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CHRONO-AGE ESTIMATION BASED ON FACIAL IMAGES USING DEEP CONVOLUTIONAL NEURAL NETWORKS WITH RMSPROP OPTIMIZATION

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ABSTRACT

Chronological age estimation from facial imagery is an important research domain within computer vision and biometric analytics. Reliable age prediction systems support applications in intelligent surveillance, digital forensics, access control, healthcare monitoring, and adaptive human–computer interaction. Earlier age estimation approaches relied on handcrafted feature engineering techniques, including anthropometric measurements and texture descriptors, which often exhibited limited robustness to pose, illumination, and demographic variations. This study proposes a deep learning-based Chronological Age Estimation Framework utilizing a Convolutional Neural Network (CNN) architecture optimized with Root Mean Square Propagation (RMSProp). The model performs automated feature learning from facial images and classifies individuals into predefined age categories. A dataset comprising 19,906 facial images was employed, with 70% allocated for training and 30% for testing. Experimental evaluation demonstrates that the proposed CNN model achieves 91.5% classification accuracy with a Mean Absolute Error (MAE) of 2 years. Comparative analysis shows significant improvement over Support Vector Regression (SVR), Random Forest Regression, and Linear Regression methods. The results validate the effectiveness of deep hierarchical feature learning combined with adaptive optimization for robust age prediction.

Keywords: Age-estimation, Convolutional neural network, Deep learning, RMSProp, Facial biometrics, Computer vision.

1.0 INTRODUCTION

Age estimation from facial imagery is a critical soft biometric task in intelligent vision systems. Humans naturally infer approximate age from facial appearance; replicating this ability computationally has practical implications in surveillance systems, automated border control, online age verification, forensic profiling, and personalized digital services (Ross and Jain, 2016).

Unlike identity recognition, chronological age estimation involves modeling complex nonlinear aging processes influenced by genetic, environmental, and lifestyle factors (Farkas and Kolar, 2017). Consequently, designing accurate computational models remains challenging. Early age estimation methods relied heavily on handcrafted geometric and texture descriptors. For instance, wrinkle density analysis and anthropometric ratios were employed to distinguish age groups (Kwon and Lobo, 1999). Active Appearance Models (AAM) later provided improved facial representation, but aging processes are highly nonlinear, limiting the performance of quadratic aging functions (Lanitis *et al*., 2012). Age estimation techniques may be categorized into classification-based, regression-based, and hybrid methods (Angulu, 2018).

Kwon and Lobo (1999) introduced early anthropometric classification methods. Lanitis *et al*. (2014) explored classifier comparisons using Active Appearance Models. However, handcrafted features often failed under varying illumination and pose conditions (Pontes *et al*., 2016). Guo *et al*. (2008) implemented SVR for regression-based age estimation. Although moderately successful, SVR performance depended heavily on kernel selection. Deep learning significantly improved robustness. Levi and Hassner (2015) demonstrated CNN superiority in age and gender classification tasks. Rothe *et al*. (2015) introduced DEX, achieving state-of-the-art performance through deep CNN modeling. Machine learning techniques such as Support Vector Machines (SVM) and Support Vector Regression (SVR) improved performance but required manual feature extraction (Guo *et al*., 2008). The advent of deep learning fundamentally transformed image analysis by enabling automatic hierarchical feature extraction (LeCun *et al*., 2015). CNN-based approaches, including Deep EXpectation (DEX), demonstrated substantial improvements in age prediction tasks (Rothe *et al*., 2015). These advancements justify adopting CNN architectures for robust age estimation.

Motivated by these advances, this research proposes a CNN-based Chronological Age Estimation System optimized using RMSProp. The primary contributions include:

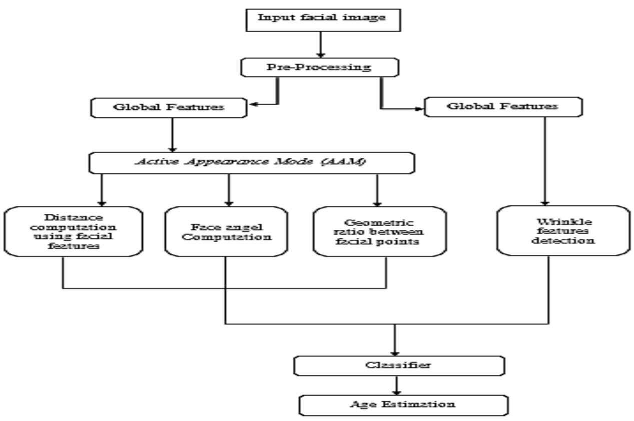
i. Development of a CNN architecture for hierarchical facial feature extraction.
ii. Integration of RMSProp adaptive optimization for stable convergence.
iii. Comprehensive performance comparison with traditional regression algorithms.
iv. Empirical validation using a large-scale facial dataset.

2.0 Materials and Methods

This study adopted the Incremental Software Development Model for the design and implementation of the proposed Chronological Age Estimation System. The model was selected because of its flexibility, reduced development cost, and ability to produce a functional system early while allowing continuous improvement through incremental modifications. The dataset used for this research was obtained from the Kaggle online machine learning repository and contains 19,906 labeled facial images categorized into different age bins. The dataset was divided into training and testing subsets, where 70% of the images were used for model training and the remaining 30% were used for testing and performance evaluation. Prior to model training, image preprocessing operations were performed to improve image quality and ensure consistency across the dataset. These preprocessing stages included face detection using OpenCV techniques, image resizing into uniform dimensions, pixel normalization, and illumination balancing. These operations enhanced facial feature visibility and improved the robustness of the neural network model under varying imaging conditions.

2.1 Chrono-Age Estimations System Design

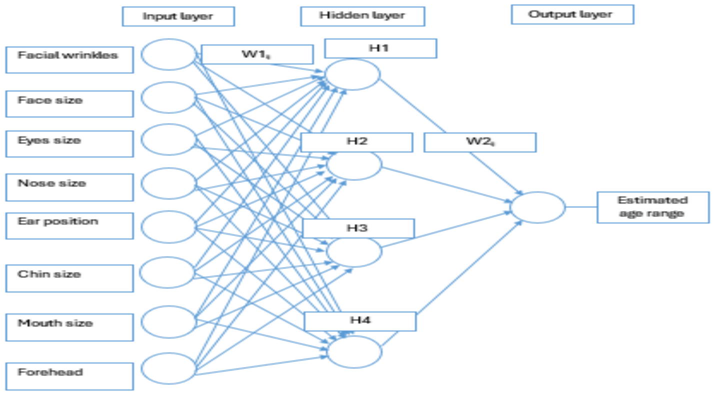
The proposed system framework in figure 1 consists of dataset acquisition, preprocessing, neural network training, RMSProp optimization, and age estimation output generation.



Source(s): Figure by Authors

Figure 1: Chrono-age estimations system framework

The proposed system was designed using an Artificial Neural Network (ANN) optimized with the Root Mean Square Propagation (RMSProp) algorithm. Figure 2 is the neural network architecture; it consists of an input layer, hidden layer(s), and an output layer. The input layer receives facial image data, while the hidden layers extract and learn important age-related facial features such as wrinkle patterns, facial structure, and skin texture variations. The output layer performs age classification and generates the estimated age range of the subject.



Source(s): Figure by Authors

Figure 2: Proposed Chrono-Age estimator Neural Network Architecture

To improve convergence speed and optimization performance, RMSProp was employed during training. RMSProp adaptively adjusts the learning rate for each network parameter using the moving average of squared gradients. The update equations are expressed as:

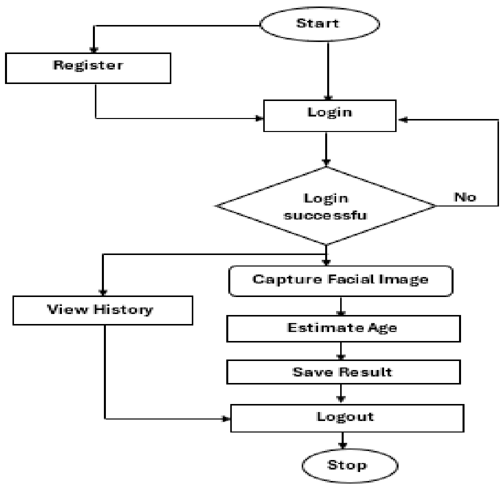
$$E[g^2]_t = \beta E[g^2]_{t-1} + (1-\beta)\left(\frac{\partial C}{\partial w}\right)^2 \quad (1)$$

$$w_t = w_{t-1} - \frac{\eta}{\sqrt{E[g^2]_t + \epsilon}} \frac{\partial C}{\partial w} \quad (2)$$

where:

$E[g^2]_t$ represents the moving average of squared gradients,
β is the decay parameter,
η is the learning rate,
ϵ is a small constant used to prevent division by zero,
$\frac{\partial C}{\partial w}$ represents the gradient of the cost function.

Clearly, the neural network architecture used for the proposed system illustrates the flow of data from the input layer through the hidden layers to the output layer responsible for age estimation. Furthermore, the operational workflow of the proposed system was represented using a flowchart illustrating the step-by-step estimation process from user authentication to age prediction and result display.



Source(s): Figure by Authors

Figure 3: Flowchart of the Proposed Chronological Age Estimation System

2.3 Chrono-Age Estimation System Evaluation

The performance of the proposed system was evaluated using Classification Accuracy and Mean Absolute Error (MAE). Classification accuracy here indicates how well the proposed system correctly classifies facial images into their corresponding age groups. The Classification Accuracy is mathematically expressed as:

$$Accuracy = \frac{N_c}{N_t} \times 100 \quad (3)$$

where: N_c represents the number of correctly classified samples; N_t represents the total number of test samples. Higher accuracy values indicate better classification performance and improved effectiveness of the proposed age estimation model. The MAE metric on the other hand measures the average difference between the predicted age and the actual age and is expressed as $MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$

(4)

where: y_i represents the actual age; $\hat{y}_i$ represents the predicted age; n denotes the number of testing samples. Lower MAE values indicate better estimation accuracy.

2.4 Chrono-Age Estimation System Testing

System testing verifies the functionality, reliability, and effectiveness of the developed Chronological Age Estimation System. Table 1 shows several test cases designed to evaluate major system functionalities, including facial detection, age estimation, and result display. The overall system was implemented using Python programming language in the PyCharm development environment with support from TensorFlow, Keras, and OpenCV libraries for neural network training and image processing

Table 1: System Test Cases

S/N	Test Case ID	Test Objective	Expected Outcome
1	T001	To test the system's ability to detect human faces	System should successfully detect human face
2	T002	To test the system's ability to estimate age from facial images	System should estimate age accurately
3	T003	To test the system's ability to display estimated age	System should display estimated age correctly

Source(s): Table by Authors

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3.0 RESULTS

This section presents the experimental results obtained from the proposed Chronological Age Estimation System and discusses the performance of the developed model. The effectiveness of the system was evaluated using statistical performance metrics and comparative analysis with existing machine learning approaches.

3.1 Result Presentation

3.1.1 Model performance

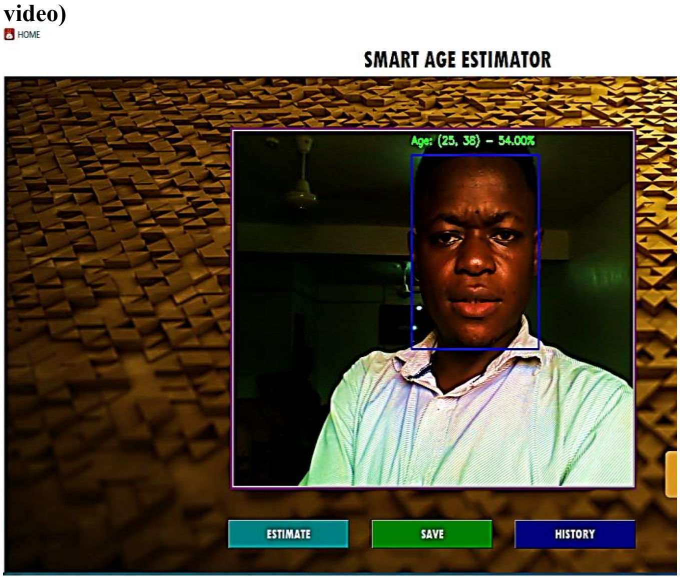
The proposed CNN model significantly performs better than the conventional regression methods. The results clearly show that the proposed CNN-based model outperformed the other machine learning algorithms in both classification accuracy and prediction error reduction. The CNN model achieved the maximum accuracy of 91.5% and the lowest MAE value of 2. The superior performance of the CNN model can be attributed to its ability to automatically learn hierarchical facial features such as wrinkle patterns, skin texture variations, and structural facial characteristics directly from image data. In contrast, traditional regression algorithms rely heavily on handcrafted features and are less effective in handling the complex nonlinear variations associated with human aging.

Table 2: Model Performance Comparison

Model	Accuracy (%)	MAE (Years)
CNN (Proposed)	91.5	2
SVR	65	6
Random Forest	55	8
Linear Regression	45	10

Source(s): Table by Authors

Sample Output Visualization (Detecting human face in a live video)



Source(s): Figure by Authors

Figure 1: Real-time facial detection and age classification output of the Chrono-age estimator

3.1.2 Test Results

The system was tested to verify the functionality, reliability, and effectiveness of the developed Chronological Age Estimation System. After executing the designed test cases, the following results were obtained.

Table 3: Test Results

S/N	Test Case ID	Result Obtained
1	T001	The system successfully detected human faces from live video input
2	T002	The system accurately estimated human age from facial images
3	T003	The system successfully displayed the estimated age on the screen

Source(s): Table by Authors

4.0 DISCUSSION

The experimental outcomes reveal that the proposed Chronological Age Estimation System performs effectively in facial age prediction tasks. The system successfully detected facial regions, extracted age-related features, and generated accurate age estimations from live video and facial image inputs. The obtained classification accuracy of 91.5% and MAE value of 2 indicate that the proposed CNN model achieved high prediction reliability and significantly outperformed conventional machine learning approaches such as SVR, Random Forest Regression, and Linear Regression. The use of RMSProp optimization contributed significantly to faster convergence and improved training stability, while the neural network architecture effectively learned discriminative age-related facial features. Overall, the results confirm that deep learning-based facial age estimation offers a robust and efficient solution for real-world biometric and surveillance applications.

This study presented a CNN-based Chronological Age Estimation System optimized using RMSProp. Experimental results demonstrated 91.5% classification accuracy and MAE of 2 years which confirms a significant improvement over SVR and regression baselines. The experimental findings demonstrate that deep convolutional feature learning substantially enhances chronological age prediction accuracy compared to traditional regression-based approaches. The top performance of the CNN model can be ascribed to several factors. First, hierarchical feature extraction enables the network to capture multilevel facial representations. Lower layers detect basic structures such as edges and contours, while deeper layers capture high-level semantic features such as wrinkle distribution, facial elasticity variations, and proportional changes associated with aging. This hierarchical abstraction is not achievable with handcrafted descriptors (LeCun *et al*., 2015). Second, the RMSProp optimizer contributes significantly to training stability. Unlike fixed learning rate optimization methods, RMSProp dynamically adapts learning rates based on gradient magnitudes. This prevents overshooting during weight updates and mitigates oscillatory behavior in high-dimensional parameter spaces. Third, the comparative analysis confirms that traditional machine learning systems such as SVR and Random Forest struggle with nonlinear facial aging patterns. These algorithms rely heavily on feature engineering and cannot automatically learn complex age-related patterns embedded in pixel distributions. However, certain limitations exist. The dataset, although sizeable, may not fully represent global demographic diversity. Age estimation models are sensitive to ethnicity, lighting conditions, and image quality. Future work should incorporate multi-ethnic datasets and domain adaptation strategies to improve generalization. Additionally, while classification-based age bin prediction achieved high accuracy, regression-based deep models predicting continuous age values may provide finer granularity.

5.0 CONCLUSION

The findings validate the effectiveness of deep hierarchical feature learning combined with adaptive optimization strategies for robust facial age estimation. Future research may explore: Transfer learning with ResNet/VGG architectures, Attention-based CNN models, Multi-task learning (age + gender) or GAN-based age progression modeling.

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