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A Multi-featured Approach by Integrating Digital Hand and Dental X-Ray for Human Age Estimation

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Abstract

Traditionally, human bone age is estimated manually by inspecting the multiple body part X-ray images, which is extremely time-consuming and prone to error. The accuracy of the human estimate depends on the experience of the medical practitioner, and thus it suffers from intra- and inter-observer variability. Hence, efficient automatic approaches are required to determine human age with high accuracy. In this work, we propose a human age estimation technique using Deep Learning (DL) technique based on hand X-ray images combined with dental orthopantomographs (OPGs) is proposed. Here, the input X-ray image is pre-processed first using Non-Local Means (NLM) first, followed by Region of Interest (RoI) extraction. Later, color and position image augmentation are performed in order to balance the dataset. Thereafter, the salient features in the image are determined, and based on these features, human age estimation is carried out using the Deep Residual Network (DRN). Here, the DRN is trained using the Beluga whale lion optimization (BWLO) algorithm. Furthermore, the BWLO_DRN is examined for its superiority considering the model accuracy and is found to obtain value of 90.1% on hand-wrist and 89.9% OPG real time dataset, thus showing superior performance for hand-wrist images.

Keywords: *Deep Learning, Optimization, Medical Image Processing, X-ray, Bone age*

1. Introduction

Human age estimation using the X-ray image is a standard process for detecting abnormalities in the skeletal growth of children. The variation in the chronological age and bone age indicates the presence of endocrine disorders, genetic problems, and growth abnormalities. Further, human age estimation is useful in forensic and archaeological application. Legal requirements for age estimation in this age range in India include inquiries about a person's criminal liability (under certain circumstances, a child under the age of 12 is not criminally liable), employability (work performed by children under the age of 14 constitutes child labor), status of majority (18 years), and eligibility for marriage. Growth varies between populations due to differences in genetic and environmental factors. As a result, population specific formulas may be required when determining age [1]. While the Greulich-Pyle (GP) method [3] uses representative hand photographs of various age groups of a sample population, the Demirjian approach [2] uses the typical stages of wisdom teeth growth, and the staging method for assessing maturation is used in the well-established X-ray imaging-based multi-factorial approach [4,5] for estimation of biological age (BA). Although there is no defined approach for combining multiple locations, guidelines suggest using the reference population's median age for the most developed anatomical site for estimating majority age [3]. In addition to the lack of a defined procedure for aggregating individual estimates, radiological approaches deal with intra- and inter-observer variability when determining from each anatomical site the phases that define minimum age. While using more objective, automated image analysis to estimate age from X-ray data of the hand has already been demonstrated in [6, 7, 8, 9,10] and for orthopantomograms (OPGs) of the teeth there are not any comparable procedures at the moment as per our research. Because legal laws in the majority of nations forbid the application of ionizing radiation on healthy persons, magnetic resonance imaging (MRI) is a novel trend in forensic age estimation research that is replacing X-ray based approaches. Automatic approaches for age assessment based on MRI data have recently been developed [11, 12], however they also only look at one anatomical site. To the best of our knowledge, no automatic image analysis technique for multi-featured age estimation has yet been reported, regardless of the imaging modality. The deep learning method enabled an efficient mapping of manually annotated input image to estimate the objective in optimal manner. In the method [8], fine-grained local information was most relevant to the prediction for clinical use that was extracted without extra manual annotations. The third [9] method, uses both global and local features and has the advantages of short diagnosis time and fourth method [10], the attention mechanism was used for improving the network capability by emphasizing more weights on selected regions of interest. Furthermore, the AXNet utilized a 3-layer residual separable convolution that reduced the probability of diminishing gradient problems during the training process.

In this paper, we investigate a multi-featured approach for estimating age from X-rays of hand bones and OPG images of teeth. Our approach is inspired by forensic investigators and radiologists who identify stages of various anatomical areas. The proposed approach automatically merges the age-relevant appearance information from digital hand X-and OPG X-ray into age. Our findings show an increase in accuracy and precision by employing a multi-featured strategy rather than depending solely on a single anatomical component.

2. Materials And Methods

TheDRN [13], which can predict bone age with high accuracy and little error, is used in this study to assess bone age. DRN is also effective at resolving overfitting problems. Increasing the number of layers is a common way for DL based approaches to attain high classification accuracy, however doing so may cause vanishing gradient problems as the error is back-propagated. The use of residual blocks in the DRN effectively addresses this issue and also has the side benefit of accelerating training. By using the feature vector on the DRN, bone age estimation is carried out [13]. The BWLO, which was produced by fusing the BWO [14] and SLnO [15] algorithms, is used to tune the DRN in this case. The BWLO algorithm, which is produced by fusing the BWO [14] and SLnO [15] algorithms, is used to tune the hyperparameters of DRN. The beluga whale algorithm (BWO) is a swarm-based optimization algorithm that is inspired by the beluga whale's swimming, hunting, and diving behaviors. The three steps of the BWO algorithm's implementation are whale fall, exploitation, and exploration. Preying is imitated during the exploration stage, which is based on the whales' swimming behavior. The BWO method has the advantages of being simple to construct and having a rapid convergence rate. It is capable of finding solutions to both multimodal and unimodal issues. On the other hand, the SLnO [15] algorithm was developed using the sealions' hunting behavior. The algorithm also takes into account the fact that sealions use their whiskers to find prey. The SLnO algorithm is implemented in several stages, including the stages of vocalization, recognizing and tracking prey, attacking, and searching. Exploitation takes place during the attacking stage, while exploration takes place during the searching stage. In addition, the hunting process is depicted in two stages using the diminishing encircling approach and circle updating location. The SLnO method effectively finds the best solution with a high rate of convergence while avoiding local optima. Therefore, the BWLO algorithm achieves great explorativeness and successfully avoids local optima by combining the SLnO method in the BWO algorithm. The BWLO algorithm used to train the DRN is implemented in the subsequent steps.

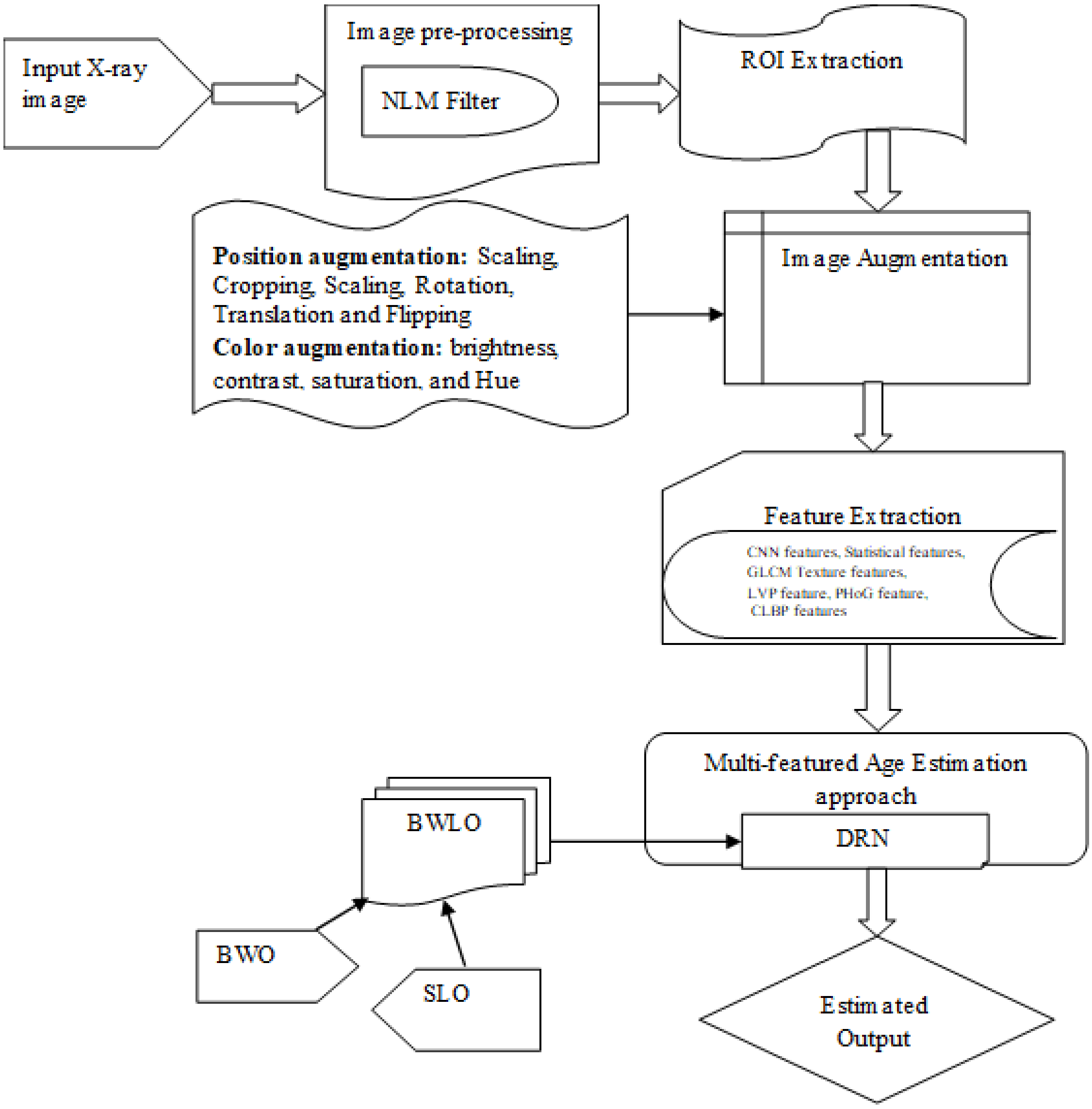


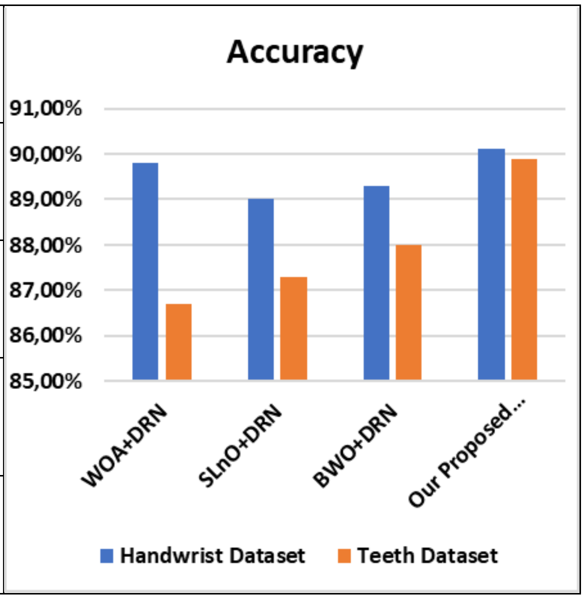
Figure 2.1 Architectural view of the BWLO_DRN approach for estimating bone age shows the pre-processing, RoI extraction, image augmentation, feature extraction, and classification

Dataset Description

The model is trained on RSNA dataset which includes 12611 images [17]. The real-time dataset consists of hospital-acquired images with labelled age. The dataset contains 503 images of hand-wrist and 1437 OPG images of teeth. The real time images were initially saved in DICOM format, then after conversion, they were saved in Portable Network Graphic format. Due to data privacy concerns, gender information has been left out of this work, which aims to develop a reliable assessment procedure that is gender-neutral.

Table 3.1 Comparative analysis of BWLO algorithm concerning accuracy performance metrics on real-time dataset

	Hand-wrist Dataset	Teeth Dataset
WOA+DRN	89.8%	86.7%
SLnO+DRN	89.0%	87.3%
BWO+DRN	89.3%	88.0%
Our Proposed Approach BWLO+DRN	90.1%	89.9%



3. Results and Discussion

The BWLO_DRN presented in this work for estimating the bone age is examined for its efficiency in this segment by comparing it with the various optimization approaches [14, 15, 16], and this is depicted in table 1. We observed that our model achieves the best accuracy by using BWLO_DRN on multiple features. The BWLO_DRN attained an accuracy of 90.1% for hand-wrist and 89.9% for teeth. The BWLO_DRN attained high accuracy for hand-wrist owing to utilization of DRN for predicting the bone age and the optimization of DRN by the BWLO. To reduce the load of professional human annotation, we suggested a framework for medical image feature extraction. We employed hybrid optimization algorithm to enhance model performance and lower the regression error further. Combining a variety of learners and modifying the data weights during training is a strong technique to use deep learning to enhance the performance of the low generalization model. This shows that hand-wrist features are more prominent than the teeth features. This is our small contribution towards forensic investigation where age related criminal cases, human trafficking and much more are handled.

4. Conclusion

This paper presents an age estimation technique that may be used as supplementary view for radiologist or forensic team in assessing bone growth. Here, bone age is estimated using the hand and teeth X-ray images by the Deep Residual Network (DRN) trained by the Beluga whale lion optimization (BWLO) algorithm. It is observed that multi-feature approach improved the results. The BWLO_DRN is examined for its superiority considering the accuracy as performance metrics and achieved 90.1% for Hand-wrist dataset in comparison with teeth dataset 89.9%.

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