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Machine learning as new approach for predicting of maxillary sinus volume, a sexual dimorphic study

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ABSTRACT

The maxillary sinus is the most prominent in humans. Maxillary Sinus Volume (MSV) has grown in popularity as a tool to predict the success of various dental procedures and oral surgeries and determine a person's gender in cases such as forensic investigations when only partial skulls are available. Because it is an irregularly shaped cavity that may be difficult to measure manually, robust imaging techniques such as cone-beam computed tomography (CBCT) used in conjunction with machine learning (ML) algorithms may offer quick and vigorous ways to make accurate predictions using sinus data. In this retrospective study, we used data from 150 patients with normal maxillary sinuses to train and evaluate a Python ML algorithm for its ability to predict MSV from basic patient demographics (age, gender) and sinus length measurements in three directions (anteroposterior, mediolateral, and superoinferior). The model found sinus length measurements had significantly higher predictive values than either age or gender and could predict MSVs from these length measurements with almost linear accuracy indicated by R-squared values ranging from 0.97 to 0.98% for the right and left sinuses.

1. Introduction

The structure of the maxillary sinus is particularly crucial to dentists considering the sinus's close relationship to the maxillary posterior teeth (Dedeoğlu & Duman, 2020). Quantifying human maxillary sinus volume (MSV) has gained popularity as a powerful predictive tool in several applications. In dentistry, the proximity of the maxillary sinus to the oral cavity can be of interest when planning effective procedures. Deformations to the maxillary sinus can profoundly affect tooth positions and oral health (Schiegnitz et al., 2017). When planning interventions to the oral or jaw regions, practitioners often choose to image the maxillary sinus as part of mapping the area to be worked on (Olivetti et al., 2019),

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(Balaji & Balaji, 2018).

In forensic science, correctly identifying a deceased individual is one of the most crucial determinations when investigating a case (Amendt et al., 2007). Accurate determination of gender (Sharma et al., 2014), for example, can be one of the most critical demographics used to narrow down a victim's identity (Pietro Campobasso & Introna, 2001). Often, bodies recovered in this field of study are incomplete, processed, or damaged; in such cases, MSV has become a popular forensic tool for determining gender when only a skull or a partial skull is available (Teke et al., 2007). MSV has exhibited a high degree of sexual dimorphism, with males having significantly higher MSV measurements than females of the same age range. Age is another significant demographic factor affecting MSV, with volumes peaking at adulthood in the 18–25 range, then typically decreasing with age after ~35 years (Aktuna Belgin et al., 2019). A trained individual has traditionally done MSV determination for the prediction of gender at the time of autopsy or bone fragment examination. Because of the irregular shapes of the maxillary sinuses, however, the degrees to which their dimensions can vary from one end of the structure to another. This type of determination by manual observation can be complicated and error-prone.

The maxillary sinus is roughly pyramid-shaped, with oblong protrusions extending downward toward the upper jaw (Schiegnitz et al., 2017). Its diameter varies significantly in the anteroposterior direction and the superoinferior and mediolateral directions, making accurate volume measurements of the cavity challenging (Sidhu et al., 2014). In addition, this sinus contains several Ostia for drainage, making extracorporeal MSV measurement via a liquid-filling complex. Traditional X-rays offer poor two-dimensional approximations of the cavity's most comprehensive dimensions, which may not provide accurate volume calculations (Kim et al., 1985). Three-dimensional computerized tomography (CT) scans provide much more accurate views of changing maxillary sinus volumes at different points in the structure (di Mauro et al., 2016)– (Bangi et al., 2017). More recently, cone-beam computed tomography (CBCT) scans (Butaric et al., 2010) have become extremely popular in this field (Sarment, 2013). Unlike traditional CT scans, which use many perpendicular X-ray scans to reconstruct a three-dimensional image then, CBCT scans use a single cone-shaped X-ray beam to capture the whole structure in a single shot, reducing both the economic cost of the procedure and patient exposure to ionizing radiation. Most studies on MSV now use CBCT images as a gold standard for reliable MSV data (Aktuna Belgin et al., 2019).

With recent advances in the field of machine learning (ML) and deep learning (DL), there has been considerable interest in applying this technique in the medical (Erickson et al., 2017), (Currie et al., 2019), and forensic fields (Nowroozi et al., 2021)– (Qadir & Noor, 2021). Machine learning is a subset of artificial intelligence that involves training algorithms on data to make predictions or decisions without explicit programming. Furthermore, as a subfield of machine learning, deep learning allows computers to learn directly from the raw data without needing human-engineered features. These algorithms are becoming the backbone of the new big data era (El Naqa et al., 2022).

In the context of maxillary sinus volume measurement, machine learning techniques can analyze medical imaging data and automatically extract relevant features for volume estimation, and this can be done using various techniques, including supervised, unsupervised, and deep learning. In medicine, ML/DL methods have been applied for the diagnosis of pneumoconiosis ("black lung disease") in coal miners from chest X-rays, and computerized tomography (CT) scans (Devnath et al., 2022), breast cancer detection from ultrasound images through CNN (Pathan et al., 2022), Covid positivity detection from X-Ray images (Haritha et al., 2020). In dentistry and oral surgery, MSV determination has been performed using ML techniques for predicting the success of various procedures, from dental implants to sinus floor augmentation (de Vos et al., 2009). The automatic separation of the maxillary sinus from surrounding tissue is vital for various diagnostic and therapeutic purposes. However, this task can be difficult and time-consuming manually on cone-beam computed tomography (CBCT) data. Convolutional neural networks (CNNs) have shown to be very effective for analyzing 3D images, achieving a dice similarity coefficient (DSC) of 98.4% in this field (Morgan et al., 2022). A machine learning algorithm called Learning-based multi-source Integration framework for Segmentation (LINKS) (Chen et al., 2020) was used on cone-beam computed tomography (CBCT) images to measure the volumetric differences in the maxilla between a group of 30 patients with impacted maxillary canines on one side and a control group of 30 healthy individuals. The algorithm automatically segmented the maxilla with a high level of accuracy, and measurements of maxillary volume and other dimensions were taken. No significant differences in maxillary volume were found between the impacted and non-impacted sides in the patient group. Still, the patient group had smaller maxillary volumes, widths, heights, and depths than the control group.

In this study, we sought to validate the accuracy of a linear regression technique for predicting MSV from a large pool of patient sinus measurements acquired using the CBCT gold standard imaging method, used in conjunction with basic demographics (age, gender) of the patients.

2. Materials and methods

Previously gathered patient data was obtained for retrospective analysis. Only maxillary sinus measurements were taken using the gold standard CBCT method to ensure maximum data accuracy, after receiving approval from the institutional review board (IRB No: 22-22–0590) of Princess Nourah bint Abdulrahman University, during the period from November 28, 2022 to January 1, 2023. A manual data review was performed to determine the appropriate eligibility criteria for this study which include normal maxillary sinus, Saudi patients were selected from picture archiving and communication system (PACS). Patient data showing any abnormalities to the maxillary sinus or surrounding regions were excluded from the study.

Data were divided into two groups based on the left maxillary sinus, denoted as Volume Left (VL), and the right maxillary sinus, denoted as Volume Right (VR). Sex-balanced (50% male/50% female) VL and VR data were used for each category. The patients' ages were also noted as an additional demographic for statistical analysis. In addition to VL and VR measurements of total MSV, maxillary sinus dimensions in several measurement directions: mediolateral (ML), superoinferior (SI), and anteroposterior (AP), were also considered. Within each group, these measurements were denoted as mediolateral left (MLL), superoinferior left (SIL), anteroposterior left (APL), mediolateral right (MLR), superoinferior right (SIR), and anteroposterior right (APR).

The ML algorithm used in this study was coded in Python using the Seaborn data visualization library (an evolution of the popular Matplotlib library). A linear regression model formed the basis for the algorithm, which was configured to adapt through training to reduce the discrepancy between its prediction and the true MSV of the patient. After being trained through 120 of the 150 data points (80%), the remaining 30 values (20%) were used to evaluate how accurate the algorithm had become with its predictive power. During training, the model was given access to primary demographic data for each patient – age and sex – as well as their MLL, SIL, APL, MLR, SIR, and APR dimensional sinus measurements, and allowed to determine how much weight to ascribe to each parameter.

After testing, the model's predictive power was evaluated as a typical linear regression model through calculated statistical outputs of adjusted mean squared error (MSE adj), mean absolute error (MSE), and coefficient of determination or R-squared values (R2, with an $R2 = 1$ value taken to indicate a perfect 100% linear correlation between predictions and accurate data). Various plots were constructed in Python using the Seaborn library to visually illustrate the various relationships between the variables.

Supplemental Figures S-1 and S-2 show the Python code used for the VR and VL group ML algorithms. (added below in appendix section).

3. Result analysis

Patients with any history of facial abnormalities, deformations, or other sinus-altering conditions were excluded from the study. After a review of the available data, 150 patient records were selected for this retrospective study. As this was, in part, an examination of sexual dimorphisms, the pool of patient data was chosen to be gender-balanced with 75 male and 75 female participants. Due to the variable nature of MSV over time, patient age was also considered a vital inclusion/exclusion criterion for this study. The ages of included patients ranged from 20 to 63 years (mean age 33.98 years, standard deviation ± 9.96 years) to limit the confounding factor of MSV shrinkage in older individuals. Data were divided into the right sinus and left sinus categories.

All measurements were done digitally in millimeters, or mL for sinus volumes, based on CBCT sinus images, in the various software programs used for image capturing. Values for SIR, MLR, APR, VR, SIL, MLL, APL, and VL were used. Data within each category were found to be normally distributed, following a typical Gaussian bell curve. Values reported for each category included mean, standard deviation, minimum value, 25% value, 50% value, 75% value, and maximum value. For VR and VL, the primary measurements considered in this study, the means were 20.60 and 17.18 mL, with standard deviations of 5.67 and 6.08 mL, respectively. Complete statistics are shown in Table 1 below.

Data were then categorized in Python as either objects (used for M/F as gender), 64-bit integers (used for patient ages), or 64-bit floating-point numbers (used for all measured values) for utilization by the Seaborn library. The complete Seaborn categorization is shown in Supplemental Tables S–I.

Patient sex and age were considered key demographics for this study and were the first to be visually correlated with VR and VL values. To provide optimal visualizations of VR and VL distributions categorized by sex, strip plots for each measurement were constructed in Python using the Seaborn library, with MSV measurements on the y-axes and M/F sex categories splitting the x-axes into two strips. Seaborn strip plots for VR and VL measurements by sex are shown below in Fig. 1.

In order to evaluate the correlations between patient age/sex demographics and sinus volumes, as well as the various other sinus measurements, several other visual plots were constructed during the model's training phase. Heat maps were selected as the most appropriate chart type to visualize the influence of age on the various sinus measurements. For other more complex relationships, including both sex and age relating to the various sinus length measurements, Seaborn pair plots were constructed. These various plots are shown in Supplemental Figs. S3–S8.

During the training phase, the algorithm gradually adjusted how much predictive value to ascribe to each parameter it was given data for predicting VR or VL MSV values. To visualize this process, we had the algorithm generate joint plots and corresponding tables that showed how much influence it assigned to each parameter. These plots and tables are shown below in Fig. 2.

Finally, the algorithm's performance was tested on the remaining 30 values for each left/right maxillary sinus data set. Using the various demographic/measurement values and the relative numerical weights it ascribed to each, the algorithm made predictions regarding sinus volumes for the patient's left and right maxillary sinuses. These 30 algorithmic predictions were then compared to the actual MSV values to evaluate the predictive power of our algorithm. Each set of 30 predictions was scored against the 30 true VR and VL values using the statistical parameters of adjusted Mean Square Error (MSE adj), Mean Absolute Error (MAE), and coefficient of determination or R-squared (R2). The results of this analysis are displayed in Table 2 below, while the complete sets of the model's predictions for VL and VR values versus the actual values are shown in Fig. 3.

4. Discussion

This study investigated the value of using machine-learning algorithms to predict maxillary sinus volume from various patient parameters. In recent years, machine learning (ML) has grown exponentially in its value as a technique to make accurate predictions based on available data. Because maxillary sinus volume (MSV) is such a versatile tool for the prediction of all sorts of POIs, including victim gender in forensic investigations (Sharma et al., 2014), (Teke et al., 2007), (Sidhu et al., 2014) and treatment outcomes in the planning of oral surgery (Schiegnitz et al., 2017), we decided to explore MSV as a versatile POI for the evaluation of the ML method. Prediction of sex from MSV would have been an evident approach for this evaluation, as this is often how sinus measurements are used in forensics (Pietro Campobasso & Introna, 2001), (Carriquiry, Hofmann, Tai, VanderPlas, 2019). However, with biological sex being a binary POI with only two options in most cases, we decided that evaluating ML with only two possible predictions would not be particularly robust regarding statistical power. We, therefore, decided to test the linear regression algorithm with a more difficult task: prediction of patient MSV using several parameters such as the basic demographics of age and sex, as well as various measurements of their maxillary sinus cavities in three directions – mediolateral, anteroposterior, and superoinferior.

As has been observed in similar studies (Teke et al., 2007)– (Sidhu et al., 2014), our study subjects typically had higher volumes of the right maxillary sinus compared to the left (mean VR = 20.60 mL, mean VL = 17.18 mL). One noteworthy observation in our dataset, however, was that patient sex did not correlate as strongly with MSV as it had in several other past studies. For the measurements used in this study, female subjects had the highest MSV measurements for both the right and left sinuses. The algorithm ascribed negative predictive values to patient sex, in fact, for both the right and left sinuses. The relative numerical predictive values it returned were −0.34 and −0.54 for the right and left

Table 1
Patient and maxillary sinus measurement demographics of study participants. SIR, superoinferior right maxillary sinus length (mm); MLR, mediolateral right maxillary sinus length (mm); APR, anteroposterior right maxillary sinus length (mm); VR, the volume of the right maxillary sinus (mL); SIL, superoinferior left maxillary sinus length (mm); MLL, mediolateral left maxillary sinus length (mm); APL, anteroposterior left maxillary sinus length (mm); VL, the volume of the left maxillary sinus (mL).

	Count	Unique %	Top	Freq	Mean	Std	Min	25%	50%	75%	max
Sex	150	2	male	75	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Age	150	NaN	NaN	NaN	33.98	9.95	20.0	27.0	31.5	39.0	63.0
SIR	150	NaN	NaN	NaN	3.79	0.27	3.16	3.65	3.80	3.95	4.32
MLR	150	NaN	NaN	NaN	2.79	0.48	1.92	2.45	2.77	3.14	3.99
APR	150	NaN	NaN	NaN	3.81	0.30	2.88	3.59	3.84	4.0	4.64
VR	150	NaN	NaN	NaN	20.60	5.67	11.02	15.93	20.26	24.92	31.67
SIL	150	NaN	NaN	NaN	3.52	0.57	2.07	3.0	3.62	3.87	4.5
MLL	150	NaN	NaN	NaN	2.63	0.49	1.52	2.3	2.72	2.89	3.85
APL	150	NaN	NaN	NaN	3.60	0.53	2.42	3.11	3.66	3.98	4.7
VL	150	NaN	NaN	NaN	17.18	6.08	7.06	12.66	16.61	21.16	28.41

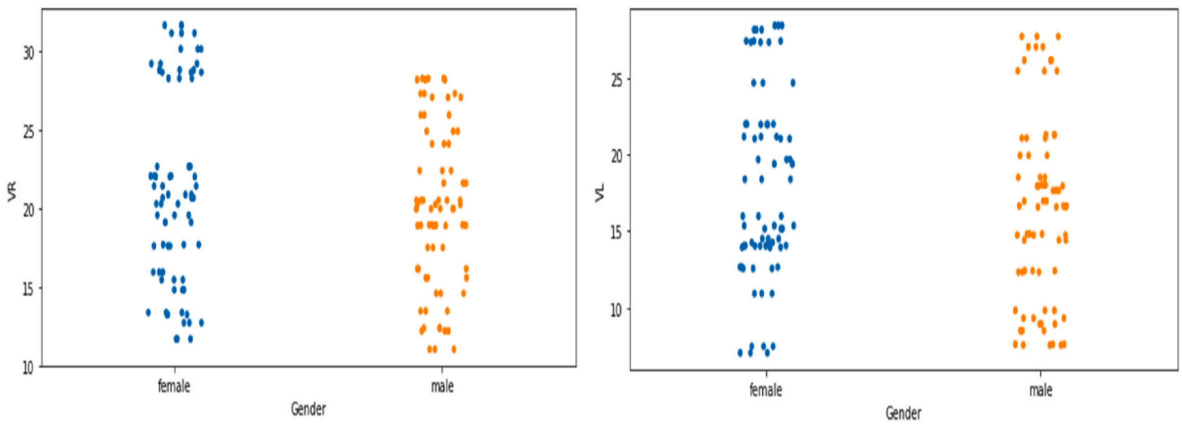
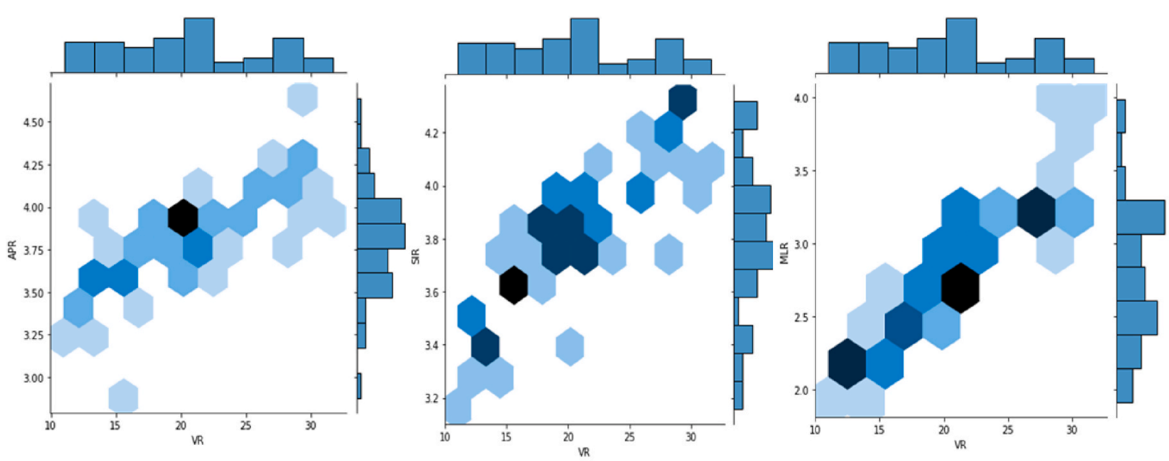
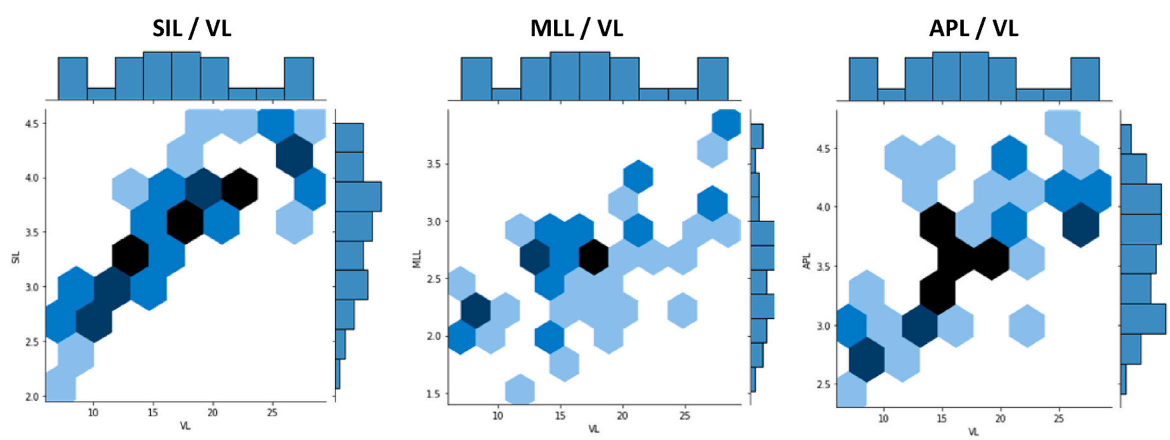


Fig. 1. Seaborn strip plots constructed in Python showing right (top) and left (bottom) maxillary sinus volumes of study subjects categorized by sex. VR, the volume of the right maxillary sinus cavity; VL, the volume of the left maxillary sinus cavity.



Intercept	Sex	Age	SIR	MLR	APR
-33.20	-0.344	0.0033	0.0005	8.087	8.1811



Intercept	Sex	Age	SIL	MLL	APL
-32.4157	-0.5412	0.035784	4.364418	6.617117	4.382487

Fig. 2. Algorithm-generated joint plots and corresponding tables detailing its evaluation of the predictive values of patient demographics (age, sex) and various maxillary sinus measurements for predicting right (top) and left (bottom) maxillary sinus volumes. SIR, superoinferior right maxillary sinus length (mm); VR, the volume of the right maxillary sinus (mL); MLR, mediolateral right maxillary sinus length (mm); APR, anteroposterior right maxillary sinus length (mm); SIL, superoinferior left maxillary sinus length (mm); VL, the volume of the left maxillary sinus (mL); MLL, mediolateral left maxillary sinus length (mm); APL, anteroposterior left maxillary sinus length (mm).

Table 2
Error evaluation of VR and VL volume with three matrices MSE adj, MAE; R2.

	MSE adj	MAE	R^2
VR	0.9477	0.5885	**0.9705**
VL	0.61522	0.72745	**0.9833**

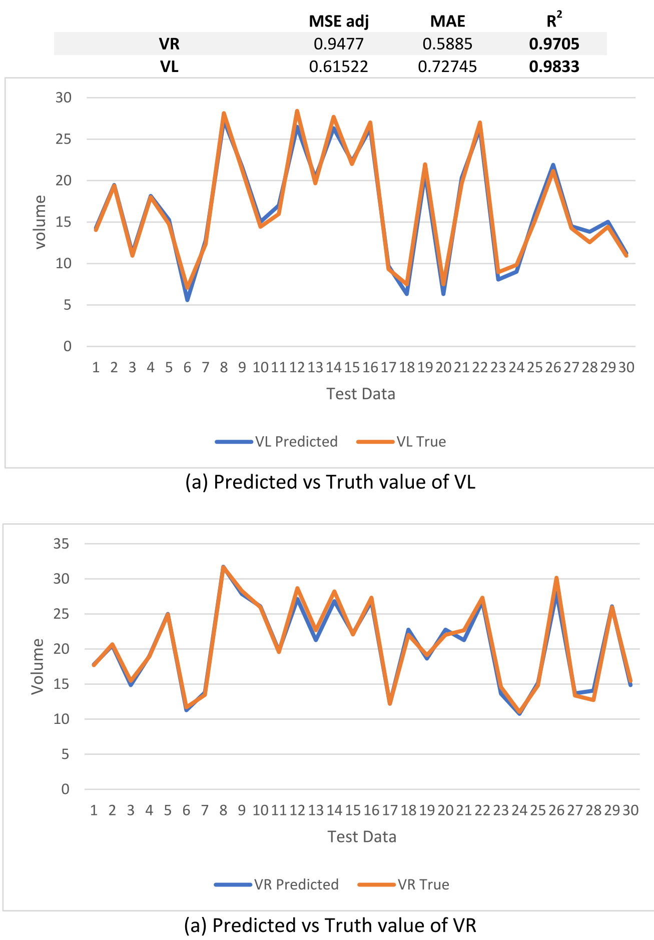


Fig. 3. Comparison between predicted and truth regression values of the right maxillary sinus (VR) volume and the left maxillary sinus (VL) volume.

sinuses, respectively.

Other studies have also noted that MSV decreases with age, beginning at around age 35 for most subjects (Aktuna Belgin et al., 2019), (Chen et al., 2020). While this is generally true of our subjects, we did not observe an undeniable correlation between their ages and MSV values. After evaluating over 120 patient datasets, our ML algorithm ascribed relative numerical predictive values of only 0.0033 and 0.036 to patients' ages for predicting right and left MSVs, respectively. In our dataset, although the left maxillary sinus is notably smaller than the right, its linear correlation to patient age is more significant than an order of magnitude.

Our ML algorithm ascribed the highest predictive values to anteroposterior and mediolateral sinus length measurements from the chosen parameters we trained it on when predicting the right maxillary sinus volumes. The model assigned relative numerical predictive values of 8.18, 8.09, and 0.0005 to the right sinus's anteroposterior, mediolateral, and superoinferior length measurements, respectively. This notable result suggests that super inferior sinus length measurements may have little practical value. However, regarding the left sinus, the same algorithm ascribed a predictive value to superior, inferior sinus length almost equal to anteroposterior length. The mediolateral length was given the highest predictive value for the left sinus, at 6.62, while the anteroposterior and superoinferior measurements were assigned 4.38 and 4.36, respectively. Our findings on patient ages suggest that variations between the left and right sinus are considerably greater than demographical variations based on factors such as age or sex.

When tested, our ML algorithm proved to be a highly robust predictive tool for MSV prediction. The algorithm's mean absolute error (MAE) was less than 1.0 for both the right and left sinuses, at 0.5885 and 0.7275, respectively. Although this would suggest a higher accuracy in the right sinus, adjusted mean squared error (MSE adj) values were calculated at 0.9477 and 0.61522 for the right and left sinuses, respectively. However, the most robust statistical indicator for linear regression models of this nature is the coefficient of correlation – often called the R-squared value (R2). This value reflects how closely the outputs of a calculated formula or algorithm mirror perfectly linear correlations to its inputs – with 0 indicating no linearity in the relationship and 1 indicating perfect linearity. Our ML algorithm was found to have R2 values of 0.9705 and 0.9833 for the right and left sinuses, respectively.

Overall, our results indicate that actual length measurements, particularly in the mediolateral and anteroposterior directions, are much more robustly correlated with total volumes for both the right and left maxillary sinuses in humans. In addition, we have shown that ML algorithms are powerful tools with which researchers can correlate maxillary sinus volumes with other parameters, particularly sinus length measurements. Finally, our model indicated that the left maxillary sinus might be easier to characterize using measurements and patient demographics; however, this conclusion should be more thoroughly evaluated using larger datasets from different patient populations. Future directions for this field could also focus on other demographics or patient measurements, such as ethnicity or skull circumference.

5. Conclusion

This study aimed to see how well machine learning algorithms predicted maxillary sinus volume depending on patient information. To examine data from 150 patients, the researchers employed linear regression methods written in Python and the Seaborn data processing package. The study concluded that patient gender and age were not good predictors of maxillary sinus volume. Still, some sinus measures, such as anteroposterior and mediolateral length, were more predictive for the right sinus, while the superoinferior length was more predictive for the left sinus. The machine learning approach predicted maxillary sinus volume accurately with a root mean squared error of less than 2 mL for both the right and left sides. So, machine learning algorithm is an advance, most accurate application for prediction of MSV. Other future studies with large sample size, multiple variables should be done and real life applications of this study is yet to be validated with live patients data.

6. Limitations

There are some limitations of this study. Firstly, the number of patients is small, larger samples are needed in the further studies. Secondly, we need more training and skills in using the program in order to add disease cases in the future.

Availability of data and materials

All data generated or analyzed during this study are included in this article.

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Declaration of competing interest

The authors declare that they have no competing interests.

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Appendix ASupplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrras.2023.100570.

Appendices

VR Algorithm:

Input: 'Gender','Age','SIR','MLR','APR'.

Output : prediction for 'VR' to ……………….

1. Dataset load:
2. Data Visualization
3. Data correlation
4. from sklearn model selection import train and test split(train size =0. 8, test size=0.2)
5. import Linear Regression Model
6. Train the Model
7. import results
8. print intercept and coefficients
9. print model score and performance
10. Print Model array predicted by y_pred =model.predict(x_test)

VL Algorithm:

Input: 'Gender','Age','SIL','MLL','APL'.

Output : prediction for 'VL' to ……………….

1. Dataset load:
2. Data Visualization
3. Data correlation
4. from sklearn model selection import train and test split(train size =0. 8, test size=0.2)
5. import Linear Regression Model
6. Train the Model
7. import results
8. print intercept and coefficients
9. print model score and performance
10. Print Model array predicted by y_pred =model.predict(x_test)

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