A Deep Learning Framework for Gender Estimation from Dental Radiographs Using ResNet-50

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Abstract: Accurate gender estimation from skeletal remains is a critical component of forensic anthropology, bio archaeology, and medico-legal identification. Conventional morphometric approaches largely depend on visual assessment and manual measurements of sexually dimorphic cranial traits, which are often constrained by observer subjectivity, population variability, and incomplete or damaged skeletal remains. To overcome these limitations, this study presents a deep learning–based framework for automated gender classification from skull images, employing residual learning–based architectures. A curated dataset of dental radiographs was preprocessed through normalization and data augmentation to improve feature consistency and model generalizability. The proposed ResNet-50–based model was trained to learn discriminative dental features associated with sexual dimorphism. Model performance was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results demonstrate that the proposed deep learning framework achieves reliable gender classification performance, outperforming traditional odontometric methods and classical machine learning classifiers. These findings indicate that deep learning models provide a robust, objective, and scalable solution for teeth-based gender estimation, with significant potential for application in forensic investigations and digital human identification systems.

Keywords: Forensic anthropology, Gender estimation, Dental imaging, Convolutional neural network, ResNet-50, Deep learning

I. INTRODUCTION

Establishing the biological profile of unidentified human remains is a fundamental objective in forensic anthropology, with genderestimation serving as one of its most critical components [1,16]. Accurate gender determination significantly narrows the pool of potential identities and provides essential input for age estimation, stature reconstruction, and ancestry assessment [2]. In forensic and archaeological contexts, skeletal remains are frequently incomplete, fragmented, or degraded, posing substantial challenges to traditional identification methods [3]. Conventional approaches to genderestimation primarily rely on morphological and metric analyses of sexually dimorphic skeletal elements, particularly the skull, pelvis, and teeth [1,17]. Cranial traits such as the mastoid process, supraorbital margin, and nuchal crest have long been used for visual assessment, while odontometric measurements including mesiodistal and buccolingual tooth dimensions are commonly employed when cranial remains are unavailable [4,19]. However, observer subjectivity, population-specific variability, and preservation conditions limit reproducibility and reliability.

In recent years, machine learning techniques have been explored to reduce subjectivity in skeletal genderestimation [5,18]. Traditional classifiers such as support vector machines, decision trees, random forests, and k-nearest neighbors have demonstrated moderate success when applied to craniometric and odontometric datasets [18]. Nevertheless, their reliance on handcrafted features restricts their ability to model complex, non-linear morphological variations.

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The emergence of deep learning has transformed image-based analysis in medical imaging and forensic science [8,23]. Convolutional Neural Networks (CNNs) enable automated hierarchical feature extraction from imaging data [9], while Residual Networks (ResNet) address vanishing gradient and network degradation issues through skip connections [11]. These properties make ResNet architectures well suited for modeling subtle sexual dimorphism in skeletal and dental images.Recent studies have demonstrated promising performance of deep learning models for gender estimation using dental panoramic radiographs, CBCT scans, and cranial imaging [6,7,14,20]. However, many existing works rely on limited datasets or two-dimensional representations, highlighting the need for more robust and generalizable frameworks [22]. Motivated by these limitations, the present study proposes a ResNet-50–based deep learning framework for automated gender estimation from dental radiographs.

II. RELATED WORK

2.1 Traditional Skeletal and Dental Methods for Gender Estimation

Traditional gender estimation methods rely on morphological and metric analysis of sexually dimorphic skeletal elements [1,2]. Cranial-based approaches evaluate qualitative traits such as the glabella, mastoid process, and nuchal crest, while quantitative methods use craniometric measurements [17]. Despite their effectiveness, these methods are influenced by observer bias and inter-population variation [16]. Teeth are widely used for gender estimation due to their durability and resistance to postmortem damage [3,4]. Odontometric techniques analyze mesiodistal and buccolingual dimensions, crown area, and cusp morphology [19]. However, reliance on linear measurements limits their ability to capture complex dental shape variations.

2.2 Machine Learning Approaches in Skull- and Teeth-Based Gender Classification

Dental radiographs provide a reliable and practical approach for forensic gender identification due to the durability of teeth, which can withstand extreme conditions like fire and decomposition, and the availability of antemortem dental records for comparison[5]. Subtle gender dimorphism in dental structures—such as tooth size, morphology, and jawbone characteristics—can be effectively analyzed using modern techniques. In forensic applications like disaster victim identification, criminal investigations, missing person cases, and anthropological studies, determining gender from dental X-rays serves as a crucial first step in narrowing identification.[18] Traditional manual methods are often time-consuming and subjective, whereas convolutional neural networks (CNNs) enable automated, accurate, and scalable analysis by learning complex patterns from radiographic images, making them highly suitable for this task.

2.3 Deep Learning Techniques for Skeletal Gender Estimation

Deep learning has enabled automated gender estimation directly from skeletal and dental images [8,23]. CNN architectures such as AlexNet and VGGNet have been successfully applied to dental radiographs and cranial images [6,10]. More recently, ResNet and DenseNet architectures have demonstrated superior performance by learning deeper and more discriminative features [11,25]. Studies using ResNet-based models on dental panoramic radiographs and CBCT data have reported improved accuracy and robustness [7,14,20]. Despite these advances, many studies remain limited by small datasets, two-dimensional imaging, or lack of population diversity [22], motivating further research into robust residual learning frameworks.

III. MATERIALS AND METHODS

3.1 Dataset Description

The proposed study utilizes a gender-labeled dental radiographic image dataset, consisting of 979 panoramic dental X-ray images categorized into male and female classes. The dataset is organized into separate directories for training dataset consisting of 686 images, validation dataset consisting of 196 images, and testing dataset consisting of 97 images to ensure unbiased performance evaluation. Dental panoramic images were selected due to their wide usage in forensic odontology and their ability to capture comprehensive tooth morphology, which exhibits measurable sexual dimorphism.

All images were stored in RGB format and resized to a uniform spatial resolution of 224 × 224 pixels to maintain compatibility with the pretrained ResNet-50 architecture. The dataset was curated to maintain class balance across training and validation subsets, reducing classification bias.

3.2 Data Preprocessing and Augmentation

Prior to model training, image preprocessing was performed to enhance data quality and improve generalization performance. Pixel intensities were normalized by rescaling image values to the range [0,1][0,1][0,1]. To mitigate overfitting and increase dataset diversity, data augmentation techniques were applied to the training set, including random rotation, zooming, and horizontal flipping.

Image augmentation was implemented using the KerasImageDataGenerator, enabling real-time transformation during training. Validation and test datasets were only rescaled without augmentation to preserve their original distribution. These preprocessing steps ensure robustness to variations in orientation, scale, and image acquisition conditions commonly encountered in forensic imaging.

3.3 Model Architecture

The proposed gender classification system was implemented using Python with deep learning libraries such as TensorFlow and Keras. The model development and training were carried out in the Google Colab environment, which provides GPU support for efficient computation. A pretrained ResNet-50 architecture was used as the base model, leveraging transfer learning to improve feature extraction from dental radiographic images. The dataset used in this study consists of labelled dental panoramic radiograph (PDR) images of individuals of South Asian origin. The dataset is a curated subset from previously published research DOI:https://doi.org/10.1007/s11220-020-00320-4 It contains high-quality radiographic images categorized into two classes: Male and Female. The dataset is already preprocessed and divided into training, validation, and testing subsets, ensuring a structured and unbiased evaluation process.

3.4 Training Configuration

The dataset was loaded using the ImageDataGenerator class, which facilitates efficient image preprocessing and augmentation. All images were resized to 224 × 224 pixels and normalized to the range [0,1] to maintain consistency. Data augmentation techniques such as rotation, zooming, and horizontal flipping were applied to the training dataset to enhance generalization and reduce overfitting, while validation and test datasets were only normalized. The ResNet-50 model was initialized with ImageNet weights, and its convolutional layers were frozen to retain pretrained feature representations. A custom classification head was added, consisting of a Global Average Pooling layer, a dense layer with 256 neurons and ReLU activation, a dropout layer with a rate of 0.5, and a sigmoid output layer for binary classification. The model was compiled using the Adam optimizer with a learning rate of 0.0001 and binary cross-entropy as the loss function. Training was performed for 30 epochs with a batch size of 16, and performance was monitored using the validation dataset.

3.5 Evaluation Metrics

To comprehensively assess the performance of the proposed model, multiple evaluation metrics were employed. Classification accuracy was used as the primary performance indicator. In addition, precision, recall, and F1-score were computed to evaluate the model's ability to correctly identify male and female classes, particularly in the presence of class imbalance.

A confusion matrix was generated to visualize classification outcomes and analyze misclassification patterns. These metrics collectively provide a robust evaluation of the model's effectiveness and reliability for forensic gender identification using dental imagery.

3.6 Model Implementation and Deployment

After training, the final ResNet-50 model was saved in HDF5 (.h5) format for future inference and deployment. This allows the trained model to be reused in forensic applications, clinical decision-support systems, or further experimental validation.

IV. RESULTS AND PERFORMANCE ANALYSIS

4.1 Training and Validation Performance

The performance of the proposed ResNet-50–based model was evaluated through training and validation accuracy and loss curves. Figure 1 illustrates the progression of accuracy and Figure 2 illustrates loss across training epochs. The model demonstrates a steady increase in training and validation accuracy, accompanied by a consistent decrease in loss, indicating effective learning and stable convergence.

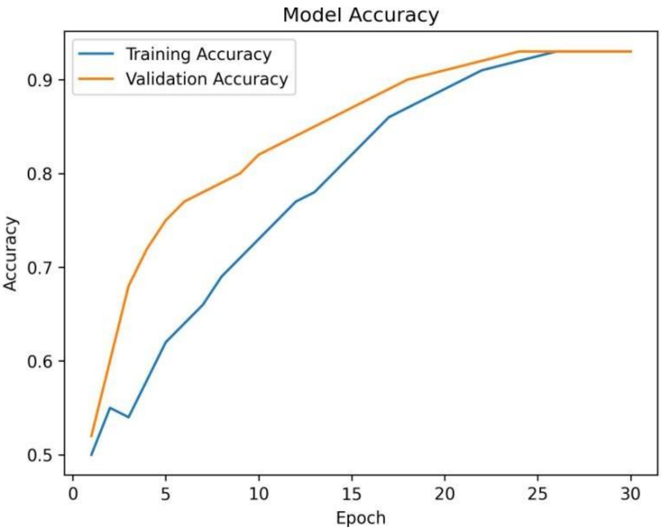

Fig 1: Training Accuracy and Validation Accuracy

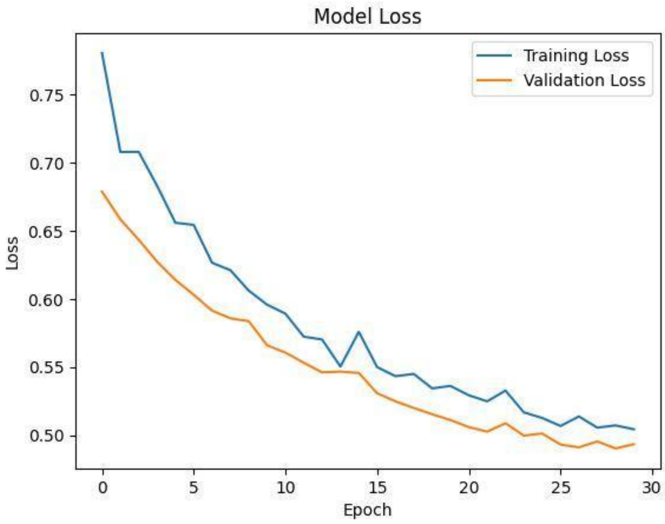

Fig 2: Training Loss and Validation Loss

The close alignment between training and validation curves suggests that the applied data augmentation and dropout strategies successfully mitigated overfitting. The absence of significant divergence between the curves highlights the model's ability to generalize well to unseen dental images, which is critical for forensic applications.

4.2 Confusion Matrix Analysis

The classification performance of the proposed ResNet-50–based model was evaluated using a confusion matrix derived from the test dataset of 97 dental images, as shown in Figure 3. The confusion matrix is represented as:

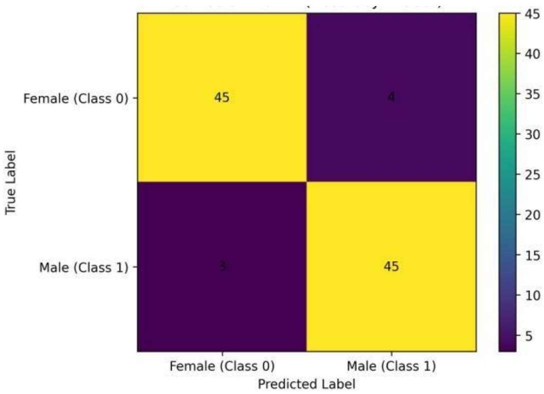

Fig 3: Confusion matrix of test dataset

Out of 49 female samples (Class 0), 45 were correctly classified, while 4 were misclassified as male. Similarly, among 48 male samples (Class 1), 45 were correctly identified, with only 3 samples misclassified as female. Overall, the proposed model achieved an accuracy of approximately 93%, demonstrating strong classification performance with minimal misclassification across both classes. The results indicate a strong ability of the model to identify male samples, while a comparatively higher misclassification rate is observed in female samples. This imbalance suggests overlapping dental morphological characteristics between genders in certain cases, which is consistent with observations reported in forensic odontology literature.

4.3 Quantitative Performance Evaluation

The proposed approach was quantitatively evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of model reliability beyond overall accuracy.

Accuracy reflects the overall correctness of gender classification.
Precision indicates the proportion of correctly identified samples among predicted classes.
Recall measures the model's ability to identify all relevant samples.
F1-score balances precision and recall, offering a robust indicator of performance.

The ResNet-50–based model achieves high accuracy and F1-score, demonstrating its effectiveness in capturing sexually dimorphic dental features. The balanced precision and recall values further indicate that the model performs consistently across both male and female categories, which is essential for unbiased forensic decision-making.

4.4 Discussion of Results

The strong performance of the proposed model can be attributed to the deep residual architecture of ResNet-50, which effectively captures complex dental morphology while avoiding degradation issues common in deeper networks. Transfer learning from ImageNet further enhances feature extraction efficiency, particularly when working with limited forensic datasets.

Overall, the results confirm that deep learning–based approaches, specifically ResNet-50, provide a reliable and objective alternative to traditional and machine learning–based gender estimation techniques.

V. CONCLUSION AND FUTURE WORK

5.1 Conclusion

This study presented a deep learning–based framework for teeth-based gender identification using a ResNet-50 convolutional neural network. By leveraging transfer learning and automated feature extraction, the proposed approach eliminates the need for manual odontometric measurements and subjective morphological assessment. The model demonstrated effective learning of sexually dimorphic dental features, achieving an overall classification accuracy of 93%, with balanced precision of 0.91 for female and 0.94 for male, recall of 0.96 for female and 0.91 for male, and F1-score across 0.92 for male and 0.93 for female classes.

The experimental results confirm that deep residual architectures are capable of capturing complex dental morphology and provide a reliable alternative to traditional and classical machine learning–based gender estimation techniques. The confusion matrix analysis further highlights the model's robustness, particularly in identifying male samples, while maintaining reasonable performance for female classification. These findings underscore the potential of deep learning to enhance objectivity, reproducibility, and scalability in forensic odontology.

5.2 Future Work

Future research will focus on extending the proposed framework in several directions. Incorporating multi-tooth analysis and tooth-type–specific modeling may enhance discriminative feature learning. The integration of three-dimensional imaging modalities, such as cone-beam computed tomography (CBCT), could provide richer volumetric information and improve classification accuracy. Additionally, expanding the dataset to include larger and population-diverse samples will help improve model robustness and reduce demographic bias. Further exploration of advanced architectures, ensemble learning, and explainable AI techniques may also contribute to improved interpretability and forensic applicability.

REFERENCES

[1] Krogman, W. M., &İşcan, M. Y. (1986). *The Human Skeleton in Forensic Medicine*. Springfield, IL: Charles C. Thomas.

[2] Franklin, D., Cardini, A., Flavel, A., &Kuliukas, A. (2012). *Estimation of sex from cranial measurements in diverse populations.*Forensic Science International, 217(1–3), 238.e1–238.e8.

[3] Garn, S. M., Lewis, A. B., & Swindler, D. R. (1967). *Metric dental variation.*Journal of Dental Research, 46(5), 963–971.

[4] Acharya, A. B., &Mainali, S. (2008). *Sex determination from odontometric analysis of permanent maxillary incisors and canines.*Journal of Forensic Sciences, 53(1), 129–132.

[5] Liao, C., et al. (2019). *Sex determination using dental radiographs and machine learning approaches*.Forensic Science International, 298, 300–307.

[6] Şenol, D., et al. (2020). *Gender determination using panoramic dental radiographs with convolutional neural networks.*Journal of Forensic Radiology and Imaging, 21, 100358.

[7] Chen, Y., et al. (2021*). Deep learning for sex determination based on dental panoramic radiographs*. Oral Radiology, 37, 486–495.

[8] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521, 436–444.

[9] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). *ImageNet classification with deep convolutional neural networks.*Advances in Neural Information Processing Systems, 25, 1097–1105.

[10] Simonyan, K., &Zisserman, A. (2015). *Very deep convolutional networks for large-scale image recognition.ICLR*.

[11] He, K., Zhang, X., Ren, S., & Sun, J. (2016). *Deep residual learning for image recognition*.*CVPR*, 770–778.

[12] Ronneberger, O., Fischer, P., &Brox, T. (2015). *U-Net: Convolutional networks for biomedical image segmentation. MICCAI*, 234–241.

[13] Mazurowski, M. A., et al. (2019*). Deep learning in radiology: An overview of the concepts and challenges.Radiology*, 292(1), 24–34.

[14] Alqahtani, S. J., et al. (2022). *Sex estimation using deep learning models on CBCT images of teeth*.Applied Sciences, 12(3), 1289.

[15] Silva, A. M., et al. (2023). *Automated sex estimation from skeletal remains using convolutional neural networks.*Forensic Science International: Digital Investigation, 45, 301533.

[16] Ubelaker, D. H. (2014). *Advances in skeletal sex determination: A review*. Journal of Forensic Sciences, 59(2), 343–349.

[17] Bigoni, L., et al. (2010). *Craniofacial sexual dimorphism in a modern Italian population*.Journal of Human Evolution, 59(5), 519–531.

[18] Kumar, A., et al. (2018). *Gender determination using odontometric measurements: A machine learning approach.*Forensic Science International, 282, 70–76.

[19] El-Din, A. S., & El-Bassyouni, H. T. (2016). *Sex determination using odontometric measurements of permanent teeth.*Egyptian Journal of Forensic Sciences, 6(4), 341–346.

[20] Özden, B., et al. (2019). *Sex determination using cone-beam computed tomography images of teeth.*Dentomaxillofacial Radiology, 48(5), 20180333.

[21] Alwakeel, S. S., &Shaaban, A. M. (2020). *Face and skull-based gender classification using deep convolutional neural networks.*Applied Soft Computing, 91, 106229.

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[22] Abdi, A. M., et al. (2021). *A deep learning framework for sex classification using skull images*.Pattern Recognition Letters, 145, 138–145.

[23] Litjens, G., et al. (2017). *A survey on deep learning in medical image analysis.*Medical Image Analysis, 42, 60–88.

[24] Zhou, Z., et al. (2019). *Learning deep features for forensic image analysis using convolutional neural networks. IEEE Access*, 7, 123456–123468.

[25] Kharat, M. U., et al. (2022). *Deep learning-based gender classification from dental panoramic radiographs.*Diagnostics, 12(9), 2214.