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Comparative Evaluation of Artificial Intelligence Models for Gender Prediction Using Coronoid Process Morphology on Digital OPG Images: A Study of Logistic Regression, Random Forest, and k-Nearest Neighbours

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Abstract:
Aim: *This study evaluates the efficacy of artificial intelligence (AI) in determining gender based on the morphological characteristics of the coronoid process observed in digital orthopantomogram (OPG) images.*
Methodology: *A dataset of 200 Orthopantomograms (OPG), comprising 100 male and 100 female images, was collected from individuals aged 18 to 45 years. Low-resolution images and OPGs with extensive dental surgeries were excluded. Coronoid processes were classified into different shapes according to Shakya et al. (2013) and further divided by gender. The dataset was split into 80% for training and 20% for testing. Preprocessing, including normalization and noise removal, was performed using Picsart software to ensure clean input data.*
Model Training and Evaluation: *Three machine learning models—Logistic Regression, Random Forest, and k-Nearest Neighbors (k-NN)—were trained and evaluated using accuracy, precision, recall, specificity, and LogLoss.*
Results: *Logistic Regression demonstrated the highest AUC (0.619) and Specificity (0.871), indicating strong performance in distinguishing gender. Despite a lower recall (0.230), it showed balanced performance across key metrics, outperforming both Random Forest and k-NN. Random Forest exhibited the lowest recall (0.190) and highest LogLoss (7.421), while k-NN had moderate performance but the highest LogLoss (16.695).*
Conclusion: *Logistic Regression proved to be the most effective model for gender determination based on coronoid process morphology. Future studies should expand datasets and integrate advanced imaging techniques to improve model generalizability and clinical applicability. This research highlights AI's potential in enhancing diagnostic accuracy in dental imaging.*
Keywords: *Coronoid process; Mandible; Shape variation; Sex determination; Hook shape*

INTRODUCTION:

The mandible's coronoid process is a flat, triangular structure that protrudes upward and forward somewhat and the gap between the coronoid and the condylar process is known as the sigmoid notch [1]. The form of these processes determines the notch's shape [2]. The temporalis muscle is attached to the coronoid process's borders and medial surface.By 10–14 weeks of intrauterine life, secondary accessory cartilage has developed in the coronoid process area. It is thought that the growing temporalis muscle causes this secondary cartilage of the coronoid process to grow. After birth, the coronoid accessory cartilage vanishes as it is integrated into the ramus's growing intra-membranous bone [3]. Hereditary determinants and functional changes that occur during the growth phase result in morphologic variances that correlate to developmental variations. Bone and muscle can dynamically influence one another's function and alter the morphology of the affected bone [4]. The coronoid and condylar processes' shapes determine how the sigmoid notch changes in shape [5].
Artificial Intelligence (AI) is revolutionizing healthcare by enabling machines to analyze complex data, recognize patterns, and make predictions with high accuracy [6]. In dentistry and maxillofacial studies, AI has shown significant potential in interpreting radiographic images for diagnostic and analytical purposes [7]. One emerging application is the use of AI to determine gender based on morphological variations in anatomical structures. The coronoid process, a triangular projection on the mandible, exhibits subtle morphological differences

between males and females [8]. These differences, though often challenging to detect through conventional methods, can be effectively analyzed using AI algorithms trained on large datasets of orthopantomogram (OPG) images [9].
By leveraging machine learning models, AI can identify and classify coronoid process shapes, assisting in accurate and efficient gender determination. This approach can be valuable in forensic science, anthropology, and dental practice, offering a non-invasive, rapid, and reliable method for gender identification. As AI continues to advance, its application in dental imaging can enhance diagnostic precision, streamline workflows, and provide new insights into morphological variations linked to gender.Since the form of the coronoid process serve as evolutionary markers and can be utilized in forensic and anthropological research, the current study was conducted to evaluate these features [10]. Additionally, maxillofacial surgeons might employ the coronoid process for reconstructive procedures.

MATERIALS AND METHODS

Ethical clearance for the study has been obtained from the Institutional research and ethical committee with the register number - **IHEC/SDC/OMED-2205/24/264**. The study utilized a dataset of 200 digital orthopantomograms (OPGs), including 100 male and 100 female images, collected from individuals aged 18 to 45 years. Images with low resolution or evidence of extensive dental surgeries were excluded to ensure the clarity and consistency of the data. The coronoid process in each OPG was categorized into different shapes based on the classification system given by Shakya et al, as shown in **figure 1**, which identifies common morphological variations [11]. The methodology followed is more or less consistent with previous AI-based diagnostic studies in dental imaging and is supported by earlier research [12], where balanced datasets were effectively employed for training and evaluating machine learning algorithms in dental anomaly classification.

Inclusion and Exclusion Criteria

Inclusion and Exclusion criteria are given in **Table-1**

Study Procedure

The dataset was curated from institutional clinical records from February 2024 to September 2024 and included a variety of anatomical presentations to ensure generalizability. All analyses were performed using orange software [13] a visual programming and data mining platform suitable for classification, visualization, and statistical analysis. Image embeddings were generated to convert the OPG images into numerical vectors usable by the machine learning models. To prepare the data for machine learning analysis, the following steps were undertaken: data processing was done by normalization of pixel intensity values to a consistent scale and noise reduction was done to remove non-diagnostic artifacts and improve image clarity. Data splitting was done into two sets: 80% training and 20% testing, a ratio that ensures sufficient data for model learning while preserving an unbiased test set.
Image embeddings were generated using the Inception V3 architecture, a deep convolutional neural network developed by Google, known for its balance between accuracy and computational efficiency. Inception V3 is a 48-layer model that utilizes advanced architectural concepts such as factorized convolutions, batch normalization, and auxiliary classifiers to extract high-level, abstract features from input images. The model was employed in a transfer learning framework, with weights pretrained on the ImageNet dataset, which comprises over 1.2 million natural images across 1,000 object categories. Although ImageNet consists of non-medical images, the lower and intermediate convolutional layers of Inception V3 capture universal visual patterns such as edges, textures, and spatial hierarchies that remain valuable in medical image analysis, including OPG data. In this workflow, the final classification layers of the model were removed, and the output from the penultimate global average pooling layer was extracted as a fixed-length numerical feature vector (embedding) for each image. Panoramic radiographs (OPGs) were first preprocessed by cropping the regions of interest encompassing the coronoid processes, resizing them to 299 × 299 pixels to comply with Inception V3 input requirements, and normalizing pixel intensities to a consistent range before being passed through the network. This embedding strategy enabled the translation of complex anatomical structures of the coronoid processes into a structured, lower-dimensional feature space suitable for input into machine learning classifiers. Inception V3 was selected due to its robust performance in medical imaging tasks, proven generalizability with limited domain-specific data, and its computational efficiency, making it a suitable and effective feature extractor for classifying morphological variations of the coronoid processes in OPG images [14].

Image embeddings were then fed into each of three supervised machine learning algorithms which were selected based on their widespread application and efficiency in classification tasks:

Logistic Regression (LR): A linear classifier valued for simplicity and effectiveness in binary and multiclass classification tasks [15].

Random Forest (RF): An ensemble learning method that builds multiple decision trees and aggregates their results for improved accuracy and robustness against overfitting [16].

k-Nearest Neighbours (kNN): A non-parametric classifier that categorizes instances based on proximity to labelled examples in the feature space [17].

Evalution metrics was done to assess the diagnostic performance of each model, the following metrics were calculated: Accuracy, Precision, Recall, Specificity, Area Under the Curve (AUC) for Receiver Operating Characteristic (ROC), Confusion matrices to visualize classification outcomes. The complete diagnostic workflow **(figure 2)** involved importing image datasets, inspecting them using the Image Viewer module, converting images into numerical embeddings, and passing them into the three AI models. Performance was evaluated using the Test and Score, Confusion Matrix, and ROC Analysis modules in orange software. Selected image results were also reviewed post-classification for validation [12].

RESULTS

The diagnostic performance of three machine learning models—Logistic Regression (LR), k-Nearest Neighbours (kNN), Random Forest (RF) — was evaluated using OPG images. Evaluation metrics included Area Under the Curve (AUC), Classification Accuracy (CA), F1 score, Precision, Recall, Matthews Correlation Coefficient (MCC), Specificity, and LogLoss [12].

The data table consisting of Accuracy, Precision, Recall, Specificity, Area Under the Curve for various machine learning models (AUC) are shown in **Table-2** and the Receiver Operating Characteristic (ROC) are shown in **Figure - 3**. Logistic Regression was the most effective model for gender determination based on the morphological characteristics of the coronoid process. Logistic Regression achieved the highest Area Under the Curve (AUC) at **0.619** indicating superior performance in distinguishing between male and female OPGs. Additionally, it recorded the highest specificity of **0.871**, reflecting its ability to accurately identify true negatives, which is crucial in minimizing false positives. However, the recall for Logistic Regression was lower at **0.230**, suggesting that while the model is effective at ruling out incorrect classifications, it misses a significant portion of true positives. Despite this limitation, the model's LogLoss value of **2.855** was the lowest among the three, highlighting its better calibration and more reliable probability predictions. The confusion matrix for Logistic Regression revealed lesser number of false positives, highlighting its reliability in determining gender by looking at the shape of coronoid process **(Figure 4)**.

The Random Forest model showed moderate performance but fell short compared to Logistic Regression. With an AUC of **0.547**, Random Forest exhibited a lower ability to differentiate between genders. Its specificity was slightly lower at **0.851**, and recall stood at **0.190**, the lowest of the three models. This poor recall suggests that the model struggles significantly to detect true positives, limiting its overall effectiveness in gender classification. The LogLoss for Random Forest was **7.421**, indicating less reliable probability predictions and a higher rate of misclassification compared to Logistic Regression. These results suggest that although Random Forest can correctly identify many negative cases, its overall balance of precision and recall is lacking.

The k-Nearest Neighbors (k-NN) model demonstrated slightly better results than Random Forest but still underperformed in comparison to Logistic Regression. k-NN achieved an AUC of **0.569** and a specificity of **0.867**, making it relatively effective at identifying true negatives. The recall for k-NN was **0.197**, which, while better than Random Forest, still indicated a tendency to miss true positive cases. Notably, k-NN had the highest LogLoss at **16.695**, suggesting that its probability predictions were the least reliable, potentially due to overfitting or sensitivity to variations in the dataset. Despite these limitations, k-NN's moderate performance in certain metrics makes it a viable secondary option, though not as dependable as Logistic Regression for gender determination based on coronoid process morphology.

DISCUSSION

Artificial Intelligence (AI) is increasingly being utilized in healthcare and forensic sciences for its ability to analyze complex data with accuracy and efficiency [16]. In dentistry, AI has proven valuable in identifying anatomical structures and detecting subtle morphological variations that may differ by gender [17]. One such structure is the coronoid process of the mandible, which exhibits distinguishable differences between males and females [18]. While traditional gender determination methods rely on manual measurements and visual assessment, they can be subjective and prone to error. AI-driven models can automate this process, providing faster, more reliable, and reproducible results. This study investigates the use of AI to determine gender by analyzing the morphological characteristics of the coronoid process in digital orthopantomogram (OPG) images.

The study utilized 200 OPGs, comprising 100 male and 100 female samples, from individuals aged 18 to 45 years. Exclusion criteria included low-resolution images and those showing extensive dental surgeries to ensure high data quality. The coronoid processes were classified (Shakya et al , 2013) into different shapes [11]. The dataset was divided by gender and further split into 80% for training and 20% for testing, ensuring balanced model development and evaluation. Image preprocessing was performed using Picsart software to normalize and remove noise. Three machine learning models—Logistic Regression, Random Forest, and k-Nearest Neighbors (k-NN)—were trained and assessed using accuracy, precision, recall, specificity, and LogLoss. ROC curves and confusion matrices were employed to visualize model performance.

Logistic Regression demonstrated the highest AUC (0.619) and specificity (0.871), indicating superior performance in distinguishing between male and female OPGs. Although the recall for Logistic Regression was lower (0.230), its overall performance was balanced across key metrics, and it exhibited the lowest LogLoss (2.855), signifying better calibration and reliable probability predictions. In contrast, Random Forest showed the lowest recall (0.190) and a higher LogLoss (7.421), suggesting poor sensitivity to true positives and less accurate probability predictions. k-NN achieved an AUC of 0.569 and specificity of 0.867 but had the highest LogLoss (16.695), indicating reduced reliability in classification despite moderate performance in other areas.

The results highlight that for the quantitative examination of mandibular cortical morphology, the artificial intelligence may prove to be a helpful instrument which is in accordance with Ruri Ogawa et al, 2022 [19]. Logistic Regression is the most reliable model for gender determination based on coronoid process morphology, with a strong balance between specificity and overall classification performance which is in accordance with Mrinal Mayank et al , 2016 [20]. Although Random Forest and k-NN provided moderate accuracy, their lower recall and higher LogLoss values suggest limitations in detecting true positive cases, making them less favorable for this application. The study's limitations include the relatively small sample size and the exclusion of lower-quality images, which may impact the generalizability of the findings. Additionally, the study focused on a narrow age range, potentially limiting its applicability to other demographics.

Future research should expand the dataset to include a broader age range and diverse populations, which could improve model generalization and robustness. Integrating advanced imaging techniques such as 3D imaging or computed tomography may also enhance the accuracy of morphological analysis. Clinical validation of these AI models in real-world scenarios will further solidify their utility in forensic science, anthropology, and dental practice. This study underscores the potential of AI as a powerful tool for gender determination, offering a non-invasive, rapid, and reliable approach to analyzing mandibular structures in dental imaging.

CONCLUSION

The findings of this study highlight the significant potential of artificial intelligence in gender determination through the analysis of coronoid process morphology in orthopantomogram (OPG) images. Among the three machine learning models evaluated, Logistic Regression demonstrated the highest accuracy, specificity, and overall balanced performance, making it the most reliable tool for distinguishing between male and female samples. Although Random Forest and k-Nearest Neighbors (k-NN) showed moderate success, their lower recall and higher LogLoss values indicate limitations in detecting true positives and producing consistent probability predictions.

This study reinforces the value of AI in automating and enhancing diagnostic precision in dental imaging, offering a non-invasive and efficient method for gender identification. While the results are promising, the study's limitations, including a relatively small dataset and a narrow age range, highlight the need for further research with larger and more diverse samples. Future efforts should focus on incorporating advanced imaging techniques and validating these models in clinical and forensic settings. In conclusion, AI-driven gender determination based on coronoid process morphology presents a novel, accurate, and scalable approach that can significantly contribute to forensic investigations, anthropological studies, and dental diagnostics, paving the way for more robust and automated analysis in the future.

Limitations and future scope

The primary limitations of this study stem from the relatively small and homogeneous dataset of 202 OPGs, which may not fully capture the diversity of coronoid process morphology across different populations and age groups. The focus on individuals aged 18 to 45 years, along with the exclusion of low-resolution images and those with extensive dental surgeries, further restricts the model's generalizability to broader patient demographics and clinical scenarios. A larger and more diverse dataset, encompassing varied age ranges and clinical conditions, would be necessary to enhance model robustness and applicability. Looking ahead, future research could integrate advanced imaging techniques such as 3D imaging and computed tomography to provide more detailed morphological data, improving model accuracy and enabling more comprehensive diagnostic applications. Additionally, clinical validation in real-world settings is crucial to establish the model's reliability and efficacy. Expanding the analysis to include other mandibular structures or pathologies could further broaden the scope of AI applications in dental and orthodontic diagnostics, enhancing its role in forensic science and patient care.

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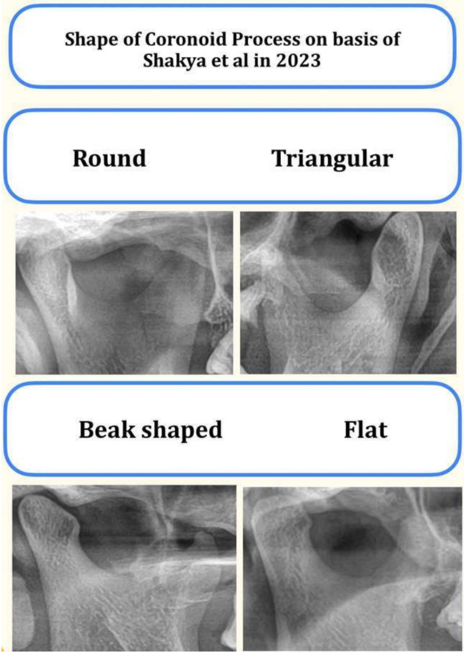

Figure 1: The coronoid process in each OPG was categorized into different shapes based on the classification system proposed by Shakya et al in 2013, which identifies common morphological variations.

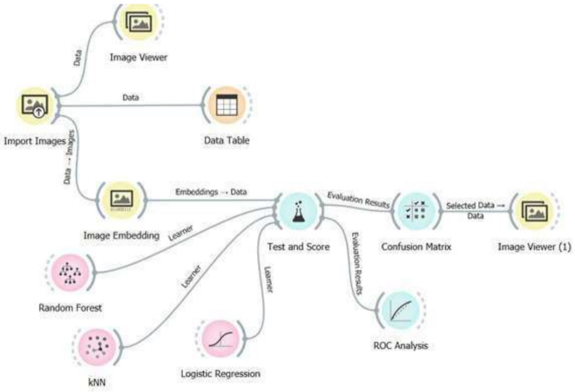

Figure 2: The workflow begins with importing image datasets, which are visualized using the Image Viewer and displayed in a structured format in the Data Table for inspection and verification. Image embeddings are then extracted to convert visual data into numerical representations suitable for machine learning models. These embeddings are passed to three supervised learning algorithms—Logistic Regression, k-Nearest Neighbors (kNN), and Random Forest—for training and evaluation. The models' performance is assessed using the Test and Score module, generating evaluation metrics such as accuracy, precision, and recall. Further analysis is conducted using tools like the Confusion Matrix for error evaluation and ROC Analysis for understanding classifier performance. Selected results are visualized again using the Image Viewer for interpretation.

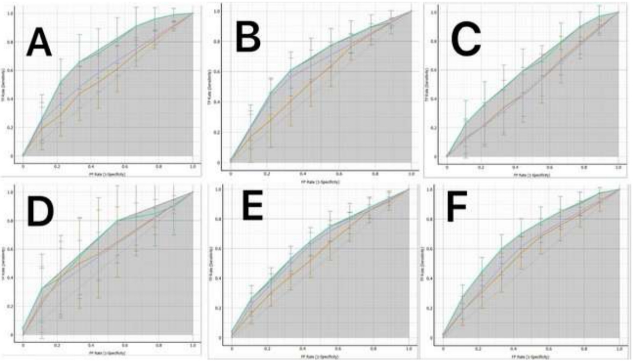

Figure 3: Receiver Operating Characteristic (ROC) curve for showing for various genders in various algorithms (A) male flat shaped (B) male round shaped (C) male triangular shaped (D) female flat shaped (E) female round shaped (F) female triangular shaped

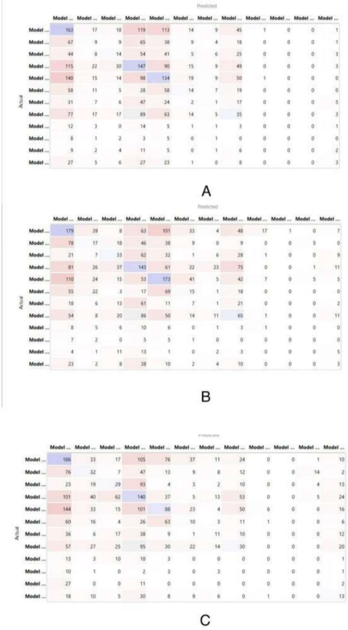

Figure 4: Confusion matrix showing for **(A) Random Tree Algorithm (B) Logistic Regression algorithm (C) kNN algorithm**

Inclusion Criteria	Exclusion Criteria
Digital orthopantomogram (OPG) images of individuals aged between 18 and 45 years	OPG images with inadequate or low resolution, compromising diagnostic clarity
OPGs depicting clear and intact morphological structures of the coronoid process	OPGs with evidence of extensive dental treatments or surgical interventions affecting mandibular anatomy
Images obtained from clinical records with ethical approval and appropriate patient consent	Incomplete datasets or cases with missing demographic or clinical information

Table 1: Inclusion and Exclusion criteria

Model	AUC	CA	F1	Prec	Recall	MCC	Spec	LogLoss
Logistic Regression	0.619	0.230	0.215	0.205	0.230	0.100	0.871	2.855
Random Forest	0.547	0.190	0.168	0.162	0.190	0.041	0.851	7.421
kNN	0.569	0.197	0.184	0.184	0.197	0.064	0.867	16.695

Table 2: The best-performing model among the three is Logistic Regression. It demonstrates the highest recall, indicating better identification of positive cases, and achieves the best Matthews Correlation Coefficient (MCC), reflecting balanced performance across all prediction outcomes. Logistic Regression also excels in specificity, accurately classifying negative cases, and has the lowest LogLoss, suggesting more reliable and confident probability predictions.