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# Enhanced Dental Age Assessment Using a Modified Extreme Learning Machine Classifier Optimized by Crow Search Algorithm

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**Abstract:**
Age identification are significant factors in the fields of forensics, bio-archaeology, and anthropology. Dental images offer valuable insights for both medical diagnoses and forensic examinations. Various techniques for dental age identification have specific limitations, such as minimum reliability and accuracy requirements. In our proposed work, the input image was improved using the Upgraded Kaun Filter and then segmented with the Active Contour model. We addressed a weight optimization issue using the Analytic Hierarchy Process. Consequently, valuable features were extracted from the segmented area, which is beneficial for age classification when applying the modified ELM-CSA classifier. The investigational outcomes intended for age identification with modified ELM-CSA approach exhibited higher performance, achieving 86.5% of exactness, specificity of 83.7%, precision of 79.21%, recall of 84.25%, and an F-measure of 74.26%. These results outperformed existing classifiers, including ELM-TLBO, ELM, SVM, and RBFN.

**Keywords:** Dental Age, Kaun Filter, Active Contour Model (ACM), Analytic Hierarchy Process (AHP), Extreme Learning Machine with Crow Search Optimization (ELM-CSA)

## 1. Introduction:

In recent times, the rising migration rates have led to a notable increase in the need for forensic age assessments in living individuals, particularly in areas where reliable birth records are not consistently accessible. Age estimations carry substantial importance in asylum cases, where different legal procedures hinge on an individual's age. Furthermore, forensic age estimation plays a crucial role in both civil and criminal legal proceedings. Currently, the established approach for forensic age estimations in adolescents entails an external examination of the body and an evaluation of skeletal and dental development stages [1-3]. The clinical process of determining chronological age is vital and relies on a reliable indicator found in teeth. Some techniques employed for age assessment using orthopantomogram (OPG) images can be quite time-consuming, and the reliability of the estimation is considerably influenced by the observer's subjectivity. [4]. X-ray images have the capability to reveal concealed structures within dental images, and the utilization of computational techniques is integral to the processes of identification and age categorization, as well as the evaluation of diseases and other crucial factors in dental images. Leveraging computational methods, the age of an unidentified individual is determined by comparing their dental, physical, and skeletal maturity to that of a known individual. [5]

## 2. Related Works:

Identifying and estimating an individual's age shows a vital part in the field of forensic ontology. Dental images serve various purposes, including diagnosis and treatment. Initially, the primary focus of research was on disease diagnosis, with later applications for age identification. Jayaraman et.al. intended to survey the fittingness of Demirjian's dataset for the southern Chinese populace. They inspected 182 all-encompassing dental tomographs, uniformly dispersed among young men and young ladies matured 3 to 16 years. Dental development scores from Demirjian's dataset were utilized to compute dental age. Hence, the assessed dental ages were contrasted with sequential ages through a matched t-test. The results uncovered a normal contrast of 0.62 years for young men ($p<0.01$) and 0.36 years for young ladies ($p<0.01$). All in all, it was resolved that Demirjian's dataset was not appropriate for assessing the times of southern Chinese kids matured 3 to 16 years [10]. Various classifiers, such as Decision Tree (DT), SVM, and K-Nearest Neighbor (KNN), utilize features extracted from the AlexNet and ResNet-based neural networks for classifying dental age [6,17]. Furthermore, some studies also consider biological features like bone, dental structures, face, and skeleton when categorizing dental images, as discussed in [7]. The estimation of dental age is accomplished using the Modified Extreme Learning Machine with Sparse Representation Classification (MELM-SRC) applied to the features obtained for age identification [8]. Dental age estimation employs a mathematical approach and the Demirjian Score, utilizing panoramic radiographs to assess an individual's dental age [9]. Mohammed et.al. conducted a study aimed at evaluating the estimation of dental age (DA) for the developmental stages of mandibular third molars across various age groups and determining the potential correlation between chronological age (CA) and DA within the South Indian population [11]. The essential features are acquired and labeled within the matrix, subsequently subjected to classification utilizing the Random Forest (RF) method. The intricacy of the matrix representation introduces complexity, resulting in an inefficient retrieval process that consumes a significant amount of time [12]. Cone beam computed tomography (CBCT) images serve as the input, and gender classification is performed using a hybrid approach that combines Genetic Algorithm (GA) and Naïve Bayes (NB). The GA extracts features for subsequent classification by NB. However, the genetic algorithm lacks effective exploitation capability, making it a time-consuming and computationally expensive process [13]. Age identification in dentistry has traditionally involved the use of various techniques, including machine learning and optimization methods. However, these methods are often time-consuming, susceptible to classification errors, and may yield low accuracy in certain algorithms. Recognizing the limitations and drawbacks of existing age assessment techniques, we propose an efficient machine learning-based optimization approach to enhance age identification. Age accuracy holds significant importance for future considerations. The need for precise age determination in image processing steps is addressed through the utilization of ELM-CSA.

## 3. Proposed Methodology:

This section delves into age identification using a machine learning-based optimization technique, a process that involves the application of numerous image processing techniques to automatically determine age

***3.1. Preprocessing Stage:***

In the preprocessing stage, The OPG image undergoes initial enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE) to mitigate contrast amplification. Subsequently, the Upgraded Kaun filter (UKF) is employed to reduce noise in the Dental OPG image while preserving its essential features.

The Kaun filter has been calculated using

$IK(x) = Im(x).\omega(x) + Im'(x)[1 - \omega(x)]$ ------- (1)

Where,

$IK(x)$ – Denoised image

$Im(x)$ – An image affected by noise

$Im'(x)$- The average image brightness in the filter's window

$\omega(x) -$ Weighted value of Kaun Filter defined by

$\omega(x) = \frac{1 - c_a^2 / c_{Im(x)}^2}{1 + c_a^2}$ ----------(2)

Where $c_a$ and $C_{Im(x)}$ represents the coefficient of variation for speckle in $a(x)$ and the image in $Im(x)$respectively. The achievement of noise reduction is anticipated based on the weight factor. The weight vector can be improved using the Random Optimization Algorithm (ROA) to enhance picture quality and reduce noise.

***3.2. Image Segmentation using ACM based AHP optimization***

The objective of OPG image segmentation is to generate an enhanced segmented image through the application of the Active Contour method. The Active Contour Model (ACM), commonly referred to as Snakes, is employed to delineate object boundaries and is employed in various approaches, including the identification of edge segments and their subsequent association. The fine-tuning process in the evolution of the snake model results in a reduction of both internal and external energy, which is determined based on the movement of control points, ultimately achieving precise object boundaries [14]. The energy function is represented as:

$E_{snake} = \int_0^1 E_{int}\big(v(s)\big) + E_{ext}\big(v(s)\big)ds$ ----- (3)

When the snake's external energy approaches the object boundary position, the gradient of the image is computed as

$\boldsymbol{E_{external}} = \boldsymbol{E_{image}} + \boldsymbol{E_{co}}$n ------------------------- (4)

The Internal Energy is computed by equation (5).

$E_{cont} = \alpha(s)|v_s(s)|^2$ ---------------------------- (5)

$E_{curv} = \beta(s)|v_{ss}(s)|^2$ ------------------------------- (6)

$E_{internal} = (\alpha(s)|v_s(s)|^2 + \beta(s)|v_{ss}(s)|^2)/2$--------------------------------- (7)

Aversion to the hidden place of the form inside nearby minima is one of the difficulties innate in ACM. As the problem size increases, it results in substantial computational efforts, which can be addressed by employing the AHP optimization algorithm.

*Analytic Hierarchy Process (AHP):*

In active contour modeling (ACM), minimizing the energy function renders the contour less sensitive to variations. AHP fills in as a multi-standards dynamic procedure utilized in perplexing situations. It involves prioritizing variables and calculating optimal weight values based on local energy. AHP transforms empirical data into a mathematical model, allowing for the computation of numerical probabilities to meet desired objectives. As a result, AHP is applied within ACM to segment regions and predict effective features for Dental age identification. [14]

*Algorithm 1: ACM with AHP optimization*

**Input:** $P(s,t)$,$E_{in}$,$E_{ext}$, t

**Output:** ROI of segmented teeth

1. The average distance among snake nodes are calculated.
2. $E_{in}$ is initialized.
3. $E_{ext}$ is also initialized.
4. The local energy is determined.
   a. The weight values are inserted into the matrix A.
   b. Reciprocal values R are generated.
   c. The fractions are converted into decimal form.
   d. Finally, the sum of each column in matrix A and Comparison Matrix A = ( ) is calculated
5. Enhancements have been made in ACM segmentation through the utilization of an energy minimization function.
6. The total energy is computed.
7. Adjustments are made to the points to minimize the overall energy.
8. Tracking of the teeth image is performed.
9. The segmented teeth image is then exhibited

### ***3.3. Feature Extraction:***

Features play a crucial role in age detection and classification, providing the necessary input for efficient categorization. These features encompass GLCM, Haralick features, Hausdorff distance, crown and root properties, tooth density, size, and geometric attributes such as roughness, concavity, convexity, area, and perimeter, all of which are extracted. [14].

### ***3.4. Feature Classification:***

The Extreme Learning Machine (ELM) calculation is employed to construct a Single Layer Feedforward Network (SLFN), as initially introduced by Huang et al. in 2006. In ELM, the main focus is on the hidden layer weights. Additionally, biases are randomly generated, and the output weight computation is established using a least-squares arrangement. Furthermore, their characteristics are determined by the target outputs and the hidden layer [15].

Let M represent a training dataset consisting $(p^i, q^i) \in S_a, i = 1,2, \dots, N$ of N samples and features. The ELM output can be computed by

$n = f(x) = \sum_{i=1}^{K} \beta^i\, g(p^i)$ --------(8)

$= \sum_{i=1}^{L} \beta^i g(\, W^i * p^j + b^i), j = 1,2, \dots, N$------------ (9)

Where L denotes the hidden nodes,

$b^i$ – Bias vector

$g$- Activation function

$\beta^i$- Weight vector between hidden node and output node

The equation (9) can be rewritten as:

$H\beta = Y$---- (10)

The network cost can be minimized and equation (10) can be calculated as $\hat{\beta} = H^{\dagger}T$ ------ (11)

The streamlining of the weight factor for the hidden nodes in ELM can be accomplished using CSA. This inturns as Modified ELM-CSA classification for dental age identification.

*Crow Search Optimization (CSA):*

CSA, a meta heuristic algorithm emulates the food-storing behavior of crows [16]. Crows are intelligent birds known for their ability to remember faces and warn their species of imminent danger. A remarkable example of their intelligence is their habit of hiding food and recalling its location.

***Algorithm***

***Inputs:*** *A teaching group of n classes* $(p^i, q^i)) \in S_a, i = 1,2,\ldots,N$ *, a model, hidden feature number H , activation function g(x),hidden node number N*

***Output:*** *Dental Age identification*

***Method:***

*1. Randomly set* $(W^i, b^i)$

*2. Calculate H using the equation (9)*

*3. Set the population size, Cpos, CMi,* $count^{max}$*, and the* $max^{iter}$

*3. Initialize the population size, crow position Cpos, Crow's memory CMi,* $Count^{max}$*, Maximum number of iterations.*

*4. do until the count>* $Count^{max}$

*5. if i=1:N do*

*i) randomly choose the crow j and define the awareness probability* $ap^i$

*ii)*$x^i > ap^i$ *then do*

$x^{i,count+1} = x^{i,count} + rand \times flylen^{i,count} \times (CM_{i,count} - x^{i,count})$

*Where,* $rand$*- Random numbers,* $flylen$*- the flight length of crowi*

*iii) else* $x^{i,count+1} = rand$

*end if*

*iv) Verify the boundary values.*

*6. Refresh the crow's memory CMi.*

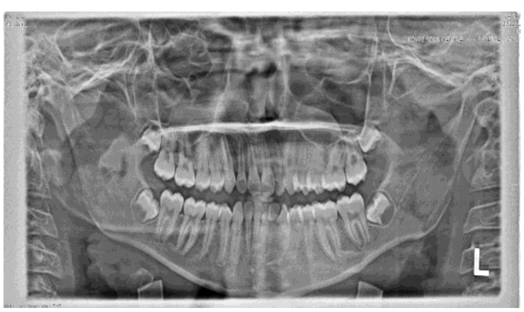
*7. Adjust the optimal weights for the hidden layer matrix H in ELM.*

*8. Update the output weight using equation (11).*

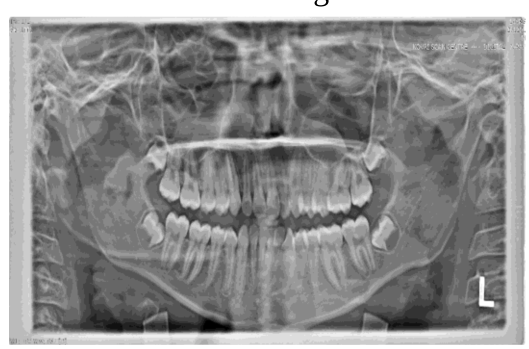
9. *Perform dental age classification and determine accuracy.*

## 4. Results & Discussions:

Input image

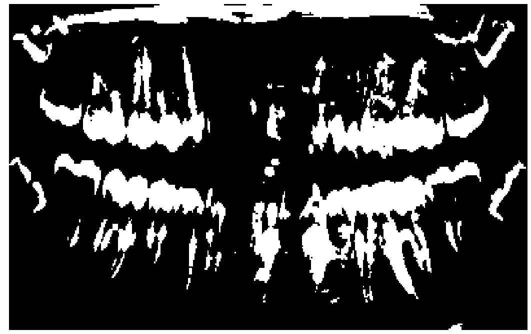


Filtered image

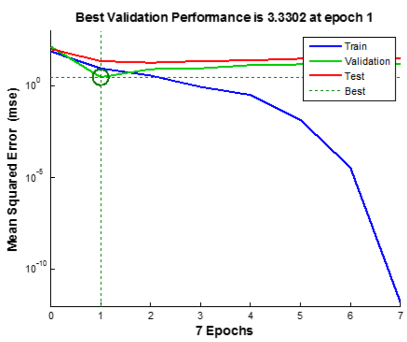


Preprocessed image

ACM output image



Testing and training performance validation




Age detection result

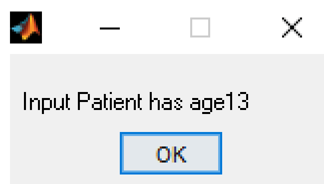



**Figure 1: Proposed ELM-CSA based of input teeth image**

Fig. 1 displays the classification results achieved using ELM-CSA. A comprehensive performance assessment for DA detection using ELM-CSA is presented in Figure 1. It is evident that ELM-CSA has achieved 86.5% of exactness, specificity of 83.7%, precision of 79.21%, recall of 84.25%, and an F-measure of 74.26%. These results outperformed existing classifiers, including ELM-TLBO, ELM, SVM, and RBFN.

Table 1: Overall performance metrics for DA Identification

| **Performance Matrices** | **Proposed ELM-CSA** | **ELM-TLBO** | **ELM** | **SVM** | **RBFN** |
|---|---|---|---|---|---|
| Accuracy (%) | 86.5 | 82.91 | 76 | 78 | 72 |
| Specificity (%) | 83.7 | 79.46 | 74.99 | 76.14 | 70.99 |
| Precision (%) | 79.21 | 77.83 | 54.66 | 64.85 | 38.79 |
| Recall (%) | 84.25 | 79.51 | 65.22 | 69.58 | 61.33 |
| F-measure (%) | 74.26 | 71.14 | 49.65 | 67.29 | 44.47 |

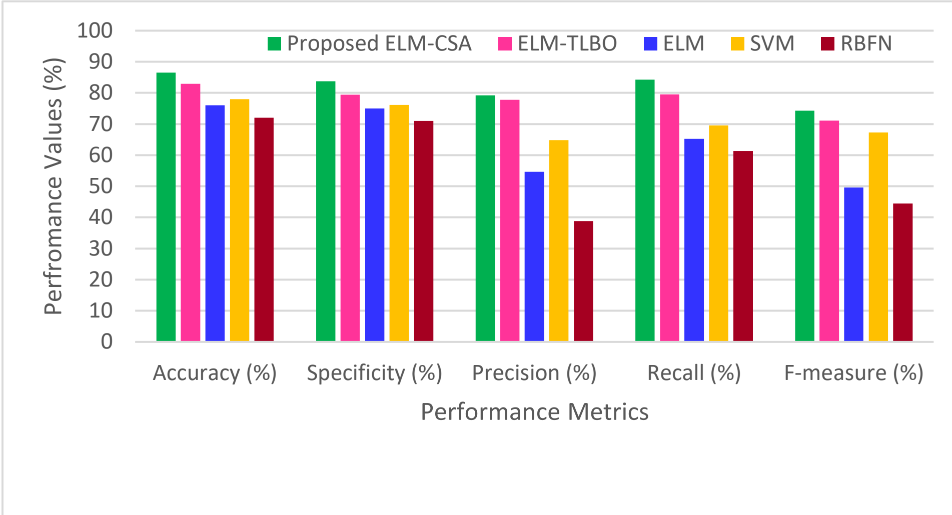



**Figure 2: Performance Evaluation for DA detection using Proposed ELM-CSA**

## 5. Conclusion

In this study, a modified ELM-CSA approach has been introduced for dental age detection and compared with the chronological age of individuals. Initially, OPG teeth images undergo preprocessing using a modified Kaun filter with a random optimization algorithm to eliminate noise while preserving edges. Subsequently, the enhanced whole teeth image is segmented using the Active Contour Model (ACM), and the weight factor selection problem of ACM is resolved using the Analytic Hierarchy Process (AHP) to improve segmentation accuracy. Relevant features are then extracted for classification purposes. The classification of dental age (DA) is performed using Extreme Learning Machines (ELM), and optimal weights are determined through CSA optimization to enhance prediction accuracy. The experimental findings demonstrate that the ELM-CSA approach attains an accuracy of 86.5%, specificity of 83.7%, precision of 79.21%, recall of 84.25%, and an F-measure of 74.26%, surpassing the performance of existing classifiers like ELM-TLBO, ELM, SVM, and RBFN. In future research, the study intends to expand the sample size to predict both dental age and gender of individuals using innovative algorithms.

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