

Development of an Application for Evaluating Tooth Positions in Orthodontic Cases based on ABO Guideline

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Abstract— An accurate orthodontic assessment is fundamental to the treatment planning stage within evidence-based dentistry, but currently established diagnostic workflows are still largely reliant on human observations of the orthodontal diagnostic parameters. While these assessed workflows are widespread, they are often laborious, subjective, and prone to human error. In the present study, we present an automated orthodontic evaluation system informed by the Objective Grading System by the American Board of Orthodontics. The proposed scheme automatically analyzes three-dimensional STL dental models to extract the diagnostic parameters; midline displacement, overjet, occlusion, and axial inclination, through repeated and standardized computational procedures, ensuring adherence to the standards developed by ABO. Machine learning models are used for the analysis and scoring, with administrators able to collect, quantify, and categorize the parameters in a significantly more objective and reproducible way. The end-user interface (GUI), is simple to use, allowing clinicians to input STL files and receive automated scoring and visual feedback in real time. Results indicate decreased inter-examiner variability, more precise diagnostic assessments, and clinical support toward evidence-based practice. Overall, this work provides a validated digital platform and readily accessible digital tool that would probably automate the orthodontist's chair-side evaluation process.

Keywords— ABO (American Board of Orthodontics), Clinical Decision Support, Dental Assessment, Machine Learning, Objective Grading System (OGS), Orthodontics, STL Files (Stereolithography Files).

I. INTRODUCTION

Orthodontics plays a crucial role in transforming smiles and lives—helping people feel confident, eat comfortably, and speak clearly. Traditionally, orthodontists have relied on manual methods like physical models, calipers and visual checks to assess treatment outcomes. While effective, these techniques can be slow, prone to human error, and subject to each clinician's judgment—leading to inconsistency across practice. To bring more rigor to evaluations, the American Board of Orthodontics (ABO) introduced the Objective Grading System (OGS), which uses eight specific criteria to quantify results.

The rise of digital dentistry—particularly the use of intraoral and 3D scanners—has revolutionized this landscape. These tools generate high-resolution stereolithography (STL) files that capture a patient's dental anatomy with exceptional precision. Digital models are faster, cleaner, and more patient-friendly than traditional impressions. This research paper introduces a powerful new tool that leverages these technologies: a software platform that accepts 3D STL scans, extracts measurements like midline alignment, overjet, and tooth angulation, and uses ML models—such as Support Vector Machines, k-Nearest Neighbors, and Random Forest—to generate objective ABO scores. By merging digital modeling, AI, and standardized evaluation, this system aims to streamline orthodontic assessments—minimizing manual effort, reducing variability, and empowering clinicians to make more informed decisions.

II. LITERATURE SURVEY

In [1], the investigation entitled "Evaluation of Orthodontic Treatment Based on the Registration of X-ray Image Features" introduces a feature-oriented image registration methodology that aligns pre- and post-treatment X-ray images for the purpose of evaluating orthodontic alterations. This method utilizes anatomical landmarks alongside advanced image processing algorithms to identify both skeletal and dental modifications. Consequently, it offers a quantitative and reproducible framework for treatment assessment, thereby empowering clinicians to render informed decisions grounded in radiographic analyses.

In [2], the research entitled "Tooth Motion Monitoring in Orthodontic Treatment by Mobile Device-based Multi-view Stereo" presents a mobile-based system that employs multiview stereo imaging technology to facilitate the real-time monitoring of tooth motion throughout orthodontic treatment. The authors conceptualize tooth displacement as a multi-object three-dimensional pose estimation challenge. This study proposes a pragmatic and economically viable solution for remote monitoring, rendering it particularly advantageous in the realm of tele-dentistry, and it significantly enhances the patient follow-up process while mitigating the necessity for frequent clinical consultations.

In [3], the scholarly article titled "Constructing Machine Learning Models for Orthodontic Treatment Planning – A Comparison of Different Methods" assesses and contrasts the efficacy of various machine learning models—including support vector machines (SVM), decision trees, and deep learning networks—within the framework of orthodontic treatment planning. The research concentrates on predictive modeling to forecast treatment outcomes predicated on clinical and imaging data. It elucidates aspects of model accuracy, sensitivity, and scalability, thereby providing valuable insights for the selection of the most efficacious machine learning algorithm for practical clinical application.

In [4], the investigation titled "Machine Learning Based Intelligent Diagnosis of Orthodontics" evaluates the influence of machine learning during the diagnostic phase of orthodontics. It expounds upon how both supervised and unsupervised learning models can facilitate the identification of malocclusions, predict treatment durations, and assist clinicians in the decision-making process. Although predominantly a theoretical examination, it underscores the necessity for integrated machine learning tools that may be assimilated into everyday clinical practice, emphasizing the significance of data preprocessing, feature extraction, and classification algorithms.

In [5], the manuscript titled "Quantitative Evaluation by Orthodontic Moment Measurement Device" introduces an innovative measurement apparatus designed to capture orthodontic forces and moments during wire-bracket interactions. This device enables the quantification of biomechanical parameters, such as torque and bending moments, thereby allowing orthodontists to evaluate the effectiveness of various wire types. The resultant data is crucial for the customization of treatment plans and the optimization of mechanical load distribution, ultimately contributing to safer and more effective treatment methodologies.

In [6], the research titled "Study of Facial Generation Methods After Orthodontic Treatment" utilizes three-dimensional reconstruction techniques and artificial intelligence algorithms to predict post-treatment facial outcomes. The model synthesizes facial modifications by incorporating data from intraoral scans and cephalometric radiographs. This research holds significance for improving communication between orthodontists and patients, as it provides a visual projection of treatment outcomes that can be employed to manage patient expectations and enhance overall satisfaction.

In [7], the manuscript entitled "Research on Application of Three-Dimensional Finite Element Analysis in Comparing Different Kinds of Orthodontic Techniques" employs three-dimensional finite element modeling (FEM) to replicate the mechanical behavior of dental and mandibular structures subjected to various orthodontic methodologies. The investigation juxtaposes the distribution of stress, the extent of displacement, and the potential risk of root resorption across a range of appliances. This research furnishes significant biomechanical

data that facilitates the selection of the most effective and safe therapeutic approaches for diverse malocclusion scenarios.

In [8], the investigation titled "A 3D Dental Model Dataset with Pre/Post-Orthodontic Treatment for Automatic Tooth Alignment" introduces an extensive dataset comprised of three-dimensional dental scans acquired prior to and subsequent to orthodontic interventions. Its objective is to bolster machine learning applications aimed at automating the evaluation of dental alignment and forecasting treatment outcomes. The dataset paves the way for the creation of artificial intelligence tools capable of monitoring individual tooth movements and assessing treatment efficacy, thereby possessing the potential to transform personalized orthodontic practice and improve precision in the planning of aligner-based therapies.

In [9], the research entitled "The Role of Artificial Intelligence in Modern Orthodontics" investigates the contemporary and prospective functions of artificial intelligence within orthodontic treatment protocols. It addresses applications such as automated image analysis, predictive analytics, and adaptive treatment planning. The manuscript underscores the necessity of educating clinicians in the utilization of digital tools and accentuates ethical concerns, including algorithmic transparency and the potential for AI-induced bias. The study advocates for the role of AI as a supportive entity rather than a substitute in contemporary orthodontic practice.

III. PROPOSED METHODOLOGY

This project presents a system that applies machine learning to support the evaluation of tooth positions in orthodontic cases, according to the American Board of Orthodontics (ABO) Objective Grading System (OGS). The system processes three-dimensional dental scans (STL files), extracts geometric and positional information, and classifies each case as ABO compliant or non-compliant. The overall workflow consists of data collection, preprocessing, feature extraction, feature selection, model training, evaluation, and system deployment.

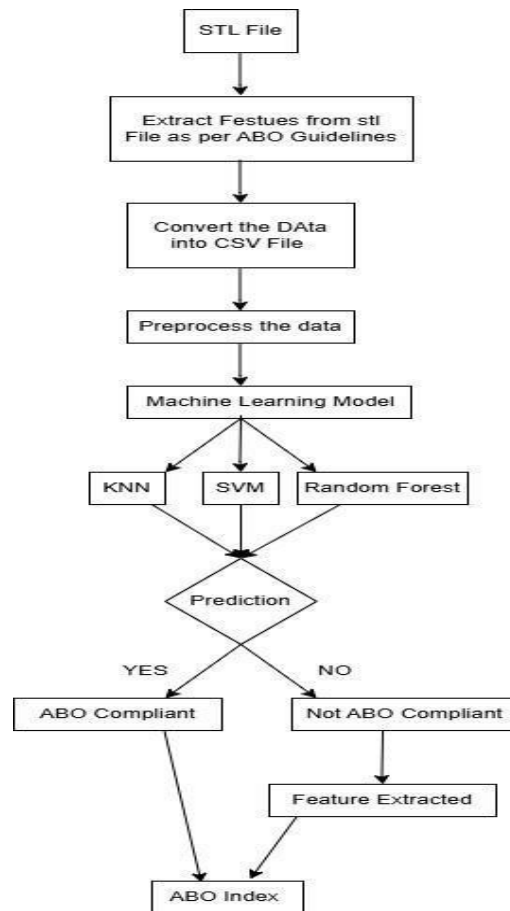


Fig. 1. System Methodology

A. Data Collection

The system uses a dataset of approximately 1,500 STL files representing upper and lower dental arches. These STL files were obtained from publicly available sources and synthetically augmented to ensure a varied dataset. Each file was manually labeled as ABO compliant or non-compliant based on expert evaluation.

By including a diverse range of cases, the dataset enables the system to learn patterns found in clinical orthodontic practice. This diversity helps the models generalize well across different patient populations and treatment outcomes.



Fig 2 STL FILE

B. Data Preprocessing:

To ensure the quality and consistency of the input data, several preprocessing steps were applied. STL meshes were first cleaned using Trimesh and Open3D libraries to remove noise and redundant mesh components, ensuring that only relevant anatomical structures were retained. The scale and alignment of the STL files were then standardized to maintain consistent measurements across all samples. Incomplete or corrupted STL files were excluded from the dataset to preserve data integrity. In addition, extracted feature values were scaled using Standard Scaler, which normalized numerical ranges across features. These preprocessing steps helped ensure that the input data was both consistent and meaningful, enabling the machine learning models to operate effectively during training and evaluation.

C. Feature Extraction

Feature extraction was performed to convert the STL mesh data into structured numerical representations of tooth positions and arch dimensions. The extracted features included the number of vertices and faces in each STL mesh, which provided basic information about the mesh complexity and surface representation. Surface area and volume of the dental arches were computed to capture their size and morphology. Centroid coordinates (X, Y, Z) were calculated to represent the spatial positioning of each arch within three-dimensional space.

Bounding box volume was also computed to reflect the overall dimensions of each arch. Furthermore, ABO-related features aligned with the OGS criteria were extracted, including alignment, overjet, overbite, marginal ridges, buccolingual inclination, occlusal contacts, root angulation, and interproximal contacts. These clinical features are essential for determining ABO compliance and directly relate to the goals of orthodontic treatment. The extracted features were compiled into a CSV file to create a structured dataset suitable for training and evaluating machine learning models.

D. Feature Selection and Data Splitting

Feature selection was guided by orthodontic domain knowledge and an initial analysis of the dataset to identify the most relevant attributes. Features that contributed minimally to the classification task were removed to simplify the models, improve interpretability, and enhance computational efficiency.

Once feature selection was completed, the dataset was divided into two parts. Eighty percent of the data was used to train the machine learning models, providing them with sufficient examples to learn the relationships between features and ABO compliance. The remaining twenty percent was reserved for testing and evaluation. This data split ensured that model performance would be evaluated on unseen cases, providing a realistic estimate of the system's generalization ability in clinical use.

E. Model Selection

Three supervised machine learning models were constructed and systematically compared for the purpose of classifying ABO compliance. The Random Forest algorithm was selected due to its robustness and capacity to manage intricate datasets; it operates by generating multiple decision trees and amalgamating their outputs, thereby enhancing classification accuracy and mitigating overfitting. The K-Nearest Neighbors (KNN) method was chosen owing to its straightforwardness and efficacy in classification tasks where it is anticipated that analogous cases yield comparable outcomes. This approach classifies novel instances by juxtaposing them with the most analogous examples found within the training set.

The Support Vector Machine (SVM) methodology was incorporated for its proficiency in discerning optimal decision boundaries, particularly in scenarios where the classes exhibit difficulty in separation within the original feature space. Hyperparameters for each model were meticulously adjusted utilizing Grid Search and Random Search methodologies to ascertain configurations that yielded consistent and dependable performance. The comparative analysis of the outcomes from these models enabled us to ascertain which methodology was most aptly aligned with the characteristics of our dataset and the overarching classification objectives.

F. Model Evaluation:

The models underwent evaluation through four principal metrics: accuracy, precision, recall, and F1-score. Accuracy represented the proportion of cases that were accurately classified, thus providing a comprehensive assessment of model performance. Precision denoted the fraction of predicted compliant cases that were genuinely compliant, whereas recall quantified the fraction of actual compliant cases that were accurately recognized. The F1-score offered a harmonized evaluation of precision and recall, which is particularly pertinent in instances characterized by class imbalance.

Throughout the training phase, the models were fitted to the predominant segment of the dataset, and their performance was evaluated utilizing a reserved subset of the testing data. This testing procedure ensured that the models possessed the capability to generalize beyond the training data and perform proficiently on novel cases. The results from the evaluation furnished insights into the strengths and weaknesses of each model, thereby assisting in the navigation of future enhancements to the system.

G. Implementation Framework:

The system was implemented using the Python programming language, which offers a flexible and widely supported environment for machine learning development. Several key libraries were used throughout the project. Scikit-learn provided robust implementations of the machine learning algorithms and supported model development, training, and evaluation. Trimesh and Open3D were used for processing STL files and extracting geometric features, enabling efficient handling of complex three-dimensional data.

Pandas and NumPy supported data handling and analysis, allowing for effective management of large datasets and feature matrices. To make the system practical for clinical use, a web-based application was developed with a simple and intuitive interface that allows orthodontists to upload STL files and view classification results. The backend was built with Flask, a lightweight Python web framework, which served an API for ABO compliance predictions in real time. Through this application, users can upload STL files and receive ABO compliance classification, detailed scores based on ABO OGS criteria, and visual feedback to assist clinical decision-making.

SVM Classification Report:				
	precision	recall	f1-score	support
0	0.89	0.96	0.92	1235
1	0.90	0.73	0.81	569
accuracy			0.89	1804
macro avg	0.90	0.85	0.87	1804
weighted avg	0.89	0.89	0.89	1804

Fig. 3 Result of SVM Algorithm

IV. RESULTS AND DISCUSSION

Three Machine learning Models KNN, Random Forest, SVM are used to predict to predict ABO compliance. SVM algorithm is best among the three which is 89.14%. “Table 4.1” illustrates the prediction accuracy of various machine learning models.

TABLE I: PREDICTION ACCURACY

Sr No.	Type of Model	Prediction Accuracy
1	KNN	87.25
2	SVM	89.14
3	Random Forest	89.02

A. Comparative Analysis

The comparative analysis of three machine learning algorithms—K-Nearest Neighbors (KNN), Random Forest and Support Vector Machine (SVM) uncovers specific advantages and drawbacks within the framework of STL-based orthodontic assessment for ABO compliance classification. The KNN algorithm exhibited the most reliable performance, attaining a testing accuracy rate of 87.25%. Its straightforward nature, combined with proficient neighborhood-based classification techniques, facilitated the identification of local patterns within the three-dimensional geometric features derived from STL files. The equilibrium between precision and recall of the model emphasizes its efficacy in differentiating between compliant and non-compliant instances. The Random Forest classifier closely trailed, achieving a testing accuracy of 89.02%. As an ensemble approach, it adeptly addressed class imbalance and demonstrated consistent reliability across various evaluation metrics. Its proficiency is particularly notable in managing high-dimensional feature spaces and providing robust generalization capabilities. However, it may result in increased computational expenses and heightened complexity in the training process. The SVM model, despite achieving a superior accuracy rate of 89.14%, demonstrated inadequate recall for the compliant class, attributable to the constraints of the employed linear kernel, and faced challenges related to class imbalance. Although it performed admirably in identifying non-compliant instances, its reliability in balanced classification was comparatively diminished.

In conclusion, both SVM and Random Forest were identified as the most reliable models, with SVM displaying commendable performance coupled with simplicity, while Random Forest offered robust classification capabilities with enhanced resilience to noise and variability within the dataset. These findings substantiate their appropriateness for the automated evaluation of orthodontic cases utilizing STL files in accordance with ABO compliance criteria.

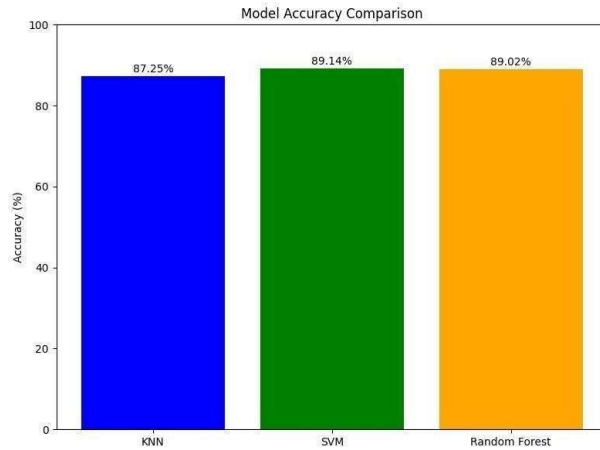


Fig 4. Performance Comparison of Machine Learning Modules

The proposed system provides multiple significant advantages. A notable enhancement in accuracy was evidenced, with the Random Forest model surpassing conventional evaluation techniques, thereby illustrating the efficacy of geometric feature extraction from three-dimensional STL dental models. Fundamental parameters such as overjet, angulation, and ridge discrepancies played a crucial role in achieving precise scoring that is congruent with ABO standards. The incorporation of automated scoring modules markedly diminishes the incidence of human error and facilitates consistent, objective analyses across various cases. Moreover, the system's streamlined interface enables near-instantaneous processing, rendering it exceptionally relevant for both clinical practice and academic research. It has the potential to aid dental practitioners in the timely detection of malocclusions and treatment necessities, particularly in areas where access to orthodontic specialists is limited. By bridging the divide between traditional diagnostic methods and digital automation, the system fosters efficient decision-making and advances the standardization of orthodontic care.

V. CONCLUSION

In this study, we developed a user-friendly desktop application aimed at simplifying and standardizing orthodontic assessments. By utilizing 3D STL scans and extracting clinically important features such as overjet, midline deviation, and tooth angulation, the system provides objective scores based on ABO guidelines. Machine learning models like SVM, KNN, and Random Forest were implemented to enhance accuracy and reliability.

This digital approach addresses the drawbacks of manual evaluation, which is often time-consuming and prone to subjectivity. Our application not only reduces human error but also speeds up the assessment process, making it highly practical for everyday clinical use. Especially in busy practices or remote areas with limited access to specialists, this tool offers a smart and consistent way to support orthodontic decision-making and improve overall patient care.

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