Photographic Analysis and Machine Learning for Diagnostic Prediction of Adenoid Hypertrophy

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Abstract*—Physiognomy has long been recorded in ancient Greece and ancient China. It predicts a person's character and health through facial features because some diseases' traits may illustrate in face. Based on this, we apply a multidisciplinary method to investigate face appearance in photograph, identify adenoidal face, and early intervene in nasal respiratory obstruction. Using computer vision in feature selection, we identified most salient feature points of adenoid face including lip thickness, inner and outer eye distances. Through machine learning techniques, predictive models are constructed to discriminate adenoid face and non-adenoid face. The model-based analytical methods this article employed included decision tree, support vector machines, KNN and XGBoost. The reliability of forecasts was assessed by 5-fold cross validation. Two specific challenges were addressed in the study: Challenge 1, solve problem of head orientation and different illumination direction; Challenge 2, identify relevant facial prediction features which could convert into regression problem; Our research suggests that, compared to other approaches, computer vision feature selection provides a more reliable outcome forecasting of adenoids face, for example with a KNN cluster accuracy of about 77.41%.

***Keywords*—Machine Learning, Data Mining, Adenoid Face**

I. Introduction and Background

Adenoid hypertrophy is the most common pathology causing upper airway obstruction in childhood [1]. Adenoid hypertrophy leads to upper airway obstruction, which may affect maxillofacial and dental growth. Airway obstruction may cause some problems, such as night discomfort, poor school performance, behavioral issues, and daytime sleepiness [2]. Nasal airway obstruction also cause mouth breathing and distinctive "adenoid face", because of large adenoids and large tonsil [2,3].

Adenoid face is considered as having an arrow or "V"-shaped upper dental arch, incompetent lip seal, a steep mandibular plane angle, increased anterior face height, and a retrognathic mandible [3,4]. This variation is explained as changing in head and tongue position and the unbalance between tongue and mandible. Children with obstructive sleep apnoea (OSA) have similar craniofacial characteristics as those with large adenoids and tonsils, moreover some children with an adenoid face would be diagnosed as having OSA. This situation needs to be prevented by early identification and treatment of causative factors, so timely removal of hypertrophic adenoids is important for craniofacial growth pattern [5]. And the preferred treatment for OSA children is to remove adenoids and tonsils. After adenoidectomy and promotion of nasal breathing, there is a report where mandible accelerates growth, and mandibular plane angle is closed [6].

Most popular way to judge adenoid hypertrophy are X-ray and nasal endoscope [6,7,8]. But most patients' families concern that X-rays are harmful to children and will reject X-ray diagnosis. Endoscopic diagnosis process also causes great uncomfortable feeling for children and increases difficulty of diagnosis process. On the other hand, relevant paper and clinicians have indicated that adenoid and tonsil hypertrophy change bone structure and affect child's face. Some article indicates those changes of face can be observed in the diagnosis and 2D images [9].

For all available information, this paper proposes a photographic method based on computer processing to investigate face appearance in photograph, identify adenoidal face, and early intervene in nasal respiratory obstruction. After all, the remainder of this paper is organized as follows. In Section 1, this article summarize overview of the related work and adenoid face in clinical research. Section 2 introduces material and experimental method, and section 3 are devoted to demonstrate three main result. Later on, Section 4 shows the results in context of adenoid face appearance. Finally, in Section 5, summarizes research principal findings and discusses future work.

In summary, our main contributions are:

- Computer vision techniques analyze adenoid facial changes and visualize features with heat map.
- A method for diagnosing adenoids face by image based on machine learning model is designed.
- PRNet[10] is used to solve different facial poses in images.

II. Material of Method

A. Material

Photographs were taken using MiPad 3. Child's head is placed as much as possible in a natural position. In addition, those images are divided into training set or test set. Data analysis and model training utilize training set, and test set only evaluates model performance. In model training process, training set is divided into five parts for cross-validation. Test set does not participate in data analysis and training model. It only verifies forward-looking of model in new dataset. Data of children's face pictures are accumulated at a professional medical institution. All screened samples are less than 16 years old, and the average age was rounded to 5 years old.

B. Data Set

Training Dataset: this set studied 255 children having between 0 and 100% of adenoids， ages 4-7(172 boys, 83 girls), and 210 cases having 50-100% adenoid tissue, 45 cases having 0-50% adenoid tissue, those children consulted professional medical institutions during 2018.The children having 0-50% adenoids were declared as negative data, and children having 50-100% adenoids were declared as positive data. The average age of this dataset is 5 years old.

Test Dataset: Test set randomly selected 332 new data from ages 4-7. 74 cases 0-50% adenoid tissue as a negative sample, and 258 cases 50-100% adenoid tissue as a positive sample. Those children also consulted in the same professional medical institutions during 2018.

C. Method

Step 1: Image preprocessing. During photo taking process, the head direction and illumination are limited by environment, which will seriously affect image quality of face. The two methods listed below can effectively solve these problems.

Head orientation: pitch, roll, and yaw are three free degrees of head, which always occurred distortion and occlusion in face image. In complex poses, it is barely to standardize face pose using traditional methods such as “Delauany Triangle Mapping” in face correction. Consequently, this problem is solved by PRNet mapping the face to front view. [10].

Illumination: Light sources in different directions will have different face shading effects. Gamma correction can reduce non-uniform illumination face caused by different light directions.

Step 2: Average face analysis. According to different genders and labels, we divide photographs into four groups. Each set of photographs produces an average face, and this work analyzes the face changes from a subjective way. Furthermore, the facial feature points in photographs were extracted using a widely face-detection software: dlib 68 points by python. The distribution of dlib points detection is shown in Fig. 1 and TABLE Ⅰ.

Fig. 1. Extract 68 point in dlib

TABLE I. FEATURE POINT DISTRIBUTION IN DLIB

Point Number	Region Expression
1 to 9	The right outline of face
9 to 17	The left outline of face
18 to 22	Right eyebrow
23 to 27	Left eyebrow
28 to 31	Nasal Bridge
32 to 36	Nasal Bottom
37 to 42	Right eye
43 to 48	Left eye
49 to 68	Mouth

Step 3: Data mining. This work aims to address effective features, and data-mining techniques are applied to identify face landmark associated with adenoid face label. Correlation matrix include correlation coefficient from face landmarks distance and adenoid label. Some undiscovered feature information in face will be found by this method. In this work, we get 2278 pixels distances, which consistent with distances between real facial feature points. For normalization calculation, all distances are divided by center distance between two eyes. If a positive sample is marked as 1 and negative sample is marked as 0, a correlation matrix of 2278 pixel distances and a label can be generated. The correlation coefficient (r) of the characteristic X and the label Y is calculated as (1). After analyzing the characteristics of correlation matrix, a feature with large correlation value is selected as training set.

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (1)$$

Step 4: Training model. Training dataset is utilized to train machine learning model. To verify the prediction performance for binary classes, a 2 × 2 contingency table (confusion matrix), as shown in Table Ⅱ, is usually constructed. The evaluation indicators of model are also shown as follows.

TABLE II. CONFUSION MATRIX PROVIDES A MECHANISM TO EVALUATE THE ACCURACY OF BINARY

		Reference	
		Positive	***Negative***
Prediction	***Positive***	TP	FP
	Negative	FN	TN

True Positive (TP)： Number of observations that correctly classified as “positive sample”

True Negative (TN)： Number of observations that correctly classified as “negative sample”

False Positive (FP)： Number of observations that incorrectly classified as “positive sample”.

False Negative (FN)： Number of observations that incorrectly classified as “negative sample”

Accuracy (ACC): ACC = (TF + TN) / Total number of observations.

Precision(P): P = TP / (TP + FP)

Recall(R): R = TP / (TP + FN)

Precision Value measures the proportion of true “Positive” observations among predicted “Positive” observations. Recall(also called sensitivity) measures the proportion of true “Positive” that are correctly classified.

III. RESULTS

A. Average Face Contrast

Average face shows similar appearance in different individuals so that it can reflect common characteristics of a group. Four average face images are gotten from different labels and genders. Each average face image is landmarked by dlib in python, and the result is shown in Fig. 2. (a)(b)(d)(e) depict landmarks of four average faces, and (c)(f) compare marked positions of same gender. In contrast to (a)(d) and (b)(e), adenoid face children have a thicker lip than non-adenoid hypertrophy children, which indicates that adenoid face is manifested in a significant change in child’s mouth. Moreover, children with adenoids have shorter nose bridge, and longer distance between exdocanthion (the point at which the outer ends of the upper and the lower eyelid meet) and exocanthion (the point at which the inner ends of the upper and the lower eyelid meet), which is difficult to observe with human’s eyes.

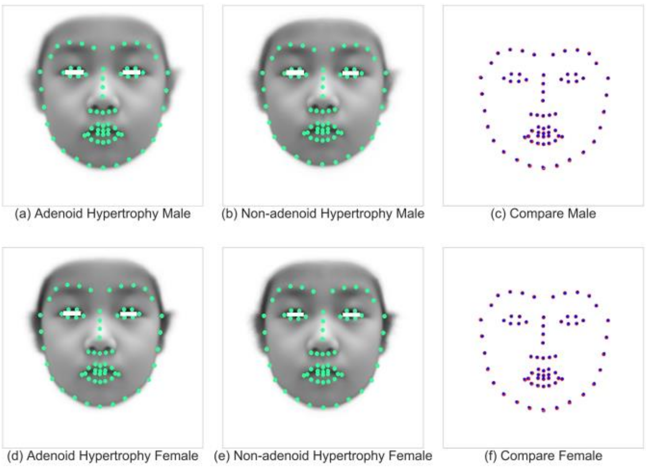

Fig. 2. Face Landmarks Comparison (Red point in (c): green landmarks in (a), Blue point in (c): green landmarks in (b). Red point in (f): green landmarks in (d), Blue point in (f): green landmarks in (e).)

B. Correlation Matrix and Deformation Heat Map

To analysis face information, the distance between two-pixel point of posture correction face is equivalent to geometric face distance, and the change of pixel distance can directly obtain scaling information of five sense organs. Adenoid face judgment can be regarded as a regression problem consisting of 2278 independent variables, and the linear correlation coefficient between labels to each distance can be obtained.

Correlation matrix: In statistics, Pearson correlation coefficient is a measure of linear correlation between two variables. When analyzing different problems, the Pearson correlation coefficient shows a different change indicating the correlation of the values. If correlation coefficient is positive, it will indicate a positive correlation, and a negative correlation coefficient symbolizes a negative relationship. To convert face diagnosis into a linear regression problem, the distribution of 68 feature points is divided into nine groups according to Table Ⅰ. Labels of adenoid hypertrophy and Non-adenoid hypertrophy are marked as 1 and 0. Finally, 2278 feature point distances could calculate correlation coefficient between labels and 2278 distances. It should be noted that the pose rotation of left and right faces also affects image landmarks recognition. Consequently, the feature distances which is applied to train the model should avoid this problems, and the value of correlation coefficient is significant in statistics.

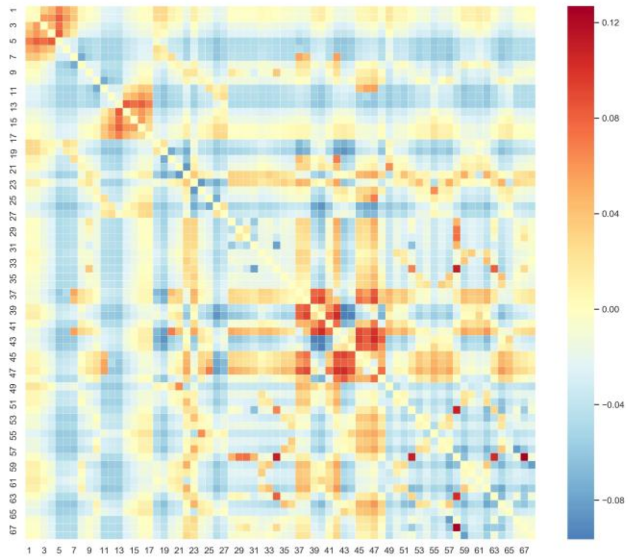

Fig. 3. Correlation coefficient matrix of facial landmarks distance

In Fig. 3, horizontal and vertical axes represent points 1 to 68, and a total of 2278 point distances constitutes a correlation matrices. Each point in correlation matrices represents correlation coefficient between x-y distance and label. Correlation coefficient matrix can be analyzed according to same facial features and different facial features in Fig. 1. The points near diagonal of correlation matrix are the same features’ correlation coefficient, which can explain the deformation of a face region. For example, 49 to 68 square indicates the degree of mouth variation. Points that are far from the diagonal indicate different face area correlation coefficients, and most of these points are poorly interpreted. This article only analyzes the points have strong explanatory.

Heat map: To understand the changes of correlation coefficient, some correlation values are mapped in a mask, and the result diagram is shown in Fig. 4. In Fig. 4, red area indicates higher correlation with adenoid face. Combined with Fig. 4 and Table Ⅲ, It is obvious to find that lip thickness, distance of exocanthion to endocanthion become larger. Eye spacing of adenoid children is shorter than that of non-adenoid children. At the same time, the position of nose tip tends to grow slightly higher, which is similar to clinical observation. Therefore, if the feature is distance of lips, eyes and nose key points, adenoid hypertrophy diagnosis will be easy to regard as a machine learning problem.

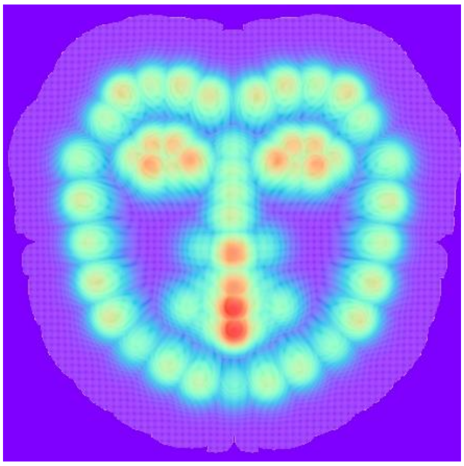

Fig. 4. Heat map of face change.

TABLE III. CORRELATION COEFFICIENT MATRIX TYPICAL VALUE DESCRIPTION

Features	Point Distance Name
Mouth	59-68, 57-66, 58-67, 58-63, 52-58, 31-34
Two eyes distance	40-43, 42-47, 37-46
Right eye	44-47, 43-46, 44-45, 43-45, 43-47, 26-47, 43-48
Left eye	39-40, 38-40, 37-40, 40-42, 40-41, 39-42, 19-42
Eyebrow	23-24, 21-22
Nose	34-58, 34-63

C. Machine Learning for Adenoid Face Detection

In machine learning training progress, Decision Tree, XGBoost, SVM and KNN four methods are used. The results of face judgment metrics are achieved in Table IV. Compared to other models, KNN has a significant improvement in the results.

TABLE IV. RESULTS OF MODEL METRICS

	Accuracy	Precision	Recall
Decision Tree	73.80%	71%	74%
XGBoost	76.71%	72%	78%
SVM	76.61%	60%	78%
KNN	77.41	82%	77%

There are prior reports of using photographic method to analyze adenoid face. For instance, Koca examines the effects of adenoid hypertrophy on maxillofacial development according to photographic method [6]. This method requires many manual annotations. and the point accuracy cannot be guaranteed. Previously identified biomarkers, as well as the salient features are identified in our study, can be used to improve diagnosis, predict disease duration, and track disease progression over time. Compared with Koca, this paper eliminates the process of manual labeling and obtains some identical conclusions. However, due to method limitations, it is not possible to analyze angle changes in side face.

IV. DISSCUSION

According to [11], face difference is reflected in expansion or contraction of face local area. Based on this research of facial features, correlation matrix is simple to observe the expansion and contraction performance of area, so this article discuss how to identify the adenoid face in image.

Using PRNet to solve posture correction problems, such as: when younger children take pictures, it is difficult to control the correct angle. It can corrects facial images by DNN and map facial image information onto the same plane.

Correlation coefficient matrix is used to extract facial features and got same conclusions as [6]. Such as lips thickness, inner and outer eye distances become larger, and the nasal demonstrates minor variation in the correlation efficient matrix.

Accident: Correlation coefficient matrix analysis found that the detection results had left and right face asymmetry effects. Therefore, this paper only selects partial distance features and combines correlation coefficient matrix analysis to avoid the influence of inconsistent left and right face information. At the same time, it was found that there was a change in adenoid face at eye shape, and long-term hypoxia causes changes in facial expression. This outcome can be analyzed in later work.

Contrast with predecessors: Compared with [6], the process of landmarks is more convenient, and the same conclusion can be obtained in an accessible way. The position of facial feature point can be accurately marked without manual labeling; based on this method, the relationship between data can be more intuitively displayed. Some new information is extracted by this method: for example, correlation coefficient matrix demonstrates that the shape of eyes is also related to adenoid face. Finally, machine learning model can distinguish whether it is an adenoid face.

However, due to limitations of this analytical method, this system still has weaknesses. For example, it can't analyze angular changes between feature points.

V. CONCLUSION

This paper analyzes the changes of two-dimensional face pictures, uses data mining method to extract features, and analyzes the changes of adenoid face key points from correlation coefficient matrix. After that, quite a few key points distances were utilized to train machine learning model. Finally, adenoid face recognition accuracy rate of KNN model is 77.41%.

The proposed method can be applied to low-cost medical aided diagnosis. At the same time, it can also learn more information about adenoid face, such as effects of different degree of adenoid hypertrophy on the face.

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