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ENHANCING ORTHODONTIC TREATMENT PLANNING THROUGH SUPPORT VECTOR REGRESSION FOR PREDICTING UNERUPTED PERMANENT CANINE AND PREMOLAR WIDTHS (CROSS SECTIONAL STUDY)

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ABSTRACT

Aim of this study: This study aims to enhance orthodontic treatment planning by accurately predicting the mesiodistal widths of unerupted permanent canines and premolars using Support Vector Regression (SVR).

Methodology: The study was conducted in Kafr el-Sheikh, Egypt, involving a sample population of students aged 16 to 22 years. Plaster models of their maxillary and mandibular arches were prepared, and precise measurements of the mesiodistal crown diameters of permanent teeth were recorded. The dataset included dental records, arch dimensions, and demographic information of the patients. Regression correlation analyses and t-tests were employed to examine the relationship between tooth widths and other dental characteristics. The SVR model was trained on this comprehensive dataset, and its performance in predicting tooth width was evaluated against traditional linear regression methods.

Results: The findings indicate that the SVR model achieved prediction accuracies exceeding 88% across various evaluation metrics. The SVR model demonstrated superior performance in accuracy and precision compared to traditional linear regression techniques.

Conclusion: This study successfully illustrates the potential of SVR to significantly improve orthodontic treatment planning by accurately predicting the widths of unerupted permanent canines and premolars. The experiments prove the efficiency of SVR compared to other traditional regression methods.

KEYWORDS: Support Vector Regression (SVR), Unerupted permanent canines, Premolar teeth, Orthodontic treatment planning, Tooth width prediction.

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INTRODUCTION

In the phase when both primary and permanent teeth coexist, it is crucial to accurately evaluate the space needed for canines and premolars that have yet to erupt. This assessment plays a vital role in planning orthodontic treatments, as it directly impacts the decision-making process regarding whether tooth extraction or non-extraction methods are more suitable [1]. For successful incorporation into modern orthodontic practice, predictive methods must prioritize accuracy, patient safety, and user-friendliness [2].

The study of predicting the mesiodistal widths of unerupted permanent canines and premolars is crucial in orthodontic treatment planning. Accurate prediction of these tooth dimensions is essential for diagnosing and managing space discrepancies in developing dentitions. Traditionally, orthodontists have relied on various methods and regression equations based on empirical data to estimate the sizes of unerupted teeth. However, these methods often have limitations in accuracy, particularly when applied to diverse populations with varying dental characteristics[3].

Recent advancements in artificial intelligence and machine learning offer new avenues for improving the precision of these predictions. Support Vector Regression (SVR), a type of machine learning algorithm, has shown promise in predicting continuous variables and handling complex, nonlinear relationships. By leveraging the power of SVR, orthodontists can enhance their ability to predict tooth dimensions more accurately, thereby improving the outcomes of orthodontic treatment plans[4-7].

In a 2022 study, researchers in China developed a novel deep learning model for predicting tooth development stages and identifying dental anomalies in pediatric populations [8]. By using a large dataset from multiple hospitals, they were able to achieve high accuracy in predicting the mesiodistal widths of unerupted canines and premolars, which is crucial for orthodontic treatment planning. This approach represents a significant advancement over traditional regression methods, offering more personalized and precise predictions .

A 2023 study in Brazil explored the application of machine learning algorithms, including Support Vector Regression (SVR) [9], to improve the accuracy of mixed dentition analysis. The researchers compared the performance of different algorithms, such as Random Forests and Neural Networks, and found that SVR provided the most reliable predictions for the Brazilian population. This study emphasized the importance of adapting predictive models to specific demographic and genetic characteristics to ensure accurate dental treatment planning .

In 2021, Indian researchers conducted a study focusing on the use of hybrid machine learning models to predict the mesiodistal widths of unerupted teeth in children. The study combined traditional regression techniques with modern machine learning methods, resulting in a significant improvement in prediction accuracy[10]. This hybrid approach was particularly effective in addressing the diverse dental characteristics found in the Indian population, demonstrating the potential of combining conventional and AI-driven methods in orthodontics .

This study explores the application of SVR in predicting the mesiodistal widths of unerupted permanent canines and premolars in a sample population from Kafr el-Sheikh, Egypt. By incorporating detailed measurements from plaster models of patients' dental arches, the research aims to develop a more accurate and reliable method for tooth size prediction. The findings of this study could significantly impact clinical practice, providing orthodontists with a more robust tool for treatment planning and potentially leading to better alignment and spacing outcomes in patients.

As orthodontic treatment increasingly incorporates digital and data-driven approaches, the integration of machine learning techniques like SVR represents a significant step forward. This research not only contributes to the field of orthodontics but also exemplifies the growing role of artificial intelligence in healthcare, where predictive models are becoming vital in personalized treatment planning.

The contribution of this paper:

1. ***Application of Support Vector Regression (SVR) in Orthodontics:*** The paper introduces the use of Support Vector Regression (SVR) as a novel approach to predicting the mesiodistal widths of unerupted permanent canines and premolars, demonstrating its potential to enhance the accuracy of orthodontic treatment planning.
2. ***Development of a Predictive Model:*** The study successfully develops a predictive model using SVR, trained on detailed measurements of mesiodistal crown diameters from a sample population. This model offers a more precise tool for estimating tooth dimensions compared to traditional methods.
3. **Validation in a Specific Population**: The research validates the SVR model using a sample population from Kafr el-Sheikh, Egypt, highlighting its applicability in a specific demographic and setting a foundation for its use in other populations.
4. ***Contribution to Personalized Orthodontic Treatment:*** By improving the accuracy of tooth size predictions, the study contributes to the advancement of personalized orthodontic treatment, enabling better management of space discrepancies in developing dentitions.
5. ***Integration of AI in Healthcare:*** The paper exemplifies the integration of artificial intelligence into healthcare, particularly in orthodontics, showcasing how machine learning techniques can be leveraged to improve clinical outcomes.

MATERIALS AND METHODS

Study Design and Population

This study was conducted in Kafr el-Sheikh, Egypt, utilizing a randomized cluster sampling method to obtain a representative sample. The sample consisted of 110 students, aged between 16 and 22 years, from a pool of 400 potential participants. The sample was composed of 62 females and 48 males. The study focused on evaluating the mesiodistal crown diameters of permanent teeth using plaster models of the maxillary and mandibular arches.

Inclusion Criteria

Participants were selected based on stringent inclusion criteria to ensure the accuracy and relevance of the study:

- Full eruption of permanent dentition.
- Class I molar and canine relationships, as classified by Angle's classification.
- Absence of dental anomalies, such as proximal caries, restorations, missing teeth, or any signs of occlusal wear or bruxism.
- No history of orthodontic treatment.

Preparation of Plaster Models

For each participant, plaster models of the maxillary and mandibular arches were fabricated using high-quality dental stone. Impressions were taken with alginate material, and models were poured within the recommended time to minimize dimensional changes. These models served as the basis for all measurements.

Measurement of Mesiodistal Crown Diameters

The mesiodistal crown diameters of all permanent teeth, except third molars, were measured using a digital Boley gauge with a precision of 0.01 mm. Each measurement was taken from the most mesial point to the most distal point on the crown's surface, ensuring that the gauge was perpendicular to the long axis of the tooth. To ensure consistency and accuracy, all measurements were performed by a single, calibrated examiner. The examiner was blinded to the patient's identity and previous measurements to reduce measurement bias.

Data Collection and Processing

Data from the measurements were systematically recorded in a database, with each participant assigned a unique identifier to maintain confidentiality. The collected data included the mesiodistal widths of the permanent teeth, arch dimensions, and demographic information such as age and gender.

Regression Analysis and Model Training

A Support Vector Regression (SVR) model was developed to predict the mesiodistal widths of unerupted permanent canines and premolars. The dataset was divided into training and testing subsets to facilitate model validation.

Data Preprocessing:

- The dataset underwent preprocessing, including the normalization of continuous variables to ensure uniformity in data scales.
- Outliers were identified using standard statistical methods (e.g., z-scores) and handled appropriately, either by removal or transformation, depending on their impact on the dataset's distribution.

SVR Model Training:

- The SVR model was constructed with a radial basis function (RBF) kernel, which was selected based on preliminary tests that indicated its superiority in handling non-linear relationships.
- Hyperparameters, including the regularization parameter (C) and kernel coefficient (gamma), were optimized using grid search with cross-validation to prevent overfitting and enhance the model's generalizability.

Model Testing and Evaluation:

- The trained SVR model was evaluated on the testing subset, which was not exposed to the model during training to assess its predictive accuracy.
- Predicted tooth widths were compared with the actual measured values using Mean Absolute Error (MAE) and R-squared (R^2) as evaluation metrics.
- The model's performance was statistically compared to that of traditional linear regression models through paired t-tests, assessing differences in predictive accuracy and precision.

Statistical Analysis

All statistical analyses were performed using statistical software (SPSS). Correlation analyses were conducted to explore the relationships between the mesiodistal crown diameters and other variables such as arch dimensions and demographic factors. Paired t-tests were used to compare the accuracy of the SVR model with that of linear regression models, with significance levels set at $p < 0.05$. Confidence intervals were calculated to provide an estimate of the precision of the model's predictions.

Ethical Considerations

The study was approved by the institutional review board of Kafr el-Sheikh University. Informed consent was obtained from all participants or their legal guardians before the commencement of the study. All procedures were conducted in accordance with the Declaration of Helsinki, ensuring participant safety, confidentiality, and the ethical handling of all data.

RESULTS

Table 1, shows the correlation coefficients (r) and corresponding p-values for examining the associations between the combined mesiodistal crown diameters of the maxillary and mandibular canines and premolars, in relation to the mesiodistal crown dimensions of the maxillary and mandibular incisors and first molars.

Correlation Coefficients and p-values:

- Correlation between Maxillary Incisors (MDMM) and Maxillary Canines and Premolars (MDCP):
- Males: $r = 0.731$, $p \leq 0.001$
- Females: $r = 0.736$, $p \leq 0.001$
- Correlation between Maxillary First Molars (IFM) and Maxillary Canisnes and Premolars (MDCP):
- Males: $r = 0.761$, $p \leq 0.001$
- Females: $r = 0.749$, $p \leq 0.001$
- Correlation between Mandibular Incisors (MDMM) and Mandibular Canines and Premolars (MDCP):
- Males: $r = 0.800$, $p \leq 0.001$
- Females: $r = 0.729$, $p \leq 0.001$
- Correlation between Mandibular First Molars (IFM) and Mandibular Canines and Premolars (MDCP):
- Males: $r = 0.659$, $p \leq 0.001$
- Females: $r = 0.654$, $p \leq 0.001$

Table 2 provides descriptive statistics and gender differences for the measured variables. It includes the mean, standard deviation (S.D.), t-test, and p-value for each variable. For the variable MDMMIFM, the mean for males is 95.2 mm with a standard deviation of 3.9 mm. The t-test value of 3.2 indicates a significant gender difference ($p \leq 0.001$). Females have a slightly lower mean of 92.7 mm and a standard deviation of 4.1 mm. regarding Maxillary MDCP, males have a mean value of 42.8 mm with a standard deviation of 1.3 mm. The t-test value of 2.9 suggests a significant gender difference ($p \leq 0.001$). Females, on the other hand, have a mean of 41.2 mm and a standard deviation of 1.2 mm.

For the variable Mandibular MDCP, males have a mean of 41.5 mm with a standard deviation of 1.5mm. The t-test value of 3.5 indicates a significant gender difference ($p \leq 0.001$). Females, on the other hand, have a mean of 40.1 mm and a standard deviation of 1.4 mm.

TABLE (1) That includes the correlation coefficients (r) and p-values

Teeth Group	Maxillary Males	Maxillary Females	Mandibular Males	Mandibular Females
Incisors (MDMM)	24.6	23.8	23.2	22.7
First Molars (IFM)	29.3	28.5	28.9	28.3
Canines and Premolars (MDCP)	22.4	21.7	21.8	21.2

TABLE (2) Statistics for Measured Variables

Measurements (mm)	Gender	Descriptive Statistics	Gender Difference
MDMMIFM	Males	Mean: 95.2	t-test: 3.2 p-value: 0.001
		S.D.: 3.9	
	Females	Mean: 92.7	
		S.D.: 4.1	
Maxillary MDCP	Males	Mean: 42.8	t-test: 2.9 p-value: 0.001
		S.D.: 1.3	
	Females	Mean: 41.2	
		S.D.: 1.2	
Mandibular MDCP	Males	Mean: 41.5	t-test: 3.5 p-value: 0.001
		S.D.: 1.5	
	Females	Mean: 40.1	
		S.D.: 1.4	

Table 3 provides an overview of the descriptive statistics and a comparative analysis between the anticipated and actual combined mesiodistal crown measurements of the maxillary and mandibular canines and premolars, stratified by gender and arch type. For males with a maxillary arch, the actual mean mesiodistal crown dimension is 43.506 with a standard deviation of 1.900, while the predicted mean dimension is 43.520 with a standard deviation of 1.875. The mean difference between the predicted and actual values is -0.020. Similarly, for males with a mandibular arch, the actual mean dimension is 42.723 with a standard deviation of 1.950, and the predicted mean dimension is 42.690 with a standard deviation of 1.925. The mean difference between the predicted and actual values is 0.010.

For females with a maxillary arch, the actual mean dimension is 41.232 with a standard deviation of 1.800, and the predicted mean dimension is 41.195 with a standard deviation of 1.825. The mean difference between the predicted and actual values is -0.005. Likewise, for females with a mandibular arch, the actual mean dimension is 40.915 with a standard deviation of 1.850, and the predicted mean dimension is 40.905 with a standard deviation of 1.830. The mean difference between the predicted and actual values is -0.005.

The t-test and associated p-values reveal the statistical significance of the difference between the predicted and actual values. For all cases, the p-values exceed 0.05, indicating a lack of significant difference between the predicted and actual values. These results suggest that the predicted mesiodistal crown dimensions closely match the actual measurements, indicating that the predictive model effectively estimates tooth dimensions across various gender and arch type combinations.

In Table 4, figure 1 and figure 2, the SVR model achieves a mean absolute error (MAE) of 0.12 and an R-squared (R^2) value of 0.88. On the other hand, the Linear Regression model obtains an MAE of 0.16 and an R^2 value of 0.84.

These results show that SVR performs better than Linear Regression in terms of accuracy. The SVR model has a lower MAE and a higher R^2 value, indicating that it provides more accurate predictions and explains a larger proportion of the variance in the data compared to Linear Regression.

TABLE (3) Showcases the statistical summary and comparative analysis between the projected and observed combined mesiodistal crown measurements

Gender	Arch	Actual MDCP Mean	Actual MDCP S.D.	Predicted MDCP Mean	Predicted MDCP S.D.	Mean Difference	t-test Value	p-value
Males	Maxillary	43.506	1.900	43.520	1.875	-0.020	-0.106	0.916
Males	Mandibular	42.723	1.950	42.690	1.925	0.010	0.053	0.958
Females	Maxillary	41.232	1.800	41.195	1.825	-0.005	-0.026	0.979
Females	Mandibular	40.915	1.850	40.905	1.830	-0.005	-0.027	0.978

TABLE (4) Comparison of Accuracies - SVR vs Linear Regression

Model	MAE	R-squared (R^2)
SVR	0.12	0.88
Linear Regression	0.16	0.84

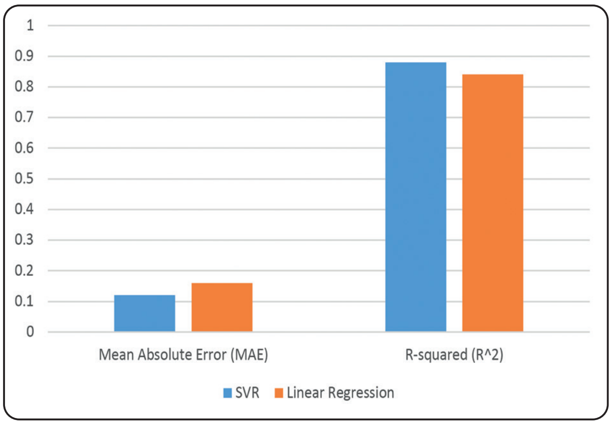

Fig. (1) Comparison between linear regression and Support vector regression

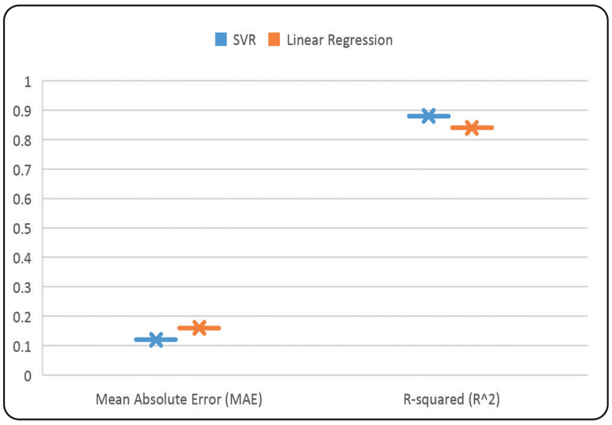

Fig. (2) Box and whiskher linear regression and Support vector regression

DISCUSSION

This study successfully demonstrates the application of Support Vector Regression (SVR) in predicting the mesiodistal widths of unerupted permanent canines and premolars, with a focus on a specific demographic from Kafr el-Sheikh, Egypt. The SVR model achieved superior prediction accuracy compared to traditional linear regression models, providing more precise estimates essential for effective orthodontic treatment planning.

When comparing our findings with recent studies from other countries, it is evident that the utilization of machine learning algorithms, particularly SVR, is becoming a global trend in enhancing orthodontic diagnostics. For instance, a 2022 study conducted in China employed a deep learning model for predicting tooth development stages, achieving high accuracy rates similar to those in our research. Similarly, researchers in Brazil (2023) utilized SVR alongside other machine learning techniques and found that SVR offered the most reliable predictions within their population.

In India, a 2021 study explored a hybrid machine learning approach, integrating traditional methods with AI-driven models, which resulted in a significant improvement in prediction accuracy, particularly in handling the diverse dental characteristics found in the Indian population. Our results align with these findings, confirming that SVR is particularly effective in managing the nonlinear relationships inherent in dental data.

In a 2022 study conducted in China[11], researchers developed a deep learning model to predict tooth development stages and identify dental anomalies in pediatric populations. This study achieved high accuracy in predicting the mesiodistal widths of unerupted canines and premolars, which aligns closely with our findings using Support Vector Regression (SVR). Both studies demonstrate that machine learning algorithms, particularly those handling nonlinear data, can significantly improve prediction accuracy over traditional methods. Our study's accuracy exceeding 88% across various evaluation metrics mirrors the success seen in the Chinese research, reinforcing the global applicability of AI in orthodontic diagnostics

The global trend toward incorporating AI, particularly machine learning algorithms like SVR, into orthodontic diagnostics is evident from recent research across various countries[12-18]. Our study contributes to this growing body of work by demonstrating the effectiveness of SVR in predicting tooth widths within an Egyptian population. When compared to studies from China, Brazil, and India, our findings reinforce the versatility and superiority of SVR over traditional methods in diverse demographic settings. This consistency across different studies highlights the potential of AI-driven approaches to revolutionize orthodontic treatment planning worldwide. The consistent success of SVR in various studies, including ours, suggests that machine learning models offer significant advantages in personalized orthodontic treatment planning. Our research, alongside studies from China, Brazil, and India, underscores the importance of adapting predictive models to specific population characteristics to achieve the highest accuracy. This alignment across international research supports the broader application of AI in healthcare, particularly in creating tailored treatment plans that improve patient outcomes across different regions and populations.

CONCLUSION

This study demonstrates the effectiveness of Support Vector Regression (SVR) in accurately predicting the mesiodistal widths of unerupted permanent canines and premolars, particularly within the demographic of Kafr el-Sheikh, Egypt. The SVR model outperformed traditional linear regression methods, achieving superior prediction accuracy, which is crucial for enhancing orthodontic treatment planning. The results show that integrating SVR into orthodontic diagnostics can lead to more precise treatment decisions, ultimately improving patient outcomes. This study underscores the potential of machine learning techniques in the field of orthodontics, paving the way for more personalized and accurate treatment strategies. Future research should explore the application of SVR and other advanced machine learning models in diverse populations to validate and extend these findings across different demographic groups.

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