance of age estimation. The contributions in this paper can be summarized as follows:

- We propose a light CNN architecture model to enhance the performance of age classification. The number of parameters in this model is reduced to be smaller in comparison to other CNN architectures.
- The proposed model achieved a high accuracy of 98.86%, as shown clearly in the classification report.

The rest of this paper is organized as follows: In Section 2, we illustrate the related work. Section 3 introduces the proposed system architecture utilizing the dataset. Section 4 presents the results of the experiment, while section 5 illustrates the conclusion.

## 2. RELATED WORK

Deep convolutional networks are being used more and more because they are improving quickly, are good at figuring out what needs to be done, and don't need any features in images that were designed by humans [12–15]. Due to its significance in various machine learning and deep learning domains, the age prediction method has garnered more attention [7, 16, 17]. However, there has been a limited focus on improving the model's architecture and CNN's time efficiency. The effectiveness of such models depends on facial features, which are a key

indicator of a person's age. Much research has been proposed for such a task and will be discussed briefly in this section.
The authors in [11] proposed a new architecture using two separate designs for learning. The first one took more time to learn since it consisted of 14 CNN models, and the second was simpler in design but included a set of existing models (VGG, senet, denseness, and mobile net). They concluded that the new architecture reduced the time it took for implementation. In [18], the authors investigate age prediction using various deep learning models (VGG16, Resnet50, MobileNetV2, and EfficientNet-B1). The findings show that the resnet50 model outperformed the other models, achieving 95% accuracy; however, the researchers could construct a CNN architecture for the same task, which could yield superior results compared to their work. The authors in [19] made another attempt to guess the age range, using various methods for finding the correct range. They used several deep learning models (VGG-16, VGG-19, Xception, Resnet50, and Inceptionv3) along with some datasets. A new approach for age prediction was implemented in [20] based on Gabor feature selection achieved by a modified CIASO-SA algorithm and SVM for prediction. The results obtained do not seem promising, and it is possible to improve the system’s performance to obtain better results by adopting more accurate features and perhaps using a more accurate classifier. Another study in [21] proposed an age and gender detection system using CNN; the task was performed using the UTKface dataset; the model achieves 79% on age detection; the accuracy of the CNN model is poor; and the architecture of the model adopted is not clear. Garain et al. [22] employed an improved architecture of residual attention networks on the UTKface to obtain 93.7%.
In [23], the loss function was discussed, and a new mechanism was adopted to reduce the loss (adaptive mean-residue loss); in the same context, a new technique was proposed in [24] based on a learning feature approach called ordinal deep feature learning in addition to introducing a deep learning model called ODL (or ordinal deep learning). Exploring some models and approaches implemented for the sake of age prediction in addition to the available datasets prepared for this task is illustrated in [3, 9, 10]. The hybrid approach of feature extraction was implemented in [25] for each type of feature collected using a CNN model; thus, three networks, Gender-Net, Age-Net, and Race-Net, were adopted. The authors in [26] proposed another hybrid approach that demonstrates feature extraction using a convolutional neural network (CNN) and an extreme learning machine (ELM) mechanism for age prediction. The model's performance increased MAE over a short range. The authors of [2] adopted a new approach to improving the training model by providing a modified version of the data using an SRGAN model. The authors in [27] used CNN to classify age groups based on the audience benchmark. Instead of using a SoftMax loss function, the proposed model uses a CNN with a multi-class focal loss function. Although the CNN model is light and well-constructed, the results obtained are somewhat weak. In [28], researchers tested a new CNN architecture on three distinct datasets. The proposed system implements three models: Resnet50, VGGnet, and a modified Unet model.
The authors in [29] used a convolutional neural network (CNN) and an extreme learning machine (ELM). Their system consists of the combination of the final decision of three aspects to explore the age group using an ELM classifier. Three models, Age-Net, Gender-Net, and Race-Net, are trained for a special task: one for predicting age class, one for gender class, and another for race class.
Upon noting the weaknesses and gaps that were identified in previous research, some of these points were addressed in this research by building a model that can be considered light based on the number of layers and the time consumed in the calculation. In addition, a high accuracy was obtained with this model.

## 3. PROPOSED SYSTEM

This paper proposes a human life stage prediction model based on analyzing face images. The overall block diagram of the system phases that have been proposed is illustrated in Figure 1.

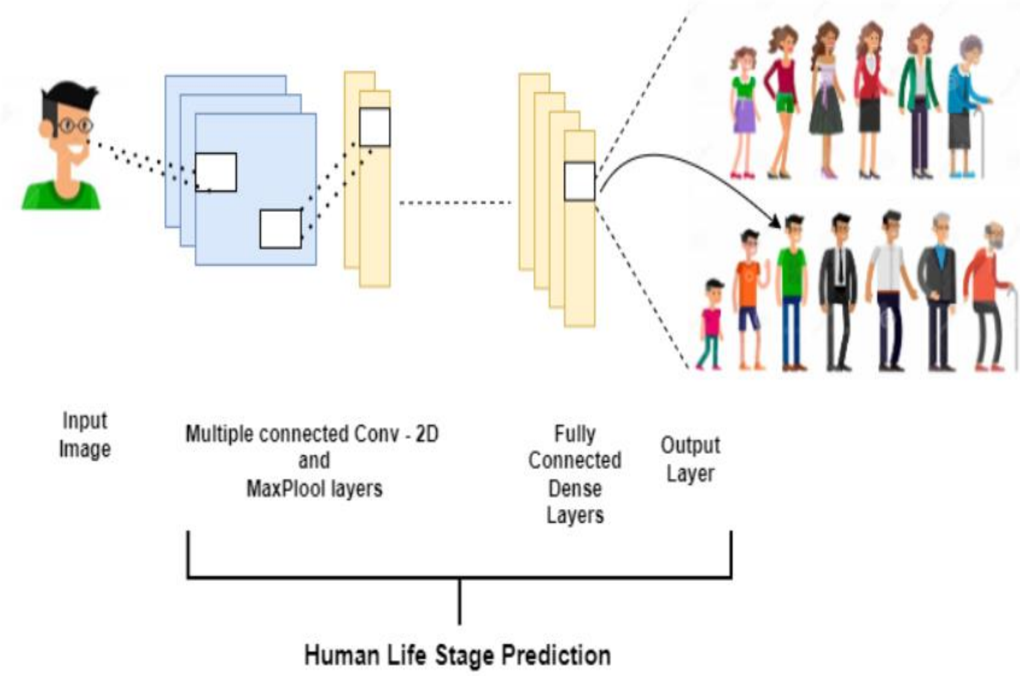


**Figure 1:** The Human Life Stages Prediction Sys-

The suggested model uses a convolutional neural network with a new light architecture to get close to the unknown functions of figuring out a person's age group and the relationships between facial features at different stages of human life. The proposed model operates in two stages: the pre-processing stage and the prediction stage, which correspond to different stages of human life. Each stage consists of some steps that perform specific functions.

*3.1. UTKFace Dataset*

UTKFace [30] is a dataset of face images that is commonly used for research in computer vision, machine learning, and other related fields. The dataset is composed of about 20,000 images of faces. Each image is labeled with the person's age, gender, and ethnicity. The dataset contains images of people from a range of ethnic origins, with individuals' ages ranging from 0 to 116. The UTKFace dataset was created by combining the datasets of the IMDB and Wiki databases and manually annotating the ethnicity labels for each image. The dataset is commonly used for research in age estimation, gender classification, and ethnicity recognition.

*3.2. PREPARING DATASET*

The dataset in the application of computer vision is composed of images/videos. The first step in training the machine learning models is collecting and preparing the data. The internet's open-sourced datasets, also known as open datasets (a vast database of data), are utilized, but they may not be compatible with the aim of the proposed model; therefore, extra requirements are needed to process before training the model.

The UTKFace dataset required some preparation work to be suitable for learning the mode. The first process is extracting the age of each image, which can be included with its name. Then, the human life stage classes are created by dividing the data set into seven human life stages according to the age extracted.

The third step includes dividing the dataset into training, validation, and testing parts according to the specific ratio for each part (70, 15, 15). The dataset information can be shown in Table 1.

**Table1 .** The dataset division

| Set name | 1.1. Partition Ratio | No. of samples (images) | Total dataset samples |
|---|---|---|---|
| Training dataset | 1.2. 70 % | 1.3. 16596 | 1.4. 23708 |
| 1.5. Validation dataset | 1.6. 15 % | 1.7. 3556 | |
| 1.8. Testing dataset | 1.9. 15 % | 1.10. 3556 | |

### *3.3. PROPOSED LIGHT CNN MODEL*

In situations where computational effectiveness, minimal memory consumption, and noise robustness are crucial factors. The proposed convolutional neural network (CNN) model has been designed with Light architecture. In comparison to other architectures, the proposed a Light CNN model is composed of a smaller number of parameters, making it more efficient and faster while executing on devices with low resources. Simultaneously, the Light CNN model can be trained and employed on resource-constrained devices to be employed on a compact network structure that requires less memory. The proposed model performs two stages, the pre-processing stage and the human life stage, the prediction stage.

#### *3.3.1. THE PRE-PROCESS STAGE*

The input image undergoes all necessary processing during the pre-processing step to be implemented in the predicted human life phases. Since the actual images can include some inappropriate data, this stage consists of three steps, including ROI extraction, resizing (scale), and normalization. The ROI extraction step crops the interesting region, which is a face, by using ‘Multi-Task Cascaded Convolutional Networks (MTCNN).’ This step involves automatically identifying and extracting the size and location of each image's human face. Scaling the dimensionality of cropped images will give the suggested model more generality. The bi-cubic interpolation method is used to alter the overall pixel count of images. Large integer value inputs can disrupt or slow down the learning process, so images are often normalized to alter the intensity range of pixel values to a more manageable range between 0 and 1. This is done for all channels by dividing the value of each pixel by 255, which is the value of the pixel with the highest value.

### 3.3.2. THE HUMAN LIFE STAGES PREDICTION

**Table 2:** A brief illustration of the proposed model.

| Block no. | 1.11. Layer (type) | Output shape | Parames no. |
|---|---|---|---|
| 1 | conv2d_1 (Conv2D) | 1.12. (None, 128, 128, 16) | 1.13. 448 |
| | max_pooling2d_1 (MaxPooling2) | 1.14. (None, 64, 64, 16) | 1.15. 0 |
| | batch_normalization_1 (Batch) | 1.16. (None, 64, 64, 16) | 1.17. 64 |
| 1.18. 2 | conv2d_2 (Conv2D) | 1.19. (None, 64, 64, 32) | 1.20. 4640 |
| | max_pooling2d_2 (MaxPooling2) | 1.21. (None, 32, 32, 32) | 1.22. 0 |
| | dropout_1 (Dropout) | 1.23. (None, 32, 32, 32) | 1.24. 0 |
| 1.25. 3 | conv2d_3 (Conv2D) | 1.26. (None, 32, 32, 64) | 1.27. 18496 |
| | max_pooling2d_3 (MaxPooling2) | 1.28. (None, 16, 16, 64) | 1.29. 0 |
| | 1.30. dropout_2 (Dropout) | 1.31. (None, 16, 16, 64) | 1.32. 0 |
| 1.33. 4 | 1.34. flatten_1 (Flatten) | 1.35. (None, 16384) | 1.36. 0 |
| | dense_1 (Dense) | (None, 500) | 1.37. 8192500 |
| 1.38. 5 | dense_2 (Dense) | (None, 250) | 1.39. 125250 |
| 1.40. 6 | dense_3 (Dense) | 1.41. (None, 30) | 1.42. 7530 |
| 1.43. 7 | 1.44. dense_4 (Dense) | 1.45. (None, 7) | 1.46. 217 |

Total params: 8,349,145
Trainable params: 8,349,113
Non-trainable params: 32

In this phase, two procedures are involved: face analysis, which involves parsing the input face image for salient features, and classification, which involves using that information to make a decision. Each stage is responsible for enacting a different layer's function. Table 2 provides a graphical summary of the proposed architecture, including details such as the number and type of layers in the model, the shape of its output, the values of its parameters (weights), and the total number of these weights.

The face analysis step included three convolution layers with filter numbers (16, 32, and 64), respectively, and kernel sizes (3, 3) for all. Each one is followed by a non-linear layer with the ReLU function, representing the activation function, and then a max-pooling layer with a window size of (2, 2), which takes a cluster of neurons at the prior layer and uses the maximal value as output. The feature maps of the input are extracted and constructed through the convolutional layers, which implies that the latter function works as local filters on the input data, and the filter kernel coefficients are set throughout the training process.

As a set of primordial patterns, the primary convolution layers construct low-level features in the input data. The subsequent convolution layers can combine primary characteristics and

generate patterns of patterns. These produce secondary features, which are then combined to form patterns of higher-level features.
To prevent the occurrence of over-fitting and to efficiently regulate noise during the training process, several dropout layers (see Table 2) are introduced by randomly picking some neurons, approximately 25% of the specified layer, and setting their weights to zero. To speed up training and coordinate the updating of several model layers, batch normalization layers are also introduced.

The classification step is a process of approximating a model relationship based on salient features extracted in the previous step to determine the human age stage. This step consists of four fully connected layers called dense layers, which have 500, 250, and 30 neurons, respectively, and apply the ReLU activation function. The last one is the output layer, which is a fully connected layer. The output layer is composed of seven neurons and implements a SoftMax function. At this phase, the dropout layer is added randomly, selecting about 25% of the neurons.

## 4. EXPERIMENTAL RESULTS

By evaluating the training and validation datasets for each epoch and plotting the learning curve, one can quickly comprehend the behavior of the proposed model's learning on a specific dataset. Accuracy is a metric that evaluates a proposed deep learning model's performance during training and provides feedback to improve it.

To determine how accurately the model can predict the outcome based on a given input, as can be shown in Figure 2. To measure the difference between the predicted output of a model and the actual output, the loss function is used to optimize the model, provide feedback, and implement regularization techniques, as shown in Figure 3.

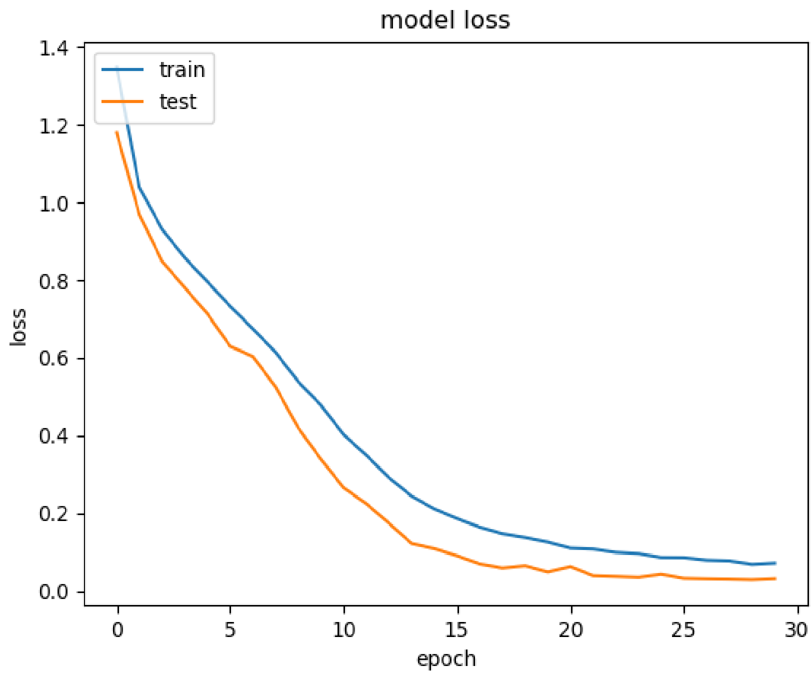


**Figure 2:** Accuracy Curve of the Proposed Model

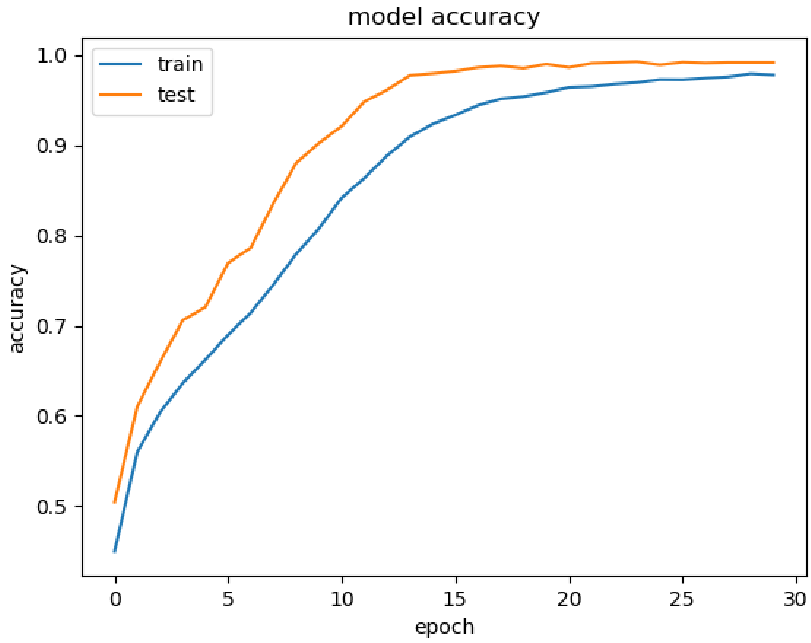


**Figure 3:** Loss Function Learning Curve of the Proposed Model

*4.1. EVALUATING THE PROPOSED MODEL*

Deep learning models are stochastic models that provide different predictions with different overall skills each time the same model is fitted to the same data.

The evaluation of the new architecture model is presented in two directions:

1. Estimating Model Skill (Controlling for Model Variance), whereby training the same model on distinct data yields varying results. This estimate is made using K-fold cross-validation. The proposed models are given k = 10 for each value of K, which splits the data set into Tr (80%) +Va (10%) = 90% and Te = 10% to record the performance of the model based on the accuracy adopted in the evaluation.

Lastly, the final result is found by taking the average of all the performances. Table 3 shows how the 10-fold CV was implemented and the results of the experiments.

**Table 3:** 10-Fold CV for the proposed model

| Fold number | Fold accuracy | Accuracy of model |
|---|---|---|
| 1 | 95.37% | |
| 2 | 98.71% | |
| 3 | 99.16% | |
| 4 | 99.10% | |
| 5 | 99.04% | |
| 6 | 99.23% | 98.86% (+/- 1.19%) |
| 7 | 99.49% | |
| 8 | 99.42% | |
| 9 | 99.36% | |
| 10 | 99.68% | |

2. The process entails estimating a stochastic model's skill while accounting for its stability. It obtains differing results when training the same model on the same data and repeating the experiment of evaluating a non-stochastic model multiple times. It is followed by the calculation of the mean of the estimated mean model skill, which is also known as the mean. Table 4 shows the proposed model's performance in terms of accuracy, recall, and the F1-measure. The macro average is the unweighted mean per label, which is the sum of all the true positives, false negatives, and false positives. For each label, the weighted average is the support-weighted mean.

**Table 4:** Evaluation of the proposed model

| class | Precision | Recall | F1-measure | Support |
|---|---|---|---|---|
| 0 | 1.00 | 1.00 | 1.00 | 315 |
| 1 | 0.99 | 0.99 | 0.99 | 287 |
| 2 | 0.98 | 1.00 | 0.99 | 344 |
| 3 | 0.98 | 0.98 | 0.98 | 1123 |
| 4 | 0.99 | 0.99 | 0.99 | 1517 |
| 5 | 0.99 | 0.99 | 0.99 | 813 |
| 6 | 1.00 | 0.99 | 1.00 | 343 |
| accuracy | | | 0.99 | 4742 |
| macro avg | 0.99 | 0.99 | 0.99 | 4742 |
| weighted avg | 0.99 | 0.99 | 0.99 | 4742 |

The Light CNN architecture has been shown to achieve high accuracy even when dealing with challenging lighting conditions, pose variations, and occlusions. The proposed Light CNN model is composed of a small number of parameters compared to other CNN architectures, making it computationally efficient and even faster while executing on limited resource devices. Table 5 shows a comparison of the proposed model with other state-of-the-art models trained and tested using the UTKFace dataset for age-stage detection.

**Table 5:**A comparison of some of the literature survey models with the proposed model

| References | Models used | Classes | Best Accuracy |
|---|---|---|---|
| [6] | 2PDG | multiclass | 96.41% |
| [22] | Residual Attention Network | multiclass | 93.7% |
| [21] | CNN | multiclass | 79% |
| **1.47. The proposed model** | **Light CNN model** | **7** | **98.86%** |

## 5. CONCLUSION

The Human Life Stage Prediction System using deep learning can offer a range of benefits across multiple industries and fields, making it a valuable tool for many applications. Forensic computing is a critical application area that can utilize the Human Life Age Stage Prediction System. It can aid in crime investigation, identify suspects, and assist in suspect identification by comparing their images with the age-estimated images in the database. This can aid in crime investigations and help law enforcement agencies apprehend criminals.

The proposed model shows good performance after applying the k-fold cross-validation approach and results with a high accuracy of (98.86%) in comparison with the state-of-the-art models. The system analyzes images of a person's face to predict their life stage. Many observations were made throughout this research that serve as conclusions:

- The proposed model's use of the ReLU activation function, which involves extracting important features while ignoring less important ones, allowed it to deal with noise in the data (eliminating all noise components from the image and only retaining those with only positive values).
- Research demonstrates that the Light CNN architecture maintains high accuracy despite challenging lighting conditions, pose variations, and occlusions. Compared to other CNN architectures, it occupies a comparatively smaller number of parameters.
- Low memory usage: The Light CNN architecture employs a compact network structure, requiring less memory than other CNN architectures. This makes it easier to train and deploy the model on resource-constrained devices.
- Robustness to noise: The Light CNN architecture uses a combination of local and global features, which allows it to be robust to noise and small variations in the input images. It can deal with noise by Normalizing input data helps to improve the model's ability to handle noisy input.
- The CNN architecture implements drop-out layers to prevent the model from relying too heavily on specific features. During training, Dropout randomly "drops out" a fraction of neurons.
- Resilient to noisy input by using batch normalization layers to normalize the activations of a layer across a mini-batch. Batch normalization helps stabilize and speed up training, potentially making the model more resilient to noisy input and avoiding overfitting.

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