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Accuracy of a deep learning–based model for treatment recommendation in adult patients with skeletal Class III malocclusion

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Introduction: Treatment planning for adult patients with skeletal Class III malocclusion remains challenging because of overlapping diagnostic criteria and subjective weighting of skeletal vs soft-tissue considerations. This retrospective study aimed to develop and evaluate the accuracy of a convolutional neural network (CNN)-based image classification in predicting treatment approach and supporting orthodontists in deciding between orthodontic camouflage and orthognathic surgery. **Methods:** Using 1826 pretreatment images of 166 adult patients with skeletal Class III malocclusion (86 camouflage and 80 surgical), a hybrid model was developed that combines both deep learning and machine learning. These images included lateral cephalometric and panoramic radiographs and 9 intraoral and extraoral photographs. Of note, 11 CNN models processed each image type to generate binary predictions that were combined into an 11-dimensional vector and classified using 7 conventional machine learning algorithms. **Results:** Support vector machine, multilayer perceptron, logistic regression, k-nearest neighbor, and naive Bayes showed no statistically significant difference compared with random forest ($P > 0.05$). Decision tree exhibited statistically significant inferior performance compared with random forest ($P < 0.01$). Significance analysis indicated that soft-tissue photographs had a higher correlation with treatment decisions than that of cephalometric radiographs, although clinical validity requires expert confirmation. **Conclusions:** A CNN-based ensemble model demonstrated high diagnostic accuracy for predicting camouflage vs surgical treatment in adult patients with skeletal Class III malocclusion within a single-center dataset. (Am J Orthod Dentofacial Orthop 2026;170:425-32)

Class III malocclusion is one of the most complex discrepancies in orthodontics. It presents particular challenges in diagnosis and treatment planning. The defining features of Class III malocclusions are not limited to the maxilla and mandible, but are expressed within the entire craniofacial complex. Such characteristics may involve a protruded mandible and a retruded maxilla. It often exhibits dental compensation with proclined maxillary incisors and retroclined mandibular incisors that mask skeletal discrepancies. This complexity has led to the development of multiple management protocols for successful treatment.[1]

These protocols greatly depend on several factors, such as the severity of malocclusion, patient age, chief complaints, clinical examination, and cephalometric analysis.[1] Treatment options are primarily used during periods of active growth, as growth modification strategies are most

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During the preparation of this work, the authors used ChatGPT in order to generate clear and structured technical descriptions of the machine learning and deep learning models used in the study. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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effective when initiated before or during the pubertal growth spurt. The growth-dependent nature of these protocols narrows therapeutic options after skeletal maturity, reinforcing the importance of accurate treatment selection in adult patients.[2,3] Treatment options are limited to orthodontic camouflage or orthognathic surgery.[3] The severity of the malocclusion dictates the choice between these treatments. However, the overlap in diagnostic parameters often complicates treatment planning and requires careful clinical judgment that integrates skeletal, dental, esthetic, and patient-specific considerations.[4]

Kerr et al[5] recommended surgical treatment in patients with ANB and incisor mandibular plane angles of less than $-4°$ and $83°$, respectively. However, the authors cautioned that these values should not be applied without broader clinical judgment. Eisenhauer et al[6] differentiated patients with Class III malocclusion suitable for orthodontic camouflage from those who required orthognathic surgery and proposed a predictive model incorporating Wits appraisal, Sella-Nasion, maxillary and mandibular ratio, and lower gonial angle. Sivarajan et al[3] conducted a systematic review to identify cephalometric measurements that may guide the choice between orthodontic camouflage and orthognathic surgery in adult patients with Class III malocclusions. These studies emphasized that treatment decisions for such patients cannot always be determined from cephalometric measurements alone because clinically relevant factors may not be captured on a lateral cephalogram. They highlighted that Class III malocclusion remains a complex anomaly to manage, increasing the risk of overtreatment or undertreatment.

With advancing technology, artificial intelligence (AI) has emerged as a transformative tool across multiple fields. AI algorithms enable the analysis of large datasets, pattern recognition, and treatment recommendations that may complement clinical judgment.[7] Convolutional neural networks (CNNs) are increasingly used for automated orthodontic image analysis, supporting cephalometric landmark detection, craniofacial assessment, and treatment decision-making.[8,9]

Recent studies have demonstrated the feasibility of Class III malocclusion treatment planning. Taraji et al[10] trained XGBoost (Extreme Gradient Boosting; developed by Tianqi Chen and contributors, Distributed Open Source Software, Seattle, Wash) classifiers on 40 manually extracted cephalometric parameters from 182 patients, achieving 93% accuracy after recursive feature elimination. Their model identified Wits appraisal, overjet, and maxillary and mandibular ratio as key predictors and incorporated soft-tissue profile attractiveness; however, reliance on manual landmark identification introduces potential operator-dependent variability.

Image-based deep learning (DL) approaches may address these limitations by eliminating manual parameter extraction, capturing visual patterns not quantified in conventional cephalometric analysis, and integrating multimodal photographic and radiographic information. Nevertheless, whether such models outperform parameter-based methods remains unvalidated, and the clinical interpretability of CNN-driven decisions requires further investigation. Although CNNs perform well in medical image analysis, their integration with conventional classifiers for complex skeletal Class III malocclusion decision-making remains limited.[11]

Accordingly, the purpose of this study was to evaluate the accuracy and reliability of a CNN-based AI model for treatment recommendation in adult patients with skeletal Class III malocclusion, with the aim of supporting clinical decision-making and guiding future AI integration into orthodontic practice.

MATERIAL AND METHODS

This retrospective study investigated adult patients treated for skeletal Class III malocclusion. The study was approved by the ethical committee of the Faculty of Dentistry, Cairo University with the number REC-D 738-3. The sample size was calculated according to the results of Lee et al[12] in 2022, in which the sensitivity of the diagnostic accuracy of AI prediction of treatment decision for skeletal Class III malocclusion was 84%. Sample size calculation was performed assuming a margin of error of 6%, a significance level (α) of 0.05, and a statistical power of 80%, yielding a required sample size of 143 patients. The study protocol was registered on ClinicalTrials.gov (registration number: NCT 06002373).

Records of 166 adult patients treated for skeletal Class III malocclusion (86 treated orthodontically and 80 treated with surgical intervention in addition to orthodontics) between 2012 and 2022 were selected from the database of the Department of Orthodontics, Faculty of Dentistry, Cairo University according to their skeletal class, skeletal age, and the presence of complete preoperative and postoperative records.

Patients included were skeletally mature with cervical vertebral maturation stage 6, negative ANB or Wits confirmation, and no congenital deformity, syndrome, cleft, or previous surgical intervention. Patients with a documented transverse functional shift in their diagnostic records were excluded from the study to avoid confounding transverse discrepancies. Although Class III malocclusion is primarily sagittal, a transverse functional shift can create a pseudo-Class III malocclusion due to mandibular displacement rather than true skeletal disharmony. Including these cases could bias the model toward transverse-driven decisions rather than the sagittal focus of this study.

All patients had good-quality preorthodontic and postorthodontic extraoral photographs, intraoral photographs, lateral cephalometric radiographs, and panoramic radiographs. Pretreatment lateral cephalometric radiographs were digitally analyzed using AudaxCeph software (Audax, d.o.o., Ljubljana, Solvenia) to detect skeletal Class III malocclusion with a measured negative ANB angle and negative Wits appraisal.

All selected cases had to be successfully treated and completed. Success was defined using prespecified objective occlusal criteria combined with a standardized esthetic assessment, consistent with routine orthodontic outcome evaluation. Occlusal success required achievement of a positive overjet of 1-3 mm, an overbite of 1-3 mm, and an acceptable incisor inclination within clinically normal ranges at the completion of treatment, 109° ± 6° for maxillary incisors and 93° ± 6° for mandibular incisors.[13,14]

To assess intraexaminer reliability, 10% of the total sample was randomly selected using a computer-generated randomization process to avoid selection bias and ensure representation across both the treatment groups. The selected patients included a proportional distribution of mild and severe Class III malocclusion presentations to reflect the overall dataset. The same examiner repeated all relevant measurements and evaluations for all the selected patients after a 2-week washout period. This time interval was chosen to minimize recall bias while maintaining consistency in the assessment conditions.

Reliability was evaluated using intraclass correlation coefficient for continuous variables. An intraclass correlation coefficient ≥0.80 was considered indicative of acceptable reliability. Values between 0.60-0.79 were interpreted as indicating moderate reliability, whereas values less than 0.60 were deemed unacceptable. Additionally, in cases in which reliability values fell below the acceptable threshold, the measurements were reassessed, and the evaluation protocol was reviewed to identify sources of inconsistency. These cases were remeasured, and consensus was reached through repeated assessment to ensure consistency before inclusion in the final dataset.

Assessment of facial esthetics was performed using standardized posttreatment extraoral photographs. Esthetic outcomes were independently evaluated by 2 experienced orthodontists, who were blinded to the study objectives, using a 5-point ordinal Likert scale (from very unsatisfactory to very satisfactory). A score of "satisfactory" or higher was considered indicative of acceptable facial esthetics. To ensure consistency, interrater reliability was assessed using Cohen's kappa statistic, which demonstrated substantial agreement between examiners. In cases of disagreement, consensus was reached through joint review.

The proposed model was designed to differentiate between orthodontic camouflage and orthognathic surgery in adult patients with skeletal Class III malocclusion. By integrating a DL model based on CNNs with traditional machine learning (ML), the system aimed to improve diagnostic accuracy and support orthodontic decision-making.

Dataset included 166 patients, each with 11 image types used as predictors. Images were resized, normalized, and augmented before CNN training. To enhance robustness and reduce overfitting, augmentation was applied only within the training folds of 4-fold cross-validation (K = 4), including rotations (±15°), horizontal and vertical flips, brightness and contrast adjustments (±10%), and zooming (≤10%).

In each fold, 75% of patients were allocated to training and 25% to testing. From the training portion, 10%-15% were randomly separated as validation data for hyperparameter tuning. Augmentation was restricted to training data, ensuring that no original or augmented images from the same patient appeared in both the training and evaluation sets. Performance metrics were averaged across folds.

Each image type was processed independently using a dedicated CNN. Transfer learning with a pretrained ResNet-50 (ImageNet weights) was used for feature extraction, with 1 model per modality. The final ResNet layer was replaced with a custom head comprising global average pooling, a fully connected layer (512 units, rectified linear unit), dropout (0.5), and a softmax output layer for binary classification ("Orthodontics" = 1; "Surgery" = 2). All networks were fine-tuned end-to-end (approximately 23,587,712 trainable parameters each) using the TensorFlow Keras API (Google LLC, Mountain View, Calif) (Fig 1).

An ensemble voting system was implemented. Each CNN produced a binary prediction that was treated as a vote. The 11 votes were concatenated into an 11-dimensional feature vector per patient and used as input for ML meta-classifiers. Overall, 7 algorithms were evaluated: decision tree (DT), support vector machine (SVM), k-nearest neighbors (KNN), random forest (RF), logistic regression (LR), naive Bayes (NB), and multilayer perceptron (MLP). Model performance was assessed using accuracy, precision, recall, F1 score, and receiver operating characteristic area under the curve; the best model was then selected.

Confusion matrices showed that RF performed best, correctly classifying 81 orthodontic and 80 surgical

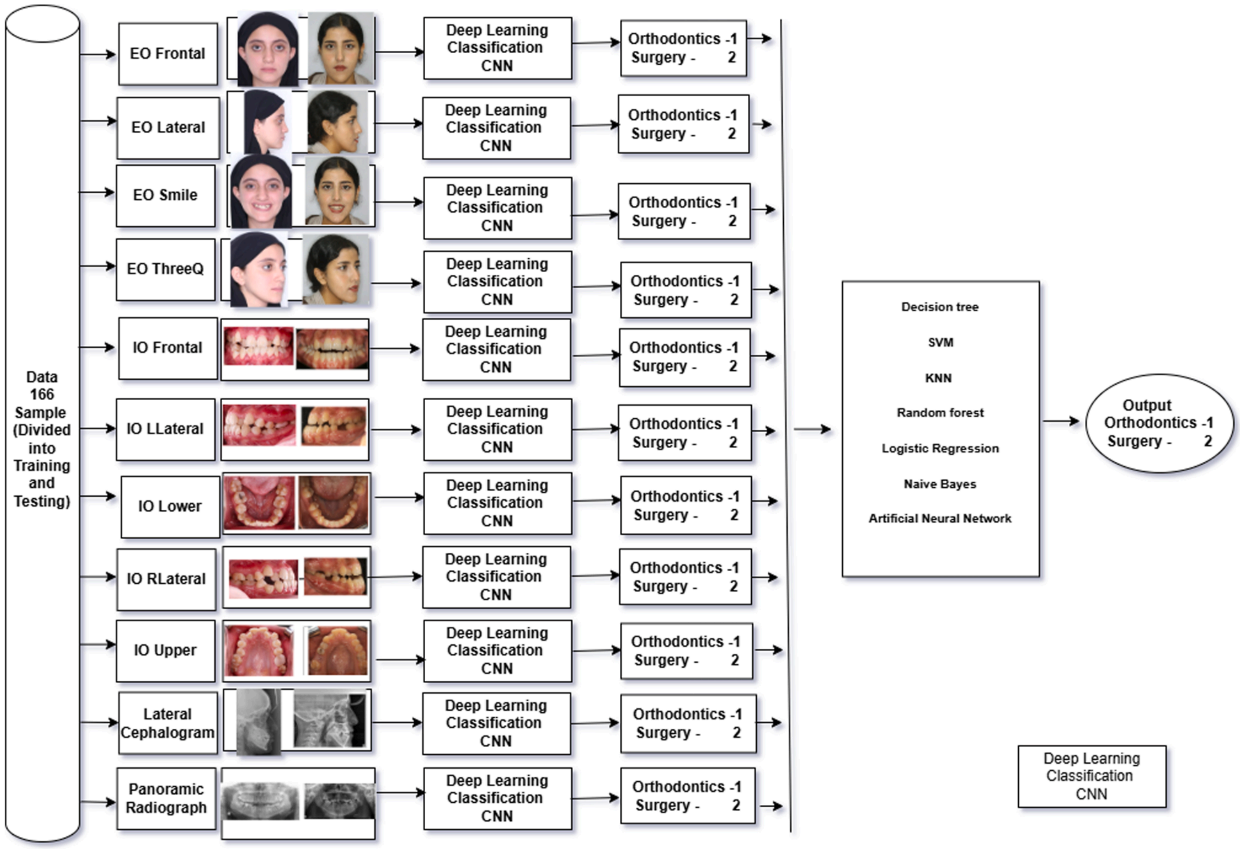

Fig 1. The proposed model framework for classification of orthodontic camouflage and orthognathic surgery decisions using CNNs and 7 ML models. *EO*, extraoral; *IO*, intraoral.

patients with minimal errors. SVM, MLP, LR, KNN, and NB showed comparable performance, whereas DT exhibited a higher misclassification rate, particularly for surgical patients (Fig 2). Overall, the ensemble showed consistent performance, with RF emerging as the most reliable classifier for treatment prediction in adult patients with skeletal Class III malocclusion.

Statistical analysis

To statistically compare the performance of the evaluated ML models, a pairwise significance analysis was conducted using the RF model as a reference, as it achieved the highest overall performance. Given the binary classification task (orthodontics vs surgery), 4-fold cross-validation, and a dataset of 166 samples, model performance was compared primarily based on classification accuracy. Statistical significance was assessed using a paired statistical test across cross-validation folds; this accounts for the dependency between models evaluated on the same data splits.

hypothesis testing was performed to compare the performance of the RF model with the other evaluated classifiers. The null hypothesis (H_0) assumed that there was no statistically significant difference in performance between RF and the compared model, whereas the alternative hypothesis (H_1) assumed the presence of a statistically significant difference. A P value <0.05 indicated statistical significance.

RESULTS

Performance metrics of the 7 ML meta-classifiers are summarized in the Table. The models were evaluated using accuracy, precision, recall, F1 score, and receiver operating characteristic area under the curve. The RF algorithm showed the strongest overall performance, achieving the highest accuracy (97.0%), high precision (97.8%), recall (96.5%), and F1 score (97.0%). It correctly classified nearly all orthodontic camouflage and orthognathic surgery patients with minimal errors (Fig 2).

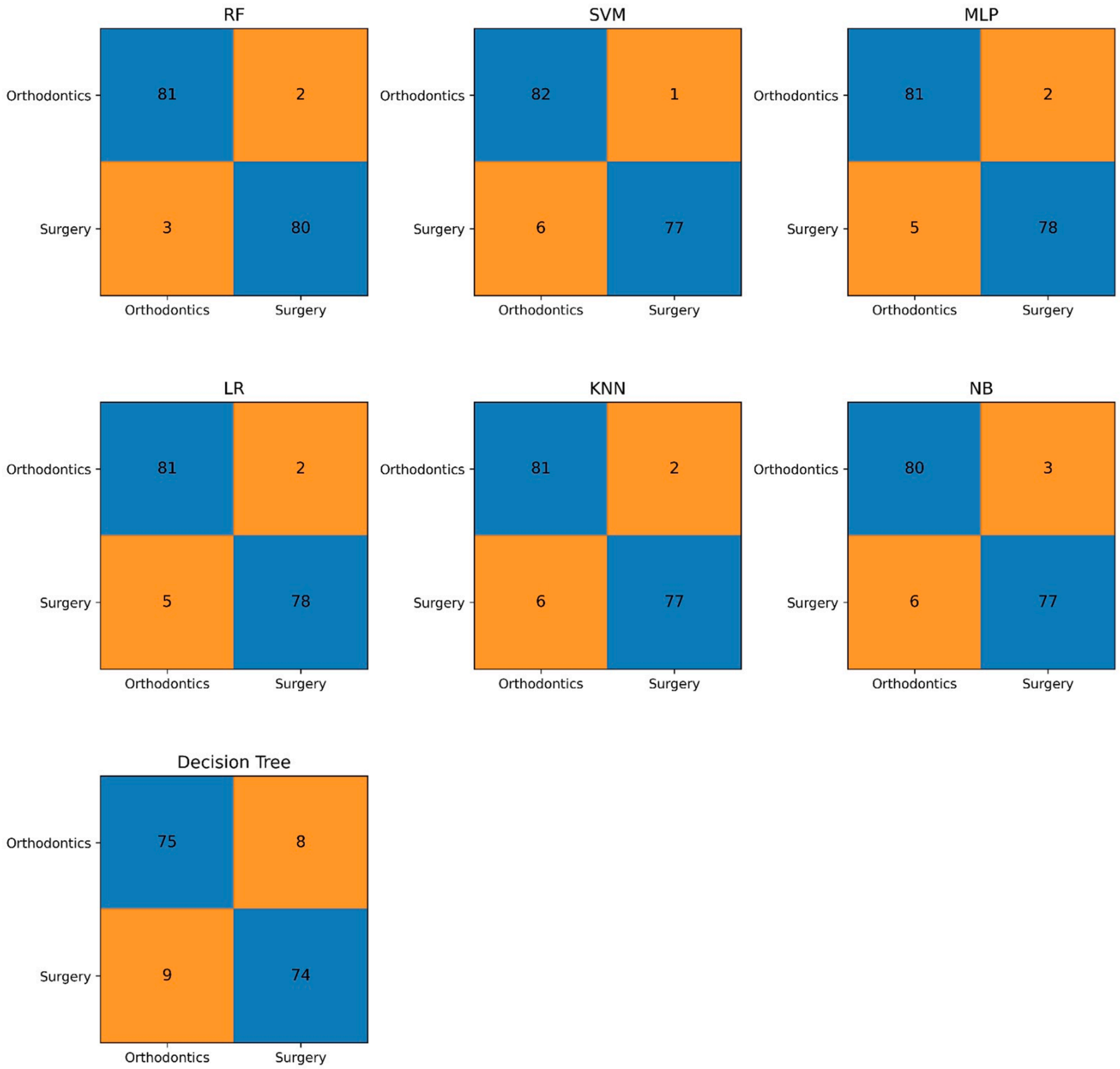

Fig 2. Confusion matrices for all classifiers showing true labels (*rows*) vs predicted labels (*columns*). Diagonal elements represent correct classifications; off-diagonal elements indicate misclassified cases.

The other algorithms including SVM, MLP, LR, KNN, and NB demonstrated no statistically significant difference compared with RF (P >0.05), despite slightly lower accuracy values. In contrast, the DT showed significantly inferior performance (P <0.01), indicating that its lower accuracy was unlikely to be due to random variation.

A heat map of the feature correlation matrix was generated to examine the relationships between predictors and the correct class (Fig 3). The intraoral left lateral photograph (0.84), extraoral smiling photograph (0.81), and extraoral 45° photograph (0.67) showed the highest correlations with the correct class, indicating stronger alignment with accurate classification. In contrast, Predictor_8 (0.05), Predictor_9 (0.05), and Predictor_7 (0.01) demonstrated weak correlations, suggesting a limited contribution.

Additionally, interpredictor correlations were observed, including Predictor_3 with Predictor_6 (0.74), Predictor_5 with Predictor_1 (0.77), and Predictor_6 with Predictor_4 (0.70), indicating potential redundancy among certain predictors.

Table. Performance comparison of the 7 ML meta-classifiers

Model	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1 score (%)*	*AUC (%)*	*P value (vs RF)*
RF	97.0	97.8	96.5	97.0	98.5	(Reference)
SVM	95.8	98.8	92.6	95.0	98.7	0.18
MLP	95.8	97.8	93.7	95.0	96.8	0.18
LR	95.8	97.8	94.0	95.0	95.9	0.18
KNN	95.2	97.5	93.0	94.8	97.6	0.12
NB	94.6	96.7	92.6	94.0	97.9	0.08
DT	89.8	90.0	89.4	89.0	90.3	<0.01*

AUC, area under the curve.
*Statistically significant difference compared with the Random Forest classifier.

DISCUSSION

The present retrospective study addressed a long-standing clinical challenge in adult patients with skeletal Class III malocclusion: selecting between orthodontic camouflage and orthognathic surgery. Most traditional decision aids have relied on manually extracted cephalometric variables or threshold-based rules, which are inherently dependent on landmark identification and operator consistency. Previously, cephalometric-based studies have attempted to reduce subjectivity by proposing cutoff values or multivariable predictors to guide treatment choice in adult patients with Class III malocclusion, but they consistently emphasize that decisions should not be made rigidly from limited parameters and that relevant determinants may fall outside what is measurable on a lateral cephalogram.[1,3-6,15-17]

In contrast, our approach is image-driven, in which each of the 11 routine diagnostic image types is independently classified by a dedicated CNN to output a binary decision ("Orthodontics" vs "Surgery"). These 11 binary outputs are then concatenated into an 11-dimensional "vote vector" and used by a conventional ML meta-classifier to produce the final recommendation. Importantly, this model operates on CNN decisions rather than deep feature embedding, meaning that the clinical value of the framework lies in multimodal ensemble agreement across standard orthodontic records rather than in end-to-end representation learning across modalities.

The present study demonstrated that a CNN-based ensemble voting framework can achieve high accuracy in predicting treatment approaches for adult patients with skeletal Class III malocclusion using routine pretreatment records. Among the evaluated meta-classifiers, the RF model consistently showed the strongest overall performance, achieving the highest accuracy of 97.0% across all metrics, indicating robust aggregation of multimodal image-based predictions.

These findings are consistent with those reported by Lee et al,[12] who retrospectively analyzed cephalometric data from 196 patients with skeletal Class III malocclusion. Their results demonstrated that RF and LR ML models can reliably support treatment planning in orthodontic patients with Class III malocclusion, with potential classification success rates of up to 90%, whereas Taraji et al[10] demonstrated that the XGBoost model can accurately predict the appropriate treatment approach for adult patients with Class III malocclusion. These results highlight the potential of AI and ML as adjunct tools to improve objectivity and consistency in orthodontic treatment planning.

In addition, a heat map was generated to illustrate which predictor predominantly affected the decision-making process and to assess the correlation between different predictors. Several intraoral and extraoral photographic views exhibited stronger associations with the final treatment decision than the lateral cephalometric radiograph. Rather than suggesting reduced clinical importance of cephalometric analysis, this finding likely reflected the complementary role of photographs in capturing soft-tissue morphology, facial esthetics, and occlusal presentation–factors that are frequently emphasized during the clinical evaluation of patients with Class III malocclusion. When multiple photographic views are available simultaneously, the incremental contribution of the lateral cephalogram to automated classification may be diminished, particularly in an image-based ensemble framework. These results align with prior evidence provided by Durao et al,[18] Currell et al,[19] and Dinesh et al,[20] who showed that lateral cephalometric radiographs do not consistently alter treatment planning decisions when comprehensive clinical and photographic information is already present, with emphasis on the importance of case-by-case evaluation to minimize patient radiation exposure and maintain diagnostic accuracy.

This innovative AI framework may help eliminate diagnostic subjectivity by providing consistent, accurate, and real-time treatment recommendations. Furthermore, this model may help inexperienced orthodontists by shortening their learning period and serve as a valuable second-opinion tool for experienced orthodontists in complex cases.

Despite these promising results, there are some limitations worth consideration. We acknowledge that our single-center dataset limits generalizability and that high accuracy raises potential overfitting concerns. Future studies will use multi-center datasets, explore additional imaging modalities, such as 3-dimensional cone-beam computed tomography scans, to enhance

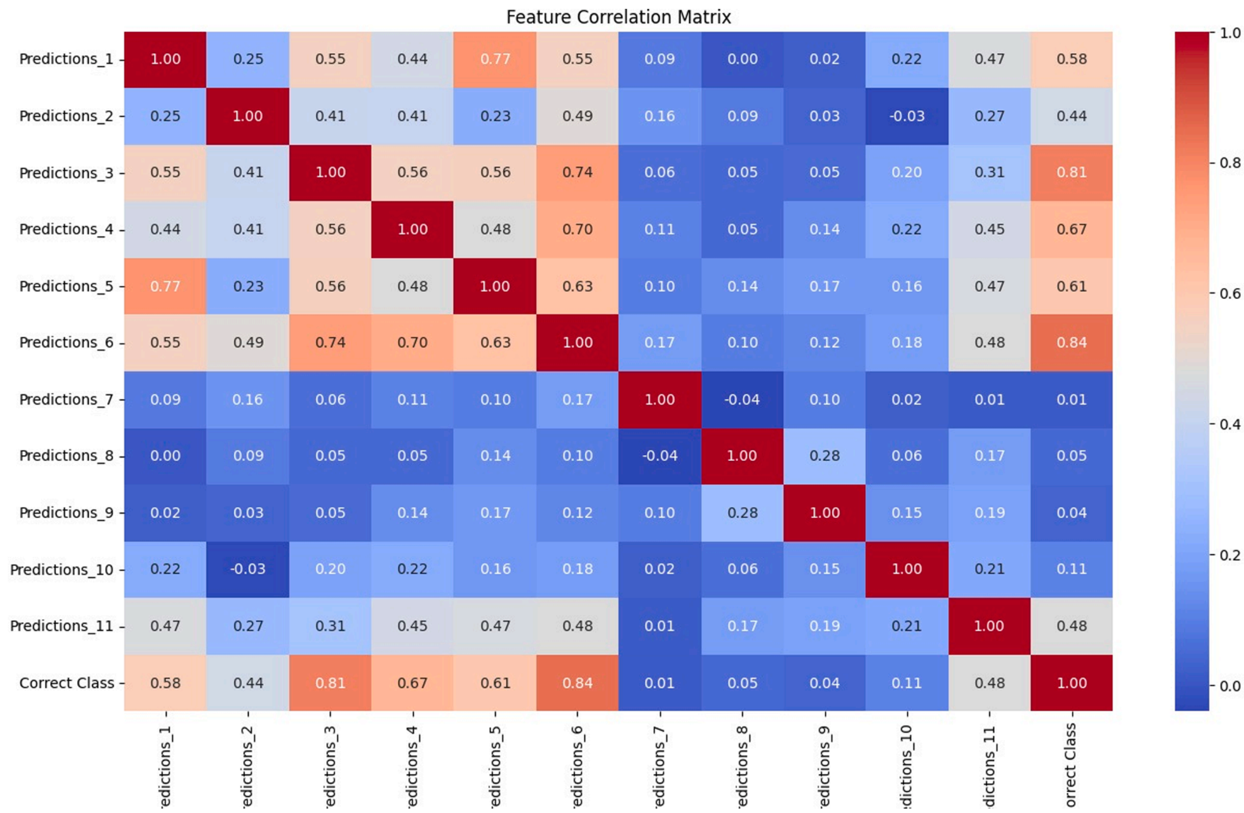

Fig 3. Feature correlation matrix illustrating the relationships between model predictors (Predictor_1 to Predictor_11) and the correct class labels.

predictive accuracy, and include expert orthodontist panels to assess model-human agreement. Nevertheless, the observed image-level associations should be interpreted cautiously, as correlation does not imply causation, and expert validation is required to determine whether the model's learned patterns correspond to clinically meaningful decision criteria.

Ethically, AI in orthodontics should function as a decision-support tool, not as a replacement for clinician expertise. Final decisions should remain under the oversight of an orthodontist. All images were anonymized, and institutional ethical review board approval was obtained.

CONCLUSIONS

Integrating CNN-based feature extraction and conventional ML classifiers brought about a highly accurate and reliable decision-making framework for recommending treatment for adult patients with skeletal Class III malocclusion. The RF model achieved 97% accuracy and 97.8% precision; this highlights the transformative potential of the AI-driven model in orthodontic treatment decisions, enhancing precision, minimizing diagnostic variability, and subsequently improving patient care.

AUTHOR CREDIT STATEMENT

Maha Swelam contributed to conceptualization, methodology, resources, data curation, and writing–original draft; Ahmed S. Fouda contributed to review and editing and visualization; Mostafa El Dawlatly contributed to review and editing, visualization, and supervision; Farid Ali contributed to methodology, software, validation, and formal analysis; and Mona M. Salah Fayed contributed to conceptualization, methodology, review and editing, and supervision.

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