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Original Article

Cephalometric Variables Prediction from Lateral Photographs Between Different Skeletal Patterns Using Regression Artificial Neural Networks

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Main Points

- These neural network models represented a new clinical implication to measure orthodontic lines and angles through lateral photographs avoiding the risk of cephalometric radiation.
- The neural network models' determination success was 0.99 for the training-test set ratio: 70-30%.
- A high level of accuracy was achieved as a result of a high correlation between the output and the target measurements of the networks.

ABSTRACT

Objective: This study aimed to design an artificial neural network for the prediction of cephalometric variables via a lateral photograph in skeletal Class I, II, and III patterns.

Methods: A total of 94 patients were recruited for this prospective study, with an age range of 15-20 years (41 boys and 53 girls) seeking orthodontic treatment. According to cephalometric analysis, using AutoCAD 21.0, they were allocated into three groups. Thirty with skeletal Class I (14 boys and 16 girls), 34 with skeletal Class II (14 boys and 20 girls), and 30 with skeletal Class III malocclusion (13 boys and 17 girls) according to SNA, SNB, and ANB angles measured from cephalometric radiographs. The study includes (1) finding the correlation of the skeletal measurements between lateral profile photographs and cephalometric radiographs for the recruited patients and (2) designing a specific artificial neural networks for the assessment of skeletal factors via lateral photographs, these artificial neural networks are trained and tested with the total of 94 standard lateral cephalograms.

Results: This novel Network provided models of regression that can forecast the cephalometric variables through analogous photographic measurements with excellent predictive power R = 0.99 and limited estimation error for each malocclusion (Class I, II, and III).

Conclusion: This study suggests that artificial intelligence would be useful as an accurate method in orthodontics for the prediction of cephalometric variables and its performance was achieved by several factors such as proper selection of the input data, preferable generalization, and organization.

Keywords: Artificial neural networks, cephalograms, artificial intelligence

INTRODUCTION

Globally, digital technology is becoming constantly one of the most important procedures in the clinical activities, and, thus, orthodontic digital revolution has been added more and more by orthodontists in their clinical practice. In orthodontics, successful treatment outcomes depend on accurate diagnosis through crucial diagnostic tools, which involves the development of a comprehensive database of patient's information; the data is obtained from case history, clinical examination, and other diagnostic aids such as study casts, radiographs, and photographs.[1]

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An important part of diagnosis is to evaluate the skeletal factors via the records. Although cephalometric is the standard for identifying skeletal and dental craniofacial morphology in clinical practice, it might not be practical for large and repeated studies of epidemiology.[2]

Additionally, certain limitations to cephalometric radiographs are mentioned, for example, for patients exposed to a certain amount of radiation; a special source of radiation and a head holder are required to produce accurate images. For these reasons, it would be valuable to have a simple, safe, low-cost technology technique for assessing craniofacial morphology. Therefore standardized facial photography might be a useful tool for characterizing craniofacial anatomy since some aspects of facial appearance are related to the morphology of underlying hard tissues.[3]

Historically, facial photographs have been crucial parts of both pretreatment and posttreatment orthodontic records. Many orthodontic texts emphasized the use of orthodontic diagnosis and treatment planning. Graber (1946) reported that the photograph assumes even greater importance when dentists do not have equipment for taking cephalograms,[4] therefore photographs can be considered as an essential diagnostic tool.[5] From a lateral view, facial height and depth, the position of upper and lower lips, and the mandibular angle are the main factors that characterize facial patterns.[6] Additionally, photographic analysis is an economical technique and safe method since the patient does not expose to potentially harmful radiation, it can be easily used to assess the head and face postures and compare those existing relationships among different craniofacial structures.[7]

Currently, many methods of multiple-factor analysis are applicable in medicine, and among these artificial neural network (ANN) model analysis is very commonly used. Several studies have been done recently about artificial intelligence and bioinformatics.[1,8] One way is machine learning using a neural network system.[9]

In a true sense, ANNs are clustering of the primitive artificial neurons in a simple way, and this clustering is composed of multiple layers connected to one another. As shown in Figure 1, the first (input) layer consists of neurons that receive input from the external surrounding. The output layer consists of neurons that communicate the output of the model to the external environment. Between these input and output layers, there are usually a number of hidden layers; however, Figure 1 is just a simple architecture with only one intermediate (hidden layer). When the input layer receives the signal, its neurons produce output and this becomes an input to the other layers of the model. The process continues until a certain condition is fulfilled or until the output layer is invoked and fires its output to the external surrounding.[10]

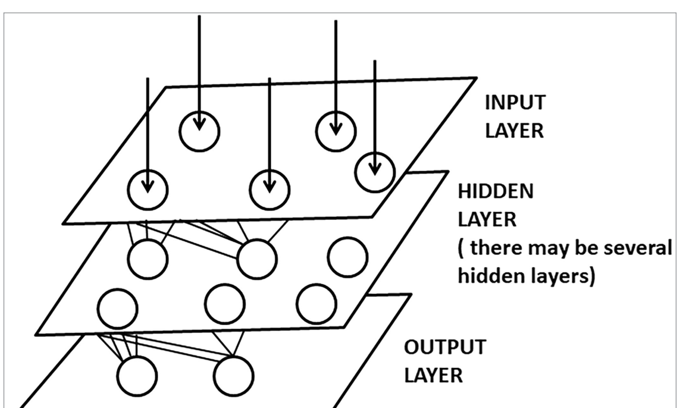

Figure 1. The structure of an artificial neural network (25)

Previously, in orthodontics, the use of ANN was recommended for the extraction[11]; the prediction of change in lip curvature[12]; and the prediction of arch form.[13] They found that ANN model analyses were more accurate as compared to the conventional ones. To our knowledge, no studies have employed the ANN for the prediction of skeletal parameters for full orthodontic diagnosis using lateral photographs. Thus this study aimed to make a new artificial intelligence decision-making model for the diagnosis of skeletal factors only through photographs using neural network machine learning between different skeletal malocclusion.

METHODS

A total of 94 patients were recruited for this prospective study, with an age range of 15-20 years (43 boys and 51 girls) seeking orthodontic treatment. According to cephalometric analysis, using AutoCAD 21.0, they were divided into 3 groups. Thirty with skeletal Class I (14 boys and 16 girls, ANB angle 2°-4°), 34 with skeletal Class II (14 boys and 20 girls, ANB angle >4°), and 30 with skeletal Class III malocclusion (13 boys and 17 girls, ANB angle <2°), according to SNA, SNB, and ANB angles from cephalometric radiographs.

This study was conducted in the Al-Shaab specialized dental center in Baghdad. This study was approved by the Human Research Ethics Committee of College of Dentistry/Baghdad University (Iraq), (Approval No:168/2019). All subjects were given consent information sheets for inclusion before participation.

Inclusion criteria were patients with age range 15-20 years, no previous orthodontic or surgical treatment, all permanent teeth erupted up to the second molar included, no craniofacial trauma, and no congenital anomalies. Exclusion criteria were patients who were not fit for orthodontic treatment (i.e., poor oral hygiene and multiple caries), patients with systemic diseases or pregnant patients, and patients who were not within the age range. Standardized right profile photographs were taken for participants in the natural head position (NHP), the teeth in centric occlusion, and the lips at rest position. Eyeglasses, earrings, and necklaces were removed. Ensure that the patient's forehead was clearly visible and the hair piled high on the head. Red indicators dots were placed on anatomic landmarks (N', A', B', Pog', Mn', Go', Tr, Or') obtained by palpation (Figure 2).

In order to obtain the NHP, a 75 × 30 cm mirror was hung on a tripod, which can be adjusted vertically according to the height

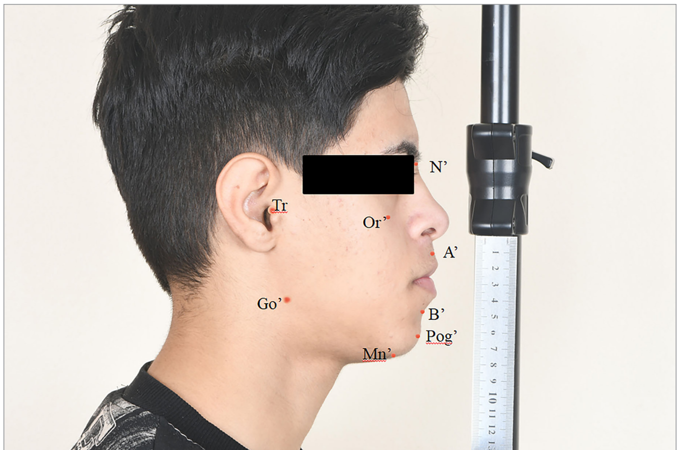

Figure 2. Red indicators dots were placed on anatomic landmarks

of the patients. Patients were asked to stand in a relaxed position and to look at the reflection of their eyes in the mirror that is located 120 cm from the patient. The patient asked to bite on fox bite to record the occlusal plane by pointing two red dots on the cheek of the patient parallel to the plane of fox bite. Then, a straight line was easily drawn by connecting these two dots by AutoCAD software. A protractor was used to record the NHP angle by placing it on the tip of the nose and the soft tissue pogonion.[14]

Digital lateral cephalometric radiographs were taken with Sirona Orthophos XG (Dentsply company, NY, USA). Cephalometric radiographs were taken in the NHP with centric occlusion and rest position of the lips. In order to register the true vertical line, the nose rode was placed in front of the patient, in the midsagittal plane, and the scale of the nose rode allowed later measurements at life size (1 : 1). Natural head position angle was checked by a modified protractor, it was placed on the tip of the nose and the soft-tissue pogonion to check if the same position achieved during the photographic record had also been obtained during the radiographic record.[14]

Both digital photographic and radiographic records were analyzed with AutoCAD (21.0) (codename nautilus) software for Windows. A specific analysis was customized using the landmarks defined for the purpose of this study (Figure 2). Traditional cephalometric angular and linear measurements included;

(A) Sagittal assessment: (1) Wits measurements indicate maxillomandibular linear discrepancy; (2) ANB angle indicates maxillomandibular angular discrepancy; (3) FNP angle indicates facial angle; (4) N.ANS.Pog; and (5) N.ANS.B angles indicate angles of facial convexity.

(B) Vertical assessment: (6) Ar.Go.Me angle indicates gonial angle; (7) FMA angle indicates Frankfurt to mandibular plane angle; (8) OPA angle indicates Frankfurt to occlusal plane angle; (9) AFH indicates anterior facial height (N-Me); (10) LAFH indicates lower anterior facial (ANS-Me) height; and (11) LPFH indicates lower posterior facial height (Ar-Go) (15) and analogous photographic ones were used for sagittal and vertical assessment which include (1) Wits' measurement indicates soft-tissue maxillomandibular linear discrepancy; (2) A'N'B'angle indicates soft tissue maxillomandibular angular discrepancy; (3) FNP'angle indicates soft-tissue facial angle; (4) N'.Sn.Pog'; (5) N'.Sn.B' angles indicate soft tissue angles of facial convexity for sagittal assessment; (6) Tr.Go'.Me' angle indicates soft tissue gonial angle; (7) FMA' angle indicates soft tissue Frankfort to mandibular plane angle; (8) OPA' angle indicates soft tissue Frankfort to occlusal plane angle; (9) AFH' indicates soft tissue anterior facial height (N'-Me'); (10) LAFH' indicates soft tissue lower anterior facial height (Sn-Me'); and (11) PFH' indicates lower posterior facial height (Tr-Go').[15] All the measurements were calculated once the landmarks were properly identified on each record; these were previously scaled to life size. Inter- and intra-examiner calibrations were performed on a sample of 27 subjects (15 boys and 12 girls) for computerized analysis of facial morphology through radiographs and photographs.

All the data of the skeletal measurements that were calculated by AutoCad software in millimeter values had arranged in the excel program (Microsoft Office 2020) in the form of tables. The first table for Class I malocclusion, the second table for Class II malocclusion, and the third for Class III malocclusion, each table included 22 variables, 11 variables for the cephalometric radiographs, and 11 variables for the lateral photographs.

In ANN programing, all the data of skeletal measurements had been copied into the MATLAB program (R2020a vs. 9.8.0/2020) from Microsoft Excel. The first neural network was for the Class I malocclusion measurements and the second and the third neural networks were for Class II and III malocclusion measurements respectively. The data were randomly allocated into 70% of data for training (Ptrian = 0.7) and 30% for testing, Feedforward backpropagation was used for these networks and the learning functions were Bayesian Regularization for all. These networks were trained by entering the 11 variables (angular and linear measurements) for the lateral photographs as input values for the network while the output values were the 11 variables (angular and linear measurements) for the cephalometric radiographs. The percentage of training data was 70% of the total data selected randomly and the percentage for testing the network was 30% of the total data (testing new data that was never trained).

Statistical Analysis

Shapiro-Wilk test for data distribution showed a non-significant difference ($P > .05$) thus data were considered normally distributed. Data were subjected to statistical analysis using the Statistical Package for the Social Sciences, version 16.0 (SPSS Inc, Chicago, Ill, USA). Descriptive statistics were performed for each photographic and cephalometric variable for the skeletal measurements networks. Sexual dimorphism was evaluated by independent sample *t*-test. Intraclass correlation coefficients (ICCs) were estimated from repeated photographic measurements and analysis of cephalometric and photographic variables to evaluate the repeatability and reproducibility of the method. Cephalometric measurements were compared with analogous photographic variables to assess Pearson correlation coefficients. Linear regression analyses were made after designing the networks for all networks between the targets (dependent variable to be estimated) and actual outputs of cephalometric variables (independent variable). Levels of $P < .05$ were considered statistically significant.

RESULTS

The ICC to evaluate the reliabilities of the photographic technique and the analysis of the skeletal measurements on cephalometric and lateral photos demonstrated excellent reliability with values ranged between 0.85 and 0.90.

The independent sample *t*-test showed no significant difference between male and female subjects except for the anterior and posterior facial height which were greater in males than females for all skeletal malocclusions in the cephalometric and facial photographs (Tables 1 and 2).

Highly significant correlations ($P \leq .001$, $r > 0.79$) were found for most sagittal and vertical diagnostic variables with higher vertical than sagittal measurements using the Pearson correlation coefficient.

Linear regression analysis was estimated for 70% of the collected data (skeletal Class I, II, III malocclusion) after designing the neural network. It showed very high coefficients of correlations between cephalometric radiographic variables of the actual output and the target during the training process (Figure 3) (R = 0.999 during training part, R = 0.999 during testing part of training process, R = 0.999 as a whole). The best training performance which means the least mean square error during training process was 0.20 337 at epoch 135 for Class I malocclusion, 0.35 917 at epoch 78, 0.43 499 at epoch 111 for Class II and III malocclusion respectively (Figure 4).

Following testing process, linear regression analysis was estimated for the other 30% of the collected data after designing the neural network. It showed very high correlation coefficients between cephalometric radiographic variables of the output and the actual target (Figure 5) ($R = 0.9991$, $R = 0.9998$, and $R = 0.9987$ for skeletal Class I, II, and III, respectively).

DISCUSSION

The cephalometric analysis creates the current gold standard for diagnosing different skeletal patterns in the clinical practice of orthodontists. However, the photographic assessment is a tremendous diagnosis tool for studies of epidemiology since there is no potentially harmful radiation and it is a cost-effective technique.[5,16]

The standardized technique of facial photography has several advantages for using as an alternative practical technique for the diagnosis of craniofacial morphology. It is easier to take measurements without skin pressure-related errors since the subjects do not move and the interaction period is potentially shorter with the subject. Furthermore, longitudinal studies are applicable since measurements can be performed repeatedly, and storing of the data is permanent.[3,17] Conversely, facial photographic technique has some drawbacks. The objects near the camera appear larger than those away from it due to distortion from the distance between the lens and the subject.[3]

Since most landmarks obtained from lateral photographs in the current study are at the midline, the effect of distortion is minimum because this effect is critical at the landmarks that are located in different planes of space.[18] Moreover, most variables used in the current study were angular which partially overcomes the problem of magnification.

Another source of error concerns is head posture, it must be the same during the recording protocol of radiographs and photographs. The landmarks' location is greatly affected even by a slight deviation of the NHP and this causes changes in the results of the measurements.[1] Additionally, mentalis muscle constriction due to jaw opening may increase the estimate of error.[19]

One of the most important aspects of anthropometry studies is the reliability of measurement, which is the ability to obtain the same measurement consistently over sequential measures.[20] In the current study, most photographic measurements were performed based on palpation of anatomic points. It is important to find the reliability in positioning the red dots without the interference of other source of error therefore a reproducibility test was conducted. Accurate establishment of landmarks is crucial to ensure standardized photography protocol. Results of this study showed that method reproducibility was satisfactory.

Although the sample in this study had different skeletal patterns (Class I, II, and III malocclusions) generally, most cephalometric measurements showed no significant gender differences which explain the identical distribution into male and female subgroups. However, differences were found only for facial height anteriorly and posteriorly (AFH, LAFH, PFH) for photographs and cephalometric radiographs which were significantly higher in male subjects. This came in agreement with many studies which reported sexual dimorphism in most parameters of the chin, nasal, and labial areas. Ferrario et al.[21] in 1993 mentioned that male faces show, on average, greater prominences of these areas as well as greater heights and lengths. Bishara et al.[22] (1995) and Fernandez-Riveiro et al.[23] (2009) had also reported significantly larger values for AFH, LAFH, and PFH in male subjects, which agrees with the findings of this study.

Highly significant correlations were found for most sagittal and vertical diagnostic variables. However, the highest coefficients were found between vertical variables as compared with sagittal variables. These findings agreed with the results of Gomes and coworkers in 2013.[15]

Good correlation coefficient was reported in this study between analogous photographic and cephalometric ANB angles ($r = 0.79$, $r = 0.79$, $r = 0.84$ in Class I, II, and III malocclusions, respectively). These results agreed with the results of Staudt and Kiliaridis[19] in 2009 who mentioned that a predictable description of the underlying sagittal jaw relationship can be obtained from

Table 1. Gender difference for Cephalometric radiographic Measurements

Measurements	**Male subjects n = 14**				**Female subjects n = 16**						
Class I	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	***t*-test**	***P***	**Significance**
Sagittal assessment											
Wits	0.50	0.41	−0.27	0.91	0.42	0.32	−0.05	0.94	0.619	.541	NS
ANB	3.33	0.65	2.00	4.00	3.50	0.89	2.00	5.00	−0.545	.590	NS
FNB	87.92	1.88	85.00	91.00	89.44	3.01	83.00	95.00	−1.536	.137	NS
N-ANS-Pog	167.25	4.25	161.00	174.00	164.88	6.70	153.00	173.00	1.074	.293	NS
N-ANS-B	164.83	4.71	157.00	171.00	161.81	6.99	150.00	172.00	1.291	.208	NS
Vertical assessment											
Ar-Go-Me	130.50	8.02	123.00	146.00	129.63	6.38	120.00	142.00	0.322	.750	NS
FMA	28.17	6.90	20.00	41.00	26.69	6.18	17.00	37.00	0.596	.556	NS
OPA	9.42	3.37	4.00	15.00	9.88	4.03	4.00	17.00	−0.319	.752	NS
LAFH	16.49	0.78	15.66	18.28	15.29	0.85	14.07	16.83	3.816	.001	**S**
AFH	9.79	0.90	8.81	12.12	8.71	0.73	7.18	9.74	3.504	.002	**S**
LPFH	6.47	0.81	4.86	7.73	5.58	0.55	4.65	6.66	3.491	.002	**S**
Measurements	**Male subjects n = 14**				**Female subjects n = 20**						
Class II	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	***t*-test**	***P***	**Significance**
Sagittal assessment											
Wits	1.14	0.58	0.43	2.56	1.10	0.43	0.37	2.03	0.275	.785	NS
ANB	7.29	2.20	5.00	12.00	7.16	1.49	5.00	10.00	0.212	.833	NS
FNB	87.43	3.27	81.00	93.00	87.28	2.56	83.00	92.00	0.157	.876	NS
N-ANS-Pog	160.21	6.53	147.00	169.00	160.52	4.80	153.00	171.00	−0.167	.868	NS
N-ANS-B	156.57	7.65	140.00	168.00	157.56	5.15	150.00	170.00	−0.482	.633	NS
Vertical assessment											
Ar-Go-Me	128.43	10.12	114.00	146.00	128.40	6.66	116.00	143.00	0.011	.992	NS
FMA	25.71	10.10	12.00	44.00	27.88	5.21	21.00	42.00	−0.887	.381	NS
OPA	9.21	3.77	3.00	17.00	11.12	3.14	6.00	19.00	−1.692	.099	NS
LAFH	16.02	1.20	14.06	17.69	15.08	0.83	13.65	16.86	2.876	.007	S
AFH	9.29	1.29	7.57	11.37	8.52	0.61	7.23	9.79	2.528	.016	S
LPFH	6.24	0.54	5.35	7.28	5.61	0.57	4.75	6.84	3.401	.002	S
Measurements	**Male subjects n = 13**				**Female subjects n = 17**						
Class III	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	***t*-test**	***P***	**Significance**
Sagittal assessment											
Wits	0.00	0.37	−0.68	0.66	0.03	0.39	−0.68	0.66	0.354	.726	NS
ANB	0.15	1.43	−5.00	1.00	−0.23	1.88	−5.00	1.00	−1.393	.176	NS
FNB	91.12	3.54	84.00	97.00	91.23	3.83	84.00	96.00	0.163	.872	NS
N-ANS-Pog	171.08	5.64	157.00	180.00	170.15	6.50	157.00	179.00	−0.829	.415	NS
N-ANS-B	169.19	5.78	154.00	179.00	168.69	6.66	154.00	179.00	−0.434	.668	NS
Vertical assessment											
Ar-Go-Me	130.54	7.96	119.00	155.00	131.15	9.84	119.00	155.00	0.387	.702	NS
FMA	25.19	6.78	16.00	45.00	25.69	7.92	16.00	45.00	0.369	.715	NS
OPA	9.81	4.41	1.00	19.00	8.31	4.29	1.00	16.00	−1.812	.082	NS
LAFH	15.86	1.47	13.99	19.34	16.71	1.51	14.86	19.34	3.600	.001	S
AFH	9.01	1.22	7.14	11.76	9.65	1.18	8.26	11.76	3.098	.005	S
LPFH	6.35	0.74	4.89	7.75	6.81	0.62	6.02	7.75	4.079	.001	S

***Wits** measurements indicates maxillomandibular linear discrepancy; **ANB angle** indicates maxillomandibular angular discrepancy; **FNP angle** indicates facial angle; **N-ANS-Pog** and **N-ANS-B angles** indicate angles of facial convexity. **Ar-Go-Me angle** indicates gonial angle; **FMA angle** indicates Frankfurt to mandibular plane angle; **OPA angle** indicates Frankfurt to occlusal plane angle; **AFH** indicates anterior facial height **(N-Me)**; **LAFH** indicates lower anterior facial **(ANS-Me)** height; and **LPFH** indicates lower posterior facial height **(Ar-Go)**; SD, standard deviation; Min, minimum; Max, maximum.

Table 2. Gender difference for lateral photographic measurements

Measurements	Male subjects n = 14				Female subjects n = 16						
Class I	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	***t*-test**	***P***	**Significance**
Sagittal assessment											
Wits	0.68	0.22	0.34	1.11	0.65	0.18	0.33	1.00	0.458	.651	NS
ANB	6.75	1.66	3.00	8.00	6.88	1.63	4.00	9.00	−0.199	.843	NS
FNB	88.42	2.68	84.00	93.00	89.25	2.65	83.00	92.00	−0.820	.419	NS
N-ANS-Pog	162.50	4.54	153.00	169.00	162.81	5.28	153.00	172.00	−0.164	.871	NS
N-ANS-B	160.75	4.37	156.00	168.00	159.81	5.66	150.00	171.00	0.476	.638	NS
Vertical assessment											
Ar-Go-Me	130.08	8.32	121.00	146.00	128.63	6.24	119.00	143.00	0.531	.600	NS
FMA	28.42	7.06	22.00	43.00	25.63	6.08	16.00	35.00	1.123	.272	NS
OPA	9.67	3.03	5.00	15.00	9.81	4.02	4.00	17.00	−0.105	.917	NS
LAFH	13.00	0.62	12.23	14.49	12.14	0.55	11.26	13.25	3.886	.001	S
AFH	7.31	0.73	6.57	9.28	6.43	0.46	5.53	7.23	3.943	.001	S
LPFH	5.51	0.60	4.30	6.16	4.85	0.49	4.02	6.00	3.195	.004	S
Measurements	**Male subjects n = 14**				**Female subjects n = 20**						
Class II	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	***t*-test**	***P***	**Significance**
Sagittal assessment											
Wits	1.30	0.51	0.69	2.55	1.10	0.38	0.52	2.03	1.360	.182	NS
ANB	10.14	1.75	7.00	13.00	9.68	1.57	7.00	13.00	0.847	.402	NS
FNB	86.86	3.63	81.00	93.00	87.40	2.27	83.00	92.00	−0.575	.569	NS
N-ANS-Pog	156.07	5.27	147.00	162.00	157.48	4.15	151.00	164.00	−0.922	.363	NS
N-ANS-B	152.86	6.02	140.00	164.00	154.68	4.22	148.00	163.00	−1.108	.275	NS
Vertical assessment											
Ar-Go-Me	128.21	9.61	117.00	146.00	128.28	6.73	116.00	140.00	−0.025	.980	NS
FMA	25.43	9.24	12.00	40.00	27.28	5.37	17.00	41.00	−0.795	.432	NS
OPA	9.21	3.93	3.00	17.00	11.32	3.35	6.00	19.00	−1.770	.085	NS
LAFH	12.69	0.78	11.28	13.95	11.98	0.63	10.93	13.47	3.094	.004	S
AFH	6.82	0.67	5.60	7.86	6.38	0.45	5.42	7.26	2.452	.019	S
LPFH	5.53	0.43	4.89	6.16	4.90	0.59	3.75	6.00	3.502	.001	S
Measurements	**Male subjects n = 13**				**Female subjects n =17**						
Class III	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	***t*-test**	***P***	**Significance**
Sagittal assessment											
Wits	0.46	0.36	−0.27	1.08	0.48	0.38	−0.21	1.08	0.212	.834	NS
ANB	4.46	1.82	−1.00	7.00	4.77	1.88	1.00	7.00	0.859	.399	NS
FNB	90.58	3.57	84.00	96.00	90.69	4.07	84.00	96.00	0.162	.873	NS
N-ANS-Pog	168.38	5.50	157.00	179.00	167.85	6.12	157.00	179.00	−0.492	.627	NS
N-ANS-B	165.19	5.17	154.00	179.00	165.08	5.50	154.00	179.00	−0.112	.912	NS
Vertical assessment											
Ar-Go-Me	129.88	7.96	119.00	156.00	130.92	9.88	119.00	156.00	0.657	.517	NS
FMA	25.04	6.43	16.00	42.00	25.38	7.15	16.00	42.00	0.269	.790	NS
OPA	10.08	4.49	1.00	18.00	8.38	4.50	1.00	17.00	−2.040	.052	NS
LAFH	12.76	1.27	10.94	15.99	13.57	1.28	12.03	15.99	4.201	.000	S
AFH	6.92	0.96	5.45	9.27	7.53	0.88	6.48	9.27	4.120	.000	S
LPFH	5.50	0.70	4.22	6.99	5.93	0.56	5.01	6.99	3.980	.001	S

Wits' measurement indicates soft-tissue maxillomandibular linear discrepancy; **A'N'B'angle** indicates soft tissue maxillomandibular angular discrepancy; **FNP'angle** indicates soft-tissue facial angle; **N'-Sn-Pog'**and **N'-Sn-B' angles** indicate soft tissue angles of facial convexity for) **Tr-Go'-Me' angle** indicates soft tissue gonial angle; **FMA' angle** indicates soft tissue Frankfurt to mandibular plane angle; **OPA' angel** indicates soft tissue Frankfurt to occlusal plane angle; **AFH'** indicates soft tissue anterior facial height **(N'-Me')**; **LAFH'** indicates soft tissue lower anterior facial height **(Sn-Me')**; and **PFH'** indicates lower posterior facial height **(Tr-Go')**; SD, standard deviation; Min, minimum; Max, maximum.

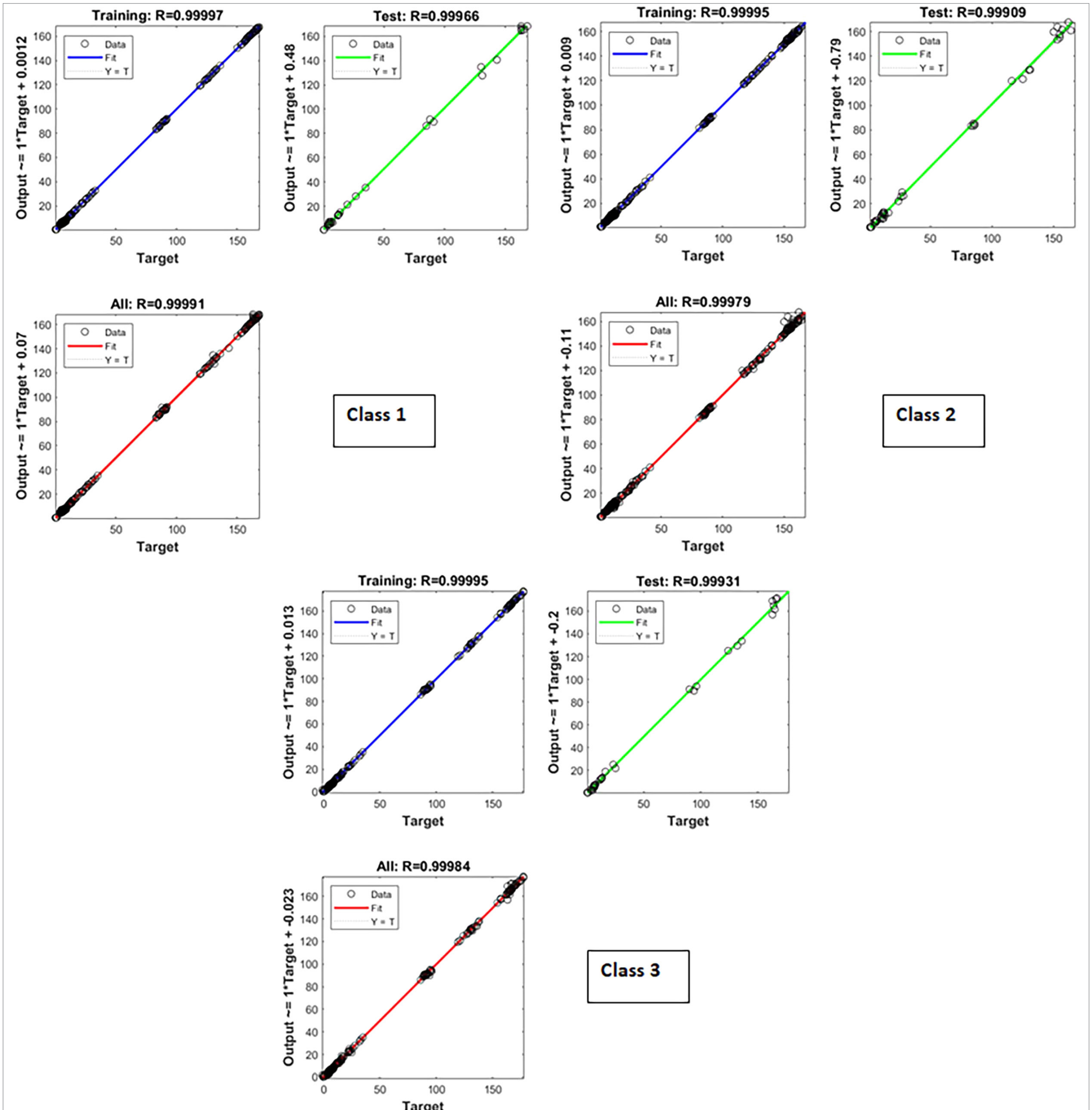

Figure 3. Scatterplots illustrating linear regression results between the cephalometric radiographic variables of the target and the actual output between different skeletal patterns during the training process

several soft tissue measurements (r = 0.80), on the other hand, Bittner and Pancherz[6] in 1990 reported moderate correlations regarding these variables (r = 0.63) and this may related to the different in thickness of soft tissue in different age groups.

Regarding Wits variable, the findings of this study showed that (r = 0.80, r = 0.86, r = 0.77 in Class I, II, III malocclusions, respectively) and this agreed with the results of previous studies,[15,16] which showed that Wits measurements of the soft tissue was significantly correlated to the conventional Wits (r = 0.77, r = 0.73) and this may related to the accurate determination of the occlusal plane by using fox bite.

On the other hand, FNB, N-ANS-Pog, and N-ANS-B variables showed a good correlation and their values between 0.75 and 0.85, and this may be related to the standardized position of the head for cephalometric and lateral photograph procedures.

Excellent correlation was found for vertical angular variables (0.90-0.95) this agreed with the results of previous studies.[6,24]

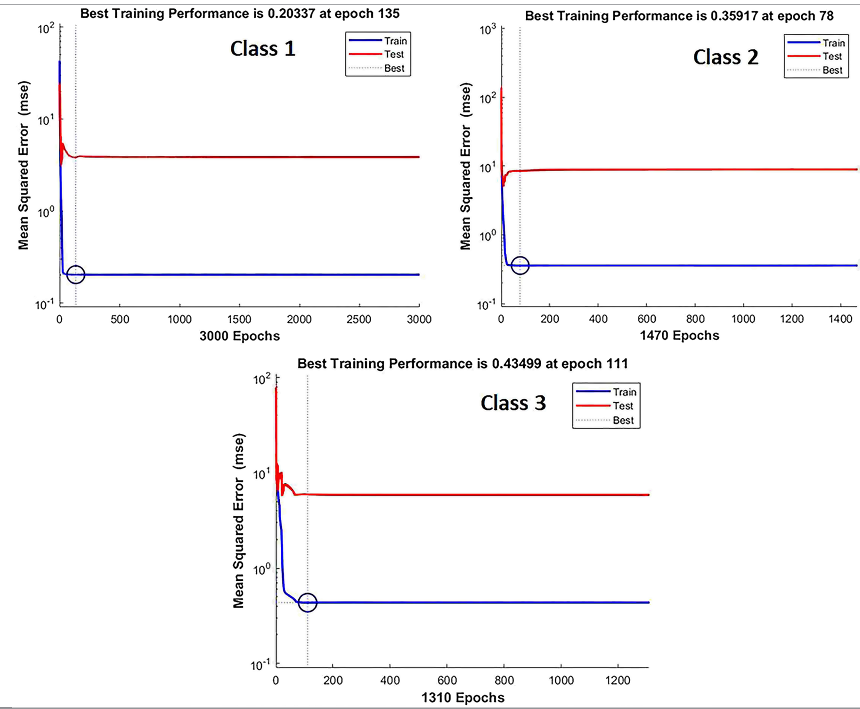

Figure 4. Best training performance for the network between the cephalometric radiographic variables of the target and the actual output for different skeletal patterns after designing the neural network during the training process

Other studies showed that the values of correlation ranged from 0.80 to 0.85.[15] Such difference might be related to individual variations in the inclination of the intracranial SN line.[25]

On comparing the vertical linear cephalometric and photographic variables for different skeletal malocclusion subjects, the results of this study showed that AFH, LAFH, and PFH have a good relationship with analogous photographic measurements. The comparison of these parameters was in conjunction with other studies.[15,24] This may be related to the low effect of magnification since these landmarks are located in midsagittal plane.

It cannot depend on the only photograph to represent the true measurement of cephalometric radiographs. A powerful prediction is essential to achieve a good correlation between cephalometric and photographic variables which can be obtained using ANNs.

Artificial neural networks represent great tools to match real targets by learning examples. These neural networks are able to find suitable information among initial data and establish a system for decision-making and results prediction. Such networks are made up of layers of neurons, typically an input layer, hidden or intermediate layers (one or more), and an output layer. These layers are fully connected to each other's. These layers are connected by synapses associated with numerical weightings. Repeated adjustments of these weightings are crucial steps for feed-forward back propagation networks until there is little difference between the real targets and the actual outputs in a training environment.[26]

No study regarding cephalometric variables predictions from lateral photographs between different skeletal patterns using ANNs was found in the literature review. Therefore, comparisons with similar studies in the literature are difficult to make. However, the present study showed another important application of ANNs in dentistry.

To verify the fitness of the model and to minimize overfitting, the samples were randomly divided into 70% of data for learning (PTrian = 0.7) and 30% for testing from the beginning in this study. In addition, the learning set was divided into the training set and the testing set and all set to make a generalized model. This has been described by Chang and Kim.[27]

A high degree of correlation between the real target and the actual output (R = 0.99) for each malocclusion was observed during the training and testing processes (Figures 3 and 5). The best training performance which means the least mean square error during the training process was 0.20 337 at epoch 135 for class I malocclusion, 0.35 917 at epoch 78, 0.43 499 at epoch 111 for class II and III malocclusion respectively (Figure 4), this makes this method very accurate for prediction of cephalometric variables as compared with other conventional methods.

This study provides models of regression that can estimate the cephalometric variables through analogous photographic measurements with a limited estimate error and a satisfactory predictive power. Further studies are recommended to evaluate the accuracy of such models.

The system constructed in this study showed high performance, however, some limitations should be mentioned. First, a large amount of data and good informatics skills were required during the training phase.[28] Secondly, frequent updating is required for models since they might change over time. Another relevant

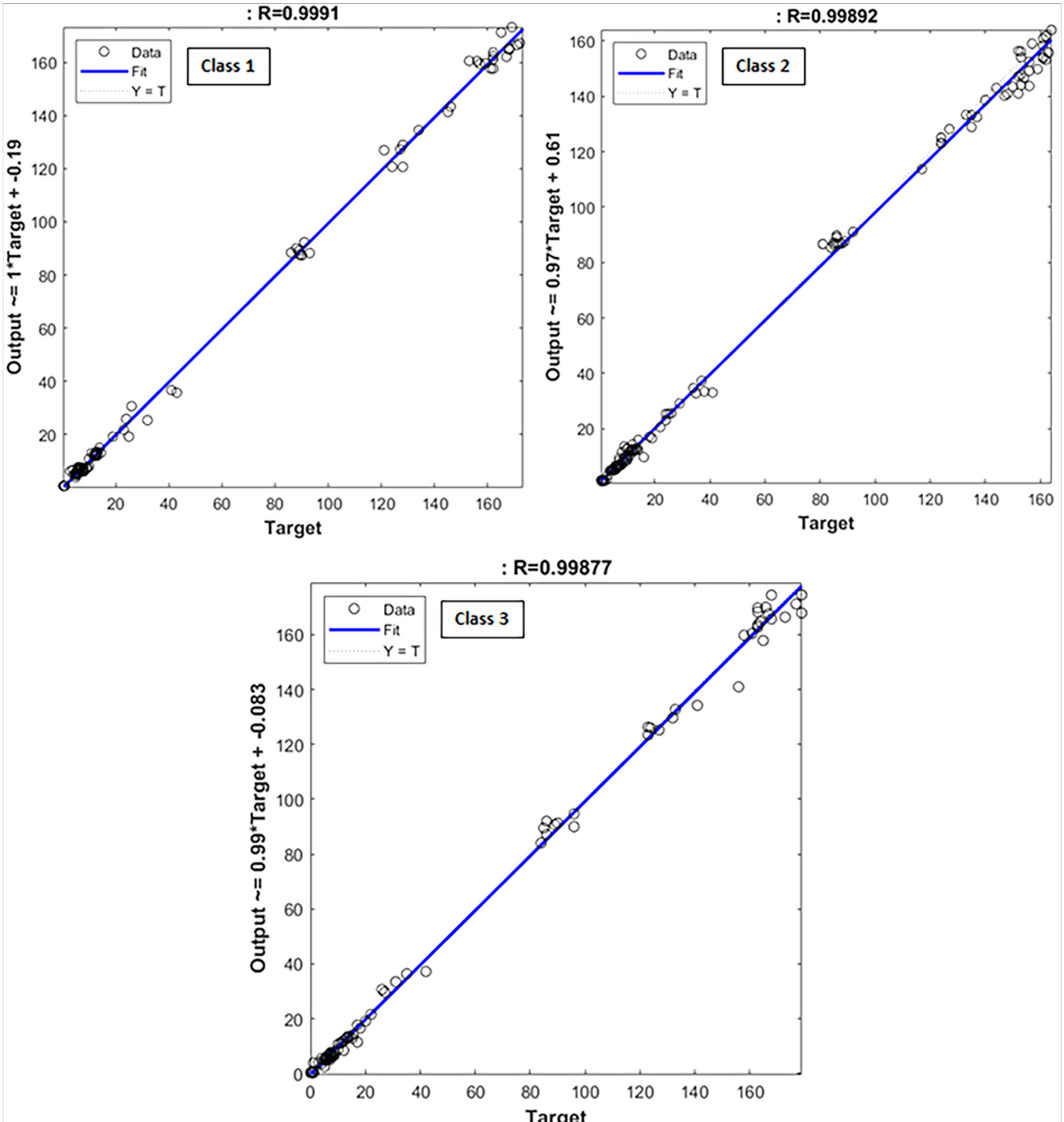

Figure 5. Scatterplot illustrating linear regression result between the cephalometric radiographic variables of the target and the actual output for different skeletal patterns after designing the neural network during the testing process

problem in their training is occurred when the algorithm is excessively custom-made to the training sample and it is called overfitting. Hence, it makes almost perfect predictions on it, but at the price of generalization, therefore its performance decreases on other populations. This issue can be solved by stopping the training when the error on the test set is at a minimum or subtle modifications to the training set.[29]

During the training, patterns that are not useful in real-life clinical practice might develop due to large amounts of low-quality data used and thus limiting the potential of classifiers.[27] Generating models separately for each skeletal pattern may limit the generalizability of the model, although there were successful results in all skeletal patterns, there may be a limitation to applying the test only to each skeletal pattern trained.

Table 3. Correlation Coefficients Between Cephalometric Radiographs and Photographic Variables

Measurement Parameters of Class I		**All subjects n = 30**		**Male subjects n = 14**		**Female subjects n = 16**	
Cephalometric radiographs	**Photographs**	**Correlation coefficient**	***p***	**Correlation coefficient**	***p***	**Correlation coefficient**	***p***
Sagittal assessment							
Wits	Wits'	0.80	0.001	0.78	0.002	0.74	0.003
ANB	A'N'B'	0.79	0.001	0.78	0.002	0.75	0.004
FNB	FNB'	0.80	0.001	0.84	0.001	0.81	0.001
N-ANS-Pog	N'-SN-Pog'	0.77	0.001	0.83	0.001	0.85	0.001
N-ANS-B	N'-Sn-B'	0.87	0.001	0.71	0.010	0.84	0.001
Vertical assessment							
Ar-Go-Me	Tr-Go'-Me'	0.94	0.001	0.91	0.001	0.93	0.001
FMA	FMA'	0.95	0.001	0.95	0.001	0.92	0.001
OPA	OPA'	0.96	0.001	0.95	0.001	0.95	0.001
LAFH	LAFH'	0.94	0.001	0.87	0.001	0.93	0.001
AFH	AFH'	0.94	0.001	0.92	0.001	0.93	0.001
LPFH	LPFH'	0.92	0.001	0.91	0.001	0.87	0.001
Measurement parameters of Class II		**All subjects n = 34**		**Male subjects n = 14**		**Female subjects n = 20**	
Cephalometric radiographs	**Photographs**	**Correlation coefficient**	***p***	**Correlation coefficient**	***p***	**Correlation coefficient**	***p***
Sagittal assessment							
Wits	Wits'	0.86	0.001	0.87	0.001	0.77	0.001
ANB	A'N'B'	0.79	0.001	0.77	0.001	0.73	0.001
FNB	FNB'	0.86	0.001	0.85	0.001	0.85	0.001
N-ANS-Pog	N'-SN-Pog'	0.79	0.001	0.79	0.001	0.79	0.001
N-ANS-B	N'-Sn-B'	0.79	0.001	0.81	0.001	0.76	0.001
Vertical assessment							
Ar-Go-Me	Tr-Go'-Me'	0.93	0.001	0.94	0.001	0.93	0.001
FMA	FMA'	0.93	0.001	0.92	0.001	0.91	0.001
OPA	OPA'	0.91	0.001	0.91	0.001	0.90	0.001
LAFH	LAFH'	0.91	0.001	0.89	0.001	0.90	0.001
AFH	AFH'	0.87	0.001	0.89	0.001	0.82	0.001
LPFH	LPFH'	0.89	0.001	0.84	0.003	0.90	0.001
Measurement parameters of Class III		**All subjects n = 30**		**Male subjects n = 13**		**Female subjects n = 17**	
Cephalometric radiographs	**Photographs**	**Correlation coefficient**	***p***	**Correlation coefficient**	***p***	**Correlation coefficient**	***p***
Sagittal assessment							
Wits	Wits'	0.77	0.001	0.82	0.001	0.79	0.006
ANB	A'N'B'	0.85	0.001	0.86	0.001	0.87	0.003
FNB	FNB'	0.92	0.001	0.98	0.001	0.85	0.001
N-ANS-Pog	N'-SN-Pog'	0.84	0.001	0.84	0.001	0.84	0.001
N-ANS-B	N'-Sn-B'	0.74	0.001	0.74	0.004	0.75	0.003
Vertical assessment							
Ar-Go-Me	Tr-Go'-Me'	0.94	0.001	0.92	0.001	0.93	0.001
FMA	FMA'	0.91	0.001	0.91	0.001	0.93	0.001
OPA	OPA'	0.92	0.001	0.93	0.001	0.91	0.001
LAFH	LAFH'	0.96	0.001	0.95	0.001	0.92	0.001
AFH	AFH'	0.95	0.001	0.94	0.001	0.93	0.001
LPFH	LPFH'	0.89	0.001	0.88	0.002	0.86	0.001

***Wits** measurements indicates maxillomandibular linear discrepancy; **ANB angle** indicates maxillomandibular angular discrepancy; **FNP angle** indicates facial angle; **N-ANS-Pog** and **N-ANS-B** angles indicate angles of facial convexity. Ar.Go.Me angle indicates gonial angle; **FMA angle** indicates Frankfurt to mandibular plane angle; **OPA angle** indicates Frankfurt to occlusal plane angle; **AFH** indicates anterior facial height (N-Me); **LAFH** indicates lower anterior facial **(ANS-Me)** height; and **LPFH** indicates lower posterior facial height (Ar-Go).

Wits', linear discrepancy of the soft tissue between maxilla and mandible; **A'N'B'**, angular discrepancy of the soft tissue between maxilla and mandible; **FNP'**, the soft-tissue facial angle; **N'-Sn-Pog'**; **N'-Sn-B'**, the soft tissue angles of the facial convexity. **Tr-Go'-Me'**, the soft tissue gonial angle; **FMA'**, soft tissue angle between Frankfurt and mandibular planes; **OPA'**, soft tissue angle between Frankfurt and occlusal planes; **AFH' (N'-Me')**, soft tissue anterior facial height; LAFH' (Sn-Me'), soft tissue lower anterior height of the face; **LPFH' (Tr-Go')**, lower posterior height of the face for the soft tissue; SD, standard deviation; Min, minimum; Max, maximum.

Despite these limitations, the results of the present study confirmed that ANNs are able to predict cephalometric variables to a clinically excellent level.

CONCLUSION

As a result of designing models for the prediction of cephalometric variables via lateral photographs between different skeletal patterns with neural network machine learning, the results of this study suggest that ANNs could be a new and alternative approach for the cephalometric radiographs for measuring angular and linear variables.

In the near future, the increasing use of ANNs in orthodontic daily practice will probably continue. After adequate validation, these could potentially facilitate daily workflow, patient satisfaction, and correct interpretation of findings, leading to accurate safe method to improve patient outcomes without any radiation risk.

Ethics Committee Approval: This study was approved by the Human Research Ethics Committee of College of Dentistry/Baghdad University (Iraq), (Approval No:168/2019).

Informed Consent: Written informed consent was obtained from the patients who agreed to take part in the study.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept - S.M.A., H.F.S., M.A.T.; Design - S.M.A., H.F.S., M.A.T.; Supervision - H.F.S., M.A.T.; Materials - S.M.A.; Data Collection and/or Processing - S.M.A.; Analysis and/or Interpretation - S.M.A.; Literature Review - S.M.A.; Writing - S.M.A.; Critical Review - H.F.S., M.A.T.

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