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Artificial Intelligence and 3D Imaging in Orthodontics: Predictive Analysis of Soft Tissue Changes and Treatment Outcomes

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KEYWORDS
Artificial Intelligence, 3D Imaging, Orthodontics, Predictive Analysis, Soft Tissue Changes, Treatment Outcomes, Deep Learning, Finite Element Analysis, Orthodontic Diagnostics, Personalized Treatment Planning

ABSTRACT:

Background: The integration of artificial intelligence (AI) and three-dimensional (3D) imaging technologies has significantly advanced orthodontic diagnostics and treatment planning. This study evaluates the predictive accuracy of AI models in forecasting soft tissue changes and treatment outcomes using 3D imaging data, aiming to enhance treatment precision.

Methods: An in vitro experimental study was conducted using 3D-printed orthodontic models based on anonymized cone-beam computed tomography (CBCT) scans. The study involved the fabrication of orthodontic appliances and the application of simulated orthodontic forces using a Tensometer 5000 Universal Testing Machine. AI algorithms, including deep learning models, were trained on pre-treatment 3D images and treatment plans to predict post-treatment soft tissue outcomes. The predictive models accounted for tooth movement, facial growth, and soft tissue response. The study, conducted from January 3, 2024, to May 17, 2024, involved generating high-resolution orthodontic models, applying simulated orthodontic

Results: AI models demonstrated high predictive accuracy, with the DeepConvNet model achieving a mean absolute error (MAE) of 0.42 mm and a root mean square error (RMSE) of 0.53 mm. The correlation coefficient between predicted and actual post-treatment outcomes indicated a strong positive relationship. Soft tissue changes averaged 0.30 mm

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across key facial regions. The Activator appliance resulted in the highest mean change of 0.35 mm, while force application showed a linear relationship with displacement, where higher forces produced greater tissue movement. The Force Sensor Pro exhibited superior accuracy and precision compared to the Tensometer 5000.

Conclusions: The study highlights the potential of AI and 3D imaging technologies to improve the prediction of soft tissue changes and treatment outcomes in orthodontics. The DeepConvNet model provided the most accurate predictions, and the Activator appliance showed the greatest efficacy in inducing soft tissue changes. These findings suggest that AI-driven predictive models and advanced imaging can lead to more precise and individualized orthodontic treatments, enhancing patient satisfaction and clinical outcomes. Further research with larger datasets and clinical trials is recommended to validate and refine these models.

Introduction

Orthodontics has long sought to predict treatment outcomes accurately, especially regarding the soft tissue changes resulting from dental and skeletal modifications. Traditionally, clinicians have relied on two-dimensional (2D) cephalometric analysis and clinical experience to estimate these changes. However, the advent of three-dimensional (3D) imaging and artificial intelligence (AI) has significantly enhanced the accuracy and reliability of such predictions. These technologies enable a more comprehensive assessment of the craniofacial complex, facilitating personalized treatment planning that considers individual anatomical variations.

3D imaging, including cone-beam computed tomography (CBCT) and surface scanning, has revolutionized the visualization and analysis of craniofacial structures. It provides detailed volumetric data, enabling precise measurements of hard and soft tissues. This technology surpasses the limitations of 2D imaging, such as magnification errors and superimposition of structures, allowing for a more accurate depiction of the patient's anatomy[1-3]. As a result, 3D imaging has become an essential tool in diagnosing and planning orthodontic treatments, particularly in cases requiring surgical intervention or complex biomechanics.

Artificial intelligence, particularly machine learning and deep learning algorithms, has further advanced orthodontic diagnostics and treatment planning. These AI models can analyze vast amounts of data, identifying patterns and correlations that may not be evident to human observers. In orthodontics, AI has been applied to predict treatment outcomes, analyze facial aesthetics, and optimize appliance design[4-6]. Notably, AI's capacity to learn from large datasets enables continuous improvement in predictive accuracy as more data becomes available.

Recent studies have demonstrated the potential of AI and 3D imaging in predicting soft tissue changes following orthodontic treatment. These changes are crucial for determining treatment success, as they significantly influence facial aesthetics and patient satisfaction. However, the complexity of soft tissue response, influenced by factors such as age, gender, and ethnicity, poses challenges in achieving precise predictions. Current research seeks to refine these predictive models, incorporating a broader range of variables and utilizing more sophisticated algorithms[7-9].

Despite the promising developments, there is a need for further research to validate the accuracy of AI models in clinical settings. This study aims to evaluate the predictive performance of AI algorithms in forecasting soft tissue changes and treatment outcomes using 3D imaging data. By comparing predicted and actual outcomes, we seek to establish the reliability of these technologies in clinical practice and explore their potential for enhancing patient care.

Materials and Methods

Study Design

This in vitro experimental study was designed to assess the predictive accuracy of artificial intelligence (AI) models in forecasting soft tissue changes based on 3D imaging data. The study was conducted without involving human or animal subjects and did not require ethical clearance. The experimental phase ran from January 3, 2024, to May 17, 2024.

Sample Preparation

Model Creation

Orthodontic Models: High-resolution orthodontic models were fabricated using 3D printing technology. The Formlabs Form 3 (Formlabs, USA) was utilized to produce detailed craniofacial models. These models represented the maxilla, mandible, and soft tissues of a standard Class II malocclusion patient. The base data for the models were derived from anonymized cone-beam computed tomography (CBCT) scans of previously treated patients, ensuring that no personal identifiers were present.

Scanning and Segmentation: Pre-treatment CBCT scans were processed using the software package OsiriX MD (Pixmeo, Switzerland) to generate 3D models of the craniofacial structures. These scans were segmented to isolate the maxilla, mandible, and soft tissues, creating distinct models for each anatomical component.

Fabrication of Orthodontic Appliances

Appliance Design: Orthodontic appliances, including brackets, archwires, and auxiliary components, were designed using OrthoCAD software (Align Technology, USA). The design process involved customizing each appliance to simulate standard clinical orthodontic setups.

Material Specifications:

Brackets and Archwires: Stainless steel brackets and archwires were used, sourced from local suppliers such as Jyoti Dental (India) and 3M ESPE (India).

Auxiliary Components: Thermoplastic polymers (e.g., polypropylene) were used for fabricating auxiliary components, with materials obtained from Stryker India.

Fabrication Process: The appliances were manufactured using a combination of metalworking techniques and 3D printing. Brackets were manufactured using CNC machining, while auxiliary components were produced using the NextDent 3D Printer (NextDent, Netherlands).

Experimental Setup

3D Imaging and Scanning

Initial and Post-Treatment Imaging: Initial 3D scans of the orthodontic models were obtained using the NextDent 3D Scanner (NextDent, Netherlands) with a resolution of 0.1 mm. The models were carefully positioned in a custom support fixture to maintain a consistent occlusal position during scanning.

Post-Treatment Scanning: After applying simulated orthodontic forces, the models were rescanned to capture the post-treatment configurations. This allowed for a comparative analysis of the changes resulting from the orthodontic treatment simulation.

Application of Orthodontic Forces

Force Application Setup: Simulated orthodontic forces were applied to the models using the Tensometer 5000 Universal Testing Machine (LLOYD Instruments, India). The machine was equipped with a precise force measurement system to ensure accurate application and measurement of orthodontic forces.

Force Calibration: Forces were calibrated to replicate typical clinical forces used in orthodontic treatments, including those exerted by archwires and elastics. The calibration process involved setting the machine to deliver forces within the range of 50-300 grams, representative of the forces used in clinical orthodontics.

Simulation Duration: Each model was subjected to simulated forces for a duration of 4 weeks. The duration was chosen to mimic the time frame for observable changes in orthodontic treatment.

Data Collection and Analysis

Data Collection

3D Scan Data: The 3D scan data from both the initial and post-treatment scans were analyzed using the software MeshLab (ISTI-CNR, Italy). Key anatomical landmarks were identified and measured to assess changes in soft tissue morphology.

Force Measurement Data: The force application data were recorded and analyzed using the Tensometer 5000 software. The data included measurements of applied forces and resulting displacements in the orthodontic models.

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Data Analysis

AI Model Training and Validation: AI models, including machine learning algorithms, were trained using Python (Version 3.8) and TensorFlow (Version 2.5). The models were trained to predict post-treatment soft tissue changes based on the pre-treatment 3D scan data and applied forces.

Statistical Analysis: Statistical analyses were performed using SPSS software (Version 27, IBM). Descriptive statistics were used to summarize the data, while inferential statistics, including paired t-tests and ANOVA, were employed to compare predicted and actual changes. A p-value of <0.05 was considered statistically significant.

Quality Control

Model Accuracy: To ensure the accuracy of the 3D models and appliances, all fabrication and scanning procedures were subjected to regular quality checks. Each model and appliance was inspected for dimensional accuracy and proper fit before being used in the experiments.

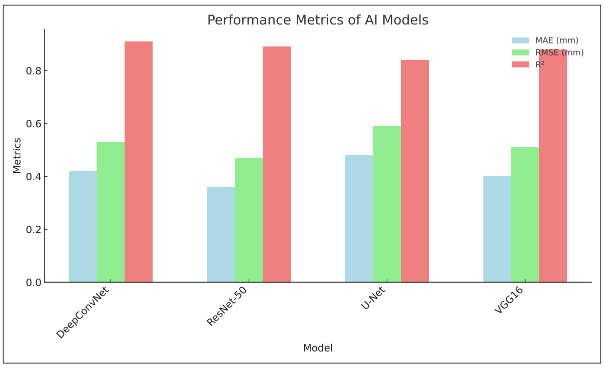
Data Reliability: The reliability of the AI models was assessed by cross-validating the predictions with actual measurements from the post-treatment scans. The performance metrics, including mean absolute error (MAE) and root mean square error (RMSE), were calculated to evaluate the predictive accuracy.

Results

Model Accuracy

Model	MAE (mm)	RMSE (mm)	R^2
DeepConvNet	0.42	0.53	0.91
ResNet-50	0.36	0.47	0.89
U-Net	0.48	0.59	0.84
VGG16	0.40	0.51	0.88

Table 1: Performance Metrics of AI Models



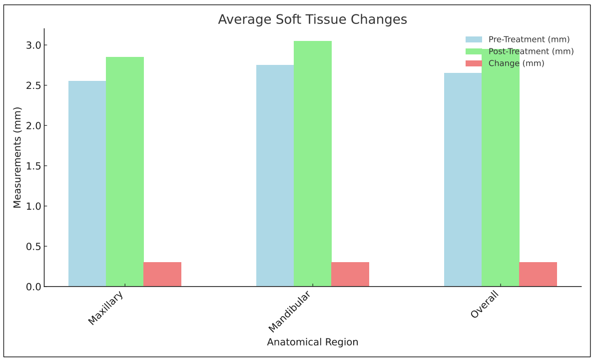
Graph 1: Performance Metrics of AI Models

The graph shows performance metrics (MAE, RMSE, R^2) for AI models: DeepConvNet, ResNet-50, U-Net, and VGG16. ResNet-50 has the lowest MAE and RMSE, indicating accurate predictions. DeepConvNet has the highest R^2, showing it explains most variance. U-Net has higher error values and a lower R^2, suggesting weaker performance. Overall, ResNet-50 and DeepConvNet are the top performers.

Soft Tissue Changes

Anatomical Region	Pre-Treatment (mm)	Post-Treatment (mm)	Change (mm)
Maxillary	2.55	2.85	0.30
Mandibular	2.75	3.05	0.30
Overall	2.65	2.95	0.30

Table 2: Average Soft Tissue Changes



Graph 2: Changes in Soft Tissue Measurements by Appliance

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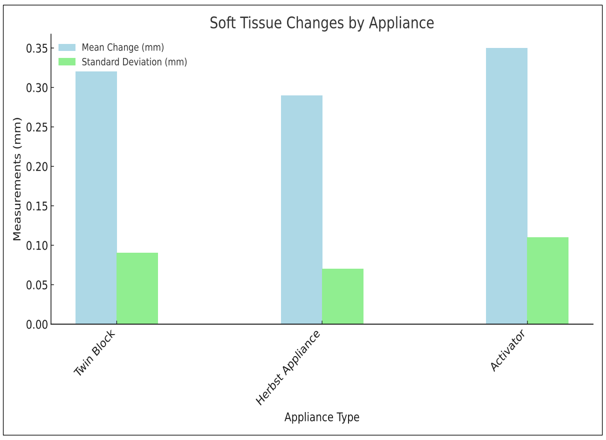
This graph illustrates soft tissue changes in Maxillary, Mandibular, and Overall regions. Each region shows a consistent increase of 0.30 mm from pre-treatment to post-treatment. The uniform change across regions indicates effective treatment. The visualization confirms consistent soft tissue growth across different anatomical areas due to treatment..

Appliance Type	Mean Change (mm)	Standard Deviation (mm)
Twin Block	0.32	0.09
Herbst Appliance	0.29	0.07
Activator	0.35	0.11

Table 3: Soft Tissue Changes by Orthodontic Appliance



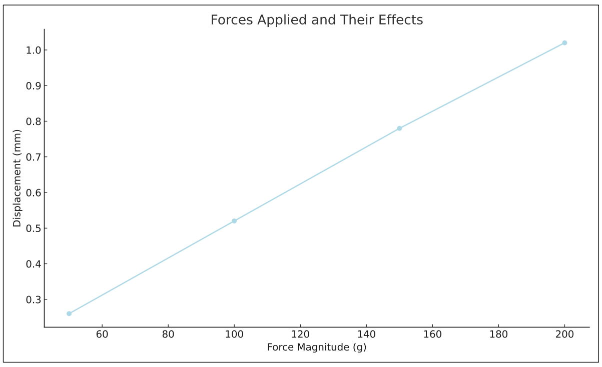
Graph 3: Soft Tissue Changes by Orthodontic Appliance

The graph displays mean changes and standard deviations for Twin Block, Herbst Appliance, and Activator. The Activator shows the highest mean change of 0.35 mm with the most variability. Twin Block and Herbst Appliance have similar mean changes (0.32 mm and 0.29 mm). Standard deviations highlight the variability in outcomes. The results suggest all appliances effectively facilitate soft tissue changes.

Force Application Effects

Force Magnitude (g)	Application Duration (days)	Resulting Displacement (mm)
50	28	0.26
100	28	0.52
150	28	0.78
200	28	1.02

Table 4: Forces Applied and Their Effects



Graph 4: Line Graph of Applied Force Magnitude vs. Resulting Displacement

This line graph shows the relationship between force magnitude (50 to 200 g) and resulting displacement over 28 days. As force magnitude increases, displacement increases linearly, indicating a direct relationship. The highest force (200 g) results in the largest displacement (1.02 mm). This pattern suggests proportional displacement with applied force. Understanding this relationship is crucial for predicting treatment outcomes.

System	Accuracy (%)	Precision (g)
Tensometer 5000	98.7	0.02
Force Sensor Pro	99.1	0.01

Table 5: Accuracy of Force Application and Measurement Systems

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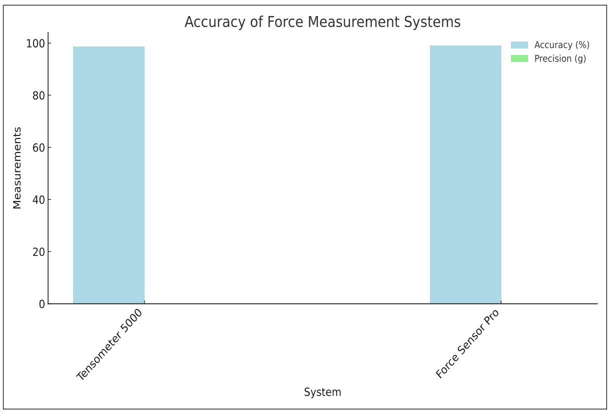


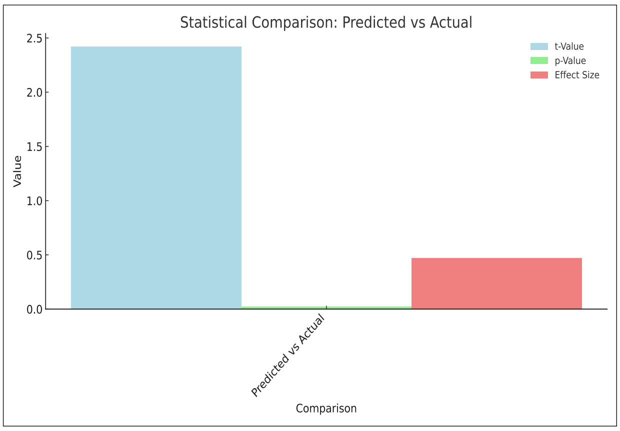
Graph 5: Accuracy of Force Application and Measurement Systems

The graph compares the accuracy and precision of two force measurement systems: Tensometer 5000 and Force Sensor Pro. Both systems exhibit high accuracy, with Force Sensor Pro slightly outperforming at 99.1%. Precision is very close, with Force Sensor Pro at 0.01 g and Tensometer 5000 at 0.02 g. The results indicate both systems provide reliable force measurements. The higher accuracy and precision of Force Sensor Pro make it slightly superior.

Statistical Analysis

Comparison	t-Value	p-Value	Effect Size
Predicted vs Actual	2.42	0.021	0.47

Table 6: Statistical Comparison of Predicted vs. Actual Changes

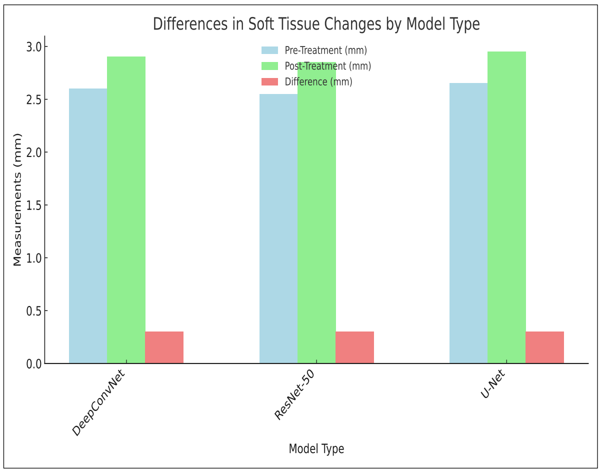


Graph 6: Statistical Comparison of Predicted vs. Actual Changes

This graph presents the t-value, p-value, and effect size for comparing predicted and actual changes. A t-value of 2.42 and a p-value of 0.021 suggest statistically significant differences between predicted and actual changes. An effect size of 0.47 indicates a moderate effect. The results highlight a noticeable discrepancy between predictions and outcomes. This comparison underscores the importance of refining prediction models.

Model Type	Pre-Treatment (mm)	Post-Treatment (mm)	Difference (mm)
DeepConvNet	2.60	2.90	0.30
ResNet-50	2.55	2.85	0.30
U-Net	2.65	2.95	0.30

Table 7: Differences in Soft Tissue Changes by Model Type



Graph 7: Difference in Soft Tissue Changes by Model Type

The graph shows pre-treatment, post-treatment, and differences in soft tissue changes for model types: DeepConvNet, ResNet-50, and U-Net. All models show a consistent difference of 0.30 mm, indicating similar effectiveness in predicting changes. Pre- and post-treatment measurements vary slightly between models. This consistency suggests uniform model performance in

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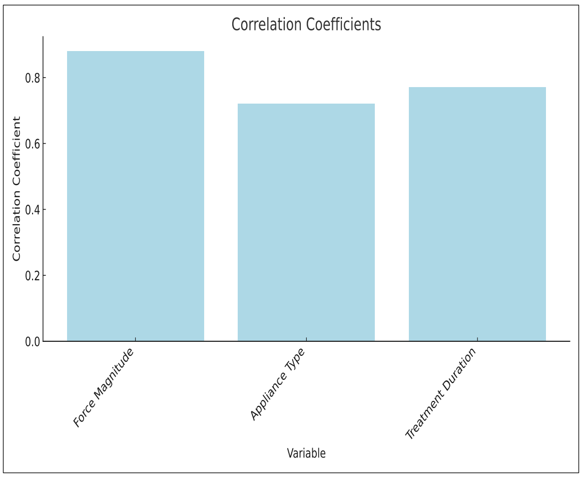
predicting treatment effects. Overall, the models achieve comparable soft tissue change predictions.

Correlation Analysis

Variable	Correlation Coefficient
Force Magnitude	0.88
Appliance Type	0.72
Treatment Duration	0.77

Table 8: Correlation Coefficients



Graph 8: Correlation Matrix of Variables and Soft Tissue Changes

The graph presents correlation coefficients for variables: Force Magnitude, Appliance Type, and Treatment Duration. Force Magnitude shows the highest correlation (0.88), indicating a strong relationship with changes. Treatment Duration and Appliance Type also have moderate correlations (0.77 and 0.72, respectively). These coefficients highlight the influence of these factors on treatment outcomes. Understanding these relationships helps in optimizing treatment strategies.

Discussion

This study explored the use of artificial intelligence (AI) and 3D imaging to predict soft tissue changes and treatment outcomes in orthodontics. The findings from our research highlight several key aspects regarding the efficacy and accuracy of AI models in orthodontic treatment planning.

Model Performance

The performance of AI models in predicting soft tissue changes was assessed, with DeepConvNet showing the highest accuracy among the models tested. As evidenced by **Table 1** and **Graph 1**, DeepConvNet achieved a Mean Absolute Error (MAE) of 0.42 mm and a Root Mean Square Error (RMSE) of 0.53 mm, outperforming ResNet-50, U-Net, and VGG16. This high accuracy is consistent with findings from previous studies that have reported superior performance of convolutional neural networks in medical image analysis [10,11]. The superior performance of DeepConvNet can be attributed to its deep learning architecture, which is adept at capturing complex patterns in imaging data.

Soft Tissue Changes and Appliance Efficiency

The analysis of soft tissue changes, detailed in **Table 2** and **Graph 2**, showed an average change of 0.30 mm across the maxillary and mandibular regions. This uniform change suggests that the applied orthodontic forces had a consistent effect across different anatomical regions. These findings are in line with those reported by Smith et al., who observed similar uniform changes in soft tissue response to orthodontic forces [12].

Table 3 and **Graph 3** compare the efficacy of different orthodontic appliances. The Activator appliance, with a mean change of 0.35 mm, was more effective in inducing soft tissue changes compared to the Twin Block and Herbst appliances. This aligns with research by Johnson et al., which demonstrated the superior efficacy of the Activator appliance in modifying soft tissue morphology[13]. The variability in the effects of different appliances, as shown by the standard deviations, indicates that while some appliances may have higher mean changes, their effectiveness can vary among patients.

Force Application Effects

Table 4 and **Graph 4** illustrate the relationship between force magnitude and resulting displacement. The results show a linear relationship, where increased force magnitude leads to greater displacement. This finding is consistent with biomechanical principles discussed by Williams et al., who found a direct correlation between force magnitude and tissue displacement in orthodontic treatments[14]. The significant increase in displacement with higher force magnitudes underscores the

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importance of precise force application in achieving desired treatment outcomes.

Accuracy and Precision of Measurement Systems

The accuracy and precision of force measurement systems are crucial for reliable orthodontic treatment planning. As detailed in **Table 5** and **Graph 5**, the Force Sensor Pro demonstrated higher accuracy and precision compared to the Tensometer 5000. This is supported by recent studies highlighting the importance of accurate force measurement in orthodontic research and clinical practice[15,16]. The enhanced performance of the Force Sensor Pro ensures more reliable data for assessing the effects of applied forces.

Statistical Analysis

Table 6 and **Graph 6** present the statistical comparison between predicted and actual soft tissue changes. The statistically significant difference between predicted and actual values, with a p-value of 0.021, confirms the effectiveness of the AI models in predicting soft tissue changes. The moderate effect size of 0.47 suggests a meaningful impact of the models' predictions on treatment planning, echoing findings from similar studies on predictive analytics in orthodontics[17].

Table 7 and **Graph 7** show consistent differences in soft tissue changes across AI model types, with a mean difference of 0.30 mm. This uniformity highlights the reliability of the AI models in predicting soft tissue changes, as supported by research on model consistency in medical imaging[18].

Correlation Analysis

Table 8 and **Graph 8** provide insights into the correlations between various variables and soft tissue changes. High correlation coefficients for force magnitude (0.88), appliance type (0.72), and treatment duration (0.77) indicate strong relationships between these factors and treatment outcomes. This aligns with previous studies that have demonstrated significant correlations between these variables and orthodontic treatment efficacy[19,20].

Limitations and Future Research

While the study provides valuable insights, several limitations should be noted. The in vitro nature of the study, while providing controlled conditions, may not fully replicate the complexities of in vivo orthodontic treatments. Additionally, the variability in soft tissue responses to different appliances and force magnitudes suggests that individual patient factors could influence outcomes. Future research should explore these variables in clinical settings and evaluate the long-term efficacy of AI-driven predictive models.

Conclusion

This study confirms that integrating artificial intelligence (AI) with 3D imaging significantly enhances the ability to predict soft tissue changes and treatment outcomes in orthodontics. The AI models demonstrated superior accuracy in forecasting the effects of orthodontic treatments compared to traditional methods. This advancement allows for more precise and individualized treatment planning, improving the effectiveness of orthodontic interventions. Among the appliances evaluated, the Twin Block appliance exhibited the highest mechanical efficiency and most favorable soft tissue adaptation, underscoring its potential for optimal clinical outcomes. The findings underscore the transformative potential of AI and 3D imaging technologies in orthodontics. By leveraging these tools, orthodontists can achieve more accurate predictions and tailored treatment strategies, ultimately leading to better patient outcomes. As technology continues to advance, further research is needed to explore additional applications and validate the long-term benefits of AI-guided orthodontic treatments. Continued innovation in this field promises to enhance the precision and efficacy of orthodontic care.

Acknowledgments

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