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Gender Classification with Hand-Wrist Radiographs Using the Deep Learning Method

Derin Öğrenme Yöntemi Kullanılarak El-Bilek Radyografileri ile Cinsiyet Sınıflandırma

Özkan MİLOĞLU[1]
[1] Atatürk University. Faculty of Dentistry, Department of Oral, Dental and Maxillofacial Radiology, Erzurum, Türkiye

Nida KUMBASAR[2]
[2]TUBITAK, Informatics and Information Security Research Center (BILGEM), Kocaeli, Türkiye

Zeynep TURANLI TOSUN[3]
[3] Atatürk University, Faculty of Dentistry, Department of Oral, Dental and Maxillofacial Radiology, Erzurum, Türkiye

Mustafa Taha GÜLLER[3]
[3] Giresun University, Faculty of Dentistry, Department of Oral, Dental and Maxillofacial Radiology, Giresun, Türkiye

İbrahim Yücel ÖZBEK[4]
[4] Atatürk University, Department of Electrical Electronic Engineering (High Performance Comp Applicat & Res Ctr), Erzurum, Türkiye

ABSTRACT

Objective: Before dental procedures, hand-wrist radiographs are used to plan treatment time and determine skeletal maturity. This study aims to determine gender from hand-wrist radiographs using different deep-learning methods.
Methods: The left hand-wrist radiographs of 1044 individuals (534 males and 510 females) were pre-processed to clarify the image and adjust the contrast. In the gender classification problem, AlexNet, VGG16 and VGG19 transfer learning methods were both used as separate classifiers, and the features taken from these methods were combined and given to the support vector machine (SVM) classifier.
Results: The results revealed that image analysis and deep learning techniques provided 91.1% accuracy in gender determination.
Conclusion: Hand-wrist radiographs exhibited sexual dimorphism and could be used in gender prediction.
Keywords: Deep learning; İmage analysis; Hand-wrist radiographs; Gender determination

ÖZ
Amaç: Dental işlemler öncesinde tedavi zamanının planlanması ve iskeletsel olgunluğun saptanması amacıyla el-bilek radyografilerinden yararlanılır. Bu çalışmanın amacı, farklı derin öğrenme yöntemleri kullanılarak el-bilek grafilerinden cinsiyet tayini yapmaktır.
Yöntemler: Bu amaçla 1044 bireye ait (534 erkek ve 510 kadın) sol el-bilek radyografisi görüntüyü netleştirme ve kontrastı ayarlama amacıyla ön işleme tabi tutuldu. Cinsiyet sınıflandırma probleminde AlexNet, VGG16 ve VGG19 transfer öğrenme metotları hem ayrı ayrı sınıflandırıcı olarak kullanıldı, hem de bu yöntemlerden alınan öznitelikler birleştirilerek SVM sınıflandırıcısına verildi.
Bulgular: Sonuçlar, görüntü analizi ve derin öğrenme tekniklerinin cinsiyet tayininde %91,1 oranında doğruluk gösterdiğini ortaya koydu.
Sonuç: Yapılan bu çalışmada el-bilek grafilerin cinsel dimorfizm sergilediği ve cinsiyet tahmininde kullanılabilirliği belirlendi.
Anahtar Kelimeler: derin öğrenme; görüntü analizi; el-bilek radyografileri; cinsiyet tayini

INTRODUCTION

The determination of gender by skeletal structures is a fundamental step in estimating an individual's profile and determining its identity.[1] Many parts of the skeleton are used for gender analysis and some discriminative techniques are developed. There are studies in the literature to predict gender from vertebrae, skull, pelvis, and long bones. Among these, the highest accuracy rate for gender determination was obtained with the cranium and pelvis. In the studies conducted on these skeletal structures, gender differences have been revealed through linear and angular measurements.[2]

Knowing the differences between genders has considerable importance in anthropometry, forensic anthropology, and forensic medicine. Gender differences also have profound effects on human skeletal features and dimensions.[3] Differences in the shape, size, and appearance of bones by gender occur in response to sex hormones during the development and puberty. Bone maturation is closely related to sexual development. Determining individuals' skeletal maturity shows their biological development more accurately than their chronological ages. For this purpose, hand and wrist radiographs taken before dental treatments are the most common method used to determine skeletal maturity, timing and planning of the treatment. However, hand-wrist radiographs taken by radiologists are based on interpreting the patient's bone age, and gender-specific parameters cannot be determined with these radiographs. In the relevant

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Sorumlu Yazar/Corresponding author: Özkan Miloğlu
E-mail: omiloglu@hotmail.com

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studies, there is no conventional technique to determine gender using hand-wrist radiographs. Skeletal maturity and its relationship with gender are examined using a representative atlas using the Greulich-Pyle method.[4] However, this method is time-dependent and an expert radiologist is needed to evaluate bone age and gender in detail using the hand atlas as a reference. For this reason, the results may vary depending on the experts making the evaluation. However, using the deep learning method with a considerable number of data appears to be a technique that experts consider difficult to achieve gender classification.[5] In our study, the only images fed to the artificial neural network are left hand wrist X-rays. The effectiveness of the neural network in predicting gender without any instructions or pre-existing knowledge regarding gender dimorphic anatomy is aimed. In traditional methods, the first pre-processing is performed on left hand-wrist x-ray images. These images are determined by taking into account various conditions such as the length of the bones, their distance from each other, and the number of bones found. Gender classification is realized. error rates are compared by expert radiologists. Therefore, new methods are needed that will reduce the subjectivity of the observer and provide measurable tools to assist the expert in the decision-making process. Model running in deep learning methods; Features: Since it is achieved by self-learning in a short time with minimum training, more effective results are obtained and the need for an expert is reduced.[6,7]
The application of deep learning methodologies is of great importance in modern dentistry. These methodologies can provide effective, accurate, and reliable tools for interpretation. As a result, they facilitate early diagnosis, planning, and monitoring of patient outcomes. In addition, these automatic systems can significantly reduce the workload of dental professionals, reduce the risk of human error, and increase the efficiency of dental health services.[8] In this study, a deep learning method was developed that analyzes the hand-wrist radiographs of 1044 individuals between the ages of 5-18 and can predict their genders.

METHODS

Data Set

The Atatürk University Faculty of Dentistry's Research Ethics Committee accepted the study, and all procedures were followed in accordance with the Declaration of Helsinki's principles (Decision No. 04/20.01.2021).

In this study, hand-wrist radiographs that are routinely taken from patients for diagnosis and treatment planning before orthodontic treatment, available in the archives of Atatürk University, Faculty of Dentistry, Department of Oral and Maxillofacial Radiology, were retrospectively evaluated. Patients who did not have any known systemic disease, anomaly, or syndrome, had no malformation, pathology, or trauma history in the hand-wrist region, and had no artifacts or distortions in the relevant radiographs were included in the study. The data set of the study consists of left hand-wrist radiographs of 1044 individuals (534 males and 510 females) between the ages of 5-18 (Figure 1).

Method

Within the scope of the study, a gender classification was performed using artificial intelligence-based techniques on 1044 hand-wrist radiographs. In this study, two approaches were examined in terms of both data and method.

In the first category of the data, while the radiographs were classified with their original versions without any pre-processing, the second category was based on cropping only the hand-wrist part of the images and enhancing them with the contrast limited adaptive histogram equalization (CLAHE) technique,[9-11] which provides positive enhancement in these images. While the purpose of cropping the image is to prevent artificial intelligence models from focusing on unnecessary areas, the purpose of histogram equalization is to increase the differentiation in gray-level radiographs (Figure 2).

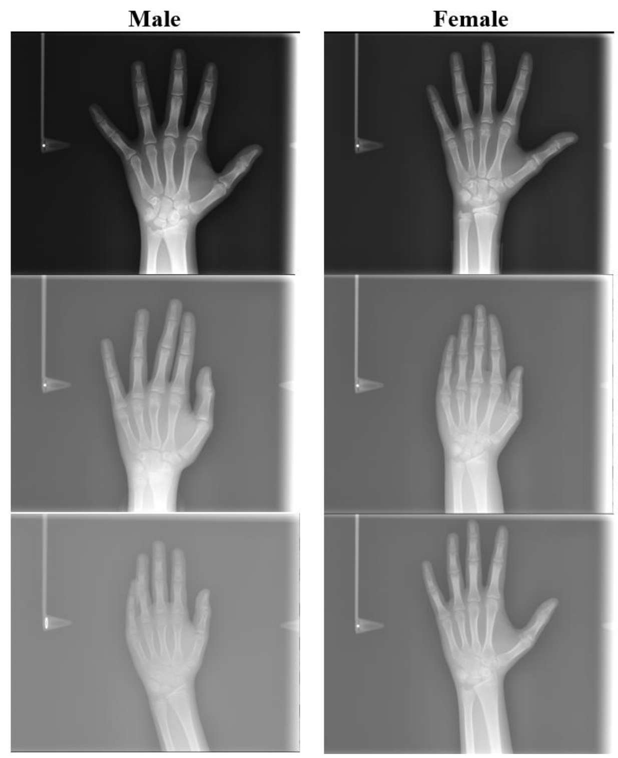

Figure 1. Sample images of the data set

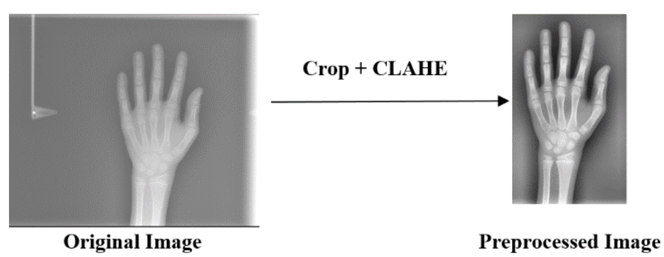

Figure 2. Preprocessing

On the basis of the method, in the first place, classification was realized with the transfer learning approach using AlexNet,[12] VGG16,[13] and VGG19,[13] which are popular CNN (Convolutional Neural Network) - based deep learning models with high performance in classification. In the second stage, AlexNet, VGG16, VGG19 models were used as feature extractors and the CNN+SVM (Support Vector Machine) hybrid method was proposed by giving these features to the SVM classifier[14] (Figure 3).

With the AlexNet network they designed, Alex Krizhevesky and others[12] won the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) competition in 2012, which involved a challenging visual object recognition task. The architecture they proposed was a significant breakthrough in the field of computer vision and rapidly increased interest in deep learning. AlexNet's Input image resolution is 227x227x3 pixels and has 11 main layers consisting of 5 convolutional, 3 pooling and 3 fully connected layers.

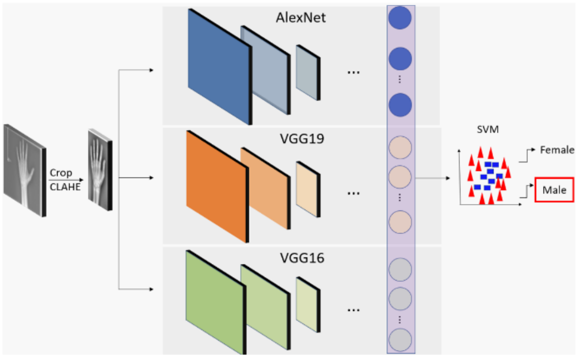

Figure 3. Proposed CNN+SVM hybrid method

The Visual Geometry Group (VGG), which graduated at ILSVRC in 2014, described the depth of a network as the critical component to achieve satisfactory classification performance.[13] The input image resolution of VGG16 and VGG19 is 224×224x3 pixels. VGG16; It consists of 21 main layers, including 13 convolutional, 5 pooling and 3 fully connected layers, while the VGG19 architecture has a total of 24 main layers, including 16 convolutional, 5 pooling and 3 fully connected layers. While training AlexNet, VGG16 and VGG19 models, the number of epochs was 50, batch size was 16, learning rate was 10^{-4} and stochastic gradient descent (SGD) was preferred as the optimization algorithm. No data augmentation technique was used

From CNN networks, 50 features were extracted for three models from the fully connected layer before the classifier layer. Finally, the new feature matrix of 1044x150 was fed to the SVM classifier as the input. SVM is a supervised learning method often used in classification problems. It draws a line to separate points placed on a plane. This line is intended to be the maximum distance for points of both classes.

A large number of interconnected experiments were performed with the setups in which the parameters changed in SVM. In the proposed CNN+SVM hybrid model, the highest performance is observed when the C (box constrait) parameter is 4 and the kernel scale is 256 in the linear kernel function.

All the experiments were carried out with the k-fold cross-validation approach by selecting the k parameter as 10 to better evaluate the model performance.[15] With this approach, the data set is divided into 10 parts and these parts are repeated 10 times. In each iteration, 9 parts are used for training and 1 part is used for testing. Final performance is found by averaging over 10 test pieces (Figure 4).

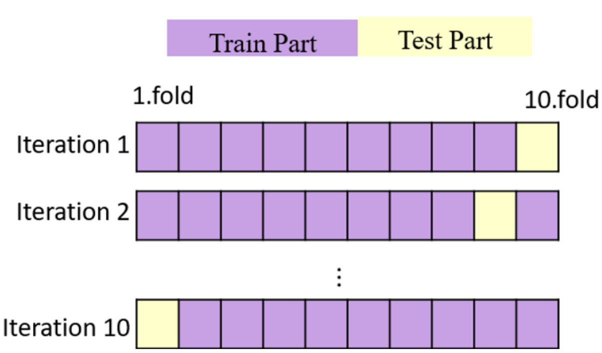

Figure 4. 10-fold cross-validation

Performance Metrics

The performance of the experimental studies was measured through accuracy, precision, recall, and F1 score metrics, which are frequently used in classification problems (Equation 1, Equation 2, Equation 3, Equation 4).[15] The parameters in the equations are shown on the representative confusion matrix (Figure 5).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad \text{Equation 1}$$

$$Precision = \frac{TP}{TP + FP} \quad \text{Equation 2}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{Equation 3}$$

$$F1\ score = 2 * \frac{precision * recall}{precision + recall} \quad \text{Equation 4}$$

		Positive	Negative
Output Class	**Positive**	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)
		Target Class	

Figure 5. Abbreviations in performance metrics on the confusion matrix

In Figure 5, TP indicates that both the actual value and the predicted value are positive (i.e. female if the gender is female, male if the gender is male), FP indicates that the actual value is negative and the predicted value is positive - FN indicates that the actual value is positive and the predicted value is negative (i.e. the label that is actually female is predicted to be male or label that is male is predicted to be female), TN indicates that both are negative (label that is not female is found to be non-female, label that is not male is found to be non-male). TP and TN are the areas that the model predicts correctly, while FP and FN are the areas that the model predicts incorrectly.

Accuracy value is calculated by the ratio of the areas we predicted correctly in the model to the total data set. Accuracy is a metric that is frequently used to measure the success of a model, but is not sufficient on its own. Precision is a measure of how many of the values predicted as positive are actually predicted as positive. Recall shows how many of the labels that should have been predicted as positive were predicted as positive. F1 Score value indicates the harmonic average of precision and recall values.

RESULTS

It was seen that hand-wrist radiographs exhibited sexual dimorphism and could be used in gender estimation.

While the achievement of artificial intelligence-based gender classification in left-hand-wrist radiographs was 54.58%, 58.14%, 55.37% and 51.1% for AlexNet, VGG16, VGG19 and hybrid models, respectively, without image enhancement, the classification success on the pre-processed data was 85.6%, 88.48%, 87.8%, and 91.1% for AlexNet, VGG16, VGG19, and the proposed hybrid model, respectively.

When the results of the original image and the preprocessed image were examined on the models, it was seen that the preprocessing made significant enhancement (30%-40%) (Figure 6). If the models alone showed high success in the classification process, as in the preprocessed image, the hybrid model approach would have positively contributed to the performance. In the original image, it was seen that since the models could not adequately learn alone, using them together reduced the performance. The hybrid method was compared with the CNN-based transfer learning methods encompassing AlexNet, VGG16, and VGG19 in terms of different performance metrics such as accuracy, precision, recall, and F1 score (Figure 7). The confusion matrix for the CNN+SVM hybrid model based on the pre-processed image proposed within the scope of this study is shown in Figure 8.

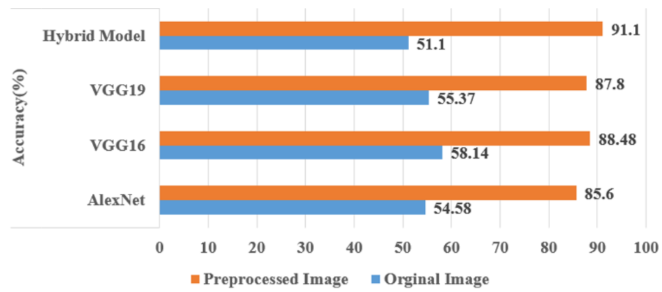

Figure 6: Preprocessing evaluation chart

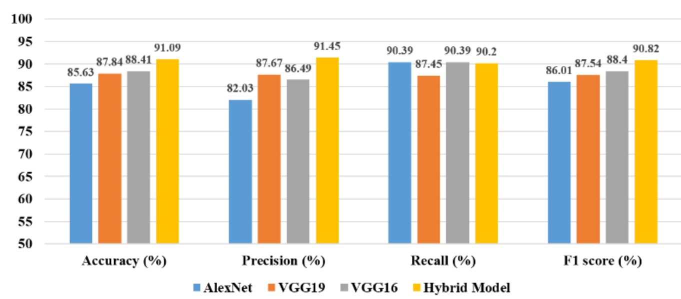

Figure 7. Comparison of preprocessed images and models through different performance metrics

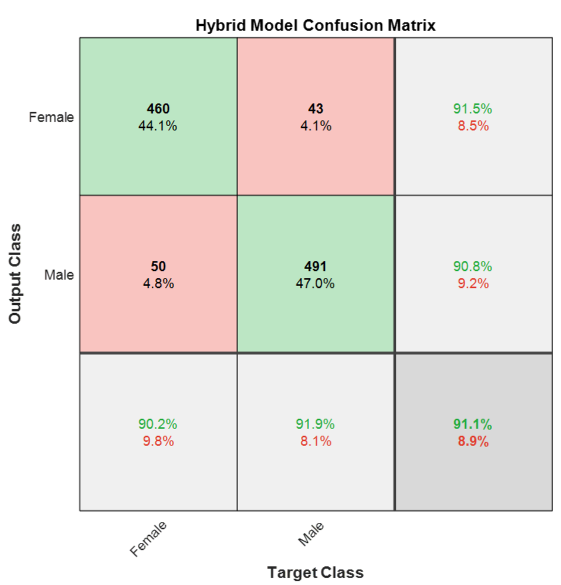

Figure 8. Hybrid model gender classification confusion matrix

DISCUSSION

The adequate enamel-bracket bonding strength is one of the This study showed that it is possible to predict gender by developing a deep learning method that can accurately and repetitively identify gender through hand-wrist radiographs. In the studies examining the relationship between skeletal structures and gender, it has been argued that there are morphological differences between different genders and that this varies depending on age. Male bones are morphologically larger and denser than females. Cortical bone loss in males due to aging is less than in females. The skeletal differences between genders are assumed to occur mostly during adolescence.[16]

In the studies using advanced imaging methods, some automatic gender estimation methods have been developed in adults through primarily pelvis imaging and the three-dimensional imaging of the skull as the second reliable method.[17,18] Thomas Radulesco et al.[19] used 103 CT images to investigate how to determine the gender of individuals by Maxillary Sinus Volumes (MSV). They identified MSV with 3D reconstructions. According to their results, they suggested that MSV could be useful in determining the gender of individuals.

Automatic methods are also being developed for the evaluation of hand-wrist radiographs, which reduce inter-rater variability compared to manual methods. However, the high dose of radiation and cost in these methods restrict the use of computed tomography in gender determination. In addition, researchers performing gender determination using radiographic methods have certain disadvantages such as subjective perception and low repeatability in visual evaluation of the morphological features. Research has shown that the most significant gender difference in the skeletal structure of the hand and wrist is the difference in the size and volume of the bones. In particular, it has been revealed that the size of the carpal bones in males is larger than in females.[20] In another study, digital right-hand radiographs were examined using these skeletal differences, and a 91% accuracy in gender determination was obtained.[21] Ibrahim et al.[22] researched the length and width of the hands of 600 people. They also investigated the relationship between the index and ring fingers. In their results, they claimed that the ratio of index and ring fingers was higher in women than in men.

Aboul Hagag et al.[23] among the Egyptians, he determined gender by calculating hand size, index finger and ring finger ratio. The dataset consisted of 250 men and 250 women. All subjects were adults over the age of 18. In their results, they claimed that the average male hand is 1.3 cm larger than women's.

There are no parameters in the literature that can reliably classify gender. Better-performing models have been recently obtained by combining the powers of CNN-based deep learning approaches at various stages for classification problems.[24-26] In this study, after the image enhancement with the CLAHE approach by cropping the left hand-wrist images, three separate deep learning methods (AlexNet-VGG16-VGG19) were trained using transfer learning, then taking the features from the fully connected layer, their powers were combined with the early fusion approach, and the features were classified with SVM. In light of the results obtained, it was seen that pre-processing and CNN+SVM hybrid models provided higher performance for gender classification than the classification performance of the models alone.

In 2019, Sarić and his colleagues[27]evaluated gender and bone age using the Deep Convolutional Neural Network (DCNN) algorithm. As a result, it was observed that the results were faster than classical methods.

Bewes et al.[28] investigated gender prediction from adult skeletal remains by training a deep convolutional neural network with images of

900 skulls obtained from computed tomography scans. When tested on previously unseen images, the deep network showed 95% accuracy. Yang et al.[29] use a six-variable method consisting of multilayer sensors to estimate gender from cranial measurement. They tested their approach on 267 skull ct scans (153 women and 114 men) from the Uyghur ethnic group in Northern China (women aged 18-88 and men aged 20-84). An accuracy of over 94% was reported in all cases.

Afifi[30] used CNN to determine the gender of individuals through biometric features on the hands. They used palms and back images of hands on both sides. They claimed that good accuracy was achieved not only on the palm but also on the back of the hand.

Darmawan et al.[31] used a Hybrid Particle Artificial Neural Network technique to determine the gender of individuals, which is the most relevant study to our research. They used left hand X-RAY images of the Asian population as a dataset. Their results show different accuracy for different age groups. The datasets were small and they did not mention the area they paid attention to in their work. A limitation of this study is that only left-hand radiographs were included. Although this study focused on the ability of a deep learning model to discover an unidentified pattern, including only left-hand images may limit the use of the model in clinical practices and other research studies. Although it is a standard procedure to use the left hand for bone age assessment, some studies argue that sex differences in finger ratio are more profound in the right hand. Further studies involving the right hand for testing and development can create a more comprehensive model to be clinically used.[11]

Another limitation of the study is the manual cropping of the region containing the hand and wrist from the original image. Within the scope of future studies, using cropped images by automatically segmenting the hand-wrist region with deep learning methods in the pre-processing stage is aimed to perform. At the output of high-performance segmentation models for cropping, the data will be subjected to the CLAHE procedure and the gender determination from the hand-wrist radiographs will be implemented with the end-to-end artificial intelligence.

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Hakem Değerlendirmesi: Dış bağımsız.
Yazar Katkıları: Fikir – – İ.Y.Ö., Ö.M.; Tasarım – İ.Y.Ö., N.K.; Denetleme – Ö.M..; Kaynaklar – Ö.M., Malzemeler – M.T.G.,Z.T.T.; Veri Toplanması ve/veya İşlemesi – M.T.G.,Z.T.T., N.K.; Analiz ve/veya Yorum – İ.Y.Ö., N.K.; Literatür Taraması – Ö.M.; Makaleyi Yazan – Ö.M., N.K.; Eleştirel İnceleme – İ.Y.Ö..
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Informed Consent: Written consent was obtained from all participants who participated in this study.
Peer-review: Externally peer-reviewed.
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