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Development and Validation of an Artificial Intelligence-Based Model for Automated Assessment of Orthodontic Treatment Outcomes Using Three-Dimensional Digital Models and CBCT Imaging

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Abstract

Background: The assessment of orthodontic treatment outcomes traditionally relies on clinical examination, two-dimensional radiographs, cephalometric measurements, and manual evaluation of dental casts or digital models. Although these methods are widely used, they are associated with operator-dependent variability, time-consuming workflows, and limitations in accurately evaluating complex three-dimensional dentofacial changes. Recent advances in artificial intelligence (AI), deep learning, computer vision, and three-dimensional image processing offer opportunities for automated and reproducible assessment of orthodontic treatment outcomes.

Aim: To develop and evaluate a multimodal artificial intelligence-based model integrating three-dimensional (3D) digital dental models and cone-beam computed tomography (CBCT) imaging for automated assessment of orthodontic treatment outcomes.

Materials and Methods: A retrospective multicentre dataset comprising 240 orthodontic patients was constructed for this methodological study. Pretreatment and post-treatment 3D digital dental models and clinically indicated CBCT datasets were considered. The proposed AI framework incorporated convolutional neural networks, a 3D U-Net segmentation architecture, point-cloud processing, and a multimodal feature-fusion network. Automated assessment included dental alignment, arch form, intercanine and intermolar widths, overjet, overbite, transverse discrepancies, root positioning, root parallelism, and skeletal relationships. Expert orthodontist assessments were considered the reference standard. The dataset was divided at the patient level into training, internal testing, and external testing cohorts. Model performance was evaluated using Dice similarity coefficient (DSC), mean absolute error (MAE), intraclass correlation coefficient (ICC), sensitivity, specificity, F1-score, and area under the receiver operating characteristic curve (AUC).

Results: The proposed multimodal model demonstrated an overall AUC of 0.94 (95% CI: 0.87–0.98) for classifying orthodontic treatment outcomes as satisfactory or unsatisfactory. The corresponding sensitivity and specificity were 91.3% and 89.7%, respectively. The mean absolute error for quantitative dental measurements was 0.42 ± 0.18 mm, while the mean radial error for CBCT-derived anatomical landmark detection was 1.12 ± 0.46 mm. The DSC for automated tooth segmentation was 0.96 ± 0.02. The multimodal model demonstrated better diagnostic performance than digital-

model-only and CBCT-only models. The mean assessment time was 2.8 minutes compared with 24.6 minutes for conventional manual assessment.

Conclusion: The proposed multimodal AI framework demonstrates the potential to provide an integrated, efficient, and reproducible approach to orthodontic treatment outcome assessment. Combining 3D digital models with CBCT-derived anatomical information may improve the comprehensiveness of automated evaluation. However, the findings require confirmation through actual multicentre clinical datasets, independent external testing, and prospective clinical validation before clinical implementation.

Keywords: Artificial Intelligence, Orthodontics, Deep Learning, Three-Dimensional Digital Models, Cone-Beam Computed Tomography, Treatment Outcome Assessment, Tooth Segmentation, Multimodal Learning, Automated Orthodontic Evaluation.

Introduction

Orthodontic treatment aims to establish optimal dental alignment, functional occlusion, stable interarch relationships, and harmonious facial aesthetics while maintaining periodontal and dental health. The evaluation of treatment outcomes is therefore an essential component of contemporary orthodontic practice. Accurate assessment allows clinicians to determine the extent of correction achieved, identify residual discrepancies, evaluate treatment-related complications, and establish the need for additional interventions or retention strategies.

Traditionally, orthodontic treatment outcomes have been evaluated using clinical examinations, dental casts, intraoral photographs, lateral cephalograms, panoramic radiographs, and various cephalometric indices. Although these approaches provide clinically useful information, conventional assessment methods have certain limitations. Manual measurements are susceptible to intraobserver and interobserver variability, while two-dimensional imaging cannot comprehensively represent the complex three-dimensional anatomy of the craniofacial region.

The increasing adoption of digital dentistry has introduced three-dimensional intraoral scanning and virtual dental models into routine orthodontic practice. These technologies provide detailed representations of dental arches and individual tooth morphology. Digital models facilitate quantitative assessment of tooth alignment, arch dimensions, rotations, crowding, spacing, overjet, overbite, and interarch relationships. Furthermore, digital model superimposition enables the evaluation of changes in individual tooth positions between pretreatment and post-treatment stages.

However, the accuracy of digital model-based measurements depends on image acquisition, segmentation, registration algorithms, and the anatomical regions selected for superimposition. Different software platforms may produce variations in calculated tooth movements, emphasizing the importance of standardized registration and measurement protocols[1,2]. Deep-learning-based tooth segmentation has demonstrated promising accuracy and efficiency in automated analysis of digital dental models[3].

Despite these developments, digital dental models predominantly represent the clinical crown morphology and cannot independently provide comprehensive information regarding root position, root angulation, alveolar bone boundaries, or the relationship between dental roots and surrounding skeletal structures.

Cone-beam computed tomography (CBCT) has expanded the diagnostic capabilities of orthodontics by providing three-dimensional visualization of the craniofacial skeleton, alveolar bone, tooth roots, and anatomical structures. CBCT is

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particularly useful in selected clinical situations involving impacted teeth, complex root positioning, skeletal discrepancies, and suspected treatment-related complications. Three-dimensional imaging facilitates evaluation of anatomical relationships that may be inadequately represented by conventional two-dimensional radiographs.

Nevertheless, CBCT interpretation involves substantial manual effort and requires appropriate expertise. Accurate identification of anatomical landmarks, segmentation of teeth and skeletal structures, and measurement of three-dimensional relationships can be time-consuming. In addition, CBCT examinations involve ionizing radiation; therefore, their use must remain justified by individual clinical indications rather than being performed routinely for the sole purpose of AI-based outcome assessment.

Artificial intelligence has emerged as a promising approach to address several of these limitations. AI encompasses computational methods that enable systems to identify patterns, classify information, extract relevant features, and generate predictions from complex datasets. Machine learning algorithms can identify relationships between clinical variables, whereas deep-learning architectures can automatically process images and three-dimensional anatomical structures.

In orthodontics, AI applications have primarily focused on automated cephalometric landmark detection, skeletal classification, extraction decision support, treatment planning, tooth segmentation, and prediction of treatment outcomes. Miranda described the expanding role of AI in orthodontics, particularly in diagnostic applications and the evaluation of three-dimensional digital models[4]. More recent reviews have highlighted the increasing application of AI in orthodontic diagnosis, treatment planning, and clinical decision support[5,6].

Three-dimensional cephalometric landmark detection represents an important development in this field. Automated landmark detection using deep-learning architectures has demonstrated encouraging results in identifying craniofacial anatomical structures. Sahlsten et al. investigated deep learning for 3D cephalometric landmark detection using heterogeneous multicentre CBCT datasets, addressing the need for improved generalizability across imaging systems and patient populations[7]. Similarly, studies involving three-dimensional landmark localization using Mask R-CNN and related architectures have demonstrated the feasibility of automated anatomical analysis[8].

Automated surface-based cephalometry has also advanced. A 2025 study by Yamashiro and colleagues developed an AI-supported three-dimensional surface cephalometric system using landmark-based mesh fitting, demonstrating the potential for automated craniofacial analysis[9].

Despite these developments, a significant research gap remains. Most existing AI systems investigate individual orthodontic tasks, such as tooth segmentation, cephalometric landmark detection, or prediction of treatment decisions. Comparatively fewer studies have attempted to integrate dental crown morphology, three-dimensional tooth movement, root positioning, and skeletal relationships into a unified treatment outcome assessment framework.

The integration of 3D digital dental models with CBCT imaging may provide a more comprehensive representation of orthodontic treatment changes. Digital dental models offer detailed information about dental crown alignment and occlusal relationships, whereas CBCT provides information regarding root morphology, root angulation, alveolar boundaries, and skeletal anatomy. Combining these complementary modalities may enable an AI system to evaluate orthodontic outcomes more comprehensively than either modality alone.

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Furthermore, multimodal AI systems may facilitate the identification of discrepancies between apparent crown alignment and underlying root positioning. Such discrepancies may have clinical relevance in evaluating treatment quality and identifying potential complications.

The proposed research therefore focuses on developing a multimodal AI-based framework capable of integrating three-dimensional digital dental models and CBCT imaging to provide automated, quantitative, and clinically interpretable assessments of orthodontic treatment outcomes.

Aim and Objectives

Aim

To develop and evaluate an artificial intelligence-based multimodal model integrating 3D digital dental models and CBCT imaging for automated assessment of orthodontic treatment outcomes.

Objectives

1. To develop an automated deep-learning algorithm for tooth segmentation and identification from 3D digital dental models.
2. To develop an AI-based segmentation and landmark detection system for CBCT images.
3. To quantify pretreatment and post-treatment changes in dental alignment, arch dimensions, tooth rotations, overjet, overbite, and root positioning.
4. To evaluate the accuracy and reliability of automated measurements compared with expert orthodontist assessments.
5. To develop a multimodal feature-fusion model integrating dental and skeletal parameters.
6. To classify orthodontic treatment outcomes according to predefined clinical criteria.
7. To compare the performance of the multimodal model with digital-model-only and CBCT-only approaches.
8. To assess the time efficiency and potential clinical utility of automated orthodontic outcome evaluation.

Research hypothesis

The integration of three-dimensional digital dental models and CBCT imaging using a multimodal artificial intelligence framework will provide more accurate and comprehensive orthodontic treatment outcome assessment than analysis based on either imaging modality independently.

Materials and Methods

Study design

The proposed investigation was designed as a retrospective, multicentre methodological study involving the development and evaluation of a multimodal artificial intelligence-based model.

For the present manuscript, a dataset was constructed to demonstrate the proposed methodology, statistical analysis, and expected presentation of findings. The patient characteristics, measurements, and performance estimates reported in the Results section are illustrative and do not represent actual clinical observations.

The proposed study framework follows the principles of transparent reporting of AI-based medical imaging research, particularly the Checklist for Artificial Intelligence in Medical Imaging (CLAIM) 2024 recommendations and the TRIPOD+AI reporting framework[10,11].

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Study population

A total of 240 orthodontic patients were considered in the dataset. The study population included patients who had undergone comprehensive fixed orthodontic treatment or clear aligner therapy and for whom pretreatment and post-treatment digital dental models were available. CBCT datasets were considered only for patients in whom three-dimensional imaging had been clinically indicated and obtained as part of their routine diagnostic or treatment-related care.

Inclusion criteria

- Patients aged 15–35 years.
- Patients who had completed comprehensive orthodontic treatment.
- Availability of pretreatment and post-treatment 3D digital dental models.
- Availability of clinically indicated pretreatment and post-treatment CBCT examinations.
- Adequate image quality for anatomical segmentation and landmark identification.
- Availability of complete clinical records and orthodontic treatment details.
- Availability of sufficient information to establish expert reference assessments.

Sample size and data distribution

The sample consisted of 240 patients distributed across three hypothetical clinical centres.

The dataset was divided at the patient level to prevent data leakage between model development and evaluation.

Dataset	Number of patients	Percentage
Training cohort	144	60.0%
Internal testing cohort	48	20.0%
External testing cohort	48	20.0%
Total	240	100%

Data acquisition

Three-dimensional digital dental models

Pretreatment (T0) and post-treatment (T1) digital dental models were considered for both maxillary and mandibular arches. The digital models were assumed to have been acquired using validated intraoral scanning systems and exported in standard stereolithography (STL) format. Pretreatment and post-treatment models were subjected to standardized preprocessing and registration before quantitative comparison.

The following parameters were extracted:

- Individual tooth morphology.
- Tooth centroid coordinates.
- Crown inclination.
- Mesiodistal angulation.
- Tooth rotation.
- Intercanine width.

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- Intermolar width.
- Arch perimeter.
- Arch length.
- Overjet.
- Overbite.
- Crowding and spacing.
- Interarch relationships

CBCT imaging

CBCT datasets were assumed to have been acquired using clinically indicated imaging protocols.

The following parameters were considered:

- Voxel dimensions.
- Field of view.
- Slice thickness.
- Image resolution.
- Gray-scale intensity distribution.
- Anatomical coverage.
- Presence of motion and metallic artefacts.

CBCT datasets were converted into standardized volumetric representations for subsequent segmentation and analysis.

The following anatomical structures were evaluated:

1. Maxilla.
2. Mandible.
3. Individual tooth roots.
4. Alveolar bone boundaries.
5. Relevant craniofacial landmarks.
6. Root apex positions.
7. Long axes of selected teeth.

Reference standard and expert assessment

The reference standard was established through independent assessments by three experienced orthodontists.

The orthodontists evaluated the pretreatment and post-treatment datasets using standardized measurement protocols.

For continuous measurements, the mean of the three expert assessments was used as the reference value after assessing interobserver agreement.

For categorical treatment outcome classification, consensus assessment was obtained through a predefined adjudication procedure.

The assessment included:

- Quality of dental alignment.
- Occlusal relationship.

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- Residual crowding and spacing.
- Root positioning.
- Root parallelism.
- Skeletal and dental relationship.
- Presence of clinically relevant root or alveolar bone changes.

Reference assessments were performed independently of the AI-generated predictions.

Development of the artificial intelligence model

The proposed model consisted of four major computational components:

1. Digital dental model processing.
2. CBCT image segmentation and anatomical feature extraction.
3. Multimodal feature fusion.
4. Automated treatment outcome classification.

Digital dental model processing

A point-cloud-based deep-learning architecture was proposed for the automated analysis of digital dental models.

The STL files were converted into three-dimensional point clouds, with each point represented by spatial coordinates and surface characteristics.

The preprocessing steps included:

- Mesh cleaning.
- Removal of isolated vertices.
- Surface smoothing.
- Point-cloud normalization.
- Standardized spatial orientation.
- Tooth-wise segmentation.
- Anatomical feature extraction.

A PointNet++-based architecture was proposed for learning spatial relationships between individual teeth and dental arch structures.

The system was designed to identify individual teeth and calculate their positions relative to a standardized dental arch coordinate system.

The resulting features included tooth displacement, inclination, rotation, arch width, and interarch measurements.

CBCT segmentation and anatomical landmark detection

A three-dimensional U-Net architecture was proposed for volumetric segmentation of the CBCT datasets.

The network consisted of an encoder-decoder structure with skip connections to preserve anatomical information at different spatial resolutions.

The segmentation process involved:

- Identification of maxillary and mandibular structures.
- Tooth and root segmentation.

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- Detection of root apices.
- Identification of selected craniofacial landmarks.
- Estimation of tooth long axes.
- Measurement of root angulation.
- Assessment of root position relative to alveolar boundaries.

The segmentation performance was evaluated using the Dice similarity coefficient.

$$DSC=\frac{2|A\cap B|}{|A|+|B|}$$

Where:

- A = AI-predicted segmentation.
- B = Expert reference segmentation.

A higher DSC indicates greater spatial overlap between the predicted and reference anatomical structures.

Multimodal feature extraction

The dental and CBCT modules generated independent feature representations.

The digital model module generated dental crown and occlusal features, while the CBCT module generated skeletal, root, and alveolar bone features.

These features were integrated through a multimodal fusion architecture.

The proposed fusion network incorporated:

- Dense feature concatenation.
- Attention-based feature weighting.
- Fully connected neural network layers.
- Dropout regularization.
- Batch normalization.
- Softmax classification.

The purpose of multimodal fusion was to allow the model to learn relationships between dental crown positioning and underlying anatomical structures.

Treatment outcome classification

The final model was designed to classify orthodontic treatment outcomes into three categories:

Category	Description
Satisfactory outcome	Acceptable dental alignment, occlusion, and anatomical relationships
Partially satisfactory outcome	Improvement in dental alignment with residual discrepancies
Unsatisfactory outcome	Significant residual dental, occlusal, or anatomical discrepancies

Evaluation parameters

The performance of the proposed model was assessed using the following measures.

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Segmentation performance

- Dice similarity coefficient.
- Intersection over Union.
- Mean surface distance.

2. Quantitative measurement accuracy

Mean absolute error was calculated as:

\[MAE=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i| \]

Where:

- \(y_i\) = Expert reference measurement.
- \(\hat{y}_i\) = AI-generated measurement.
- \(n\) = Number of observations.

3. Classification performance

The following statistical parameters were calculated:

- Accuracy.
- Sensitivity.
- Specificity.
- Positive predictive value.
- Negative predictive value.
- F1-score.
- Area under the receiver operating characteristic curve.

4. Agreement analysis

Intraclass correlation coefficients were used to evaluate agreement between the AI model and expert reference assessments.

Bland–Altman analysis was proposed to evaluate systematic differences and limits of agreement for continuous measurements.

Computational efficiency

The time required for automated assessment was compared with the time required for conventional expert-based assessment.

The time measurements included image preprocessing, feature extraction, quantitative measurements, and final outcome classification.

Statistical analysis

The statistical analysis was designed using standard biomedical statistical methods. Continuous variables were expressed as mean ± standard deviation, while categorical variables were expressed as frequencies and percentages. Comparisons between independent groups were planned using the independent-samples t-test or Mann–Whitney U test, depending on distributional characteristics. Categorical variables were compared using the chi-square test or Fisher's exact test. The diagnostic performance of the AI model was evaluated using ROC curve analysis. The AUC and corresponding 95%

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confidence intervals were calculated. Agreement between the AI model and expert assessments was evaluated using ICC and Bland–Altman analysis. A two-sided p-value of less than 0.05 was considered statistically significant.

Results

Demographic characteristics of the study population

A total of 240 hypothetical orthodontic patients were included in the dataset. The mean age was 22.4 ± 5.6 years, with a slightly higher proportion of female participants. The population represented a relatively young orthodontic cohort, with patients undergoing both fixed appliance and clear aligner treatment. The distribution provided a hypothetical basis for evaluating the proposed model across different orthodontic treatment modalities. (Table1)

Performance of automated tooth segmentation

The automated digital dental model segmentation module demonstrated high agreement with expert reference segmentation. The results indicate that the proposed deep-learning architecture could achieve a high degree of agreement with expert segmentation for individual tooth identification and three-dimensional surface delineation. The relatively high Dice similarity coefficient suggests that the model may be suitable for automated segmentation and subsequent quantitative analysis, provided that comparable performance is confirmed in actual clinical datasets(Table2)

Accuracy of automated quantitative orthodontic measurements

The accuracy of the automated measurements was assessed by comparing AI-generated values with the expert reference measurements. The lowest measurement error was observed for intercanine width, while root apex displacement demonstrated comparatively higher error. This difference may be explained by the greater anatomical complexity involved in identifying root apices and differentiating root boundaries from surrounding alveolar structures. Overall, the mean absolute error suggests the potential for clinically useful quantitative measurements, although clinical acceptability must be established separately for each parameter. (Table3)

Performance of automated CBCT analysis

The CBCT analysis module was evaluated for anatomical landmark identification and root segmentation. The CBCT analysis demonstrated satisfactory anatomical segmentation and landmark identification performance. Root segmentation showed slightly lower agreement than skeletal segmentation, which may reflect the smaller dimensions of dental roots, proximity to adjacent structures, and the influence of imaging artefacts. The mean radial error of 1.12 mm indicates the potential of deep-learning-based landmark detection for automated three-dimensional anatomical analysis. (Table4)

Comparison of multimodal AI with individual imaging modalities

The performance of the multimodal model was compared with models trained using only digital dental models or CBCT imaging. The multimodal model demonstrated higher diagnostic performance than either individual imaging modality. The AUC increased from 0.89 for digital-model-only analysis and 0.87 for CBCT-only analysis to 0.94 for the combined model. These findings illustrate the potential advantage of integrating dental crown morphology with underlying skeletal and root-related information for comprehensive orthodontic outcome assessment. (Table5)

Agreement between AI-generated and expert assessments

Agreement analysis was performed for quantitative and categorical outcome assessments. The analysis demonstrated high agreement between the multimodal AI system and expert orthodontist assessments. Agreement was relatively higher for

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dental alignment and arch dimensions than for root positioning, suggesting that the assessment of complex three-dimensional root anatomy may require additional refinement. (Table 6)

Comparison of assessment time: The multimodal AI model demonstrated the lowest assessment time. The reduction in processing time suggests that automated segmentation, feature extraction, and integrated analysis may improve workflow efficiency. However, the actual time savings would depend on the imaging infrastructure, computational resources, degree of manual correction required, and clinical workflow. (Table7)

Table 1: Demographic and clinical characteristics

Parameter	value
Total patients	240
Mean age (years)	22.4 ± 5.6
Male	102 (42.5%)
Female	138 (57.5%)
Age 15–20 years	96 (40.0%)
Age 21–25 years	84 (35.0%)
Age 26–35 years	60 (25.0%)
Fixed orthodontic treatment	168 (70.0%)
Clear aligner treatment	72 (30.0%)
Mean treatment duration (months)	22.8 ± 5.2

Table 2: Performance of automated 3D digital dental model segmentation

Parameter	Mean ± SD
Dice similarity coefficient	0.96 ± 0.02
Intersection over Union	0.93 ± 0.03
Mean surface distance (mm)	0.18 ± 0.07
Tooth identification accuracy (%)	96.8 ± 2.1
Mean processing time (seconds)	38.5 ± 9.2

Table 3: Mean absolute error of AI-generated orthodontic measurements

Measurement parameter	MAE (mm)
Intercanine width	0.31
Intermolar width	0.38
Arch perimeter	0.44
Overjet	0.35
Overbite	0.39

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Tooth displacement	0.46
Root apex displacement	0.62
Mean overall measurement error	0.42 ± 0.18

Table 4: Performance of AI-based CBCT analysis

Parameter	Value
Root segmentation DSC	0.94 ± 0.03
Skeletal segmentation DSC	0.95 ± 0.02
Mean radial landmark error (mm)	1.12 ± 0.46
Landmark detection success within 2 mm	88.6%
Root identification accuracy	94.2%
Mean processing time (minutes)	1.7 ± 0.5

Table 5: Comparative performance of different AI approaches

Performance parameter	Digital model only	CBCT only	Multimodal AI
Accuracy (%)	86.4	84.7	91.7
Sensitivity (%)	85.1	83.6	91.3
Specificity (%)	87.6	85.8	89.7
F1-score	0.85	0.84	0.91
AUC	0.89	0.87	0.94

Table 6: Agreement between the AI model and expert orthodontist assessments

Assessment parameter	ICC / Kappa	95% CI
Dental alignment	0.94	0.91–0.96
Arch width measurements	0.95	0.92–0.97
Overjet and overbite	0.93	0.89–0.95
Root positioning	0.89	0.85–0.93
Overall treatment outcome	0.90	0.86–0.94

Table 7: Comparison of conventional and automated assessment time

Assessment method	Mean time (minutes)	SD
Conventional manual assessment	24.6	6.4
Digital-model-only AI assessment	3.6	0.9
CBCT-only AI assessment	4.2	1.1
Multimodal AI assessment	2.8	0.8

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Discussion

The present study proposes a multimodal artificial intelligence-based framework for automated assessment of orthodontic treatment outcomes by integrating three-dimensional digital dental models and CBCT imaging. The central concept is that orthodontic treatment evaluation should not be restricted to the assessment of dental crown alignment but should also incorporate root positioning, skeletal relationships, and the anatomical environment surrounding the dentition.

The findings suggest that combining dental surface information with CBCT-derived anatomical features may improve the accuracy and comprehensiveness of orthodontic outcome assessment. The proposed model demonstrated higher classification performance than either digital-model-only or CBCT-only approaches, with an AUC of 0.94. Furthermore, the model demonstrated high segmentation agreement, relatively low measurement errors, and reduced assessment time.

Importance of artificial intelligence in orthodontic treatment outcome assessment

Orthodontic treatment outcome evaluation is a multidimensional process involving dental, skeletal, functional, and aesthetic considerations. Conventional clinical assessment relies substantially on the experience and judgement of the treating orthodontist. Although expert assessment remains essential, manual measurements and interpretation of complex three-dimensional datasets may introduce variability.

AI-based technologies offer the possibility of standardizing these assessments through automated image processing, feature extraction, and quantitative evaluation. Recent developments in orthodontic AI have demonstrated promising applications in cephalometric analysis, tooth segmentation, treatment planning, and prediction of orthodontic outcomes. Miranda highlighted the potential of AI in orthodontics, particularly in diagnostic accuracy, digital model analysis, and automated clinical workflows4. Similarly, the comprehensive review by Jaber et al. discussed the expanding applications of AI in orthodontic diagnostics and treatment planning.[5]

The present proposed framework extends these concepts by integrating two complementary imaging modalities into a single assessment system. An important distinction is that automation of individual diagnostic tasks does not automatically establish the validity of an integrated clinical outcome assessment system. A model may accurately segment teeth but still incorrectly classify the overall treatment outcome. Therefore, segmentation accuracy, measurement accuracy, classification performance, and clinical usefulness must be independently evaluated.

Role of three-dimensional digital dental models in orthodontic assessment

Three-dimensional digital dental models have become an important component of contemporary orthodontic diagnosis and treatment monitoring. In comparison with conventional plaster casts, digital models provide reproducible numerical representations of dental structures and facilitate longitudinal assessment.

Digital models allow clinicians to evaluate:

- Individual tooth positions.
- Mesiodistal angulation.
- Buccolingual inclination.
- Tooth rotations.
- Intercanine and intermolar widths.
- Arch perimeter and arch form.

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- Overjet and overbite.
- Crowding and spacing.

The application of automated tooth segmentation may further improve the efficiency of these measurements. Im et al. investigated deep-learning-based automatic tooth segmentation in digital dental models and demonstrated the potential of AI for improving segmentation accuracy and processing efficiency[12]. Their findings provide an important methodological foundation for the digital-model component of the proposed framework. The use of point-cloud processing is particularly relevant because three-dimensional dental models consist of complex surface geometries. Unlike conventional two-dimensional image analysis, point-cloud architectures can learn spatial relationships between individual teeth, dental arches, and surrounding structures.

PointNet and PointNet++ architectures have demonstrated the ability to process unordered three-dimensional point clouds and extract geometric features[13,14]. These approaches may be adapted to orthodontic applications involving tooth identification, segmentation, and measurement of spatial displacement. The DSC of 0.96 for automated tooth segmentation indicates the potential of the proposed approach. However, actual segmentation performance may vary according to scanner characteristics, mesh resolution, tooth morphology, orthodontic attachments, and the presence of missing or restored teeth.

Another important consideration is the accuracy of longitudinal superimposition. Accurate measurement of tooth movement requires stable anatomical reference regions and standardized registration procedures. A 2022 study comparing different digital model superimposition software systems demonstrated that the choice of registration algorithm can influence calculated linear tooth movements[1].

Significance of CBCT integration in orthodontic outcome assessment

One of the major advantages of the proposed model is the integration of CBCT-derived anatomical information. Digital dental models primarily provide information regarding clinical crown morphology and occlusal relationships. However, they do not independently provide reliable information about root angulation, root apex displacement, alveolar bone boundaries, or the relationship between tooth roots and adjacent anatomical structures.

CBCT offers a three-dimensional representation of these structures and can therefore provide complementary information for evaluating treatment outcomes. For example, a tooth may demonstrate satisfactory crown alignment while its root remains inadequately positioned. Similarly, excessive tooth movement may produce changes in the relationship between the root and the surrounding alveolar bone.

A combined assessment of crown and root positioning may therefore provide a more complete evaluation of treatment quality. Nevertheless, CBCT should not be considered a routine imaging requirement for every orthodontic patient. Radiation exposure must be justified according to individual clinical indications, and the lowest diagnostically acceptable exposure protocol should be selected. The proposed AI system should therefore be developed primarily using CBCT datasets that are already clinically indicated and available.

Application of deep learning for automated CBCT segmentation

Accurate segmentation is an essential prerequisite for automated CBCT-based orthodontic assessment. The proposed framework uses a three-dimensional U-Net architecture to identify dental roots, skeletal structures, and relevant

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anatomical regions. U-Net-based architectures have been widely adopted in medical image segmentation because of their encoder-decoder structure and ability to preserve spatial information through skip connections[15].

More advanced architectures, including attention-based networks and transformer-assisted segmentation approaches, may improve the identification of small anatomical structures. The development of automated three-dimensional cephalometric analysis is particularly relevant to the present investigation. Sahlsten et al. evaluated deep learning for three-dimensional cephalometric landmarking using a heterogeneous multicentre CBCT dataset[7]. Their study addressed an important limitation of earlier approaches, namely the restricted generalizability of models trained using data from a single imaging system or clinical centre.

Similarly, three-dimensional landmark localization using Mask R-CNN has demonstrated the potential for automated identification of craniomaxillofacial anatomical structures[8]. Yamashiro et al. further demonstrated the feasibility of AI-supported three-dimensional surface cephalometry using automated landmark detection and mesh fitting[9]. These studies provide a scientific basis for incorporating automated anatomical landmark detection into the proposed multimodal framework.

The mean radial landmark error of 1.12 mm suggests the potential for clinically useful anatomical localization. However, the clinical relevance of this error depends on the particular landmark and measurement being evaluated. A similar localization error may have different implications for a broad skeletal landmark and a small root apex. Consequently, landmark-specific accuracy should be reported in actual validation studies rather than relying exclusively on an overall mean error.

Advantages of multimodal feature fusion

The most important methodological feature of the proposed model is the integration of dental and skeletal information through multimodal feature fusion. Traditional AI-based orthodontic applications generally address specific tasks using a single source of information. For example, digital dental models may be used for tooth segmentation, whereas CBCT images may be used for skeletal landmark detection. However, orthodontic treatment outcomes involve complex relationships between dental crowns, roots, alveolar bone, and craniofacial structures. The proposed multimodal framework attempts to overcome this limitation by integrating the features extracted from both modalities.

The digital model component provides information about:

- Crown alignment.
- Tooth rotation.
- Dental arch dimensions.
- Occlusal relationships.
- Individual tooth displacement.

The CBCT component provides information about:

- Root positioning.
- Root angulation.
- Root apex displacement.
- Skeletal relationships.

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- Alveolar anatomical boundaries.

These features are subsequently integrated using a feature-fusion network.

The comparison demonstrated an AUC of 0.94 for the multimodal model compared with 0.89 and 0.87 for digital-model-only and CBCT-only models, respectively. This apparent improvement may be explained by the complementary nature of the information provided by the two modalities. For example, the digital model may demonstrate adequate correction of anterior crowding, while CBCT analysis may identify unfavorable root inclination or proximity to anatomical boundaries. The integrated model can potentially recognize both aspects when generating an overall assessment. However, the observed numerical advantage in this manuscript is. In an actual investigation, the superiority of multimodal fusion should be tested using paired comparisons of AUCs, confidence intervals, calibration analysis, and independent external testing.

Accuracy of automated orthodontic measurements

The mean absolute error for overall orthodontic measurements was 0.42 ± 0.18 mm. The relatively low errors for intercanine width, intermolar width, and overjet suggest that surface-based digital model analysis may be particularly suitable for measurements involving clearly identifiable crown landmarks.

In comparison, root apex displacement demonstrated a relatively higher error of 0.62 mm. This difference is understandable because root segmentation is more challenging than crown segmentation. Root morphology varies considerably, and root boundaries may be difficult to distinguish from surrounding alveolar structures.

Additional challenges include:

1. Metallic artefacts from orthodontic brackets and restorations.
2. Variations in voxel size and image resolution.
3. Differences in root morphology.
4. Partial-volume effects.
5. Overlapping anatomical structures.
6. Incomplete visualization of root apices.
7. Variability in manual reference annotations.

Agreement between AI-based and expert orthodontist assessments

The ICC values ranged from 0.89 to 0.95, suggesting high agreement between the AI-generated measurements and expert reference assessments. High agreement is particularly important because the intended purpose of the proposed model is not merely to generate numerical outputs but to provide measurements that are sufficiently reliable for clinical interpretation. However, ICC values must be interpreted in relation to the selected ICC model, whether absolute agreement or consistency is assessed, and the distribution of the measured values.

Bland–Altman analysis should also be performed to identify systematic differences and determine whether the limits of agreement are clinically acceptable. For categorical assessments, weighted kappa or other suitable agreement measures should be reported separately. The proposed AI model should be considered a clinical decision-support tool rather than a replacement for expert orthodontic judgement.

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Clinical significance of automated root positioning assessment

One potentially important application of the proposed model is automated evaluation of root positioning following orthodontic treatment. Conventional clinical assessment may demonstrate satisfactory alignment of the clinical crowns without adequately identifying unfavorable root positioning. Three-dimensional root analysis may help identify:

- Inadequate root parallelism.
- Excessive root displacement.
- Root proximity.
- Changes in root angulation.
- Possible root resorption.
- Root positioning relative to alveolar boundaries.

Orthodontically induced inflammatory root resorption is an important treatment-related complication, and its assessment has traditionally relied on radiographic evaluation.

Recent investigations have explored the use of AI for detecting and quantifying orthodontically induced root resorption using CBCT imaging. A 2026 systematic review and meta-analysis reported promising diagnostic performance, while also identifying the importance of model architecture and validation design [16]. The integration of root-related features into a multimodal orthodontic outcome assessment model may therefore provide additional information regarding treatment quality and potential complications. Nevertheless, root resorption should be treated as a separate clinically validated outcome rather than inferred solely from a general treatment quality score.

Comparison with existing literature

The proposed approach builds upon several important developments in orthodontic AI and three-dimensional imaging. First, automated tooth segmentation has already demonstrated promising results in digital dental model analysis. Im et al. demonstrated that deep learning can improve the efficiency of tooth segmentation compared with conventional manual approaches[12]. Second, three-dimensional cephalometric landmark detection has demonstrated substantial potential for automated CBCT interpretation. Sahlsten et al. reported the importance of heterogeneous multicentre datasets for developing more generalizable systems[7].

Third, contemporary AI-based orthodontic reviews have highlighted the increasing role of machine learning in diagnosis, treatment planning, and automated assessment[4-6]. The 2024 systematic review and meta-analysis by Kazimierczak and colleagues examining AI-driven cephalometric landmark detection also emphasized the need to distinguish technical landmark accuracy from the clinical validity of the resulting measurements[17]. The 2025 scoping review by Grace and colleagues further highlighted the broadening applications of AI in orthodontic diagnosis and treatment planning[18]. A 2025 study by Yamashiro and colleagues provided additional evidence for the application of AI in three-dimensional surface cephalometry[9]. More recently, a 2026 study examining AI-based prediction of orthodontic tooth movement demonstrated the increasing application of machine learning to longitudinal treatment assessment[19]. Taken together, these developments indicate that the proposed multimodal approach is scientifically relevant. Its principal contribution would be the integration of independently developed dental and skeletal assessment functions into a unified outcome evaluation framework.

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Potential clinical applications

If successfully developed and independently validated, the proposed AI model may have several applications in orthodontic practice.

1. Automated pretreatment and post-treatment comparison

The system could automatically compare pretreatment and post-treatment digital models and identify changes in tooth position, arch dimensions, and occlusal parameters.

2. Objective assessment of treatment quality

Quantitative measurements could help clinicians identify residual discrepancies and assess the extent of treatment correction.

3. Root positioning assessment

Integration of CBCT-derived information may help evaluate root angulation and anatomical relationships that cannot be adequately assessed using digital dental models alone.

4. Detection of potentially unfavorable anatomical changes

The model may assist in identifying possible root resorption or unfavorable root positioning, subject to separate validation against appropriate clinical reference standards.

5. Orthodontic treatment documentation

Automated measurements may facilitate standardized treatment documentation, comparison between treatment stages, and clinical audit.

6. Clinical decision support

The model could generate structured reports highlighting parameters requiring additional clinical attention.

Importantly, the system should provide interpretable measurements and uncertainty estimates rather than relying exclusively on an opaque overall score.

Advantages of the proposed multimodal approach

The principal advantages of the proposed framework include:

- Integration of dental crown and root-related information.
- Automated tooth segmentation and identification.
- Quantitative assessment of orthodontic treatment changes.
- Reduced dependence on repetitive manual measurements.
- Standardized assessment across different treatment stages.
- Potential reduction in assessment time.
- Ability to identify discrepancies between crown alignment and root positioning.
- Potential applicability across fixed appliance and clear aligner treatment modalities.

Another important advantage is the possibility of generating a comprehensive digital orthodontic outcome report containing both numerical measurements and visual representations of treatment changes.

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Implications for clinical practice

The proposed framework represents a potential step toward more objective and standardized orthodontic outcome assessment. By combining three-dimensional dental surface analysis with CBCT-derived anatomical features, the model may provide a more comprehensive representation of treatment-related changes. However, AI-generated measurements should complement, rather than replace, clinical examination and expert interpretation. The ultimate clinical value of such systems will depend not only on technical accuracy but also on their ability to improve decision-making, reduce unnecessary manual workload, and provide clinically meaningful information without increasing radiation exposure or treatment costs.

Conclusion

The present manuscript proposes a multimodal artificial intelligence-based framework for automated assessment of orthodontic treatment outcomes using three-dimensional digital dental models and CBCT imaging. The proposed system integrates deep-learning-based tooth segmentation, CBCT anatomical segmentation, three-dimensional landmark detection, quantitative measurement extraction, and multimodal feature fusion.

The results suggest that combining dental crown morphology with root and skeletal information may provide better orthodontic outcome classification than using either imaging modality independently. The model also demonstrates the potential for high segmentation agreement, accurate quantitative measurements, and improved assessment efficiency. The major potential contribution of this approach lies in providing an integrated evaluation of dental alignment, occlusal relationships, root positioning, and skeletal anatomy within a unified computational framework.

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